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Transmission Expansion Planning

A multiyear approach considering uncertainties

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vf

We are what we share.

Charles Leadbeater, often cited by

Diogo Vasconcelos

Prediction is difficult, especially of the future.

Niels Bohr

The scientist does not study nature because it is useful; he studies it because he delights in it, and he delights in it because it is beautiful. If nature were not beautiful, it would not be worth knowing, and if nature was not worth knowing, life would not be worth living.

Henri Poincaré

ABSTRACT

Power network activities, both in transmission and distribution, have been object of substantial changes and are now provided in Europe in terms of regulated concessions. The integration of large amounts of generation assets using volatile primary sources, as wind, is also placing new challenges to transmission planning. Another major challenge is related with the advent of micro-generation devices that are being connected to low voltage networks. The increasing uncertainty on generation and on loads requires the improvement of the sustainability and robustness of the network, which determines the need for new models and applications in several areas, namely in the Transmission Expansion Planning (TEP). In view of these aspects we are certainly facing a new paradigm on the network expansion studies.

A TEP model aims at determining the timing, the type and the location of the new transmission facilities that should be added to an existing network in order to ensure an adequate transmission capacity taking into account future generation options and load requirements. TEP modelling is of great importance, since it is invariably associated with high investment, the licensing procedures are increasingly complex, and investments have great impact on the economy, not only due to its own cost, but also because of the energy tariffs, which are regulated, and the economic implications and constraints associated with the quality of energy. TEP models are usually very complex. This complexity is due largely to non linear large models, with a significant computational burden.

This thesis focuses on a real dynamic TEP model, since it considers the influence of the branches selected to be installed in the previous periods over the following ones. It meets technical, financial and quality of service constraints, as well as the uncertainty in loads, which are modeled with fuzzy numbers. The dynamic TEP model we propose is based on DEPSO, a discrete evolutionary particle swarm heuristic, a new approach proposed also in this thesis, supported by chaotic mutation, which allows the scheduling of projects in an efficient and accurate way.

The model was tested in well known networks, and proved to be accurate, converging to the expected solutions. In addition, it was observed that it needed fewer iterations and less time to converge, when compared with other methods. It is therefore a model with development potential, which can be applied to real networks.

RESUMO

As operações de transmissão e distribuição de energia elétrica têm sido objeto de grandes alterações no passado recente, sendo atualmente na Europa objeto de concessões reguladas. A integração na rede de centrais de produção de energia elétrica a partir de fontes renováveis, como o vento, constitui-se também como um novo desafio no planeamento da transmissão. Outro desafio a ter em conta está relacionado com o advento dos sistemas de micro geração que são ligados em quantidades crescentes a redes de baixa tensão. O aumento da incerteza ao nível da geração e das cargas requer a melhoria da sustentabilidade e robustez das redes, que determina a necessidade de novos modelos e aplicações em várias áreas, nomeadamente no planeamento de redes de transmissão (TEP). Atendendo a todos estes aspetos, poderemos concluir que estamos perante um novo paradigma nos estudos do planeamento de expansão das redes elétricas.

Um modelo TEP tem por objetivo a definição do momento, do tipo e da localização de novas infra-estruturas a incluir na rede de transmissão existente, para assegurar uma capacidade de transmissão adequada, tendo em conta as opções futuras em termos de geração e a evolução previsível das cargas. A importância desta modelização é de especial relevo se atendermos ao facto de estar invariavelmente associada a grandes investimentos, a processos de licenciamento cada vez mais complexos e a investimentos com enorme impacto na economia, não só devido ao seu custo, mas também pelo seu impacto nas tarifas, que são reguladas, e na qualidade da energia oferecida, esta também com repercussões económicas. Os modelos TEP são normalmente muito complexos. Esta complexidade decorre do facto de serem modelos não lineares de grande dimensão, com elevada exigência em termos computacionais.

Esta tese está focalizada num verdadeiro modelo TEP dinâmico, uma vez que considera a influência dos ramos instalados nos períodos anteriores sobre o desempenho da rede nos que se seguem. Acomoda restrições técnicas, financeiras e de qualidade de serviço, bem assim como a incerteza nas cargas, que é modelizada por recurso a *fuzzy numbers*. O modelo que propomos é baseado na heurística DEPSO, *Discrete Evolutionary Particle Swarm Optimization*, uma nova abordagem que aqui apresentamos, suportada por mutações caóticas, e que permite a calendarização de projetos de forma eficiente e precisa.

O modelo foi testado por recurso a redes muito conhecidas em estudos de planeamento de redes, e verificou-se que era preciso, uma vez que convergiu para as soluções esperadas. Verificou-se ainda que a convergência é conseguida em menos iterações e em menos tempo, quando comparado com outros modelos. É, por isso, um modelo com grande potencial de desenvolvimento, susceptível de ser aplicado a redes reais.

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LIST OF ACRONYMS

AC	Alternating Current
ACO	Ant Colony Optimization
AI	Artificial Intelligence
AIS	Artificial Immune System
CHA	Constructive Heuristic Algorithms
CoS/RoR	Cost of Service / Rate of Return
CPSO	Chaotic Particle Swarm Optimization
DC	Direct Current
DC OPF	Direct Current Optimum Power Flow
DE	Differential Evolution
DESPO	Discrete Evolutionary Particle Swarm Optimization
DGE	<i>Direcção Geral de Energia - Portugal</i>
EA	Evolutionary Algorithm
EC	Evolutionary Computation
EDP	<i>Electricidade de Portugal</i>
EDM	<i>Electricidade de Moçambique</i>
EENS	Expected Energy Not Supplied
EHV	Extra High Voltage
EEM	European Energy Markets
ENS	Energy Not Supplied
EP	Evolutionary Programming
EPSO	Evolutionary Particle Swarm Optimization
ERSE	Entidade Reguladora dos Serviços Energéticos

ES	Expert System
ES	Evolution Strategies
EU	European Union
FACTS	Flexible Alternating Current Transmission Systems
FS	Fuzzy Set
GA	Genetic Algorithms
GHG	Green House Gases
GIS	Gas Insulated Switchgear
GRASP	Greedy Randomized Adaptative Search Procedures
GTU	Generalized Theory of Uncertainty
GWP	Global Warming Potential
HC	Hill Climbing
HV	High Voltage
IEEE	Institute of Electrical and Electronic Engineers
IFAC	International Federation of Automatic Control
JPSO	Jumping Particle Swarm Optimization
LTMP	Long Term Marginal Prices
LV	Low Voltage
MA	Memetic Algorithms
MV	Medium Voltage
NH 1	Hierarchical level 1(topology of the transmission system)
NH 2	Hierarchical level 2 (local nature topology)
NR	Network Retailing
OECD	Organisation for Economic Co-operation and Development
OMEL	Market Operator of the Spanish Electricity Market (before 2007)

OMI	Iberian Market Operator, <i>Operador de Mercado Ibérico</i>
OMIE	Iberian Market Operator, Spanish Pole
OMIP	Iberian Market Operator, Portuguese Pole
OPF	Optimum Power Flow
OTC	Over The Counter
PB	Population Based
PDFs	Probability Density Functions
PDSSE	Doctoral Program in Sustainable Energy Systems
PNS	Power Not Supplied
PPDA	<i>Planos de Promoção do Desempenho Ambiental</i>
PSCC	Power Systems Computation Conference
PSO	Particle Swarm Optimization
RARI	<i>Regulamento de Acesso às Redes e às Interligações (ERSE)</i>
REE	<i>Red Eléctrica de España</i>
REN	<i>Redes Energéticas Nacionais</i>
RNT	<i>Rede Nacional de Transporte</i>
RQS	<i>Regulamento de Qualidade de Serviço</i>
RR	Regulated Retailing
RTS	Reliability Test System
SA	Simulated Annealing
SEP	<i>Sistema Eléctrico de Serviço Público</i>
SFE	Supply Function Equilibrium Approach
SI	Swarm Intelligence
STMP	Short Term Marginal Prices
SVC	Static Var Compensator

TEP	Transmission Expansion Planning
TGUS	Tariffs for the Global Use of the System
TIC	Transmission Investment Costs
TOC	Transmission Operating Costs
TS	Tabu Search
TSO	Transmission System Operator
TUDN	Tariffs for the Use of Distribution Networks
TUTN	Tariffs for the Use of Transmission Networks
UIC	Unit Interruption Cost
UN	Unascertained Numbers
UPB	Unit Postponement Benefit
VAR	Volt-Ampere Reactive

NOMENCLATURE

X^{it}	population in iteration it , including n_{pt} particles;
X_{pt}^{it}	particle pt in iteration it , including j projects taken from a specified list;
$X_{pt,j}^{it}$	integer variable with the value 0 if project j is not selected, with the value p if the project is selected to be commissioned in period p and with value $np+1$ if the project is delayed beyond the last period in the horizon;
$K_{pt,j}^{it,p}$	flag for iteration it , particle pt , and project j , taking the value 1 when $X_{pt,j}^{it} = p$
n_{pt}	number of particles in the population;
n_{pj}	number of projects in each particle;
np	number of periods in the planning horizon;
$niter$	maximum number of iterations;
pt	particle index
it	iteration counter;
V_{pt}^{it}	velocity vector of particle pt in iteration it ;
b_{pt}	best solution found for particle pt in previous iterations;
b_G^*	best global: best overall solution ever found by the swarm in its past life, that is in all iterations; The symbol $*$ means that the variable undergoes mutation
$w_{pt,j,t}^{it*}$	weights conditioning the mutation of particle pt in iteration it ; $t = 1$: inertia; $t = 2$: memory; $t = 3$: cooperation;
w_4^{it*}	weights conditioning the mutation of the best global particle in iteration it ;
p	communication factor;
k_a	constant used on the Lamarckian evolutionary process, set to np ;

k_b	constant controlling the mutation of the particles on the Lamarckian evolutionary process, $k_b \in [0,1]$;
k_c	constant controlling the mutation of the best global particle, $k_c \in [0,1]$;
IC_j	investment cost of project j, (€);
ir, if	interest and inflation rates;
$max\ prj$	maximum number of projects admitted per period;
OC_{pt}	operational cost associated to particle pt;
α_y	penalty factors assigned to the evaluation function of a particle;
c_k	generation cost;
Pg_k, Pl_k	generation and load at node k;
G	penalty assigned to PNS in DC OPF studies;
a_{bk}	sensitivity coefficient relating the active flow in branch b with the injected power in node k;
Pg_k^{min}, Pg_k^{max}	minimum and maximum generation in node k;
P_b^{min}, P_b^{max}	minimum and maximum flows in branch b;
$PNS(n)_p$ and $PNS(n-1)_p$	power not supplied in period p, for the intact system, when all components are available, and for contingencies of type n-1.

1. INTRODUCTION

How to identify the most appropriate time schedule for the transmission expansion projects along the planning horizon?

1.1. THE NEW ENERGY PARADIGM

We live at a time when Energy and Sustainability are on the agenda of policy makers and the general public. In a recent survey of trends promoted by Pedro Barbosa, which resulted in the book "Speculations & Trends, Trends 2010-2012," the author made an inquiry involving 712 people around the world. Power has been the trend indicated by the majority of respondents, reaching a share of 65%, and was top of mind (first enunciated trend) in 45%. It is well recognized as the most influential in the coming years¹. This priority is understood, because energy conditions in a decisive way, not only the economy and politics, but also sustainability (Barbosa, 2009). The trends associated with sustainability are top of mind, as they were identified as the fifth most important family of trends. This theme comes to stay, closely related to the trend leader, energy. More than a fad, it is a new form of environmental awareness, gaining ground on other interests.

Electrical power network activities, both in transmission and distribution, have been object of substantial changes and are now provided in terms of regulated concessions. The companies provide transmission services according to public obligations related with the free and transparent access to the networks while complying with quality and security of service indices. The integration of large amounts of generation assets using volatile primary sources, as wind, is placing new challenges to transmission planning. Wind parks were originally connected to distribution networks but, as the installed capacity started to increase, it is getting more common to connect wind parks directly to transmission substations.



FIGURE 1-1 VISION AND STRATEGY FOR FUTURE EUROPE'S ELECTRICITY NETWORKS
(Source: Smart Grids Project)

¹ In a list that includes the following families of trends: Energy, Economics & Politics Crisis, Living, Health, Sustainability, Technology & Innovation, Consumer, Other.

Apart from this aspect, another major challenge is related with the advent of micro-generation devices that are being connected to low voltage networks. In any case, the impact upwards will always be felt because the liquid demand seen by transmission network reflects all the primary resources connected downwards. The increasing amount of this type of generation certainly requires the improvement of the sustainability and robustness of the network which determines the need for new models and applications in several areas, namely in the Transmission Expansion Planning (TEP). In view of these aspects we are certainly facing a new paradigm on the network expansion studies.

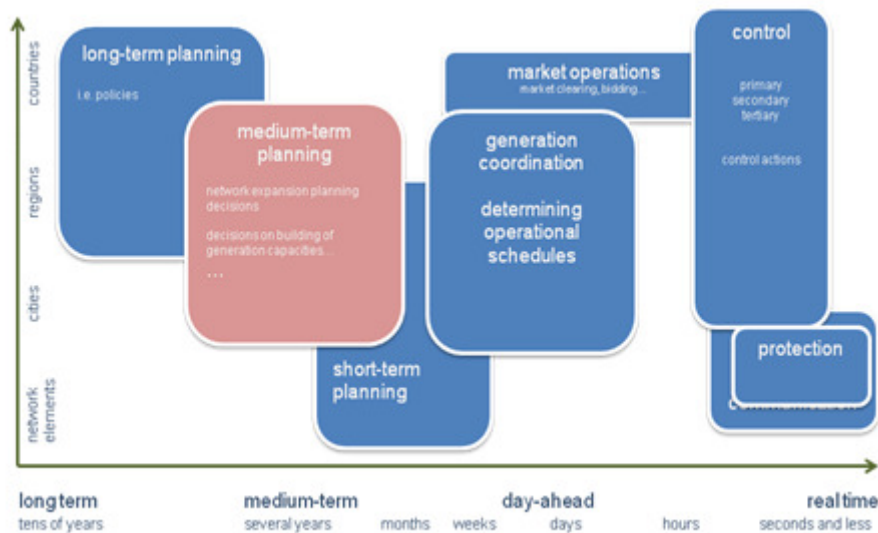


FIGURE 1-2 ELECTRIC ENERGY SYSTEM PLANNING

On the legal and regulatory side, the European Parliament and the European Council approved the Directive 2003/54/EC, aiming at establishing common rules for the internal market of electricity. TEP is clearly identified as a major responsibility of Transmission System Operators (TSO), as these operators are responsible for ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity². In this scope, article 9a) indicates that “*each transmission system operator shall be responsible for ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity*” and article 11 no 3 stipulates that “*a member state may require the system operator, when dispatching generating installations, to give priority to installations using renewable energy sources or waste or producing combined heat and power*”. More recently, the Commission Regulation (EU) No 838/2010 of 23 September 2010, on laying down guidelines relating to the inter-transmission system operator compensation mechanism states that “*(...) the union-wide assessment of electricity transmission infrastructure associated with facilitating cross-border flows of electricity should be carried out by the Agency for the Co-*

² Directive 2003/54/EC article 9 a)

operation of Energy Regulators as the body responsible for coordinating the activities of regulatory authorities who must carry out a similar function at a national level.” All these aspects contribute to turn a complex problem as TEP into a most challenging one since it is affected by several types of uncertainties, it has a multiyear nature and its accurate modelling requires the use of integer variables³.

1.2. THE TRANSMISSION EXPANSION PLANNING (TEP)

According to the European legislation⁴, ‘transmission’ means the transport of electricity on the extra high-voltage and high-voltage interconnected systems in order to be delivered to final customers or to distributors, but not including supply. The responsibility of this activity is assigned in Europe to TSO’s. These entities must ensure the long-term ability of the system to meet reasonable demands and to be accessed by the producers. TSO’s are also responsible for the operation, maintenance and development of the facilities, including the interconnections with neighbour systems.

A TEP model aims at determining the timing, the type and the location of the new transmission facilities that should be added to an existing network in order to ensure an adequate transmission capacity taking into account future generation options and load requirements (Fonseka, et al., 2002). When addressing the TEP problem, one can identify two different types of investments: network deepening investments, and independent network expansion investments (Alvarez, et al., 2006). The network deepening investments are the result of improvement or maintenance decisions on the existing network. These decisions may include the addition, replacement or upgrade of conductors or cables on existing branches, as well as upgrades in substation facilities, transformers, and capacitor banks or in protection and control devices. These types of investments also occur when voltage is changed to a higher level. The independent network expansion investment addresses the problem of constructing new transmission lines and facilities. Other authors, like Reis, divide the investment decisions in two levels: the hierarchical level 1, for those decisions that correspond to changes in the network topology, and hierarchical level 2, for the decisions which correspond to changes in the local nature network topology (Reis, 2005).

More and more it is very difficult to have the required information available, as energy markets, loads, technologies and natural resources are very dynamic and, most of the times, unknown and hardly predictable. It is not easy to overcome this situation and some authors realize that the transmission “crystal ball” becomes extremely “cloudy” because of greater unknowns in future load, generation, and transfers—three most important inputs if an accurate planning model is to be built. Therefore, and as a general

³ Lines or power plants are built according to a number of rated power and voltage levels, and the investment can be scheduled for one or several years.

⁴ Directive 2003/54/EC, Article 2

remark TEP decisions have to be supported by sophisticated models as the complexity cannot be simply dealt by human mind alone (Drayton, et al., 2005).

1.3. WHY IS TEP IMPORTANT?

This question will be answered taking into consideration all the stakeholders, namely the regulatory authorities, the TSO's and the network users.

TEP is important for the regulatory authorities because they need a benchmark, a network planning to serve as reference in the analysis of the plans that are submitted by the TSO's. As an example, in Portugal the New Network and Interconnections Access Code⁵ (ERSE /RARI 2011) stipulates, in Article 24, that investment projects referred to the following three years should be submitted to ERSE.

TEP is also a fundamental tool for the TSO's, for the huge investments they have to do in facilities to keep the security and the reliability of the network. In Portugal REN is planning an investment of 1,43 billion Euros for the period 2009 - 2014.

Finally, TEP is very important for the network users, as through the approved tariffs they typically have to pay both investment and operation costs.

1.4. WHY IS TEP RELEVANT FOR SUSTAINABLE ENERGY SYSTEMS?

TEP is relevant for Sustainable Energy Systems as it:

1. Identifies the most appropriate investment plan for the forecasted load and production;
2. Allows solutions with lower investment levels, or better performance for the same investment;
3. Creates conditions for the full exploitation of the installed capacity (resources);
4. Identifies solutions with less infrastructure, and so with lower environmental impacts.

⁵ The RARI approved in 2003, which was valid up to 2011, stipulated, in Article 18, that the Investment Plan for the RNT must include 6 years following the year in which it is presented, and should be submitted to ERSE every two years, until 30 November. RARI 2011 no longer talks about expansion plan to be approved by ERSE, but only in individual projects. It seems that any global transmission plan prepared by REN is only for an internal use, and that REN has only to inform ERSE on individual projects. Apparently, ERSE is admitting losing sight of the overall problem.

Environmental costs can also be incorporated in the analysis by the internalization of external costs related to the solutions identified for each of the periods under review.

1.5. THESIS OBJECTIVES

Our goal is to develop a methodology to schedule projects in the transmission networks, in the medium-term. The solution will be better as verifying the assessment criteria in Table 1.1.

TABLE 1-1 OBJECTIVES AND ASSESSMENT CRITERIA

Assessment Criteria	Objective:
Investment	As reduced as possible, while respecting limits for each period and for the global investment
Operation Costs	Losses, as low as possible Internalization of environmental cost
Reliability	$PNS(n) \text{ and } PNS(n-1) = 0$

We aim at developing a mathematical model and the corresponding computational application to perform dynamic TEP studies, considering a number of features:

- Multiyear approach; an investment plan is not just the addition of decisions identified separately for each individual period in the horizon; the whole horizon must be addressed in a holistic way so that couplings are adequately modelled and treated;
- Uncertainties treatment; the developed model will address the volatility of several parameters and we want to build robust plans as much as possible in the sense that they are able to accommodate uncertainties;
- Reliability; this analysis will be considered as an indicator to measure the quality of the service inherent to the investment plan; this indicator can correspond, for instance, to the Power Not Supplied (PNS) or Energy Not

Supplied (ENS), in each year of the planning horizon and can assume a global nature or can be used to detect local situations in which the supply would eventually be more degraded thus requiring particular attention.

Our hypothesis is that, selecting the right tools already available, as meta-heuristics, it will be possible to develop a new model to perform dynamic TEP studies on realistic transmission systems, in an accurate and reliable way, and taking into consideration uncertainties and vagueness inherent to the new energy paradigm.

We seek to answer some questions, including the following:

- I. How to identify the projects to strengthen a network, taking into account the existing knowledge?
- II. How to bring the list of works sufficiently robust, including the investments that are actually the most relevant to the objectives to be achieved?
- III. How to identify the most appropriate timing for the projects?
- IV. How to deal with uncertainties?

1.6. THESIS ORGANIZATION

The thesis is organized into the following chapters:

Chapter 1 – Introduction

It is the first chapter of the thesis, where we make a brief presentation of the theme, the objectives of the thesis and its organization.

Chapter 2 - Recent evolution of generation and transmission power systems

In this chapter are reviewed the main concepts associated with Power Generation and Transmission Systems, such as its classification, the concepts of quality and reliability, and the types of equipment. This chapter also discusses the concepts of electricity energy markets and sustainable energy system, as well as the electricity market reform, especially in the Iberian Peninsula. At the end of the chapter, we approach the market modeling.

Chapter 3 - TEP in the literature

The TEP literature review includes aspects such as the initial information, the planning horizon, the market approaches, the models (such as mathematical, heuristic and meta-heuristic models), and even some specific techniques to solve large scale problems. The drawbacks of existing methods are also addressed.

Chapter 4 - Evolutionary computation and particle swarm optimization

This chapter reviews the main concepts of optimization methods that we will adopt, including those involving agent based computing, evolutionary computation and particle swarm optimization. It concludes with a review of Evolutionary Particle Swarm Optimization (EPSO), which underlies the model proposed by this thesis.

Chapter 5 - Discrete Evolutionary Particle Swarm Optimization

Discrete Evolutionary Particle Swarm Optimization (DEPSO) is the model we introduce with this thesis. TEP will be addressed based on this optimization model. This chapter discusses DEPSO fundamentals, namely the concept, its development, and the coding. It addresses topics such as Chaos and Lamarckism, incorporated in the algorithm as tools that contribute to convergence. We conclude the chapter with a comprehensive description of DEPSO.

Chapter 6 - Multiyear TEP formulation with DEPSO

In this chapter we present the modeling of multiyear TEP based on DEPSO. It is explained how to define the initial data, the expansion plan, the coding of solutions and the relevant features of the search space. The DEPSO includes a first phase, which is multiyear and deterministic, that identifies a population of good solutions. It is followed by a complementary phase that includes the load uncertainties and the final assessment of the deterministic solutions.

Chapter 7 - Case studies

The case studies use both the Garver network and IEEE RTS 24. The behavior of DEPSO, including parameterization options and the influence of different blocks for convergence, is introduced in detail. One may also find in this chapter the presentation of results of the multiyear TEP model applied to Garver and IEEE RTS 24 networks,

some of which have been published in conferences such as the PSCC 2011 and EEM 2011.

Chapter 8 - Conclusions, contributions and future work

This is the final chapter of the thesis, which presents its conclusions and contributions, as well as proposals for future work.

References

Under this item are listed the references consulted during the investigation.

Annexes

The thesis includes the following annexes:

- Annex A - Garver network
- Annex B - IEEE RTS 24 network
- Annex C - Meta-heuristic models
- Annex D - DC OPF method
- Annex E - Paper presented in EEM 2011
- Annex F - Paper presented in PSCC 2011

2. RECENT EVOLUTION OF GENERATION AND TRANSMISSION POWER SYSTEMS

*“European electricity market is undergoing two fundamental changes:
one is liberalization;
the other is the integration into a single pan-European market.”*

(Patrícia Pereira da Silva and Isabel Soares, 2008)

2.1. SCOPE

The generation and transmission power systems have undergone a remarkable evolution in recent years, all over the world. In this chapter we provide a literature review of recent trends in this market.

This Chapter starts with the characterization of power systems, with special focus on power quality and power systems reliability.

There is also an approach on energy markets and sustainable energy systems, outlining the reforms of recent years particularly in Portugal and the Iberian Peninsula. A comprehensive description of MIBEL is done before a short review on markets modeling.

The motivation for the thesis is best understood in this context of change.

While recognizing that the DC networks have become increasingly important, particularly because of its use in off-shore networks⁶ or in geographic areas with high economic development⁷, our work will focus on AC networks. The literature review was restricted to such networks, which, moreover, remain the most common.

⁶ Further information may be found in (Alegría, et al., 2009), (Garzillo, et al., 2010).

⁷ Further information may be found in (Dong, et al., 2010).

2.2. POWER SYSTEMS

2.2.1. INTRODUCTION

Electricity has specific features that are very different from those of other forms of energy⁸ (Pereira da Silva, 2007) (Sucena Paiva, 2007):

- Except in very special circumstances, electricity can't be stored, and has to be consumed a few fractions of a second after having been generated;
- There must be a constant and perfect balance between supply and demand;
- Once delivered to the network, it has no individuality;
- It does not flow in transmission lines along the “more desirable route”;
- It is simultaneously an asset (power) and a service (transport, distribution and system operation).

For these characteristics, electricity is part of a system that is known as the power system. Any power system, usually very large and complex, can be divided in five fundamental components, as follows: sources; converters; transmission networks; distribution networks; and loads.

Some key concept definitions for a better understanding of the power systems, can be found in the 2nd article of Directive 2009/72/EC. Those related with transmission activities are:

- ‘transmission’ means the transport of electricity on the extra high-voltage and high-voltage interconnected system with a view to its delivery to final customers or to distributors, but does not include supply;
- ‘transmission system operator’ (TSO) means a natural or legal person responsible for operating, ensuring the maintenance and the development of the transmission system in a given area⁹, and for ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity;

⁸ Strictly speaking, according to some authors, such as Professor Eduardo de Oliveira Fernandes, electricity is not a form of energy but an energy carrier, like in the future will be the hydrogen.

⁹ Where applicable, the TSO is also responsible for the interconnections with other systems.

- ‘long-term planning’ means the planning of the need for investment in generation, transmission and distribution capacity on a long-term basis, with a view to meeting the demand of the system for electricity and securing the supply to customers;
- ‘interconnected system’ means a number of transmission and distribution systems linked together by means of one or more interconnectors;
- ‘ancillary service’ means a service necessary for the operation of a transmission or distribution system in a secure and reliable way;
- ‘electricity undertaking’ means any natural or legal person carrying out at least one of the following functions: generation, transmission, distribution, supply, or purchase of electricity, which is responsible for the commercial, technical or maintenance tasks related to those functions, but does not include final customers.

A well designed power system should meet the following requirements:

- electricity should be provided at any location where it is requested;
- generation must match the load plus losses at each moment, since electricity cannot be stored;
- power must meet well-defined quality criteria: constant frequency, voltage within narrow limits, sine wave, high reliability;
- The cost of the delivered power must be minimized;
- The environmental impact of entire system must be contained.

Transmission and distribution networks are crucial for the normal operation of power systems, and have an increased influence on the trade-offs in electricity markets connecting generation and demand. Some specific attributes of transmission networks are crucial in determining prices and have therefore a direct impact on electricity markets (Pereira da Silva, 2007): the need for an instantaneous equilibrium between supply and demand; the physical constraints on transmission networks in terms of capacity; the efficient coordination between the sequential functions of the various stakeholders; the economies of scale and natural monopolies (geographic); the regulation and the need for the inclusion of stranded costs¹⁰.

¹⁰ In the Portuguese Power System “Custos de Manutenção de Equilíbrio Contratual” are example of stranded costs. They refer to parcels to be included in the tariffs, to ensure that generation companies that lead long term contracts under the structure prior to market implementation receive an equivalent remuneration under the new legal framework.

2.2.2. CLASSIFICATION OF ELECTRICITY NETWORKS

Electricity power networks are normally operated in AC balanced three phase system. The grids or networks are usually classified under the following criteria (Sucena Paiva, 2007), (Delgado, 2010): the rated voltage, the function, the topology and the power supply structure.

a) Rated voltage

The rated voltage of a network is the voltage at which the network works. It should be noted that the voltage contributes to determine the power capacity, the dimensioning of overhead lines or underground cables, and the characteristics of the equipment of substations.

A primary objective in defining the electricity network voltage levels is the optimization of transmission conditions. This has a significant influence in reducing the losses by Joule effect, which is very relevant in the economic analysis of the systems. In situations where large distances or very large powers are involved, rated voltage should be chosen as high as possible.

$$S = \sqrt{3} * U * I \quad (2.01)$$

In equation (2.01) S is the Apparent Power, in kVA, V is the line-to-line voltage, in kV, and I is the line current, in A. This equation clearly shows that, in order to transmit a fixed amount of Apparent Power over a transmission line, a higher voltage is preferable to a lower one, as it results in lower currents. The lower the current, the lower the losses will be and the voltage drops, due to the conductor impedance. This permits the use of thinner and lighter conductors.

In this respect one can distinguish the following voltage levels:

- Low voltage (LV), below 1000 V; the typical values are 400/231 V (three-phase, phase-phase and phase-neutral, respectively) in Europe and 240/120 V (mono-phase) in the USA;
- Medium voltage (MV), between 1 and 45 kV; these networks are commonly referred to as distribution networks; the rated voltages are normalized at 10 kV, 15 kV, 20 kV (only in some few European countries) and 30 kV; on industrial plants it is also common a voltage of 6 kV;
- High voltage (HV), between 45 kV and 110 kV; in Portugal the voltage of 60 kV is the most common in these networks;

- Extra high voltage (EHV), above 110 kV; this voltage level is used in transmission networks, with typical values of 150 kV (in Portugal), 220 kV and 400 kV, in Europe, and 230 kV, 345 kV, 500 kV and 765 kV in the USA.

The alternating current (AC) networks are widely used for their great advantages. The voltage can be transformed to higher or lower levels by means of power transformers, whose operation is based on changing magnetic fields in the windings of the transformer. The networks considered in this work are operated with three phase balanced¹¹ sinusoidal alternating voltages, with 50 Hz frequency¹².

b) The function

Electricity networks can be classified according to their function on the electrical system, as follows:

- Distribution networks; the function of these networks is to bring energy to consumers; low voltage networks are typically radial; medium voltage networks in urban areas are meshed¹³, and composed by underground cables, to ensure greater continuity of service; in rural areas MV networks are radial, based on overhead lines; in a very recent past they were typically passive, because were fed by just one of its ends, at high or low voltage; one assists lately to a significant development as these networks are nowadays fed not only by transmission networks or distribution higher voltage networks, but also by distributed generation, taking advantage from endogenous resources, (typically from hydro, solar, wind and geothermal facilities), or by cogeneration power plants;
- Transmission networks; these networks are settled in very high voltage, on a regional or national basis; they ensure large power flows among the major generation centers and substations which are connected to distribution networks or large consumers;
- Interconnections; these interconnections provide the link between transmission networks operated by different companies, for example between countries or contiguous regions; European networks are typically connected at 220 kV or 400 kV, at the same frequency (50 Hz).

The existence of interconnections has several advantages:

¹¹ Balanced systems are composed by three voltages with the same amplitude and lagged from each other 120°.

¹² In some electrical areas, like in the USA, the power frequency is 60 Hz.

¹³ Even though meshed, these networks are most commonly operated in a radial way.

- Improves network security, since with the interconnections networks can be used to support the interconnected systems in emergency situations;
- Allows a reduction of the reserves, either static or rotating, in each network;
- Allows trading between producers and consumers of distinct areas, an indispensable condition for the electricity markets to be extended.

High-voltage DC lines or transformers can be used to interconnect two alternating current networks which are not synchronized with each other. This provides the benefit of interconnection without the need to synchronize an even wider area. Important steps were taken for the operation and planning of transport networks on a transnational scale by publication¹⁴ of Regulation (EC) No 714/2009 of the European Parliament and of the Council of 13 July 2009, on conditions for access to the network for cross-border exchanges in electricity and Commission Regulation (EU) No 838/2010, of 23 September 2010, on laying down guidelines relating to the inter-transmission system operator compensation mechanism and a common regulatory approach to transmission charging.

c) The topology

The most common topologies are:

- Radial networks; in this topology lines are supplied by a single feeding point, and never meet nor bind electrically beyond the feeding point; radial network reliability is low, but its costs are also lower than those of other networks; it is the type of network commonly used in MV rural areas networks and in LV; when there is no distributed generation linked, the power flow on these networks is unidirectional, always in the same direction;

¹⁴ See the legislative package published in 2009, which aims at liberalizing the energy sector, consisting of the following acts:

- Regulation (EC) No 713/2009 of the European Parliament and of the Council of 13 July 2009, establishing an Agency for the Cooperation of Energy Regulators;
- Regulation (EC) No 714/2009 of the European Parliament and of the Council, of 13 July 2009, on conditions for access to the network for cross-border exchanges in electricity;
- Commission Decision of 10 November 2010, amending Chapter 3 of Annex I to Regulation (EC) No 715/2009 of the European Parliament and of the Council on conditions for access to the natural gas transmission networks;
- Directive 2009/72/EC of the European Parliament and of the Council, of 13 July 2009, concerning common rules for the internal market in electricity;
- Directive 2009/73/EC of the European Parliament and of the Council, of 13 July 2009, concerning common rules for the internal market in natural gas.

- Complex mesh networks; in this case all consumers can be fed by several branches, which are arranged so that they can form closed loops; the power flow from generators or injection points to loads can be established by various routes; typically all lines have been sized to transmit the power required in the event of failure of another line (criterion n-1); reliability is substantially better than in radial networks; the cost of mesh topologies restrict their application to transmission and to some medium voltage urban distribution grids;
- Mesh networks, but with radial operation; this design is common in urban networks with high density loads; it corresponds to a radial network operation, but with the option of closing any loops (or opening, depending on the circumstances) in case of unavailability of any line, to ensure service continuity.

d) The power supply structure and features

One can distinguish between two types of networks: multilateral powered networks (usually ring or mesh networks) and unilateral powered networks.

- Multilateral supply networks (ring networks); these networks are characterized by the existence of at least one power supply in at least two of its points; this means that normal load currents and eventual short circuit currents may flow in different directions; the existence of at least two different power sources at least at two different points of a ring network increases service continuity in case of failure of one of them or in case of failure of a ring; these networks can be considered as active networks, since in case of loss of one or more power sources they can still be fed by another one;
- Unilateral power networks (radial networks); this type of network is characterized by the existence of one or more power sources in parallel, only at one end of the network; in this case load currents or short circuit flows occur only in one direction; these networks are also called passive, as if one loses the only power source or a problem arrives on the network, loads will no longer be fed.

With the spread of decentralized generation, often connected to the power system through radial low voltage or medium voltage networks, so far with unidirectional power, these networks also become active circuits. Beyond security, command and control issues, it must also be considered the possibility of short-circuit currents increase and voltage profile changes. In some less robust or isolated systems, there can be changes in frequency stability.

The power supply in a three-phase system has four key features: amplitude, frequency, waveform and symmetry. These characteristics may deviate from the established

standards¹⁵ due to disturbances, which must be anticipated and corrected (Delgado, 2010). The voltage amplitude can be affected by voltage dips and fluctuations. The voltage dips are deep voltage drops, over 10% of rated voltage, and brief, lasting between 10 milliseconds and a few seconds. Voltage fluctuations correspond to random amplitude changes, but not exceeding 10% the nominal value. The variation on voltage amplitude can lead more sensitive equipment protections to trigger, or even to trigger the entire system. The frequency remains close to its nominal value while verifying a reasonable balance between the loads and the power injected into the electrical system. Important frequency fluctuations can result in difficulties on system control, leading to the triggering of protection systems. The waveform and symmetry of the power supply, sinusoidal in normal conditions, are subjected to irregularities due to the presence of harmonic terms¹⁶ or because of over-voltage phenomena¹⁷.

2.2.3. *QUALITY AND RELIABILITY IN POWER SYSTEMS*

With the development of industrialization and information systems, modern society is highly dependent on energy. The power systems are fundamental for daily life activities all over the world. Especially in urban areas, electricity power networks are key infrastructures that may paralyze the community in case of a significant problem. Electricity power networks are getting larger and more complex, and thus harder to control. Furthermore, natural disasters, technical failures, human errors, terrorism and acts of war may cause disturbances in the infrastructures. Electrical power quality and reliability are two key issues on power system operation.

a) Electrical power quality

Electrical power quality is a topic of concern to stakeholders operating in the electricity market. The definition of objectives and indices of electricity power quality can be found in the norms IEC 50160, IEC 61000, IEEE 1159 and IEEE 1250-1995.

The main instrument of standardization in Portugal is the RQS - Quality of service regulation, published by Direcção-Geral da Energia in 2003, and updated in 2006

¹⁵ Please address to NP 50160, especially for LV and MV networks.

¹⁶ Power with harmonics have frequencies that are integer multiples of the fundamental frequency, 50 Hz in Europe; the vector addition of these signals results in a distorted sine wave, also causing changes in the wave form; high levels of harmonics can lead to abnormal heating of certain equipments and may disturb the operation of electronic systems, protection relays and breakers.

¹⁷ Over-voltages are damped phenomena, sporadic, manifested in the form of abnormal voltage for very short periods, usually less than 10 ms; can have various origins, namely the closing or opening of a circuit-breaker, or due to surge lightning; overvoltage's can operate the overvoltage protection systems, leading to system triggering; they may affect the insulation, reducing its useful life, or even leading to its rupture.

(DGE, 2006). This code establishes the minimum technical and commercial standards that should be followed by entities of the National Electricity System¹⁸.

The service quality key concepts are:

- Power continuity; is characterized by the number and duration of interruptions; these values can be measured individually (by customer), and compared with general patterns; the infringement of defined quality pattern, can lead to penalties; these penalties act as an incentive to search for quality improvement;
- Power quality; is becoming a very important aspect for distributors and end customers, especially those with sensitive equipment; the parameters used to define the power quality are featured on the Portuguese standard NP EN 50160, for medium and low voltage, and in international standards, as IEC 61000;
- Quality of the commercial service; with the main concern of the commercial relationship quality between a supplier and its customers.

The comprehensive review of compliance with the regulation on quality of service is in Portugal responsibility of ERSE. This regulation foresees that TSO and distributors¹⁹ have to recall and record the information necessary to verify compliance with the regulation. The verification of compliance with technical standards is based on a monitoring plan, to identify possible areas of improvement. The power quality monitoring can take place in equipment that may influence power quality, or may be carried out continuously²⁰.

b) The reliability and the blackouts

*“We regret the tremendous inconvenience the recent rolling blackouts have caused to our customers and society since March 14th due to the tight supply-demand balance of electricity. As a result of widespread cooperation from our customers in conserving electricity, the supply-demand balance has improved significantly. Hence, in principle, we have decided to cease the implementation of rolling blackouts and will do our best to maintain the supply of electricity aiming to achieve "Zero Rolling Blackouts" in principle during the summertime. Your continuous cooperation in saving electricity would be highly appreciated.”*²¹

¹⁸ In Portuguese, “Sistema Eléctrico de Serviço Público” (SEP)

¹⁹ EDP, Electricity of Portugal, the main company responsible for power distribution and former monopoly, published in December 2005 his "Handbook of Power Quality" (EDP, 2005)

²⁰ An important document on power quality monitoring is the “IEEE Recommended Practice for Monitoring Electric Power Quality” (IEEE 1159, 1995).

²¹ <http://www.tepco.co.jp/en/index-e.html>, consulted in 21/4/2011

Masataka Shimizu

President of the Tokyo Electric Power Company, Incorporated, April 2011

As mentioned before, natural disasters, technical failures, human errors, terrorism and acts of war may cause disturbances in the infrastructures of the electric power system. Two different situations may arise: blackout, power outage or power failure; rolling blackout, or load shedding.

A blackout is a short (or long) term loss of the electricity power to an area. The causes of power failures in a power system may include overloading, short circuits, faults at power stations, and damages on electric transmission lines, substations or other parts of the distribution system.

The 2005 Java–Bali blackout is to date the largest and most widespread power outage in history²². It was a power outage across Java and Bali on 18th August 2005, affecting some 100 million people. The supply shortfall was 2.700 MW, roughly half of the original supply. Jakarta lost power completely²³.

Another well known blackout occurred in Italy in the 28th September, 2003. It affected all Italy (except the islands of Sardinia and Capri) for 12 hours. Some areas in Switzerland, near Geneva, were also affected during 3 hours. ENEL, the Italy's Electricity Transmission and Distribution Company stated that the power line which supplied electricity to Italy from Switzerland was damaged by storms, causing it to trip. It caused also the two 400kV power lines between France and Italy to trip as well, due to sudden load increase. The cascading effect disrupted power supply to Italy from France and Switzerland. A total of 56 million people have lost power. Several hundred people were trapped in underground trains. Coupled with heavy rain at the time, many people spent the night sleeping in train stations and on streets in Rome. Throughout Italy, 110 trains were cancelled, with 30,000 people stranded on trains. During that event, all flights in Italy were cancelled. The restoration of service was not easy. After 3 hours, power was restored in northern regions. Most cities were powered on again during the morning of the next day (29th September). Rolling blackouts continued to affect about 5% of the population on the next two days after the blackout.

A rolling blackout, or load shedding, is an intentionally-engineered electrical power outage. Due to very important reasons, power delivery is stopped for non-overlapping periods of time over geographical regions. Rolling blackouts are more extreme measures used by an electricity company in order to avoid a total blackout of the power system, in response to a situation where the demand for power exceeds the power

²² Donnan, Shawn (August 19, 2005). "Indonesian outage leaves 100 million without electricity". Financial Times. http://www.ft.com/cms/s/0/bffd3f32-1044-11da-bd5c-00000e2511c8.html?nclink_check=1; consulted in 21/4/2011.

²³ A transmission line between Cilegon and Saguling, both in West Java, had a failure which led to a set of events. This failure shut down two units of the Paiton plant in East Java and six units of the Suralaya plant in West Java.

supply capability of the system. Rolling blackouts generally result from two causes: insufficient generation capacity or inadequate transmission infrastructure to deliver sufficient power to the areas where it is needed.

Insufficient generation capacity may arise from any extreme situation due to the weather conditions, as for example unusual very cold or warm days. In April 2006, parts of Texas experienced rolling blackouts due to excessive air conditioner use, because of unexpectedly very high temperatures. Due to very low temperatures, in February 2011, North and Central Texas experienced also rolling blackouts due to 50 power plants tripping offline²⁴. Insufficient generation capacity may also arise from reduction on fuel supplies. It was the case of the Three-Day Week of January to March 1974, in United Kingdom. To conserve coal supplies, which were severely reduced due to industrial action, a limit on power consumption was introduced, meant that non-essential commercial users were only allowed to consume electricity for three days each week. Home electricity supplies were also limited in some areas.

Natural disasters may affect power systems and cause rollout. Starting on 14th March, 2011, Japan instituted rolling blackouts due to power shortages caused by the 2011 Tōhoku earthquake and tsunami. The Tokyo Electric Power Company, which normally provides approximately 40 GW, announced that it could only provide about 30 GW, a shortfall of 25 percent. This is due to the fact that about 40 percent of the electricity used in the greater Tokyo area was supplied by nuclear reactors in the Niigata and Fukushima prefectures. The six reactors in the Fukushima Nuclear Power Plant sustained major damage related to the earthquake, and subsequent tsunami, and had been automatically taken offline.

Blackouts have been subject of analysis and research over the years, to have a broader and precise view on this issue. It is not economically reasonable to have full reliability. The effective measures for improvement should be translated into preventive attitudes, especially in areas of training, operational methodologies and power technologies. More information on this topic can be found in (Carreras, et al., 2003), (Berizzi, 2004), (Dizdarevic, et al., 2004), (Vournas, et al., 2005), (Li, et al., 2007), (Shaobo, et al., 2010), (Terzija, et al., 2010).

2.2.4. ELECTRICAL NETWORKS EQUIPMENTS

Electricity networks are the whole set of facilities that provide the necessary linkages between the generation and the loads. Electricity networks are formed by overhead lines and underground cables. In addition to the lines and cables, networks also include substations, with functions including switching, protection and measurement. It is this

²⁴ <http://www.dallasnews.com/news/community-news/dallas/headlines/20110202-cold-cripples-50-power-plants-triggering-blackouts-for-thousands-across-dallas-fort-worth.ece>, consulted in 21/4/2011

set of equipment that contributes to the reliability and safe operation of the entire power system.

a) Substations

Substations are the nodes in the power system, where several lines and transformers are connected together. Transmission substations are the interconnection nodes on the main transmission system. At these substations the voltage is raised to the transmission system levels or stepped down to distribution levels.

Substations can be either conventional air insulated (outdoor) type, or gas insulated switchgear type (GIS). GIS substations use SF₆²⁵. The use of SF₆, a gas with exceptional insulating properties, facilitates the design of very compact substations. In GIS a co-axial tubular system is used in all components, such as circuit breakers and isolators, to form the main bus bars of the substation. SF₆-based solutions have the advantage of being much more compact than conventional air insulated solutions. Its choice is appropriate in urban environments, where availability of land is limited or when its price is too high, or in more aggressive environments.

Regardless of the type, substation equipments include power transformers, protection equipments (circuit breakers, surge arresters and fuses), switches (breakers, switches), insulation devices (isolators and earthing switches) and measuring equipment (voltage and current transformers). Substations are also equipped with on site control, remote control, synchronization, alarm, and relays.

The isolators are usually installed on both sides of equipments such as transformers and circuit breakers, to allow disconnection during maintenance of the equipment. Isolators are not designed to interrupt full load or fault currents. They should only be operated under no-load conditions. The most important equipments are the circuit breakers, as they can interrupt full load and fault currents. They receive triggering signals from relays and operating signals from local control or dispatch centres. Substations are usually abandoned and operated remotely. The facilities that are not equipped with transformation equipment are usually identified as insulating stations.

b) Power overhead lines and cables

High voltage feeders interconnect high voltage substations, either in the form of overhead power lines or underground cables.

Overhead lines are used in most branches of power networks, not only for historical reasons, but mainly due to price. The overhead line cost per km is much lower than the

²⁵ Sulphur Hexafluoride.

alternative with underground cables²⁶. The biggest drawbacks of the overhead lines have to do with their visual impact and the growing opposition from communities and environmental organizations to the establishment of new corridors, especially in urban areas or in protected environments.

Electricity cables have been experiencing a strong development in recent years. The dielectric behaviour of materials used in the cables has nowadays increased insulating characteristics, capable of supporting higher voltages. For this reason, cable adoption has been increasing on the last years. The dielectrics materials began to be oil based, and have been progressively replaced by polymeric materials. Cables are relatively common in medium voltage distribution networks. However, given the high costs when voltage levels are higher, they are only adopted in transmission networks when it is not possible another alternative. Some examples are electricity interconnection of different areas (e.g. with different levels of frequency), offshore installations²⁷, and crossing of urban or protected areas. Apart from the cost, one of the biggest drawbacks of electric cables has to do with their repair in case of incident: it can take from one to four months, while repairs on an overhead line, depending on severity, can be done just in few days.

²⁶ According to REN, the cost per kilometer for a 220 kV overhead line is about 220.000 Euros, while a cable installation in trench costs about 2 million Euros and cable installation in technical gallery may arrive to 6 million Euros. See http://www.ren.pt/vPT/Electricidade/Transporte/Documents/REN_FAQs_A4.pdf, accessed in 18/04/2011.

²⁷ About transmission alternatives for offshore electrical power see (Alegria, et al., 2009)

2.3. ELECTRICAL ENERGY MARKETS AND SUSTAINABLE ENERGY SYSTEMS

2.3.1. HISTORICAL ASPECTS

“Energy is the life blood of our society. The well-being of our people, industry and economy depends on safe, secure, sustainable and affordable energy. At the same time, energy related emissions account for almost 80% of the EU's total greenhouse gas emissions. The energy challenge is thus one of the greatest tests which Europe has to face. It will take decades to steer our energy systems onto a more secure and sustainable path. Yet the decisions to set us on the right path are needed urgently as failing to achieve a well-functioning European energy market will only increase the costs for consumers and put Europe's competitiveness at risk.”

European Commission²⁸

At the present time, society depends on electricity and electrical engineering for almost all its activities, from leisure, to business and manufacturing.

TABLE 2-1 THE EIGHT AGES OF TECHNOLOGY
(Source: adapted from (Jones, 1991))

Technology	Age
1. Manpower	3 million BC
2. Animal power	circa 10 000 BC
3. Water power	circa 150 BC
4. Wind power	700 AC
5. Steam power	18th century
6. Electrical power	19th century
7. Electronics and computers	20th century
8. Information	21st century

All this started with discoveries made in the 18th and 19th centuries, which led to the knowledge of electromagnetic phenomena. With the application of these phenomena,

²⁸ “Energy 2020, A strategy for competitive, sustainable and secure energy”, (Comissão Europeia, 2010).

the profession of electrical engineering was born (Jones, 1991). People as Nikola Tesla, Thomas Edison, Faraday, Charles Steinmetz, Charles Parsons, George Westinghouse, Ernst Werner von Siemens, Alexander Graham Bell and Lord Kelvin, turned electricity from a scientific curiosity into an essential tool for modern life, becoming a driving force for the so called second industrial revolution. Many electricity technologies from the 19th century, in power generation²⁹, electric motors, lighting³⁰ or communications³¹, are still in use.

At that time, until the early twentieth century, the electricity industry was private, and competition between the companies was strong, not only in commercial terms, but mainly in technology. Over the years the technologies have been stabilizing, having stood out and spread the three-phase systems.

Electricity networks were still very incipient in the early twentieth century but turned out to be essential for extending the benefits of electricity throughout the economy. To give one example, in 1921 about one half of British factories already used electric power. The benefits of the grid improved this figure to 84% by 1936. Individual electric motors for each machine were more flexible and safer. They allowed production lines to be set up for cars, aircraft and all industries. Electric power enabled industry to move away from the coalfields, from traditional sectors and tap new sources of labour.

The power industry, including generation, transmission and distribution, was considered for several decades a monopoly in each country and in many cases, as in Portugal, has even been state owned. This paradigm lasted almost throughout the world until the late twentieth century.

With the arriving of the XXIst century there was a liberalization and international integration movement of the industry. This movement, especially in Europe, has been neither linear nor simple. Following the Single European Act mainframe, the European industry is characterized today by the following fundamental principles: freedom of investment, free trade, electricity consumer's choice among several potential suppliers. Apart from economic issues, including energy prices, electricity markets are still largely dependent on one of its fundamental technical principles: the balance between generation and demand.

Accordingly, and regardless of the legal frame and market rules, the role of electricity networks appears to be increasingly important for the proper operation of the market

²⁹ The steam turbine principle, from Sir Charles Parsons (1884), using a variety of heat sources, is still adopted in generation of about 80% of the electric power in the world.

³⁰ The incandescent light bulb was introduced in the 1870s. Since then lighting become one of the most important applications of electrical power.

³¹ The first intercontinental telegraph system was established in the 1860s, which enabled communications in minutes across the globe.

and the satisfaction of the consumers power needs, as well as to transfer large amounts of power from one area to another.

2.3.2. SUSTAINABLE ENERGY SYSTEMS³²

On the living standard of the population one may include the sustainability principles, which consider social, economical and environmental aspects. The Brundtland Report, released in 1987 by the United Nations, defines sustainable development as *'development which meets the needs of the present without compromising the ability of future generations to meet their own needs'* (Brundtland, 1987).

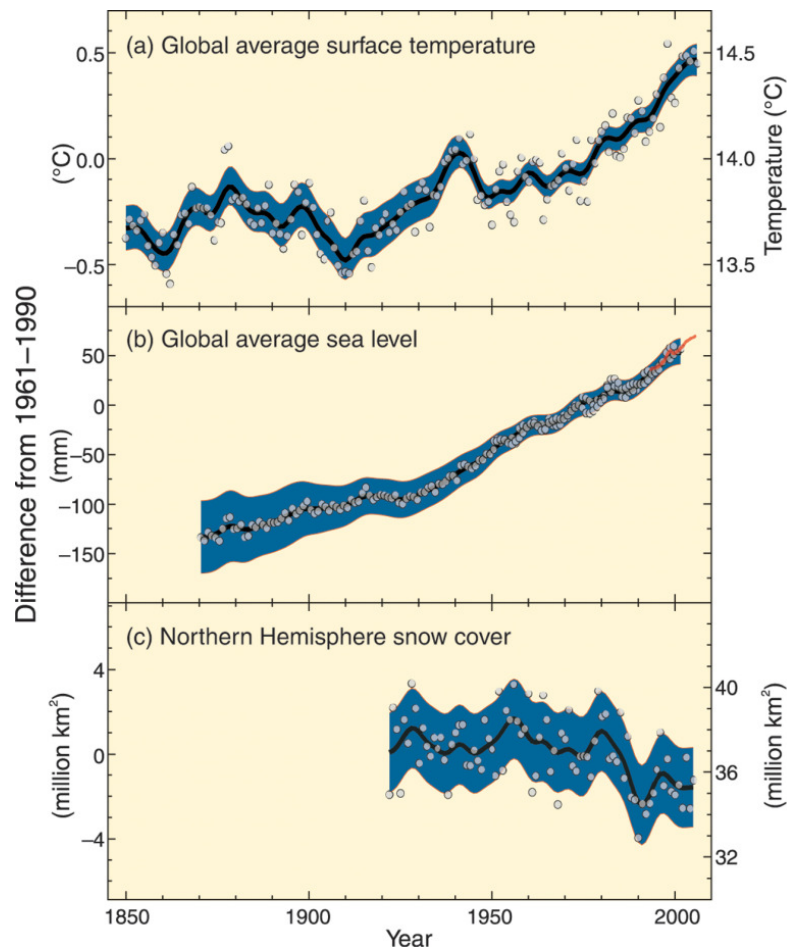


FIGURE 2-1 CHANGES IN TEMPERATURE, SEA LEVEL AND NORTHERN HEMISPHERE SNOW COVER
(Source: (IPCC, 2007))

³² Here we are referring more specifically to sustainable electricity energy system.

One of the main problems for future generations will be the global warming due to Greenhouse Gas (GHG) emissions. As can be seen in Figure 2.1, the global average surface temperature is rising since the 50^{ties}. Global total annual anthropogenic GHG emissions, weighted by their 100-year Global Warming Potential (GWP)³³, have grown by 70% between 1970 and 2004. As a result of anthropogenic emissions, atmospheric concentrations of N₂O now far exceed pre-industrial values spanning many thousands of years, and those of CH₄ and CO₂ now far exceed the natural range (IPCC, 2007). In order to stabilize atmospheric CO₂ concentration at 500 ppm, which is generally accepted as the most economic balance between mitigation of causes and adaptation to effects, reductions in CO₂ emissions of 90% or more are needed (Apt, 2006). In Europe, energy related emissions account for almost 80% of the EU's total GHG emissions. Electricity industry emissions are from a limited number of generating stations, making them easier to limit and regulate than other sources, such as transportation sector³⁴ (Jewell, 2008).

Electricity industry emissions have origin in the generation power plants operating with fossil fuels. Even though not directly responsible for GHG emissions, transmission systems are responsible for some impacts that have to be considered, as those related to the use of toxic materials in the equipments, the effects in terms of land occupation, loss of biodiversity, visual intrusion and noise associated with the installation of overhead lines. Possible adverse effects on human health associated with electromagnetic fields also constitute an environmental impact of this activity (Antunes, et al., 2003). The installation of overhead transmission lines involves the conditioning of the soil in their area of influence where defined corridors with widths dependent on the voltage level³⁵, within which there can be no construction or being developed activities that violate the prescribed distances. Some estimates indicate that the activity of electricity transmission is responsible for conditioning the soil use in an area of tens of thousands of hectares.

However, the development of adequate policies to expand transmission networks can contribute to reduce GHG emissions by the potential to reduce network losses, and the easier integration of energy derived from renewable sources, namely water and wind (Bishop, et al., 2009). In addition, adequate TEP policies enable an improved life quality by improving the quality of service offered and the possibility of contributing to better market operation, which may be relevant in terms of tariffs.

Regulators can have an important role on the environmental performance promotion among the transmission and distribution companies. In Portugal, Decree-Law No. 97/2002 assigns ERSE to contribute to the progressive technical, economic and

³³ Global warming potential (GWP) is a relative measure of how much heat a greenhouse gas traps in the atmosphere. It compares the amount of heat trapped by a certain mass of the gas in question to the amount heat trapped by a similar mass of carbon dioxide. A GWP is calculated over a specific time interval, commonly 20, 100 or 500 years.

³⁴ Automobiles, buses, lorries, diesel trains and vessels.

³⁵ In the case of 400 kV overhead lines the corridor width is 60 meters.

environmental improvement in the regulated sectors, namely, the adoption of practices that promote the efficient use of electricity and natural gas, and the existence of adequate standards of service quality and defence of the environment. Environmental policies that may be implemented by transmission and distribution companies have consequences in terms of business costs, many of these being regulated by ERSE. The “Plan for environmental performance promotion” (PPDA), promoted by ERSE³⁶, is a program that regulated companies operating in these sectors can accede in a volunteer basis, and which comprises the implementation of actions to improve environmental performance³⁷. The associated costs may be accepted by ERSE in order to be integrated into the rates to be paid by customers. The existence of these incentives intended to ensure that economic regulation to which companies are subjected does not have a meaningful effect on their environmental performance. This concern assumes greater prominence in companies subject to regulation by a price cap, which creates increased incentives to improve business efficiency as it allows them to take ownership of efficiencies that are accomplished. As a result of the incentives for efficiency, the company would tend to reduce investment in network improvements or maintenance costs with consequences in terms of quality of service or environmental performance. Additional regulatory mechanisms are adopted to minimize or prevent such behaviours, being examples the Quality of Service Regulations and the PPDA. The PPDA's in the Portuguese electricity sector began to be implemented in 2002. The current rules for the PPDA were published by the Order No. 22282/2008 from ERSE, in conjunction with an application guide. Among the new rules are the competition at the selection of the applications proposed by companies, the implementation of monitoring procedures for the measures and the creation of a PPDA Evaluation Panel.

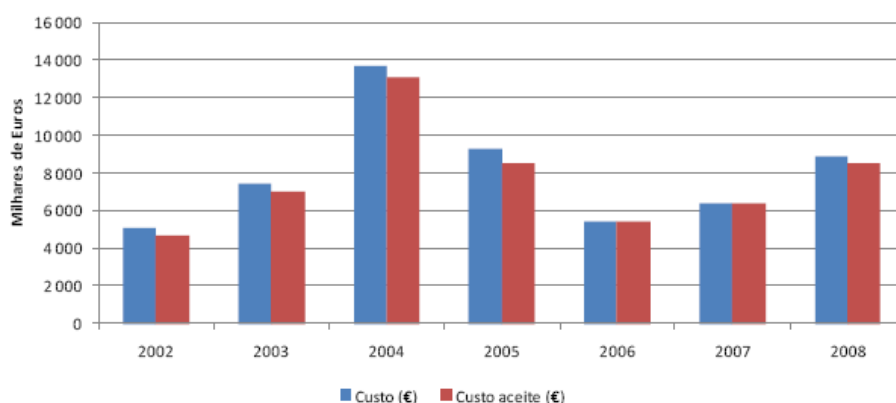


FIGURE 2-2 COSTS OF MEASURES INCLUDED IN THE PPDA'S ACCEPTED BY ERSE (2002 -2008)
(Source: (ERSE, 2010))

³⁶ More data can be found in <http://www.erse.pt/pt/desempenhoambiental/ppda/Paginas/default.aspx>

³⁷ Some examples of PPDA costs that can be accepted by ERSE and included in the tariffs are the costs with bird protection in medium voltage overhead lines, landscaping of an EHV substation and mitigation actions for the installation of REN pipelines in Ponds.

Costs of measures included in the PPDA accepted by ERSE between 2002 and 2008 are presented in Figure 2.2.

For the period 2009-2011 ERSE approved investments made by REN in measures of environmental performance promotion amounting to 6.4 million Euros.

2.3.3. ELECTRICITY MARKET REFORM

“With a few exceptions, the benefits of market reform appear to have outweighed the costs, but it is not necessarily easy to say by how much. Nor have all the benefits accrued to ultimate consumers, occasionally enriching generators, investors, or distributors more than the ultimate consumers.”

Fereidoon Sioshansi³⁸

Currently the value chain of the electricity sector has three main activities: generation, transmission and distribution, and trading activity or final sale, as shown in Figure 2.3 (Pereira da Silva, 2007). In order to increase competition in electricity markets, some experts, such as Hogan (Hogan, 1997), Joskow (Joskow, 1997) and Kahn (Kahn, 1998), support the thesis that the monopoly activities, as transmission, should be separated from potentially competitive ones, as generation and distribution.

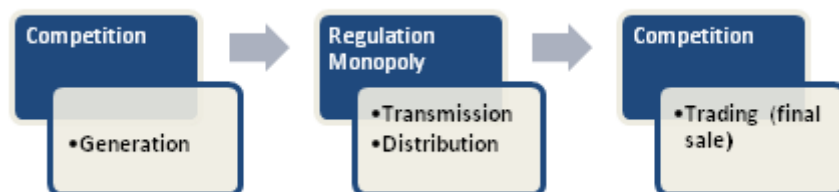


FIGURE 2-3 VALUE CHAIN OF THE ELECTRICAL SECTOR

(Source: (Pereira da Silva, 2007))

The motivations for changing the organization of the industry and the regulatory regime vary from country to country, but are generally driven by a desire to make the sector more efficient through the introduction of competition among the players (Sioshansi, 2006). Other researchers, like Wolak and Patrick, emphasize the successful introduction of competition in wholesale markets in the United Kingdom and Norway as well as the finding that electricity prices vary significantly in different European countries to explain the motivation for restructuring the electricity market (Wolak, et al., 2001).

³⁸ (Sioshansi, 2006)

The productivity improvements resulting from competition are believed to include better rationalization of costs, superior investment decisions and allocation of risks and enhanced customer service. It is expected that these factors lead to lower electricity prices, improved services, benefiting ultimate consumers, while inducing additional investment attraction into the power sector.

The introduction of competition into the electricity market implies (Dominguez, et al., 2007): the installation of smaller and more strategically located power generating stations which reduce costs and construction time, the improvement of transmission lines so that capacity is increased and energy losses are reduced, the development of the interconnection between regions, and market liberalization.

The introduction of market reform is done generally as follows:

- Acknowledgement of problems associated with the existing system (gross inefficiencies in operations or performance, poor system reliability, high prices, and supply inadequacies) and search for alternative ways to organize, operate, manage, and regulate the market;
- Debate on what has to be changed, and the best way to do it (in most cases, new laws must be passed and the organization of the market must be changed before a new market structure can be implemented);
- Implementation of the new market rules and creation of new institutions; sometimes, technically sound principles do not translate well in practice, resulting in problems and chaos.

The last phase, an on-going process, generally starts with the recognition that the introduction of the initial market reform initiatives and does not necessarily or automatically lead to many of the expected benefits and outcomes. External events (political, economic, or natural) disturb what could otherwise be an acceptable outcome. In nearly all cases, initial market reform has led to unforeseen and unintended consequences, which must be addressed in subsequent “reform of the reforms.” (Sioshansi, 2006)

A well functioning competitive market usually includes the following desirable attributes:

- Low and stable retail prices or consumer ability to hedge against price volatility and risks;
- Competitive transparent wholesale markets;

- Option to choose from among competing suppliers, adequate number of suppliers, and ease of comparing and switching for those who wish to do so;
- Supply reliability, power quality, product/service innovation, customer service;
- Adequate number of generators, lack of market power, and/ or diligent market monitoring;
- Adequate transmission and well-defined transmission rights;
- Ability of market to attract or maintain sufficient investment, and to survive natural or man-made disturbances.

Since the mid-1980, several countries around the world have engaged reforms, looking to acquire these attributes for their electricity markets. The terminology used to describe various approaches to changing the structure and organization of the market is presented in Table 2.2.

TABLE 2-2 TERMINOLOGY USED TO DESCRIBE VARIOUS APPROACHES ON ELECTRICITY MARKET REFORM
(Source: (Sioshansi, 2006))

Restructuring is a broad term, referring to attempts to reorganize the roles of the market players, the regulator and/or redefine the rules of the game, but not necessarily “deregulate” the market. For example, when California restructured its market, it “deregulated” its wholesale market by lifting nearly all restrictions to how wholesale prices could be set by generators, but kept its retail market fully “regulated”, in this case capped. Many problems ensued.

Liberalization is synonymous with restructuring. It refers to attempts to introduce competition in some or all segments of the market, and remove barriers to trade and exchange. The European Union, for example, refers to its efforts under this umbrella term.

Privatization generally refers to selling government-owned assets to the private sector, as was done in Victoria, Australia, with forms SECV, in Italy with ENEL, and is being done in France with EdF and GdF. It must be noted that one can liberalize the market without necessarily privatizing the industry, as has successfully been done in Norway and in New South Wales, Australia.

Corporatization generally refers to attempts to make state-owned enterprises (SOES) look, act, and behave as if they were for-profit, private entities. In this case, a SOE is made into a corporation with the government treasury as the single shareholder. For example, former SOEs in New South Wales, Austria, have been corporatized. They vigorously compete with one another, while all belonging to the same, single shareholder, namely the Government of NSW.

Deregulation is essentially a misnomer. No electricity market has been (or, in fact, can be) fully deregulated. Experience suggests that even well-functioning competitive markets need a regulator, or at a minimum, a market monitoring and anti-cartel authority. Until recently, Germany was the only major country attempting to go without a regulator but with an anti-cartel office monitoring the behaviour of market participants.

Chile, in 1987, and England and Wales, in 1989, were the precursors of market reforms, with privatization and liberalization schemes that have been investigated and followed in other countries. Market reform cannot mean tangible and immediate benefits without some risks, which make it politically untenable to push for market reform. Even when the design and structure of the reformed market are sound, the implementation and transition to the new regime can go wrong, sometimes with serious consequences. It was the case of California (USA), Russia³⁹, South Korea and Thailand. Table 2.3 summarizes the market reform highlights, with additional comments, in selected countries.

TABLE 2-3 ELECTRICITY MARKET REFORMS IN SELECTED COUNTRIES

(Source: (Sioshansi, 2006))

Country	Market Reform Highlights & Comments
Argentina	Has experienced problems due to external economic crises.
Australia	Various dates in various states; some states have privatized, others corporatized, resulting in un-level playing field but the outcome has proven workable thus far.
Brazil	Initial market reforms continue to be modified due to problems with initial market design.
Canada	Alberta and Ontario introduced competition. Ontario has rescinded it due to public pressure that followed price increases, while Alberta has succeeded. Progress stalled in other provinces.
Chile	First to introduce market reform in 1987; continues to evolve.
Colombia	Introduced market reform in 1994-95, is experiencing problems in retail, wholesale & capacity markets, reform of reforms in progress.
England & Wales	Introduced massive privatization and restructuring in 1989, has gone through at least three major phases of reform, continues to evolve, and has been widely studied and copied as a successful model.
European Union	25 members of EU continue to make slow progress. Various deadlines for unbundling and introduction of retail competition have been set but not fully implemented, and full retail competition is expected in 2007 but may not change the status quo. The goal of a fully integrated Pan European market remains elusive.
Japan	Has introduced limited competition to date with cautions pace. The new Japan Electric Power Exchange (JEPX) is in place but there is limited volume of trading.
Korea	Has created Korea Power Exchange (KPX) and broken up KEPCO into several generation companies. Full liberalization, however, has stalled due to political and labor opposition.
New Zealand	Experienced some problems in the absence of a regulator, which has been introduced, and has a rather complicated nodal pricing scheme.
Nordic Countries	Considered among the most successful markets based on bilateral trading, has expanded to include all Nordic countries, market survived a major drought without meltdown.
Singapore	Considered successful despite a small market, limited number of players, and a complicated nodal pricing regime.
Thailand	Liberalization and privatization stalled due to labor union opposition and lack of political support.
U.S.	Wholesale competition encouraged since 1992 with passage of Energy Policy Act and considered successful; retail competition introduced in selected markets since 1998 with mixed results, progress stalled after California electricity crisis in 2000-01, no retail progress since opening of Texas market in 2002.

³⁹ Market liberalization has been on the Russian agenda since 2000, and the wholesale prices have tripled between 2000 and 2006. (Sioshansi, 2006)

However, in the OECD area, there is a growing convergence in the process of restructuring of electricity markets, where the reforms share the following attributes (Hogan, 2002):

- Introduction of free choice for all consumers;
- Obligation to provide access on a non-discriminatory third party to transmission and distribution;
- Independence of the transmission activity; and
- Liberalization of electricity trade.

The implementation of market reform has been more challenging in large interconnected markets such as those in the U.S. and Europe.

One can say that an important step for the market reform in Europe was the European Union (EU) “White Paper — an energy policy for the European Union”, (Comissão Europeia, 1995), giving the European energy policy the following goals: competitiveness, energy supply security and environmental protection. Since then, the joint opening of the internal market for electricity and natural gas was identified as an important objective, which can provide new business opportunities and more cross-border trade. Since then, important steps have been taken to meet liberalisation objectives in the energy market.

Patrícia Pereira da Silva and Isabel Soares defend that the European electricity market is undergoing two fundamental changes: one is liberalisation; the other is the integration into a single pan-European market. For them, the intentions of the European Directives⁴⁰ are to establish a competitive market for generation and supply

⁴⁰ The electricity directive 96/92/EC and the gas directive 98/30/EC defined the rules for real competition and to give consumers a free choice of energy suppliers. The directives 2003/54/EC and 2003/55/EC, replaced these directives and gave a decisive contribution towards the creation of the internal energy market; however, the rules on legal and functional unbundling as provided for in Directive 2003/54/EC have not led to effective unbundling of the transmission system operators; Directive 2003/54/EC introduced also a requirement for Member States to establish regulators with specific competences; however, experience shows that the effectiveness of regulation is frequently hampered through a lack of independence of regulators from government, and insufficient powers and discretion. The Directive 2006/32/EC of the European Parliament and of the Council of 5 April 2006 on energy end-use efficiency and energy services, focused on helping consumers reducing their energy costs; The Commission Decision 2007/394/EC of 7 June, amending the Annexes to Directive 90/377/EEC, establish the methodology for collecting and compiling price of gas and electricity for industrial customers; The Directive 2009/72/EC of the European Parliament and of the council of 13 July 2009 repeal Directive 2003/54/EC and establishes common rules for the generation, transmission, distribution and supply of electricity, together with consumer protection provisions, with a view to improving and integrating competitive electricity markets in the Community; The Committee of European Securities Regulators (the

with several unbundled companies on one hand, and a separate, naturally monopolistic, regulated sector for transmission and distribution on the other, and replacing the pre-liberalisation system – where electricity supply in given geographical areas was provided by single vertically integrated companies (Pereira da Silva, et al., 2008).

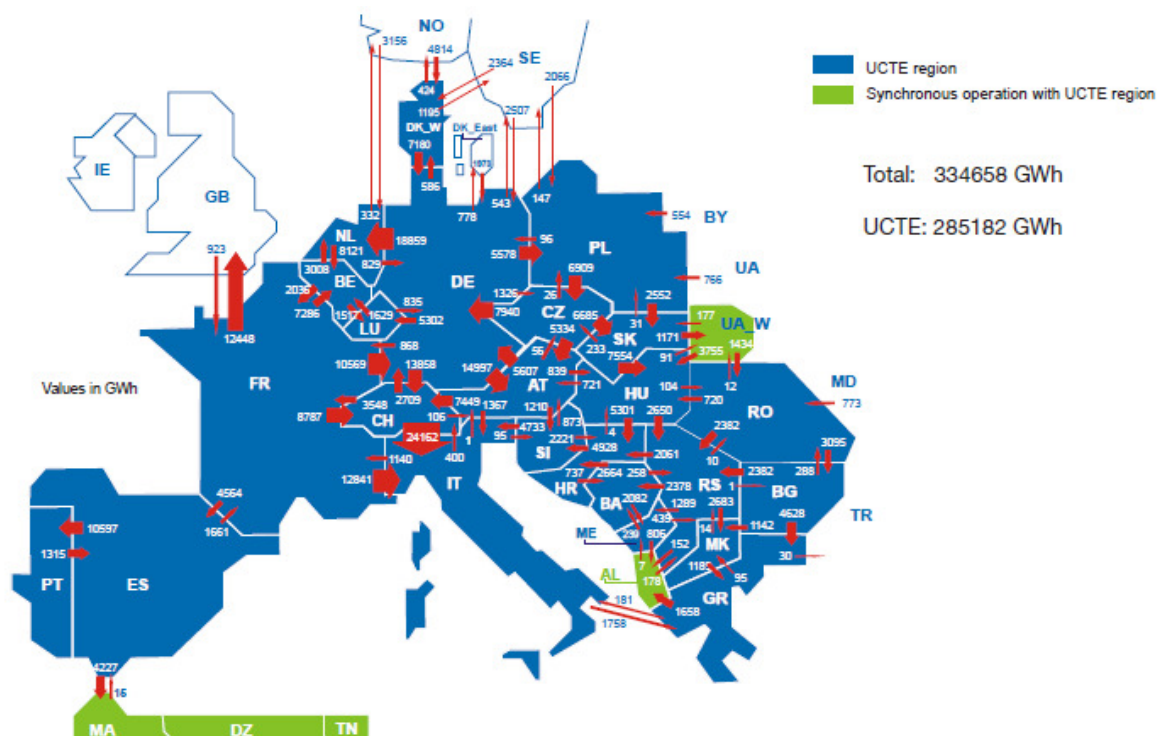


FIGURE 2-4 PHYSICAL POWER EXCHANGES IN EUROPE (UCTE REGION, 2008)

(Source: www.entsoe.eu)

‘CESR’) was established by Commission Decision 2009/77/EC ; CESR should confer and advise the Commission in regard to Guidelines defining further the record-keeping requirements; The Agency for the Cooperation of Energy Regulators (the “Agency”) was established under Regulation (EC) No. 713/2009 of the European Council and of the Parliament; Regulation (EC) No 714/2009 of the European Parliament and of the Council of 13 July 2009 on conditions for access to the network for cross-border exchanges in Electricity; Regulation (EC) No 715/2009 of the European Parliament and of the Council of 13 July 2009 on conditions for access to the natural gas transmission Networks recognise that equal access to information on the physical status and efficiency of the system is necessary to enable all market participants to assess the overall demand and supply situation and identify the reasons for changes in the wholesale price; Commission Regulation (EU) No 774/2010 of 2 September 2010 on laying down guidelines relating to inter-transmission system operator compensation and a common regulatory approach to transmission charging establishes a mechanism for the compensation of transmission system operators for the costs of hosting cross-border flows of electricity and a common regulatory approach to transmission charging; that Regulation expired on 2 March 2011. Commission Regulation (EU) No 838/2010, of 23 September 2010, on laying down guidelines relating to the inter-transmission system operator compensation mechanism and a common regulatory approach to transmission charging, beyond March 2011; The European Commission published in November a communication Com(2010) 639 “Energy 2020, A strategy for competitive, sustainable and secure energy”; The European Commission published in December Com(2010) 726, a proposal for a “Regulation of the European Parliament and of the Council on energy market integrity and transparency”.

In many countries electricity markets are evolving into hybrid forms. They are not completely unbundled, privatized, nor fully competitive. Hybrid markets fall into three basic groups (De Vries, et al., 2006):

- Markets that have been liberalized but are not fully privatized;
- Markets that are privatized but are not fully liberalized, in the sense that competition is restricted; and
- Markets that are privatized and behave competitively, and where the government or the regulator is very active on prices or in defining investment rules.

One can say that electricity markets within the EU are highly diverse. In general, it is clear that the interconnectivity is low and that pricing is complex and dependent on the regulatory framework, transmission capacity and global energy prices. While a number of European countries have liberalized in practice both electricity and gas markets, others have done so only on paper. Some reasons for the regulatory and policy difficulties to create a unified and competitive energy market in Europe are the deliberate state interference motivated by a desire to support the national energy companies, the lack of interest by dominant players or governments to build additional transmission lines to facilitate cross-border trade, and the weak enforcement of EU directives at country level.

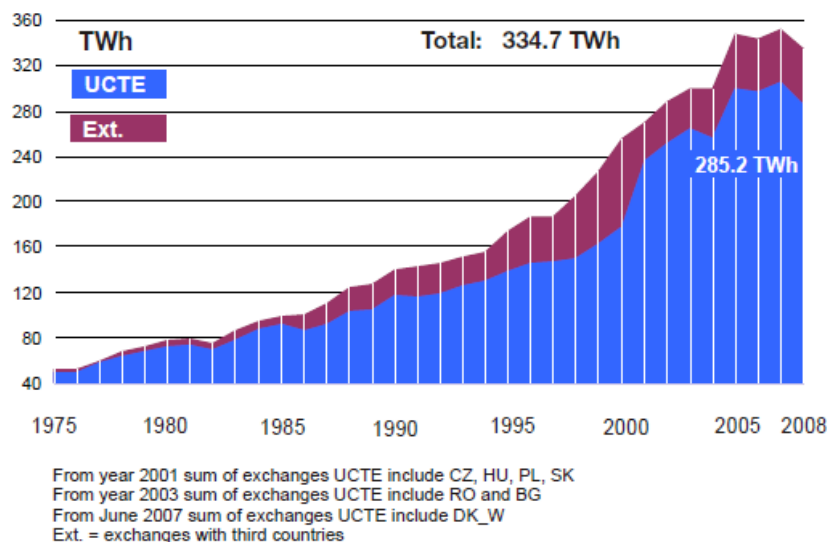


FIGURE 2-5 SUM OF ELECTRICITY EXCHANGES ON THE UCTE IN TWh (1975-2008)

(Source: www.entsoe.eu)

However, the greatest barrier to trade in the European electricity market seems to be the lack of capacity on cross-country interconnectors. As, in the former paradigm, they have only been built to provide emergency reserve and support capacity, rather than to provide major competitive flows, national TSO's have generally over-invested in internal transmission systems and under-invested in interconnections. An important indicator is the large price divergence that is patent among peripheral systems like OMEL⁴¹. Would transmission capacity over the border be unlimited and transmission costs negligible, then market forces would most probably suffice to make prices converge (Pereira da Silva, et al., 2008). But despite these reasons and difficulties, power trade has been increasing in Europe on the last decades, as shown in Figure 2.5, which means that, even though not perfect, there is already an existing electricity market in Europe⁴².

Two decades after market reforms introduction, many previously unbundled companies have re-bundled, usually by combining generation with retail business. Moreover, there is empirical evidence to suggest that such combinations are efficient, can manage risks and price volatility, and may be preferred by investors (Chao, et al., 2005). In the same direction, Meeus (Meeus, 2011) defends more recently that European electricity market infrastructures have been becoming more monopolistic because of two main reasons: a wave of mergers and acquisitions⁴³ and power exchanges that are increasingly organizing trade between zones⁴⁴. For Meeus, even though building “cartel” of “incumbent” and merchant power exchanges that is proposing to “monopolize” the organization of trade across borders is questionable from an economical point of view, it is likely to be the only institutionally feasible way to eliminate the significant cross-border trade inefficiencies that Europe is currently experiencing. A theoretical alternative to this cartel could be to adopt the cost-of-service regulated power exchange model all over Europe because such a power exchange has no profit incentives to abuse the monopoly of cross-border trade. However, it would require having all of them perfectly regulated, while coordinating and harmonizing across borders is far from just another regulated task in a mainly national regulatory frame. Meeus conclude that there are several promising regulatory actions that could help preventing that Europe's increasingly monopolistic market infrastructure would generate new trade inefficiencies. First, the reinforced market power of power exchanges could be tempered by enhancing transparency requirements, introducing governance rules to prevent that the cooperation among power exchanges could become closed cartels, and

⁴¹ These price differences are more relevant between Spain and France; in the last years the price differences between Portugal and Spain were strongly reduced or even eliminated in a large majority of the hours of the year.

⁴² A comprehensive analysis of the restructuring of the electricity sector in Europe, with details on the situation in the Iberian Peninsula countries (Spain and Portugal) can be found in (Pereira da Silva, 2007).

⁴³ For instance, APX taking over Belpex (the Belgian power exchange) in 2010, and Powernext (originally the French power exchange) and EEX (originally the German power exchange) merging into EPEX in 2009.

⁴⁴ Which has traditionally been the territory of the Over The Counter (OTC) electricity trading business in Europe.

continuing to allocate physical long term transmission rights. Second, the power exchanges' quality-of-service in the context of the EU market integration could be rewarded and the lack of it could be sanctioned.

2.3.4. THE PORTUGUESE ELECTRICITY MARKET REFORM

a) The Iberian Peninsula

Portugal and Spain share the Iberian Peninsula territory. They have much in common, but there are significant differences in geographic, economic and energy terms. The land surface of Portugal is one-fifth of that of Spain, and the population of Spain is four times larger. The population densities in Spain and Portugal are just above 90 and 110 inhabitants per square kilometre, respectively.

As can be seen in Table 2.4, the per capita electricity consumption on the Iberian peninsula countries (5939 kWh/inhabitant in Spain and 4684 kWh/inhabitant in Portugal, in 2007) is below the average for the EU-15 (6566 kWh/inhabitant). This difference has been falling due to the higher average rate of growth of demand in Portugal and Spain over the last years in relation to that of the EU-15.

TABLE 2-4 ELECTRICITY CONSUMPTION PER CAPITA COMPARISON (EU-15)

(Source: ERSE, European Commission and IEA)

	Unid. kWh				
	1970	1980	1990	2000	2007
FI	4 289,77	7 782,43	11 813,08	14 605,87	16 502,84
SE	6 982,59	10 216,61	14 055,38	14 506,31	14 612,02
LU	9 754,78	9 879,25	10 732,98	12 984,05	13 958,33
BE	2 720,30	4 391,93	5 818,62	7 563,93	8 107,34
AT	2 817,20	4 372,76	5 574,37	6 515,23	7 180,72
FR	2 258,93	3 794,30	5 195,03	6 335,70	7 031,05
NL	2 813,52	4 163,13	5 051,18	6 330,86	6 855,92
DE	3 330,22	6 365,53	7 194,92	5 882,85	6 603,45
DK	2 652,40	4 215,46	5 525,29	6 088,42	6 318,68
IR	1 542,49	2 527,92	3 394,18	5 342,11	6 018,31
ES	1 275,53	2 389,31	3 225,56	4 681,60	5 939,38
GB	3 703,54	4 159,42	4 794,10	5 593,86	5 750,37
IT	1 890,52	2 831,63	3 783,56	4 794,35	5 373,08
GR	939,94	2 056,85	2 804,84	3 957,13	5 133,93
PT	716,66	1 464,26	2 354,00	3 755,13	4 684,26
UE15	2 700,88	4 147,67	5 216,03	5 910,91	6 566,69

b) The Portuguese electricity sector reform

Until 1995 the Portuguese electricity sector was characterised by only one vertically integrated company, EDP – Electricidade de Portugal. The liberalization process started in 1988, with renewables and cogeneration.

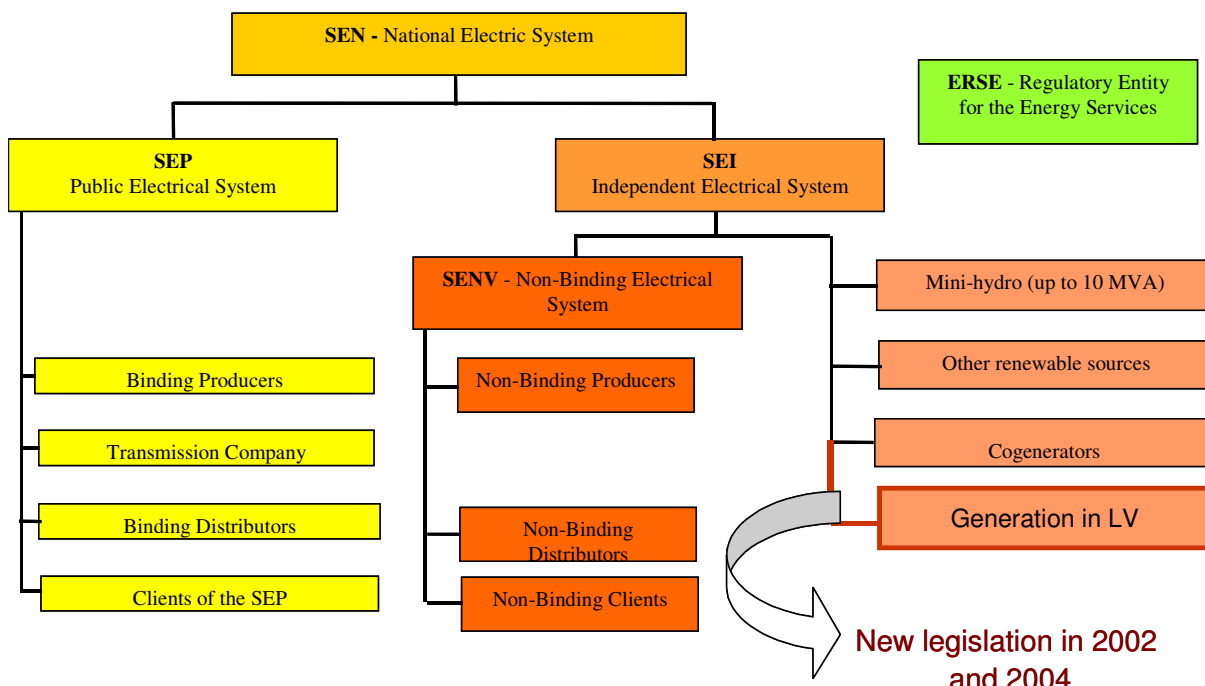


FIGURE 2-6 ORGANIZATION OF THE PORTUGUESE ELECTRICAL SECTOR (1995)

(Source: Prof. Tomé Saraiva)

ERSE, the Portuguese regulatory agency, is responsible for regulating the gas sector and electricity. ERSE is a legal person of public law, endowed with administrative and financial autonomy and its own property, governed by its Statutes adopted by Decree-Law n.º 97/2002, from 12nd April.

In 1995 a new organisation of the Portuguese electricity sector was defined by Decree-Laws 182/95 to 187/95. The sector changed from a vertical to a market driven and a regulated sector. EDP was split into child companies: 4 distribution companies, a transmission provider and a large producer (thermal and hydro). The Laws from 95 were amended by Decree-Laws 56/97 and 198/2000. In 2003 Decree-Laws 184/2003 and 185/2003 initiated a revision process of the National Electricity System, addressing the adaptation of the Portuguese system to the new Iberian market (MIBEL).

Since 2000 the majority of EDP holding shares are private. In July 2000 transmission was separated from EDP. REN operates the national transmission grid, on an exclusive basis. This concession is valid for 50 years from 6th September, 2000, when the contract was signed.

The Decree-Law No. 172/2006, of 23rd August 2006, completes the transposition of Directive 2003/54/EC, and develops the general principles governing the organization and functioning of the National Electricity System, approved by Decree-Law No. 29/2006 of 15th February, regulating the legal regime applicable to the exercise of generation, transmission, distribution and marketing of electricity and the organization of the electricity markets.

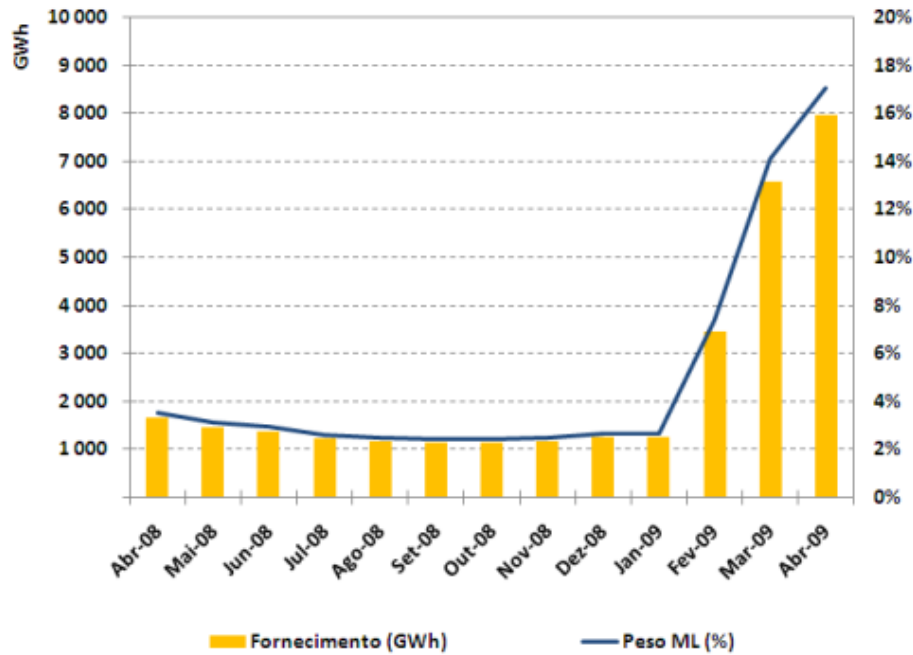


FIGURE 2-7 ANNUALIZED CONSUMPTION IN LIBERALISED MARKET (PORTUGAL)

(Source: ERSE)

The generation system is characterised by two regimes: the normal competitive regime (for organized markets or bilateral contracts) and the special regime (for renewables and cogeneration). Transmission and distribution became regulated public service concessions, and in the energy retailing there coexists competition with a regulated retailer. Consumers were given the right to choose the retailer. Until September 2006 only EHV, HV, MV and LV customers with contracted power higher than 41,4 kW (about 52.000 consumers, which corresponded to 55% of the demand) were eligible. From September 2006 all consumers are full eligible. The annualized consumption in the liberalized market in Portugal is presented in Figure 2.7. One can realise the strong increase since the beginning of 2009.

Tariff setting is a responsibility of ERSE, in an independent way from the government. A Tariff Code was passed in 1998. By that time network tariffs were set according to a Postage Stamp Basis⁴⁵.

Since 2002, the tariff system comprised the following tariffs: Access tariffs, which include the Tariff for the Global Use of the System - TGUS; Tariff for the Use of the Transmission Networks - TUTN; Tariffs for the Use of Distribution Networks - TUDN⁴⁶; Network Retailing - NR; and integral regulated tariffs, which include Access plus Energy, E, and Regulated Retailing, RR, tariffs. From 2009 onwards, the Network Retailing activity and the corresponding regulated tariff were eliminated.

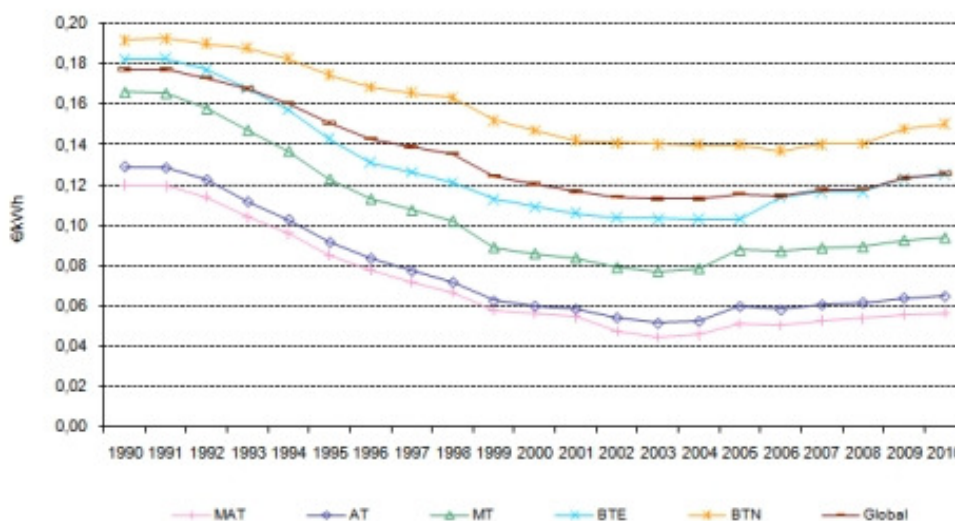


FIGURE 2-8 AVERAGE PRICE TREND ELECTRICITY PORTUGAL CONTINENTAL 2010 - CONSTANT PRICES
(Source: ERSE)

On the transmission activity two main topics have to be addressed:

- Tariff for the Use of the Transmission Networks (TUTN); it is set on a Cost of Service/Remuneration Rate⁴⁷ (CoS/RoR) basis, and includes the High Voltage and Extra High Voltage Terms, and prices for power (€/kW.month) and for reactive energy received or supplied;
- Transmission Expansion Planning; the transmission provider submits 5-year expansion plans to the Regulatory Agency; these plans are prepared in order to meet security indices agreed also with the Regulatory Agency; if the plan is accepted, the investment costs are included in the tariff (TUTN).

⁴⁵ The postage stamp is the simplest pricing systems. Under this system, a fixed price per energy unit is charged for transporting a given amount of electrical energy over the grid, independent of the distance or the voltage level.

⁴⁶ There was another tariff, Network Retailing, eliminated in 2009 Tariff Code.

⁴⁷ The current rate is 7% (9% till 2005).

In the current regulatory Period [2009-2011] ERSE decided to implement a new regulation model to the transmission activity, based on “revenue cap” on operating costs and unit reference costs to investments, including:

- Mechanism for encouraging increased availability of the network assets,
- Mechanism for encouraging maintenance of equipment at the end of life; and
- Incentives for new investments.

Investment in the transmission network has favoured the expansion and strengthening of capacity, as demonstrated by the developments in the lines and substations (Figure 2.9).

REN is active on the search for new solutions that reinforce the transmission system to enable transferring large amounts of power from renewables (including wind offshore) and facilitate electricity trading, use of higher voltage levels or even HVDC, maximize use of existing corridors, allow operating reserve, deepen the monitoring capacity of the system in real time, in order to implement new "preventive" solutions (Baptista, 2009).

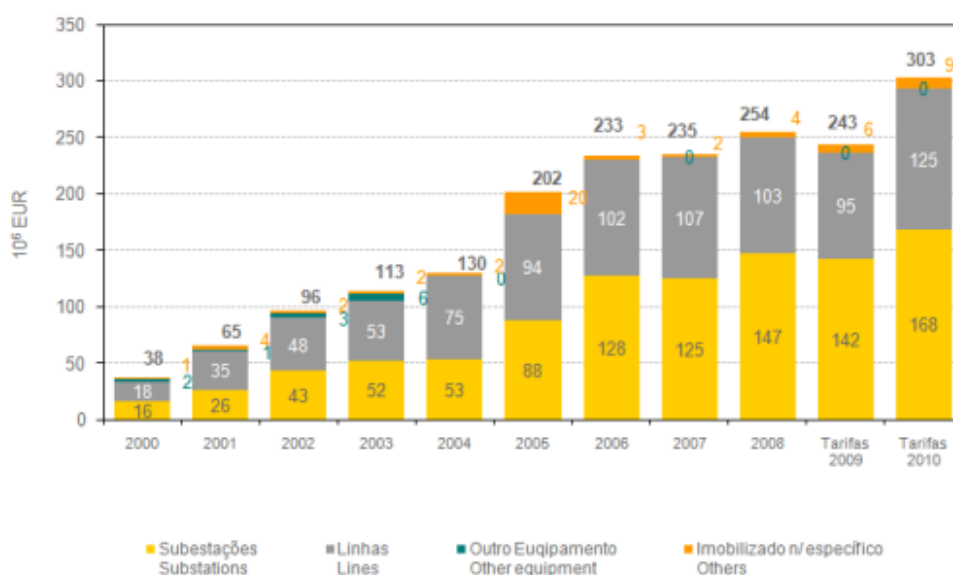


FIGURE 2-9 INVESTMENT IN THE PORTUGUESE TRANSMISSION GRID
(Source: REN)

An overview of the Portuguese electricity market can be found in (Ferreira, et al., 2007). Dominguez and Bernat published a useful work on the restructuring and generation of electrical energy in the Iberian Peninsula (Dominguez, et al., 2007). Two other important references on the analysis of the Portuguese market are (Ferreira, 2010), in

the area of regulation, and (Tomé Saraiva, 2002), in regulation and pricing of network usage.

c) The Iberian Market Operator (OMI)⁴⁸

The Iberian Electricity Market (MIBEL) constitutes a joint initiative from the Governments of Portugal and Spain, with a view to the construction of a regional electricity market. With the materialisation of MIBEL, it becomes possible for any consumer in the Iberian zone to acquire electrical energy under a free competition regime, from any producer or retailer that acts in Portugal or Spain.

MIBEL's main goals are:

- To benefit the electricity consumers of both countries, through the integration of the respective electricity systems;
- To structure the market organisation based on the principles of transparency, free competition, objectivity, liquidity, self-financing and self-organisation;
- To support the development of the electricity market of both countries, with the existence of a single reference price for the whole of the Iberian Peninsula;
- To allow all the participants free access to the market, under equal conditions of rights and obligations, transparency and objectivity;
- To promote economic efficiency of electricity sector companies, encouraging free competition amongst them.

The convergence of the Portuguese and Spanish power systems was formally initiated with the signing of the "Protocol for collaboration between the Portuguese and Spanish Administrations for the formation of an Iberian Electricity Market", in November 2001. In that document, the two countries established the foundations necessary to begin cooperation between the various entities with responsibilities in the sectors framework - administrations, regulators and operators - with a view to harmonising the participation conditions of economic agents on MIBEL.

The organizational model for MIBEL was decided in October 2002, based on the existence of the Iberian Market Operator (OMI⁴⁹) and the main goals for creating MIBEL were established. The conditions set forth as necessary to ensure MIBEL operability were:

⁴⁸ Please address to www.omip.pt for more information.

⁴⁹ In Portuguese "Operador de Mercado Ibérico"

- Deployment of all operational procedures for the operation of both poles of the market - the Portuguese pole with the financial futures markets (OMIP) and the Spanish pole with the daily and intraday markets (OMIE) – and their integration into the single Iberian Market Operator (IMO) in the medium term;
- Harmonization of the regulation of electricity markets in Portugal and Spain;
- Resolving most of the Energy Purchase Agreements in Portugal;
- Institutionalization of the Iberian Regulatory Council, with representatives from two national regulators.

The "Agreement between the Portuguese Republic and the Kingdom of Spain for the Constitution of an Iberian Electrical Energy Market" was signed in Lisbon, January 20th 2004. The Agreement consolidated the foundations for the construction of the common market, outlining the general development of the project, not just at a legislative and regulatory level but also outlining the market's operational solutions. One of the most significant aspects of this Agreement was the reciprocal recognition of agents. Besides this, the Agreement also established the foundations for the new market.

As integration factors of MIBEL, two entities were foreseen, responsible for the management of the organised markets, before the creation of OMI: OMEL (Spanish division), responsible for the management of the day and intraday market and OMIP (Portuguese division), responsible for the management of the derivative markets.

The start of the integrated working of the two MIBEL entities should have happened on April 20th 2004. Officially, the settled time frame for MIBEL was delayed due to significant political changes in Portugal, with the election of a new Government, which only came into power in March 2005, the lack of legal developments needed to launch the MIBEL derivatives market and uncertainties in the regulatory framework of MIBEL, provoked by the Spanish government initiative to produce a "White Book" on the electricity sector, and its impact on the organizational and working model of MIBEL. Dominguez had also identified the difficulties from the introduction of the MIBEL (Dominguez, et al., 2007): the acquisition contracts between Portuguese producers and REN give rise to an “a priori” market reference price which will have to be adjusted to the overall charge based on real market prices; the asymmetry of distribution in the countries; in Portugal there was a single distributor of electricity and gas, in Spain there were five and three, respectively; differences in rates between the countries, as transmission and distribution costs, among others, were higher in Portugal; it would be therefore necessary to establish rates which properly reflect the costs of provision; the limited capacity of the interconnections; this determined congestions which occur from the adoption of measures which efficiently reduce the risk of exercising market power or market price control while the system goes from 1200 MW of interconnection capacity to 3000 MW in 2015.

As agreed in Évora's Summit, in November 2005, the entry into force of the MIBEL Derivatives Market effectively happens in July 2006, more precisely in day 3, simultaneously with the start-up of the Regulators Committee. In November 2006, during the XXII Portuguese-Spanish Summit of Badajoz the Governments of Portugal and Spain reiterated their commitment to expand the Iberian Electricity Market (MIBEL), to extend to the Iberian Natural Gas Market (MIBGAS) and to establish an agreement that would allow the formation of oil and natural gas reserves within the Iberian zone.

On January 2008, and with a view to speeding up the development of the Iberian Electricity Market, both Governments signed in Braga an Agreement with the following fundamental points:

- Builds the foundations for the Iberian Market Operator (OMI), based on two management entities with investment stakes, with head offices in Portugal and Spain and cross stakes of 10% where each company will hold 50 % of each of the market management companies; Timings are set for the constitution of OMI;
- Establishes the role of last recourse retailers on the derivatives market;
- Clarifies some points in relation to the economic management of the interconnection between Portugal and Spain;
- The principles regarding the setting of last recourse tariffs are agreed upon;
- The role of the Regulators Board is detailed.

Both Governments agreed in Zamora, on January 2009, to the definitive constitution of the Iberian Market Operator through the integration of both operating organisms, until June 2009, and the creation of a joint working group to accompany the process. Also stated was that the work to strengthen the electricity interconnections, foreseeing the installed capacity reach 3000 MW in 2014, was moving along without problems⁵⁰.

The regime entering into force of the MIBEL has the following mutual benefits (Dominguez, et al., 2007):

- Greater security of supply, as there will be a larger number of generating installations available to cover unforeseen failures;

⁵⁰ The Project for the gas interconnection between Viseu and Zamora was also launched. At the same time a working group was created for regulatory harmonisation between the two countries.

- Greater efficiency from increased competition in the sector, due to the rise in the number of operators; and
- Greater benefits for the consumers of both countries provided that they have access to the market under conditions of equality, transparency and objectivity.

d) Extra high voltage (EHV) Iberian interconnections

EHV interconnections between national electricity systems have historically been developed in parallel with the internal networks of each country. Interconnections initially sought external support in the event of any failure affecting the national security of electricity supply.

A series of blackouts in summer 2003 in several countries (U.S., 14th August, the United Kingdom (London and Birmingham), 28th August and 5th September, Sweden, 23rd September, and Italy, 28th September 28), affecting more than 100 million people were conveyed by the various national authorities, regulators or operators, as not related to the generation level, but with aspects of the transmission capacity and lack of interconnections.

The existing price differences between national markets have also increased the demand for interconnection capacity (Pereira da Silva, et al., 2008). However, it has been demonstrated that the interconnections are not only useful for emergency situations or for economic reasons, but also in normal operating conditions they offer outstanding advantages:

- Optimization of the daily production of electric power plants;
- Better opportunities for renewable energy exploitation;
- Creating competition and improving security of supply.

The importance of these interconnections explains why European TSO's are currently working on around fifty projects to strengthen existing transmission networks, under the guidelines of the European Union. Among these projects, the Spain-France interconnection is considered of priority.



FIGURE 2-10 SPAIN / FRANCE EHV INTERCONNECTIONS

(Source: (REE, 2010))

The EHV interconnection between Spain and France currently⁵¹ consists of 4 lines: two in the Basque Country (Arkale-and Hernani-Argia Argia), one in Aragon (Biescas-Pragnères) and one in Catalonia (Vic Baixas). It has a total commercial capacity of 1.400 MVA exchange, ie, it represents only 3% of the maximum current demand in the peninsula, far below the 10% that the European Union established as the minimum level at the Barcelona Summit in 2002. A new 400 kV line (see Figure 2.10) will double the current EHV interconnection capacity and reach 6%, which will ensure greater security of supply and, above all, greater stability of the system to increase the link with the European system.

TABLE 2-5 SPAIN / PORTUGAL EHV INTERCONNECTIONS

(Source: (REN, 2010))

kV	Linha	Capacidade em regime nominal [MVA]	
		Inverno	Verão
400	Alto Lindoso - Cartelle 1 ²	1386	1386
	Alto Lindoso - Cartelle 2 ²	1386	1386
	Falagueira - Cedillo	1386	1300
	Alqueva - Balboa ²	1386	1280
	Lagoaça-Aldeadávila	1706	1469
220	Pocinho - Aldeadávila ¹	435	374
	Pocinho - Aldeadávila ²	435	374
	Pocinho - Saucelle	430	360
130	Lindoso - Conchas ³	131	90

⁵¹ October 2010.

The EHV Interconnection lines between Spain and Portugal in December 2010, which are integrated with REE and REN transmission networks, are shown in Table 2.5. The global capacity is 8681 MVA in winter and 8019 MVA in summer time. In the short term, in 2011-2012, REE and REN will continue to carry out their investment plan, which stands for the purpose of interconnection capacity, the conclusion of the 400 kV axis between Recarei and Lagoaça, the entry into service of Armadale (Spain) - Recarei (Portugal) 400 kV overhead line, and the construction of the interconnection Portimão Tavira (Portugal) - P. Guzman (Spain).

The construction of a second 400 kV line Minho-Galicia which, together with the implementation of internal reinforcements already identified in joint studies REN-REE, is foreseen until 2014, and will provide a more efficient and safe operation of the Iberian electricity networks, as well as future and significant increases in interconnection capacity.

2.3.5. MARKET MODELING

In the new energy paradigm, electricity industry firms are exposed to significant risks and their need for suitable decision-support models has greatly increased. Regulatory agencies and other stakeholders also require analysis support models in order to supervise and monitor market behaviour. Traditional electricity operation models are not suitable and don't fit to the new circumstances since market behaviour was not modelled in. Competition trends in the electricity sector have led to the development of decision and analysis support models adapted to the new market context.

Two main features determine the complexity of such models: the product “electricity” cannot be stored and its transportation requires a physical link, the transmission lines (Ventosa, et al., 2005). These features explain why on modelling the electricity market one has to take into consideration the representation of the technical characteristics and the limitations of the generation assets. Pure economic or financial models, adopted in other activities, do an improper job on explaining electrical market behaviour. Good models, in most cases, have to deal with imperfectly competitive markets, much more complex to represent, as only a limited number of firms are expected to participate in the wholesale electricity markets. Several researchers have already addressed the classification of electricity market modelling approaches: (Smeers, 1997), (Kahn, 1998), (Hobbs, 2001), (Day, et al., 2002) and (Ventosa, et al., 2005).

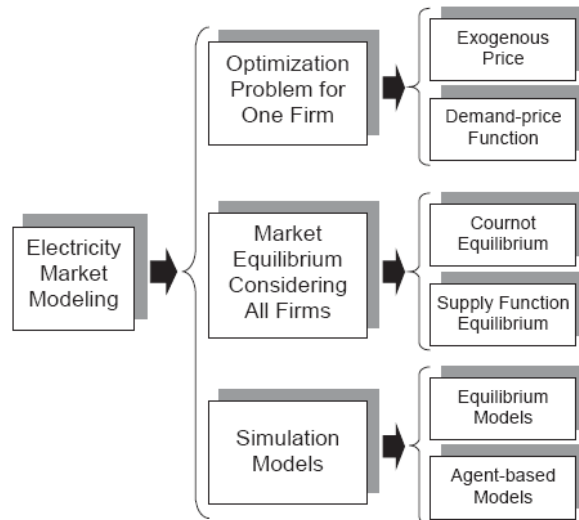


FIGURE 2-11 SCHEMATIC REPRESENTATION OF THE ELECTRICITY MARKET MODELLING
(Source: (Ventosa, et al., 2005))

The numerical techniques for analyzing market power in electricity are usually focused on equilibrium models, based on participants profit maximization in an oligopolistic competition. Two kinds of equilibrium are usually selected: the Cournot competition, where firms compete in quantity and the Supply Function Equilibrium approach (SFE), where firms compete both in quantity and in price. The usual conclusion is that Cournot is more flexible and tractable. For this reason it has attracted more interest than SFE. However, the SFE approach presents certain advantages, in particular, when predicting medium-term prices of electricity. This advantage results from the fact that it does not rely on the demand function, as the Cournot model, but on the shape of the equilibrium supply functions decided by the firms. Also firms' strategies do not need to be modified, as demand evolves over time. Quite the opposite, supply functions are specifically conceived to represent the firms' behaviour under a variety of demand scenarios. This SFE approach flexibility, however, leads to important limitations on numerical tractability. To date, only under very sharp assumptions have SFE approaches been solved when applied to real cases. Ventosa representation of the electricity market modelling trends, from a structural point of view, is shown in Figure 2.11.

In addition to the classification presented in Figure 2.11, which is based on the mathematical structure of each model, Ventosa suggests that electricity market models can be categorized considering more specific attributes, which are useful in understanding the advantages and limits of each model. The taxonomy presented considers the following issues: degree of competition; time scope of the model; uncertainty modelling; inter period links; transmission constraints; generating system representation; market modelling.

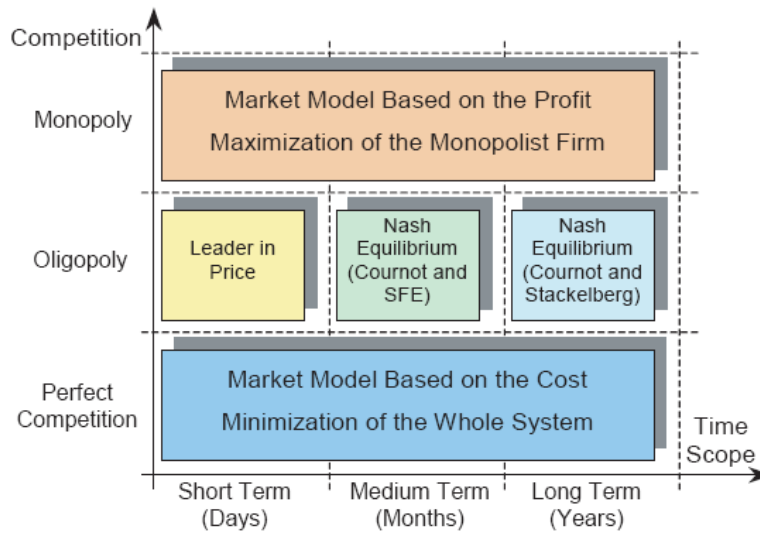


FIGURE 2-12 THEORETICAL ELECTRICITY MARKET MODELS DEPENDING ON COMPETITION AND TIME SCOPE

Source: (Ventosa, et al., 2005))

As shown in Figure 2.12, for a long term approach in an oligopoly situation, as it is the case for example in the Iberian Peninsula Electricity Market, the suitable model would be the Stackelberg Equilibrium, due to its sequential decision-making process. In these situations there is a leader firm that first decides its optimal capacity. Then, the follower firms make their optimal decisions knowing the capacity of the leader firm.

Inter period links are important, not only in long term studies, but also in the short term, especially in what with transmission and generation⁵² is concerned.

Transmission constraints divide electricity market models into two main types: single-node models and transmission network models. Even though the majority of market based models do not consider the transmission network, there are examples of transmission expansion planning models⁵³:

- Transshipment approach, that omits Kirchhoff's voltage law although the model allows for inter temporal constraints regarding investment decisions (Wei, et al., 1999);
- DC OPF (Berry, et al., 1999), (Hobbs, et al., 2000), (Hobbs, et al., 2001);
- Nonlinear AC network model (Ferrero, et al., 1997);

⁵² Production medium term decision are typically oriented to derive optimal annual management policies for hydro reserves that must consider the dynamic process of inflows and thus take the form of a set of monthly or weekly operation decisions. Similarly, short-term models must take into account the inter-temporal constraints implicit in thermal unit commitment decisions.

⁵³ From a computational point of view, only two of these approaches permit solving realistically sized problems: Hobbs, and Wei and Smeers (Ventosa, et al., 2005).

- Combined gas and electricity network optimisation (Chaudry, et al., 2008);
- Risk analysis and regret criterion (Miranda, et al., 1997), (Miranda, et al., 1998 b), (Schweickardt, et al., 2007);
- Game Theory (Contreras, 1997), (Minoia, et al., 2006), (Lima, et al., 2008), (Molina, et al., 2010).

The contribution of simulation models has been significant as inspiration, on account of their flexibility to incorporate more complex assumptions than those allowed by formal equilibrium models. In these models, agents learn from past experience, improve their decision making and adapt to changes in the environment. This suggests that adaptive agent-based simulation techniques can be useful on the understanding of certain features of electricity markets ignored by static models and therefore these techniques will be helpful in the new energy paradigm (Ventosa, et al., 2005).

Agent-based simulation models have experienced lately an increasing popularity amongst electricity market modellers. This development can be explained by the additional opportunities that this modelling paradigm offers for the analysis of economic systems, as compared to more traditional equilibrium or optimisation models. An overview of the agent-based simulation of electricity markets research can be found in (Sensfuß, et al., 2007) and (Kim, et al., 2009).

2.4. CONCLUSION

Energy markets have suffered in recent years significant changes in their organization. In addition, the increasing share of energy derived from renewable sources raises challenges in terms of planning, not only in generation, but also on transmission networks. Addressing these challenges is critical for the quality of service and reliability of power systems.

Restrictions in the interconnections between the transmission systems of several countries are considered a major obstacle to the functioning of the European market of electricity. The interconnections between Portugal and Spain are already at an acceptable level, but the interconnection between Spain and France continues to be insufficient, according to the parameters set by the European Union. This fact helps to realize the importance of making TEP studies on an European scale, following the most recent guidelines of the European Union.

From the power systems progress emerges the need for powerful tools for modelling and optimization, allowing better management of resources and improving the quality of service provided by the TSO's across Europe.

Agent-based simulation models have been adopted on recent years by electricity market modellers. Adaptive agent-based simulation techniques are considered helpful on the understanding the dynamics of electricity markets in the new energy paradigm.

3. TEP IN THE LITERATURE

“TEP should be seen rather as a decision making problem.”

(Vladimiro Miranda and Luis Miguel Proença, 1998)

3.1. SCOPE

TEP is a fascinating discipline in the area of networks and energy markets, given its importance for the normal functioning of the electrical infrastructure, its economic impact and for the consumer's quality of life. Given its complexity, a fact generally recognized in the published literature, it is important to know the latest research and available tools.

The next sections of this chapter include a literature review on TEP, that can be complemented by consulting (Latorre, et al., 2003), (Lee, et al., 2006) and (Molina, et al., 2010).

We begin with an introduction focusing on the principles, criteria and modelling of the TEP.

The input data, particularly in terms of uncertainty and vagueness, and the option for Fuzzy Numbers as a way to handle this situation are then addressed.

Planning horizons are studied, by characterizing the static approaches (single period) and the dynamic approaches (multi period).

Due to the opening of markets to multiple operators, market based planning strategies are becoming increasingly important and are also covered in our analysis.

In Section 3.6 models based on the mathematical methods and heuristics are presented. On this section one gives a special emphasis on meta-heuristics, making up a description of the various approaches (trajectory meta-heuristic, evolutionary algorithms and swarm intelligence) and presenting a comparison between different models.

At the end of the chapter some specific techniques to solve large problems are mentioned. Among these techniques is artificial intelligence.

We conclude with the presentation of the drawbacks of the methodologies that are now being followed up.

3.2. THE TRANSMISSION EXPANSION PLANNING

3.2.1. INTRODUCTION

Despite all efforts to improve energy efficiency of systems, the fact is that TSO's continue to base their estimates on rises in global energy consumption. In the Portuguese case, REN in their estimates of consumption trends considered a load increase of 4.3% per year, which correspond at final consumption net of own consumption of 68.7 and 83.9 TWh respectively in 2014 and 2019 (REN, 2008). Other important aspects to be considered in TEP are the increasing distributed generation, particularly from renewable sources, and interconnections with adjacent power areas. Thus, it remains pertinent to study the reinforcement of the transmission networks.

The basic principle of TEP is to minimize the network construction and operational costs while satisfying the requirement of delivering electric power safely and reliably to load centres along the planning horizon (Jalilzadeh, et al., 2007).

The expansion of a transmission network may include the construction of new overhead lines or underground cable in new corridors, and the upgrading of existing lines or cables in corridors already in use by increasing the number or the capacity of lines or cables, increasing the rated voltage, the improvement on the capacity and control equipments (FACTS, Capacitors, ...). In a more broad sense, one may also consider the introduction of generators in appropriate places to allow a better balance between generation and loads, and better use of the network, increasing the transmission capacity of the network.

From the stake-holders point of view, transmission expansion should attend the following targets (Buygi, et al., 2006), (Delgado, 2010):

- Encourage and facilitate competition among market participants;
- Provide non-discriminatory access to cheap generation for all consumers;
- Alleviate transmission congestion;
- Minimize the investment, the risk of investments and operation costs;
- Increase the reliability of the network;
- Increase the flexibility of system operation while reducing the network charges;
- Minimize the environmental impacts;
- Allow better voltage level regulation.

Even though the principles are quite simple, the complexity of the problem and the impact on society due to the heavy investments that have to be made, together with the costs incurred due to failures, transform TEP on a challenging issue:

- Complexity of the problem; TEP is a complex problem as it has a mixed integer non linear programming nature that in fact corresponds to a combinatorial problem. It is also a complex mathematical problem as it involves, typically, a large number of variables (Sadegheih, et al., 2008).
- Heavy investments; Even in small countries, like Portugal, network expansion means important investments. As an example, REN – Rede Eléctrica Nacional, the Portuguese TSO, plans to invest 1.43 bln euros in 2009-2014 to modernise and expand its electricity networks, integrate renewable energy generation centres and enable Portugal to become a net exporter of energy in the medium-term⁵⁴. According to the Portuguese regulatory system, network investment once validated by the regulatory board are integrated in the access tariffs, which mean that they will ultimately be paid by network users.

Since the introduction of deregulation, addressing this problem is becoming even more complicated (Wu, et al., 2006). The models have to change to meet new challenges, some of which result from the fact that:

- One or more entities owned generation systems and other or others own and operate the transmission system⁵⁵ (Wu, et al., 2006);
- The capacity of transmission lines determines the degree to which generators in different locations can compete (Minoia, et al., 2006);
- In most countries and power systems, the developers of new wind parks are already asked to invest themselves on the distribution or even transmission grid reinforcement and to pay the interconnection lines to the already existing network (Estanqueiro, et al., 2007);
- There is the substitution effect of transmission by generation or by load via demand-side management (Wu, et al., 2006);

⁵⁴ <http://www.forbes.com/markets/feeds/afx/2008/03/11/afx4758706.html>, research made on the 29/4/2008

⁵⁵ The technical requirements for connection of decentralized production to the network are set by the network operator's given the power to be connected, the characteristics of the network and the need to ensure a power quality within the limits set by regulations in force. For the network operator the problem lies in the decentralized production unit operation in parallel with the network, forcing the owner of that unit to conform to the requirements imposed by the operator.

- Depending on the size of the distributed generation⁵⁶ units, their location and the ownership, network can help to reduce market power and thereby lead to a more efficient market (Ackermann, 2007);
- There are more and more environmental constraints, such as limits on pollution produced by power plants (Marcato, et al., 2007) and on the construction of new lines;
- The new organizational structure of the electricity industry leads to new relations between agents, to a progressive decoupling between the flow of electricity and the flow of money, and it requires an unbundling of traditional tariff schemes, namely with the creation of specific tariffs to remunerate network providers for their costs (Braga, et al., 2005).

The number of organizations to take into account in planning the expansion of transmission networks has increased very significantly with deregulation. One has to realise that each of them pursue his own goals, often discordant. Such stakeholder groups require coordination procedures, including incentives, so that investors realize the attractiveness of complementary⁵⁷ investments in transmission.

TEP is a challenging research area and many authors all over the world dedicate much of their efforts on developing new methods on this topic. Transmission networks have reached different levels of complexity according to the economic development and energy needs of the countries. The technology and location of power plants, the geography of the area and the location of loads have strong influence on the transmission systems. The load profiles, either in daily or yearly bases, and forecasts, have to be taken into consideration. Regulations and legal norms vary also a lot from market to market, and suggest the adoption of different models on planning and operation. Most of the developed countries, in particularly in Europe, went through a deregulation process during the last two decades. Therefore, without considering market conditions and regulations, the TEP approach is academically sound, but in

⁵⁶ This is based on the observation of the most obvious characteristics of this generation model: there are generation units, sometimes small, a few hundred kW, sometimes bigger, in the tens of MW, which are connected to medium or high voltage networks. This connection is done in a dispersed way, sometimes without having been subject to coordinated study and without having been provided with the necessary infrastructure to be controlled centrally. Thus, decentralized generation highlights, at the same time the geographic dispersion and small size of the groups, and their non-systematic integration in existing control centralized systems on medium and high voltage networks. This new paradigm is contrary to the prevailing one until the end of the XXth century, based in large classical generation centers. These centers usually represent a large concentration of installed power in some locations on the network, which were planned in a coordinated way and with a centralized control. This new paradigm is also contrary to the former, in which the large generation centers had to participate in the provision of ancillary services, such as frequency and voltage regulation. The decentralized generation is evolving in order to also include these functions in the future (Delgado, 2010).

⁵⁷ This means that joint or coordinated investments in generation and transmission assets are needed.

many cases there are not sufficiently developed commercial tools available, which are fundamental for real life scale (Lee, et al., 2006 a).

3.2.2. PRINCIPLES AND CRITERIA OF TEP

The principles and criteria of the expansion plans of transmission networks result of joint discussions between the agencies involved, such as TSO's, regulators, large customers and potential investors in power plants.

According to REN, the grid expansion investment projects are usually the result of different needs (REN, 2008):

- Link to large power plants;
- Link at special regime distributed generation;
- Strengthening the capacity of interconnection; in the Portuguese case, this includes the objectives of exchange capacity levels with the Spanish network;
- Connection to the distribution networks;
- Link at final customers;
- Strength the national transmission network, for example replacing equipment reaching the end of life;
- Management of reactive power and voltage control in the network.

For an easier handling of projects and decision making, these different needs can be aggregated into hierarchical levels of decision, as proposed by Francisco Reis (Reis, 2005):

- Hierarchical level 1 (NH1): Hierarchical level of decisions that correspond to changes in the topology of the transmission system in respect to its structure; here are included significant changes to network operations, occupation of corridors and linking the different voltage levels. The priority of these projects is very high, and includes reinforcements on branches where the power flows are important and at the interconnections between different voltage levels. These investments are typically over half of the budgeted investment plans;
- Hierarchical level 2 (NH2): Hierarchical level of decisions which correspond to changes in local nature network topology; these changes are not structural but may have an important relevance to the local performance level of the network. The

reinforcements included in this hierarchical level depend on factors such as local variations in consumption, the stated policies of reserve between neighbouring substations at the point of consumption and network capacity in place to manage the distribution corresponding flows.

Like other TSO's, REN set in Portugal in 2001 the "Standards for Security Planning of the National Transmission Network" which are followed in his studies (REN, 2001). Investments have to verify the criteria associated with the "n-1" contingencies and a limited number of "n-2" contingencies, or when it is put into question acceptable voltage profiles, which is binding corrective measures by changing the network⁵⁸.

The criteria to select network investment projects are based on techno-economic analysis of different alternatives to satisfy the identified needs, resulting in the lowest discounted value. In making this assessment two topics are considered:

- The benefits that are achieved with the investment, including the reduction of energy or power not supplied, the reduction of losses, changes in operating costs and quality of service improvements;
- The costs associated with the investments, including also those associated with the operation and maintenance of new infrastructure.

Other planning principles that are followed are:

- Reduction of environmental impacts⁵⁹;
- Management of fault current levels⁶⁰;
- Joint optimization with the generation and distribution subsystems⁶¹;
- Interconnection capacity management⁶².

⁵⁸ In some networks still in the early stages, as the EDM transmission network in Mozambique, less stringent contingency criteria of N-½ compared to N-1 are used for generation and transmission planning. In these early stage networks the transmission distances are usually very long and the associated costs of a reserve line are very high. Allow generator unit tripping after line faults releases the contingency criteria and permits a reduction in overall transmission investments.

⁵⁹ For example, by enhancement and more efficient reuse of existing corridors for the overhead lines, particularly by renovation and reconstruction of lines either for higher voltages or double lines; in the case of remodeling or building substations, especially those located in urbanized areas, adopting solutions with low environmental impact as the GIS type compact substations.

⁶⁰ One search for a techno-economic compromise between the appropriate degree of enmeshing the network and the resultant increase in short-circuit power, which involves the use of more expensive equipment.

⁶¹ Technical and economic reviews are conducted at the boundary between the transmission and distribution levels, looking for a comprehensive overview of the power system.

In addition to the improvement of network equipment, TSO investments also include projects in the area of communications, dispatch, control and protection, and information technology. The strict criteria related with these investments are different from those for the network equipment and are usually associated with replacement of equipment at end of life, or allowing new functions or activities of the TSO.

3.2.3. TEP MODELING

A model in general, and a TEP model in particular, is a tool that, from a starting point, taking into account input information and expansion options, will desirably provide an optimal solution.

In the scientific context, optimization is a process that tries to find the best possible solution for a given problem (Schweickardt, et al., 2010). The procedure that performs the search is called program and has three main elements:

- A set of possible solutions or feasible solutions, which are often referred to as the search space;
- A search strategy, which is usually expressed in general terms, an algorithm, or individuals in which case one speaks of principle, dependent on your application, the problem addressed, and
- A criterion to discriminate the best solutions among the feasible ones.

However many real problems, as the TEP, correspond to very complex problems. In several cases the planner gets satisfied with solutions that improve some performance indices, although eventually not corresponding to the global optimal plan. Apart from the relaxation of the optimality criterion, it should be recognized that TEP typically corresponds to a multi-criteria combinatorial problem.

Combinatorial optimization problems exhibit the following characteristics (Lawler, et al., 1985):

- The objective is to find the maximum / minimum of a given objective function over a finite set of solutions, indicated as S ;
- There is, on the decision variables of which depend on the objective function, a set of constraints that identifies a subset of S , S_f , which contains the so-called feasible solutions; depending on the context, these sets are referred as S_f or S , alternatively, as the search space;

⁶² For example, based on the targets set under the MIBEL, either for import or for export, studies are made, both in Portuguese and in Spanish networks, so that all may achieve their goals.

- The objective function or the definition of the set S are not subject to any condition;
- As S is finite, variables are, in general, discrete, restricting its domain to a finite set of values;
- The number of elements in S ($|S|$) is very large, making it impractical to enumerate and evaluate all solutions in order to determine the optimum.

These features complicate even more the search for a solution in multi-objective optimization problems.

So, a combinatorial optimization problem $P = (S, f)$, can be defined by:

- A set of variables, $X = (x_1, \dots, x_n)$;
- The variable domains, $D_1, \dots, D_n$;
- Some constraints among variables;
- An objective function f to be minimized (or maximized), where $f: D_1 \times \dots \times D_n, \mathbb{R}$.

The set of all possible feasible assignments is $S = \{s = \{(x_1, v_1), \dots, (x_n, v_n)\}, s \text{ satisfies all the constraints}\}$. S is usually called a search (or solution) space, as each element of the set can be seen as a candidate solution. To solve a combinatorial optimization problem one has to find a solution s with the minimum objective function value.

As already mentioned, a TEP model will desirably provide optimal solutions. However,

“TEP should be seen rather as a “decision making” problem”
(Miranda, et al., 1998 a),

in the sense that one can conceive a solution approach that includes some degree of interaction with the decision maker so that the final solution will always be determined by some degree of subjectiveness. This means that the interaction with the planner may not be just limited to some settings and small adjustments (Latorre, et al., 2003) but can in fact correspond to a crucial decision step in the whole scheduling or planning exercise. This theme will be addressed in Chapter 6.

3.3. INPUT INFORMATION

3.3.1. UNCERTAINTIES AND VAGUENESS

The quality of the input information has strong influence on the final plan or plans. Power system data is becoming more and more uncertain and vague. Restructuring and deregulation of the power industry have increased the uncertainties (Torre, et al., 1999), (Pereira, et al., 2000), (Buygi, et al., 2003), (Nadira, et al., 2003).

As transmission network owners and investors are focused on their own profit, rather than in maximizing the social welfare (David, et al., 2001), the input data in the new energy paradigm has a different characterization:

- Private investment, which normally shows greater economic rationality than public investment, since it is subject to market forces⁶³;
- Investment subject to regulation; given the attention of the regulator, it must be possible to ensure the quality of service required by law; the TSO can not jeopardize the performance of the generators or the service provided to consumers;
- Opening of markets; no one knows who, when and where investments will be made.

Researchers have different approaches and use sometimes the same word when referring to very different concepts. This is the case of uncertainties and vagueness.

To some authors, like Barros, the TEP problem can be classified as a function of the uncertainties under consideration (Barros, et al., 2007):

- Deterministic, when there is no explicit consideration of uncertain variables;
- Probabilistic, when random variables are taken into account, such as equipment forced outages;
- Under uncertainty, when it includes uncertainties that cannot be represented through probability theory.

Others, like Buygi, classify uncertainties in two categories, random and non-random uncertainties, and also refer to the concept of vagueness⁶⁴ (Buygi, et al., 2006).

⁶³ On the regulation and projects evaluation see “Portugal bem Regulado”. (Ferreira, 2010)

⁶⁴ According with Buygi, the limitation of deterministic approaches is that they consider only the worst cases of the system without considering the probability of occurrence or degree of importance of these cases. Non-deterministic methods consider many cases with assigning a probability of occurrence or a

Random uncertainties are related to phenomena that have a repeated nature in the sense that it is possible to reproduce them under the same conditions as many times as we want. In this case, the possible outcomes are known and completely characterized and the source of uncertainty relies on the complexity of the model that would have to be developed to predict the next event. For these situations, past observations can be an excellent source for statistic purposes. In other cases, there are non-repeatable events that can be termed as related to non-random uncertainties. Finally, uncertainty can also be related to vague information resulting in most cases from the lack of information or to the incomplete characterization of the possible outcomes of a phenomenon themselves. In these cases, the planner or expert can formulate statements expressing their judgments regarding the possible behaviour of a parameter namely reflecting their past experience.

Sources of random uncertainties in unbundled power systems that can be treated using probabilistic models are:

- Load levels;
- Generation costs and bids;
- Power and bids of independent power producers;
- Wheeling transactions; and
- Availability of system facilities.

Non-random uncertainties can correspond to

- Generation expansion/closure;
- Load expansion/closure;
- Installation/closure of transmission facilities;
- Replacement of transmission facilities;
- Transmission expansion costs and market rules.

degree of importance to each of them and hence are able to model the past experience, future expectations and uncertainties. This researcher aggregates the main non-deterministic approaches which have been used for TEP as: a) Probabilistic load flow, b) Probabilistic reliability criteria, c) Scenario techniques, d) Decision analysis and e) Fuzzy decision making. Then he classifies uncertainties in two categories: random and non-random uncertainties. For him, approaches a) and b) are able to take into account random uncertainties, c) and d) non-random uncertainties, and e) imprecision and vague data.

Scenario techniques are one of the suitable tools to deal with these non-random uncertainties (Reis, 2005). Stake-holders decision making and planning criteria, among others, are examples of sources of vague information that can be modelled using fuzzy concepts (Buygi, et al., 2006).

The reference “Toward a generalized theory of uncertainty (GTU)—an outline”, from Zadeh, summarizes the theory of uncertainty and represents a significant change both in perspective and direction in dealing with uncertainty and information (Zadeh, 2005). Uncertainty is an attribute of information. For Zadeh, a fundamental premise of GTU is that information, whatever its form, may be represented as what is called a generalized constraint. Generalized constraints may be qualified, combined and propagated. In GTU, reasoning under uncertainty is treated as propagation of generalized constraints, in the sense that rules of deduction are equated to rules which govern the propagation of generalized constraints. A concept which plays a key role in deduction is that of a protoform (abbreviation of prototypical form).

For Cheng, uncertain information in power network planning does not have only one characteristic of uncertainty but many (Cheng, et al., 2004). They proposed the adoption of Unascertained Numbers⁶⁵ (UN) to deal with information that varies within some range and with different probability. These numbers are considered as being effective and feasible to describe and to deal with the unascertained information and are a powerful tool to determine the impacts of uncertain data in the results.

Some relevant papers addressing uncertainties in power systems have been published on the last years under the new energy paradigm:

- TSO revenue reconciliation problem (Braga, et al., 2005);
- Demand uncertainty and capacity of the lines (Alvarez, et al., 2006);
- Uncertainties in load forecasting and generator sitting (Chennapragada, et al., 2006);
- Unreliability costs in TEP (Barros, et al., 2007);
- Environmental constraints in generation expansion problems (Marcato, et al., 2007);
- Modeling several resources, in particular hydro (Barroso, et al., 2007);

⁶⁵ Unascertained mathematics is a tool to describe subjective uncertainty quantitatively. It deals with unascertained information, which refers to the information demanded by decision—making over which the message itself has no uncertainty but, because of situation constraints, the decision-maker cannot grasp the whole information needed. Uncertainty is then “produced” by the decision-maker.

- Hydrothermal Systems Under Uncertainty (Oliveira, et al., 2007);
- Short-term Hydropower Planning Coordinated with Wind Power (Matevosyan, et al., 2007);
- Distributed resources and re-regulated electricity markets (Ackermann, 2007);
- Wind power uncertainty (Holttinen, et al., 2007);
- Terrorist threat problem (Carrion, et al., 2007);
- Impact of uncertainties in load and generation at the power flow level, when no statistical information is available (Matos, et al., 2008);
- Demand and generation cost uncertainty modelling in power system optimization studies (Gomes, et al., 2009).

3.3.2. FUZZY NUMBERS

“A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one.” (Zadeh, 1965)

In the most common power system problems it is not always possible to make measurements or have a clear picture of what may happen in the future. One may have only perceptions, which may be considered as vague information (Zadeh, 1999). Perceptions are different from measurements, as measurements can be modelled in a crisp way or admitting some probability distribution of their error, whereas perceptions are fuzzy, as shown in Figure 3.1.

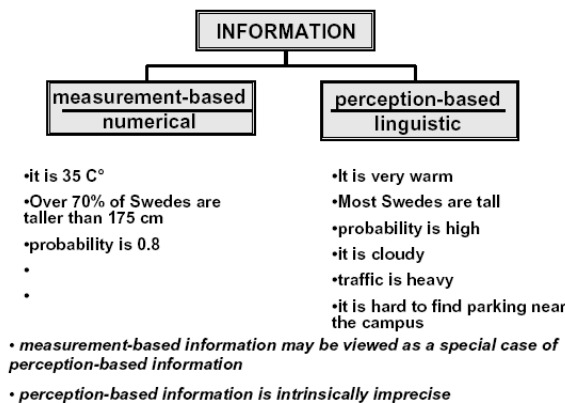


FIGURE 3-1 MEASUREMENT-BASED VS PERCEPTION-BASED INFORMATION
(Source: (Zadeh, 2005))

In a fuzzy set one has grades of membership. According with the membership function, a grade of membership ranging between zero and one is assigned to each element of the fuzzy set, as illustrated in Figure 3.2.

Fuzzy numbers are a very convenient framework to integrate vague information in models. Performing unary and binary arithmetic operations is based on very fast formulas that nevertheless provide adequate and useful results (Tomé Saraiva, et al., 1994 b).

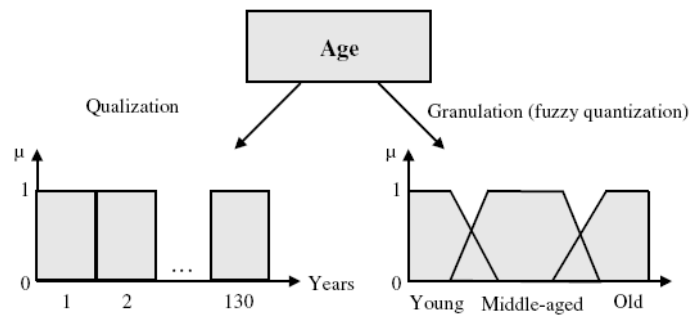


FIGURE 3-2 THE FUZZY QUANTIZATION

(Source: (Zadeh, 2005))

Zadeh published a series of articles summarizing the research in this area as the following:

- “Fuzzy sets” (Zadeh, 1965);
- “From Computing with Numbers to Computing with Words, From Manipulation of Measurements to Manipulation of Perceptions” (Zadeh, 1999);
- “Toward a generalized theory of uncertainty (GTU)—an outline” (Zadeh, 2005).

Other authors who have developed important research in this area are Mamdani (Mamdani, et al., 1975), Bezdeck (Bezdek, 1981), Kaufmann and Gupta (Kaufmann, et al., 1985), Zimmerman (Zimmermann, 1985), Dubois and Prade (Dubois, et al., 1996), and Yager (Yager, 2002).

An important reference on fuzzy sets applications to power systems is the book “Electric Power Applications of Fuzzy Systems” (El-Hawary, 1998). A bibliography review on fuzzy set theory applications in Power Systems can be found in (Momoh, et al., 1995), for publications up to 1994, (Bansal, 2003), from 1994 to 2001, and (Osman, 2007).

A selection of research works on power systems adopting Fuzzy Set theory is shown below:

- Distribution system planning (Miranda, et al., 1989);
- Load forecasting (Miranda, et al., 2004);
- Evaluation of risk bounded distribution expansion (Schweickardt, et al., 2002);
- Power flow (Miranda, et al., 1992 b), (Tomé Saraiva, et al., 1994 b), (Tomé Saraiva, et al., 2004), (Gouveia, et al., 2007), (Matos, et al., 2008);
- Renewable energies market evaluation (Monteiro, et al., 1997);
- State estimation (Pereira, et al., 2002);
- Active and reactive power control (Gomes, et al., 2006);
- Demand and generation cost uncertainties (Gomes, et al., 2007), (Gomes, et al., 2009).

3.4. PLANNING HORIZON

The treatment of the period under analysis will define the TEP model as static or dynamic as it will be detailed in the next paragraphs.

3.4.1. *STATIC PLANNING*

A TEP model is static if the planning horizon is one period, usually one year. These static approaches are also termed as single stage models. The planner is focused on finding the optimal network for a future single definite situation (Latorre, et al., 2003). Usually, the available references on TEP are dedicated to the static planning problem, which is already difficult to solve for complex systems (Escobar, et al., 2004). Usually a multi-year horizon is decoupled in several isolated periods treated separately and in sequence. Therefore, the expansions and reinforcements obtained for the first period are included in the network as available for the second one and so on. In this sense, an expansion plan is just a collection of local expansions or reinforcements determined without taking into account the dynamic and the relationships between periods.

As already mentioned before, even when considering only deterministic aspects, it is very difficult to find the optimal solution for TEP problems, since one has to make use of combinatorial algorithms. When uncertainties and chronological aspects are added to these problems, the optimal solution becomes “almost inaccessible” (Rezende, et al., 2010). Even though losing the dynamic and the relationships between periods, static approaches are adopted as they are less demanding in terms of computation.

Some static models for transmission planning are presented by (Latorre, et al., 2003), (Fonseka, et al., 2004), (Sadegehieh, et al., 2008) and (Gajbhiye, et al., 2008). A comparison between PSO and EPSO in a static TEP study can be found in (Pringles, et al., 2007 b). Another comparison, among Discrete Monkey Algorithm⁶⁶ (DMA), Primary Monkey Algorithm (PMA), Improved Genetic Algorithm (IGA) combining elitism, and simulated annealing and Basic Particle Swarm Optimization (BPSO) in a static TEP approach was recently introduced by (Wang, et al., 2010).

⁶⁶ Monkey algorithm derived from the simulation of monkeys' mountain-climbing process; it is another variation on swarm intelligence algorithms. Consisting of three major processes as climb process, watch-jump process and somersault process, MA is suitable for solving non-linear, multidimensional and multimodal optimization problems (Wang, et al., 2010).

3.4.2. DYNAMIC PLANNING

The TEP is dynamic when an optimal expansion strategy is outlined along the whole planning horizon of several years (Latorre, et al., 2003). The chronological aspect refers to the multi-stage nature of the TEP problem (Rezende, et al., 2009 a). Considering chronological aspects requires the consideration of multi-time periods, in order to identify stage-by-stage possible sequences of transmission reinforcements. For this, such a dynamic problem is also addressed as a multistage and coordinated planning (Escobar, et al., 2004).

Dynamic models for TEP problems can be found in the following references:

- Mathematical optimization technique (Kaltenbatch, et al., 1970);
- Dynamic optimization (Dusonchet, et al., 1973);
- The Ortie model (Dodu, et al., 1981);
- Optimal AC load flow (Meliopoulos, et al., 1982);
- The Loden program, a linear methodology (Bertoldi, et al., 1984);
- Maximum principle (Kim, et al., 1988);
- Competitive environment (Haffner, 2000);
- Hybrid model, with genetic algorithm (Escobar, et al., 2001);
- Revenue reconciliation, with Simulated Annealing (Braga, et al., 2005);
- Reinforcement scheduling convergence (Reis, 2005);
- Transmission capability between two areas (Assis, et al., 2007);
- Ordinal optimization (Xie, et al., 2007);
- Genetic algorithms (Romero, et al., 2007);
- A mixed-integer LP, in a competitive pool-based market (Torre, et al., 2008);

- Differential evolution (DE) and DC power flow-based model (Sum-Im, et al., 2009);
- Artificial Immune Systems and DE Based Approaches (Rezende, et al., 2010);
- Evolutionary Particle Swarm Optimization (Guamán, et al., 2010).

The current and future development of the EHV power grid in China, where further research and development efforts are being pursued, may be found in (Dong, et al., 2010). The 2020 EHV transmission expansion plan in China consists of 66 transmission lines (1000kV AC and 800kV DC) for a total distance of 38,800 km.

All dynamic approaches face an huge task, due to the problem dimension. Usually the Garver System, with 6 nodes, is adopted for model test purposes. When using real systems, the authors have to focus also on very small networks. It is, for example, the case of Rezende, who selected a real sub-transmission network which belongs to CEMIG (State Energy Company of Minas Gerais, Brazil), with 12 buses, 6 loads, 1 interconnection and 1 generation bus. The peak load of this subsystem is 780.05 MW and the maximum local generation capacity is 226.76 MW. The considered expansion horizon was 10 years, with an average load increase rate of 5% per year. A maximum of three transmission lines per corridor were accepted. Even for this small sub-transmission network, a total of 3.29×10^{38} reinforcement sequences are eligible for this TEP problem. As usual, the final objective was to find the best sequences that minimize the present value cost of investments and ohmic transmission losses⁶⁷ (Rezende, et al., 2010).

3.4.3. PSEUDO - DYNAMIC PLANNING

Dynamic planning usually adopts combinatorial algorithms and has to take into consideration uncertainties and chronological aspects. These features allow a coordinated planning, but make the algorithms very heavy and time consuming. For these reasons, pseudo-dynamic planning is a possible solution to simplify dynamic TEP approaches.

The coupling among the years on the planning period cannot be lost, and the constraints have to be respected along the years. This planning approach results in many variables and detailed constraints, and requires a huge computational effort.

Usually authors focus on deriving a small set of plans that are worthwhile to find good enough solutions with reduced computational effort. As a result, the TEP is often simplified into series of static sub problems. These approaches are also called pseudo-dynamic procedures and were adopted during the last thirty years. (Senra, et al., 1978),

⁶⁷ An important result from this research is that better results were achieved when an initial good quality population was defined through a process termed as Intelligent Initialization or Seeding.

(Dechamps, et al., 1980), (Limmer, 1980), (Monticelli, et al., 1982), (Pereira, et al., 1985), (Nasser, et al., 1989), (Pereira, et al., 1987), (Levi, et al., 1991), (Binato, et al., 2001), (Latorre, et al., 2003).

There are two possible methods for pseudo-dynamic TEP:

- The “forward method” is adopted by Binato and consists in solving static transmission expansion plans, starting from the first year and sequentially for all years (Binato, et al., 1995); in the next years the approach considers the investments that had been done in the previous years;
- The “backward method” is a different approach; here the procedure consists in start solving the problem by the last year and considers the new features to solve the violations on intermediate periods (Platts, et al., 1972).

Backward methods usually produce better solutions than forward methods. Binato introduced a combined method “backward-forward” on the search for more consistent and economic long-term expansion plans (Binato, et al., 1992).

Pseudo-dynamic TEP is not just a series of static planning sub plannings, as the starting sets are the result of a selection made by the decision maker, which allow the reduction of the computational effort without losing the focus on the worthwhile good enough solutions. Due to developments in computer resources, these methods have been abandoned in favor of pure dynamic planning.

3.5. MARKET BASED PLANNING STRATEGIES

The TEP can be addressed based on the transmission costs. Transmission costs, both in the short-term, and in the long-term, have to be evaluated and properly allocated to network users (Braga, et al., 2005).

Cost allocation is usually classified in average, incremental and marginal methods. Competitive electricity markets use marginal prices to settle the transactions between generator owners and consumers. A marginal price at a given node can be interpreted as the sensitivity of the cost regarding a change in load at that node (Amarasinghe, et al., 2007). These approaches may include short-term operation cost, in Short Term Marginal Prices (STMP) methods, or also include investment costs, in Long Term Marginal Prices (LTMP) methods. Even though STMP are easily computed, these methods have a drawback as they originate revenue reconciliation problems. Typically, they are only able to recover a small percentage of the transmission regulated costs. Methods based on LTMP are heavy, as LTMP are difficult to compute, but they allow a very accurate recovery of the whole costs. Marginal prices are very interesting approaches and give good economic signals, inducing improvements on efficiency and network use.

Braga describes a multi criteria long-term TEP problem and an approach to compute LTMP. The formulation considers four criteria: operation costs, investment costs, a reliability index corresponding to the Expected Energy Not Supplied and a risk index represented by the Exposure Index as a way to deal with uncertainties in demand along the planning horizon. The LTMP reflect both investment and operation costs, thus being able to conveniently address the Revenue Reconciliation Problem that would arise if short-term approaches were used (Braga, et al., 2005).

A value-based TEP algorithm was proposed by Lee. The algorithm makes use of the probability density functions (PDFs) of locational marginal prices (LMPs) to deal with the changes in power flow patterns due to the changes in the bid prices set by generation companies (Lee, et al., 2006).

Transmission line congestion as a primary indicator for transmission expansion planning has been investigated by Lu et al. The calculation of congestion costs under single side bid Poolco market is proposed as the social surplus difference between the transmission line before and after congestion. The generator's bidding price change is considered as a result of market factors in a deregulated electricity market (Lu, et al., 2006).

A TEP model in deregulated electricity markets considering transmission congestion, wind power integration and double-sided bidding power-pool operation for both generation and demand was developed by Orfanos et al. (Orfanos, et al., 2010). A compromise between the congestion revenue and the investment cost is used to determine the optimal expansion scheme, considering the lines outage rates. Both the level of congestion and the price deviation in the network are used as the driving indicators for the need of network expansion. The uncertainty in wind power generation introduces the probabilistic locational marginal prices (LMPs) and the estimated congestion revenue for a specific configuration.

Schuller proposed an Efficient Pricing and Capital Recovery for Infrastructure over Time, based on Incentives and Applications for TEP. By integrating the assessment and assignment of congestion fees with other economic principles like “peak-load-pricing” and the “inverse elasticity” rule for apportioning capital costs, a sequence of pricing rules is suggested that can lead to a smooth, efficient and fair evolution of prices over space and time. These pricing principles also result in compatible incentives for all parties, and they complement several existing electricity system planning processes (Schuler, 2011).

3.6. MATHEMATICAL AND HEURISTIC METHODS

TEP can be classified according to the method adopted to build the expansion plans. These methods can be classified into three types: mathematical, pure heuristic and meta-heuristic approaches (Latorre, et al., 2003). In the next paragraphs we will detail models in these three classes.

3.6.1. MATHEMATICAL METHODS

Mathematical models are focused on optimization processes, with cost minimization objective function subject to sets of constraints (Lee, et al., 2006 b). As the plan is usually obtained under large simplifications, as it is not possible to consider all details of the network on the problem model, it should be verified according to technical, environmental and financial points of view before any decision is taken.

Many researchers have developed mathematical models using different approaches and techniques:

- Classical programming techniques:
 - Linear Programming (Garver, 1970), (Kaltenbatch, et al., 1970), (Hashimoto, et al., 2003);
 - Dynamic Programming (Dusonchet, et al., 1973) (El-Abiad, et al., 1973);
 - Quadratic Programming (El-Metwally, et al., 1993);
 - Non Linear Programming (Youssef, et al., 1989), (Sanchez, et al., 2005);
 - Mix Integer Programming (Lee, et al., 1974), (Haffner, et al., 2000), (Torre, et al., 2008);
- Mathematical decomposition techniques:
 - Benders Decomposition (Pereira, et al., 1985), (Binato, et al., 2001), (Marcato, et al., 2007);
 - Hierarchical Decomposition (Romero, et al., 1994), (Romero, et al., 2002);
 - “Branch and Bound” Algorithm (Pinto, et al., 1990), (Haffner, et al., 2008), (Rider, et al., 2008);
- Other optimization techniques:

- Interior Point (Xie, et al., 2000), (Alguacil, et al., 2003), (Sanchez, et al., 2005), (Rider, et al., 2008), (Silva, et al., 2011);
- Ordinal Optimization (Guan, et al., 2006), (Xie, et al., 2007).

Mathematical optimization methods can experience difficulties on solving large-scale TEP problems. We have to keep in mind that these problems are nonlinear and non-convex in nature. The computational effort is huge and the obtained optimal solution can correspond to a local optimum due to intrinsic limitations of the searching process (Lee, et al., 2006 a).

On the other hand, many of these methods require the relaxation of the binary to continuous variables. The rounding process may potentially lead to solutions far from the optimum, but with the advantage of having lower computational burden.

3.6.2. *HEURISTIC METHODS*

The solution of combinatorial optimization problems has to do with finding optimal solutions from a discrete set of feasible solutions. However, many of these problems cannot be solved to optimality in reasonable computation times, due to their dimension or to their characteristics. Reaching optimal solutions is also meaningless in many real situations, since one is often dealing with not precise data and rough simplifications of reality. So, the goal of approximate algorithms, or heuristics, is to produce good approximate solutions as quick as possible, without necessarily providing any guarantee of solution optimality.

Heuristic methods go step-by-step generating, evaluating, and selecting expansion options, with or without interacting with the planner (interactive or non interactive) (Latorre, et al., 2003). These methods are inventive techniques based on engineers' experience (Lee, et al., 2006 a). Taking advantage from this experience, the computational performance of heuristic methods is usually better than that of the mathematical methods.

Local searches are performed, following rules defined by the planner. The solutions are classified according to the rules, which can be either logical or empirical, and consider different information like technical, financial and service data. The process is stopped when no further improvement is possible on the best solution found.

Heuristic models include the following approaches:

- “Overload networks”, which are procedures based on the analysis of the flow through fictitious lines of unlimited capacity (Garver, 1970), (Villasana, et al., 1985), (Levi, et al., 1991);

- Decomposition between the investment and the operation sub-problems (Bayona, et al., 1994);
- Sensitivity analysis, which aims at identifying additional circuits that may improve the performance of the network (Lee, et al., 2006 a); all of them start from an initial plan and, after successive evaluations, they improve it until obtaining a quasi-optimal plan (Senra, et al., 1978), (Romero, et al., 2005), (Sanchez, et al., 2005).

It is possible to find good feasible solutions with a reasonable computational effort using heuristic algorithms. However, the quality of these solutions is not guaranteed, in the sense that it is not possible to prove that they are the best ones.

3.6.3. META-HEURISTIC METHODS

Meta-heuristic methods combine mathematical optimization with heuristic concepts. These methods have been subjected to deep research on recent years. Even when applied to large problems, meta-heuristic methods are able to identify quasi-optimal solutions with acceptable computational effort.

Some approaches on Meta-heuristic models and their applications to TEP are:

- Trajectory meta-heuristics; use a single solution during the search process and the outcome is also a single optimized solution; most of trajectory meta-heuristics are extensions of simple iterative improvement procedures that incorporate techniques that enable the algorithm to escape from local optima; trajectory-based meta-heuristics include: Hill Climbing (HC); Simulated Annealing (SA) (Romero, et al., 1996), (Gallego, et al., 1997), (Braga, et al., 2005); Tabu Search (TS) (Areiza, 1997), (Gallego, et al., 2000), (Silva, et al., 2001), (Sadegheih, et al., 2008), (Silva, et al., 2008), (Silva, et al., 2008), (Silva, et al., 2011) and Greedy Randomized Adaptive Search Procedures (GRASP) (Binato, et al., 2001), (Festa, et al., 2004);
- Evolutionary Algorithms (EA); EA refers to a subset of the evolutionary computation (EC) that explores biological evolution mechanisms, as reproduction, mutation, recombination (crossover) and selection; several algorithms share these characteristics as Evolutionary Programming (EP); Genetic Algorithms (GA) (Escobar, et al., 2004) (Reis, 2005), (Silva, et al., 2005), (Romero, et al., 2007), (Sadegheih, et al., 2008); Evolution Strategies (ES) (Silva, et al., 2006), (Silva, et al., 2008), (Silva, et al., 2011); Differential Evolution (DE) (Dong, et al., 2006) (Rezende, et al., 2009), (Silva, et al., 2011); and Artificial Immune Systems (AIS) (Rezende, et al., 2009 b), (Silva, et al., 2011);

- Swarm Intelligence (SI); SI is the property of a system whereby the collective behaviour of agents interacting locally with their environment causes coherent functional global patterns to emerge; SI provides a basis with which it is possible to explore problem solving without centralized control or the provision of a global model; the metaheuristics included in this group, Particle Swarm Optimization (PSO) and Ant Colony optimization (ACO), are composed by a population of simple agents that interact with each other and with the environment; although the agents follow quite simple rules and there is no control structure responsible for guiding the behaviour of the agents, the emergence of a global intelligent behaviour is observed, unknown to individual agents; some references on PSO are as follows (Kennedy, et al., 1995), (Kennedy, et al., 2001), (Sensarma, et al., 2002) (Ren, et al., 2002), (Jin, et al., 2007), (Li, et al., 2008), (Poli, 2008), (Ren, et al., 2010) and (Silva, et al., 2011); ACO references may be found in (Dorigo, et al., 2004), (Rezende, et al., 2009 b), (Silva, et al., 2010) and (Silva, et al., 2011).

The literature also includes several approaches that combine different meta-heuristic models:

- GA, Probabilistic Choice and Risk Analysis (Miranda, et al., 1997);
- GA, SA and TS (Gallego, et al., 1998);
- ES and mathematical methods (Kandil, et al., 2001);
- GA, SA and TS to solve dynamic problems (Fonseka, et al., 2002);
- GA and Monte Carlo simulation (Yang, et al., 2005);
- FS and “Branch and Bound” (Choi, et al., 2005);
- FS and risk analysis (Schweickardt, et al., 2007);
- GA, TS and mathematical programming (Sadegheih, et al., 2008).

Jin et al. introduced a discrete method for particle swarm optimization and applied it in transmission expansion planning. They also made a comparison among this PSO method, genetic algorithm and ant colony optimization. The test was performed adopting the Garver network and a 18 busbar simplified system of Southwest China. From the results one can conclude that PSO proved to be a good option for static TEP (Jin, et al., 2007).

A comparison of meta-heuristics for scheduling jobs on computational grids is performed by Abraham, involving Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) Algorithm.

The PSO approach is based on fuzzy matrices to represent the position and velocity of the particles in PSO, in which a new mapping between the job scheduling problem and the particle is constructed. The approach is to dynamically generate an optimal schedule so as to complete the tasks in a minimum period of time as well as utilizing the resources in an efficient way. The results clearly illustrate the success of nature inspired heuristics, as ACO and PSO, in providing real-time good solutions especially when the search space is very large (Abraham, et al., 2008).

Leite da Silva made a performance comparison of metaheuristics to solve the multistage transmission expansion planning (Silva, et al., 2011): Evolution Strategies (ES), Differential Evolution (DE), Artificial Immune Systems AIS, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Tabu Search (TS). Unfortunately EPSO was not included in this comparison. The adopted case studies were the Garver Network, with 6 buses, and a real sub-transmission network with 12 buses, including six loads, one interconnection, and one generation bus. It is the same network mentioned before, adopted by Rezende (Rezende, et al., 2010).

The performance of the metaheuristic approaches was evaluated through a so called Quality Index, Iq (%), which measures the quality of the best sequences found. From expression (3.01), one concludes that the lower this index, the better the sequences.

$$Iq(\%) = \frac{1}{n_{best}} \sum_{b=1}^{n_{best}} \frac{f(S^b) - f(S^{best})}{f(S^{best})} \times 100 \quad (3.01)$$

In this expression n_{best} corresponds to the number of best sequences selected at the end of the optimisation process; $f(S)$ is the function that minimises the costs in present value, S^b indicates one of the best sequences stored after the end of the search; and S^{best} refers to the best sequence known for the problem, independently if it is not found in a given simulated case. The performance of the tested metaheuristic approaches for the mentioned real sub-transmission network is shown in 3.

Based on the two studied networks, Leite da Silva concluded that the metaheuristics ES and AIS can be considered the most recommended to solve TEP problem, since they achieved the best-quality indices. The performance of these metaheuristics was considered comparable since their evolutionary operators are quite similar. However, it was observed that the ES metaheuristic presents good performance even for small population sizes.

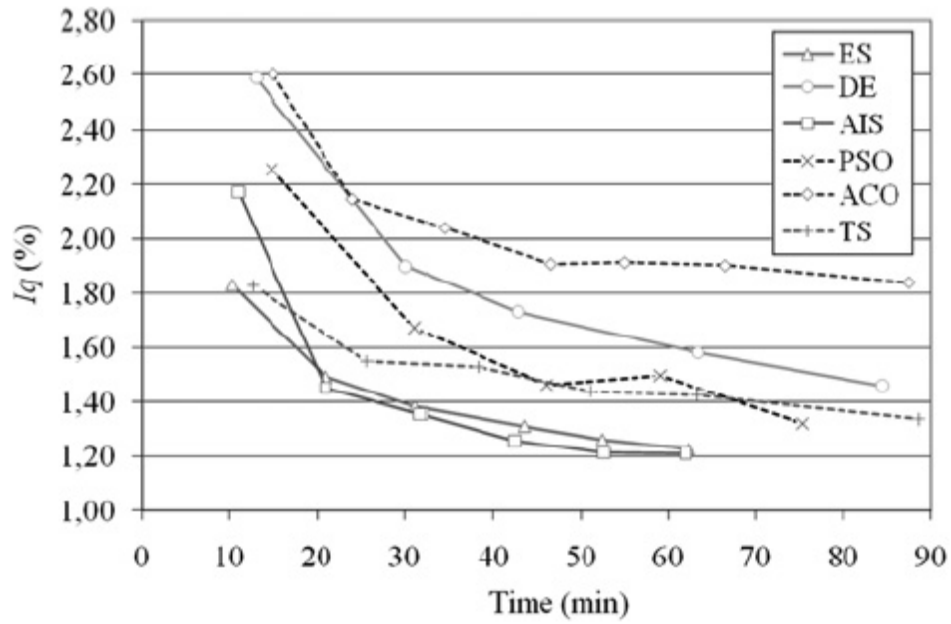


FIGURE 3-3 META-HEURISTIC PERFORMANCE COMPARISON (REAL SUB-TRANSMISSION NETWORK)
(Source: (Silva, et al., 2011))

A brief presentation of the different meta-heuristics can be found in Annex C. A good reference on this subject is the book “Modern heuristic optimization techniques, theory and applications to power systems” (Lee, et al., 2008).

3.7. SOME SPECIFIC TECHNIQUES TO SOLVE LARGE SCALE PROBLEMS

Even using heuristics or meta-heuristics, large-scale problems are difficult to solve and several approaches were developed and tested trying to minimize the computational effort or to accelerate the output.

3.7.1. *PARALLEL PROCESSING*

Large-scale studies can be easier solved using parallel processing tools. Parallel processing requires specific approaches, which combine usually parallel processing with GA (Rudnick, et al., 1996), (Gallego, et al., 2000), (Escobar, et al., 2001) or other methods, like Simulated Annealing (Gallego, et al., 1997). Matlab 2009 version already permits parallel processing.

3.7.2. *PRUNING*

Pruning techniques are used to limit the number of TEP scenarios and reduce the computational effort. Barros defines two concepts: Unit Interruption Cost—UIC (\$/MWh) and Unit Postponement Benefit (UPB) (Barros, et al., 2007). The delay in implementing a set of circuits is advantageous when the associated UPB is higher than the adopted UIC. Whenever $UPB < UIC$ is true, the rescheduling is not allowed and all deriving combinations that encompass this postponement are pruned.

3.7.3. *SPARSE MATRIXES ALGORITHMS*

The complexity of power systems calls for the development of efficient methods. However, direct application of standardized methods may be unfeasible. The performance of such methods can be improved considerably by taking into account the structure of the underlying problem. Some authors, like Rommes, explore the sparse descriptor matrices, taking advantage of the efficient algorithms for descriptor matrix formulations that have been developed recently (Rommes, et al., 2009). Matlab has already some routines based on this sparse matrix approaches.

3.7.4. *DECOUPLING METHODS*

Some authors, like Pereira, Binato and Marcato adopted Benders Decomposition as an approach to solve large scale problems, taking advantage of the decoupling observed in

some areas of the networks (Pereira, et al., 1985), (Binato, et al., 2001), (Marcato, et al., 2007) or between investment and operation subproblems.

3.7.5. ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the science and engineering of making intelligent machines, especially intelligent computer programs. (McCarthy, 2007) John McCarthy coined the term in 1956. He also defend that AI is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.

AI is the study and design of intelligent agents, which are anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors (Russell, et al., 1995).

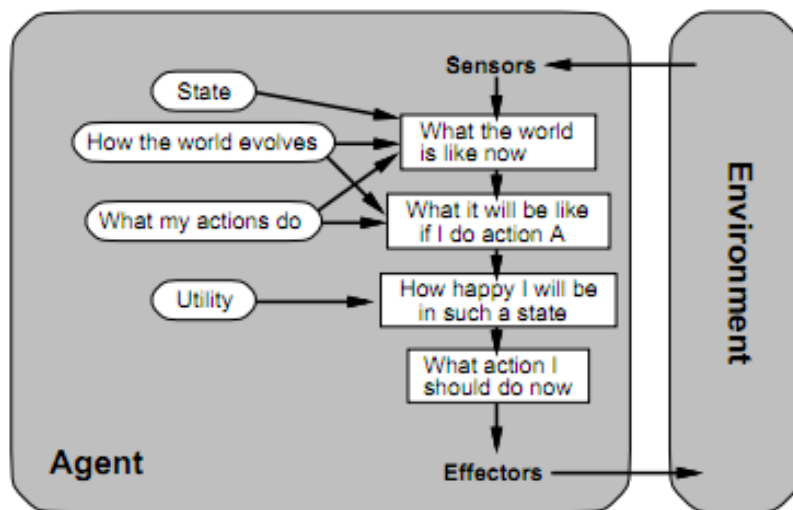


FIGURE 3-4 COMPLETE UTILITY-BASED AGENT
(Source: (Russell, et al., 1995))

The rationality at any given stage depends on four topics: the performance measure that define the degree of success; everything that the agent has perceived so far (the complete perceptual history, the percept sequence); what the agent knows about the environment; the actions that the agent can perform. An ideal rational agent, for each possible percept sequence, should do whatever action is expected to maximize its performance measure, on the basis of the evidence provided by the percept sequence and whatever built-in knowledge the agent has (Russell, et al., 1995).

An agent that possesses an explicit utility function can make rational decisions, but may have to compare the utilities achieved by different courses of actions. Goals enable the

agent to pick an action right away if it satisfies the goal. In some cases, moreover, an utility function can be translated into a set of goals, such that the decisions made by a goal-based agent using those goals are identical to those made by the utility-based agent, as illustrated in Figure 3.4.

Artificial intelligence techniques are commonly used to solve combinatorial problems of high difficulty, hardly solved with other approaches. In Section 3.6 we already identified a number of models usually included in the AI applications, including meta-heuristics to solve TEP problems. Chapter 4 presents in detail methodologies based on evolutionary computing and swarm intelligence, which are within the area of AI and that will be adopted in our work.

3.8. DRAWBACKS OF EXISTING METHODS

Transmission planning researchers have worked and set their interest mostly on static planning models. The dynamic and pseudo dynamic planning models are still in an undeveloped status and they have some limitations for their application to real power systems. In general, regardless of the approach used to solve the problem, the models developed until now have one or more of these drawbacks:

- The operation, reliability, security, and quality costs are not taken into account by the planning algorithm (i.e., usually these costs are calculated *a posteriori* considering a set of alternative plans that were selected minimizing only the investment and load curtailment costs);
- Hydrological scenarios are not considered;
- The treatment of the uncertainty level introduced by the electricity sector deregulation is limited;
- The change in the load curtailment cost according to its magnitude is neglected; In some cases the same load curtailment cost is considered for the entire power system;
- Alternative options like redesigning, rearranging, upgrading, etc. are not considered by the planning algorithm;
- Network modelling does not consider the ohmic losses;
- Multiple contingencies are not considered (failure of more than one system element);
- Demand changes in each year in the planning horizon are neglected;
- Usually, the models are not interested in establishing when the circuits should be installed, that is, they only seek the optimal addition set for a single year (static planning);
- Usually the approaches are either static or pseudo-dynamic.

3.9. CONCLUSION

TEP problems are complex and computationally very demanding. The way these problems are approached is crucial for the feasibility of the methodology to be implemented. As explained in section 3.2.2., one has to select only those projects that have significant implications in the transmission network, and avoid those who have a local nature.

On the other hand, some fundamental elements for planning, as loads, are vague or uncertain, which requires the use of appropriate techniques such as fuzzy numbers.

Mathematical optimization methods can experience difficulties on solving large-scale TEP problems, which are nonlinear and have non-convex in nature. The computational effort is huge and the obtained optimal solution can correspond to a local optimum due to intrinsic limitations of the searching process. On the other hand, many of these methods require the relaxation of the binary to continuous variables. The rounding process may potentially lead to solutions far from the optimum, but with the advantage of having lower computational burden.

The artificial intelligence techniques are commonly used to solve combinatorial problems of high difficulty, hardly solved with other approaches, as it is the case of TEP. Meta-heuristics are among the artificial intelligence techniques. On Leite da Silva meta-heuristic performance comparison on a real sub-transmission network it was observed that the ES meta-heuristic presents good performance even for small population sizes (Silva, et al., 2011).

Given the state of the art and the size of the problem to be solved, new approaches are needed. The findings included in (Abraham, et al., 2008), (Rezende, et al., 2010) and (Silva, et al., 2011) support our thesis⁶⁸, that an approach based on agent based models and evolutionary strategies is appropriate to treat the dynamic TEP problem.

As defended by Miranda, rather than an optimization problem, TEP should be seen as a decision making problem.

⁶⁸ This thesis was started in 2007.

4. EVOLUTIONARY COMPUTATION AND PARTICLE SWARM OPTIMIZATION

“They solve problems, but they do not solve the problem of how to solve problems.”

(Fogel, 2000)

4.1. SCOPE

In the previous chapter we present the TEP literature review, concluding that the most appropriate tools to deal with the uncertainty of the data and the complexity of the problem are needed to perform successful planning.

The latest research points to the advantage of the algorithms based on evolutionary computing techniques and particle swarm optimization. These techniques and methodologies are analyzed in detail in this chapter.

We begin by explaining the motivation for the adoption of evolutionary particle swarm optimization (EPSO), which integrates the concepts of agent based computing, combining evolutionary computation with particle swarm optimization.

Then, the agent based computing is characterized, including concepts of evolutionary computation and multi agent population, where swarms are integrated.

On the next Section the basics of evolutionary computation, as the encoding, the fitness function and the basic operators (such as mutation, recombination and selection) are addressed. One concludes by summarizing the advantages and the drawbacks of evolutionary computation.

The particle swarm optimization (PSO), its principles, the particle populations, the formulation, the advantages and the drawbacks are introduced in the following section, where a synthesis of the numerous applications of PSO to power systems is done.

Following an identical structure, the approach to EPSO includes topics as recombination, evolution and selection. The merits of EPSO over other heuristics are summarized, as well as the application of EPSO to Power Systems.

Our model, which is detailed in Chapters 5 and 6, is based on the EPSO, where some innovation is introduced to the algorithm so that it displays an improved behavior in the treatment of discrete problems.

This Chapter is complemented with the description of several meta-heuristics in Annex C.

4.2. MOTIVATION FOR EPSO ADOPTION

TEP is a complex combinatorial problem. In real complex combinatorial problems the search space is very large and non continuous, and many of its positions do not need to be evaluated since they violate constraints that are specified for the problem. To deal with TEP one needs an algorithm that can avoid wasting time with non-relevant solutions, avoid getting trapped in local minima and incorporate dynamic intelligent strategies, so that the search can, as soon as possible, be guided to the quasi-optimal solutions.

As mentioned in Chapter 3, when applied for large networks, meta-heuristic methods are able to identify expansion plans with acceptable computational effort. Several researches confirm the superiority of meta-heuristic approaches in dealing with large size, complex, nonlinear, and combinatorial problems, whose alternatives increase exponentially with network dimension (Asada, et al., 2008). Meta-heuristics show ability to avoid getting entrapped into local optima, and despite the large solution space, it is possible to analyse only a small fraction of alternatives. Other aspects, like the problem formulation, the heuristic tailoring to the problem and control parameters tuning, have also strong influence on the final results.

Our motivation is inspired by Asada, since he says that

“... so far, no solid proposals are known about dynamic transmission expansion planning with application of meta-heuristics.” (Asada, et al., 2008)

Our motivation for EPSO adoption is also based on the finding of other researchers highly respected as Alves da Silva and Djalma Falcao, when saying that

“... the first applications to power systems appeared in 1998, with Professor Vladimiro Miranda⁶⁹. Since then, GA's have applied not only to pure optimization problems in power systems but also to model identification, control, and neural network training. After a necessary period of maturing, GA are being used now frequently in combination with conventional optimization techniques, for solving large scale problems.” (Alves da Silva, et al., 2008)

EPSO already became a tradition at Faculdade de Engenharia da Universidade do Porto, where several research teams are developing work in this field. This thesis is a contribution to the application of EPSO to complex discrete problems and to dynamic transmission expansion planning. As we will show on the following chapters, EPSO fulfils all the requirements to be a successful approach on TEP.

⁶⁹ See Miranda V, Srinivasan D, Proenca LM. “Evolutionary computation in power systems”. Electrical Power & Energy Systems 1998; 20(2): 89–98.

4.3. AGENT BASED COMPUTING

4.3.1. INTRODUCTION

“Agents were thought of as collision-proof birds, and the original intent was to graphically simulate the graceful but unpredictable choreography of a bird flock.” (Kennedy, et al., 1995)

“In short, the agent-based approach should be regarded as the foundation of the networked generation of computer systems.” (Jennings, 2000)

As mentioned in Chapter 3, when applied for large networks, meta-heuristic methods are able to identify good solutions with acceptable computational effort. The meta-heuristics like EPSO can be classified as Agent Based Algorithms.

There is much debate on what exactly a agent is. An increasing number of researchers find the following characterisation adequate:

“An agent is a system that is situated in some environment and that is capable of flexible and autonomous action in that environment in order to meet its design objectives.” (Wooldridge, 1997)

Agent-based approaches emphasize autonomous actions and flexible interactions. Jennings defends that agent-based computing represents an exciting new synthesis both for artificial intelligence and computer science, and it has the potential to improve the theory and the practice of modelling, designing, and implementing computer systems. He also recommends that agent-based computing should not be viewed merely as a good solution technology, but it should be rather seen as a general-purpose model of computation that naturally encompasses the major trends in software (Jennings, 2000).

For Dash, the need for computer systems that operate according to a decentralized control regime is increasing. These systems are characterised as being open (individual components can enter and leave at will), and contain several components representing distinct stakeholders with different aims and objectives. Some relevant examples of complex systems are mobile computing, peer-to-peer systems and grid computing. For these systems, agent-based are suitable computational models. In designing such multi-agent systems, one has to address two fundamental topics: specify the protocols that govern the interactions⁷⁰, and define each agent's strategy, given the prevailing protocol, mapping from state history to action (Dash, et al., 2003).

⁷⁰ These protocols includes the way agents' actions translate into an outcome, the range of actions available to the participants, and whether the interactions occur over steps or are one-shot.

The development of robust and scalable software systems requires autonomous agents that can complete their objectives while situated in a dynamic and uncertain environment, that can engage in rich, high-level social interactions, and that can operate within flexible organisational structures.

Despite intense interest on agent-based software engineering, some relevant questions about its nature and use have to be deepened (Jennings, 2000):

- What are the essential concepts and notions of agent-based computing?
- What makes the agent-based approach an appealing and powerful computational model?
- What are the drawbacks of adopting an agent-oriented approach?
- What are the wider implications for AI and computer science of agent-based computing?

Agent-based software engineering is being applied in many areas (please see Table 4.1.). Agent-based software applications range from academic models to large-scale decision support systems. Decision support models tend to be large-scale applications designed to answer real-world policy questions. These models include real data and have to be subjected to validation tests in order to be reliable.

TABLE 4-1 AGENT-BASED MODELLING APPLICATIONS
(Source: (Macal, et al., 2005))

Business and Organizations	Society and Culture
• Manufacturing	• Ancient civilizations
• Consumer markets	• Civil disobedience
• Supply chains	Terrorism
• Insurance	• Social determinants
Economics	• Organizational networks
• Artificial financial markets	Military
• Trade networks	• Command & control
Infrastructure	• Force-on-force
• Electric power markets	Biology
• Hydrogen economy	• Ecology
• Transportation	• Animal group behavior
Crowds	• Cell behavior
• Human movement	• Sub cellular molecular behavior
• Evacuation modeling	

North et al. introduced an electricity market complex adaptive system, an agent-based simulation model of the electric power market. This model was designed to investigate market restructuring and deregulation and to understand the implications of a competitive market on electricity prices, availability, and reliability (North, et al., 2002). As a prerequisite for a realistic model, agents in electricity power market complex adaptive systems are constrained by the physics of the electric power grid.

4.3.2. *AGENTS, ENVIRONMENTS, TASKS AND BEHAVIORS*

In the previous chapter we have said that there is much debate on what exactly a agent is, and we adopted Wooldridge definition for Agent, understood as a system that is situated in some environment and which is capable of flexible and autonomous action in that environment in order to meet its design objectives (Wooldridge, 1997). Russel and Norvig define an agent as an entity that can be viewed as perceiving its environment through sensors and acting upon its environment through effectors (Russell, et al., 1995). For Coen, agents are programs that engage in dialogs, negotiate and coordinate the transfer of information (Coen, 1995). Another definition of agent is presented by Costa. An agent is anybody capable of interacting with the environment guided, in general (but not necessarily) by objectives (Costa, et al., 2008).

An agent has a very simple structure, including:

- A mechanism that allows it to collect information from the environment (perception);
- Some mechanisms that allow it to act over the environment (action); and
- Some processes that allow it to define the best action to be taken (decision).

In addition, agents may be characterised as they have a “body”⁷¹, exist in space and time (they have a location), have a set of tools to understand and act on the environment (have skills) and have mechanisms to support clever action (decision mechanisms). Decision mechanisms will be more sophisticated as more complex would be the task or the environment.

Following Rudowsky and Costa, agents can be characterized according to the following properties (Rudowsky, 2004), (Costa, et al., 2008):

- Reactivity (responds in time to changes in the environment);
- Pro-activeness/objectives driven (have initiative and are not limited only to act in response to environment);
- Social ability/communication (communicate with other agents, possibly different);
- Veracity (an agent will not knowingly communicate false information);
- Benevolence (agents do not have conflicting goals⁷² and every agent will therefore always try to do what is asked for);

⁷¹ It may be virtual.

⁷² Some researchers, like Axelrod, defend that agents may compete (Axelrod, 1997).

- Learning/adaptation (change its behaviour according to previous experience and improve performance over time);
- Mobility (capable of transporting itself from machine to machine); and
- Character (has his own personality).

An agent builds strategies eventually enabling it to be successful in the tasks it has to solve, either imposed by the external environment, or determined by the agent own goals. Some agents may use a measure of performance in order to gain awareness of their strategies and whether or not they are successful. (See Figure 4-1)



FIGURE 4-1 AGENTS, ENVIRONMENTS AND TASKS
(Source: adapted from (Costa, et al., 2008))

In some situations, agents live in a environment together with other agents, a population of agents, each one possibly with different strategies. There are cases when it is of interest to consider the population of agents, their strategies and the environment as a whole set, called system. If there are strong interactions between the elements of a system, the system is said to be complex. The interactions can be blind or not, that is, the agents may or may not realize they are interacting with other agents. In order to solve a given task, the interaction can take the form of cooperation. When a complex system contains agents who seek to improve the quality of their performance, regardless of whether they succeed or not, we say that we are dealing with a complex adaptive system (Costa, et al., 2008).

Holland identifies both the properties and the mechanisms common to complex adaptive system⁷³: Aggregation, Nonlinearity, Flows, and Diversity (Holland, 1995). Booch

⁷³ Aggregation: allows groups to be formed; Nonlinearity: invalidates simple extrapolation; Flows: allow the transfer and transformation of resources and information; Diversity: allows agents to behave differently from one another and often leads to the system property of robustness.

identifies the techniques for tackling complexity⁷⁴: Decomposition, Abstraction, and Organization (Booch, 1994).

The tasks (or problems) that an agent is called to perform are varied and can be classified according to different perspectives not always easy to organize. One may adopt the agent perspective. Under this perspective, the aspects that characterize the tasks⁷⁵ are Deliberation, Change, Interaction, and Imposition (Costa, et al., 2008). It is important to emphasize that the different tasks exhibit these characteristics to a greater or lesser degree, and not in a completely absolute way.

Agents have to deal with different kinds of environments, some more complex than others. In addition, the way an agent seizes the environment depends heavily on its capabilities. Thus, any environment classification or typology must be taken by the point of view of the agent. That is to say that the complexity classification of an environment depends largely on the complexity of the agent. According to Russell, some important aspects that can help classify the environments⁷⁶ are Episodic (vs non-episodic); Discrete (vs. continuous); Accessible (vs. inaccessible); Deterministic (vs. non-deterministic); Static (vs. dynamic) (Russell, et al., 1995).

The more complex environments are those that are discrete, inaccessible, non-deterministic and non-static (dynamic). The environment determines the agent design.

Jennings defends that the precise form of the match process arguments in favor of agent-based software engineering can be expressed as follows: agent-oriented decomposition is an effective way of partitioning the problem space of a complex system; key abstractions of the agent-oriented mindset are a natural means of modeling

⁷⁴ Decomposition: the most basic technique for tackling large problems is to divide them into smaller, more manageable problems each of which can then be dealt with in relative isolation; Abstraction: the process of defining a simplified model of the system that emphasizes some of the details or properties, while suppressing others; Organization: the process of identifying and managing the interrelationships between the various problem solving components.

⁷⁵ Deliberation: some tasks require the agent to possess sophisticated decision-making processes, while others do not; Change: some tasks involve some major changes, either at the agent level (decision mechanisms, for example), or at the level of the environment itself; Interaction: many tasks can only be tackled by a strong interaction between the agent and the environment; and Imposition: there are tasks that are determined primarily by the environment.

⁷⁶ Episodic vs non-episodic: an episode is a combination of the agent sensing and then acting; Discrete vs. continuous: if the states of the environment (what is sensed) are countable, then the environment is said discrete; Accessible vs. inaccessible: an environment will be accessible if the agent can withdraw from the environment all the information it needs to determine the best action; Deterministic vs. non-deterministic: when the evolution of the environment can't be determined uniquely from the current situation and the action of the agent over the environment, the environment is not deterministic; Static vs. dynamic: an environment is said to be static if it does not change while the agent is to decide the action to perform; for example, a weather forecasting system has to deal with an environment that is not static (or dynamic).

complex systems; agent-oriented philosophy for dealing with organizational relationships is appropriate for complex systems (Jennings, 2000).

Despite significant gains in knowledge of agent systems, pragmatic engineering of these systems is not yet well understood: agents do not make the impossible possible; agents are not an universal solution; there are situations where a conventional software development paradigm (e.g., object oriented) may be far more appropriate; projects that employ agents because of the hype about agents but with no clear picture of what benefits agents will bring to the project are likely to fail; building a successful prototype with agents does not guarantee it will prove scalable and reliable in solving a real-world problem; the design does not leverage concurrency; there are too few or too many agents; a multi agent system cannot be developed successfully by throwing together a number of agents and letting the system run (Wooldridge, et al., 1998).

We will develop the concepts related to adaptive agents for the interest that they have for our thesis. Very comprehensive approaches to this topic can be found in (Back, et al., 1997), (Wooldridge, 2002), (Costa, et al., 2008) and (Lee, et al., 2008 a). We will follow these approaches in the following sections.

4.3.3. ADAPTIVE AGENTS AND EVOLUTIONARY COMPUTATION

Living beings that do not adapt to their environment are more likely not to survive. Instead, the fittest, those that evolve, live longer and reproduce on a larger scale, passing good qualities to their offspring. These principles, presented in a systematic way by Darwin, are now universally accepted. The evolutionary algorithms are the computational version of the principles of Darwinian natural selection and Mendelian genetics.

There are four major families of evolutionary algorithms (Back, et al., 1997): Genetic Algorithms (GA), Genetic Programming (GP), Evolution Strategies (ES) and Evolutionary Programming (EP). All these techniques have many common aspects, and so are all included in the wider area known as evolutionary computation. There are aspects that distinguish them from each other, which will be addressed further on.

The term “computational intelligence” was originally coined in 1994 by Cercone and McCalla (Cercone, et al., 1994). For Back, there exists a strong relationship between evolutionary computation and some other techniques, like fuzzy logic and neural networks, usually regarded as elements of artificial intelligence (Back, et al., 1997). Bezdek et al. defend that their main common characteristic lies in their numerical knowledge representation, which differentiates them from traditional symbolic artificial intelligence (Bezdek, 1994). They also suggested the term computational intelligence for this special branch of artificial intelligence, with the following characteristics:

- Numerical knowledge representation;
- Adaptability;
- Fault tolerance;
- Processing speed comparable to human cognition processes;
- Error rate optimality (e.g., with respect to a Bayesian estimate⁷⁷ of the probability of a certain error on future data).

4.3.4. GENETIC ALGORITHMS

Genetic algorithms (GA) are stochastic optimization techniques, proposed by John Holland (Holland, 1962), (Holland, 1975), (Holland, et al., 1978), and inspired in the process of evolution by natural selection proposed by Charles Darwin and complemented by the principles of genetics proposed by Mendel. Initially, Holland proposed GA as tools for studying the phenomenon of adaptation of living beings in nature. Later, GA found great potential for problem solving, and by far, the largest application of the techniques is in the domain of optimization (De Jong, 1992). Goldberg is an excellent reference on GA's and their implementation (Goldberg, 1989). Among others, GA had been studied by Davis, Eshelman, Forrest, Koza, Mitchell, Riolo and Schaffer. A comprehensive reference list may be found in (Back, et al., 1997).

GA's typically use a population of candidate solutions for a given problem. The individuals in this population are selected for reproduction according to their quality. The reproduction typically involves the exchange of information among the parents in a process known as recombination. The new individuals can also be changed through localized effects of a mutation operator. Given an optimization problem, with a high degree of difficulty, one can find an efficient process through GA that finds near optimal solutions⁷⁸.

In general, any optimization problem can be seen as a problem that is intended to be solved, which, in turn, can be described as a search through a space of solutions. When the search space is small, any algorithm to carry out an exhaustive search is sufficient to find the desired solution. However, if the search space is large, these methods are no longer effective and must be set aside. In this case artificial intelligence techniques are adopted. GA's are included in these intelligent techniques and distinguished themselves because they work simultaneously with several alternatives.

⁷⁷ A Bayesian estimate minimizes the posterior expected value of a loss function. The most common risk function used for Bayesian estimation is the mean square error, also called squared error risk.

⁷⁸ Near optimal solutions ou quasi-optimal solutions.

As mentioned above, a GA allows the search in complex search spaces, usually intractable by traditional methods. In order for the algorithm to solve the problem in question, it is fundamental that it is correctly encoded. Thus, it is necessary to carefully define the basic elements of a genetic algorithm, which are:

- The representation to be used by individuals in the population⁷⁹;
- The selection method to ensure that the best individuals in the population are more likely to survive and reproduce;
- The operators to be applied to obtain new individuals and how likely they will act;
- The evaluation function for assessing each individual merits; and
- The characteristics of the population: size, generation of initial population.

GA's have been shown to behave well on multimodal functions⁸⁰. However, numerous studies have shown that functions on which GA's fail are pathological, and generally fail to be optimized by any other known technique, except exhaustive search (Bethke, 1980).

Goldberg has shown that, even though the algorithm may be misled, it will converge for a wide range of starting conditions and under unfavorable conditions (Goldberg, 1987).

4.3.5. GENETIC PROGRAMMING

Genetic Programming (GP) is considered as a branch of genetic algorithms by several researchers (Koza, 1992), (Kinnear, 1994), (Koza, et al., 1996), (Francone, et al., 1996). Genetic programming was introduced by Koza and is essentially a technique of automatic learning of how to solve complex problems (Koza, 1992). These genetic programs are evolved using analogies with many of the mechanisms used by natural biological evolution. Evolutionary search is applied to the space of tree structures, which may be interpreted as computer programs in a language suitable to modification by mutation and recombination.

⁷⁹ In some problems a solution is a vector of real values that specify the dimensions of the key parameters of this problem. In traditional approaches GA uses a binary representation to encode the candidate solutions to the problem.

⁸⁰ There is no known necessary and sufficient condition under which a function can be genetically optimized.

The global structure of a GP algorithm is very similar to GA. As in GA, GP uses recombination⁸¹ and mutation operators.

GP differs fundamentally from GA in the following issues:

- Every individual of the population is a program (the solution is obtained by implementing the program and not by a direct encoding, as in GA);
- The genetic material is organized hierarchically in a tree structure;
- The genetic material is of variable size during the evolutionary process;
- The recombination operator exchanges sub-trees between two parents and must preserve the syntax of the genetic material;
- The initial population consists of random generation of functions and terminals, which are programs.

4.3.6. *EVOLUTIONARY STRATEGIES*

The evolutionary strategies (ES) are based on the work of Rechenberg and Schwefel, who used it to solve engineering optimization problems (Rechenberg, 1973), (Schwefel, 1974). ES were designed for solving very difficult discrete and continuous parameter optimization problems.

In its initial version, the ES uses only one individual, which evolves using a mutation operator (Costa, et al., 2008). The parameters of the problem are represented by vectors of real numbers. The mutation operator is a random modification of the individual alleles⁸², using a normal distribution (or Gaussian), with zero norm and standard deviation σ , to determine the value of the change, ie value to be added to each parameter. The selection problem really doesn't arise, as there is only one individual. The single individual is selected, mutated, and if better, it replaces the parent. This form of ES is known for (1 +1).

⁸¹ Recombination is used to generate the next generation of individuals, from two-parent programs chosen by a selection method based on the value assigned by the evaluation function. Parents are usually of different size and shape. The recombination operator consists of exchange between two parents of sub-trees randomly determined.

⁸² An allele is one possible forms of a gene. Different alleles can result either in different traits, such as color, or have the same result in the expression of a gene.

Nowadays it is common to self-adapt and control some ES parameters, such as the magnitude of change⁸³. The use of recombination operator and ES populations with more than one individual are also common. Given a population of μ individuals, they are used to generate λ offspring. To build the next generation population two strategies are possible: the first chooses the new μ individuals from the set of parents and children, and is commonly referred to as the $(\mu + \lambda)$ strategy; the second chooses the new individuals only from the descendants, and is commonly called the (μ, λ) strategy.

The more common recombination operators are the uniform crossover operator⁸⁴ and the arithmetic operator⁸⁵.

Although GA and ES have much in common, we can identify some distinctive aspects, including the following (Costa, et al., 2008):

- In GA the recombination operator is dominant, whereas in the ES is the mutation operator;
- In ES all individuals are mutated, whereas in GA only a small proportion of total genes is affected by the mutation;
- The criterion for individuals replacement is stochastic in GA and deterministic in the ES, based on the absolute ranking of individuals according to their merit;
- In ES the number the generated offspring λ is fixed and above the number of individuals in the population, whereas in the GA depends on the probability the recombination;
- In its classic version, GA are algorithms that favours a global search, while ES are able to explore small promising areas;
- ES allows the self-adaptation of the parameters that control the genetic operators.

⁸³ Each element x_i is associated with a control parameter σ_i . Each component x_i of the vector solution is varied in accordance with a value obtained from a normal distribution with mean zero and standard deviation σ_i . The lower σ_i , the greater the likelihood of changing the value of a parameter is small.

⁸⁴ A descendant allele at a given position is chosen among the alleles of the parents in this position with a probability of 50%.

⁸⁵ In the arithmetic operator the descendant allele is replaced by the arithmetic mean of the alleles of the parents. These operators affect equally the parameters x_i and the control parameters σ_i .

4.3.7. *EVOLUTIONARY PROGRAMMING*

Evolutionary programming (EP) was first introduced by L. J. Fogel (Fogel, 1962), (Fogel, 1964), (Fogel, et al., 1966). His work was extended by Burgin (Burgin, 1969), (Burgin, 1973), Atmar (Atmar, 1976), and D. B. Fogel (Fogel, 1988), (Fogel, 1992), just to mention the most relevant. EP was originally offered as an attempt to create artificial intelligence (Back, et al., 1997).

One of EP distinctive features is that individuals are finite state machines, which are considered programs to evolve, as in the case of GP. A finite state machine is characterized by a set of states (one initial, and some finals) and transitions between states. These transitions depend on input values and produce output values. The finite state machines correspond to transducers.

Like in ES, in EP one uses only a mutation operator based on variations determined by a probability distribution. Poisson and Cauchy distributions are often adopted. Mutations affect the elements of the transducer representation. Among other possible changes one may mention the removal or addition of states and the transitions in the outputs. The mutation operator undergoes change, reducing their rate as it approaches the desired result. The selection method can be seen as a variant of the selection ($\mu + \lambda$) from ES. The difference is that in EP one generally uses a tournament selection mechanism involving the $\mu + \lambda$ individuals, instead of a deterministic selection where the best μ individuals are selected from the $\mu + \lambda$ available.

Given its characteristics, the comparison of GA with EP is similar to that presented to the ES (Costa, et al., 2008).

4.3.8. *MULTI-AGENT POPULATIONS: ANT COLONIES AND SWARMS*

The simplest community or population has only two agents. If two agents have goals that collide, they naturally would come into competition. But, even in very simple societies, agents can cooperate instead of compete.

One of the most classic examples is the prisoners' dilemma. The prisoners prefer not to report the colleague to the police, thereby avoiding a heavier sentence. In this field is worth mentioning the work of Robert Axelrod, whose studies became well known by the iterated prisoner's dilemma. Axelrod has studied what happens when the game can be played an indefinite but finite number of times (Axelrod, 1984). The interest of this study is to determine to what extent a cooperative strategy can emerge, without requiring the existence of a central authority, when each player only cares about its self-interest and acts in accordance. Axelrod proved that if the game is played an indefinite big enough number of times, then the rational attitude is to cooperate. When testing the various strategies in several tournaments the results pointed always the same conclusion

known as TIT FOR TAT. On this strategy the first player began not denouncing his opponent and then played always the same way as opponent's last choice. According to Axelrod, this strategy is very simple and robust for the following characteristics: it is a friendly strategy, because it avoids conflicts, not denouncing the other as he fails to do so; it is reactive, because it reacts to a complaint denouncing; forgive, when his opponent returns to cooperate after denouncing; of simple behaviour, as the other player can easily understand the pattern of play⁸⁶.

Societies have usually multiple agents. These may be either of the same or of different classes. Their objectives may be similar or opposite. They can communicate with each other, directly or indirectly. They can form alliances, may negotiate, may have the same power or there may be hierarchical power relationships. I.e., they can establish between themselves various types of interaction (Costa, et al., 2008). Agents lead to complex societies, regardless of each agent being simple in its architecture and capabilities or in establishing interactions with other agents also present in the environment.

Even integrated in a multi-agent population, agents are often autonomous. Fayyad et al define autonomous agent as a subsystem that interacts with its environment, which probably consists of other agents, but acts relatively independently from all other agents (Fayyad, et al., 1996). As usually there is no leader in the population, the autonomous agent does not follow its commands or any other global plan (Flake, 1999). So, there is no need for a leader.

“Since agents make decisions about the nature and scope of interactions at run time, it is imperative that this key shaping factor is taken into account. Thus organizational relationships need to be represented explicitly.”
(Jennings, 2000)

These relationships are often subject to ongoing change and can vary significantly. Agents have to cope with this variety and dynamic. For this, several approaches have been developed by researchers: protocols that enable organisational groupings to be formed and disbanded; mechanisms to ensure groupings act together in a coherent fashion; and structures to characterise the macro behaviour of collectives (Jennings, 2000).

Many researchers found the social behaviours that emerge in biological agent societies useful for complex problems solving. They take their inspiration from the way ants act in seeking for food, as birds move harmoniously together, or how certain social insects, such as bees or ants, communicate through weird dances (Costa, et al., 2008). According to authors such as Kennedy and Eberhart, these metaphors highlight the

⁸⁶ An Axelrod's reference book is "The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration" (Axelrod, 1997).

aspects of problem solving based on the ideas of distribution, direct or indirect communication of simple agents, flexibility and robustness (Kennedy, et al., 1995).

The optimization algorithms based on ant colonies (Ant Colony Optimization) are inspired by the mechanisms described after and were initially proposed by (Dorigo, 1992). Ants are a paradigmatic example of the ability to solve complex problems. In searching for food, they are able to solve the problem of finding the shortest path that goes from the nest to the place where the food is. The concept is relatively simple. Ants leave a trace of a chemical called pheromone when they move. The pheromone evaporates over time, so the concentration of pheromone in the different paths from nest to food will be different depending on the number and frequency of ants that go through. The ants are attracted by the smell of pheromone. The first choices in an attempt of identify the best path are random. The ants choosing the shortest path are quickly returning to the nest, and tend to increase pheromone concentration on that shorter path. After some time the ants tend to choose the shortest path as first choice, further reinforcing the concentration of pheromone. The ant colony functions like a distributed multi-agent system, in which agents communicate indirectly through the pheromone. None of the ant has the notion of the shortest path, but collectively this is the behaviour that emerges.

Meanwhile emerged a new approach based on the idea of social behaviour of some species, such as birds. The way the band handles the flight direction changes and the decision to land are based on a simple set of four rules that each bird separately apply (Grosan, et al., 2006):

- Homogeneity: every bird in flock has the same behaviour model; the flock moves without a leader, even though temporary leaders seem to appear;
- Separation, collision avoidance: a bird tries to maintain a constant distance from birds that surround it, avoiding nearby flock mates;
- Alignment, locality: a bird seeks to align itself with the birds that surround it; the motion of each bird is only influenced by its nearest flock mates; Vision is considered to be the most important senses for flock organization;
- Cohesion, flock centring: a bird tries to keep up integrated into the group of birds that surrounds it, and stay close to nearby flock mates.

Four collective behaviours were identified by Couzin et all (Couzin, et al., 2002):

- Swarm: an aggregate with cohesion and a low level of polarization among individuals (parallel alignment);

- Torus: individuals rotate around an empty core, with the rotation being random;
- Dynamic parallel group: individuals are polarized and move as a coherent group; individuals can move right through the group; the density and the group form can change;
- Highly parallel group: density and form variation are minimal, which makes this group type more static in terms of swap of spatial positions within the group.

All these rules and behaviours involve local interactions of each bird with a small group of birds that surround it, its neighbourhood. From these local interactions emerges the global behaviour of the flock flight.

Particle Swarm Optimization (PSO), originally proposed by Kennedy and Eberhart (Kennedy, et al., 1995), is based on these ideas. Each agent is a particle, characterized by its position and velocity. Given a population, each particle evolves with time. However, there are neither classical selection mechanisms nor genetic operators of recombination and mutation. Each particle has an associated neighbourhood that is not necessarily geographic. Similarly to adaptive agents, each position is associated with a performance value or quality of the particle. Each particle has in memory the best location that has found, and can also determine the best global situation of all its neighbours. The movement of each particle identifies a new position, which is nothing more than a compromise between the aforementioned positions, which work like attractors for that particle. The ultimate objective of the particles consists in finding the position which corresponds to the best possible performance in the search space. PSO algorithm is detailed in Section 4.5.

4.3.9. *TACKLING DRAWBACKS OF AGENT BASED COMPUTING*

According to Jennings, there are two major drawbacks associated with the agent-based approaches (Jennings, 2000):

- The patterns and the outcomes of the interactions are inherently unpredictable;
- Predicting the behaviour of the overall system based on its constituent components is extremely difficult (sometimes impossible) because of the strong possibility of emergent behaviour.

Jennings defends a new level to be defined, and call it the social level (Jennings, et al., 1997). This social level provides the social principles and foundations for agent-based systems, and should sit immediately above the knowledge level. By adopting this approach, the overall system's behaviour and key conceptual structures can be studied without the need to explore the implementation details or the interaction protocols,

making the prediction of the behaviour of the overall system more easily. It also aids the engineering aspects of agent-based systems. As it allows the identification of the key components and their inter-relationships, the social level provides a sound basis for developing tools that can support the development of agent-based systems (Jennings, 2000).

4.3.10. AGENT BASED COMPUTING ADOPTION

Answers for long-standing questions are becoming better understood every day as agent-based modeling can offer new insights and distinct advantages to traditional modeling approaches. For Macal and North it is beneficial to think in terms of agent based computing when (Macal, et al., 2005):

- There are decisions and behaviors that can be defined discretely (with boundaries);
- It is important that agents adapt and change their behaviors, learn and engage in dynamic strategic behaviors, have a dynamic relationship with other agents, form organizations, and adaptation and learning are important at the organization level, have a spatial component to their behaviors and interactions;
- The past is no predictor of the future;
- Scaling-up to arbitrary levels is important;
- Process structural change needs to be a result of the model, rather than a model input.

4.4. EVOLUTIONARY COMPUTATION BASICS

4.4.1. INTRODUCTION

As mentioned before, evolutionary computation adopts natural evolution concepts as a powerful mechanism for complex problem solving.

The different algorithms adopt the collective learning process of a population of individuals. On the search for good quality solutions, evolutionary computation methods evolve individuals, which represent solutions to problems. The solutions are ranked according to the results achieved by a fitness function. This function provides a measure of the individual's quality.

In genetic algorithms operators rely on discrete genetic representation of individuals, which genes are exchanged among each other. On the contrary, in evolutionary approaches individuals have phenotype characteristics, and the main operators are mutation and recombination.

Since EPSO is considered an evolutionary algorithm, and has more to do with ES and EP than with GA, on the next chapters the basics of evolutionary computation are introduced.

4.4.2. ENCODING

The codification of a specific problem is the most crucial aspect of the structure of the EC. It facilitates or complicates the implementation of the EC mechanisms.

The first codification step is the representation of the individuals, that is, the potential solutions of the problem. A decision must be taken on how the parameters of the problem will be mapped into a finite string of symbols, known as genes (with constant or dynamic length), encoding a possible solution for a given problem. The selection of an appropriate representation is crucial for the search. The symbol alphabet used may be binary⁸⁷, integer or real.

“Complex applications suggest non binary alphabets. Integer or continuous valued genes are typically used in large-scale function optimization problems. Another advantage of non binary representations, particularly the real-valued one, is the easy definition of problem specific operators.”
(Alves da Silva, et al., 2008)

⁸⁷ Gray Codes are adopted in some problems. Gray code is an encoding where adjacent numbers differ by a single digit.

In evolutionary computation one can distinguish among three forms of representation of an individual:

- Pure phenotypic: the individual is represented by the same variables that are used by the fitness function; a pure phenotypic representation is a string of data whose interpretation is straightforward;
- Transformed phenotypic: the coding representing an individual is composed of variables that, under a suitable transformation, may be mapped into the variables used by the fitness function;
- Genetic: the coding representing an individual must be interpreted as a program that allows building a phenotypic representation of the individual (Miranda, 2008).

In what genes position it may concern, real valued encoding and recombination operators turn positions irrelevant, which does not necessarily mean an easier way to a good solution (Alves da Silva, et al., 2008).

When designing the coding, a special attention should be given to the size of the individual. On one hand, claiming to have a smaller particle, you can influence in a decisive way the results, leading to a bad solution that may possibly not include any data that it should. On the other hand, an overly complex or extensive particle can be as difficult to work that leads to poor performance of the algorithm. Long chromosomes have a negative effect as they define a much larger search space. This means that the whole process of convergence will be slower (it will require many more generations than for smaller search space). Also such indiscriminate coverage of the search space is, in some sense, a waste, because it allows the representation of solutions that common sense, engineering judgment, and constraints, indicate will be either unfeasible or unacceptable due to their characteristics or high cost (Miranda, 2008).

The importance of the design is, thus, very relevant. In order to achieve good performance, encoding must be matched to the search problem at hand. The only way to succeed is by using domain-specific knowledge to select an appropriate representation (Alves da Silva, et al., 2008). The complexity of the dynamic analysis suggests a deep research on the best approach. Some inspiration on this topic can be found on (Fonseka, et al., 2002), (Keko, et al., 2007), (Carvalho, 2008), (Miranda, et al., 2008 b) (Miranda, et al., 2008 b) (Miranda, et al., 2008 b) and (Wang, et al., 2010).

4.4.3. *FITNESS FUNCTION*

“The fitness function is a measure of how well a candidate solves the problem.” (Lai, et al., 2008)

a) Fitness Function and Objective Function

It is fundamental to understand the differences between the objective function and the fitness function:

- The objective function provides a measure of performance with respect to a particular set of gene values, independently of any other string;
- The fitness function transforms that measure of performance into an allocation of reproductive opportunities.

While the objective function is a measure of absolute performance, the fitness defines a relative performance of the particle with respect to other members of the current population. In each iteration, and after decoding the chromosomes if necessary (i.e., applying the genotype to phenotype transformation), each particle is assigned a fitness value. Then, the fitness values are employed to relatively ponder the particles evaluation in the population (Alves da Silva, et al., 2008).

b) Main problems associated with fitness function specification

According to Alves da Silva and Falcão, the main problems associated with the fitness function specification are the following (Alves da Silva, et al., 2008):

- Dependence on whether the problem is related to maximization or minimization;
- When the fitness function is noisy for a nondeterministic environment;
- The fitness function may change dynamically as the algorithm is executed;
- The fitness function evaluation can be so time consuming that only approximations to the fitness values can be computed;
- The fitness function should allocate very different values to different strings in order to make the selection operator work easier;
- It must consider the constraints of the problem; and
- It could incorporate different sub-objectives.

c) Constraint violation and penalties

The fitness function can be formulated as the sum of the objective function and penalties for constraint violation (Lai, et al., 2008). Infeasible offspring appear quite frequently, as they result from operators (crossover and mutation) that do not take into account feasibility. These off-springs violate the boundaries of the search space, and they should be either penalized, or rejected or repaired.

There are two basic techniques for handling constraints (Alves da Silva, et al., 2008):

- With no penalty factors; three techniques are possible: the rejecting technique (infeasible chromosomes are discarded all over the generations; it is the simplest alternative), the repairing procedure (which uses a converter to transform an infeasible chromosome into a feasible one) and the adoption of problem-specific genetic operators, to preserve the feasibility of chromosomes;
- With penalty factors; when a constraint is violated, a penalty factor is considered in the fitness function.

It is possible to combine both techniques in the same algorithm. The approaches with no penalty factors do not generate infeasible solutions, which is not usually an advantage. For large scale problems, as power system problems, where the optimal solutions usually are on the boundaries of feasible regions, these approaches often lead to poor solutions. One possible way for overcoming this drawback is to apply the repairing procedure only to a fraction (10%, for instance) of the infeasible population.

Penalty functions allow the exploration of infeasible subspaces, and this may be considered an important advantage. As a matter of fact, an infeasible point close to the optimum solution generally contains much more information about it than a feasible point far from the optimum. However, the design of penalty functions is difficult and problem dependent. As there is not a priori information about the distance to optimal points, penalty methods consider only the distance from the feasible region. Penalties based on the number of violated constraints do not work well (Alves da Silva, et al., 2008).

A fitness function with penalty term may have two forms (Alves da Silva, et al., 2008):

- The addition form; it is represented as $g(x) = f(x) + p(x)$ where for maximization problems $p(x) = 0$ for feasible points, and $p(x) < 0$ otherwise; the maximum absolute $p(x)$ value cannot be greater than the minimum absolute $f(x)$ value for any generation, in order to avoid negative fitness values;
- The multiplication form; it is represented as $g(x) = f(x) * p(x)$ where for maximization problems $p(x) = 1$ for feasible points, and $p(x) < 1$ otherwise; the penalty term should

vary not only with respect to the degree of constraint violations, but also with respect to the GA iteration count; therefore, besides the amount of violation, the penalty term usually contains variable penalty factors, too (one per violated constraint, for example).

Miranda suggests that a simple and yet claimed as effective way of adding the effect of the violation of constraints, in a problem of maximization, is to count the number of violated constraints or add up the amount of violations, and attribute the fitness value according to the following rule (Miranda, 2008):

$$\text{If no violations occur, } \text{Fitness}(X) = F(X) \quad (4.01)$$

$$\text{If violations occur, } \text{Fitness}(X) = -\sum \text{violation\_values}_i, i \in \text{Constraint\_Set} \quad (4.02)$$

In a problem of minimization the last expression would have a positive sign, instead of negative.

Alves da Silva and Falcão defend that the key for a successful penalty technique is the proper setting of the penalty factors. Small penalty factors can lead to infeasible solutions, and very large ones totally neglect infeasible subspaces. The absolute values of the objective and penalty functions should be similar. At least in theory, the parameters of the penalty functions can, also, be encoded as the other algorithm parameters. This procedure creates an adaptive method, which is optimized as the algorithm evolves toward the solution (Alves da Silva, et al., 2008).

The enforcement of constraints may be done during (Miranda, 2008):

- The mutation phase; each time a new individual is mutated, it can be checked for feasibility; if the constraints are not met it may be either discarded or replaced; mutations can be also conditioned so that no possibility for an unfeasible descendant to be created; this process is very time consuming; the individual fitness can also be assigned an adequate fitness value (penalty);
- The selection phase; during the selection phase those individuals that violate constraints are attributed an adequate fitness value (penalty).

4.4.4. BASIC OPERATORS

To generate new points in the state space, the action of the reproduction operators is required. While some algorithms give relevance to the mutation operator, others rely mostly on the recombination operator.

a) Mutation

Mutation is an operator acting on a single individual or particle. It generates a new point in the search space by modifying the coordinates of a previous one. The definition of the mutation operator should be done according to the particular problem under study.

Only mutation, with its random perturbation mechanism, allows the exploitation of new regions of the search space. The purpose of the mutation operator is to maintain diversity within the population and inhibit premature convergence to local optima by randomly sampling new points in the search space.

The classical mutation procedures adopt Gaussian or Lognormal random perturbations of each variable. The mutation amplitude is governed by the variance of the distribution and its square root (standard deviation) is often called *learning rate*. In self-adaptive evolutionary algorithms, the learning rates are transformed into variables and added to the chromosome (Schwefel, 1974), (Fogel, 1992). During the process, they are themselves subjected to mutation and selection and eventually they acquire values that allow a near optimal progression rate towards the optimum (Beyer, 1996).

b) Recombination or crossover

Recombination generates a new individual by combining features from a set of individuals in the population. Many forms have been proposed. Classical variants are uniform crossover, intermediary recombination and point crossover (Miranda, 2008).

In swarm optimization the recombination scheme is different from that of GA. In PSO and EPSO the off-springs are generated by recombination of the particles, modelled by the movement rules⁸⁸.

Mutation and recombination schemes must balance the exploitation of the complete search space with the research on the most promising regions. This balance is not easy to achieve. A good review on this topic is found in (Meyer-Nieberg, et al., 2007).

c) Selection

Selection, more than crossover and mutation, is the operator responsible for determining the convergence characteristics. Selection pressure corresponds to the degree to which the best individuals are favoured. The higher the selection pressure, the more the best

⁸⁸ Please refer to expressions (4.12) and (4.13)

individuals are favoured. The convergence rate is determined largely by the magnitude of the selection pressure. Higher selection pressures imply higher convergence rates. If the selection pressure is too low, the convergence rate will be slow, and the algorithm will unnecessarily take longer to find a high-quality solution. However, if the selection pressure is too high, it is very probable that the algorithm will converge prematurely to a bad solution. Selection schemes should preserve population diversity, in addition to providing selection pressure. One possible solution to achieve this goal is to maximize the product of selection intensity and population fitness standard deviation. When two selection methods have the same selection intensity, the method giving the larger standard deviation of the selected parents is the best choice (Alves da Silva, et al., 2008).

Many selection schemes are currently in use. They can be classified in two groups (Alves da Silva, et al., 2008):

- Proportionate-based procedures; these procedures select individuals based on their fitness values relative to the fitness of the other individuals in the population; and
- Ordinal-based procedures; individuals are selected not based on their fitness, but based on their rank within the population.

Conclusive statements about the performance of each procedure are difficult to make. When compared with rank-based selection schemes, by suitable (and tricky!) adjustment, proportionate selection can give similar performance.

Selection schemes may include:

- Tournament selection; choose some number of individuals randomly from the population, copying the best individual from this group into the intermediate population, and repeating it until the mating pool is complete.
- Truncation selection; a subset of the best individuals is chosen to be possibly selected, with the same probability; this procedure is repeated until the mating pool is complete.
- Linear ranking selection; the individuals are sorted according to their fitness values, and the last position is assigned to the best individual, whereas the first position is allocated to the worst one.
- Exponential ranking selection; it differs from linear ranking selection only in that the probabilities of the ranked individuals are exponentially weighted.
- Elitist selection; the best solutions known so far will remain in the population and have more opportunities to produce offsprings; and

- Proportional selection; the probability that an individual will be selected is simply proportionate to its fitness value, that must be larger than zero.

4.4.5. *ADVANTAGES OF EVOLUTIONARY COMPUTATION*

The most significant advantage of using evolutionary search lies in the gain of flexibility and adaptability to the task at hand, in combination with robust performance (although this depends on the problem class) and global search characteristics (Back, et al., 1997). When a mathematical expression is available for the objective function, it does not need to be differentiable.

A main flowchart that describes the evolutionary algorithm concept is depicted in Figure 4.2.

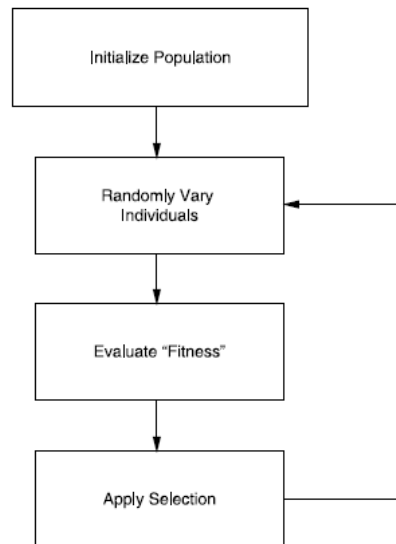


FIGURE 4-2 EVOLUTIONARY ALGORITHM CONCEPT
(Source: (Fogel, 2008))

Evolutionary computation offers several advantages when facing difficult optimization problems (Fogel, 2008):

- Conceptual simplicity;
- Broad applicability;
- Outperform classic methods on real problems;
- Potential to use knowledge and hybridize with other methods;
- Parallelism;
- Robust to dynamic changes;
- Capability for self-optimization; and
- Able to solve problems that have no known solutions.

It is always reasonable to incorporate domain-specific knowledge into an algorithm when addressing particular real-world problems (Fogel, 2008). Evolutionary algorithms offer a framework such that it is comparably easy to incorporate such knowledge, for example in variation operators, when applied to particular representations, mutation or recombination operations and in the evaluation and selection. The incorporation of researcher's knowledge in the algorithm allows a more efficient exploration of the search space of possible solutions and contributes to increase its performance.

Evolutionary algorithms can also be combined with other techniques. Some examples are: Seeding an initial population with solutions derived from other procedures; Optimize the performance of neural networks using evolutionary computation; Combine fuzzy systems with evolutionary computation.

One can use the evolutionary process itself to optimize the algorithm parameters as part of the search for optimal solutions (Rosenberg, 1967). A typical evolutionary algorithm would use Gaussian random variations on current parent solutions to generate offspring's (Fogel, 2000).

“They solve problems, but they do not solve the problem of how to solve problems”(Fogel, 2000).

Classic algorithms require human expertise and may be applied impressively to difficult problems requiring great computational speed, but they generally do not advance our understanding of intelligence. Evolution algorithms provide a method for solving the problem of how to solve problems even in the absence of human expertise. It is a recapitulation of the scientific method that can be used to learn fundamental aspects of any measurable environment (Fogel, 2008).

4.4.6. DISADVANTAGES OF EVOLUTIONARY COMPUTATION

While they can quickly identify good solutions, even for problems and complex search spaces, evolutionary algorithms have some drawbacks. The most important disadvantages are (Valle, et al., 2008):

- The tendency for premature converge to local minim;
- The weak local search performance; and
- The run time, which may mean that the solution of some particular problems with conventional methods can be faster and lead to better results.

4.5. PARTICLE SWARM OPTIMIZATION

4.5.1. INTRODUCTION

“Natural creatures sometimes behave as a swarm. One of the main streams of artificial life research is to examine how natural creatures behave as a swarm and reconfigure the swarm models inside a computer”

(Fukuyama, 2008)

As already mentioned in Section 4.3.8., the Particle Swarm Optimization (PSO) was originally proposed in 1995 by Kennedy and Eberhart (Kennedy, et al., 1995), and is based on the analogy of swarms of birds and fish schooling. PSO is based on the idea of each agent being a particle, characterized by its position and velocity. A set of particles form a population (a “swarm”). The particles evolve according with the so called movement rule. The ultimate objective of the particles consists in finding the position which corresponds to best possible performance in the search space.

This section focuses the details and formulation of PSO as an intelligent technique, underling also its advantages and drawbacks. It is also presented a bibliographic review on the use of PSO in Power Systems.

4.5.2. PSO BASIC CONCEPTS

One of the basic backgrounds of PSO is the result of Reynolds research on modeling the behavior of each agent inside a swarm by three vectors (Reynolds, 1987):

- Step away from the nearest agent,
- Go towards the destination,
- Go to the centre of the swarm.

Another background, and according to Boyd and Richerson (Boyd, et al., 1985), is that individuals utilize two kinds of experience information in their decision process:

- Their own experience and
- Other people’s experiences.

Kennedy summarise the characteristics of every PSO versions as follows (Kennedy, 2006):

- Employs a population of particles, with these being far less than in the usual evolutionary algorithm, typically from twenty to fifty;
- Has some sort of topology describing the interconnections among the particles; the classical topology includes *gbest*, a fully interconnected population, and *lbest*⁸⁹, where every particle is connected to the particles on either side of the population; this latter topology reveals slower on convergence, but less susceptible to get trapped in local optima;
- Has some choice of a change rule, to be adopted for the particle movement through the search space; a well designed particle swarm must be able to search simultaneously multiple regions of the search space; particles must be allowed to switch flexibly from one locally optimal region to another;
- Has some choice of an interaction rule; this rule can take many forms, which are currently under investigation by many researchers; it determines how the particles interact with each other in the definition of new particles.

The cornerstones of PSO identified by Valle et al. can be described as follows (Valle, et al., 2008):

- Social concepts; “*The sweep of culture allows individuals to move towards more adaptive patterns of behaviour*”;
- Swarm intelligence principles: proximity, quality⁹⁰, diverse response, stability, adaptability;
- Computational characteristics: swarm intelligence is an extension of evolutionary computation⁹¹.

There are other algorithms also based on swarm intelligence, as the *ant colony optimization* (ACO) and *Stochastic diffusion search*⁹² (SDS). Comprehensive overviews on PSO can be found in (Kennedy, 2006), (Poli, et al., 2007) and (Valle, et al., 2008).

⁸⁹ *gbest* – global best; *lbest* – local best.

⁹⁰ According to this principle, the population should be able to respond to quality factors in the environment.

⁹¹ Swarm intelligence provides a useful paradigm for implementing adaptive systems, whose states are dynamic and may change simultaneously in many directions; the main computational attributes of PSO are the individual particles parallel update, the new particles dependence only on the previous value of the particle and its neighbor, and the fact that all updates are performed according to the same rules.

⁹² *Stochastic diffusion search* was first introduced in 1989 by Bishop (Bishop, 1989)

4.5.3. THE PARTICLE

Each individual is coded in a particle, in its original or phenotypic representation. A particle is a member of the population, which moves through the search space. Particles, in PSO approach, are mass-less and volume-less, and are subject to velocities. Some particles and population arrangements can be found in Figures 4.3 to 4.5.

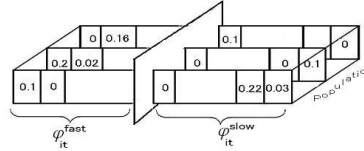


FIGURE 4-3 AN EXAMPLE OF PSO PARTICLES ARRANGEMENT (VAR DEVICES ALLOCATION)
(Source: (Yorino, et al., 2007))

In Figure 4.3., each particle X_j consists of two parts including the allocation data of slow and fast VAR resources. The values of particle j , which are represented by ϕ_{ij} , are the capacity of the VAR resources which is scheduled to be installed in bus number i . By this arrangement candidate buses for slow and fast VAR resources can be determined independently.

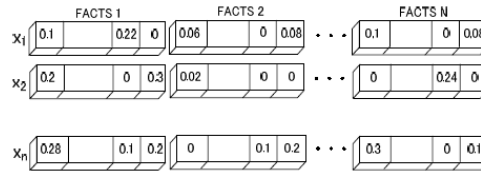


FIGURE 4-4 AN EXAMPLE OF PSO PARTICLES ARRANGEMENT (FACTS ALLOCATION)
(Source: (Eghbal, et al., 2009))

In Figure 4.4, each particle X_j includes the allocation data of different types of FACTS devices. The value of each cell is the capacity of the FACTS device which is scheduled to be installed.

$$S^k = \begin{bmatrix} s_{11}^k & s_{12}^k & \cdots & s_{1l}^k & \cdots & s_{1n}^k \\ s_{21}^k & s_{22}^k & \cdots & s_{2l}^k & \cdots & s_{2n}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{t1}^k & s_{t2}^k & \cdots & s_{tl}^k & \cdots & s_{tn}^k \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{y1}^k & s_{y2}^k & \cdots & s_{yl}^k & \cdots & s_{yn}^k \end{bmatrix}$$

FIGURE 4-5 AN EXAMPLE OF PSO PARTICLES ARRANGEMENT (TEP)

(Source: (Silva, et al., 2011))

In Figure 4.5 solution matrix S^k corresponds to the candidate plan k, where n indicates the number of possible network branches allowed to receive reinforcements, y corresponds to the number of stages along the planning horizon, and s_{tl}^k refers to the total number of reinforcements at stage t and branch l in relation to the base system network configuration.

When the search space is real, the individuals are modelled as particles moving through the problem hyperspace. The position of each particle (each individual or solution) is determined by the vector $x_i \in R^n$ and its movement is determined by the velocity of the particle $v_i \in R^n$. The particles movement allows the identification of new solutions. These movements are performed according to the expressions introduced in the next sections.

4.5.4. THE POPULATION AND THE NEIGHBORHOODS

The information available for each individual is based on both its own experience, that is the decisions that it has made so far, and the success of each decision, and the knowledge of the performance of other individuals in its neighbourhood (Valle, et al., 2008).

Valle argues that the algorithm's performance depends on the principles of swarm intelligence, previously mentioned in section 4.5.2.: proximity, quality, diverse response, stability and adaptability (Valle, et al., 2008). The role of population topologies have been underlined by several studies in PSO that have shown that there exists an important link between the way individuals are organized and their aptitude to find global optima (Mendes, et al., 2004 a). Mendes concluded that successful topologies had an average of four neighbours. Bigger multiple individual neighbourhoods will cancel each other and reduce the possible benefits of considering their knowledge.

Mendes, Kennedy and Neves defend that each individual is not simply influenced by the best performer among his neighbours and decided to search the behaviour of “fully informed” individuals. The standard two-term PSO is a simpler case of the fully

informed particle swarm. The results were very promising, as informed individuals seem to find better solutions in all the benchmark functions. However, increasing the size of the neighbourhood deteriorates the performance of the swarm (Mendes, et al., 2004).

Xiaohui Hu and Russell Eberhart adopted a concept of dynamic neighbors. The dimensions of the neighborhood vary from generation to generation, based on the fitness values. Dynamic neighborhood PSO proved to be an efficient and general method to locate the Pareto front of multi-objective optimization problems (Xiaohui, et al., 2002).

Not all studies show that an increased population size is always better. The size of the population should be chosen depending on the difficulty of the problem and the dimension of the search space. Eghbal made a simulation with swarm sizes of 20, 40, 60 and 80 individuals. The optimal result got better by increasing the swarm size until 60 and then becomes smoother (Eghbal, et al., 2007). Gibbs et al studied the minimum number of generations required for convergence of genetic algorithms on two test functions (Gibbs, et al., 2006). They found that in case there exists epistatic⁹³ interactions between decision variables, the optimal population size increased with the size of the problem, and that when no interactions exist between decision variables, that is, for a separable function, the smallest population size produced the best results, regardless of the problem size or the convergence criteria. In the case of small populations the algorithm should not generate the initial population at random, but systematically, in order to get individuals that allow a broader coverage of the search space (Costa, et al., 2008). Malan and Engelbrecht conducted several algorithm comparisons and also studied the significance of population size (Malan, et al., 2008). They show that the size of the population has a significant effect on the performance of population-based optimization algorithms, even when the total number of function evaluations is kept constant.

4.5.5. FORMULATION

Each particle includes information, as follows: the position, as a potential solution of the problem, and its fitness value, the velocity of the particle and the memory corresponding to its previous best position and the corresponding fitness value. A new particle is generated from an ancestor, according to a “movement rule” given by (4.03).

In this movement rule, V_i is called velocity of the particle i , is defined according with expression (4.04), and is illustrated in Figure 4.6.

⁹³ Epistasis is the term that refers to the action of one gene upon another.

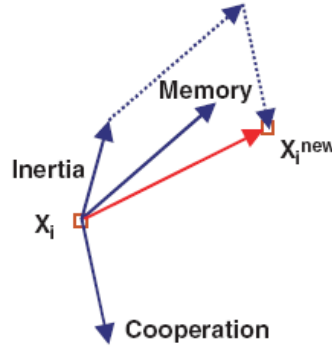


FIGURE 4-6 PARTICLE MOVEMENT IN PSO
(Source: (Miranda, et al., 2007))

$$X_i^{new} = X_i + V_i^{new} \quad (4.03)$$

$$V_i^{new} = V_i + Rnd().Wm_i(b_i - X_i) + Rnd().Wc_i(b_G - X_i) \quad (4.04)$$

In this expression:

V_i Inertia term; the particle keeps moving in the direction it had previously moved;

$b_i - X_i$ Memory term; the particle is attracted to the best – past – point in its trajectory;

$b_G - X_i$ Cooperation term; the particle is attracted to the best point found by all particles;

Wm_i Diagonal matrix with memory weights, fixed in the beginning of the process;

Wc_i Diagonal matrix with cooperation weights, fixed in the beginning of the process;

$Rnd()$ Random numbers sampled from a uniform distribution in [0,1].

This “movement rule” scheme proved to be adequate to make the swarm converge to the zone of the optimum but failed to assure fine tuning in convergence to an accurate optimum position. A new scheme, given by (4.05), has been proposed by (Beyer, 1996).

The importance of the inertia term is decreasing through the function $Dec(t)$. A new weight factor Wi_i was included.

$$V_i^{new} = Dec(t) Wi_i V_i + Rnd().Wm_i(b_i - X_i) + Rnd().Wc_i(b_G - X_i) \quad (4.05)$$

The velocity of a particle V_i^k is a stochastic variable and may be the cause for uncontrolled trajectories, making the particle follow wider movements in the search space (Eberhart, et al., 2001), (Hu, et al., 2004). Some researchers suggested that upper and lower limits can be defined for the velocity in order to damp these oscillations (Yang, et al., 2004). These damping can be modelled by (4.06) and (4.07).

$$\text{If } v_i > v_{\max} \text{ then } v_i = v_{\max} \quad (4.06)$$

$$\text{Else If } v_i < -v_{\max} \text{ then } v_i = -v_{\max} \quad (4.07)$$

Even though $v_{\max}$ is most of the time selected empirically, one has to note that if the value of this parameter is too high, then the particles may move erratically, going beyond a good solution. On the other hand, if it is too small, then the particle's movement is limited and the optimal solution may not be reached within a reasonable time (Valle, et al., 2008).

Fan and Shi showed that dynamically changing $v_{\max}$ can improve the performance (Fan, et al., 2001).

Abido proposed a maximum velocity given by (4.08) to ensure uniform velocity throughout all dimensions. In this expression N is the number of intervals in the th dimension selected by the user, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum values found so far by the particles (Abido, 2001), (Abido, 2002 a).

$$v_{\max} = \frac{x_{\max} - x_{\min}}{N} \quad (4.08)$$

Comprehensive approaches on search space, swarm explosion and convergence control, for example by the application of constriction coefficients, may be found in (Clerc, et al., 2002), (Kennedy, et al., 2002), (Mendes, et al., 2004). We will address this topic in Chapter 5.

4.5.6. ADVANTAGES OF PSO

PSO has many advantages over other optimization techniques, like:

- Is a derivative-free algorithm (Lee, et al., 2006 c), (AlRashidi, et al., 2009);
- Has the flexibility to be integrated with other optimization techniques to form hybrid tools (AlRashidi, et al., 2009);
- Is less sensitive to the nature of the objective function, i.e., convexity or continuity (Lee, et al., 2006 c), (AlRashidi, et al., 2009);

- Has less parameters to adjust unlike many other competing evolutionary techniques (Lee, et al., 2006 c), (Valle, et al., 2008), (AlRashidi, et al., 2009);
- The impact of parameters to the solutions is considered to be less sensitive compared to other heuristic algorithms (Eberhart, et al., 2001);
- Has the ability to escape from local minima (AlRashidi, et al., 2009);
- Is easy to implement and program with basic mathematical and logic operations (Lee, et al., 2006 c), (AlRashidi, et al., 2009);
- Can handle objective functions with stochastic nature (AlRashidi, et al., 2009);
- Does not require a good initial solution to start its iteration process (AlRashidi, et al., 2009);
- As being less dependent from a set of initial points compared to other evolutionary methods, one may say that the convergence process is more robust (Lee, et al., 2006 c);
- Has a more effective memory capability than the GA; every particle remembers its own previous best value as well as the neighbourhood best (Valle, et al., 2008);
- Can generate high-quality solutions within shorter calculation time and stable convergence characteristics than other stochastic methods (Gaing, 2003);

PSO has shown superiority over other techniques when applied to multiple problems (Gaing, 2003), (Park, et al., 2005).

4.5.7. *WEAKNESSES OF PSO*

PSO has many advantages but also some weaknesses. The main limitations of PSO are:

- May converge prematurely;
- Has difficulty in maintaining acceptable levels of diversity in the population; there is a tendency for the particles to converge to the same points;
- Needs large computational time; when problems are not complex classical methods are better;
- Has difficulty on balancing local with global search;

- Falls easily into local optimization solution and low convergence velocity, especially in the final stage.

Miranda defends that (Miranda, et al., 2002):

- It depends of a number of parameters defined externally by the user, after a delicate tuning work. Miranda also concluded that the external definition of the decreasing function $Dec(t)$ is un-natural as it is imposed and does not derive from any inner property. Also if the inertia term is eliminated at an early stage of the process, the algorithm risks to get trapped at some local minimum. To avoid this problem some authors have suggested a kind of “re-seeding” procedure, generating new particles at different places in the search space;
- The random factors $Rnd()$, while introducing a useful stochastic flavour, only have a heuristic basis and are not sensitive to the evolution of the process.

PSO can be observed as a proto-evolutionary process. New iterations include the generation of new particles, rather than particle movements. Even though the algorithm shows a positive progress rate (the movement rule induces such property implicitly), it has not an explicit selection mechanism in the Darwinist sense (Miranda, et al., 2002).

Silva, in the publication already mentioned in Chapter 2, compared the performance of PSO with other Meta-Heuristics (Evolution Strategies (ES), differential evolution (DE), Artificial Immune Systems (AIS), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Tabu Search (TS)) (Silva, et al., 2011). In the performance test PSO achieved a weak performance in the 6-bus system study case. In addition, the best expansion plan known for this system was found in only one simulated case among all population sizes. For the real sub-transmission network, the performance was relatively better, but worse than ES, AIS and TS meta-heuristics. Although velocity and position are updated in each iteration, one cannot guarantee that expansion plans of the next iteration are better than the previous ones. Therefore Silva confirms that PSO has some difficulties to intensify the search in a local area, since the expansion plans may not be improved in the next iterations by the update process. This difficulty is increased in systems that need a high number of reinforcements along the planning horizon, as in the case of the 6-bus system (Silva, et al., 2011).

Lee concludes that for the application in the real-world problems, it is necessary to combine the conventional mathematical approach with the PSO methods based on their own merits (Lee, et al., 2006 c). PSO-based approaches have limitations that didn't restrain their evolution and the emergence of variations to reduce the difficulties. A comprehensive approach on PSO variations can be found in (Valle, et al., 2008).

4.5.8. *PSO APPLICATIONS TO POWER SYSTEMS*

PSO is a relatively new technique, but its applications are already very numerous. Results from several research teams in different areas are also expected in the next few years.

On Table 4.2 several PSO references in different applications fields can be found.

A comprehensive literature review on PSO can be found in (AlRashidi, et al., 2006), (Valle, et al., 2008) and (AlRashidi, et al., 2009).

TABLE 4-2 REFERENCES ON PSO APPLICATIONS TO POWER SYSTEMS

Application Field	References
Neural Network learning algorithm	(Eberhart, et al., 1996), (Salerno, 1997), (He, et al., 1998), (El-Gallad, et al., 2001), (Mendes, et al., 2002), (Hirata, et al., 2002), (Gudise, et al., 2003), (Lee, et al., 2008 b), (Geethanjali, et al., 2008)
Battery charging	(Peng, et al., 2000), (Kennedy, et al., 2001), (Huang, et al., 2006), (Welch, et al., 2007)
Reactive power and voltage control	(Yoshida, et al., 1999), (Yoshida, et al., 2000), (Fukuyama, 2000) (Mantawy, et al., 2003), (Zhang, et al., 2003), (Zhang, et al., 2004) (Coath, et al., 2004), (Yu, et al., 2004), (Zhao, et al., 2005), (Esmine, et al., 2005), (El-Araby, et al., 2005), (Chuanwen, et al., 2005), (Krami, et al., 2006), (Hernandez, et al., 2006), (Valle, et al., 2006), (Yorino, et al., 2007), (Eghbal, et al., 2007), (Keypour, et al., 2010)
State estimation	(Fukuyama, 2001), (Naka, et al., 2003), (Tong, et al., 2006), (Niknam, et al., 2009)
Power system stabilizer design	(Abido, 2001), (Abido, 2002 b), (Okada, et al., 2002), (Al-Musabi, et al., 2003), (Abdel-Magid, et al., 2003), (Juang, et al., 2004), (Ghoshal, 2004), (Gaing, 2004), (Karimi, et al., 2005), (Chun-Feng, et al., 2005), (Venayagamoorthy, 2005), (Das, et al., 2006), (Qiao, et al., 2006), (Shayeghi, et al., 2008), (Das, et al., 2008), (Shayeghi, et al., 2010)
Reliability studies	(Nara, et al., 2001), (Kurutach, et al., 2004), (Robinson, 2005), (Mozafari, et al., 2006), (Singh, et al., 2008), (Basu, et al., 2008)
Security assessment	(Kassabalidis, et al., 2002), (Al-Hinai, et al., 2009)
Economic dispatch	(El-Gallad, et al., 2001), (El-Gallad, et al., 2002), (Kumar, et al., 2003), (Gaing, 2003), (Gaing, 2004), (Sinha, et al., 2004), (Zhao, et al., 2004 a), (Aruldoss, et al., 2005), (Lai, et al., 2005), (Victoire, et al., 2005 a), (Park, et al., 2005), (Lee, et al., 2006 c), (Wang, et al., 2006), (Coelho, et al., 2008), (Coelho, et al., 2009), (Park, et al., 2010), (Jeong, et al., 2010), (Niknam, et al., 2011)
Short term load forecast	(Huang, et al., 2005), (Duan, et al., 2011)
Optimal operation of cogeneration	(Tsukada, et al., 2004) (Kitagawa, et al., 2004), (Tamiru, et al., 2009), (Piperagkas, et al., 2011)
Optimal power flow	(Abido, 2002 a), (Xie, et al., 2002), (El-Dib, et al., 2004), (Zhao, et al., 2004 b), (He, et al., 2004), (Vlachogiannis, et al., 2005), (Acharjee, et al., 2009), (AlRashidi, et al., 2010)
Feeder reconfiguration	(Chang, et al., 2002), (Shen, et al., 2002), (Jin, et al., 2004), (Victoire, et al., 2005 b), (Olamaei, et al., 2008), (Niknam, 2009)
Generation planning	(Slochanal, et al., 2004), (Kannan, et al., 2004), (Kannan, et al., 2005), (Meza, 2006)
Transmission expansion planning	(Sensarma, et al., 2002), (Ren, et al., 2002), (Jin, et al., 2007), (Li, et al., 2008), (Ren, et al., 2010), (Silva, et al., 2011)
Generation maintenance scheduling	(Koay, et al., 2003), (Yare, et al., 2008)
Short term scheduling hydroelectric system	(Chuanwen, et al., 2005), (Yu, et al., 2007), (Yuan, et al., 2008), (Hota, et al., 2009)
Electric machinery	(Bao, et al., 2004), (Emara, et al., 2003), (Geethanjali, et al., 2008)
Wind power	(Pappala, et al., 2008), (Pousinho, et al., 2010), (Wan, et al., 2010), (Catalão, et al., 2011), (Piperagkas, et al., 2011)

4.6. EVOLUTIONARY PARTICLE SWARM OPTIMIZATION

4.6.1. INTRODUCTION

Evolutionary Particle Swarm Optimization (EPSO) is an evolutionary meta-heuristic proposed by Miranda and Fonseca (Miranda, et al., 2002).

Adopting the PSO movement rule to recombine the particles, together with self-adaptation schemes, EPSO improves the convergence speed and develops a sense of self-adaptation, reducing the dependence on the pre-set values of the weights. In fact, EPSO may be seen either as an evolutionary computing method of the self adaptive (SA) evolutionary strategy type, with a special rule for the replication of individuals instead of ordinary crossover and mutation of object parameters, or as a special PSO method where the weights that condition the movement in space undergo self-adaptive mutation (Miranda, 2008).

4.6.2. THE PARTICLE

The EPSO particle structure and behaviour is similar with that of PSO. As mentioned before, each individual is coded in a particle, in its original or phenotypic variables. In this topic applies the insights on PSO from section 4.5.

4.6.3. THE POPULATION

The EPSO population structure is similar with that of PSO. In this topic applies the insights on PSO from section 4.5.

4.6.4. FORMULATION

The EPSO algorithm structure is the following (Miranda, et al., 2002):

Procedure EPSO

Initialize a random population P of μ elements

REPEAT

Replication – each particle is replicated r times;

Mutation – each particle has its strategic parameters mutated;

Reproduction – each particle generates an offspring through recombination, according to the particle movement rule and using the mutated strategic parameters;

Evaluation – each offspring has its fitness evaluated;

Selection – by stochastic tournament or other selection procedure, the best particles survive to form a new generation, composed of a selected descendant from a new generation;

Test - for termination (based on fitness, on number of generations or other criteria);

Until test is positive.

End EPSO

4.6.5. REPLICATION

In classical approaches to EPSO, each particle is cloned twice ($r=2$) so that one can perform the search with two populations.

However, other replication rates may be adopted. For example, Schweickardt and Miranda made a research on Fuzzy Sets applied to combinatorial optimization problems, with $r = 5$ (Schweickardt, et al., 2010).

4.6.6. MUTATION

The symbol $*$ indicates that the parameter will undergo mutation. The mutation of the strategic parameters W into W^* is accomplished using either (4.09) or (4.10). In these expressions, σ and τ are learning parameters that have to be fixed externally.

$$\text{Multiplicative Lognormal random numbers} \quad W_i^* = W_i \cdot [\log N(0,1)]^\tau \quad (4.09)$$

$$\text{Additive Gaussian distributed random numbers} \quad W_i^* = W_i + \sigma \cdot N(0,1) \quad (4.10)$$

Another distinctive characteristic of EPSO is the way the global best is treated. In the most effective EPSO variant, not only the weights affecting the components of movement are mutated but also the global best (b_G) particle is randomly disturbed, according to (4.11).

$$b_G^* = b_G + W_{i4}^* \cdot N(0,1) \quad (4.11)$$

W_{i4} controls the “size” of the neighbourhood of b_G where it is more likely to find the real global best solution. Instead of being attracted to the best point ever found, the particles are driven to a sort of “foggy best-so-far region” where it is more likely to find the real global best solution. With this procedure, the population continues to be “agitated” even when the particles have converged to the same region of the search space (Carvalho, 2008).

As EPSO relies on the mutation and selection of strategic parameters, just as any self-adaptation process, it can also be classified as a self-adaptive algorithm (Miranda, et al., 2002).

4.6.7. RECOMBINATION

a) The movement rule

The off-springs are generated by recombination of the particles, which can be modelled by the rules (4.12) and (4.13). This movement is illustrated in Figure 4.7.

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (4.12)$$

$$V_i^{k+1} = W_{i1}^* \cdot X_i^k + W_{i2}^* (b_i - X_i^k) + W_{i3}^* (b_G^* - X_i^k) \cdot p \quad (4.13)$$

In these expressions:

X_i^k	Location of the particle i in generation k
X_i^{k+1}	Location of the particle i in generation $k+1$
b_i	Best point found by particle i in its past life up to the current generation
b_G^*	Best overall point found by the swarm of particles in their past life up to the current generation
$V_i^k = X_i^k - X_i^{k-1}$	Velocity of particle i at generation k
W_{i1}^*	weight conditioning the <i>inertia</i> term
W_{i2}^*	weight conditioning the <i>memory</i> term
W_{i3}^*	weight conditioning the <i>cooperation</i> term
W_{i4}^*	weight conditioning the <i>best global</i> particle
P	communication factor

Figure 4.7 illustrates the EPSO movement rule. It must be underlined that the vector associated with the cooperation factor does not point exactly to the global optimum b_G but to a mutated location. This is as an extra touch Miranda has added to the classical PSO concept, by defining a blurred target instead of a single point, which also contributes to improve the quality of the results (Miranda, et al., 2002).

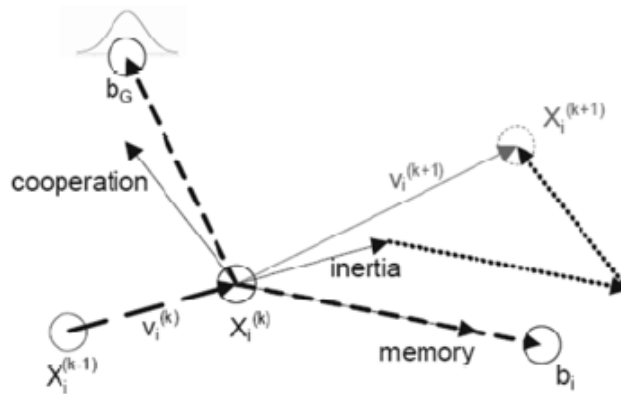


FIGURE 4-7 EPSO MOVEMENT RULE
(SOURCE: (Miranda, 2008))

b) The communication factor p

The communication factor p induces a stochastic star topology for the communication among particles. It is a diagonal matrix affecting all dimensions of an individual, containing binary variables of value 1 with probability p and value 0 with probability $(1-p)$. The p value controls the information flow within the swarm and is 1 in classical formulations⁹⁴.

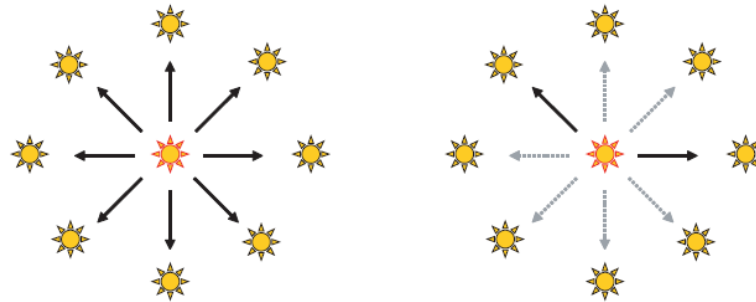


FIGURE 4-8 EPSO COMMUNICATION TOPOLOGIE
(SOURCE: (Miranda, et al., 2008 b))

In Figure 4.8 are introduced the star communication topology (left) and the stochastic star topology (right). In this latter case, the information of the location of the global best is only communicated to a subset of the swarm (thick arrows) and the composition of this subset varies from iteration to iteration.

This stochastic scheme oscillates between the star arrangement and a selfish version called cognitive model (Kennedy, 1997), where no communication exists and a descendent of an individual is built only using the contributions from its ancestor line. Experimental results have suggested that a communication probability of $p = 0.20$ leads in many cases to better results than a classical deterministic star model with $p = 1$ (Miranda, et al., 2008 b).

One is lead to believe that restraining the free flow of information about the global best allows more local search by each particle and avoids premature convergence. As it is easily observed, this is yet another way of acting on the recombination operator.

c) Populations considered in the recombination

As indicated by Miranda, adopting the “movement rule” of PSO allows one to consider enlarged populations, including not only the active particles but also the direct ancestors and the set of the past best ancestors (Miranda, et al., 2007). This reasoning can be illustrated by expressions (4.14 – 4.17).

⁹⁴ This corresponds to the star arrangement.

$$V_i^{k+1} = A.V_i^k + B.(b_i - X_i^k) + C.(b_G - X_i^k) \quad (4.14)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1}; \quad (4.15)$$

$$V_i^k = X_i^k - X_i^{k-1} \quad (4.16)$$

$$X_i^{k+1} = X_i^k + A.(X_i^k - X_i^{k-1}) + B.(b_i - X_i^k) + C.(b_G - X_i^k) \quad (4.17)$$

The new particle X_i^{k+1} is formed as a combination of:

X_i^k	Direct ancestor;
X_i^{k-1}	Ancestor of its ancestor;
b_i	Past best ancestor;
b_G	Global best of the swarm.

In (4.17) the sum of the parameters A, B and C, multiplying the corresponding contributions of the four ancestors, is equal to 1. In EA it is possible to identify an analogous expression when recombination's with $\mu=4$ parents coupled with a special rule to determine who the parents are. In intermediary recombination's, each offspring variable is assigned a value that results from contributions from all the parents.

This recombination rule has the remarkable property of pushing the population towards the optimum, as the PSO algorithms have demonstrated. Therefore, if joined together with a selection mechanism, which also pushes the population towards the optimum, one may expect that some cumulative effect may improve the performance of an optimization algorithm.

4.6.8. EVALUATION AND SELECTION

The first step on the selection process is the evaluation of all the offsprings. This evaluation is done by assigning a value to the offspring, which is the result of the fitness function for the particle. The fitness function may include some factors to handle constraints, as explained before. The best fitness may correspond either to the largest or to minimum value of the function.

The offspring selection may be done by stochastic tournament or other selection procedures. The particles that survive to form a new generation are a selection of descendants from individuals in the previous generation. In EPSO the selection is

modelled from the stochastic tournament concept: among the offspring of each particle, one compares the best one with another particle randomly sampled, and the best is selected with probability $(1 - \text{luck})$, where the *luck* parameter is defined in $[0,1]$ but is usually small. If $\text{luck} = 0$ we have elitist selection.

4.6.9. END CRITERIA

The most usual end criteria are the following:

- Maximum number of iterations;
- Number of iterations without improvement;
- Minimum objective function error.

4.6.10. MERITS OF EPSO

Several researchers compared the performance of EPSO with other heuristics, and have concluded that EPSO reveals advantage. Below, Table 4.3 summarizes some references where these comparisons can be found.

TABLE 4-3 EPSO PERFORMANCE AND OTHER HEURISTICS

Comparisons	References
EPSO / GA	(Win Oo, et al., 2005), (Miranda, et al., 2007), (Eghbal, et al., 2009), (Vale, et al., 2010)
EPSO / PSO	(Kitagawa, et al., 2005), (Miranda, et al., 2007), (Keko, et al., 2007), (Pringles, et al., 2007), (Yorino, et al., 2007), (Miranda, et al., 2008 b), (Cagnoni, et al., 2008), (Eghbal, et al., 2009)
EPSO / Other heuristics	(Mori, et al., 2005), (Mori, et al., 2006), (Hilbert, 2008)

Mori proposed a new method for state estimation in radial distribution systems. The proposed method makes use of EPSO and the LI-norm. The simulation results have indicated that EPSO provides better results than others in terms of solution accuracy. In this particular, it is noteworthy that EPSO reduces 28% and 15% of the cost function errors for TS and PSO, respectively (Mori, et al., 2006).

Miranda has conducted a large number of experiments, some of them performed on classic test problems, such as Schaffer, Rosenbrock, Sphere, or Alpine functions, comparing EPSO and PSO performances, with advantage for EPSO (Miranda, et al., 2007). Eghbal, El-Araby, Yorino and Zoka performed a comparative study for GA, PSO

and EPSO, with application of these meta-heuristic methods to reactive power planning. From the results they conclude that EPSO is in general faster, simpler and more accurate than conventional PSO and also GA (Eghbal, et al., 2007). Hilbert shows the effectiveness of his AGEBOM⁹⁵ algorithm when compared to EPSO, but with the interpretation that the AGEBOM is well adapted to the problem under study. Hilbert admitted that more complex problems may result in better relative performance by the EPSO algorithm (Hilbert, 2008). Stefano Cagnoni et al. analyze separately the effects of two modifications introduced to PSO in EPSO: adaptive parameter setting and selection based on an evolution strategies-like approach. The results obtained on a set of multimodal benchmark functions show that they may have opposite and complementary effects. In particular, using only parameter adaptation when optimizing 'harder' functions yields better results than when both modifications are applied (Cagnoni, et al., 2008). In 2009 Eghbal compared the application of GA, PSO and EPSO to SVC Placement Problem. He concluded that with the same population size and the maximum iteration number, EPSO has better performance than PSO and GA (Eghbal, et al., 2009).

In comparing EPSO with classic PSO, the results may be summarized as follows (Miranda, 2008):

- EPSO displays a faster convergence;
- EPSO is more accurate (EPSO has an average best result superior to PSO);
- EPSO is more robust (the variance of the results is much smaller than for PSO);
- EPSO is more insensitive to weight initialization (the performance of PSO degrades very easily with the variation of parameters compared with EPSO).

EPSO behaves well and converges as it is a method belonging to the self-adaptive ES family. As in any ES, the generation of offsprings is regulated by the operations of mutation and crossover. The selection operator, acting on random mutations (and transformations), provides a positive push toward the optimum (Miranda, 2008).

One may say that the merits of EPSO are based on:

- The adoption of the movement (or reproduction) rule of PSO, that has proven to be an improver of solutions, which means that, on average, each generation will be better than the previous;

⁹⁵ An algorithm developed for Power Distribution Systems Maintenance Optimization.

- The Darwinist selection procedures; as selection acts on a generation that is already on average better than the preceding, the effects are additive;
- The self-adaptive characteristics; the procedure will learn the characteristics of the search space in the evolutionary sense and will self-tune the parameters in order to produce an adequate rate of progress toward the optimum.

4.6.11. EPSO APPLICATIONS TO POWER SYSTEMS

EPSO performance has been tested in demanding power system problems by several researchers. Several applications are reported in the references in Table 4.4.

TABLE 4-4 EPSO APPLICATIONS TO POWER SYSTEMS

Application Field	References
Neural network learning algorithm	(Bessa, 2008), (Moreira, 2009)
Reactive power and voltage control	(Mori, et al., 2005), (Peças Lopes, et al., 2005), (Keko, et al., 2007), (Eghbal, et al., 2007), (Yorino, et al., 2007), (Miranda, et al., 2008 b)(Eghbal, et al., 2009), (Madureira, et al., 2009)
State estimation	(Mori, et al., 2006)
Power system stabilizer design	(Mendonça, et al., 2003), (Castrillon, et al., 2008)
Reliability studies	(Hilber, et al., 2007), (Carvalho, 2008)
Dynamic security assessment	(Schweickardt, et al., 2010)
Economic dispatch	(Mori, et al., 2010)
Optimal operation of cogeneration	(Kitagawa, et al., 2005)
TEP (static)	(Pringles, et al., 2007)
TEP (dynamic)	(Guamán, et al., 2010)
Maintenance scheduling	(Hilbert, 2008)
Electric machinery and protection devices	(Leite, et al., 2009), (Leite, et al., 2010)
Unit commitment	(Miranda, et al., 2006), (Miranda, et al., 2007), (Mori, et al., 2009)
Market simulation platform	(Win Oo, et al., 2005)
System design	(Miranda, et al., 2007)
Micro grids, distributed generation	(Resende, et al., 2007)
Wind forecast	(Bessa, 2008)

Both Guamán and Pringles adopted as network test the well known Garver Network⁹⁶.

⁹⁶ This network can be found in (Garver, 1970).

4.7. CONCLUSIONS

Our challenge, to develop a model for multi-year TEP, requires powerful tools, as previously described in Section 4.2.

The agent based computing tools are appropriate to address complex problems. EA and PSO have been applied to power systems problems since the late twentieth century. PSO-based models have numerous applications in Power Systems, as described in section 4.5.

Since its introduction in 2002, EPSO has been increasingly applied to solve complex problems in Power Systems, including static and dynamic TEP. As mentioned in Section 4.6, when compared with other methods, EPSO has revealed advantage.

5. DISCRETE EVOLUTIONARY PARTICLE SWARM OPTIMIZATION

“Due to the non-repetition of chaos, it can carry out overall searches at higher speeds than stochastic ergodic searches that depend on probabilities.”

(Coelho, et al., 2009)

“One must not blindly trust in the blind force of a revolutionary process – especially when it is built in a naïve way by humans who expect it to find a particular optimum as quickly as possible. Therefore, one must “help”, say, by introducing some Lamarckism in a fundamentally Darwinist process.”

(Miranda, 2008)

5.1. SCOPE

The discrete EPSO used in this thesis is a new approach of the EPSO model and it is able to tackle problems with non-continuous and integer search spaces. Its main characteristics will be detailed in this Chapter.

We first introduce the main motivations for the Discrete Evolutionary Particle Swarm Optimization (DEPSO) development.

The fundamentals of discrete particle swarm optimization are reviewed, with particular attention given to the codification. Then, the chaos and Lamarckism are introduced, focused on convergence problems of particle swarm algorithms.

DEPSO model is then detailed, including the search space, the populations and the particles description, and the algorithm in all its steps: the initialization, the replication, the mutation, the recombination, the Lamarckian evolution, the fitness Function, the evaluation and the selection.

5.2. MOTIVATION FOR DEPSO DEVELOPMENT

The production and transmission of electrical energy, with particular focus on planning, have long been the researcher main interest in research. However, the dynamic TEP is discrete, inaccessible, non deterministic and non static, as mentioned in Section 4.3.2. According to Russel, such problems correspond to the more complex environments (Russell, et al., 1995). It is sometimes considered in the literature an "impossible" problem when one is dealing with real size networks!

As a student, the researcher was always fascinated with the decision support algorithms. These algorithms have been for long developed by colleagues of INESC Porto and FEUP. During the teaching phase of the PhD the researcher had contact with EPSO. As mentioned in Chapter 4, this tool was developed by Miranda (Miranda, et al., 2002). It is a combination of evolutionary concepts and particle swarms, which has proved to be suitable for the treatment of various Power Systems problems. In addition, some papers have been published with EPSO applied to static TEP. It seemed to make sense to seek for an evolution of EPSO, and implement it to solve dynamic TEP. However, the researcher was warned that particle swarms were not adequate to address integer problems. This is another "impossible" problem.

So, two "impossible" problems were identified to be overcome: the dynamic TEP, and the particle swarms to solve integer problems.

Given this double challenge, one wanted to develop a tool that would end up with these paradigms, and which could treat complex problems in a simple and reliable way. This tool could result from the combination of existing models which allow overcoming the limitations of each. The objective would be to benefit from their joint strengths and to overcome each one's limitations.

We were seeking to improve EPSO, adjusting it to treat integer problems right from the origin and not based on the treatment of real problems which, at the end of each iteration, were round up to integers. That is, we wanted the whole algorithm to work in an integer base, taking into attention the idiosyncrasies of the non continuous space, and basing the assessment on the particles that directly emerge from the algorithm.

As the difficulties rise, and soughing for solutions, some ideas occurred which were in parallel tested and in-depth reviewed on the literature:

- The Chaos, for mutation improvements;
- The Lamarckian evolution, which complements the classical Darwinist evolution;
- The adoption of a Tabu List, to improve the population diversity;
- The dynamic local or global search, by adoption of a 3rd population.

One of the tasks more often repeated in Particle Swarm based models is the assessment of particles. In the particular case of dynamic TEP, the evaluation of the particles corresponds to the evaluation of each solution for each period, by running several Power Flows. As is well known, power flows are very time consuming. Although adopting simplified and very fast power flow models⁹⁷, one intended to minimize the number of evaluations in order to reduce the run time. It should converge quickly, which would require populations with few particles, and should also be able to escape from local minima⁹⁸. The achieved results are promising!

⁹⁷ We adopted the DC-OPF from Matlab, improved to consider the effect of losses.

⁹⁸ This feature is even more relevant in our case, where the search space is discontinuous, and consists of equidistant points.

5.3. DISCRETE PARTICLE SWARM OPTIMIZATION (DPSO) FUNDAMENTALS

5.3.1. THE CONCEPT

The original PSO model was developed to tackle problems in continuous search spaces. However, many real problems have discrete nature and recently different discrete PSO models were proposed.

The first discrete PSO approach was proposed by Kennedy and Eberhart for binary-valued solution elements (Kennedy, et al., 1997 b). The entire algorithm of the binary version of PSO is almost the same as that of the basic continuous version, except for the state equations listed below. The position of each particle is a vector in the d -dimensional binary solution space, $x_i \in \{0,1\}^d$ and the velocity is a vector in the d -dimensional continuous space. In their model, the probability of an agent's deciding yes or no, true or false, or making some other decision is a function of personal and social factors as suggested by equation (5.01).

$$P(X_{pt,j}^{it+1} = 1) = f(X_{pt,j}^{it}, V_{pt,j}^{it}, pbest_{pt,j}, gbest_{pt,j}) \quad (5.01)$$

The parameter $V_{pt,j}^{it}$ is an agent's alternative choice tendency and determines a probability threshold in the range $[0, 1]$. If $V_{pt,j}^{it}$ is higher, the agent is more likely to choose 1, and lower values favour 0 choice. One of the functions accomplishing this threshold range is the sigmoid function, presented in equation (5.02), which is usual in artificial neural networks.

$$sig(V_{pt,j}^{it}) = \frac{1}{1 + \exp(-V_{pt,j}^{it})} \quad (5.02)$$

Like in the basic PSO continuous (real) version, the formula for the discrete (binary) PSO version can be described by the equations (5.03 – 5.05).

$$V_{pt,j}^{it+1} = V_{pt,j}^{it} + rand_1 \cdot (pbest_{pt,j} - X_{pt,j}^{it}) + rand_2 \cdot (gbest_j - X_{pt,j}^{it}) \quad (5.03)$$

$$\rho_{pt,j}^{it+1} < sig(V_{pt,j}^{it}) \quad \text{then } X_{pt,j}^{it+1} = 1 \quad (5.04)$$

$$\text{else } X_{pt,j}^{it+1} = 0 \quad (5.05)$$

In these expressions:

- rand_1 and rand_2 are positive random numbers, drawn from a uniform distribution, with a predefined upper limit;
- $\rho_{pt,j}^{it+1}$ is a random number between 0 and 1.

These equations are used in an iterative repeated way over each j dimension of each particle. The second and the third term of (5.03) can be weighted like in the basic continuous version of PSO.

$\text{sig}(V_{pt,j}^{it})$ should not get too close to the limits of the interval $[0,1]$ to ensure good chances for bit flipping. This can be achieved by limiting the maximum value of $V_{pt,j}^{it}$, which is often set in $[-4,+4]$.

Kennedy and Eberhart make clear what is meant by trajectory and velocity in a discrete space. The first important concept to be understood is that in a binary space a particle may be seen to move to nearer and farther corners of the hypercube by flipping various numbers of bits. In this context, the velocity may be defined by the Hamming distance⁹⁹ between the positions $X_{pt,j}^{it}$ and $X_{pt,j}^{it+1}$ of a particle pt . However, this approach is not seen by Kennedy and Eberhart as appropriate to describe $V_{pt,j}^{it}$. For them, trajectories and velocities have to be defined in terms of changes of probabilities that a bit will be either in one or in the zero state (Kennedy, et al., 1997 b).

“Unlike evolutionary algorithms, the particle swarm has “memory” of past successes, and tends to converge upon regions of the search space that have afforded success previously. There is no mechanism for catastrophic leaps from one region to another. Evolutionary algorithms featuring crossover, however, combine aspects of the parents in a way that allows leaps. In cases such as neural networks, where many unique global optima exist, this feature of genetic algorithms works against them: two networks may be better than any combination of their parts. The particle swarm performs especially well on those kinds of problems. On the other hand, where a leap from one region to a distant other region is necessary, crossover is probably the preferred operator. Note that the particle swarm performed quite well on these first two functions, consistently return very good evaluations, but it had trouble jumping out of good local optima.” (Kennedy, et al., 1997 b)

⁹⁹ The Hamming distance between the positions of a particle in two successive iterations corresponds to the number of bits that are changed.

5.3.2. *THE DEVELOPMENTS*

After the contribution of Kennedy and Eberhart mentioned in the previous section, several other researchers developed other approaches to this problems as it will be mentioned in the next paragraphs.

Al-Kazemi and Mohan introduced another PSO approach, whose particles are influenced alternatively by their own best position and by the best position among their neighbours (Al-kazemi, et al., 2002).

Schoofs and Naudts were the first who adopted the swarm intelligence on the binary constraint satisfaction problem (Schoofs, et al., 2002). Hu et al. modified PSO in a discrete way, to deal with permutation problems (Hu, et al., 2004). Particles and velocities were defined as permutations of a group of unique values. Velocities define the mutation rate of particle permutations. In order to prevent the current best particle from being trapped in local optima it is introduced a mutation factor. This algorithm succeeded when applied to the n-queens problem, which showed that this approach is also promising in solving constraint satisfaction problems. This research on solving constraint satisfaction problems was later on continued by Yang et al (Yang, et al., 2006).

Elbeltagi et al. made a comparison among five evolutionary-based optimization algorithms on solving discrete optimization problems: genetic algorithms, memetic algorithms, particle swarm, ant-colony systems, and shuffled frog leaping (SFL) (Elbeltagi, et al., 2005). PSO was generally found to perform better than other algorithms in terms of success rate and solution quality, while being the second best in terms of processing time, where SFL was faster. To take advantage of the fast speed of the SFL algorithm these authors suggest the use of a weight factor in the velocity equation, similar to that used for PSO¹⁰⁰.

Yang et al. showed that hybrid discrete particle swarm algorithm is able to solve hard binary constraint satisfaction problems (Yang, et al., 2006). They adopt the classical DPSO and combine it with Simulated Annealing. They believe that one can improve the performance of the algorithm by reducing the effect of the local best position and adopting Simulated Annealing after the update of positions, to get better quality solutions based on the best global. While these improvements are focused on local search improvements, diversity was guaranteed by two simple but effective

¹⁰⁰ The inertia weight was initially an improvement proposed by Shi and Eberhart to control the impact of the previous history of velocities on the current velocity (Shi, et al., 1998). This operator plays an important role on balancing the global with the local search. It was proposed to decrease linearly with time from a value of 1.4–0.5. The preliminary experiments conducted by Elbeltagi showed good results.

complementary procedures: eliminating repeated particles¹⁰¹ and avoiding cycling using a tabu list¹⁰².

Correa et al. introduced a discrete particle swarm algorithm applied to attribute selection in bioinformatics data set (Correa, et al., 2006). The algorithm variables are discrete, and the population of candidate solutions contain particles of different sizes. The criteria used for performance comparison include the predictive accuracy (that should be maximized) and the data attributes dimension (that should be minimized). This approach was developed for data mining and it differs from traditional PSO algorithms because its particles do not represent points inside an n-dimensional Euclidean space (continuous case) or lattice (binary case). Instead, each particle represents a combination of selected attributes¹⁰³. DPSO adopts proportional likelihoods instead of a vector of velocities as in the standard PSO algorithm. For Correa et al., the notions of proportional likelihood and velocity are similar. However, the coding approach has to be different from the classical one. In this case, every particle is associated with an array of proportional likelihoods, with dimension 2-by-n. Each particle element $V_{pt,j}^{it}$, $j \in [1, n]$ is represented by expression (5.06).

$$V_{pt,j}^{it+1} = \begin{pmatrix} (\text{proportional likelihood row})_j \\ (\text{attribute index row})_j \end{pmatrix} \quad (5.06)$$

Each of the n elements in the first row represents the proportional likelihood that an attribute be selected. The second row shows the indices of the attributes associated with the respective proportional likelihoods. There is a one-to-one correspondence between the columns of this array and the attributes of the problem domain. The particle in iteration it+1 is defined by ranking the columns in $V_{pt,j}^{it+1}$ by the values in its first row¹⁰⁴.

The results indicate that DPSO algorithm performed as well as the binary PSO algorithm, both algorithms obtained a similar level of predictive accuracy. However,

¹⁰¹ The Hamming distance is adopted to calculate the “distance” between the current particle and the global best particle. If it is zero, then the two particles have the same position, which is useless. In these cases, some elements of the current particle are changed, which helps on enlarging the diversity among particles.

¹⁰² As stochastic search algorithm, particle swarm optimization may find a position repeatedly. Yang introduced a short tabu list to avoid cycling. In each iteration the global best position is recorded and compared with the elements in the tabu list. If the global best position already exists in the tabu list, a repair procedure is activated by a more chaotic Simulated Annealing procedure. When the global best particle arrives at a new position it is added into the tabu list.

¹⁰³ According with Correa et al., “*The objective of attribute selection is to simplify a data set by reducing its dimensionality and identifying relevant underlying attributes without sacrificing predictive accuracy. By doing that, it also reduces redundancy in the information provided by the selected attributes.*”

¹⁰⁴ That is, the elements in the first row of the array are ranked in a decreasing order of value and the indices of the attributes, in the second row, follow their respective proportional likelihoods.

DPSO algorithm shows an advantage as it is able to find smaller subsets of attributes¹⁰⁵. This behaviour may be due to the differences on the way in which the initial population is generated in each algorithm.

Moreno-Perez et al. proposed a different approach that abandons the concept of velocity given that the search space is non continuous and the movement is discrete. For this reason, the mutation weights are interpreted as probabilities, which make each particle to behave randomly or to be guided by the effect of the attractors. In such discrete search space, the moves are jumps from one solution to another and so this approach is termed Jumping Particle Swarm Optimization (JPSO) (Moreno-Pérez, et al., 2007).

Liao et al. introduced a discrete version of particle swarm optimization for flow shop scheduling problems (Liao, et al., 2007). A local search scheme was incorporated into the proposed algorithm. Computational results showed that the local search can be really guided by PSO and also that it performs well in flow shop scheduling, but it required more computation time than classical PSO approaches.

Xu et al. proposed a cooperative framework, extending the cooperative approach to a discrete PSO version. They demonstrate that if complex combinatorial problems were split into lower dimensional search spaces, then the rate at which each sub-swarms converge onto solutions contained in their subspaces became significantly faster than the rate of convergence of the standard DPSO on the original n-D search space (Xu, et al., 2008).

Jun and Chang combine Genetic Algorithm and Simulated Annealing, on a discrete binary version of an improved particle swarm optimization algorithm (Jun, et al., 2009). It combines the traditional binary particle swarm algorithm with the Simulated Annealing to guide the evolution of the optimal solution to improve the convergence rate. The structure of the algorithm is simplified by the adoption of the cross-operation of the genetic algorithm, on the update operation of the velocity and position. The results showed that the binary improved particle swarm algorithm performed better in the convergence speed, in the global optimization capacity and in the stability of the algorithm when compared with the classical PSO and its variations considering only one of each suggested improvements (binary Simulated Annealing particle swarm optimization algorithm and the binary cross particle swarm optimization algorithm).

Although binary PSO-based approaches have been successfully applied to the combinatorial optimization problems in various fields, the binary PSO algorithm has some important drawbacks, such as the premature convergence on heavily constrained problems.

¹⁰⁵ For a review of the attribute selection task using genetic algorithms see A. A. Freitas. Data Mining and Knowledge Discovery with Evolutionary Algorithms. Springer-Verlag, October 2002

Jeong et al. proposed a Quantum inspired binary PSO, which combines the conventional binary PSO with the concept and principles of quantum computing (as quantum bit and superposition of states) (Jeong, et al., 2010). The Quantum inspired binary PSO introduces a Q-bit individual for the probabilistic representation, which replaces the traditional PSO velocity update procedure. Another difference is that the classical weight factor and the two acceleration coefficients used in the PSO traditional framework are removed and only a factor, the rotation angle, is considered. The results showed that the proposed Quantum inspired binary PSO algorithm can be used as an excellent optimizer in solving large-scale Unit Commitment problems.

Shayeghi et al. presented an improved DPSO with mutation based on similarity algorithm for optimization of transmission lines loading. This approach is based on the similarity between each particle and the current global best particle in the swarm, as a way to prevent the premature convergence of DPSO around the local solution (Shayeghi, et al., 2010 a).

Several approaches proved adequate for some particular problems, but the implementation complexity or the parameter tuning turned difficult their dissemination to other applications.

5.3.3. THE CODIFICATION

DPSO is different from traditional PSO, not only in operation¹⁰⁶, but also in encoding. The particles are vectors composed of integers, instead of real numbers.

For Gallego et al. there are three alternative codification approaches¹⁰⁷ (Gallego, et al., 1998): binary codification, codification by independent bits, and decimal codification.

Others, like Jin et al., mention discrete codification, instead of decimal codification, as alternative to binary codification for solving the transmission expansion planning problem based on the PSO technique (Jin, et al., 2007).

Binary representations are the most common. However, Gallego et al. defend that there are some reasons for not using them in the TEP problems (Gallego, et al., 1998):

- Mutation and cross-over can generate off-springs which are too different from their parent configurations; this may create chaotic behaviour in the genetic algorithm;
- Hamming cliffs; for example, two sequential integer numbers 3 and 4 are represented by 011 and 100, respectively, which means that moving from 3 to 4 requires

¹⁰⁶ Operations are based on updating the vectors. It is possible that minor changes on an element will result in not acceptable solutions.

¹⁰⁷ These approaches were written in a classic genetic algorithm context, but one may consider they are also valid in particle swarm optimization context.

changing all three digits (a big difference in terms of hamming distance); another example is the single mutation from 000 to 100; with only one bit change, the final result displays a variation from 0 to 4; Gray codes may be used to map binary integers so that adjacent objective variables may be transferred to each other by a single bit flip on the binary integers;

- Binary representation provides a less uniform behaviour of the algorithm when compared with the decimal representation; for instance, in TEP representation mutation adds one circuit to a given branch or removes one circuit.

Thus, even though the binary representation provides a natural way for implementing the mechanisms of mutation and crossover, the decimal (or discrete) representation is favoured for the TEP application. Shayeghi et al. defend the adoption of the discrete particle swarm optimization to avoid difficulties that appear at the coding and decoding phases, which allow a faster convergence and simpler code (Shayeghi, et al., 2010).

5.4. CHAOS, LAMARCKISM AND CONVERGENCE

5.4.1. WHAT IS CHAOS?

In recent years there has also been a growing interest in chaos research, in areas as diverse as in physics, biology, chemistry, engineering, with distinct applications in control systems and optimization.

Chaos has to be characterized in the context of dynamic numerical time series¹⁰⁸. Before proposing a definition for Chaos, it is important to clarify the concept of attractor, for which we will adopt the definitions proposed for Peitgen et al.

Definition 1: Given a dynamic system of the form $dx/dt=f(x)$, not satisfying Liouville's Theorem¹⁰⁹ (conservative systems theorem) and that contracts its volume in all (or at least some) parts of phase space, the set of points in the phase space where the volumes are contracted is called an attractor.

Definition 2: An attractor can have an integer dimension (e.g., points have dimension zero, lines have dimension one, plane surfaces have dimension two, etc.), or they have fractal dimension: in this case, they are called a strange attractor. For the case of a map $dx/dt=G(x)$, a volume contraction or expansion is determined by computing the determinant J of Jacobian matrix. Then, all points for which $J<1$ define the contraction subspace; correspondingly, all points for which $J>1$ define the expansion subspace and, finally, the subset of the phase space where $J=1$ indicates a limit cycle. (Peitgen, et al., 1992)

From a temporal perspective, a chaotic system can be characterized by broad spectrum signals, which are highly dependent from initial conditions. Lyapunov exponents can be used to perform a more analytical analysis. To illustrate this let us consider an orbit $x(t)$ whose long-term limit fills out the attractor. For this orbit there should exist an initial condition $x(0)$ and a second initial condition displaced by an infinitesimal distance $\delta x(0)$ from $x(0)$, as per expression (5.07).

¹⁰⁸ Chaotic dynamics based number generators.

¹⁰⁹ Liouville's theorem: every bounded entire function must be constant. In other words, every holomorphic function f for which there is a positive number M such that $|f(z)| \leq M$ for $z \in C$ is constant. A holomorphic function with one or more complex variables is a complex function that is differentiable in the neighborhood of any point of the domain. This condition of derivability is very important as it ensures that the holomorphic function is infinitely differentiable and equal to its own Taylor series. The complex analysis is particularly focused on analytic functions of complex variables (meromorphic functions in more general terms).

$$x'(0) = x(o) + \delta x(0) \quad (5.07)$$

If there is an orientation $\delta x(0)$ such that condition (5.08) holds, then the attractor is chaotic and h is called a Lyapunov exponent (Caponetto, et al., 2003).

$$h = \lim_{t \rightarrow \infty} \frac{1}{t} \left(\frac{\delta x(t)}{\delta x(0)} \right) > 0 \quad (5.08)$$

Schuster describes chaos as

“a bounded nonlinear system with deterministic dynamic behavior that has ergodic¹¹⁰ and stochastic properties¹¹¹” (Schuster, 1988).

Liu also defends that

“although chaos appears to be stochastic, it occurs in a deterministic non-linear system under deterministic conditions” (Liu, et al., 2005).

Chaos is very sensitive to the initial conditions: small variations in initial parameters may cause important differences in the results even after some iteration¹¹². Even though it shows some regularity elements, one may say that chaos is random and unpredictable (Chuang, et al., 2011).

Peitgen identifies in these characteristics an apparent paradox:

“An apparent paradox is that chaos is deterministic, generated by fixed rules which do not themselves involve any element of change. We even speak of deterministic chaos” (Peitgen, et al., 1992).

In principle, the future is completely determined by the past, but in practice small uncertainties are amplified, with the effect that even though the behaviour is predictable in the short term, it is unpredictable over the long term.

¹¹⁰ A stochastic process is said ergodic when it's mean and variance and other statistical properties can be deducted from a single and sufficiently long sample of the process.

¹¹¹ A stochastic or random process is the counterpart to a deterministic process. Even when the initial conditions are known, there are many possibilities for future developments of the process. Some of these paths may be more probable than others.

¹¹² This phenomenon is usually known as the “Butterfly effect”.

5.4.2. CHAOS CONTRIBUTION TO SOLVE CONVERGENCE PROBLEMS OF CLASSICAL DPSO

Excess attraction promoted by the best particles leads to premature convergence of the algorithm to solutions that can be far from the best. This is one of the problems most recurrently pointed to DPSO (Angeline, 1998) (Shayeghi, et al., 2010).

It is important to ensure that there is a balance between the research of the most promising areas of the search space and the local search. The literature presented different ways of approaching this problem, and one of the most interesting and promising includes the concept of chaos.

The application of chaotic sequences in evolutionary algorithms has been investigated for more than a decade. Caponetto et al. showed that chaotic sequences improve the performance of Evolutionary Algorithms (Caponetto, et al., 2003). Additional relevant information about this topic can be found in several papers, particularly in (Determan, et al., 1999), (Wang, et al., 2001 a), (Coelho, et al., 2009) and (Krohling, et al., 2011).

“Convergence can be enhanced using particular chaotic series applied to all variation operators.(...) Particular chaotic sequences are able to increase the algorithm-exploitation capability.”
(Caponetto, et al., 2003)

“Due to the non-repetition of chaos, it can carry out overall searches at higher speeds than stochastic ergodic searches that depend on probabilities.”
(Coelho, et al., 2009)

Another aspect to meet in assessing the algorithms has to do with their performance in terms of speed of convergence to the optimal solution. The algorithms that tend to get stuck in local minima show worst performances in terms of convergence speed. In addition to the ability to improve the exploitation of the search space, the chaos-based approaches also allow for faster convergence, which contributes to better performance of the algorithms. Chaos can be complemented with Lamarckian approaches, which allow refining the local search around the best particles. An interesting jump strategy to escape from local minima was developed by Krohling based on the fact that particles do not need to follow the same strategy (Krohling, 2006). This approach was improved with a jump strategy generated from a chaotic sequence, with very good results (Krohling, et al., 2011).

Chaos may be applied for optimization purposes in two different ways: incorporating chaotic dynamics into neural networks and through chaotic optimization algorithms (Liu, et al., 2005).

Chaotic neuron dynamics explores the richness of combining non equilibrium dynamics with concomitant attractors to search for global optimum following ergodic orbits (Aihara, et al., 1990). Gustafson research on chaos in discrete learning systems departs

from the customary view of the sigmoid function as smooth nonlinearities introduced into multilayer preceptor networks to enable continuously differentiable gradient descents toward optimal solutions that minimize some error norm, and advance a different point of view: the intrinsic local dynamics of the network become that of the quadratic map of the chaos theory (Gustafson, 2000). This approach aids understanding the importance of supervised learning algorithms, as the widely used back propagation scheme. This algorithm employs a sigmoid function between classification regions. The standard sigmoid function f enjoys an important property, shown in (5.09), where β is the gain specified for the sigmoid threshold amplification. This expression is very similar to that of the quadratic map of the chaos theory, shown in (5.10). Equation (5.11) is equivalent to (5.10).

$$f'(x) = \beta \cdot f(x) \cdot (1 - f(x)) \quad (5.09)$$

$$x \rightarrow ax(1 - x) \quad (5.10)$$

$$x \rightarrow x - \mu \cdot x^2 \quad (5.11)$$

It is important to underline that the sigmoid property (5.09), as employed in feed-forward error back propagating neural networks, is implemented not in continuous but rather in discrete fashion (Gustafson, 2000). In (5.11), μ represents the network local effective gain. When it becomes sufficiently large, one may enter the ergodic regime¹¹³ of the quadratic map. Within this regime the back propagation neural network algorithm enjoys a wide and rapidly varying local weight-change search capability, until sufficient convergence is achieved to reduce the local effective gain to lower values, whereupon that neuronal weight nears its final value.

Chaos optimization algorithms are the second way of applying chaos on optimization (Li, et al., 1998). These approaches explore the chaotic evolution of variables. Optimization algorithms based on the chaos theory are search methodologies that differ from any of the existing traditional stochastic optimization techniques. Due to the non-repetition of chaos, they can perform searches at higher speeds than stochastic ergodic searches that depend on probabilities. In this context, the literature contains several optimization algorithms using chaotic sequences for solving design problems (Li, et al., 1998), (Caponetto, et al., 2003), (Lu, et al., 2003), (Liu, et al., 2005), (Coelho, et al., 2009).

Chaos implementation in algorithms is usually done in two steps: a first step, which includes the mapping of the search space, and a second step which involves the exploration of space considering chaotic dynamics rather than random search. Chaotic sequences are able to increase the performance of the algorithm with respect to random sequences. It can also be shown that chaotic sequences help on overcoming the

¹¹³ Quadratic map ergodic regime is described in detailed in (Devaney, 1986).

drawback of EAs being extremely sensitive to different random sequences (Caponetto, et al., 2003).

5.4.3. CHAOS MAPPING

A map is an evolution function. Maps parameterization can be done by the time parameters, which can be either discrete or continuous. Discrete maps usually take the form of iterated functions. There are many chaotic time series, some of them represented below.

a) Logistic map

The Logistic Map, represented in function (5.12), is one of the simplest dynamic systems evidencing chaotic behavior, and was already introduced in equation (5.10).

$$x_{k+1} \rightarrow ax_k(1 - x_k) \quad (5.12)$$

In this function:

α is the control parameter,

x_k is a variable, and

$k=0,1,2,3,\dots$ is the iteration (or the period)

Although the above equation is deterministic, it exhibits chaotic dynamics when $\alpha=4$ and $x_0 \notin \{0,0.25,0.5,0.75,1.0\}$. x_k can travel ergodically all over the search space, and has the characteristics of ergodicity, pseudo-randomness and irregularity that are typical of chaotic variables (Liu, et al., 2005).

Typical settings are $x_0 = 0.27$ and $a = 4$ (Caponetto, et al., 2003). Further reading on this map may also be found on (Parker, et al., 1989).

b) Tent map

The Tent map is similar with the Logistic Map, and it is represented by equations (5.13) and (5.14). Typical setting is $x_0 = 0.27$. Further reading on this map can be found on (Peitgen, et al., 1992).

$$x_{k+1} = G(x_k) \quad (5.13)$$

$$G(x_k) = \begin{cases} \frac{x_k}{0,7}, & \text{if } x_k < 0,7 \\ \frac{1}{0,3} x_k (1 - x_k), & \text{otherwise} \end{cases} \quad (5.14)$$

c) Sinusoidal iterator

The Sinusoidal iterator is another chaotic generator, represented by equation (5.15). It can be simplified, as per equation (5.16). Possible start settings are $a = 2,3$ and $x_0 = 0,7$.

$$x_{k+1} = ax_k^2 \sin(\pi x_k) \quad (5.15)$$

$$x_{k+1} = \sin(\pi x_k) \quad (5.16)$$

Further reading on this map may be found on (Peitgen, et al., 1992).

d) Gauss map

The Gauss map is another transformation similar with the quadratic map. It allows a complete analysis of its qualitative and quantitative features (Caponetto, et al., 2003). Gauss map can be found in literature in (Peitgen, et al., 1992), and the map functions are given by equations (5.17) and (5.18).

$$x_{k+1} = G(x_k) \quad (5.17)$$

$$G(x_k) = \begin{cases} 0, & x_k = 0 \\ \frac{1}{x_k} \bmod 1, & x_k \in (0,1) \end{cases} \quad (5.18)$$

e) Hénon map

Hénon map was introduced in (Hénon, 1976), and is a simplified version of the Poincaré map of the Lorenz system. The Hénon equations are given by (5.19) and (5.20). Very particular attractor may be obtained for $a = 1.4$ and $b = 0.3$.

$$y(t) = 1 - a \cdot y(t-1) - z(t-1) \quad (5.19)$$

$$z(t) = b \cdot y(t-1) \quad (5.20)$$

Coelho et al. proposed a novel chaotic PSO, using Hénon map sequences, combined with an implicit filtering local search method to solve economic dispatch problems. The chaotic PSO approach is used to produce good potential solutions, and the implicit filtering is used to fine-tune of final solution of PSO (Coelho, et al., 2009).

f) Lozi map

Lozi map is a simplified version of Henon's attractor, whose transformation expressions are given in (5.21) and (5.22).

$$(x_{k+1}, y_{k+1}) = H(x_k, y_k) \quad (5.21)$$

$$H(x_k, y_k) = (|1 + y_k - ax_k|, bx_k) \quad (5.22)$$

Further reading on this map may be found on (Peitgen, et al., 1992) and (Caponetto, et al., 2003).

g) Chua's map

Chua's map has a simple mathematical model, and a very rich variety of dynamical behaviors (Parker, et al., 1989). The equations are dimensionless and are shown in (5.23), (5.24) and (5.25).

$$\dot{x}(t) = \alpha(y(t) - l(x(t))) \quad (5.23)$$

$$\dot{y}(t) = x(t) - y(t) + z(t) \quad (5.24)$$

$$\dot{z}(t) = -\beta y(t) - \iota z(t) \quad (5.25)$$

With

$$l(x) = m_1 x + 0.5(m_0 - m_1)(|x + 1| - |x - 1|) \quad (5.26)$$

This map equations use three state variables (x , y and z) and five dimensionless system parameters (α , β , ι , m_0 and m_1).

Chua's oscillator shows a double scroll attractor if settings are as follows: $\alpha=9$, $\beta=14,286$, $\iota=0$, $m_0=-1/7$ and $m_1=2/7$.

Chua Map is used to derive discrete chaotic time series, by adequately time sampling.

h) Final remark

A literature review on chaotic maps or chaotic time series sequences can be found in (Coelho, et al., 2009). In general, these chaotic time series sequences have parameters that require settings, which we feel that somehow affect the approach to the problem and the convergence to the solution.

5.4.4. THE IMPORTANCE OF THE CHAOTIC BEHAVIOR OF PARTICLE SWARM WEIGHTS

The chaotic sequences have been applied not only to the particle swarm algorithms, but also to evolutionary algorithms. Caponetto et al. adopted chaotic sequences in various phases of evolutionary algorithms (Caponetto, et al., 2003):

- Initial population; chaotic sequences may be used to generate the first individuals;
- Selection; chaotic sequences can be adopted for the choice of individuals according to some method (ex. the roulette wheel method);
- Crossover; chaotic sequences can be used either for the choice of points inside the chromosomes, or for the generation of bit masks, and also to decide whether or not to apply the operator;
- Mutation; chaotic sequences may help on choosing the positions of the chromosome's bits to be changed and to decide whether or not to apply the operator.

So, chaotic sequences may influence the behavior of all evolutionary algorithm operators, as the operators work following chaotic sequences instead of the usual standard random generators.

Weights are relevant parameters on particle swarm algorithms. The inclusion of an inertia weight w in the PSO algorithm was introduced by Shi and Eberhard, and first published in 1998, as given by equation (5.27) (Shi, et al., 1998).

$$V_{hij}^{new} = wV_{hij} + c_1r_1.(L_{hij} - X_{hij}) + c_2r_2.(G_{ij} - X_{hij}) \quad (5.27)$$

One may say that the inertia weight w is the factor that, in each iteration, controls the impact of the particle's velocity on the previous iteration. It is the value of w that

dictates the balance between exploration and exploitation in PSO. Thus, proper control of the inertia weight is very important to find the optimum solution accurately and efficiently: larger inertia weights pressure towards global exploration, while smaller inertia weights pressure toward fine-tuning of the current search area (Liu, et al., 2005).

Shi and Eberhart improved the performance of PSO adopting a linearly varying inertia weight from 0.9, at the beginning of the search, to 0.4, at the end of the search (Shi, et al., 1999).

The implementation of the inertia weight adopted either constant or dynamic values for the entire search, for all particles and each dimension:

- Constant w values: (Shi, et al., 1998);
- Dynamic w values: (Shi, et al., 1999), (Clerc, 1999), (Eberhart, et al., 2001), (Zheng, 2003), (Liu, et al., 2005), (Adriansyah, et al., 2006), (Chatterjee, et al., 2006), (Liu, et al., 2007), (Malik, et al., 2007).

In a search for a trade-off between exploration and exploitation, Liu set w varying adaptively in response to the objective values of the particles, in a so called adaptive inertia weight factor (Liu, et al., 2005). This factor is determined by equation (5.28).

$$w = \begin{cases} w_{\min} + \frac{(w_{\max} - w_{\min}) \cdot (f - f_{\min})}{f_{\text{avg}} - f_{\min}}, & f \leq f_{\text{avg}} \\ w_{\max}, & f \geq f_{\text{avg}} \end{cases} \quad (5.28)$$

In this expression:

$w_{\max}$ and $w_{\min}$ denote the maximum and minimum of w respectively;

f is the current objective value of the particle;

f_{avg} and $f_{\min}$ are the average and the minimum objective values of all particles, respectively.

With this adaptive inertia weight factor, good particles tend to perform exploitation to refine results by local search, while bad particles tend to perform large modification to explore space with large step. So, an adaptive inertia weight factor provides both a good way to maintain population diversity and to sustain good convergence capacity.

Based on the proposed PSO with adaptive inertia weight factor and the chaotic local search, Liu et al. proposed a two-phased iterative strategy named Chaotic PSO (CPSO),

in which PSO with Adaptive Inertia Weight Factor is applied to perform global exploration and chaotic local search, based on a Logistic Map, is employed to perform locally oriented search (exploitation) for the solutions resulted by PSO (Liu, et al., 2005).

Malik et al. propose a PSO optimizer with sigmoid increasing inertia weight and sigmoid decreasing inertia weight. Experiments show that PSO with increasing inertia weight gives better performance with quick convergence capability and aggressive movement narrowing towards the solution region (Malik, et al., 2007). The sigmoid function is given by (5.29).

$$S = \frac{1}{1 + e^{-t}} \quad (5.29)$$

Figure 5.1 below represents this function in two variants: growing, with a positive sign to affect t , and descending, with a negative sign to affect t , as represented in equation (5.29).

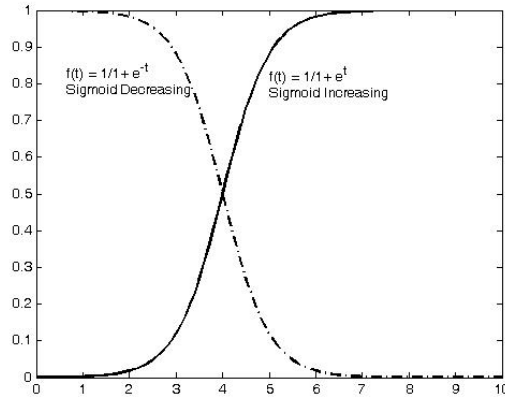


FIGURE 5-1 SIGMOID DECREASING AND INCREASING INERTIA WEIGHT

Source: (Malik, et al., 2007)

The sigmoid function is a useful tool for decisional processes. Equation (5.29) is utilized in equation (5.30), for sigmoid increasing inertia weight, and equation (5.31), for sigmoid decreasing inertia weight, as follows:

$$w_k = \frac{(w_{start} - w_{end})}{(1 + e^{-u \cdot (k - n.gen)})} + w_{end} \quad (5.30)$$

$$w_k = \frac{(w_{start} - w_{end})}{(1 + e^{u \cdot (k - n.gen)})} + w_{end} \quad (5.31)$$

$$u = 10^{(\log(gen) - 2)} \quad (5.32)$$

In these expressions:

- w_k is inertia weight at k ,
- w_{start} and w_{end} are inertia weight at the start and inertia weight at the end of a given run, respectively;
- u is the constant to adjust sharpness of the function;
- ger is the maximum number of generations to run; and
- n is the constant to set partition of sigmoid function.

From the results obtained by Malik et al., one may conclude that the sigmoid function has contributed to getting minimum fitness function while linearly increasing inertia weight contributes to quick convergence ability. The sigmoid constant (n) plays an important role in searching for the optimal solution in SIIW (Malik, et al., 2007).

As an illustration of the use of this type of approaches, Acharjee and Goswami developed a load flow algorithm based on chaotic particle swarm optimization (CPSO), and they design two sets of formulae for inertia weight and constriction factors. These authors claim the efficiency and effectiveness of the proposed algorithm, which was tested on different systems (Acharjee, et al., 2010).

5.4.5. CHAOTIC PARTICLE SWARM OPTIMIZATION

Several approaches have been proposed that combine PSO with chaotic maps, either by adding a perturbation implemented as a mutation operator to the velocity update equation, or even replacing the random numbers by chaotic sequences. In Meng et al. a chaotic search mechanism is adaptively embedded in PSO to avoid the algorithm to be trapped in local minima and to increase the speed of convergence (Meng, et al., 2004). Chuanwen and Bompard introduced chaos mapping into the PSO and presented an approach based on a hybrid method of chaotic PSO (PSO combined with chaos mapping) and linear interior point. These authors claim that this approach can improve both the convergence and the accuracy of the results (Chuanwen, et al., 2005). Liu et al. proposed a so called chaotic PSO, combining PSO and chaotic searching behavior, based on a Logistic mapping (see Figure 5.2).

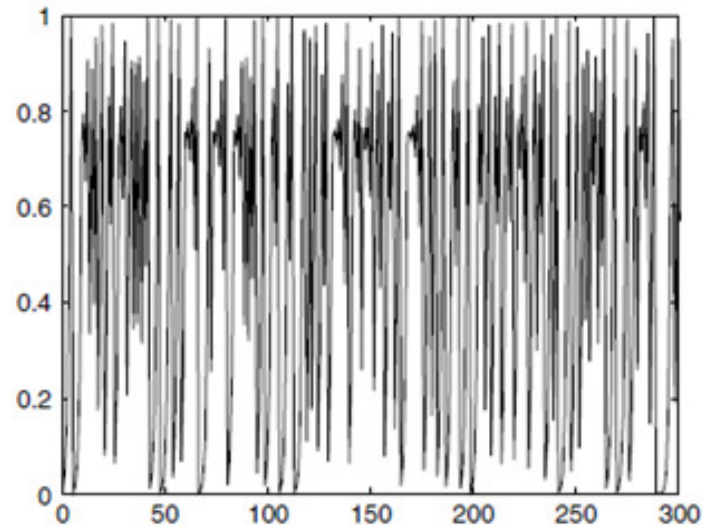


FIGURE 5-2 DYNAMICS OF THE CHAOTIC LOGISTIC MAP

Source: (Liu, et al., 2005)

It was demonstrated that chaotic PSO can effectively enhance the searching efficiency and improve performance greatly (Liu, et al., 2005). Liu et al. continued their research on this topic and investigated the chaotic dynamics in PSO and showed that a high maximum Lyapunov exponent usually achieves better performance, especially for multimodal functions (Liu, et al., 2007). Meanwhile Tatsumi et al. proposed a chaotic dynamical system for PSO with sinusoidal perturbations (Tatsum, et al., 2006). Coelho and Herrera¹¹⁴ proposed a chaotic Zaslavskii map combined with PSO, including also clustering methods to identify Takagi-Sugeno fuzzy models applied to a nonlinear yo-yo motion system (Coelho, et al., 2007). Xiang et al. analyzed the performance and limitations of approaches combining chaotic search with PSO and presented an improved PSO algorithm combined with piecewise linear chaotic map with interesting results (Xiang, et al., 2007). Yang et al. proposed an improved hybrid algorithm that combines PSO with chaotic sequences and concluded that the efficiency of the hybrid optimization algorithms is influenced by the statistical property of chaotic/stochastic sequences generated from chaotic/stochastic algorithms (Yang, et al., 2007). In Yang and Nomura a chaotic search is introduced into quantum-behaved PSO, so that a chaotic search is carried out in neighborhoods of the particles which are trapped into local optima (Yang, et al., 2008). Alatas et al. used chaotic number generators each time a random number is needed by the classical PSO algorithm (Alatas, et al., 2009). Wang and Liu proposed a chaotic particle swarm optimization approach to generate the optimal or near-optimal assembly sequences of products (to provide the preferable assembly sequences of each particle) (Wang, et al., 2010 a).

¹¹⁴ Chaos has also been combined with other algorithms as Ant Colony. As an example, Coelho and Mariani proposed new combinations of an ant colony inspired algorithm and chaotic sequences which have been applied to engineering design optimization (Coelho, et al., 2008 a).

We stress the work of Yu et al which adopts chaotic particle swarm optimization (CPSO) to solve the dynamic multi-stage transmission network expansion planning (Yu, et al., 2008). This CPSO algorithm adopts the logistic map. It produces a large number of initial particles with chaos carrier, and chooses the best individuals to be part of the initial population. CPSO modifies the current particle position with chaos perturbation carrier, and makes it trip-out local optimal positions. We consider that the modeling of the problem results rather complex, as it adopts a range of large variables and involves the setting of the selected mapping.

Based on a new paradigm suggesting that particles do not need to follow the same strategy, Krohling developed a strategy to escape from local minima using jumps, with promising results (Krohling, 2006). Later on, this approach was improved by generating the jumps from chaotic sequences (Krohling, et al., 2011). The jumps are used in the dynamic regime where the particles are trapped into local optima. The property of the adopted logistic map to generate random numbers near the two extremes of the interval range $[0; 1]$ is very useful to generate points away from the neighborhoods of the current particle positions, where no fitness improvement occurs.

Chuang et al. used chaotic maps to improve the solution quality of Catfish PSO since they avoid entrapment in local optima by virtue of their characteristics of ergodic orbits and aperiodicity (Chuang, et al., 2011). Simple Catfish PSO include catfish particles into PSO which improve the performance of PSO considerably. When the global optimum fitness value does not change for a certain number of consecutive iterations, the so called catfish particles are positioned on the boundaries of the search space and initialize a new search from these extreme points of the search space. This approach guides the entire swarm to promising new regions of the search space, accelerates the search and results in further opportunities of finding better solutions for the swarm.

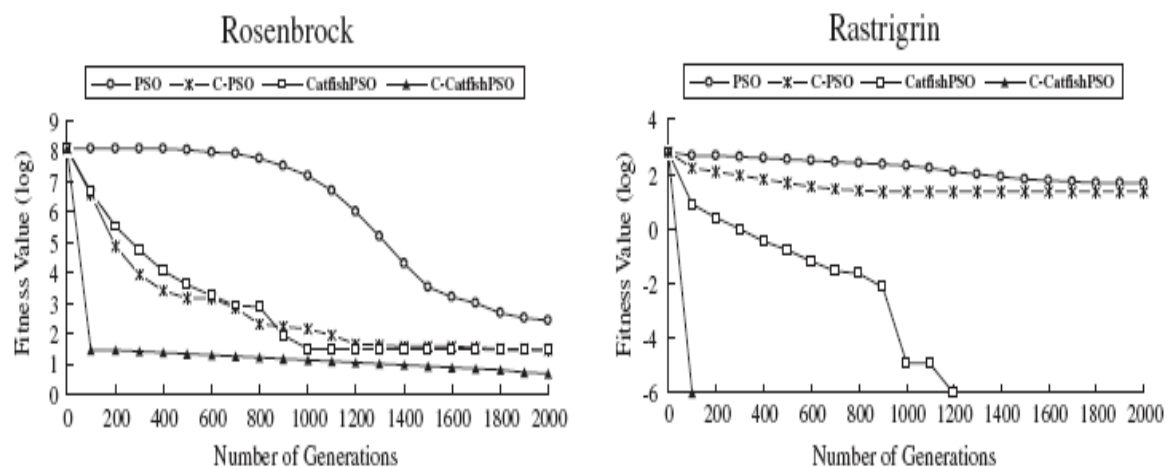


FIGURE 5-3 PSO, CHAOTIC PSO AND CATFISH PSO, FOR ROSEN BROCK AND RASTRIGRIN FUNCTIONS

Source: (Chuang, et al., 2011)

Figure 5.3 represents the results of tests involving the four approaches (PSO, CPSO, Catfish PSO and C-Catfish PSO-C) and two test functions (Rosenbrock and Rastrigrin). These results indicate the rapid convergence of PSO versions, complemented by the Catfish methodology and the Chaos.

5.4.6. LOCAL SEARCH AND LAMARCKISM

Despite all its advantages, the lessons to be learned from past experience with genetic algorithms are that

“The search performance of the genetic algorithms can be improved by introducing a local search method.” (Hart, et al., 1994)

Chuanwen et al. introduced a method combining particle swarm optimization (PSO) with linear interior point. Furthermore chaos mapping is included into the particle swarm optimization (Chuanwen, et al., 2005). The local exploration ability of linear interior point within the neighborhood of the optimal point allows the improved performance of new method on both convergence and results' accuracy.

Some researchers, like Coelho, defend the use of chaotic sequences in PSO to escape from local optima and Gaussian distribution for a faster convergence in local search (Coelho, et al., 2008 a). Others, like Miranda, defend that

“One must not blindly trust in the blind force of a revolutionary process – especially when it is built in a naïve way by humans who expect it to find a particular optimum as quickly as possible. Therefore, one must “help”, say, by introducing some Lamarckism in a fundamentally Darwinist process.”
(Miranda, 2008)

Miranda explains the differences¹¹⁵ between Darwinism and Lamarckism by quoting Dawkins, Gould and Krasnogor:

- Darwinism: “*evolution is the external and visible manifestation of the differential survival of alternative replicators*” (Dawkins, 1978); Survival is due to competition among phenotypes, and not as the result of any instruction or learning processes;
- Lamarckism: is “a theory of directed variation” (Gould, 1979); the effects resulting from processes of learning, or instruction sets at the macroscopic level, result in changes of genotypes, which translates into future changes in phenotypes; in other

¹¹⁵ There is another idea on evolution, introduced by Baldwin in 1898: chromosomes may encode a predisposition for learning beneficial behaviors. A Baldwinian mechanism for GA do local search and assigns any improvement fitness as the fitness of the chromosome, but does not modify the chromosome.

words, the fitter neighbour replaces the original candidate solution (Krasnogor, et al., 2005).

Taking into account the experience of researchers, understanding the differences in the two principles of evolution, assuming that research does not have to follow closely what happens in nature, Miranda states that most of the models proposed in GA are, in fact, full of Lamarckian potential (Miranda, 2008). Lamarckian are suitable approaches to perform local search in GA¹¹⁶. This conclusion was drawn from previous comparisons of different algorithms involving Lamarckian concepts. Morris compared simulated annealing, genetic algorithm and a so called Lamarckian genetic algorithm (Morris, et al., 1998). The results showed that Lamarckian genetic algorithm was more efficient and more reliable than the other methods. Also to illustrate the importance of Lamarckism, Miranda compared the performance of three models, using the same fitness (objective) function (Miranda, 2008): simple genetic algorithm, genetic-based algorithm, and genetic-based algorithm with gradient search. The results presented by Miranda show the benefit of genetic-based algorithm with gradient search, and Lamarckism approach, over the classical genetic algorithms.

Another example presented by Miranda to show the convenience of Lamarckism is based on a unit commitment problem. A so called “neighbourhood digging” is launched at certain generations. It tries to displace the start-up and shut-down times of generators in order to improve solutions (which are selected with a given probability). From the results one can identify the better performance of “neighbourhood digging” algorithm, where a Lamarckian approach was adopted.

Trapping the algorithm in local optima is a real danger when it is not properly designed. Diversity is important for the exploitation of the search space. There are some questions that may be stated to address this topic (Krasnogor, et al., 2005): What is the best trade-off between local search and the global search provided by evolution? Where and when should local search be applied within the evolutionary cycle? Which individuals in the population should be improved by local search, and how should they be chosen? How much computational effort should be allocated to each local search? How can the genetic operators’ be best integrated with local search in order to achieve a synergistic effect?

Thus, the Lamarckian operators or procedures should only be activated according to particular conditions, for example, when the fitness of the individuals is worst than a threshold.

¹¹⁶ Some researchers, like Moscato, name the combination of GA with local search as memetic algorithms (MA) (Moscato, 1998). A tutorial for memetic algorithms can be found in (Krasnogor, et al., 2005). However, specialists on evolutionary algorithms, like Kennedy, defend that “*it does not seem reasonable to believe that memes are evolutionary at all*” (Kennedy, 2006). Further information regarding this topic can be found in Chapter 4.

“The selection of such a threshold value depends on the trade-off between how-much-time-we-can-spend and how-good-results-we-want-to-achieve”.

(Miranda, 2008)

Houck et al have investigated the benefits of “partial Lamarckism” and concluded that Lamarckian strategies reduce the problem of not having a one-to-one genotype to phenotype mapping, but require more computational time to obtain the optimal. Therefore, a partial Lamarckian strategy is suggested (Houck, et al., 1997).

To achieve an optimal synergy between operators (recombination and mutation) and Lamarckian type local search operators, avoiding the discard of new high performance individuals, it is more adequate to perform local search on offspring, prior to selection (Krasnogor, et al., 2005).

5.5. DISCRETE EVOLUTIONARY PARTICLE SWARM OPTIMIZATION (DEPSO)

5.5.1. INTRODUCTION

The discrete EPSO used in this work is a new approach of the EPSO model able to tackle problems with non-continuous and integer search spaces. The main differences between this approach and classical EPSO are:

- the elements in the particles are integers¹¹⁷,
- the mutation rules are based on chaotic behaviours and
- it is introduced a Lamarckian evolution concept.

However, DEPSO includes the same main blocks of classic EPSO.

In this work, we adopted an EPSO based approach instead of PSO or other meta-heuristic, since it performs better when dealing with very complex problems, as it is detailed in (Miranda, et al., 2002 a).

5.5.2. THE SEARCH SPACE, THE POPULATIONS AND THE PARTICLES

a) Definitions

Many real life problems are solved in discrete contexts. In such situations, the real space is replaced by discontinuous spaces, whose positions can be described by binary or integers elements. TEP is an example of such situations. The scheduling of projects consists on the definition of periods in which the projects are completed. A project can only be assigned to a given period.

For a better understanding of the coding and algebraic operations associated with Discrete Particle Swarm Optimization, we will refer to a set of definitions proposed by Xu et al. which will be adapted to DEPSO, with some differences arising from the fact that our model works only with vectors, while the model of Xu et al. works with matrixes (Xu, et al., 2008).

¹¹⁷ As mentioned in Section 3.6.1., most of the methods, even meta-heuristics, adopt or require the relaxation of the binary to continuous variables. The rounding process may potentially lead to solutions far from the optimum, but with the advantage of having lower computational burden. That's why on intend to develop a method able to tackle with discrete variables.

Definition 1 - Position is an n-dimensional (n-D) vector:

$$X_{pt}^{it} = \{x_{pt,j}\}, j = 1, \dots, n \quad (5.33)$$

Where n is the vector dimension, $x_j \in \{1, \dots, m\}$ and m is the number of periods each vector position can be assigned. X_{pt}^{it} is the particle pt , which is part of a population in iteration it .

Definition 2 - Fitness; Given an n-dimensional (n-D) vector X_{pt}^{it} , its fitness is calculated by a function f , that is, the fitness of X_{pt}^{it} is given by $f(X_{pt}^{it})$.

Definition 3 - Velocity is n-dimensional (n-D) vector:

$$V = \{v_j\}, j = 1, \dots, n \quad (5.34)$$

Where $v_j \in \{-round(m/2), \dots, 0, \dots, +round(m/2)\}$ and m is the number of periods.

Definition 4 - New position = Position + Velocity: A velocity added to a position results in a new position:

$$X_{pt}^{it+1} = X_{pt}^{it} \oplus V \quad (5.35)$$

In this expression, the new position, X_{pt}^{it+1} , is found by applying the following operations orderly:

for $j = 1$ to n ,

$$\text{do } x_{pt,j}^{it+1} = x_{pt,j}^{it} + v_j$$

end

As velocity is a vector centered at 0 with range m , any element of the position vector may evolve into positions corresponding to a forward or a backward movement.

b) The search space and the coding

To better understand the coding proposed for the equivalent Job Scheduling problems, we will explain the concept of codification of projects. Projects may take the state corresponding to the period when they are considered complete and available. In addition to these states, two more are possible, corresponding to situations of non-implementation of a particular project: either the possibility of not being chosen, or the possibility of being postponed beyond the periods under review. So, $np+2$ possible states are possible. For example, in a four period analysis this results in 6 possible states: state 0, which corresponds to not choosing the Project, states 1 to 4, the period in which the Project will be completed, and state 5, corresponding to the postponement of the Project. In this case, in each iteration, one has $X_{pt,j}^{it} \in [0,5]$.

TABLE 5-1 EXAMPLE OF DISCRETE SEARCH SPACE DIMENSIONS

Number of new projects	Number of periods	Number of states	Alternative solutions
28	1	3	$3^{28} = 22,8 \times 10^{12}$
28	4	6	$6^{28} = 6,1 \times 10^{21}$

To have an idea about the dimension of the search space, the case of a problem with a project list with 28 new projects is introduced. The search space has the dimensions mentioned in Table 5.1. One has to keep in mind that the search for the solution is harder as the search space dimension increases.

c) The particles

A particle is a possible solution to the problem, and is a vector of integers, with npj positions. A set of npt particles forms a population x^{it} . As the population evolves in each iteration, one must refer to the population x in iteration it . Populations are usually composed of 30 to 200 particles. The definition of the number of particles of a population depends on the size of the search space and on the complexity of the problem.

d) The populations

Each population is characterized by:

- the number of particles $npt, np \in \{1..npt\}$;
- the number of projects $npj, j \in \{1..npj\}$ and
- the number of possible periods in the horizon, $period \in \{0..np+1\}$.

e) The first and the second populations

The model proposed in this thesis considers three populations, each of which has npt particles. Two of these populations (population 1 and population 2) are clones of the best population, and are subjected to changes according to the principles of Evolutionary Particle Swarm Optimization, adapted to the integer search space.

f) The third population

The third population is composed of clones of particles selected among those on the best population, which evolve in a Lamarckian way, and which will promote local search around the best particles ever found. The selection of the particle to be cloned is done as follows:

- The best global, if $stop\_counter < k$;
- A particle randomly selected among the best population, if $stop\_counter \geq k$.

In our algorithm it was considered $k = 6 * npr$. This option is based on the feeling that for a few iterations it would be possible to identify any particle with best fitness in the vicinity of the global best. The search around the global best should be dynamic and dependent on the number of periods under review. When it is not possible to improve around the global best, one admits that this shall be a local minimum and that the improvement of the solution is a search to be performed around particles belonging to the best population. In this case the particle to be cloned shall be identified by generating a random number between 1 and npt . This additional third population has npt particles cloned from the particle identified. The particles are mutated adopting a partial Lamarckian evolution, as described in Section 5.5.7.

g) The seeding procedure

In the case of complex problems and large dimension search spaces some previously acquired knowledge can be incorporated in the population. This approach may include the introduction in the first population of an eligible particle, not subjected to any

penalty. This procedure is commonly known as seeding, and may accelerate the convergence without interfering with the final solution. We adopt a seeding procedure in our model when dealing with TEP problem¹¹⁸.

h) Maintaining the diversity in the best population

“Diversity has been recognized as playing an important role in exploring the search space.” (Mahfoud, 1995)

It is noted that for complex problems, and after tens of iterations (about 100), the best population begins to reveal a concentration of equal or very similar particles. This situation is characterized by a lower diversity and ultimately leads to the premature convergence to local minima.

This problem is most severe when the population is small and affects the progression towards the optimum. The convergence conditions are better ensured if one avoids premature convergence to local minima and by ensuring diversity in the population.

To avoid this premature convergence an elimination approach was adopted by Yang in a research on Hybrid Discrete Particle Swarm Algorithm for Hard Binary problems (Yang, et al., 2006). These authors proposed the elimination of repeated particles (based on Hamming distances) and the adoption of a tabu list. This list is intended to prevent the particles included in the tabu list to be evaluated and considered in the evolution of the algorithm.

Our approach is different. To improve the convergence and maintain the diversity in the best population, instead of eliminating the particles which converge to positions that have been global best in the past or that belong to the best population (and hence positions already visited and known), we implemented a Lamarckian evolution of these particles, as explained in section 5.5.7..

5.5.3. THE ALGORITHM

We follow the same structure of classic EPSO, and the algorithm is organized as follows¹¹⁹.

¹¹⁸ This feature is inspired in the research of Rezende (Rezende, et al., 2010).

¹¹⁹ See Chapter 4 for more information on the structure of the classic EPSO algorithm.

Procedure DEPSO

Initialize a random population P of μ elements

REPEAT

Replication – each particle is replicated r times;

Mutation – each particle has its strategic parameters mutated;

Reproduction – each particle generates an offspring through recombination, according to the particle movement rule, and using the mutated strategic parameters;

Selection – by elitist selection procedure, the best particles survive to form a new generation;

Test - for termination criteria (based on fitness, on number of generations or other criteria)

Until test is positive

End DEPSO

Two important differences between DEPSO and EPSO are on the mutation and reproduction operators, as is explained in the next Sections.

The off-springs are generated by recombination of the particles, following similar recombination rules (5.36) and (5.37).

$$X_{pt,j}^{it+1} = X_{pt,j}^{it} + V_{pt,j}^{it+1} \quad (5.36)$$

$$V_{pt,j}^{it+1} = w_{pt,j,1}^{it*} \cdot X_{pt,j}^{it} + w_{pt,j,2}^{it*} \cdot (b_{pt,j} - X_{pt,j}^{it}) + w_{pt,j,3}^{it*} \cdot (b_{G,j}^* - X_{pt,j}^{it}) P_j \quad (5.37)$$

5.5.4. REPLICATION

Like in EPSO, the best population is cloned twice.

In addition to these populations, in each iteration it is formed a third population, as explained in Section 5.5.2.

5.5.5. MUTATION

Two item groups relating to populations 1 and 2 are subjected to mutation: the mutation weights and the best global.

a) Mutation of the weights

As in the classical EPSO approach, there are three weights that are subjected to mutation: inertia, memory and cooperation.

A different mutation operator was adopted, as indicated in (5.38).

$$w_{pt,j,t}^{it+1*} = \left(0.5 + rand() - \frac{1}{1 + \exp\left(-w_{pt,j,t}^{it*}\right)} \right) \quad (5.38)$$

The well known sigmoid function (5.39) is included as a map in function (5.38). The sigmoid function¹²⁰ (5.39) was adopted as a map due to its chaotic behaviour, and also to keep the self adaptation capabilities of the swarm while respecting a narrow variation range that could help on the particles movement control (see Figure 5.4).

$$\frac{1}{1 + \exp(-W_{ij})} \quad (5.39)$$

Unlike other approaches that use this expression to choose among two alternatives (usually binary approaches), in our model we propose the adoption of this expression itself as a mapper in the expression (5.38). This operation results in a real multiplier with chaotic behavior, as illustrated in Figure 5.4.

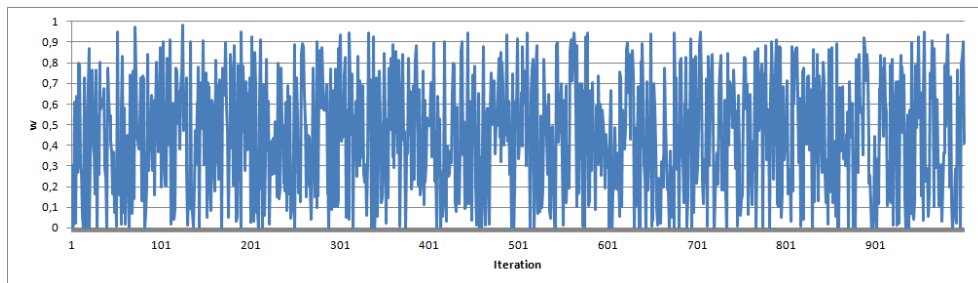


FIGURE 5-4 MUTATED WEIGHTS CHAOTIC EVOLUTION

¹²⁰ Function (5.39) is frequently adopted in artificial neural networks and was also employed in binary PSO approaches.

It is a very simple expression, which includes the previous value of the weight to mutate, that is, it carries the influence of the weights of the previous iterations for the following iterations. It also allows an easy integration in the classical mutation expressions, which contributes to a simple and fast algorithm¹²¹.

b) Mutation of the best global

The best global particle is a vector, whose positions are mutated only when randomly generated numbers take values less than $k_c \in [0,1]$.

The tests we have performed suggest that $k_c = 0,4$ led to the best convergence results¹²².

$$b_{Gj}^* = b_{Gj} + \text{round}(2 \cdot w_4^{it*} - 1) \quad (5.40)$$

The weights are updated by (5.38) and the mutation of particle b_G is obtained by (5.40).

5.5.6. RECOMBINATION

a) Movement rule

A major difficulty of using particle swarms is the control of the population movement, ruled by velocity V . In the case of DEPSO this situation is even more relevant, since the space is not continuous, and one must ensure that the movement of particles makes them move from one position to another while respecting the search space.

$$X_{pt,j}^{it+1} = X_{pt,j}^{it} + V_{pt,j}^{it+1} \quad (5.41)$$

$$V_{pt,j}^{it+1} = \text{round}\left(w_{pt,j,1}^{it*} \cdot X_{pt,j}^{it} + w_{pt,j,2}^{it*} \cdot (b_{pt,j} - X_{pt,j}^{it}) + w_{pt,j,3}^{it*} \cdot (b_{G,j}^* - X_{pt,j}^{it}) P_j\right) \quad (5.42)$$

The movement rules in DEPSO are similar to those of EPSO, but all elements in X (expression 5.41) and V (expression 5.42) are integers. It should be noted that expression (5.42) includes a rounding process to obtain integer elements in V .

¹²¹ The algorithm is fast namely because it has no need for intermediate conversions.

¹²² The value of 0.4 was inspired by the work of Houck on Partial Lamarckism, which is referred to in the following pages (Houck, et al., 1997). It was found that convergence is optimized when Lamarckism is adopted in 20 to 40% of total particles.

Because the space is discontinuous, this approach results in a movement that has characteristics similar to a jump from one position to the next. It can be said that due to the fact that it also adopts a chaotic behaviour for the moments of inertia, our proposal has something in common with what is suggested by Krohling, when proposing an approach combining swarm algorithms with the jump strategy to escape from local minimum (Krohling, et al., 2011). Here, however, the jump strategy is based on a chaotic logistic map.

b) Movement control

We adopted the same expressions of the classic EPSO, which we round up to integers. When the particles exceed the search space boundaries, they are returned to the search space, either being placed on the edge or in a contiguous position (functions 5.43, 5.44).

$$X_{pt,j}^{it} = 0 + \text{round}(\text{rand}()) \quad (5.43)$$

$$X_{pt,j}^{it} = np + 1 - \text{round}(\text{rand}()) \quad (5.44)$$

This procedure repairs particles that are positioned outside the search space. Other authors in similar circumstances adopt some kind of penalty for the particle. In our opinion, repairing is more useful than the penalizing strategy, given the discontinuity of the search space. Repairing allows the repositioning of the particles in allowed positions, raising the possibility of being identified as better solutions.

The proposed repair procedure has some similarities with the concept of Catfish, addressed by Chuang. When the algorithm turns out because of being trapped in a local minimum, the Catfish model moves particles to the periphery of the search space (Chuang, et al., 2011).

Although our procedure is applied only to particles leaving the search space, in our algorithm we combine the particle repositioning in the border of the search space, as proposed by the author, with a chaotic behavior of moments of inertia (see section 5.4.)

c) The communication factor p

The communication factor concept was addressed in Section 4.6.7., having then been noted that this is another factor that enables the recombination operator of EPSO. Miranda experimental results show that a communication probability of $p = 0.20$ leads to better results than a classical deterministic star model, with $p = 1$ (Miranda, et al., 2008 b). DEPSO will be set to $p = 0.3$ (please refer also to section 7.2.9).

5.5.7. LAMARCKIAN EVOLUTION

Local search for better solutions near the best particles known to date can be promoted by a kind of Lamarckian evolution. The Lamarckian evolution should be performed in a controlled way, since there is a risk that the algorithm does not converge. This issue was the subject of research, including a team of MIT, using different test functions. The partial Lamarckianism, understood as the evolution of a few individuals in the population, was studied, and the conclusions were that neither the pure Lamarckian nor pure Baldwinian strategies consistently yielded the best performance (Houck, et al., 1997).

Our approach is slightly different. The concept of partial Lamarckism we adopt applies to the positions of each particle, which are eventually mutated in only 40% of cases, more than to the particles in the population. This option is justified by the fact that a particle that does not undergo mutation does not contribute to the convergence to the solution. So, what we care is to mutate the particles and prevent a null velocity. On the other hand, the excess of mutation can change the particle to the point that it loses its outstanding features. This corresponds to take the particle far away from its position, undermining the local search of better solutions.

a) Lamarckian evolution when $V = 0$

When the velocity of a particle is zero, a Lamarckian evolution of that particle is promoted, using (5.45). The particle only sees some of his positions mutated, those when randomly generated numbers take values less than kb .

The value of kb defines whether a given position of the particle is mutated or not. Based on the work of Houck et al¹²³, and after some tests, kb was set to 0.4. The value of ka defines the velocity range, ie, the possible variation of a particle's position. For populations 1 and 2, ka is set to np , since we are interested that V can take any value between $+np$ and $-np$, so that the corresponding position of the particle evolve in any direction and may reach the limits of the permissible range. In this case one admits a wider velocity range than in case of velocities associated with population 3, as one is dealing with particles that stalled without reaching a position that corresponds to a good fitness. Higher speeds can lead the particle to most promising regions.

$$V_{pt,j}^{it} = round \left(2.ka \left(0.5 + rand_1() - \frac{1}{1 + \exp(-rand_2())} \right) - ka \right) \quad (5.45)$$

If one wants to have a completely simetric probability, $rand_2()$ has to be changed by 0. When there is the need to favor the anticipation of the projects, the adoption of a

¹²³ According to Houck et al the best results are achieved convergence to values between 20% and 40%. (Houck, et al., 1997)

normal randomly generated number is more suitable. In our tests we have adopted $\exp(0)$ instead of $\exp(rand_2())$.

b) Lamarckian evolution of population 3

The particles of population 3 are mutated by Lamarckian evolution, adopting expression (5.46), similar to the expression (5.45).

$$Va_j = round\left(2.ka.*\left[0.5 + rand() - \frac{1}{1 + \exp(-rand())}\right] - ka\right) \quad (5.46)$$

The particles only see some of its positions mutated those when randomly generated numbers take values less than kb. In early iterations, until the tenth iteration, we assume that there is greater interest in promoting diversification in the search as the fitness of the best particle is still very poor. Therefore a pure Lamarckian strategy was chosen, which admits Lamarckian evolution in all positions of each particle of the population. When the global best is updated there is advantage in promoting a more local search. In these situations, kb is reduced to 0.5. kb is always kept at 0.4 after iteration 10.

The value of ka has a dynamic behavior, which is function of number of eligible positions, the updating of the global best and the number of iterations.

ka has also a dynamic behaviour and is set to

nper	when b _G is updated
2 (if nper > 1) or 1 (if nper = 1)	when stop_counter > 1
1	when iteration > 10

As one can see, after iteration ten only unitary variations are allowed as a way to prevent an excessive broad search, leading no longer to an effective local search.

As in (5.45), if one wants to have a completely simetric probability, $rand_2()$ has to be changed by 0. When one needs to favor the anticipation of the projects, the adoption of a normal randomly generated number is more suitable. In our tests we have adopted $\exp(0)$ instead of $\exp(rand_2())$.

c) Lamarckian evolution of particles belonging to “tabu list”

To improve the convergence and maintain the diversity in the best population, the particles which converge to positions that have been global best in the past or that belong to the best population are subject to the Lamarckian evolution, in a similar way as explained in a).

d) Lamarckian evolution, local search and global search

As summary, it is now important to recall the questions proposed by Krasnogor, referred in section 5.4.6 (Krasnogor, et al., 2005), and present the answers that result from our model:

- *What is the best trade-off between local search and the global search provided by evolution?*

In our case we have two populations to promote the classical search, complemented with Lamarckian evolution applied to immobilized particles, and one population to promote local search, whose evolution is based on a partial Lamarckism strategy;

- *Where and when should local search be applied within the evolutionary cycle?*

Local search is promoted in the population with clones of particles with good fitness, and in all iterations, from the first;

- *Which individuals in the population should be improved by local search, and how should they be chosen?*

The particles to be included in local search are those in the third population, which are clones either of the best global or of one of the particles of the best population, randomly chosen; the search is first promoted around the global best, moving then to search around other particles from the best population when it is not possible to identify any improvement around the global best;

- *How much computational effort should be allocated to each local search?*

The computational effort required by the search model proposed site is perfectly acceptable, and allows, even when it involves complex problems such as TEP, the convergence to near optimal solutions in reasonable time as it will be detailed in the following chapters;

- *How can the genetic operators' best be integrated with local search in order to achieve a synergistic effect?*

The third population consists of clones of particles that belong to the best population. This population is updated every iteration. This way one ensures that local search is always promoted from one of the best known particles, benefiting from the synergies of the model. After identifying a new Best Global particle from the third population, the particle becomes part of the best particles population, contributing to better solutions even in populations 1 and 2.

5.5.8. *FITNESS FUNCTION, EVALUATION AND SELECTION*

a) Fitness function

A problem dependent fitness function is used for the evaluation and selection of particles. In some cases, the fitness function is composed of several parcels or multipliers, each corresponding sub-evaluation functions. The sub-evaluation functions that are computationally heavier should be performed in last place, and only for particles that have not been penalized.

b) Evaluation and selection

In order to spare computation time, we considered that it is not necessary to test particles that are already known, either as previous best globals, or because they belong to the best population. When penalizing particles that are already known, it is possible to spare time and accelerate the search. This approach increases also the diversity in the population and reduces the risks of the premature convergence to local minima.

In our model we have three populations, whose particles have all to be evaluated, since the selection is made between the three elements in the same position of each of the three populations. At each position survives the clone whose fitness is better than the best particle of the best position. The best global will be updated if some of the best particles has best fitness.

c) Handling constraints with DEPSO

The DEPSO model we propose allows restrictions by additive penalties in the evaluation function. It considers the penalties associated with the algorithm (e.g. particles that belong to a Tabu List) or with the problem (e.g. in case of TEP problem, it considers penalties for excessive number of projects, beyond the limit defined, or by excessive partial or total investment).

5.6. ADVANTAGES OF DEPSO

The merits of DEPSO result from the EPSO own merits (see section 6.4.10). In addition, as DEPSO was specially designed to address integer problems, in the treatment of the same problems, it shows some advantages, even over EPSO:

- DEPSO displays a faster convergence;
- DEPSO is more accurate;
- DEPSO is more robust (the variance of the results is much smaller than for EPSO);
- EPSO is insensitive to weight initialization (like EPSO).

The DEPSO does not require adjustment in the parameterizations, shows an easy convergence, allows smaller populations (which reduces the number of evaluations and reduces the time required for each run) and is able to escape from local minima.

5.7. CONCLUSIONS

The model on which the dynamic TEP will be based is introduced in this Chapter. Being a discrete approach to EPSO, we refer to our model as Discrete Evolutionary Particle Swarm Optimization (DEPSO).

This model integrates a set of features aimed at deal with combinatorial problems, and overcome the typical difficulties of particle swarm optimization methods: premature convergence, low diversity on populations, getting trapped in local minima, difficult balance on global and local search, the need for the relaxation of the binary to continuous variables.

The mentioned features include:

- The chaos, for mutation improvements;
- The Lamarckian evolution, which complements the classical Darwinist evolution;
- The adoption of a Tabu List, to improve the population diversity;
- The dynamic local or global search, by adoption of a 3rd population.

Given its characteristics, and despite having been specifically developed for dynamic TEP, DEPSO is likely to be applied to any complex combinatorial problem.

The modeling of dynamic TEP based on DEPSO is presented in Chapter 6. In Chapter 7 some results obtained from its application to two test networks may be found. The results are quite promising.

6. MULTIYEAR TEP FORMULATION WITH DEPSO

“How much does the failure of the system costs, considering all its possible consequences?”

(Carvalho, 2008)

6.1. SCOPE

A dynamic or multiyear TEP model aims at determining the timing, the type and the location of the new transmission facilities to be added to an existing network along an extended planning horizon in order to ensure an adequate transmission capacity taking into account future generation options and load requirements.

A dynamic approach is made with a long-term horizon, typically organized on a yearly basis and with all sub periods considered jointly in the planning exercise. The dynamic approaches consider the influence of investments in a given period over the network performance in other periods, as described in Chapter 3.

The model takes into account this long-term horizon approach, as well as the requirements of DEPSO explained in Chapter 5, in order to explore all the advantages of evolutionary algorithms, namely the ability to evolve intelligently from a solution to a better one.

This approach is innovative, since it is a model which works with integers, and combines different techniques, such as Chaos, the Lamarckism, Evolutionary Techniques, Particle Swarms and DC OPF with losses.

6.2. THE IMPORTANCE OF TEP MODELING

In the last 20 years, power systems went through a process of liberalization and restructuring that determined changes at different levels, as detailed in Chapter 3. Apart from peculiarities that characterized this process in different countries, there are some relevant common aspects:

- The segmentation of the traditional vertically integrated utilities namely in generation, transmission, distribution and retailing;
- The advent of independent regulation;
- The increase of the number of agents namely in the generation and retailing activities now provided under competitive schemes and the decoupling between market functions, assigned to Market Operators; and
- The technical operation and monitoring functions assigned to System Operators.

On the other hand, the nature of electricity and of the required investments, typically lead to regulated monopolies to provide transmission and distribution services.

This modification of traditional utilities also had important consequences in terms of tariffs as well as in operation and planning activities. Regarding tariffs, till the advent of liberalization and restructuring there were no clear cost allocation procedures to each activity. Cross subsidies were common and final end user tariffs were typically determined using average approaches.

The segmentation of the industry imposed the clarification of this process, the clear identification of costs and their assignment to the agents or activities responsible for them and the construction of additive tariff systems based on elementary tariffs per activity, namely including tariffs for the use of transmission and distribution networks to pay network operation, management and investment costs. On the other hand, operation planning is now done in day ahead markets or via bilateral contracts and these economic schedules have to be submitted to System Operators for technical checking and for contracting ancillary services. Finally, in the past expansion planning was typically done in an integrated way in the sense that long-term studies regarding new generation capacity typically included the planning of the required transmission expansion and reinforcement. This integrated view no longer exists since now generation companies prepare their own expansion plans based on expectations on future profits and taking into account uncertainties affecting, for instance, the demand, the electricity price and the operation and investment costs.

Transmission providers face a challenging task in preparing their expansion plans in view of this more decentralized and uncertain environment. On the legal and regulatory side, the European Parliament and the European Council approved the Directive 2003/54/CE, aiming at establishing common rules for the European internal market of electricity. TEP is clearly identified as a major responsibility of Transmission System Operators (TSO), as these operators are responsible for ensuring the long-term ability of the system to meet reasonable demands for the transmission of electricity.

More recently, the Commission Regulation (EU) No 838/2010 of 23 September 2010, on laying down guidelines relating to the inter-transmission system operator compensation mechanism states that “(...) the union-wide assessment of electricity transmission infrastructure associated with facilitating cross-border flows of electricity should be carried out by the Agency for the Co-operation of Energy Regulators as the body responsible for coordinating the activities of regulatory authorities who must carry out a similar function at a national level.”

At a national level TSO's typically have to prepare expansion plans to be submitted to the Regulatory Agency for approval. This means that building new lines and substations has to be justified namely because their costs, once approved, will then be reflected in the tariffs paid by consumers for the use of transmission networks.

As already mentioned in Chapter 3, TEP modelling is of great importance, since:

- It is invariably associated with high investment costs;
- The licensing procedures are increasingly complex, due to more demanding legislation and larger environmental concerns;
- Investments have great impact on the economy, not only due to its own cost, but also because of the energy tariffs, which are regulated, and the economic implications and constraints associated with the quality of energy.

TEP models are usually very complex. This complexity is due largely to non linear large models, with a significant computational burden, and which is reflected in algorithms that take too long to run. Therefore, models should be developed as simple and efficient as possible, so that the adopted solutions algorithms are fast and reliable.

The first effort has to do with the correct definition of the scope, even before using any model. One should proceed to a careful targeting of investments, which may be segmented in hierarchical levels, as proposed in (Reis, 2005) and mentioned in Chapter 3.2.2:

- Hierarchical level 1 (NH1): Hierarchical level of decisions that correspond to changes in the topology of the transmission system in respect to its structure;

- Hierarchical level 2 (NH2): Hierarchical level of decisions which correspond to changes in local nature network topology.

One may say that the NH1 is the structural level. This is the segment we will focus in our work and that is addressed in the developed model to be described in the next sections.

The second effort should be focused on the choice of the methodologies that contribute to lower as much as possible the computational burden, without jeopardizing the quality of the solutions. The meta-heuristic we introduced combines a discrete version of EPSO with the concept as Chaos and Lamarckism, as explained in Chapters 4 and 5.

To characterize the solutions proposed for each year, the power flow algorithm has to run thousands of times. So, it is also important to select a power flow model that does not compromise the performance of the global solution procedure. Our algorithm adopts the DC power flow model, which is very fast without compromising the accuracy level required for the type of network and the horizon addressed in typical planning exercises.

6.3. THE INITIAL DATA

6.3.1. INITIAL NETWORK

The initial network should be characterized with the following information:

- Power lines and underground cables: resistance, reactance, capacitance, nominal section, length, interconnection nodes, voltage level and transmission capacity; situations of parallel lines shall be marked clearly;
- Substations: number of transformers or auto transformers, nominal power, reactance and voltage levels;
- Power transmission network characterization: identification and location of nodes.

For planning purposes lines and transformers can be treated as branches of the network, provided that one keeps in mind the technical and economic characteristics that differentiate them.

The description of the network, and also the list of works that are included in the expansion plan explained in Section 6.4, will follow a data organization as in the Matpower Matlab file `idx_brch.m`, where the lines and transformers are organized as follows:

%	1	F_BUS	f, from bus number
%	2	T_BUS	t, to bus number
%	3	BR_R	r, resistance (p.u.)
%	4	BR_X	x, reactance (p.u.)
%	5	BR_B	b, total line charging susceptance (p.u.)
%	6	RATE_A	rateA, MVA rating A (long term rating)
%	7	RATE_B	rateB, MVA rating B (short term rating)
%	8	RATE_C	rateC, MVA rating C (emergency rating)
%	9	TAP	ratio, transformer off nominal turns ratio
%	10	SHIFT	angle, transformer phase shift angle (degrees)
%	11	BR_STATUS	initial branch status, 1 - in service, 0 - out of service
%	12	ANGMIN	minimum angle difference, angle(Vf) - angle(Vt) (degrees)
%	13	ANGMAX	maximum angle difference, angle(Vf) - angle(Vt) (degrees)

It should be noted that the field 11 `BR_STATUS`, indicates whether the branch (line or transformer) is on or off.

6.3.2. GENERATION

The expansion of the generation system depends essentially on the evolution of consumption, the attractiveness of the markets¹²⁴, the energy policy adopted by each country or imposed by the European Union directives, and the adopted criteria for safety and reliability. It is becoming increasingly difficult to accurately gather information from generation planning studies, given the opening of the sector and the increasingly larger number of competing agents in this activity.

It is not always possible to know in advance decisions concerning the construction of new generation centres, especially in countries where the preparation of an indicative central plan is not required in the legislation. Furthermore, the increasing use of natural gas in generation centres provided a steady decrease in the period of construction of these plants¹²⁵. Due to the mentioned reasons, power generation data may be subject to uncertainties.

The relevant information to take into account on this topic includes:

- New power centres (traditional, or using renewable resources);
- Reinforcement of existing generation centres;
- Decommissioning of existing power stations or units.

The characterization of each generation centre includes the following information:

- Type of station;
- Location, Identification of the connection node;
- Date of entry into service and date of decommissioning;
- Number of generation units and Characteristics of each unit.

The generation costs of thermal power plants are typically represented by quadratic expressions and are dependent on fuel prices. These prices are uncertain in the long run because they are influenced by:

- The behaviour of the international fuels and energy markets;
- The energy policies; and
- The economic, social and environmental atmosphere of each country.

¹²⁴ This can be measured by prevailing generation prices.

¹²⁵ It is now the usual term of two years between the decision-making regarding the construction of new central and its entry into service.

In order to guarantee the feasibility of the model, and without prejudice to the results to be achieved, we will consider in our model linear cost functions and will not take into account the uncertainties in generation.

6.3.3. *LOAD*

For planning purposes it is necessary to know detailed forecasts regarding the development of the distribution system in a given geographical area. The distribution system is seen by the transmission network as a consumer, and it is important to develop forecasts of consumption for the planning horizon under consideration. Owners of these networks usually prepare and submit investment plans to the regulators. These plans have to take into consideration the increase on distributed generation in the median and low voltage levels.

Distribution networks are treated as consumer entities, characterized by:

- Network type (urban or rural);
- Identification of the connection node to the transmission network;
- Voltage level;
- Consumed active power (forecast);
- Consumed reactive power (forecast).

One has also to include on the planning model the influence of large industrial or institutional high and medium voltage consumers, characterized with similar data as distribution networks.

Load data may be subject to uncertainties. These uncertainties may be associated with the demand level in each period and at every bus bar. It may appear that in some places the load is growing at a rate higher than in others. It is even possible that there are increases in some points and demand reductions elsewhere.

6.3.4. *ECONOMIC AND FINANCIAL DATA*

Economic data, such as inflation, interest and discount rates, is essential in long term planning. These values depend on the economic situation of each country and its main economic international partners, the energy markets as a whole and the economic value (in quantitative and qualitative terms) of the assets addressed by the planning exercise.

The values of inflation, interest and discount rates for the long term are set based on forecasts that, as for other factors mentioned above, may be subject to uncertainties.

6.4. THE DEFINITION OF THE EXPANSION PLAN

6.4.1. *THE COMPLEXITY OF THE EXPANSION PLAN DEFINITION*

An expansion plan is a set of infrastructure network investments, scheduled over the planning horizon. Investments have to be selected according to various criteria, and be considered as a whole in a coordinated manner.

There is an important dynamic component to be considered, since investments in a given year may have impact in the following years in different areas, some of them geographically distant:

- A project that is concluded and is commissioned in period p will be also available in the following periods;
- A decommissioned installation in period p will continue unavailable until further notice;
- An investment in a given period can be justified given the operating conditions of prior periods and by the evolution of generation and demand in subsequent periods;
- A scheduled investment to respond to a particular problem may be useful to overcome problems in other areas of the network, given that transmission networks are typically meshed.

So, in response to operating conditions for the years included in the planning horizon, alternative expansion plans can be prepared, which are evaluated according to several criteria, including those imposed by law. After appropriate evaluation of the different plans, decisions are made on the investments, based on the plans that were considered more appropriate.

The installation of new equipment may be limited for several reasons (Braga, et al., 2005):

- Finance; resources are scarce and there may be some kind of financial constraints that limit the investment to the available credit or financial resources;
- Environmental; it is not possible to install lines or substations close to urban centres or in protected areas;
- Physical space; the physical available space is typically limited close to the more important demand centres, and the installation of lines or substations

can't therefore be carried out easily; in many cases a simple extension of existing resources is also object of limitations;

- Standardization; lines and transformers are found in the market on standard values for voltage and capacity; capacity is usually measured in current intensity (A) or power (KVA);
- Technical reasons; different voltage levels, impedance adaptation.

For example, in a certain constrained area the only possible expansion of the network in a given corridor may be to convert a single line in a triple line or to upgrade the voltage level of the existing line. The problem is so complex that assumptions have to be done in order to make the TEP exercise feasible. The assumptions presented in the following chapter allow isolating the less relevant aspects and focusing on those one intends to investigate.

6.4.2. *THE ASSUMPTIONS*

For a multi-period analysis¹²⁶, we consider the following basic assumptions:

- Load growth at a fixed rate per period to be specified by the planner;
- For the sake of simplicity, the effect of technological change and market competitiveness is considered to outweigh the effect of inflation;
- Evolution is always made by adding new lines or transformers with characteristics similar to those existing in the same corridor, and never by the removal of lines; each solution for multi-period, identifies the configuration for each year; the power flows of the following years depend on the previous year's configurations;
- The focus is restricted to transmission lines or transformers, namely in terms of reliability of different solutions; the variations on markets, resources and generation are not included in the model, and only a general load uncertainty is assumed.

We considered the following assumptions on establishing the list of works that can be used for network evolution:

- New lines or transformers can only be installed in existing corridors, except those needed to link new generator centres or new relevant EHV loads;
- Each corridor can accommodate a maximum of 4 lines or transformers;

¹²⁶ The results presented in Chapter 7 studies are made in 4 period analyses.

- The lines or transformers, once in service, are always considered as available.

The assumptions for the projects¹²⁷ were:

- The introduction into the network of any of the projects included in the list is likely to improve network performance;
- The cost of each project is known, including costs of investment and costs related with the internalization of external costs (including environmental externalities);
- There is no precedence and there is no relationship among the projects¹²⁸; in the limit, and provided there is funding available, projects can all be scaled to the same period;
- The projects are characterized by the period in which they enter in service, and not by the duration of their implementation¹²⁹.

As starting conditions (period 0) one assumes that the branches of the initial network are connected and that the new branches are all disconnected. Any new branch (line or transformer) can only be switched on the following year after its conclusion.

On the mutation and recombination processes of DEPSO¹³⁰ one has to respect the following rules:

- A branch that is connected can be disconnected at any moment;
- A branch that is disconnected can only be connected if it already exists and it is ready to be connected¹³¹;

¹²⁷ For a given project there may be different implementation modes. Because we intend to focus on planning models, rather than on models of performance analysis of alternative projects, we consider that each project will have a unique way of implementation.

¹²⁸ The precedence should be viewed with some caution; for example it is not reasonable to connect a line to a substation where the line voltage level is not yet available; in our model this situation is up to the user, as a matter of simplicity and performance.

¹²⁹ Some authors consider one or more periods on the project implementation; this is not relevant in our model; what is really relevant for us is to determine the period in which each project should enter into service, to cope with the load that must be supplied in terms of quality and reliability as defined for the network.

¹³⁰ Please refer to sections 5.5.5 and 5.5.6 for details.

¹³¹ We assume that there are no failure or maintenance states.

- When mutating the particles, the mutation is done through real numbers that will be then transformed to binary numbers through a rounding model, but always following previous rules.

6.4.3. THE TIME HORIZON

Dynamic Transmission expansion planning problems have a temporal horizon that can go from one year to several years. However, the time horizon rarely exceeds 10 years. For example, in Portugal the New Network and Interconnections Access Code¹³² (ERSE /RARI 2011) stipulates, in Article 24, that investment projects referred to the following three years should be submitted to ERSE.

We tested the model in a four period base since it becomes computationally very heavy as the number of periods increases and we intend to demonstrate that it is possible to run this type of models in cheap machines available in the market. On the other hand, when the horizons are broader, as for example up to 10 years, the networks are usually simplified so that the problem can still be manageable¹³³.

In our model the number of periods is associated with np . Setting the time horizon influences the number of states of the problem, as will be explained in section 6.5.

6.4.4. THE EXPANSION PLAN PROJECT LIST

The TEP project list is based on npj projects, and a time frame, based on np periods, typically associated to yearly stages. As already mentioned in section 6.3.1 for the initial network, each new project, either a new line or a new transformer, is defined by the following information: origin bus, destination bus, technical data and investment cost. A solution X_i of the TEP problem corresponds to a plan that includes a number of projects selected among this list, including their time frame. The search space under analysis is discrete and integer, as explained in section 6.5.2. It typically includes a large number of possible alternative plans, given by $(np+2)^{npj}$.

The list of possible projects is defined by the planner, based on his experience and available data. If the planner does not prepare a "good list" he will certainly condition

¹³² The RARI approved in 2003, which was valid up to 2011, stipulated, in Article 18, that the Investment Plan for the RNT must include 6 years following the year in which it is presented, and should be submitted to ERSE every two years, until 30 November. RARI 2011 no longer talks about expansion plan to be approved by ERSE, but only in individual projects. It seems that any global transmission plan prepared by REN is only for an internal use, and that REN has only to inform ERSE on individual projects. Apparently, ERSE is admitting losing sight of the overall problem.

¹³³ See the example shown in (Silva, et al., 2011).

the solution that can be obtained, by not considering any fundamental branch for network expansion, which may cause future degradation in service quality, economic losses for operators and eventually an increased cost associated to a less quality expansion plan.

A possible alternative to the definition of a network expansion list would be admitting that all branches are likely to be elected to the expansion, up to a certain number of lines or transformers in parallel. This is the option of some authors who have addressed previously the TEP, as Pringles (Pringles, et al., 2007) or Silva (Silva, et al., 2011). One may admit that this option can provide the correct solution in the static approach without resulting in a relevant loss of performance of the algorithm. However, in the case of dynamic approaches, this would lead the problem to reach such a magnitude as to be practically unsolvable. In addition, the consideration of a comprehensive list of expansion branches is not likely to be useful: there are potential links that are known in advance not to contribute to the improvement of network performance; on the other hand, other connections are not feasible due to constraints the planner knows in advance. So, it makes no sense to consider all possible links at the same level, since that would result in a more complex problem that would condition the performance of the solution algorithm.

Given the fact that only listed projects may be included in the solution, one has to find a compromise between the projects to be considered, the dimension of the problem and the feasibility of the model. As TEP solutions are usually tuned over a process that includes several runs of the model, if the planner finds that some projects are systematically selected, he should consider adding some more projects in the most saturated areas in order to relieve overload branches.

Briefly, the definition of the expansion plan project list includes the following topics:

- Periods - correspond to periods of time in which projects are scheduled and are implemented, e.g. 4 years;
- List of projects - projects selected to be implemented; each project has a cost, reported to year 0; the planner lists the project, but does not indicate if and when the project is implemented (this is performed by the model)¹³⁴;
- Available resources - human and financial resources are always limited; this constraint is usually materialized by setting a maximum number of projects that can be implemented; it can be set individually for each period or globally for all

¹³⁴ A new project may involve the removal of any line or transformer; for example, upgrading the voltage level of an existing line corresponds to the disconnection of the existing line and the entry into service of a new line of higher voltage level; these situations are not considered in our model.

the periods considered¹³⁵; it must be set a penalty to apply to the solutions that do not respect these constraints;

- Quality of service - a minimum threshold of quality of service has to be set; in our case we will consider the power not supplied both for the entire system in operation $PNS(n)$ and for first order contingencies $PNS(n-1)$.

The data organization of the expansion plan follows the same frame as in the Matpower Matlab file `idx_brch.m`, as already explained in Chapter 6.3.1. for the description of the network. Any change to the existing network, unless switching a line on or off, means that new information has to be included in the algorithm. Various situations can occur in this scope, as indicated in Table 6.1.

¹³⁵ Reis, on his PhD thesis, page 171, consider that NH1 projects are not subject to resource constraints; we defend that any kind of Project, even those classified as NH1, are subject to resource constraints (Reis, 2005).

6. Multiyear TEP formulation with DEPSO

TABLE 6-1 TRANSMISSION EXPANSION CHARACTERIZATION

Sit. n°	Description	How to deal	What has to be defined	Obs
1	New Line	Create a new line	Line Data ¹³⁶ and connection schedule	
2	Upgrade of an existing line, increasing the voltage level	Switch off the existing line Create a new line, with the higher voltage level and further data	Switch off Schedule New line data and connection Schedule	
3	New node inside an existing line	Switch off the existing line Define the new node Create a new line upstream Create a new line downstream	Switch off Schedule New upstream line data and connection Schedule New downstream line data and connection Schedule	Corresponds, for example, to the creation of a new substation or the installation of a new substation on an existing branch
4	Upgrade of an existing line, maintaining the voltage level	Switch off the existing line Create a new line, with the higher capacity level and further data	Switch off Schedule New line data and connection Schedule	
5	New line, in parallel with a existing line in the same corridor	Create a new line	New line data and connection Schedule	Corresponds to an increase in capacity, taking advantage of the existing corridor; the costs should be lower than those in situation 1
6	Installation of a new transformer on existing substation	The same as creating a new line	New transformer data and connection Schedule	The new transformer is connected between two existent nodes.

¹³⁶ Includes technical specifications and amount of investment

6.5. THE SEARCH SPACE, THE POPULATION AND THE SOLUTION MODELING

6.5.1. THE NUMBER OF PERIODS AND THE NUMBER OF STATES

Projects may take the state corresponding to the period when they are considered complete and available. In addition to these states, two more states are possible, corresponding to situations of non-implementation of a particular Project: either the possibility of not being chosen, or the possibility of being postponed beyond the periods under review. So, $np+2$ possible states are considered for each project in the list. For example, in a four period analysis we have six states: 0, which corresponds to not choosing the Project, 1..4, the period in which the Project can be completed, and 5, corresponding to the postponement of the Project. This means that $x_{pt,j}^{it} \in [0,5]$.

6.5.2. THE PARTICLE

A literature review on particles in PSO was already done in section 4.5.3. Particle representation in EPSO is identical to that adopted by PSO, as noted in section 4.6.2.

The complexity of the TEP dynamic analysis suggests a deep research on the best approach. Some inspiration on this topic can be found on (Fonseka, et al., 2002), (Keko, et al., 2007), (Carvalho, 2008), (Miranda, et al., 2008), (Yu, et al., 2008) and (Silva, et al., 2011).

In a dynamic transmission planning using a genetic algorithm, it was adopted the structure presented in Figure 6.1. This approach leads to very long vectors, whose size is highly dependent on the characteristics of the networks under study (Fonseka, et al. 2002).

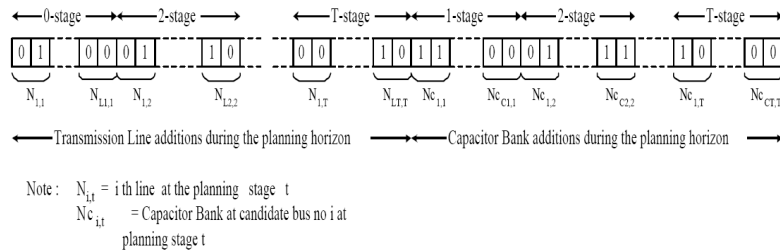


FIGURE 6-1 TRANSMISSION PLANNING BINARY CODE PARTICLE
 (SOURCE: (Fonseka, et al., 2002))

Carvalho, in power system reliability indices calculation, adopted a state vector with a dimension equal to the number of units of the system under analysis, since each dimension represents the state of the particular generating unit, which, according to the two-state Markov model, is up or down, represented by the number 1 and 0,

respectively (Carvalho, 2008). This author simplified the state vector by making the search be driven to find the number of equal units that are in the up state, instead of trying to find the state of a particular unit.

Keko and Miranda follow the same structure and encoded the variables in a search space vector as follows: the first N_c variables represent the reactive power injection in a particular node, ranging from $Q_{\min}$ to $Q_{\max}$, NT variables represent settings of transformer taps, ranging from $T_{\min}$ to $T_{\max}$ and finally N_{VR} variables represent N_{VR} settings for voltage-regulated nodes, ranging from minimum to maximum voltages for each node. The number of space dimensions is $N_c + NT + N_{VR}$. These variables are repeated N_s times in order to represent the situation for each load level at each structural configuration scenario. This means that the algorithm searches for optimal solutions for each period “separately”: the reactive power device sizes in different load levels are independent and not correlated until the solution evaluation. These authors underline that in the first place, new reactive injection devices are inserted into network topology and afterwards, the second phase sets the transformer taps and voltage levels for voltage-regulated nodes (Keko, et al., 2007), (Miranda, et al., 2008).

Several authors, such as Yu et al. and Silva et al., use matrices in multi-period analysis TEP (Yu, et al., 2008) and (Silva, et al., 2011). Silva et al adopted an array as depicted in Figure 6.2, where:

- n is the number of corridors where it is possible to consider any expansion;
- $X_{i,j}^t$ is the number (integer) of additional branches in the corridor j in period t , for the solution i

$$X_i = \begin{bmatrix} x_{i1}^1 & x_{i1}^2 & \dots & x_{i1}^T \\ x_{i2}^1 & x_{i2}^2 & \dots & x_{i2}^T \\ \vdots & \vdots & \dots & \vdots \\ x_{in}^1 & x_{in}^2 & \dots & x_{in}^T \end{bmatrix}$$

FIGURE 6-2 DYNAMIC TRANSMISSION PLANNING PARTICLE
(SOURCE: (Silva, et al., 2011))

In this approach this researcher defines the corridors where he considers that there could be expansion, as well as the maximum number of branches that he admits per corridor. One may say that in this approach this researcher can only influence the solution in the sense that restricts the corridors and the maximum number of branches per corridor that will come to define the solutions. The particle that results from this approach is a matrix of integers, and its mathematical treatment is much heavier than other alternatives as that we propose. On the other hand, this mathematical complexity increases with the

size of the network and the number of periods that are considered in the planning exercise.

The approach of Silva et al implicitly considers that the experience of the planner is crucial in the design of the particle. In fact, the selection of the corridors implies deep knowledge of the network. It is also based on this knowledge and experience of the planner¹³⁷ that we propose an approach for the solutions design. As the first step of a TEP we propose the development by the planner of a list of projects which he admits might integrate the solution expansion. This list may include multiple projects in the same corridor, assuming that the number of projects per corridor may be different from each other, and limited by the projects included on the project list.

As mentioned in Chapter 5, each particle represents a possible solution. In our case it is a vector with as many positions as the projects that can be implemented. Each vector position is represented by an integer, which defines the period that the project it represents can enter into service. For example, if in a certain position of the vector is the number 2, this means that the associated project will enter into service in period (or state) 2 (see Figure 6.3).

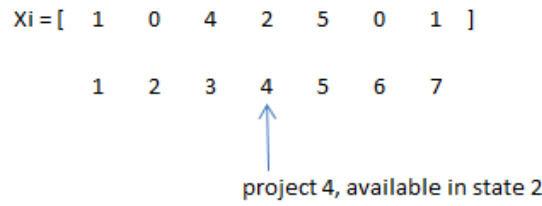


FIGURE 6-3 DEPSO TRANSMISSION PLANNING PARTICLE DESIGN

One could say that such particle can be interpreted as a Commissioning Schedule, a plan for the entry into service of a set of np_j projects in a given horizon of np periods.

When coding job scheduling problems, two more states are possible in addition to those corresponding to the periods when the projects are ready for service. These two states correspond to situations of non-implementation of a particular project: either the possibility of not being chosen, or the possibility of being postponed beyond the periods under review. So, $np+2$ possible states are possible, as already exemplified in section 5.5.2.

A drawback that can be referred to the particle definition we propose has to do with the fact that the planner conditions the solution as he designs the list of possible projects to be included on the expansion plan, as mentioned in section 6.4.4. As also noted, TEP processes are usually iterative, with different lists being analyzed for different

¹³⁷ The experience and knowledge are two important features when dealing with heuristics.

evolutions of load and generation, either in time or space. This may enable any correction on the first list design.

We think, however, that the advantages in its use outweigh the limitations mentioned before. The advantages arise from:

- Its simplicity and ease of integration into DEPSO;
- The immediate interpretation without any decoding key;
- Its independence from the dimension of the problem to be addressed.

In fact, on treating problems with very different characteristics, we may have particles with exactly the same size, depending only on the number of projects identified and the number of states in each case. Moreover, by comparison with other approaches mentioned before, it implies a lighter mathematical treatment.

Each position of the particles belonging to the first population is randomly generated with integers ranging from 0 to $n_p + 1$, with a uniform probability distribution. The Matlab code used was the following:

```
function [part]=first_particle_generation(nproj,nper)
    part = int16(fix(rand(1,nproj,1)*(nper+1)))
end
```

The integrity of the particle is maintained. After the evolutionary processes, those particles that fall outside the search space are subject to a correction according to a Lamarckian algorithm which is detailed in Chapter 5.

Some authors present the possibility of the first population to be generated by other techniques:

- Heuristically generated (Alves da Silva, et al., 2008);
- Adopting a relaxed version of the DC model; this version is known as Transportation Model, in which only the first Kirchhoff law is considered; (Gallego, et al., 1998)
- Using configurations obtained with Constructive Heuristic Algorithms (CHA)¹³⁸.

¹³⁸ A topology found by CHA can be considered good if it presents one or both of the following characteristics: 1) it has an excellent objective function value, and 2) the topology has a large number of circuits that form part of the optimal topology (Escobar, et al., 2004).

With regard to these alternatives, our choice is more generic, and does not affect the evolution of the algorithm.

In our model, the first population may be subject to a seeding procedure, which may contribute to accelerate convergence to acceptable solutions on the first iterations.

6.5.3. *THE POPULATIONS*

Particle Swarm heuristics are based on populations of particles, which do evolve, and among which the best solutions are identified.

In our approach, a population is characterized by the number of particles (npt, population size, 1st dimension, i), the number of positions of a particle (npj, particle size, 2nd dimension, j) and the number of periods¹³⁹ (np, 3rd dimension). Each particle is a possible solution to the problem and the main difference between this approach and classical EPSO is that the elements in this particle are integers, and not real.

As explained in Chapter 5, we use three populations, two of them with classical evolution, similar to that adopted by Miranda in EPSO (Miranda, et al., 2002 a), and a third population with purely Lamarckian evolution, to promote diversity or local search, according to the progress of the algorithm.

As in the TEP approach by EPSO, we use fixed size populations throughout the process. In addition, the three populations have the same number of particles. This option was based on the fact that one seeks to maintain consistency with the EPSO basis, and also by the fact that this option matches a greater simplicity of code and admitting different numbers of particles in each population was not considered critical to the performance of the algorithm.

The size of the populations, combined with the number of iterations allowed, has a direct impact on the quality of the identified solutions. Usually, to deal with simpler problems one takes smaller populations than when treating more complex problems. These complex problems usually correspond to larger search spaces, which need bigger populations to be explored.

One of the simplest networks used in TEP to test solution approaches is the Garver network (Garver, 1970). Pringles, Miranda and Garcés studied the static expansion of the Garver network, using EPSO with populations of 10, 30, 50, 80 and 100 particles (Pringles, et al., 2007). These authors suggested that the populations which represent the best compromise between quality of results and computational effort are those that comprise 50 and 80 particles. Silva et al studied the same network with algorithms

¹³⁹ The number of possible states in each particle position is np+2.

based on Evolutionary Strategies and Particle Swarm Optimization, but in a dynamic approach up to 8 years, allowing adding up to 3 branches per corridor. They adopted populations with 25, 50, 75, 100 and 125 particles (Silva, et al., 2011).

In more complex studies using real networks, parts of the Brazilian power system are often used. For the Southeast Brazilian System, with 46 nodes, and admitting to add up to four circuits connecting each of the 79 pairs of nodes allowed, which means a search space with a dimension of $(4+1)^{79} = 2^{183} = 1,226 \cdot 10^{55}$, Pringles et al have used populations with 800 particles and 250 iterations (Pringles, et al., 2007).

Silva et al adopted a network with 12 buses, six loads, an interconnection bus and a generation reference bus, modelling the power system in the North Region of Minas Gerais, Brazil (Silva, et al., 2011). This network is characterized by 20 transmission circuits operating with two voltage levels: 138 and 345 kV. The study, with an horizon of eight years, admits that 22 new circuit connections can be added to the original network and that a maximum of three transmission lines per corridor are accepted. The search space has the dimension of $3,29 \cdot 10^{38}$. These authors do not indicate the number of iterations that were performed in the tests, but they report the size of the populations: with ES populations of 25, 50, 75, 100, 125 and 150 particles were used, and with PSO the population dimension was 50, 100, 150, 200 e 250 particles.

As seen by these two examples, for complex systems the size of populations is in the hundreds of particles.

To limit the computational burden of the calculation of power flow studies, the tests to be reported in Chapter 7 (in particular that one based on the IEEE 24 bus RTS network) are limited to 4 periods and to a list of 28 new projects, so that populations may have a reasonable size of few hundreds of particles.

6.5.4. THE SEARCH SPACE

The search space is discrete and characterized by a mesh of points equidistant from each other by one. Its size is calculated by the expression (6.01).

$$Dimention = (np + 2)^{npj} \quad (6.01)$$

In our case we will adopt the IEEE RTS network, which has 24 nodes, 35 lines and 32 generators. The planning horizon is either one or four periods. In the case of four periods it corresponds to six states, and the expansion project list has a total of 28 new projects. The size of the search space is therefore of $(4+2)^{28} = 6,14 \cdot 10^{21}$.

6.6. MULTIYEAR TEP MODEL (DETERMINISTIC DEMAND)

6.6.1. *THE NUMBER OF PERIODS AND THE NUMBER OF STATES*

In our model each period corresponds to a one year. The number of states, as explained in section 6.5.2, is given by $np + 2$.

6.6.2. *THE MULTIPLE OBJECTIVES*

As mentioned in section 3.2.1., the basic principle of TEP is to minimize the network construction and operational costs while satisfying the requirement of delivering electric power safely and reliably to load centres along the planning horizon.

We have also mentioned in section 3.2.1. that from the stake-holders point of view, transmission expansion should attend the following objectives:

- Encourage and facilitate competition among electricity market participants;
- Provide non-discriminatory access to cheap generation for all consumers;
- Alleviate transmission congestion;
- Minimize the risk of investments;
- Minimize the investment and operation costs;
- Increase the reliability of the network;
- Increase the flexibility of system operation while reducing the network charges;
- Minimize the environmental impacts;
- Allow better voltage level regulation.

In our approach we simplified this framework and studied only the expansion of the transmission network, assuming the expected evolution of the generation system as an input¹⁴⁰.

TEP is a multi-objective problem. Literature reviews of evolutionary multi-objective models can be found in (Zitzler, et al., 1999), (Ishibuchi, et al., 2008) e (Ngatchou, et al., 2008).

¹⁴⁰ The reliability calculations consider only the lines.

“Compared with single-objective optimization problems, which have a unique solution, the solution to multi-objective problems consists of sets of tradeoffs between objectives. The goal of multi-objective optimization algorithms is to generate these trade-offs”. (...)

“A solution belongs to the Pareto set if there is no other solution that can improve at least one of the objectives without degrading any other objective”. (Ngatchou, et al., 2008)

Ngatchou et al divide the methods for solving multi-objective problems in Classical Methods and Intelligent Methods.

a) Classical methods;

The multi-objective problem is converted into a single objective problem by:

- Aggregating the objective functions (weighted aggregation ¹⁴¹, goal programming¹⁴²);
- Epsilon-constraint method; proposed in 1967 by Marglin, this method is regarded as the most intuitively appealing multi objective programming; it consists of optimizing the most relevant objective and treat all the others as constraints bound by some allowable range epsilon; the problem is repeatedly solved for different values of epsilon to generate the entire Pareto set (Hwang, et al., 1979).

These methods have as main advantage their simplicity.

The main drawbacks are:

- They require a lot of computations in evaluating the set of the Pareto solutions (Mori, et al., 2010); the examination of all possible trade-offs requires systematic variation of the aggregation parameters before solving the problem, which makes the approach inefficient although simple to implement; (Ngatchou, et al., 2008)
- It is difficult to control the diversity of solutions in the approximation set; (Ngatchou, et al., 2008)

¹⁴¹ A simple method that is a special case of the utility function method, which converts the multi-objective problem into a single objective problem by applying a function operator to the objective vector; conventional weighted aggregation misses concave portions of the Pareto front.

¹⁴² The goal programming or goal attainment technique is a method that seeks to minimize the deviation from pre specified goals. As in the weighted aggregation approach, the main drawback of this approach is the need for a priori information.

- These techniques are sensitive to the shape of the global Pareto front. (Ngatchou, et al., 2008);
- It needs the assumption of the convex solution space or a prior knowledge of the problem (Mori, et al., 2010);
- It is necessary to tune up to the weights for the cost functions (Mori, et al., 2010).

b) Intelligent methods

When the multi-objective problems are handled by evolutionary algorithms one has to take two issues into account (Zitzler, et al., 1999):

- *How to accomplish fitness assignments and selection, respectively, in order to guide the search towards the Pareto set of solutions¹⁴³?*
- *How to maintain a diverse population in order to prevent premature convergence and achieve a well distributed trade-off front?*

Fitness assignment controls convergence, guiding the population to non-dominated solutions. Diversity mechanisms as niching are used to prevent premature convergence to a region of the front and to control the spread of the approximation set. A form of elitism is applied to prevent the deterioration problem whereby non dominated solutions may disappear from one generation to the next (Ngatchou, et al., 2008). In fact, in 1999 Zitzler showed that

Elitism is shown to be an important factor for improving evolutionary multi-objective search. (Zitzler, et al., 1999)

The main advantages of these methods are as follows (Ngatchou, et al., 2008):

- They can successfully address the limitations of the classic approaches;
- They can generate multiple solutions in a single run;
- The optimization can be performed without a priori information about the objectives' relative importance; they can handle problems with incommensurable or mixed-type objectives;
- They are not susceptible to the shape of the Pareto front.

¹⁴³ One says Pareto set of solutions, as it is meaningless to talk about optimality in multi objective problems.

However, they have drawbacks such as:

- *Deterioration of the search ability of Pareto dominance based evolutionary multi-objective optimization algorithms, when the number of objectives increases (Ishibuchi, et al., 2008); this performance degradation is their main drawback as the number of objectives increases, as there do not exist computationally efficient methods to perform Pareto ranking (Ngatchou, et al., 2008);*
- *Exponential increase in the number of solutions required for approximating the entire Pareto front (Ishibuchi, et al., 2008);*
- *Difficulty on the visualization of solutions (Ishibuchi, et al., 2008);*
- *They require additional parameters such as a sharing factor, or the number of Pareto samples (Ngatchou, et al., 2008).*

Although in our problem one can say that we have several objectives, indeed the aim is to minimize costs, while enforcing a set of constraints. On the other hand, we can convert several issues that enable evaluating the performance of the network, including reliability, quality of service, loads not feed or externalities, in a fitness function.

In the developed algorithm we applied a solution approach that was inspired in the epsilon-constrained method¹⁴⁴. In fact, all objectives except the investment plus operation costs were converted in constraints by the specification of limits to the level of losses, to the number of projects per period and along the entire the horizon as well as for the PNS computed for the n and for the $n-1$ regimes. However, given the complexity of the problem and the computational burden to identify and analyze solutions, we decided not to discard immediately solutions in which some of these limits were not provided. In this way, when such violations are detected, we decided to include penalty terms in the objective function of the problem, originally written in terms of operation plus investment costs. We consider that this approach was sufficient and defensible for our purpose, and that other approaches may require more time and could derail the solution of the problem, given the number of times the evaluations are performed¹⁴⁵.

¹⁴⁴ In epsilon-constrained methods, as described before on this Section 6.6.2, all objectives but one are converted to constraints by specifying limits for these objectives. So, for each iteration the algorithm checks all these restrictions. Those who fulfill the restrictions belong to the Pareto front. Then, by varying these limits, the algorithm runs more often and we have obtained the Pareto front. Our approach is somewhat different, as constraints are evaluated and when not verified, instead of being eliminated, these solutions are penalized on their fitness function. In this sense, each particle is a possible solution that allows one to evaluate the costs and enable the associated penalty terms.

¹⁴⁵ To bypass the problem of time associated with the evaluation of each solution, we had considered the hypothesis of creating a list of tested solutions, to avoid repeating evaluations already done; various algorithms were tested; in all cases the size of the resulting list was too large; the algorithm to search for a

6.6.3. MATHEMATICAL MODEL

The formulation of the TEP model can thus be given by (6.02 - 6.07).

$$\min CostX_{i,it} = \sum_{p=0}^{np+1} \left[\sum_{j=1}^{npj} IC_j \cdot K_{ij}^p + OC_{p,i} \right] / (1+ir)^p \quad (6.02)$$

Subjected to:

$$\text{Physical constraints;} \quad (6.03)$$

$$\text{Financial constraints;} \quad (6.04)$$

$$\text{Quality of service constraints;} \quad (6.05)$$

$$i = 1, 2, \dots, npt \quad (6.06)$$

$$it = 1, 2, \dots, niter \quad (6.07)$$

This problem aims at minimizing the objective function (6.02) that includes operation and investment costs along the horizon referred to the initial year. The feasibility of solutions X_i , corresponding to possible expansion plans, and their operational cost, in particular PNS, are evaluated running a DC Optimal Power Flow for each period, formulated by expressions (6.09 - 6.13). In each period the network integrates the installations commissioned previously and the forecasted demand.

The objective function (6.02) is subjected to:

- Physical constraints, namely associated to the capacity of the generators and of the available branches;
- Financial constraints associated to limitations on the amounts that the company can invest on each year on during the entire horizon; and
- Quality of service constraints, for instance expressed by maximum amounts of PNS in n and in $n-1$ regimes.

position in the list did not prove to be advantageous compared to solutions which perform exhaustive test of all the solutions generated; it should be noted that each solution, ie each particle, is assessed for each period; the performance in each period – it corresponds to different configurations and different loading regimes - is evaluated, and each particle assessment corresponds to the sum of each evaluation.

Failure to comply with the constraints set leads the solutions to be penalized, as explained in detail in section 6.6.6, with the following penalty terms α_i :

- α_1 if the level of losses exceeds a reference value;
- α_2 if the PNS(n) is not zero;
- α_3 if maximum number of projects per period is exceeded;
- α_4 if investment value over the entire horizon is exceeded;
- α_5 if the PNS (n-1) is not zero.

Considering the objective function (6.02) plus the five penalty terms mentioned above, we formulate the fitness function, used to evaluate the particles using (6.08).

$$CostX_{i,it} = \sum_{p=0}^{np+1} \left[\sum_{j=1}^{npj} IC_j \cdot K_{ij}^p + OC_{p,i} \right] / (1+ir)^p + \sum_{y=1}^5 \alpha_y \quad (6.08)$$

All particles are evaluated in each iteration using this expression (6.08).

6.6.4. THE COSTS

Our model splits the costs in investment costs and operational costs. Given that the plan is multi-annual, costs should be updated and referred to the first year.

a) Investment costs

The activity of the TSO when exploring the transmission network is run on a natural monopoly, and is heavily regulated. For each period it is assigned by the regulator a tariff that clients have to pay for the service provided by the TSO. In several countries, this entity also has the mandate to approve the investment plan submitted by the TSO. This plan should seek to minimize the investment, not putting at risk the quality of service. If the quality of service is compromised, the TSO may face the risk that plan is not approved by the regulator.

The investment costs result from the sum of the updated values for each project included in the solution under analysis, considering the interest rate defined in the beginning of the process.

Costs related to the internalization of externalities, such as habitats replacement, can be considered as an investment.

b) Operating costs

Operating costs may include the generation costs, losses, maintenance and costs associated with ancillary services, and externalities. As it is necessary to use simple models, usually linear optimization models are adopted.

We've simplified our model and limited operating costs to the value of the transmission losses. Transmission losses in each year of the planning horizon are estimated according to the procedure to be detailed in the next paragraphs¹⁴⁶.

6.6.5. THE CONSTRAINTS

Our model considers three types of constraints: physical, financial and quality of service¹⁴⁷.

a) Physical constraints

The formulation (6.02-6.07) includes a number of constraints as physical limits of the network, physical limits of the generators, number of projects that can be developed simultaneously, value of a reliability index to ensure the quality of the expansion plan. Several of these constraints are inherently related with power flow calculation, which is considered in the DC-OPF formulation (6.09 - 6.13). This includes the limits of the branches and of the generators. On the other hand, if a particular plan displays in a particular year of the horizon a non-zero value of PNS, then this is penalized in (6.08) and so the global cost of this particle also becomes penalized.

The power flows in each period are estimated by solving a deterministic DC OPF¹⁴⁸ algorithm formulated by expressions (6.09 - 6.13).

$$\min f = \sum c_k \cdot P_{gk} + G \cdot \sum PNS_k \quad (6.09)$$

Subject to:

$$\sum P_{gk} + \sum PNS_k = \sum Pl_k \quad (6.10)$$

$$P_{gk}^{\min} \leq P_{gk} \leq P_{gk}^{\max} \quad (6.11)$$

$$PNS_k \leq Pl_k \quad (6.12)$$

$$P_b^{\min} \leq \sum a_{bk} \cdot (P_{gk} + PNS_k - Pl_k) \leq P_b^{\max} \quad (6.13)$$

¹⁴⁶ The generation costs are not used directly in the assessment of particles, but are used in power flows to evaluate the solutions.

¹⁴⁷ This includes reliability constraints.

¹⁴⁸ See explanation of the DC OPF in Annex D, based on a didactic text published in FEUP, written by Prof. Manuel Matos (Matos, 1999).

While doing this, network and generator limit constraints are enforced. However, if transmission or generation capacity is insufficient, then PNS will be non zero, thus increasing the value of the objective function (6.09). This means that using this strategy we are inherently penalizing particles that are not adequate in terms of being able to connect adequately generation and demand. On the other hand, this formulation assumes that the network is lossless. In order to increase the realism of the model, this DC-OPF was enhanced to include an estimate of transmission losses.

There are no ideal procedures for active loss allocation. These procedures should have most of the desirable properties stated below:

- Be consistent with the result of a power flow;
- Depend on the amount of energy either produced or consumed;
- Depend on the relative location in the transmission network;
- Easy to understand and implement.

In our case a very simple and consistent procedure is identified, as the main algorithm is very heavy and time consuming.

Considering that voltage magnitudes are 1.0 pu, active losses in branch b, from node i to node j, are approximately calculated by the equation (6.14):

$$Loss_{ij} \approx 2 \cdot g_{ij} \cdot (1 - \cos \theta_{ij}) \quad (6.14)$$

At the end of each DC-OPF run, voltage phases and branch losses are computed and half of the losses in each branch are added to the load in each extreme bus. This change on loads leads to a change in generation and thus in voltage phases.

These calculations are repeated until convergence is reached (the differences between voltage phases, in each node, are inferior to a specified deviation level). Convergence is reached usually in less than 5 iterations, depending on the admitted deviation level.

For each solution, this procedure is used in each period to estimate the corresponding transmission losses.

Losses can be included in the evaluation function in two different manners: either as a cost¹⁴⁹, or with a penalty factor, when they exceed a threshold value defined as acceptable. In our case we chose the second option: if the level of losses exceeds a reference value, then this particle is penalized with a term α_1 in the fitness function.

¹⁴⁹ These costs are reported to the first period.

The value of losses is due to the physical characteristics of the network and is a cost that the TSO has to accommodate. It has, therefore, a relevant implication in financial terms. The limitation of losses to a maximum level forces the investment in new power lines that benefits the entire system, not only in terms of capacity and losses reduction, but mainly in terms of overall system reliability development. So we think it is tenable to think in limiting losses also as a financial constraint. On the other hand, several European countries approved in recent years plans with measures against the climate change. Among them, it is usual to include limitations on the losses in electricity sector, discriminated by transmission and distribution networks. The existence of such values is another reason supporting treating transmission losses as indicated above.

In a similar way, the solution of the problem (6.09) to (6.13) also outputs the value of PNS admitting that all system components are available. Using this result, if the PNS(n) is not zero, then the penalty term α_2 is introduced in the fitness function (6.08).

b) Financial constraints

The economic and financial issues are very relevant in planning problems. Thus, if a project is, in terms of investment, beyond the available resources, it cannot be implemented. The same is also valid for a set of projects and in a multi-period analysis. Thus, making this assessment early on in the evaluation process, if the investment is beyond the resources, you can simply apply a penalty and thus avoid the assessment under the other evaluation criteria, which is very painful and lengthy. We will consider investments updated to year 0, at the rate of $x\%$ to be specified by the planner.

To turn the problem more realistic we also admitted that the planner can specify limits associated with the financial resources or with the number of projects that can be implemented simultaneously.

So, we considered two main kinds of financial constraints. The first one corresponds to the maximum number of projects that can be implemented per period. This limitation arises due to financial or operational reasons and if it is violated we consider a penalty term α_3 in the fitness function. The second one corresponds to the maximum investment value over the entire horizon and it models a global financial constraint. If it is violated, then a penalty term α_4 is included in the fitness function.

c) Quality of service and reliability constraints

Power systems deliver to costumers two products: electric energy and reliability. The economic development of a country is highly correlated with the reliability of its power system since most of its economic agents rely on this type of energy to boost up their development. Frequent interruptions on power supply can jeopardize their activities,

forcing the implementation of expensive solutions, by their own, to improve the reliability of the power system to assure a minimum quality level.

One must distinguish between reliability adequacy and reliability security (Carvalho, 2008):

- Reliability adequacy is related to the existence of sufficient resources within the system to meet the customer demand and the system operational requirements. This includes resources for generation, transmission and distribution needed to “carry” the energy to the individual consumption points. The adequacy evaluation is associated with the static conditions and does not include the dynamics of the system and the response to the transient perturbations: the different system states are evaluated without taking into consideration possible instable situations that may be introduced by failure of the system components;
- On the other hand the security is related to the system ability to respond to the dynamic or transient disturbances that might occur. Thus the security evaluation is associated with the reaction of the system to any disruption to which it can be subjected. This includes sudden loss of generation and/or transmission capability that can lead to transient instability, frequency instability, voltage instability among others.

Most of the currently available techniques for assessing the reliability are in the field of adequacy evaluation. The ability to evaluate the security is still very limited mainly due to the complexity associated with the modelling of the dynamic behaviour of the electric power systems. Most of the assessed reliability indices are, in fact, adequacy indices and not security indices, although they are commonly designated as so (Billinton, et al., 1996).

The basic function of an electric power system is to supply the load demand as economically as possible within pre-defined continuity, quality and security patterns. However due to the enormous quantity of components in these systems, combined with their unique operation characteristics, there is a possibility of failure of the entire system simply by failure of a component or a group of crucial components. Even though these types of events have a low probability of occurrence, one may raise the question:

“How much does the failure of the system costs, considering all its possible consequences?”

(Carvalho, 2008)

Heavy investments in the electric power system are always needed, since low reliability generally leads to an unsustainable development.

From a mathematical point of view, power not supplied can arise when the scheduled generation is not enough to feed the load or when there is lack of transmission capacity.

In these situations, some virtual generators (“installed” in the demand nodes) will be turned on. These virtual generators have very high “production costs”, much higher than those of the real ones. When running the OPF, some power can be assigned to these virtual generators. The sum of all virtual generators power represents the Power Not Supplied (PNS), and corresponds to real load that will not be supplied with power.

On the reliability evaluation the developed approach penalizes plans in which the PNS is non-zero for configurations of the network associated to n-1 contingencies and, if necessary (namely from a regulatory point of view) for a selected number of n-2 contingencies. The penalties over PNS (n-1) are made using the term α_5 in the function (6.08).

6.6.6. EVALUATION PROCESS

Due to the evaluation process complexity, in our case based on running a large number of DC OPF problems, a simple, but effective analysis of the particles is adopted so that only those particles with suitable characteristics are fully evaluated, as represented in Figures 6.4 to 6.6.

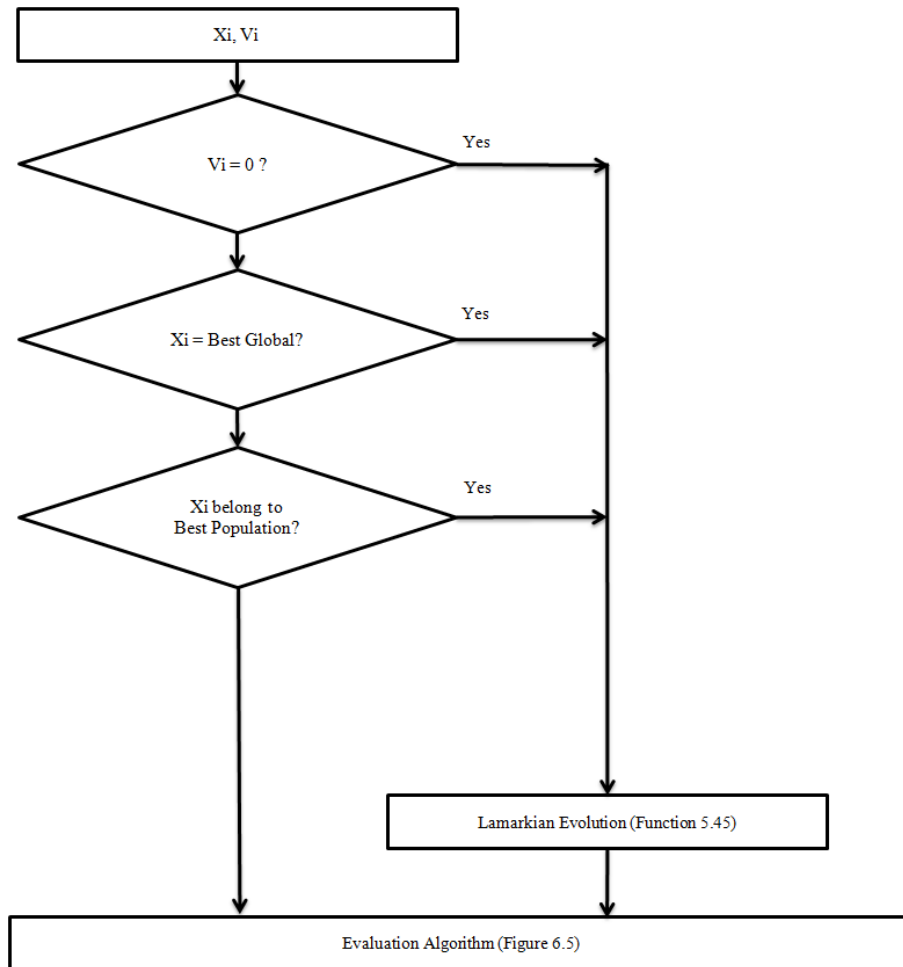


FIGURE 6-4 EVALUATION OF THE ELIGIBILITY OF THE PARTICLES

The evaluation process includes three quite distinct phases:

- The evaluation of the eligibility of the particles X_i ;
- The evaluation of solutions obtained for the deterministic demand;
- The assessment of the best population, admitting that the demand is affected by uncertainties.

The first phase includes the assessment of all solutions generated by the deterministic algorithm, and consists of the evaluation of the eligibility of the particles X_i . We considered that it is not necessary to test particles that are already known. When the velocity vector V_i is null, the particle won't move and remains in the same place, which means that it was already evaluated before. Even if this particle is a good one, it is already known, and it makes no sense to evaluate it again. Other situations correspond to the particle being equaled, either to the previous best global, or to any particle of the best population. In these situations we found more proper to submit the particle to a Lamarckian evolution, as shown in Figure 6.4.

This approach has several advantages:

- Increase the diversity in the population;
- Reduce the risks the premature convergence to local minima;
- Avoid waste of time;
- Accelerate the search.

The second phase consists of the evaluation of the solutions obtained for the deterministic demand, and is represented in Figure 6.5.

The first two evaluations (number of projects and global investment value) are very easy and are performed in the beginning of the assessment process. If the maximum number of projects that can be implemented per period is exceeded, the solution is penalized by α_3 . If the investment value over the entire horizon is exceeded, the solution is penalized by α_4 .

The third evaluation consists of running a DC-OPF including the transmission loss estimation iterative process to compute the losses and the $PNS(n)$ for all periods. Only those particles that passed the previous steps will perform the third evaluation. The solution is penalized by α_1 , if the level of losses in any period exceeds a reference value, and by α_2 , if the $PNS(n)$ is not zero in any of the periods.

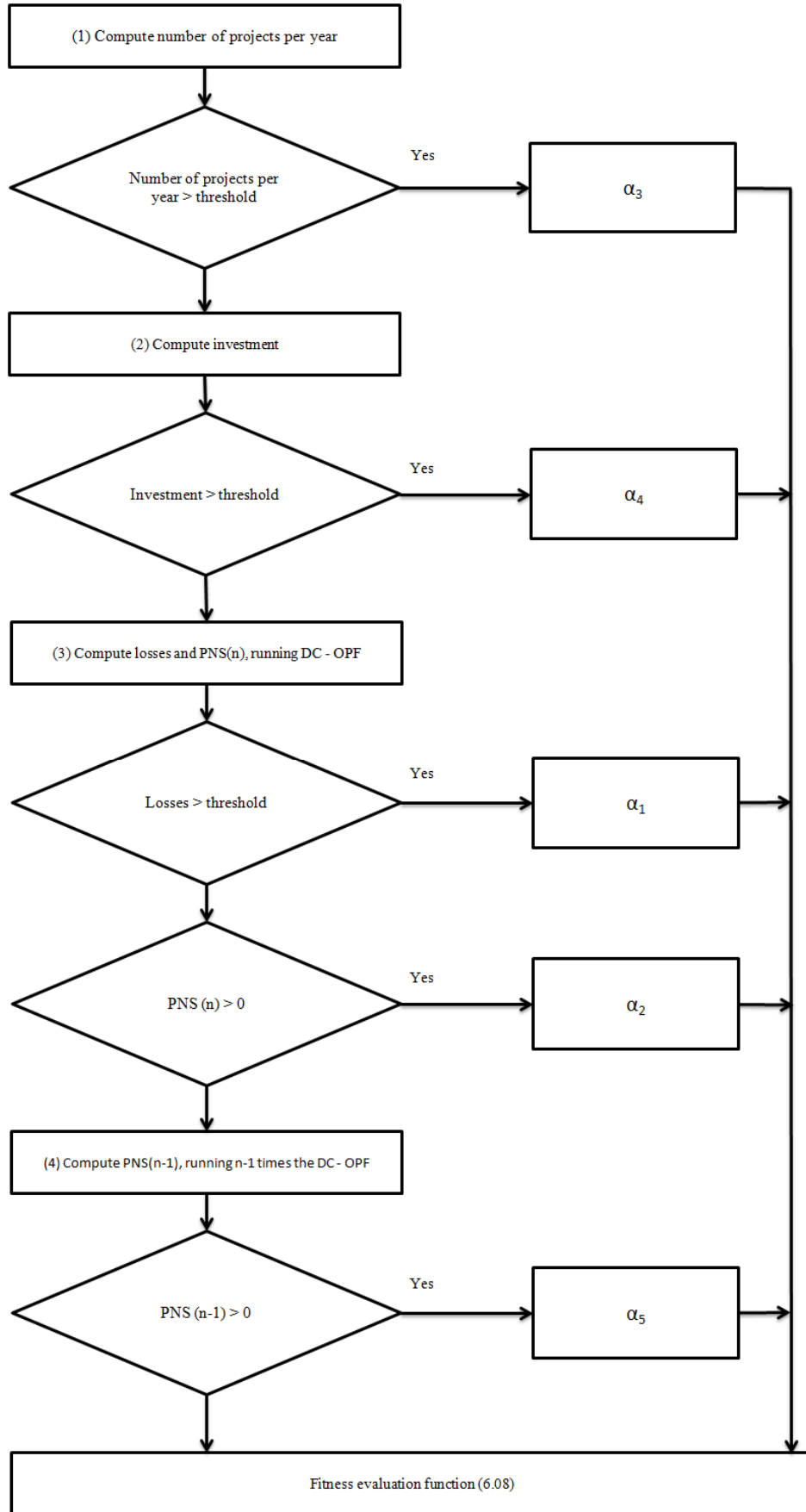


FIGURE 6-5 EVALUATION OF THE SOLUTIONS OBTAINED FOR THE DETERMINISTIC DEMAND

The heaviest evaluation process is the PNS(n-1) , which is performed in the last step. Only particles that have passed all previous steps of the assessment will be evaluated in this step. The DC-OPF is run $(n-1)*np$ times in case of a complete PNS(n-1) evaluation, where n is the number of lines and transformers that integrate the solution (existing plus new lines and transformers¹⁵⁰). This assessment corresponds to, successively removing a line from the network, and for each of the periods under review, verify if there is any situation with non zero power not supplied. If so this solution is penalized by α_5 .

The third phase of the evaluation is the assessment of the best population when affected by uncertainties. This assessment is explained in detail in section 6.7.

6.6.7. ALGORITHM MAIN BLOCS

The diagram in Figure 6.6 illustrates the main blocs of the multiyear TEP algorithm (deterministic demand).

The first steps are the initial data definition, the DEPSO setting and the definition of a particle to be used for seeding purposes.

The first population is generated with so many particles as those defined in the initial data, and following a procedure as described in section 6.5.2.

This population can be enriched with a particle that we know in advance to be viable, as belonging to the search space, and this can contribute to a faster convergence of the algorithm in the early iterations. This process is called seeding procedure, and do not affect the identification of the final solution.

The assessment of the first population allows to characterize all its particles and identify the first best global. This first population becomes the first best population.

After this initial procedure, one enters in the cycle of DEPSO, with the cloning of the best Population in three populations. These populations evolve as explained in detail in section 5.5.

Once completed one of the stopping criteria¹⁵¹, the algorithm stops, having as output a population that includes the best solutions of the multiyear TEP problem (deterministic demand), including what we call the best global.

¹⁵⁰ These new branches are those branches to be added in the network, identified by the algorithm in the list of projects.

¹⁵¹ These criteria may include global iterations, number of iterations without Best Global improvement, and convergence.

6. Multiyear TEP formulation with DEPSO

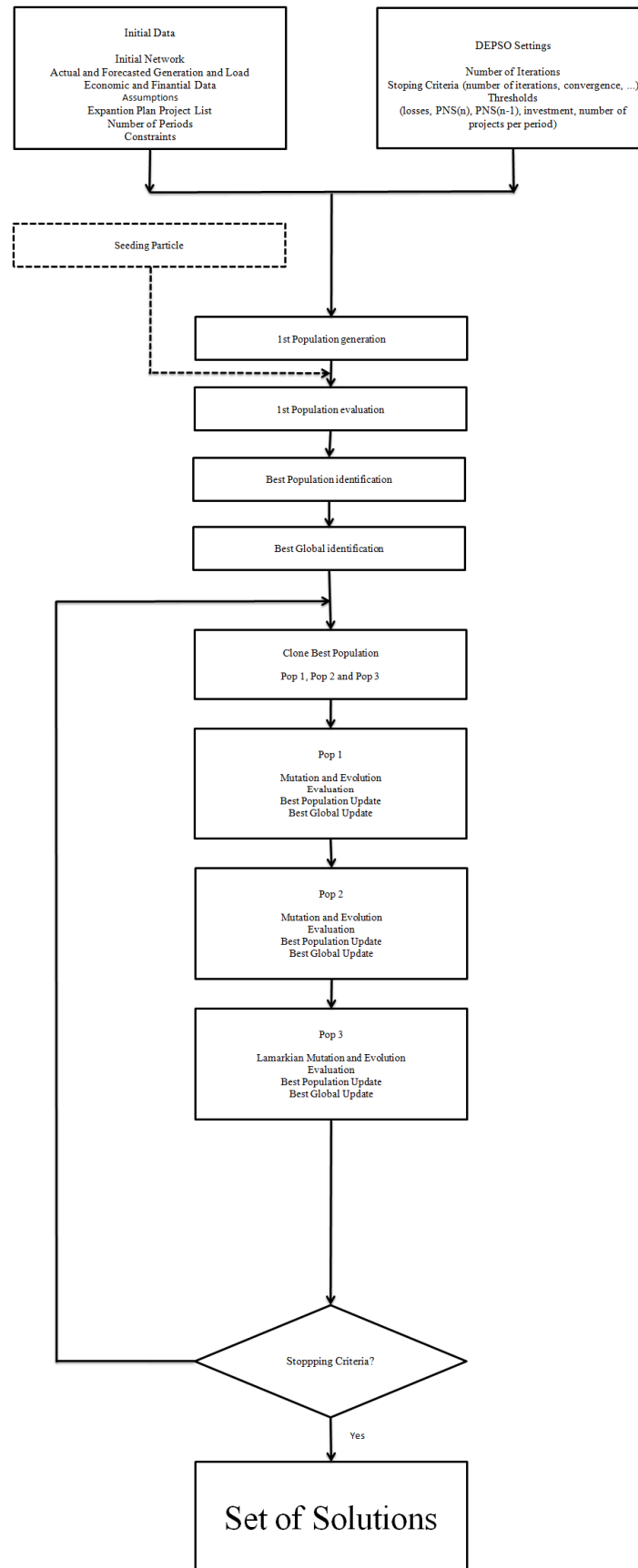


FIGURE 6-6 MULTIYEAR TEP MODEL (DETERMINISTIC DEMAND)

6.7. MULTIYEAR TEP CONSIDERING LOAD UNCERTAINTIES

6.7.1. LOAD UNCERTAINTIES MODELING

Several TEP data is actually affected by uncertainties: load demand evolution, new load demand (value, location, year), generation costs, new generation (technology, location, year), resources (as wind power, which is highly volatile, water inflows and fuel prices), market development, regulations, and tariffs.

Uncertainty in the future behavior of data has long been addressed using scenario analysis, sensitivity approaches and probabilistic models. However, in several power system problems, it was recognized that the uncertainty one has to deal with has not a probabilistic nature or one has not enough information to build reliable probabilistic distributions. So, in the early 1990's, fuzzy set models started to be applied to power systems, namely in planning models. Miranda, Matos and Tomé Saraiva introduced in 1990 the first DC and AC models admitting that at least one generation and demand are modeled by fuzzy numbers (Miranda, et al., 1990). Since then, several studies represent load, generation, voltages and branch flows by fuzzy numbers, expressing the possible behavior of the system, given the specified uncertainties.

More recently, Gomes and Tomé Saraiva describe the formulations and the solution algorithms developed to include uncertainties in the generation cost function and in the demand on DC OPF studies. On their approach uncertainties are modelled by trapezoidal fuzzy numbers and the algorithms are based on multi-parametric linear programming techniques (Gomes, et al., 2009). They extend the fuzzy optimal power flow problem, considering, not only load uncertainties, but also generation cost uncertainties. The model, even though very accurate, has the draw-back of being very demanding in terms of computational capacity, which makes it not suitable for our approach given the large number of problems that would be required to solve.

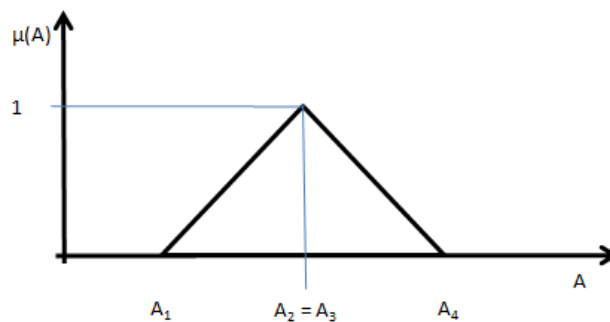


FIGURE 6-7 TRIANGULAR FUZZY LOAD

Given the fact that the dynamic TEP modelling is computationally very heavy, and that in the developed model we want to consider the reliability criteria n and $n-1$, which require time and have high computational burden, we'll just focus on the uncertainties affecting the loads, within a range of $\pm 5\%$, without consideration to market uncertainties and uncertainty in resources and generation.

In order to also simplify the model, without compromising its validity, the uncertainty of the loads will be modelled by a triangular membership function as shown in Figure 6.7. In this figure A_2 corresponds to the deterministic load adopted in the study, $A_1 = 95\% * A_2$ and $A_4 = 105\% * A_2$.

When one combines the uncertainties affecting two loads we obtain the polygon shown in Figure 6.8. The combination of two loads, affected by uncertainty, results in a pyramid. The point of maximum membership corresponds to the coordinates (A_2, B_2) . If, for reasons of simplicity, one assumes that both loads are correlated and with progression in the same direction, this pyramid can be reduced to two of its edges, namely the edge $((A_1, B_1) - (A_2, B_2))$ and the edge $((A_2, B_2) - (A_4, B_4))$. That is, to study the uncertainty affecting the loads, and under the mentioned assumptions, it is sufficient to study points that lie along these two edges.

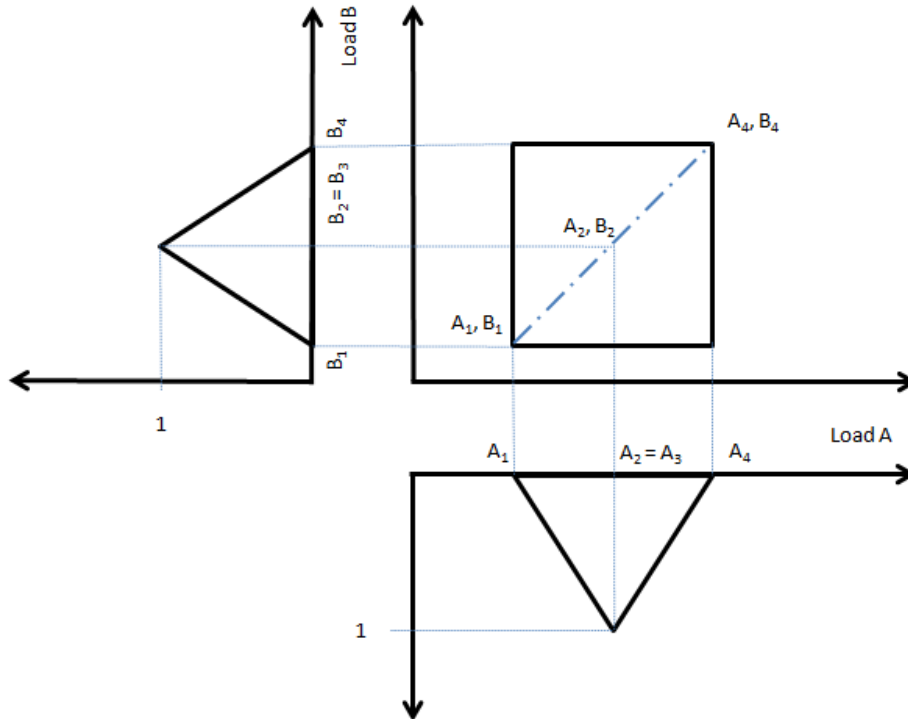


FIGURE 6-8 COMBINATION OF TWO TRIANGULAR FUZZY LOADS

Regarding this simplification, it should be noted that when analyzing the performance of particle, that is, a possible expansion plan in terms of accommodating load uncertainties, we are mainly concerned in checking if the system is able to supply the demand affected by uncertainty still with a null level of power not supplied. For the problem under analysis, it is not our concern to identify the possible behavior of a particular generation or branch flow but in fact to assess power not supplied. In order to check that these assumptions did not compromise the characterization of the possible behavior of power not supplied, we ran numerous simulations sampling load combinations associated to the specified load uncertainties, and we concluded that analyzing the two mentioned edges is enough if the purpose is to assess the possible amount of power not supplied.

If, instead of considering only two loads, one considers all network loads, and combine their uncertainties, and if one wants to do the same type of study with the same simplifications, the subject to be studied are the edges of an hyper-volume connecting the point having the maximum membership value to the points of minimum load and to the points of maximum load.

6.7.2. *MULTIYEAR TEP MODEL CONSIDERING LOAD UNCERTAINTIES*

The assessment of multiyear TEP considering uncertainties can be made by adopting the same expression (6.08) listed before, but considering an additional penalty factor when the solution (obtained for the deterministic load) affected by uncertainty is affected by non null values of power not supplied. If power not supplied is non null the particle will be penalized and will hopefully evolve while enforcing all problem constraints (6.03-6.05). Thus, the fitness function can be rewritten considering this additional penalty factor, as represented in the expression (6.15).

$$CostX_{i,it} = \sum_{p=0}^{np+1} \left[\sum_{j=1}^{npj} IC_j \cdot K_{ij}^p + OC_{p,i} \right] / (1+ir)^p + \sum_{y=1}^6 \alpha_y \quad (6.15)$$

The particle evaluation considering uncertainties is presented in Figure 6.9.

At the end of the process described in Figure 6.6, we obtain a set of possible solutions, as many as the particles that belong to the best populations in DEPSO. The next step is the evaluation of these solutions considering the effect of uncertainties in loads.

Several points on the hyper volume are defined, corresponding to different membership degrees of fuzzy loads, for instance, 0, 0.5 and 1. The membership degree of 1

corresponds to the deterministic solution, whose evaluation is already known. The other four points are those that will be assessed in the developed approach.

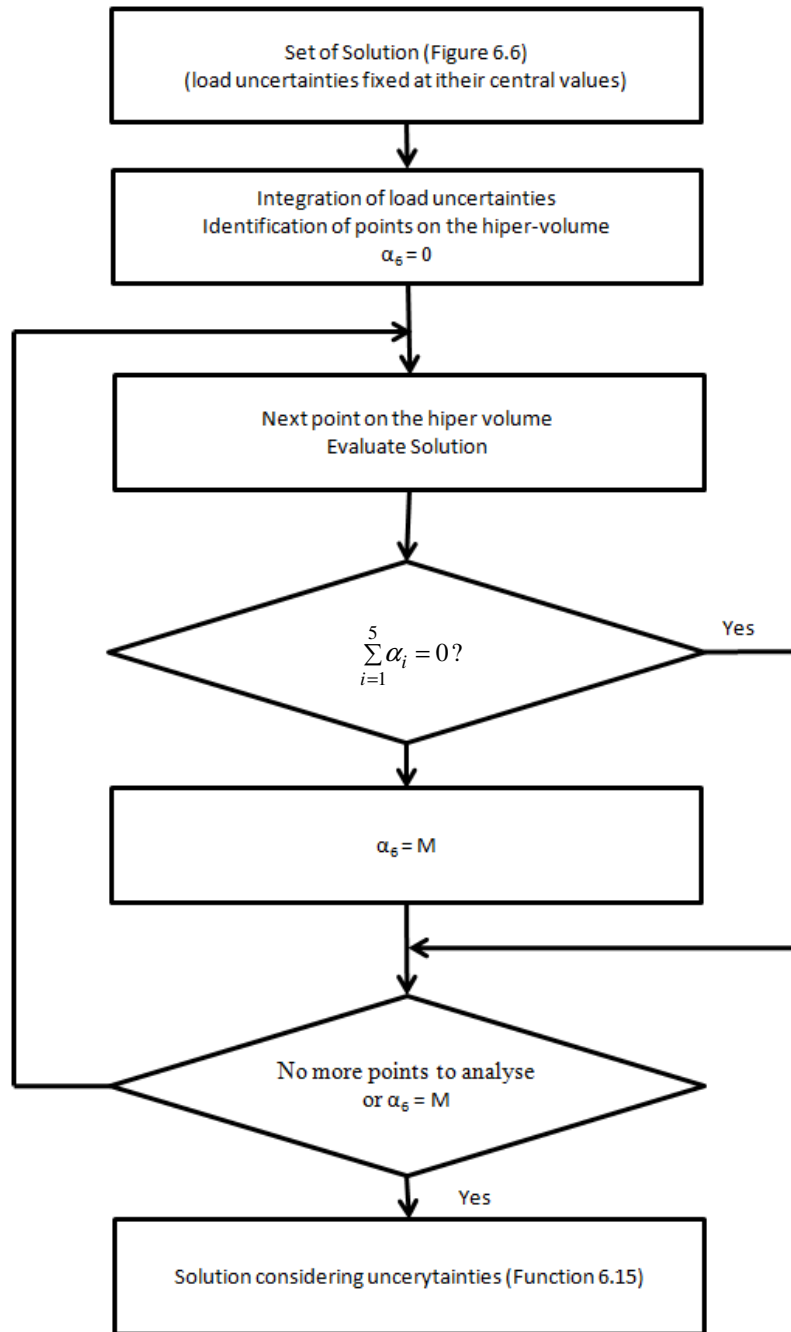


FIGURE 6-9 PARTICLE EVALUATION CONSIDERING UNCERTAINTIES

If the assessment conditions are not likely to penalize the solutions, they maintain the value of the first stage assessment. On the contrary, if some of the constraints are not met for any of the points and in any period, the solution is penalized.

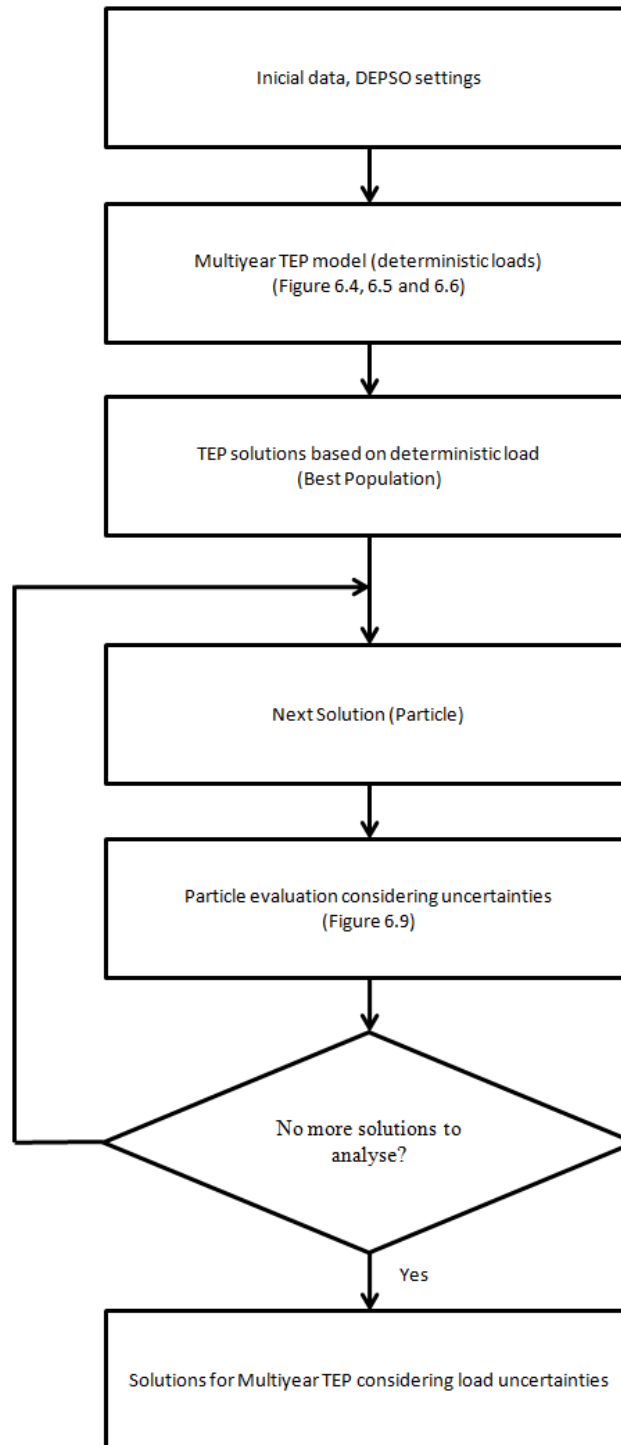


FIGURE 6-10 MULTIYEAR TEP MODEL CONSIDERING UNCERTAINTIES

Once analyzed all the particles affected by the specified load uncertainties, as represented in Figure 6.10, one obtain a set of solutions to the problem.

6.8. CONCLUSIONS

We present in this chapter the dynamic or multiyear TEP model, based on heuristic DEPSO developed in Chapter 5.

The proposed approach is a real dynamic model, since it considers the influence of the branches selected to be installed in the previous periods over the following ones. It meets technical, financial and quality of service constraints, as well as the uncertainty in loads.

The model includes the calculation of losses, with an improved version of DC OPF, and the evaluation of quality of service through the PNS (n) and PNS (n-1). It also incorporates the possibility of resource restrictions, by defining a maximum number of eligible projects per period, as well as setting an investment limit (to any period or for the overall plan).

One of the critical points on particle swarms based methodologies is the huge number of solutions that need to be assessed. The evaluation of TEP solutions requires running many OPF's, considering the periods, the dimension of the network and the expansion plan, with enormous impact in terms of run time. For this reason evaluation was broken down into several steps, so that the heaviest steps are actually only performed for those solutions that have revealed good performance in the previous ones.

Once a set of deterministic solutions (with excellent quality of service, $PNS(n) = 0$ and $PNS(n-1) = 0$) is obtained, it is then assessed considering load uncertainty, modeled by fuzzy numbers.

The output of the model is the set of solutions included in the best population and their fitness.

The model was tested in well known networks, and proved to be accurate, converging to the expected solutions. In addition, we observed that it needed fewer iterations and less time to converge, when compared with other methods.

It is therefore an interesting model with development potential, which can be applied to real networks, and make use of parallel programming to benefit from greater computing power and decrease the run time.

7. CASE STUDIES

7.1. SCOPE

This chapter presents the results of the tests using DEPSO to multiyear TEP problems considering uncertainties.

The tests are carried out using two networks:

- The Garver Network, introduced by Garver in 1970 (Garver, 1970);
- The IEEE RTS Network, with 24 busbars; the demand is set at 8.550 MW and the installed generation capacity is set at 10.215 MW, three times more than the original values that can be found in (IEEE, 1979).

These networks were chosen for the following reasons:

- These are reference networks in many scientific TEP studies;
- The result of the static planning is known in both cases.

In addition, we wanted a test network that would be larger than the ones usual in the literature on dynamic TEP, as for example in (Rezende, et al., 2010) and (Silva, et al., 2011).

In these two references a real sub-transmission network which belongs to CEMIG (State Energy Company of Minas Gerais, Brazil) was adopted. In Table 7.1 this network is compared with IEEE RTS 24, adopted in our tests.

TABLE 7-1 COMPARISON OF IEEE RTS WITH CEMIG NETWORK

	CEMIG sub-transmission network	IEEE RTS 24
Busbars	12	24
Loads	6	17
Generation buses	1	10
Interconnections	1	0
Voltage level zones	1	2
Peak load	780,05 MW	8.550,00 MW
Maximum local generation capacity	226.76 MW	10.215,00 MW
Average annual load increase rate	5%	5%
Periods under study	10	4

The algorithm detailed in Chapter 6 was programmed in MATLAB, and MATPOWER libraries were used to perform the DC Optimal Power Flow.

A HP Pavilion dv 6000 with 2CPU Core T5600 processor at 1.83 GHz 2 GB RAM and 32-bit operating system was used on the first phases. The results obtained using this PC are presented in Sections 7.2 and 7.3.

The remaining tests were performed with remote access in the server of the Faculty of Engineering, University of Porto.

7.2. TEST 1: DEPSO PRELIMINARY TESTS WITH GARVER NETWORK

7.2.1. INTRODUCTION

The study we present is generic for DEPSO methodology, and is independent from any problem under analysis. This means these tests were conducted to gain insight on the behavior of the DEPSO algorithm, namely regarding its few settings. In any case, as it will be concluded from the results obtained for subsequent tests, the settings are acceptable for use in any situation.

The behavior of DEPSO can naturally be improved by investigating other parameterization options. This is proposed as a possible future work.

Even though included in this section, one may say that population size definition is not a DEPSO setting. We only intend to show the influence of the population size on convergence, and give an example on how to identify the most adequate size of the population to deal with a given problem.

The tests are normally performed in sets of 10 or 100 trials for each setting option, to assess the frequency of occurrence of the expected result.

The Garver network is used in these tests for two reasons:

- There is a known solution for the case of single expansion period;
- It is a simple network, whose expansion study can be performed in very short time.

The tests conducted using the Garver network cover the following topics:

- Population dimension;
- Seeding procedure;
- Diversity in the population;
- Chaotic mutation operator;
- Mutation of the best global;
- Communication factor p ;
- Populations 1 and 2, the Lamarckian evolution when $V=0$;
- Population 3, Lamarckian evolution:
 - Clone origin;
 - Threshold to change clone origin;
 - Clone mutation parameters.

At the end of the first phase of preliminary tests, it was possible to get a first version of DEPSO settings.

Then we tested the effectiveness and efficiency of DEPSO in the following studies:

- DEPSO single period test;
- DEPSO multi period test;
- DEPSO performance compared with GA;
- DEPSO performance compared with EPSO.

These first tests are used to validate the following critical aspects, which we had assumed at the beginning of the thesis:

- The virtues of a very simple particle, a vector of integers, which allows an easy integration in the DEPSO model and an immediate interpretation in terms of the obtained solution;
- The easy convergence of a discrete model, on the assumption that covering only points in the search space might lead to an easier convergence to the quasi optimal solution;
- The advantage of the option for the use of chaotic mutation operators; these operators, despite having a chaotic behavior, integrate the influence of previous iteration operators and range between limits that allowed greater control over the particles speed.

7.2.2. TEST CONDITIONS

These tests were performed in an early development stage of the algorithm, with the main objective of testing the validity of the approach. For this reason, and also for simplicity and speed, some of the features specified on the model on Chapter 6 were released:

- Losses; the losses were not included in this phase;
- $PNS(n-1)$; it was only considered $PNS(n)$ at this stage; enforcing that $PNS(n)$ is zero is enough as the network is very small and it makes no sense to consider $PNS(n-1)$ reliability;

- States and search space; when these tests were performed one was only reasoning in terms of $np+1$ states; the state corresponding to the postponement of projects was introduced latter.

In any case, these conditions do not alter the validity of the results obtained on testing DEPSO algorithm.

The well known Garver network (Garver, 1970) was adopted in the first test. This network was introduced by Garver in 1970, and the network data is presented in Annex A. To evaluate the PNS, in each load bus we considered a fictitious generator.

7.2.3. EXPANSION PLANNING

The network should be expanded from the original situation to the demand levels defined in (Garver, 1970), as indicated in Table 7.2.

TABLE 7-2 GARVER NETWORK EXPANSION BUS BAR LOADS

Busbar n.	Pd (MW)
1	80
2	240
3	40
4	160
5	240
6	0
Total	760

Table 7.3 represents a project list for the Garver network expansion problem. This list includes 17 projects, and is based on the projects identified in several publications using Garver network.

The search space has $2^{17} = 1,3 \times 10^5$ positions, for a single period analysis, and $5^{17} = 7,6 \times 10^{11}$ positions, in the case of four period analysis.

TABLE 7-3 GARVER NETWORK EXPANSION PROBLEM PROJECT LIST

Branch no	From bus	To Bus	Resist. (pu)	React. (pu)	Cap. (MW)	Cost (10 ⁶ \$)
1	2	6	0,0800	0,0300	100	30
2	2	6	0,0800	0,0300	100	30
3	2	6	0,0800	0,0300	100	30
4	2	4	0,1000	0,4000	100	40
5	5	6	0,1476	0,6100	78	61
6	3	5	0,0500	0,2000	100	20
7	3	5	0,0500	0,2000	100	20
8	3	5	0,0500	0,2000	100	20
9	4	6	0,0800	0,3000	100	30
10	4	6	0,0800	0,3000	100	30
11	4	6	0,0800	0,3000	100	30
12	4	6	0,0800	0,3000	100	30
13	4	6	0,0800	0,3000	100	30
14	1	4	0,1500	0,6000	80	60
15	1	5	0,0500	0,2000	100	20
16	1	2	0,1000	0,4000	100	40
17	2	3	0,0500	0,2000	100	20

7.2.4. DEPSO SETTINGS, POPULATION DIMENSION

Objective of the test: assess the influence of the population size on the convergence to the expected solution.

TABLE 7-4 TEST CONDITIONS, POPULATION DIMENSION TEST

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; Pe; communication factor	0,3
Number of periods:	1	Best Global; Pb (k _c); mutation threshold	0,4
Number of states	2	Pop 1 and 2; Pv (k _b); mutation threshold when V = 0	0,4
Population dimension	Test	Pop 3; K; clone origin threshold	
Iterations	100	Pop 3; clone origin	
Number of serials	4 * 100	Pop 3; mutation amplitude	
File	CAP07002	Pop 3; mutation threshold	

The test conditions are enumerated in Table 7.4. The Figure 7.1 shows the results that were obtained for populations of 5, 10, 20 and 30 particles in terms of the frequency the

optimal solution (3/5: 1 new line; 4/6: 3 new lines) was obtained when the algorithm is ran 100 times for each population size.

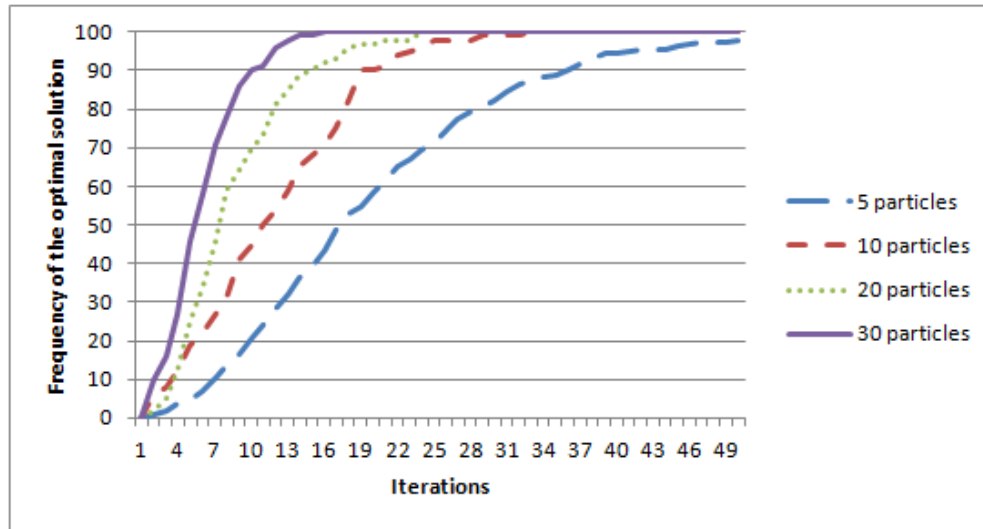


FIGURE 7-1 RESULTS OF THE POPULATION DIMENSION TEST

It should be noted that even for populations with fewer particles (case of 10 particles) the algorithm converged well, as can be concluded by comparison with the performance of other approaches (please address the Sections 7.2.17 and 7.2.18, where DEPSO performance is compared with GA and EPSO).

7.2.5. DEPSO SETTINGS, SEEDING PROCEDURE

This test was performed with the IEEE network, and the results are presented in section 7.4.4.

7.2.6. DEPSO SETTINGS, DIVERSITY IN THE POPULATION

It was found that the algorithm had a significant tendency to get sucked on certain local minima particles, not only as usual with particle swarm heuristics, but also as a direct result of the discontinuity of the search space. As the algorithm progresses, the population lose diversity and many particles tend to be equal. The ability to search for better solutions is strongly penalized for this behavior of premature convergence to local minima.

To improve the diversity in the population, a tabu list comprising all the Global Best found so far and the particles of the best population in the current iteration is created. When any particle evolves and becomes equal to a particle belonging to the tabu List, it is subject to Lamarckian evolution (please refer to section 5.5.7).

This test was performed with the IEEE network, and the corresponding results are presented in Section 7.3.6.

7.2.7. DEPSO SETTINGS, CHAOTIC MUTATION OPERATOR

When we started the development of DEPSO we used the classical mutation operators of EPSO. Their expressions are presented in section 4.6.6.

The tests were performed not only with the additive type operator, but also with the multiplicative type operator, without success. The results were very bad, as the algorithm did not converge.

It was found that this difficulty in convergence was due to the fact that operators of mutation (which have a multiplier effect in expressions 4.09 and 4.11) easily assume very large values, which made the velocity vectors to move the particles to the limit or beyond the search space.

When thinking about a solution to this difficulty we considered the following aspects:

- In expression (4.09) it would be important to have mutation operators (multipliers) that don't force excessively the velocity, which means that the multiplier should not vary beyond the range [0,1];
- The mutation operator should be influenced by the value it had in the previous iteration;
- It was assumed that one could experience, in addition to a random classical mapper, other mappers based on chaotic behaviour¹⁵².

The mutation operator adopted was indicated in Chapter 5, expression (5.38), now revisited (7.01).

$$w_{pt,j,t}^{it+1*} = \left(0.5 + rand() - \frac{1}{1 + \exp\left(-w_{pt,j,t}^{it*}\right)} \right) \quad (7.01)$$

The map adopted in the mutation operator function is the well known sigmoid function due to its chaotic behaviour, and also to keep the self adaptation capabilities of the swarm while respecting a narrow variation range that could help on the particles movement control.

As one can see in Figure 7.2, the operator has a chaotic behavior, ranging between 0 and 1, while conditioned by the value of the operator in the previous iteration.

¹⁵² As explained in Chapter 5, we found out later that other authors had already used operators with chaotic behavior combined with PSO. However, this is the first approach that combines chaotic operators with EPSO.

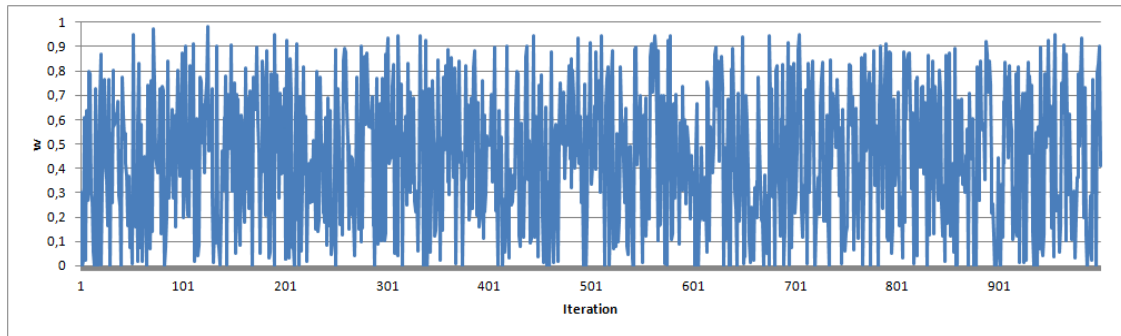


FIGURE 7-2 CHAOTIC BEHAVIOUR OF MUTATION OPERATOR

It should be emphasized that the adoption of this mutation operator contributed to improve the convergence of the algorithm and consistency in the solutions obtained.

7.2.8. DEPSO SETTINGS, MUTATION OF THE BEST GLOBAL

The best global particle is a vector, whose positions are mutated only when randomly generated numbers take values less than $k_c \in [0,1]$. The tests we have performed suggest that $k_c = 0,4$ led to the best convergence results¹⁵³. The weights are updated by (5.38) and the mutation of particle b_G is obtained by (5.40), now revisited (7.02).

$$b_{Gj}^* = b_{Gj} + \text{round}(2 \cdot w_4^{it^*} - 1) \quad (7.02)$$

Objective of the test: assess the influence of k_c in the convergence to the expected solution.

TABLE 7-5 TEST CONDITIONS, MUTATION OF THE BEST GLOBAL

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; P_e ; communication factor	0,3
Number of periods:	1	Best Global; P_b (k_c); mutation threshold	Test
Number of states	2	Pop 1 and 2; P_v (kb); mutation threshold when $V = 0$	0,4
Population dimension	5	Pop 3; K ; clone origin threshold	
Iterations	100	Pop 3; clone origin	
Number of serials	4 * 100	Pop 3; mutation amplitude	
File	CAP07004	Pop 3; mutation threshold	

¹⁵³ The value of 0.4 was inspired by the work of Houck et al on Partial Lamarckism, (Houck, et al., 1997). Houck et al found that convergence is optimized when Lamarckism is adopted in 20 to 40% of total particles. In our case, the mutation occurs in 40% of the positions of the particles, rather than in 40% of the particles.

The test conditions are enumerated in Table 7.5, and Figure 7.3 presents the results that were obtained once again in terms of the frequency the optimal solution was obtained for different values of the parameter k_c .

As one can see in Figure 7.3, $k_c = 0.4$ leads to the best results.

It must be stressed the fact that this test, on a two states search space, was done with a population of only 5 particles. The convergence and the speed are appreciable.

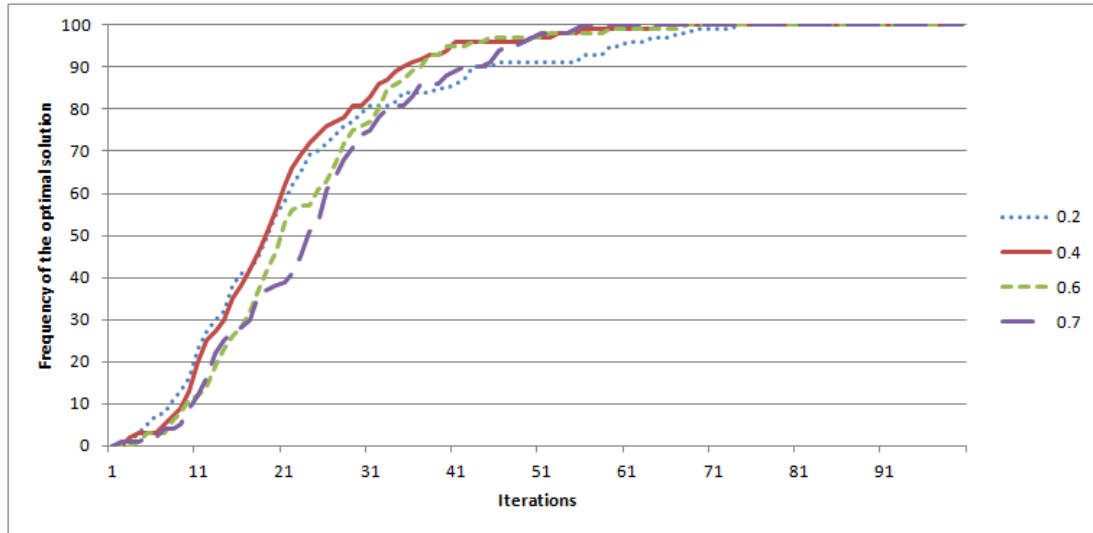


FIGURE 7-3 RESULTS OF THE MUTATION OF THE BEST GLOBAL TEST

7.2.9. DEPSO SETTINGS, THE COMMUNICATION FACTOR p

The communication factor concept is explained in Section 5.5.6. In the case of a real search space, the best results were achieved with a p less than 1.

DEPSO is applied to discrete and discontinuous search spaces, and it is important to verify the influence of the best global on the convergence conditions. The test that we present was based on a simple code for the definition of the random situations where $p = 1$.

Objective of the test: access the influence of p on convergence.

The test conditions are described in Table 7.6, and Figure 7.4 presents the results that were obtained in terms of the frequency the optimal solution was obtained for different values of the factor p_e .

TABLE 7-6 TEST CONDITIONS, COMMUNICATION FACTOR P

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; P_e ; communication factor	Test
Number of periods:	1	Best Global; $P_b(k_c)$; mutation threshold	0,4
Number of states	2	Pop 1 and 2; $P_v(k_b)$; mutation threshold when $V = 0$	0,4
Population dimension	5	Pop 3; K ; clone origin threshold	$6 \cdot np$
Iterations	100	Pop 3; clone origin	
Number of serials	$3 \cdot 100$	Pop 3; mutation amplitude	
File	CAP07005	Pop 3; mutation threshold	

On a static approach, the best results were obtained with $P_e = 1$. Noting however that the performance could be very similar, we gave preference to $P_e = 0.3$ as this setting allows an easier escape from local minima (a situation that occurs in the figure beyond 40 iterations).

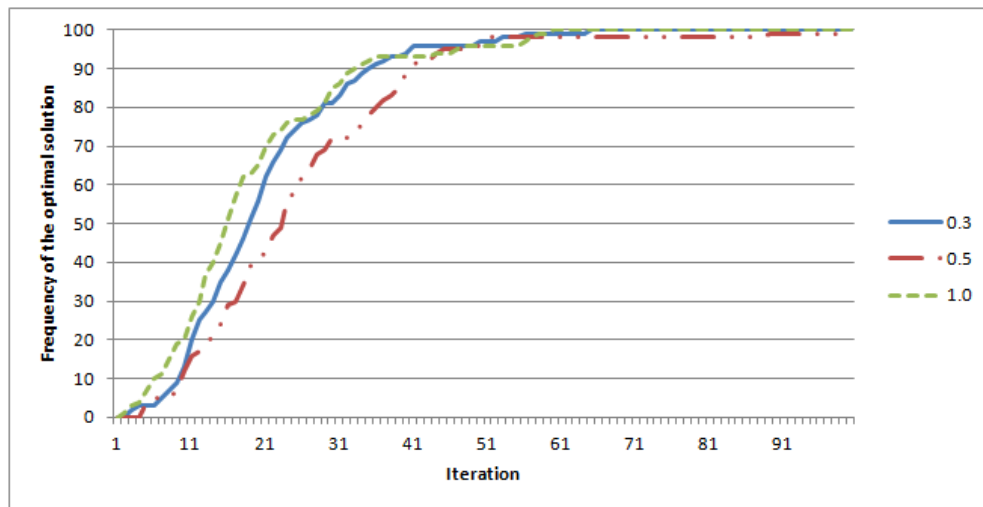


FIGURE 7-4 RESULTS OF THE COMMUNICATION FACTOR P TESTS

7.2.10. DEPSO SETTINGS, THE LAMARCKIAN EVOLUTION WHEN $V=0$

To avoid not contributing to the solution, the particles of populations 1 and 2 with null velocity are subject to a Lamarckian evolution by (5.45), as explained in Section 5.5.7.

TABLE 7-7 TEST CONDITIONS, LAMARCKIAN EVOLUTION WHEN $V=0$

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; P_e ; communication factor	0,3
Number of periods:	4	Best Global; P_b (k_c); mutation threshold	0,4
Number of states	5	Pop 1 and 2; P_v (k_b); mutation threshold when $V = 0$	Test
Population dimension	50	Pop 3; K ; clone origin threshold	
Iterations	100	Pop 3; clone origin	
Number of serials	5 * 100	Pop 3; mutation amplitude	
File	CAP07007	Pop 3; mutation threshold	

This mutation has two parameters:

- One factor which defines the evolution amplitude; in order to diversify the search, this factor is set to np ;
- One factor P_v , which defines, whether or not, each bit undergoes mutation; mutations only take place when a randomly generated number is less than k_b .

Objective of the test: test the influence of the mutation threshold k_b on convergence.

The test conditions are detailed in Table 7.7, and Figure 7.5 details the results obtained in terms of the frequency.

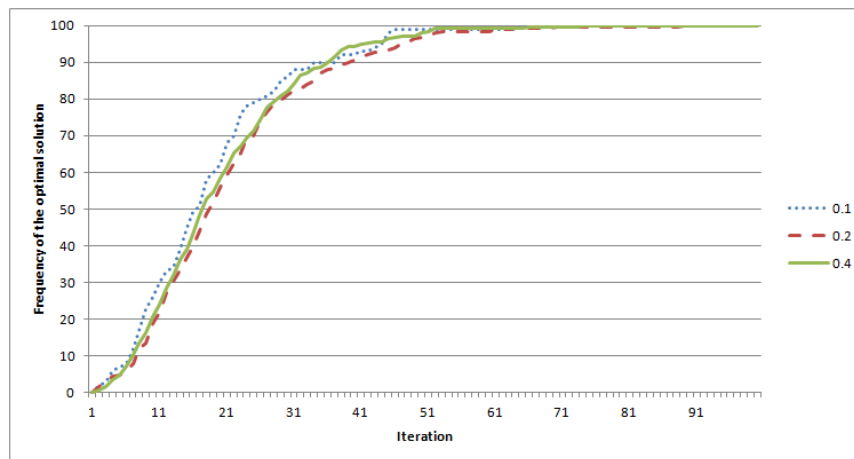


FIGURE 7-5 RESULTS OF THE LAMARCKIAN EVOLUTION WHEN $V=0$ TEST

This factor has not a great influence in convergence. However, we have decided to adopt $k_b = 0.4$, as the progression with this setting is more regular and the behavior between iterations 30 and 50 showed that it could be more adequate to escape from local observed minima.

7.2.11. DEPSO SETTINGS, THE POP 3 LAMARCKIAN EVOLUTION, CLONE ORIGIN

During the development of the DEPSO algorithm, one tested if the creation of a third population, resulting from the mutation of clones of good solutions, could contribute, not only to faster convergence to the optimal solution, but also to allow the algorithm escape from local minima. In this section, we present the tests that were performed in order to realize how these particles should be identified.

The alternatives were the following:

- Base; Pop 3 = best pop;
- Block A; Pop 3 = best global¹⁵⁴;
- Block Ba; if $\text{rand}() < Y$ ¹⁵⁵ then Pop 3 = best part else Pop 3 = best pop;
- Block B; Pop 3 = best global; if (more than K iterations without improving best global), Pop3 = best pop;
- Block C; Pop 3 = best global; if (more than K iterations without improving best global), Pop 3 = a particle of best pop randomly selected;

The last three alternatives have a dynamic behavior. The alternatives B and C are dynamic and depend on the evolution of the algorithm in terms of convergence to set the clone source.

Objective of the test: identify the best origin for the clone to be used in the creation of the population 3.

TABLE 7-8 TEST CONDITIONS, THE POP 3 LAMARCKIAN EVOLUTION, CLONE ORIGIN

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; Pe; communication factor	0,3
Number of periods:	4	Best Global; Pb (k_c); mutation threshold	0,4
Number of states	5	Pop 1 and 2; Pv (k_b); mutation threshold when $V = 0$	0,4
Population dimension	50	Pop 3; K; clone origin threshold	Test
Iterations	100	Pop 3; clone origin	Test
Number of serials	5 * 10	Pop 3; mutation amplitude	
File	CAP07007	Pop 3; mutation threshold	

¹⁵⁴ That is, all particles of population become equal to global best. Global best has the same meaning of best part.

¹⁵⁵ Y must be between 0 and 1.

The test conditions are detailed in Table 7.8, and Figure 7.6 presents the results that were obtained considering the alternatives. These results are once again presented in terms of the number of times that the optimal solution was identified in function of the number of iterations.

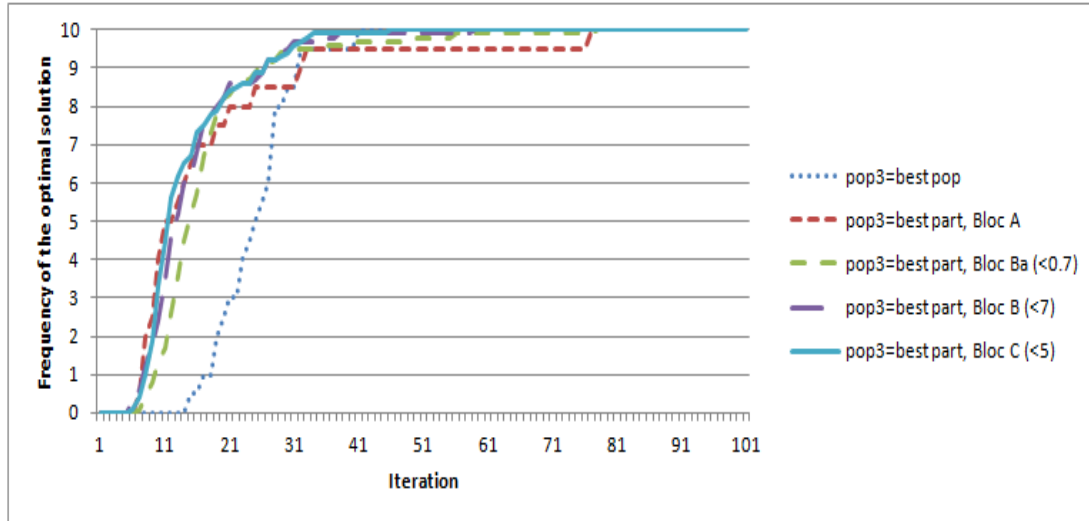


FIGURE 7-6 RESULTS OF THE POP 3 LAMARCKIAN EVOLUTION CLONE ORIGIN TEST

As one can see in Figure 7.6, the alternative corresponding to block C is the most consistent, especially in situations where more iterations are required to achieve the optimal solution. In the next test we assess the most appropriate threshold for the selection of the particle to be cloned, either from the best pop or from the best global.

7.2.12. DEPSO SETTINGS, THE POP 3 LAMARCKIAN EVOLUTION, THRESHOLD

Population 3 is composed of clones of a particle. According with the evolution of the algorithm, the selected particle will be either the best global or one of the particles in the best population, randomly identified:

- The best global, if *stop_counter* < k;
- A particle randomly selected among the best population, if *stop_counter* ≥ k.

Objective of the test: assess the influence of k on the convergence to the expected solution.

TABLE 7-9 TEST CONDITIONS, THE POP 3 LAMARCKIAN EVOLUTION, CLONE ORIGIN THRESHOLD

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; Pe; communication factor	0,3
Number of periods:	4	Best Global; Pb (k_c); mutation threshold	0,4
Number of states	5	Pop 1 and 2; Pv (k_b); mutation threshold when $V = 0$	0,4
Population dimension	50	Pop 3; k; clone origin threshold	Test
Iterations	100	Pop 3; clone origin	Block C
Number of serials	3 * 10	Pop 3; mutation amplitude	
File	CAP07001	Pop 3; mutation threshold	

The test conditions are described in Table 7.9 and Figure 7.7 illustrates the results obtained for different values of the parameter k. These results indicate the frequency the optimal solution was identified for different values of k and for different numbers of iterations.

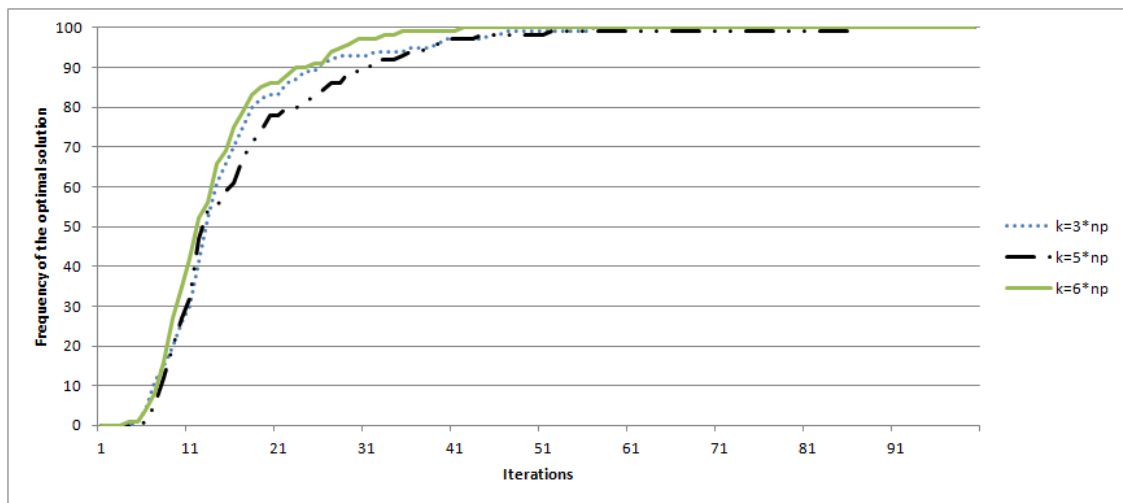


FIGURE 7-7 RESULTS OF THE POP3 LAMARCKIAN EVOLUTION CLONE ORIGIN THRESHOLD TEST

As shown in this figure, $k = 6 * np$ improves convergence. This parameter is directly proportional to the number of periods under review.

7.2.13. DEPSO SETTINGS, THE POP 3 LAMARCKIAN EVOLUTION, MUTATION

Similar to the Lamarckian evolution of populations 1 and 2 when $V = 0$, population 3 is subject to Lamarckian evolution by (5.46)), as explained in Section 5.5.7.

This mutation has two parameters, which were tested with different values included on the code blocks introduced later:

- Factor $k3_a$, to define the amplitude;
- Factor $k3_b$, which defines whether, or not, each bit undergoes mutation;

Objective of the test: test the influence of $k3_a$ and $k3_b$ on convergence.

The test conditions are described in Table 7.10 and Figure 7.8 illustrates the results that were obtained for different settings.

TABLE 7-10 TEST CONDITIONS, THE POP 3 LAMARCKIAN EVOLUTION MUTATION

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; Pe; communication factor	0,3
Number of periods:	3	Best Global; Pb (k_c); mutation threshold	0,4
Number of states	4	Pop 1 and 2; Pv (k_b); mutation threshold when $V = 0$	0,4
Population dimension	30	Pop 3; K; clone origin threshold	$6 \cdot np$
Iterations	100	Pop 3; clone origin	Block C
Number of serials	3 * 10	Pop 3; $k3_a$ mutation amplitude	Test
File	CAP07008	Pop 3; $k3_b$ mutation threshold	Test

In this test were used the following blocks:

```

BLOCK 1
capa = 6*np;
k3a = nper;
if stop_k > capa
    if iteration > 10
        k3a = 1;
        k3b = 0.3;
    else
        k3a = 1;
        k3b = 0.1;
    end
end
else
    if iteration > 10
        k3a = nper;
        k3b = 0.3;
    else
        k3a = nper;
        k3b = 0.1;
    end
end
end

```

BLOCK 2

```

k3a = nper;
k3b = 1;
if stop_k > 1
    k3a = 2;
    k3b = 0.5;
end

```

BLOCK 3

```

k3a = 1;
k3b = 0.5;
if stop_k > 3
    k3a = nper;
    k3b = 1;
end

for g=1:nproj
    muta = rand();
    if muta < k3b
        matrizV3(p,g)=round(2*k3a*(0.5+rand()-1/(1+exp(-rand())))-k3a);
    end
end

```

It was found that Block 2 showed faster convergence, and it was decided to implement a second test in order to improve this routine.

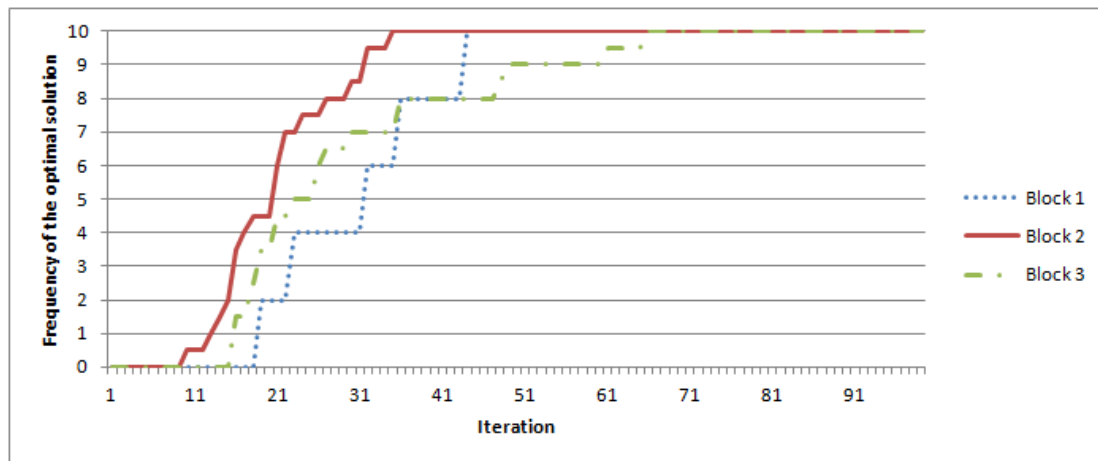


FIGURE 7-8 RESULTS OF THE POP 3 LAMARCKIAN EVOLUTION MUTATION

The conditions adopted for this second test are described in Table 7.10 and Figure 7.8 illustrates the results obtained for different alternatives of Block 2. These results are presented in terms of the frequency the optimal solution was obtained for different values of the iterations.

TABLE 7-11 TEST CONDITIONS, THE POP 3 LAMARCKIAN EVOLUTION MUTATION, 2ND TEST

		Variable or module of the algorithm	Setting
Network:	Garver	Best Global; Pe; communication factor	0,3
Number of periods:	4	Best Blobal; Pb (k _c); mutation threshold	0,4
Number of states	5	Pop 1 and 2; Pv (kb); mutation threshold when V = 0	0,4
Population dimension	30	Pop 3; K; clone origin threshold	6*np
Iterations	100	Pop 3; clone origin	Block C
Number of serials	3 * 10	Pop 3; k _{3a} mutation amplitude	Test
File	CAP07009	Pop 3; k _{3b} mutation threshold	Test

In this new test we used the following blocks:

BLOCK 2

```
k3a = nper;
k3b = 1;
if stop_k > 1
    if nper == 1
        k3a = 1;
    else
        k3a = 2;
    end
    k3b = 0.5;
end
```

BLOCK 2 c

```
k3a = nper;
k3b = 1;
if nper == 1
    k3a = 1;
else
    k3a = 2;
end
if stop_k > 1
    k3b = 0.5;
end
if iteration > 10
    k3b = 0.4;
    k3a = 1;
end
```

```
for g=1:nproj
    muta = rand();
    if muta < k3b
        matrizV3(p,g)=round(2*k3a*(0.5+rand()-1/(1+exp(-rand())))-k3a);
    end
end
```

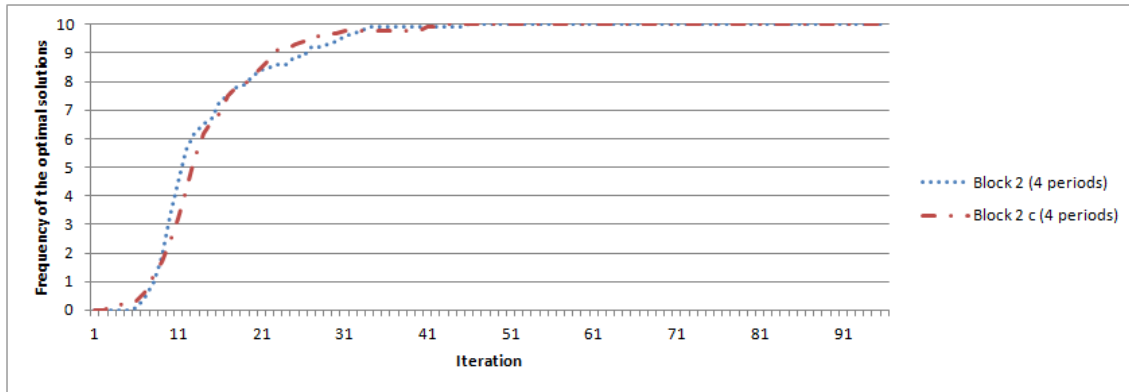


FIGURE 7-9 RESULTS OF THE POP 3 LAMARCKIAN EVOLUTION MUTATION, 2ND TEST

As suggested by Figure 7.9, the alternative corresponding to Block 2c showed slightly better results than those of Block 2, especially at the stage the algorithm exceeds 20 iterations and starts to have more difficulty to escape from local minima.

7.2.14. DEPSO SETTINGS, FINAL CONFIGURATION

The final settings and final configuration of DEPSO is summarized in Table 7.12.

TABLE 7-12 FINAL SETTINGS OF THE DEPSO ALGORITHM

Variable or module of the algorithm	Setting
Best Global; P_e , communication factor	0,3
Best Global; P_b (k_c); mutation threshold	0,4
Pop 1 and 2; P_v (k_b); mutation threshold when $V = 0$	0,4
Pop 3; K ; clone origin threshold	$6 \cdot n_p$
Pop 3; clone origin	Block C
Pop 3; k_{3a} , mutation amplitude	Block 2c
Pop 3; k_{3b} , mutation threshold	Block 2c

7.2.15. DEPSO SINGLE PERIOD TEST RESULTS¹⁵⁶

The solution identified for the single period analysis of Garver network is the same as that found in the literature: branch 3-5, 1 new line; branch 4-6, 3 new lines.

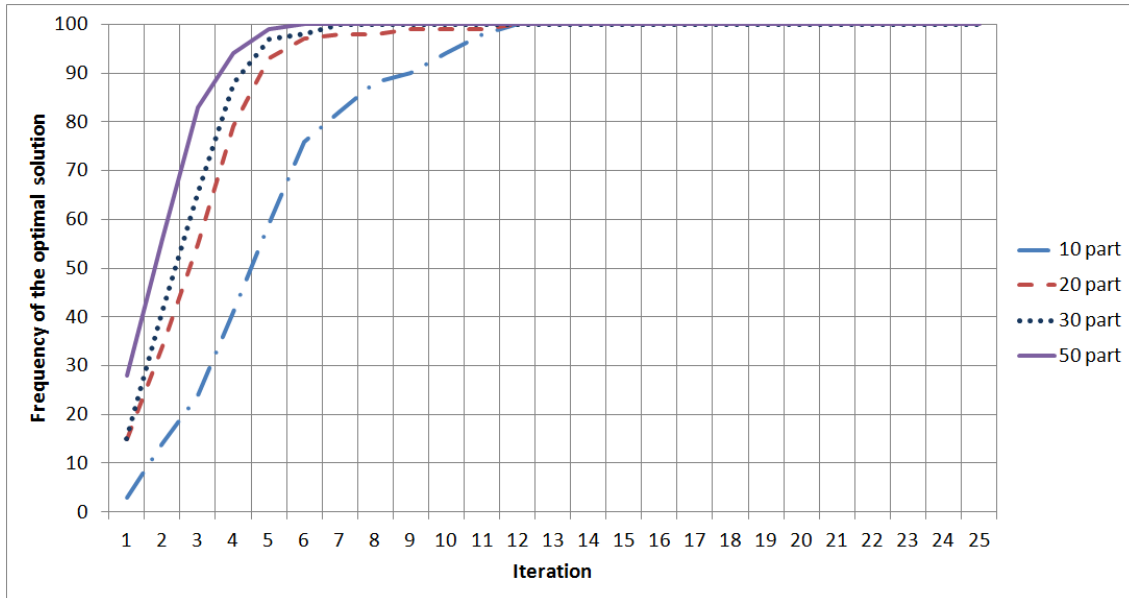


FIGURE 7-10 DEPSO TEST WITH 10, 20, 30 AND 50 PARTICLES (SINGLE PERIOD, GARVER NETWORK)

The algorithm was run 100 times with populations of 10, 20, 30 and 50 particles. According to the results in Figure 7.10, the performance of the developed DEPSO was remarkable, given that convergence was obtained for a very small number of iterations, even for populations of 10 particles. For populations with at least 20 particles in 98% of cases the optimal solution was found in less than 10 iterations.

7.2.16. DEPSO MULTI PERIOD TEST RESULTS

The second study using the Garver network includes a planning horizon with four periods. This test was designed with the following assumptions:

- Load increase of 5% per period;
- Fixed investment costs (for the sake of simplicity, it was considered that the effect of technological and market competitiveness outweighed the effect of inflation and capital discount rates)¹⁵⁷;

¹⁵⁶ The results of sections 7.2.15 and 7.2.16 were presented at the 2011 PSCC (Rocha, et al., 2011 a).

- Lines available from the year of entry into service; it should be underlined that the network configuration, and the corresponding power flows for subsequent years depend on previous year's configuration.

Several solutions were identified with the same fitness value, which corresponds to an investment of 160 M\$.

In some cases the solution of the four periods analysis complements¹⁵⁸ the solution obtained for the single period run with two additional lines (ex. period 1: 2-6, (1 line); **3-5 (1); 4-6 (3)**, 1-5 (1)). Other solutions are different from what was obtained for the single period (ex. period 1: 2-6 (1); **3-5 (1); 4-6 (1)**; 1-5 (1); Period 3: **4-6 (1)**; Period 4: **3-5 (1)**).

As for the single period test, the algorithm was run 100 times with populations of 10, 20, 30, 50 and 80 particles.

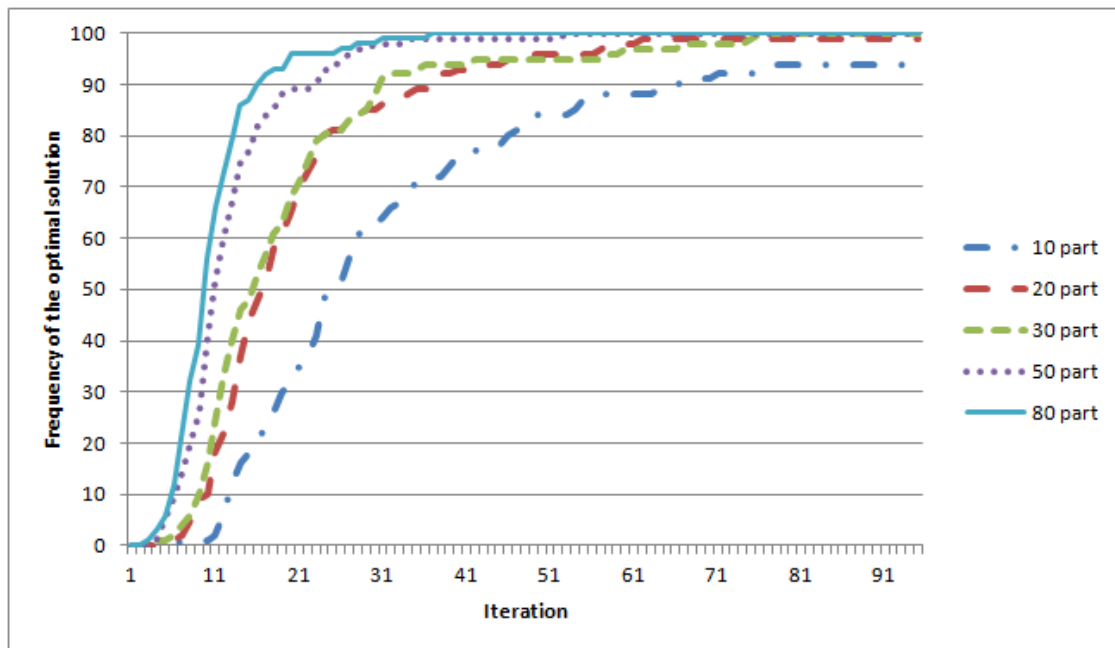


FIGURE 7-11 DEPSO TEST WITH 10, 20, 30, 50 AND 80 PARTICLES (MULTI PERIOD, GARVER NETWORK)

¹⁵⁷ The rate of increase in investment costs has to do with the changes in costs of raw materials (copper, steel, ...) and hand labour, and even as funding costs. It may be e.g. 2% per year. The update rate of investments for the first period has to do with financial matters, including the assessment of business risk, return on capital, the prize for investors. It can be for example 5 or 7% per year. This rate compares with others of similar risk investments.

¹⁵⁸ The branches included on the single period expansion analysis are on bold.

According to the results presented in Figure 7.11, the 10 particles population appeared to have a need for more iterations to converge, but in 94% of cases it reached the optimum in 100 iterations. Using populations of 30 particles one reaches the optimum in 95% of cases after 42 iterations, while with 80 particles similar results are found in 20 iterations.

7.2.17. *DEPSO PERFORMANCE COMPARED WITH GA*

We have seen in Section 7.2.15 that the model is effective, since it is able to find the solutions already identified by other researchers on the static expansion of the Garver network.

The efficiency of DEPSO can be assessed by comparison with the performance and the results obtained by other researchers for the same network adopting different methodologies.

A comparison between DEPSO and GA can be made based on the study published in 1998 by Gallego (Gallego, et al., 1998). On this study it is presented a static TEP on the Garver network, based on GA. Gallego¹⁵⁹ says that with GA usually about 21 to 30 iterations are required to get the results.

In our model are needed fewer iterations to achieve the solution. Even with populations of 10 particles, only 11 iterations are needed.

7.2.18. *DEPSO PERFORMANCE COMPARED WITH EPSO*

The performance of DEPSO can be assessed in Figure 7.12, which compares the results obtained using the EPSO reported in (Pringles, et al., 2007) and our results with DEPSO¹⁶⁰. This figure shows the frequency of the best fitness for 25, 50 and 100 iterations. In each test 100 runs were performed with 10, 30, 50 and 100 particles. As it can be seen, DEPSO has better performance than the classical EPSO.

¹⁵⁹ “With population varying from 16 to 24 configurations convergence to the optimal solution was typically obtained after 25 to 35 generations (the initial population was generated randomly and the convergence rate depends on the average fitness of the initial generation). (...) When rescheduling was allowed the algorithm took 15% fewer iterations to converge.” (Gallego, et al., 1998) This is our case, so it should be reasonable to take $(25 \text{ to } 35) * 0.85 = (21 \text{ to } 30)$ iterations to the solution.

¹⁶⁰ On this assessment one is comparing our DEPSO approach for the four period analyses (5 states) and a vector of 17 positions, with the EPSO approach of Pringles. His study was for a static TEP, but with an entire vector of 15 positions, with 5 possibilities (0-4 lines per branch). The assessment is made solely based on the investment value.

Comparing the search spaces, in our case we have 5^{17} combinations¹⁶¹ and in the case of Pringles there were 5^{15} possible combinations. Although our search space is 25 times bigger, the results are better.

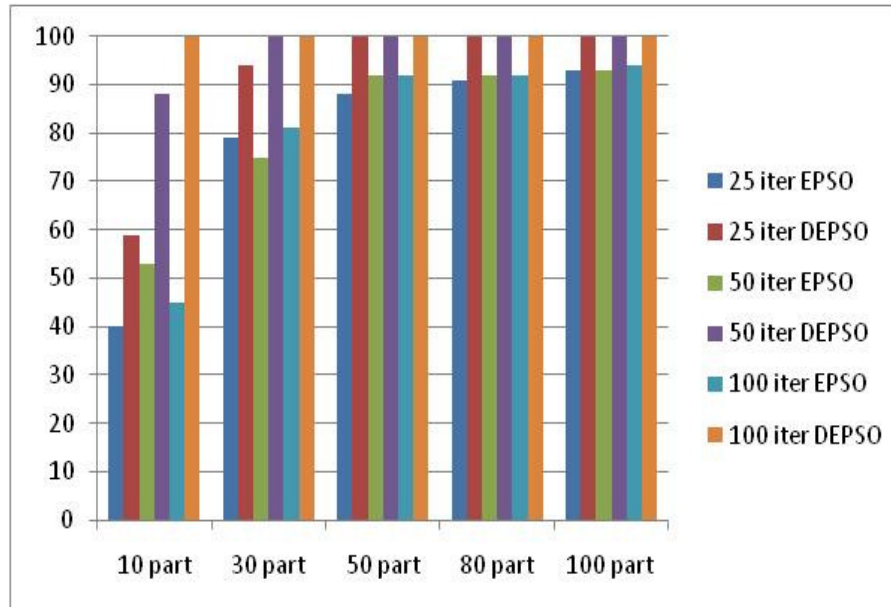


FIGURE 7-12 DEPSO AND EPSO PERFORMANCE COMPARISON

DEPSO needs less iterations and smaller populations than EPSO to get the same results. DEPSO is also able to escape from local minima, as it reaches 100% of optimal solutions in 100 iterations, independently from the population dimension.

¹⁶¹ $5^{17} = 762.939.453.125$

7.3. TEST 2: IEEE RTS 24 NODES NETWORK (PRELIMINARY DETERMINISTIC LOAD TESTS)

7.3.1. TEST CONDITIONS

The IEEE RTS network has 24 nodes, 35 lines and 32 generators and its original data can be found in (IEEE, 1979) and in Annex B.

In order to obtain a more stressed network, and in line with other recent research works, the demand was set at 8,550 MW and the installed generation capacity to 10,215 MW, 3 times more than the original values, as adopted by many researchers.

On the multi period tests, it was admitted that the demand evolves by 5% per period. The investment value update to period 0 was made at a 10% rate per period. In this case, two new generators were added to cope with the demand increase: one in bus 4 (300 MW, similar to the generators in bus 7), and another in bus 19 (591 MW, similar to the generator in bus 13). The fitness function included investment costs and penalties when the number of projects per period is larger than 6, active transmission losses are larger than 6% of the generation and $PNS(n)$ is not zero. Finally, the penalization if $PNS(n-1)$ is not zero was considered when mentioned, and it was not considered any limitation to the global investment amount.

The stopping criteria adopted were:

- Maximum number of iterations (1000 iterations);
- Maximum number of iterations without best global improvement ($1000/5 = 200$ iterations).

These preliminary deterministic load tests were performed on runs with 1000 iterations due to the limited computing capacity of the PC that was being used.

7.3.2. EXPANSION PLANNING

The list of possible projects on the expansion planning is shown in Table 7.12. The search space has $3^{28} = 22,8 \times 10^{12}$ positions, for a single period analysis, and $6^{28} = 6,1 \times 10^{21}$ positions, for a four period analysis.

TABLE 7-13 PROJECT LIST FOR THE IEEE RTS NETWORK EXPANSION PROBLEM

Branch no	From bus	To bus	Resist. (pu)	React. (pu)	Cap. (MW)	Cost (10 ⁶ \$)
1¹⁶²	3	24	0,0000	0,4195	400	500
2	9	11	0,0000	0,4195	400	500
3	10	11	0,0000	0,4195	400	500
4	10	12	0,0000	0,4195	400	500
5	1	5	0,1090	0,4225	175	220
6	1	5	0,1090	0,4225	175	220
7	2	4	0,1640	0,6335	175	330
8	2	4	0,1640	0,6335	175	330
9	2	6	0,2485	0,9600	175	500
10	2	6	0,2485	0,9600	175	500
11	6	10	0,0695	0,3025	175	160
12	7	8	0,0795	0,0032	175	160
13	7	8	0,0795	0,0032	175	160
14	8	10	0,2135	0,8255	175	430
15	11	13	0,0305	0,2380	500	660
16	11	13	0,0305	0,2380	500	660
17	14	16	0,0250	0,1945	500	540
18	15	21	0,0315	0,2450	500	680
19	15	24	0,0335	0,2595	500	720
20	16	17	0,0165	0,1295	500	360
21	16	17	0,0165	0,1295	500	360
22	16	19	0,0150	0,1150	500	320
23	17	18	0,0090	0,0720	500	200
24	20	23	0,0140	0,1080	500	300
25	11	13	0,0305	0,2380	500	660
26	12	13	0,0305	0,2380	500	660
27	11	14	0,0305	0,2380	500	580
28	14	16	0,0250	0,1945	500	540

¹⁶² The first four expansion projects correspond to the installation of new transformers.

7.3.3. SINGLE PERIOD TEST RESULTS¹⁶³

In these tests with IEEE RTS, the network as described in 7.3.1 was adopted. The fitness has considered the investment costs, no limit was imposed for the number of projects to be added and the quality of service was only evaluated with $PNS(n) = 0$.

TABLE 7-14 IEEE RTS NETWORK, NEW ADDITIONS FOR A SINGLE PERIOD EXPANSION

Investment (M€)	New Lines and Transformers	Frequency in 100 part test
2150	Transformers: 9/11; 10/11 Lines: 2/4; 6/10; 11/13	
2160	Transformers: Lines: 6/10; 7/8(2); 16/17(2); 20/23; 11/13	1/20
	Transformers: Lines: 2/4(2); 2/6; 6/10; 7/8(2); 16/19; 17/18	4/20
	Transformers: 3/24 Lines: 1/5; 6/10; 7/8(2); 20/23; 11/13	15/20

A set of 20 tests, 1000 iterations each, with 10, 30 and 100 particles was performed. The best solution ever found means an investment of 2150 M€ and it includes two new transformers (9/11; 10/11) and three new lines (2/4, 6/10 and 11/13). The most frequent investment value is 2160 M€, and it corresponds to three different solutions: one solution with frequency 1/20 (new lines 6/10; 7/8(2); 16/17(2); 20/23; 11/13), one solution with frequency 4/20 (new lines: 2/4(2); 2/6; 6/10; 7/8(2); 16/19; 17/18) and one solution with frequency 15/20 (new lines: 1/5; 6/10; 7/8(2); 20/23; 11/13). The results are presented in Table 7.14.

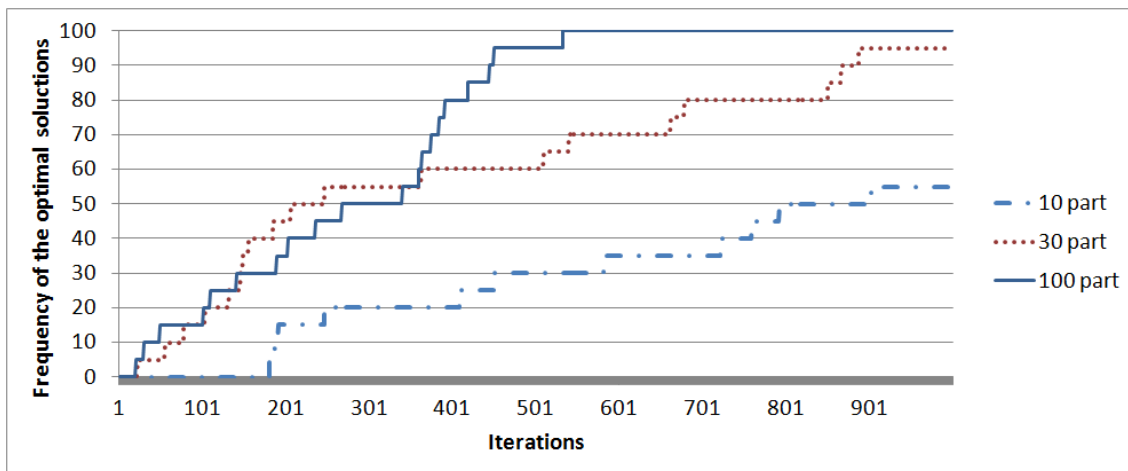


FIGURE 7-13 IEEE RTS NETWORK SINGLE PERIOD EXPANSION ANALYSIS (10, 30 AND 100 PART)

¹⁶³ The results of Section 7.3.3 and 7.3.4 were presented at the 2011 EEM (Rocha, et al., 2011).

As indicated in Figure 7.13, with populations of 100 particles one reaches the fitness of 2160 M€ in 100% of the runs and 600 iterations are enough to find the better solution in all runs. With populations of 30 particles the success frequency was of 95% of the cases.

One has to keep in mind that with 1000 iterations and a population of 30 particles 90.000 solutions are tested, in a search space with 22.876.792.454.961 possible solutions.

TABLE 7-15 COMPARISON OF THE SINGLE PERIOD EXPANSION PLANS

solutions	iterations	investment	1	2	3	4	5	6	7	8	10	11	12	13	15	17	20	21	22	23	24	25	26
			3/24 500	9/11 500	10/11 500	10/12 500	1/5 220	1/5 220	2/4 330	2/4 330	2/6 500	6/10 160	7/8 160	7/8 160	11/13 660	14/16 540	16/17 360	16/17 360	16/19 320	17/18 200	20/23 300	11/13 660	12/13 660
Without losses																							
Romero G3		2020	0	0	0	1	0	0	0	0	0	1	1	0	0	1	1	0	0	0	1	0	0
Aguacil without losses		1640	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1
our test *	5000	1280	0	0	0	0	1	1	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0
With losses																							
Aguacil with losses		2380	0	0	1	0	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	1
our test	1000	2160	1	0	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	0	1	1	0
our test	1000	2160	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	1	1	0	0	0
our test	1000	2160	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	0	0	1	0	0
our test	1000	2150	0	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0

* this test was performed with the improved network adopted for the multiperiod test

As can be seen in Table 7.15, the comparison of results obtained by our tests with those obtained by other researchers¹⁶⁴ support the following conclusions:

- In the analysis with losses, the solutions we have identified represent less investment than those identified by Aguacil; however, several branches, such as the transformer 10/11 and lines 6/10 and 7/8 are referenced in both approaches;
- In the analysis without losses, the expansion plan identified by us is far more economical than the solutions presented so far in the literature for classical IEEE RTS network; however, the solution presented here is only to be taken as reference, as it was obtained for the improved network with two additional generators (the network adopted for the multistage tests) on a 5000 iterations run.

7.3.4. MULTI PERIOD TEST RESULTS

As stated in Section 7.3.1, for these tests, and to cope with the demand increase, two new generators were added, in bus 4 (300 MW, similar to the generators in bus 7), and in bus 19 (591 MW, similar to the generator in bus 13).

¹⁶⁴ (Alguacil, et al., 2003) and (Romero, et al., 2005).

TABLE 7-16 FOUR PERIOD'S EXPANSION SOLUTION FOR THE IEEE RTS NETWORK

Period	New Lines and Transformers
1	Transformers: 10/12 Lines: 6/10; 7/8; 11/13; 14/16; 15/21
2	Lines: 11/13
3	Lines: 7/8
4	Lines: 2/4

The best solution found¹⁶⁵ on the preliminary tests has a fitness of 3.345,6 M€, and it was obtained with a run with 100 particles, in 694 iterations and includes: in period 1, one new transformer (10/12) and five new lines (6/10; 7/8; 11/13; 14/16; 15/21); in period 2 one new line (11/13); in period 3 one new line (7/8) and in period 4 one new line (2/4). This solution is also presented in Table 7.16.

7.3.5. POPULATION DIMENSION IN THE PERFORMANCE OF THE ALGORITHM

The population size and the number of iterations have a direct influence on the duration of each run. In fact, the more iterations are needed to achieve the solution, the longer will be the runs. On the other hand, the larger the population, the greater the number of particles to be evaluated in each iteration, which also influences the running time of the algorithm.

As can be seen in Figure 7.13, on the single test period, the algorithm demonstrates a very interesting convergence in the first iterations (up to 350 iterations), with comparable results obtained with populations of 30 or 100 particles, reaching in 60% of the runs the desired result. However, as expected, the use of populations with 100 particles achieves the result in about 530 iterations, while in the case of populations with 30 particles it is almost necessary to complete the 1000 iterations to achieve the same. Given the scale of the problem, the population of 10 particles appeared to be insufficient for a proper progression of the algorithm for the solution in only 1000 iterations¹⁶⁶.

¹⁶⁵ These results were presented at the 2011 EEM (Rocha, et al., 2011).

¹⁶⁶ One can get better solutions being possible more iterations (5000 instead of 1000, for example).

In multi period analysis the search space is much larger, and more iterations to get the results are required. We adopted populations of 100 particles, clearly smaller than those used by other authors, who come to use 500 or more particles.

7.3.6. ALGORITHM BLOCKS PERFORMANCE TEST

Several tests under single period analysis were performed to verify the influence of some algorithm blocks:

- repeated particles in the population; Corresponds to have a tabu list of forbidden solutions, which prevents that particles can assume the position of already existing particles in the populations or that have been previously identified as best global. This allows helping free the populations of local minimums and foster diversity in the populations (see sections 5.5.2 and 5.5.7);
- particles with zero speed, which mean that they don't move in a iteration; if it is detected that the velocity vector is zero, the particle would not move; in these cases a Lamarckian evolution is promoted; this allows helping to free the population of local minimums and foster diversity in the population;
- local search by population 3; in the case of 30 particles populations, this new population is composed of 30 clones of the best global in the early iterations, up to $6 \cdot np$ without no improvement on best global; after-words the population will be composed of clones of a particle randomly chosen among the better particles already identified.

The series of tests that were performed have included the following features:

- Series 1: repeated particles in the populations allowed; admissible particles with null speed in any iteration; no local search (population 3 inactive);
- Series 2: no repeated particles in the populations; admissible particles with null speed in any iteration; no local search (population 3 inactive);
- Series 3: no repeated particles in the populations; no particles with null speed in any iteration; no local search (population 3 inactive);
- Series 4: no repeated particles in the populations; no particles with null speed in any iteration; local search (population 3 active).

For each series the test was run 20 times with a population of 30 particles and completed 1000 iterations. The last series includes all code blocks and shows prominently the best performance of all tested situations.

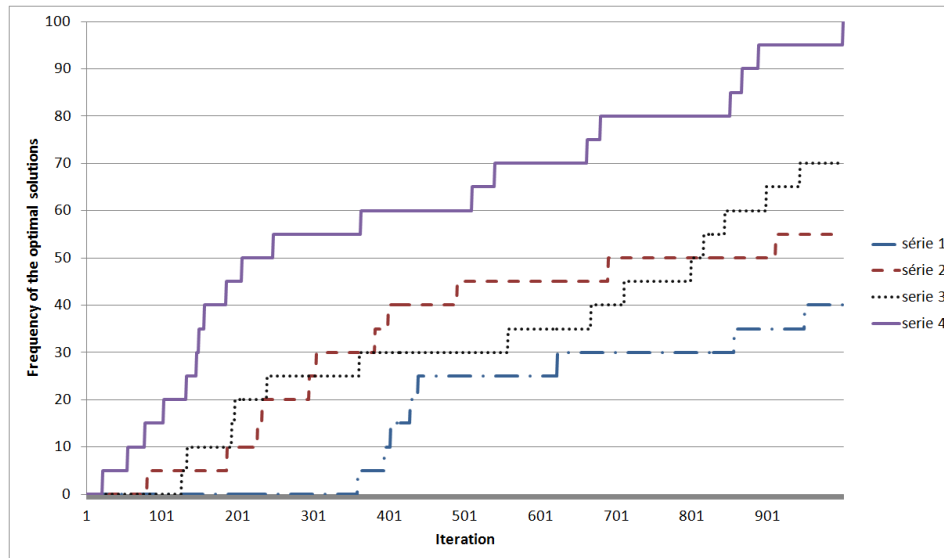


FIGURE 7-14 DEPSO ALGORITHM BLOCKS PERFORMANCE TEST

Figure 7.14 presents the results that were obtained with these tests. These results clearly show the relevance of the local search in the performance of the algorithm. In each run, population 3 contributes in average with 4,4 best global (standard deviation of 1,88), while populations 1 and 2 contribute in average with 11,1 best global (standard deviation of 3,61). It should be underlined that the contribution of population 3 for the best global identification is not felt only when a best global is identified, but also when this population contributes for the improvement of the best population.

This test was run under a single period analysis.

7.3.7. PARTICLES OUT OF THE SEARCH SPACE

When a particle leaves the search space it can be either penalised or repaired. Our option was to repair these particles, as explained when addressing the movement control in Section 5.5.6.

On average, only 8% of the generated bits in populations 1 and 2 required reparation. On population 3 the repaired bits are only 6% of the generated bits. This is a direct consequence of the speed control carried out.

The fact that most of the generated particles are valid ensures that the particles move in a normal way in the search space, leaving it only in a very small percentage of cases. This helps to accelerate the process of identifying the best solution.

This test was run under a single period analysis.

7.3.8. LAMARCKIAN EVOLUTION

The Lamarckian evolution happens in three different situations.

The first case is that of particles of population 3, whose mutation is only done through Lamarckian evolution. The other cases are in particles of populations 1 and 2 with null speed vector and in particles that are mutated to a position either of a previous best global or of any particle of the existing best population.

We have noticed that only about 10% of the particles of populations 1 and 2 are subject to this kind of evolution.

This test was run under a single period analysis.

7.3.9. NUMBER OF OPF RUNS AND EVALUATION OF ACCELERATION

When analysing the number of OPF runs and the evaluation of acceleration of the algorithm, one should remember that:

- Any particle has to be evaluated for $PNS(n)$ and $PNS(n-1)$ in all periods;
- When assessing the particle by a DC OPF, it is enough that in one period $PNS(n) \neq 0$ for the particle to be penalized; that is, it may be the case of the particle doesn't be fully evaluated if $PNS(n) \neq 0$ occurs in the first periods;
- If in $PNS(n-1)$ evaluation process we find not null values for PNS for a given situation, the particle is immediately penalized and the evaluation process is finished.

This approach results in important time saving, as can be confirmed by the results. We performed 60 runs, each of them with 1000 iterations, under a single period analysis. Each run corresponds to an analysis of 1000 iterations * 30 particles * 3 populations, that is 90.000 particles. Due to the evaluation diagrams adopted in Section 6.6.6, only about 27.000 particles in average are evaluated through OPF, which results in significant time savings.

It should be underlined that for the PNS (n-1) evaluation one has to do the assessment of (n-1) configurations for each solution. We analyse this in a multi period test, with a population of 30 particles and 1000 iterations. From the total generated particles only 19% were evaluated using OPF and only 5,7% were fully assessed for PNS(n-1) evaluation.

7.3.10. SEEDING

As mentioned in Section 3.4.2, better results are achieved when initial good quality populations are defined through Intelligent Initialization (Rezende, et al., 2010). The seeding was tested in the four period analyses. Two runs with 30 particles were selected to be included in this text, one run with seeding¹⁶⁷ and another run without seeding. Both runs converged to similar fitness values¹⁶⁸ (3.491 M€ (without seeding); 3495 M€ (with seeding)).

As one can see in the Figure 7.15, in the early iterations the convergence is faster when there is seeding. At the end of the run, seeding has no relevant impact in terms of iterations. As shown, the run without seeding needed less iterations¹⁶⁹ to reach the best solution. A big difference may be noticed on the convergence rate to the last step (about 3.900 M€) before the best fitness is identified: while with the seeding effect one reaches a fitness of 3.912 M€ at iteration 121, without this effect, a fitness of 3.929 M€ was only reached at iteration 370.

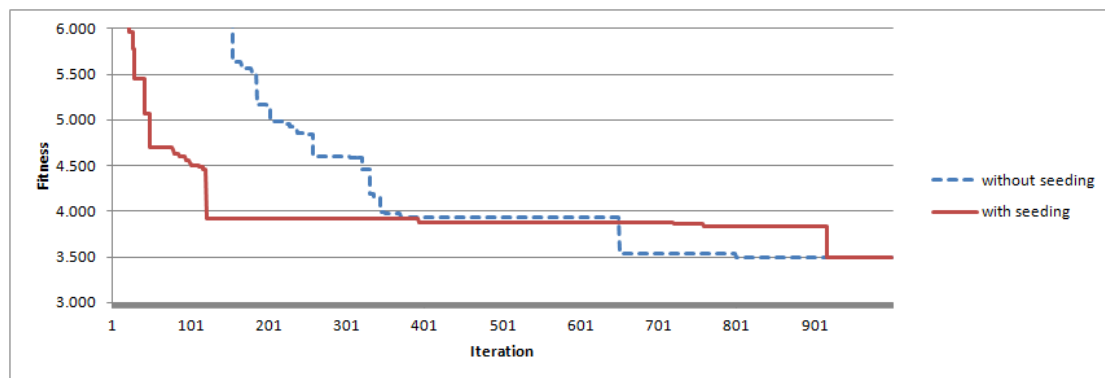


FIGURE 7-15 SEEDING PROCEDURE INFLUENCE IN THE ALGORITHM CONVERGENCE

One may say that the main advantage is the total run time. The run time was 16% lower when the seeding procedure is included (103.258 sec against 87.107 sec, in both cases for 1000 iterations).

¹⁶⁷ The particle has the following configuration: [4,3,2,1,4,3,2,0,4,3,1,3,1,2,3,1,1,1,3,4,0,2,3,4,2,2,5,4]. This particle corresponds to an investment cost of 8.728 M€.

¹⁶⁸ These runs with populations of 30 particles have fitness (3.491 M€ (without seeding) and 3495 M€ (with seeding)) slightly higher than the ones obtained with populations of 100 particles (3.345,6 M€).

¹⁶⁹ Take into account that needs less iteration, but more time.

7.4. TEST 3: IEEE RTS 24 NODES NETWORK (FINAL DETERMINISTIC LOAD TESTS)

7.4.1. TEST CONDITIONS

These final deterministic load tests were run on the same IEEE RTS network, as described in Section 7.3.1. They were performed using the FEUP server.

Only multi-period tests have been performed, under the following conditions:

- The seeding procedure was considered;
- Losses were not considered;
- A maximum limit of 6 projects per period was imposed;
- Reliability was evaluated with PNS (n) and PNS (n-1);
- The stopping criteria adopted were:
 - Maximum number of iterations (5000 iterations);
 - Maximum number of iterations without Best Global improvement ($5000/5 = 1000$ iterations).

As mentioned on Section 7.3.1 for the multi-period tests, also in these cases the same two new generators were added to the original network: one in bus 4 (300 MW, similar to the generators in bus 7), and another in bus 19 (591 MW, similar to the generator in bus 13).

7.4.2. EXPANSION PLANNING

The list of possible projects on the expansion planning is shown in Table 7.13. The search space has $6^{28} = 6,1 \times 10^{21}$ positions, for a four period analysis.

7.4.3. MULTI PERIOD TEST RESULTS COMPARED WITH SINGLE PERIOD TEST RESULTS

Several tests with populations of 30, 100 and 150 particles were performed to identify the best solutions in multi-period analysis.

As can be seen in Figure 7.16, and as expected, the performance of the run with 150 particles is much more interesting than those with 30 and 100 particles, not only

because fewer iterations are needed to identify a solution, but also because the solution is slightly better (less expensive).

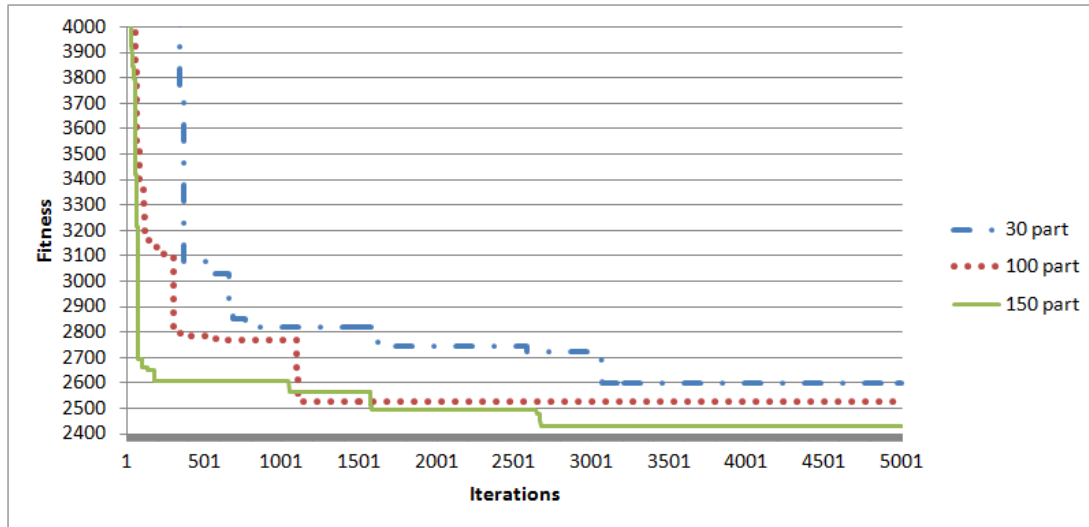


FIGURE 7-16 DETERMINISTIC MULTI-PERIOD TEST FITNESS EVOLUTION WITH 30, 100 AND 150 PARTICLES

On Table 7.16 one can see that the solutions obtained are identical (they identify mostly the same projects). In particular the first and second solutions differ only in the project 2/6, which in the run with 100 particles is postponed from the second period to the fourth period.

TABLE 7-17 DETERMINISTIC EXPANSION PLANS FOR SINGLE AND MULTI-PERIOD

solutions	investment	Expansion Projects											
		3/24	10/12	1/5	1/5	2/6	6/10	7/8	7/8	11/13	11/13	16/17	11/13
		500	500	220	220	500	160	160	160	660	660	360	660
4 periods													
030 part	2.599,16	0	1	1	5	2	1	1	2	1	3	5	5
100 part	2.527,44	0	1	1	5	4	1	1	2	1	3	0	0
150 part	2.427,72	4	1	1	5	0	1	1	2	0	0	4	1
1 period													
	1.280,00	0	0	1	1	0	1	1	1	0	0	1	0

Among the single period and multi-period solutions one finds significant differences (please see Table 7.17):

- The Project 16/17, identified in the single period solution, is only selected in the fourth period in one of the multi-period solutions;
- One of the projects 7/8 is delayed from period 1 to period 2;
- Several projects not elected in the single period solution are included in the multi-period solution: 3/24¹⁷⁰, 10/12, 2/6 and 11/13.

¹⁷⁰ The projects 3/24 and 10/12 are transformers.

One may conclude that a multi-period analysis is not necessarily a combination of static schedules, and that not always the elected projects for a single period solution are considered in dynamic multi-period analysis.

7.4.4. POPULATION DIVERSITY

Diversity is fundamental so that the model can identify, effectively and efficiently, the solutions.

At the end of a test one gets a significant volume of solutions, as many as the particles which integrate the best population. The planning can be based, not only on the best global, but also in any other particle that the planner's decision criteria may identify.

One way to verify the diversity is to examine the fitness values (in this case, investment) corresponding to the particles that integrate the Best Population at the end of the test. Figure 7.17 shows the fitness values of 100 particles of a Best Population at the end of 5000 iterations, in a multi-period analysis¹⁷¹.

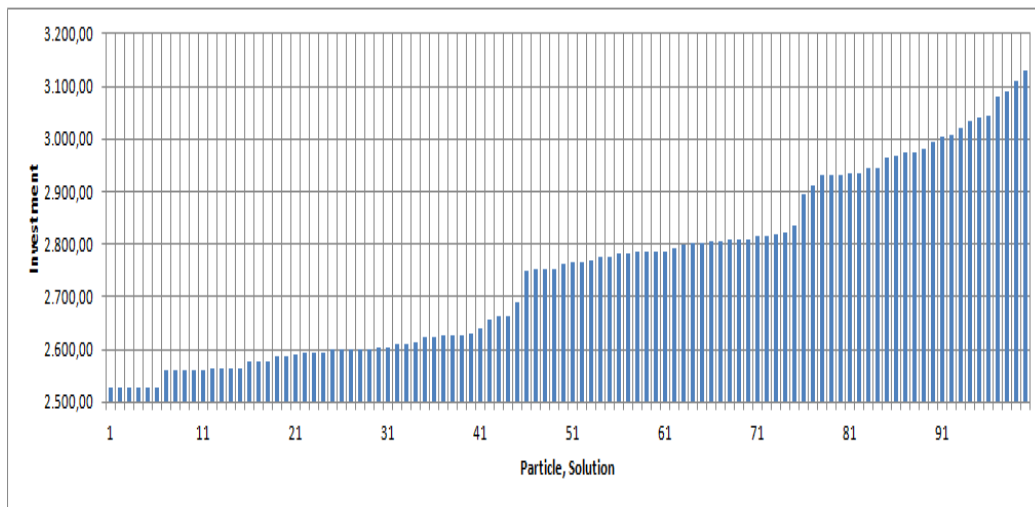


FIGURE 7-17 BEST POPULATION PARTICLES FITNESS

The particles are all different, although some may have the same fitness. This happens as the project list may have several lines in the same corridor. Some solutions may select different lines in the same corridor. In these cases the particles are different, but electrically they have the same frame and the same fitness. This may be confirmed by the analysis of Table 7.18.

¹⁷¹ We will proceed on the tests with the 100 particles population, as the better fitness with the 150 particles population was found later on the research. This option does not condition the results or the conclusions.

7. Case Studies

TABLE 7-18 BEST POPULATION PARTICLES FITNESS, PROJECTS AND PNS(N-1) CONSIDERING UNCERTAINTIES

Solution	Investment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	n° proj	PNS(n-1)				
		3/24	9/11	10/11	10/12	1/5	1/5	2/4	2/4	2/6	2/6	6/10	7/8	7/8	8/10	11/13	11/13	14/16	15/21	15/24	16/17	16/17	16/19	17/18	20/23	11/13	12/13	11/14	14/16		Load				
		500	500	500	500	220	220	330	330	500	500	160	160	160	430	660	660	540	680	720	360	360	320	200	300	660	660	580	540		-5,0%	-2,5%	0,0%	2,5%	5,0%
1	2527	0	0	0	1	5	1	0	5	4	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
2	2527	0	0	0	1	1	0	0	5	4	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
3	2527	0	0	0	1	5	1	0	5	4	0	1	2	1	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
4	2527	0	0	0	1	5	1	0	5	4	0	1	1	2	0	1	5	5	0	5	5	0	5	5	5	0	3	0	0	8	0	0	0	0	0
5	2527	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	5	5	0	5	5	0	5	5	5	1	3	0	0	8	0	0	0	0	0
6	2527	0	0	0	1	5	1	0	5	4	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	5	5	0	0	8	0	0	0	0	0
7	2562	0	0	0	1	5	1	0	5	3	0	1	2	1	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
8	2562	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	5	5	0	5	5	0	5	5	0	1	3	0	0	8	0	0	0	0	0
9	2562	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	5	5	0	5	5	0	5	5	5	1	3	0	0	8	0	0	0	0	0
10	2562	0	0	0	1	5	1	0	5	3	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
11	2562	0	0	0	1	1	0	0	5	3	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
12	2565	0	0	0	1	5	1	0	5	4	0	1	1	3	0	1	5	5	0	5	5	0	5	5	5	0	0	2	0	8	0	0	0	0	0
13	2565	0	0	0	1	1	0	0	5	4	0	1	1	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
14	2565	0	0	0	1	5	1	0	5	4	0	1	3	1	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
15	2565	0	0	0	1	5	1	0	5	4	0	1	1	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
16	2577	0	0	0	1	5	1	0	5	4	0	1	1	2	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
17	2577	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	5	5	0	5	5	0	5	5	0	1	2	0	0	8	0	0	0	0	0
18	2577	0	0	0	1	5	1	0	5	4	0	1	2	1	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
19	2587	0	0	0	1	5	1	0	5	2	0	1	1	3	0	1	5	5	0	5	5	0	5	5	0	0	3	0	0	8	0	0	0	0	0
20	2587	0	0	0	1	5	1	0	5	2	0	1	1	3	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
21	2592	0	0	0	1	5	1	0	5	5	0	1	1	2	0	0	3	3	0	5	5	0	5	5	5	1	5	0	0	8	0	0	0	0	0
22	2592	0	0	0	1	5	1	0	5	5	0	1	1	3	0	0	2	4	0	5	5	0	5	5	5	1	5	0	0	8	0	0	0	0	0
23	2593	0	0	0	1	2	1	0	4	0	0	1	2	1	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
24	2593	0	0	0	1	2	1	0	4	0	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
25	2599	0	0	0	1	4	1	0	4	5	0	1	3	1	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
26	2599	0	0	0	1	4	1	0	4	5	0	1	1	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
27	2599	0	0	0	1	5	1	0	5	3	0	1	1	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
28	2599	0	0	0	1	5	1	0	5	2	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
29	2599	0	0	0	1	5	1	0	5	3	0	1	3	1	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
30	2604	0	0	0	1	5	1	0	5	5	0	1	2	1	0	0	2	4	0	5	5	0	5	5	5	1	5	0	0	8	0	0	0	0	0
31	2604	0	0	0	1	5	1	0	5	5	0	1	1	2	0	0	2	4	0	5	5	0	5	5	5	1	5	0	0	8	0	0	0	0	0
32	2611	0	0	0	1	4	1	0	4	5	0	1	1	2	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
33	2611	0	0	0	1	5	1	0	5	3	0	1	2	1	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	0	0	0	0
34	2614	0	0	0	1	3	1	0	4	5	0	1	1	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
35	2625	0	0	0	1	3	0	0	5	4	0	1	2	2	0	1	1	5	0	5	5	0	5	5	5	0	5	0	0	8	28	0	0	1	0
36	2625	0	0	0	1	5	1	0	5	3	0	1	2	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	0	8	0	48	0	0	105
37	2626	0	0	0	1	3	1	0	4	5	0	1	1	2	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
38	2628	0	0	0	1	5	1	0	5	4	0	1	2	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	48	0	0	105
39	2628	0	0	0	1	5	1	0	5	4	0	1	3	2	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	48	0	0	105
40	2629	0	0	0	1	5	1	0	5	5	0	1	1	3	0	0	2	3	0	5	5	0	5	5	5	1	5	0	0	8	0	0	0	0	0
41	2640	0	0	0	1	5	1	0	5	4	0	1	2	2	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	48	0	0	105
42	2658	0	0	0	1	5	1	0	5	5	0	1	2	1	0	0	1	4	0	5	5	0	5	5	5	1	5	0	0	8	34	0	0	0	0
43	2662	0	0	0	1	5	1	0	5	3	0	1	2	3	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	8	0	48	0	0	105
44	2662	0	0	0	1	4	1	0	4	5	0	1	3	2	0	1	2	5	0	5	5	0	5	5	5	0	5	0	0	9	0	48	0	0	105
45	2691	2	0	0	1	5	1	0	5	5	0	1	1	2	0	0	4	5	0	5	5	0	5	4	5	1	5	0	0	9	0	0	0	0	0
46	2749	1	0	0	1	5	1	0	5	5	0	1	1	2	0	0	4	5	0	5	5	0	5	4	5	1	5	0	0	9	25	3	0	0	0
47	2752	1	0	0	1	3	0	0	4	0	0	1	1	0	0	0	2	5	0	5	5	0	5	5	5	1	5	0	0	8	27	33	0	0	21
48	2753	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	3	5	0	5	5	0	5	5	3	1	5	0	0	9	0	0	0	0	0
49	2753	0	0	0	1	5	1	0	5	4	0	1	2	1	0	0	3	5	0	5	5	0	5	5	3	1	5	0	0	9	0	0	0	0	0
50	2763	0	0	0	1	5	1	0	5	4	0	1	1	3	0	0	3	5	0	5	5	0	5	5	2	1	5	0	0	9	0	0	0	0	0

7. Case Studies

Solution	Investment	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	n° proj	PNS(n-1)				
		3/24	9/11	10/11	10/12	1/5	1/5	2/4	2/4	2/6	2/6	6/10	7/8	7/8	8/10	11/13	11/13	14/16	15/21	15/24	16/17	16/17	16/19	17/18	20/23	11/13	12/13	11/14	14/16		Load				
		500	500	500	500	220	220	330	330	500	500	160	160	160	430	660	660	540	680	720	360	360	320	200	300	660	660	580	540		-5,0%	-2,5%	0,0%	2,5%	5,0%
51	2766	0	0	0	1	5	1	0	5	3	0	1	2	1	0	0	3	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
52	2766	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	3	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
53	2770	0	0	0	1	5	1	0	5	4	0	1	1	3	0	0	2	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
54	2775	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	3	5	0	5	5	0	5	5	2	1	5	0	0	9	0	0	0	0	0
55	2775	0	0	0	1	5	1	0	5	4	0	1	2	1	0	0	3	5	0	5	5	0	5	5	2	1	5	0	0	9	0	0	0	0	0
56	2782	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	2	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
57	2782	0	0	0	1	5	1	0	5	4	0	1	2	1	0	0	2	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
58	2785	1	0	0	1	5	0	0	5	4	0	1	1	2	0	0	3	5	0	5	5	0	5	5	5	1	5	0	0	8	27	33	0	0	21
59	2785	1	0	0	1	5	0	0	5	4	0	1	2	1	0	0	3	5	0	5	5	0	5	5	5	1	5	0	0	8	27	33	0	0	21
60	2787	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	3	5	0	5	5	0	5	5	3	1	5	0	0	9	0	0	0	0	0
61	2787	0	0	0	1	5	1	0	5	3	0	1	2	1	0	0	3	5	0	5	5	0	5	5	3	1	5	0	0	9	0	0	0	0	0
62	2793	0	0	0	1	5	1	0	5	3	0	1	1	4	0	0	2	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
63	2798	0	0	0	1	5	1	0	5	3	0	1	1	3	0	0	3	5	0	5	5	0	5	5	2	1	5	0	0	9	0	0	0	0	0
64	2802	0	0	0	1	5	1	0	5	4	0	1	2	1	0	0	2	5	0	5	5	0	5	5	3	1	5	0	0	9	0	0	0	0	0
65	2802	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	2	5	0	5	5	0	5	5	3	1	5	0	0	9	0	0	0	0	0
66	2804	0	0	0	1	5	1	0	5	2	0	1	1	2	0	0	3	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
67	2804	0	0	0	1	5	1	0	5	3	0	1	1	3	0	0	2	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
68	2808	1	0	0	1	5	1	0	5	5	0	1	1	2	0	0	3	5	0	5	5	0	5	3	5	1	5	0	0	9	25	3	0	0	0
69	2809	0	0	0	1	5	1	0	5	2	0	1	1	3	0	1	5	5	0	5	5	0	5	5	0	0	1	0	0	8	1	0	0	1	7
70	2810	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	3	5	0	5	5	0	5	5	2	1	5	0	0	9	0	0	0	0	0
71	2816	0	0	0	1	5	1	0	5	4	0	1	2	2	0	0	3	5	0	5	5	0	5	5	3	1	5	0	0	9	0	48	0	0	105
72	2816	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	2	5	0	5	5	0	5	5	4	1	5	0	0	9	0	0	0	0	0
73	2820	1	0	0	1	5	0	0	5	3	0	1	1	2	0	0	3	5	0	5	5	0	5	5	5	1	5	0	0	8	27	33	0	0	21
74	2823	1	0	0	1	3	1	0	5	5	0	1	1	2	0	0	3	5	0	5	5	0	5	5	5	1	5	0	0	9	25	3	0	0	0
75	2835	1	0	0	1	5	0	0	5	4	0	1	1	2	0	0	2	5	0	5	5	0	5	5	5	1	5	0	0	8	27	33	0	0	21
76	2895	1	0	0	1	5	0	0	5	5	0	1	1	2	0	0	3	5	0	5	4	0	5	5	4	1	5	0	0	9	27	33	0	0	21
77	2912	0	0	0	1	5	1	0	5	4	0	1	2	1	0	0	3	5	0	5	5	0	5	4	2	1	5	0	0	10	0	0	0	0	0
78	2930	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	3	4	0	5	5	0	5	5	5	1	5	0	0	9	0	0	0	0	0
79	2930	0	0	0	1	5	1	0	5	3	0	1	2	1	0	1	3	4	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
80	2930	0	0	0	1	5	1	0	5	3	0	1	1	2	0	1	3	4	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
81	2933	0	0	0	1	5	1	0	5	4	0	1	1	2	0	0	3	3	0	5	5	0	5	5	5	1	5	0	0	9	0	0	0	0	0
82	2933	0	0	0	1	5	1	0	5	4	0	1	1	2	0	1	3	3	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
83	2946	0	0	0	1	5	1	0	5	4	0	1	1	2	0	1	2	4	0	5	5	0	5	5	5	0	5	0	0	9	0	0	0	0	0
84	2946	0	0	0	1	5	1	0	5	3	0	1	1	2	0	0	3	5	0	5	5	0	5	4	2	1	5	0	0	10	0	0	0	0	0
85	2963	0	0	0	1	4	1	0	3	4	0	1	1	3	0	0	2	5	0	5	5	0	5	5	5	1	5	0	0	10	0	0	0	0	0
86	2968	0	0	0	1	3	1	0	4	4	0	1	1	2	0	0	2	5	0	5	5	0	5	5	5	1	5	0	0	10	0	0	0	0	0
87	2974	0	0	0	1	4	1	0	5	4	0	1	1	2	0	1	4	5	0	5	5	0	5	4	4	0	5	0	0	11	0	0	0	0	0
88	2975	0	0	0	1	4	1	0	3	4	0	1	1	2	0	0	2	5	0	5	5	0	5	5	5	1	5	0	0	10	0	0	0	0	0
89	2980	0	0	0	1	4	1	0	4	5	0	1	1	2	0	0	2	4	0	5	5	0	5	5	5	1	5	0	0	10	0	0	0	0	0
90	2995	0	0	0	1	5	1	0	4	4	0	1	1	3	0	1	2	5	0	5	5	0	5	5	4	0	5	0	0	10	0	0	0	0	0
91	3003	0	0	0	1	3	1	0	5	4	0	1	1	2	0	1	4	5	0	5	5	0	5	3	4	0	5	0	0	11	0	0	0	0	0
92	3007	0	0	0	1	5	1	0	4	4	0	1	1	2	0	1	2	5	0	5	5	0	5	5	4	0	5	0	0	10	0	0	0	0	0
93	3019	0	0	0	1	4	1	0	5	4	0	1	1	2	0	1	3	5	0	5	5	0	5	4	4	0	5	0	0	11	0	0	0	0	0
94	3034	0	0	0	1	3	1	0	5	4	0	1	1	2	0	1	3	5	0	5	5	0	5	4	4	0	5	0	0	11	0	0	0	0	0
95	3040	0	0	0	1	4	1	0	5	4	0	1	1	2	0	1	3	5	0	5	5	0	5	4	3	0	5	0	0	11	0	0	0	0	0
96	3045	0	0	0	1	5	1	0	5	2	0	1	1	2	0	1	3	5	0	5	5	0	5	5	5	0	5	0	2	9	0	0	0	0	0
97	3079	0	0	0	1	4	1	0	5	4	2	1	1	3	0	0	3	5	0	5	5	0	5	5	5	1	5	0	0	10	0	0	0	0	0
98	3090	1	0	0	1	5	1	0	5	4	0	1	1	2	0	0	4	5	0	5	5	0	5	4	5	1	5	0	0	10	25	3	0	0	0
99	3111	1	0	0	1	5	3	0	5	4	0	1	1	2	0	0	4	5	0	5	5	0	5	5	4	1	5	0	0	10	27	33	0	0	21
100	3131	0	0	0	1	4	1	0	3	4	0	1	1	2	0	0	3	5	0	5	5	0	5	5	4	1	5	0	0	11	0	0	0	0	0

7.5. TEST 4: IEEE RTS 24 NODES NETWORK (MULTI PERIOD TEP CONSIDERING UNCERTAINTIES)

For this test we adopt the multi period TEP model presented in section 6.7.2, in particular the expression (6.15) and the diagrams on Figures 6.9 and 6.10. As input for this model we adopt the best population of 100 particles that resulted from the tests presented in Section 7.4, and displayed in table 7.18.

The uncertainty in each load is modeled using a fuzzy number with a triangular membership function. Each particle is tested in five points of the membership function, as represented in Table 7.19:

TABLE 7-19 FUZZY LOAD DEFINITION

	Load	Membership
1	95,0 %	0,0
2	97,5 %	0,5
3	100,0 %	1,0
4	102,5 %	0,5
5	105,0 %	0,0

It should be noted that point no 3 corresponds to the deterministic solution, already tested in the previous section. All particles were tested by assessing the PNS (n-1) with the fuzzy load, and the results are summarized in Table 7.18.

From the results we observe the following:

- The solutions which have identified the inclusion of a transformer 3/24 have often poor quality of service in the presence of load uncertainties;
- Some solutions that have identified the exclusion of certain lines (such as 1/5 and 11/13, which interconnect generating buses with relevant loads) also show poor quality of service, being very sensitive to load variations;
- Only 19% of the 100 solutions that integrate the population failed the load uncertainty test;

- The 34 particles with better fitness showed no problem in accommodating load uncertainties;
- There is no correlation between the number of projects and network behavior, as it was observed that solutions with fewer projects and better fitness have better performance than solutions with more projects and worst fitness (higher investment).

7.6. CONCLUSIONS

We may summarize the following conclusions from the tests:

- About DEPSO:
 - The model was tuned when testing DEPSO with Garver network; its performance is remarkable, with an excellent convergence to nearly optimal solutions;
 - In comparison with other heuristics, especially with classic EPSO, the convergence took fewer iterations and a great ability to get rid of local minima was observed; the model needs smaller populations to achieve the same results, which also contributes to faster run time;
 - The diversity in the population is guaranteed, which results in a variety of solutions, among which the investigator can choose the one that best suits his needs;
- About dynamic TEP modelled with DEPSO:
 - The test with Garver network allowed model tuning; it was found that its performance is superior to static models based on classic EPSO;
 - The proposed model has worked well with IEEE RTS network, which is larger than those normally used for dynamic models testing;
 - When losses are included in the constraints, and solutions that exceed a predetermined loss value are penalized, one is forcing the investment, with the inclusion of more projects on the solutions; this situation leads to more robust networks, with better quality of service;
 - The inclusion of criteria for evaluating the quality of service, especially PNS (n) and PNS (n-1), although quite demanding in terms of run time, does not condition the convergence of the model; one can state with confidence that the solutions obtained this way are more robust;
 - The network analysis with load uncertainty helps on identifying the most critical branches, those which reveal a greater influence on PNS (n-1); this knowledge may be useful on the adjustments in the dynamic TEP project list.

It is possible to conclude that the models presented are robust and reliable:

- DEPSO can be applied to other complex combinatorial problems;
- Dynamic TEP based on DEPSO can be applied easily to real networks on a transnational scale, obviously considering the availability of an appropriate server.

8. CONCLUSIONS, CONTRIBUTIONS AND FUTURE WORK

8.1. CONCLUSIONS

This thesis presents a dynamic model for transmission expansion planning, which is based on an agent based meta-heuristics, considering uncertainty in loads. We have called this heuristic Discrete Evolutionary Particle Swarm Optimization (DEPSO).

We began by presenting overviews on the recent evolution of power generation and transmission systems, on transmission expansion planning, and on evolutionary computation and particle swarm optimization. These overviews were made not with the objective of detailing specific behavior in markets or features on models, but to identify the relevant constraints and cost (to be included on the assessment of the solutions) and the advantages or drawbacks of the existing models and heuristics (so that the better approach could be identified).

While maintaining the classic EPSO structure, changes to the algorithm were made in DEPSO development, to make it suitable for the treatment of integer discrete combinatorial problems. In addition some other features were included, as mutation based in operators with chaotic behaviors, Lamarckian evolution, and a dynamic local vs global search, based on a third population. Finally, a Tabu List integrating the best particles ever identified was used to ensure diversity within the best population.

The dynamic TEP model took advantage of the DEPSO concept simplicity, and was organized in order to take full advantage of its structure, most in particular from the evaluation process. The evaluation consists of several steps, with the OPF's those who take longer. In order to minimize the run time, these were included in the final evaluation step, which is not performed by most of the particles. The dynamic TEP includes a first phase, which is multiyear and deterministic, that identifies a population of good solutions. It is followed by a complementary phase that includes the load uncertainties and the final assessment of the deterministic solutions.

The model was applied on the dynamic analysis of the Garver and IEEE RTS networks.

One may conclude that a multi-period analysis is not necessarily a combination of static schedules, and that not always the elected projects for a single period solution are considered in dynamic multi-period analysis.

Although DEPSO is an optimization model, its output is always a population of solutions. This approach is suitable when dealing with the dynamic TEP as a decision-making problem, as defended by Miranda. The researcher gets a set of solutions among which one can choose according to additional criteria to those included in the modeling.

Based on the research carried out and on the test results, we are now able to answer the questions formulated at the beginning of this thesis.

I. How to identify the projects to strengthen a network, taking into account the existing knowledge?

The list of possible projects is defined by the planner, either based on his experience and available data, or based on automatic systems.

II. How to bring the list of works sufficiently robust, including the investments that are actually the most relevant to the objectives to be achieved?

One possibility is adopting automatic systems, as those admitting that all branches are likely to be elected to the expansion, up to a certain number of lines per corridor or transformers in parallel. As mentioned in Section 6.4.4, it makes no sense to consider all possible links, since that would result in a more complex problem that would condition the performance of the algorithm. Even though this option can provide the correct solution in the static approach without resulting in a relevant loss of performance of the algorithm, in the case of dynamic approaches, it would lead the problem to reach such a magnitude as to be practically unsolvable. In addition, the consideration of a comprehensive list of expansion branches is not likely to be useful, as there are potential links that are known in advance not to contribute to the improvement of network performance and other connections are not feasible due to constraints the planner knows in advance.

An alternative is that the list of possible projects is developed by the planner, based on his experience and available data on the network. Of course that if the planner does not prepare a "good list" he will certainly condition the solution that can be obtained. It was already mentioned in Section 6.4.4 that given the fact that only listed projects may be included in the solution one has to find a compromise between the projects to be considered, the dimension of the problem and the feasibility of the model. As TEP solutions are usually tuned over a process that includes several runs of the model, if the planner finds that some projects are systematically selected, he should consider adding some more projects in the most saturated areas in order to relieve overload branches and improve the quality of service, and repeat the study.

III. How to identify the most appropriate timing for the projects?

Investment projects scheduling, such as of those associated with the expansion of transmission networks, is a complex task, subject to several constraints and economic evaluation criteria.

The number of possible combinations among projects and periods is so big that the most appropriate way to identify the most appropriate timing for the projects involves the use of meta-heuristics, enabling the combination of computing capacity with the experience of the planner. Otherwise, and although its formulation could be possible, the problem would take such dimension that it would computationally be impossible to solve.

The dynamic model of TEP we propose is based on DEPSO, a discrete evolutionary particle swarm heuristic supported by chaotic mutation, and allows the scheduling of projects in an efficient and accurate way.

The model structure allows the accommodation of the most varied constraints, including technical (inherent to physical aspects of the network), financial (such as the limitations on technical, human or financial resources), and constraints inherent to the quality of service and reliability (measured by PNS (n), PNS (n-1) and, when necessary, PNS (n-2), for instance under the form of a restricted list of n-2 contingencies). On the other hand, the model also considers the different terms which may constitute themselves as the basis for the fitness assessment, and where one can consider the investment and operation costs, including the cost of network losses. Terms relating to the environmental burden can easily be associated, both in terms of investment and rent.

When tested in a 24 bus network (ten with generation and seventeen with load, and two voltage levels) in a four years horizon, the model showed an excellent efficiency and repeatability.

IV. How to deal with uncertainties?

We had used fuzzy numbers to model the uncertainty on loads, in a very simple but appropriate way. This approach is also suitable for modeling and allows robust results. In addition to the loads, fuzzy numbers can be applied to all items that may be affected by uncertainties, such as the generation and market prices.

To sum up, in this thesis it was proved that DEPSO, combining EPSO with specific other techniques¹⁷², can be used as a reliable and efficient technique for applications in combinatorial complex problems, as for scheduling projects in dynamic transmission expansion planning.

¹⁷² Fuzzy numbers, chaos, Lamarckian evolution, tabu lists and local vs global search techniques.

8.2. CONTRIBUTIONS

The proposed dynamic TEP model based on DEPSO is a contribution for the application of EPSO to complex combinatorial problems.

DEPSO, as a new approach for evolutionary particle swarm optimization, bring up some innovations, such as:

- An integer and discrete approach of evolutionary particle swarm optimization, that does not require settings adjustment depending on any particular application;
- The combination of evolutionary particle swarm optimization with special features:
 - Chaos concepts on the mutation;
 - Lamarckian evolution, which complement the Darwinist evolution;
 - Tabu list to avoid having repeated particles on the best population;
 - Chromosome repair, on those particles either leaving the search space or with null speed;
 - A third population adopted, either for local search, or for wider search, on a dynamic way depending on the convergence evolution.

The contributions of our research on the dynamic TEP modelization with DEPSO may be summarized as follows:

- Multiyear approach; the model is a true dynamic TEP approach; the whole horizon is addressed in a holistic way and couplings among the periods are adequately modeled and treated;
- Uncertainties treatment; the model addresses the volatility of load and allows to build robust plans in the sense that they are able to accommodate these load uncertainties;
- Reliability; this model considers as an indicator to measure the quality of the service inherent to the investment plan the Power Not Supplied (PNS); PNS(n) and PNS(n-1) are evaluated for all eligible potential solutions along the planning horizon;

- The consideration of constraints as:
 - Physical constraints, as the capacity of the generators and of the available branches, that are taken into consideration on Power Flows;
 - Financial constraints associated to limitations on the resources the company may allocate to the projects on each period or during the entire horizon; and the
 - Quality of service constraints, expressed by PNS in n and in $n-1$ regimes;

The model was designed to be appropriate for use with real networks. It was tested on more complex networks than those that are commonly used in dynamic models testing.

By design, the model is suitable for parallel programming, which may allow an acceleration of assessments and, consequently, facilitate its application to real networks.

Most of the limitations outlined in Section 3.8 for existing models were overcome in our model.

8.3. FUTURE WORK

We hope this thesis to be an inspiration for other researchers. Here are some suggestions for future work:

- DEPSO:
 - Further assessment of DEPSO behavior, allowing eventually performance improvement by changing some of the parameters mentioned in Chapter 5;
 - Further assessment of DEPSO behavior when compared with EPSO and other heuristics, such as PSO, ACO, ES and TS; (Silva, et al., 2011) can be taken as a benchmark work;
 - Develop a multi-objective DEPSO; some inspiration may be found in (Mori et al., 2010);
 - Test the use of neural networks to model network behavior and speed up solutions assessment;
 - Use parallel processing to evaluate each of the three populations.

- Dynamic TEP modeling:
 - Consider the decommissioning of lines and transformers; the entry of a new branch or transformer may involve the removal of an existing one, especially when the new item is installed in the same corridor;
 - Accommodate some congestion on the lines, this way expanding each line capacity; an alert message must be sent, since this situation could not occur in continuous mode; this solution could somehow be penalized, but could be considered interesting if some investment can be postponed;
 - Consider the introduction of new production centers during the planning horizon, seeking somehow to accommodate the evolution of the power generation system;
 - Include uncertainties in the modeling of the generation (available resources) and markets (prices and rates);
 - Apply the model to the Iberian and the European network, analyzing in particular the known constraints, including the interconnections between France and Spain, and between Italy and the rest of Europe, detailing the results in terms of investments, losses, reliability and quality of service.

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ANNEXES

ANNEX A - GARVER NETWORK

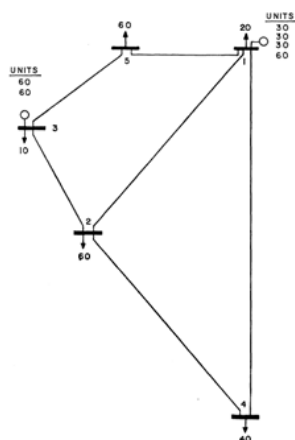


FIGURE ANNEX A-1 ORIGINAL GARVER NETWORK
(Source: (Garver, 1970))

Bus data

- 1 bus number (1 to 29997)
- 2 bus type
 - 1 = PQ bus
 - 2 = PV bus
 - 3 = reference bus
 - 4 = isolated bus
- 3 Pd, real power demand (MW)
- 4 Qd, reactive power demand (MVar)
- 5 Gs, shunt conductance (MW (demanded) at $V = 1.0$ p.u.)
- 6 Bs, shunt susceptance (MVar (injected) at $V = 1.0$ p.u.)
- 7 area number, 1-100
- 8 Vm, voltage magnitude (p.u.)
- 9 Va, voltage angle (degrees)
- 10 baseKV, base voltage (kV)
- 11 zone, loss zone (1-999)
- 12 maxVm, maximum voltage magnitude (p.u.)
- 13 minVm, minimum voltage magnitude (p.u.) bus_i bus number

TABLE ANNEX A-1 GARVER NETWORK SINGLE PERIOD BUS DATA

1	2	3	4	5	6	7	8	9	10	11	12	13
bus_i	type	Pd	Qd	Gs	Bs	area	Vm	Va	Base KV	zone	V _{max}	V _{min}
1	3	20	0	0	0	1	1	0	6	1	1.1	0.9
2	1	60	0	0	0	1	1	0	6	1	1.1	0.9
3	2	10	0	0	0	1	1	0	6	1	1.1	0.9
4	1	40	0	0	0	1	1	0	6	1	1.1	0.9
5	1	60	0	0	0	1	1	0	6	1	1.1	0.9

Generator data

- 1 bus number (-) (machine identifier, 0-9, A-Z)
- 2 Pg, real power output (MW)
- 3 Qg, reactive power output (MVA_r)
- 4 Q_{max}, maximum reactive power output (MVA_r)
- 5 Q_{min}, minimum reactive power output (MVA_r)
- 6 V_g, voltage magnitude setpoint (p.u.)
- 7 mBase, total MVA base of this machine, defaults to base MVA
- 8 status, > 0 - machine in service
 ≤ 0 - machine out of service
- 9 P_{max}, maximum real power output (MW)
- 10 P_{min}, minimum real power output (MW)

TABLE ANNEX A-2 GARVER NETWORK SINGLE PERIOD GENERATOR DATA

#	1 bus	2 Pg	3 Qg	4 Q _{max}	5 Q _{min}	6 V _g	7 M Base	8 Status	9 P _{max}	10 P _{min}
1	1	30	0	0	0	1	100	1	30	0
2	1	30	0	0	0	1	100	1	30	0
3	1	30	0	0	0	1	100	1	60	0
4	1	60	0	0	0	1	100	1	60	0
5	3	60	0	0	0	1	100	1	60	0
6	3	60	0	0	0	1	100	1	60	0

Generator cost data

- 1 model, 1 - piecewise linear, 2 - polynomial
- 2 startup, startup cost in US dollars
- 3 shutdown, shutdown cost in US dollars
- 4 n, number of cost coefficients to follow for polynomial cost function, or number of data points for piecewise linear
- 5 and following, cost data defining total cost function
 - For polynomial cost: c₂, c₁, c₀
 where the polynomial is $c_0 + c_1 \cdot P + c_2 \cdot P^2$
 - For piecewise linear cost: x₀, y₀, x₁, y₁, x₂, y₂, ...
 where $x_0 < x_1 < x_2 < \dots$ and the points (x₀,y₀), (x₁,y₁),
 x₂,y₂), ... are the end- and break-points of the cost function.

TABLE ANNEX A-3 GARVER NETWORK SINGLE PERIOD GENERATOR COST DATA

#	1	2	3	4	5(c ₂)	6(c ₁)	7c(0)
1	2	0	0	3	0	5	0
2	2	0	0	3	0	5	0
3	2	0	0	3	0	5	0
4	2	0	0	3	0	8	0
5	2	0	0	3	0	8	0
6	2	0	0	3	0	8	0

Branch data

- 1 f, from bus number
- 2 t, to bus number
- 3 r, resistance (p.u.)
- 4 x, reactance (p.u.)
- 5 b, total line charging susceptance (p.u.)
- 6 rateA, MVA rating A (long term rating)
- 7 rateB, MVA rating B (short term rating)
- 8 rateC, MVA rating C (emergency rating)
- 9 ratio, transformer off nominal turns ratio (= 0 for lines)
(taps at 'from' bus, impedance at 'to' bus, i.e. ratio = V_f / V_t)
- 10 angle, transformer phase shift angle (degrees), positive => delay
(Gf, shunt conductance at from bus p.u.)
(Bf, shunt susceptance at from bus p.u.)
(Gt, shunt conductance at to bus p.u.)
(Bt, shunt susceptance at to bus p.u.)
- 11 initial branch status, 1 - in service, 0 - out of service

TABLE ANNEX A-4 GARVER NETWORK SINGLE PERIOD BRANCH DATA

1	2	3	4	5	6	7	8	9	10	11
F bus	T bus	r	x	b	Rate A	Rate B	Rate C	Ratio	Angle	Status
1	2	0.10	0.4	0	100	100	100	0	0	1
1	4	0.15	0.6	0	80	80	80	0	0	1
1	5	0.05	0.2	0	100	100	100	0	0	1
2	3	0.05	0.2	0	100	100	100	0	0	1
2	4	0.10	0.4	0	100	100	100	0	0	1
3	5	0.05	0.2	0	100	100	100	0	0	1

The results presented on the next tables were obtained running a DC OPF with no losses on the original Garver network. It was adopted the DC OPF available in the MATLAB library. It converges in 0.06 seconds and the objective function value is 1160.00 \$/hr

The bus and branch data for the DC OPF with losses are presented in Tables Annex-5 and Annex-6.

TABLE ANNEX A-5 DC OPF RESULTS: GARVER NETWORK BUS DATA, NO LOSSES

Bus		Voltage		Generation		Load		Lambda(\$/MVA-hr)	
#		Mag (pu)	Ang (deg)	P (MW)	Q (MVar)	P (MW)	Q (MVar)	P	Q
1		1	-0.000	124.99	0.00	20.00	0.00	8.00	-
2		1	-7.466	-	-	60.00	0.00	8.00	-
3		1	-3.066	65.01	0.00	10.00	0.00	8.00	-
4		1	-9.980	-	-	40.00	0.00	8.00	-
5		1	-4.971	-	-	60.00	0.00	8.00	-
Total				190.00	0.00	190.00	0.00		

TABLE ANNEX A-6 DC OPF RESULTS: GARVER NETWORK BRANCH DATA, NO LOSSES

Branch	From	To	From Bus Injection		To Bus Injection	
#	Bus	Bus	P (MW)	Q (MVar)	P (MW)	Q (MVar)
1	1	2	32.58	0.00	-32.58	0.00
2	1	4	29.03	0.00	-29.03	0.00
3	1	5	43.38	0.00	-43.38	0.00
4	2	3	-38.39	0.00	38.39	0.00
5	2	4	10.97	0.00	10.97	0.00
6	3	5	16.62	0.00	-16.62	0.00

To consider the losses on the calculation it is necessary to integrate the DC OPF in a cycle, as shown in Section 6.6.5, expressions (6.09) to (6.14).

The time it takes to run the program applied to this network is 0.14 seconds, more than the double necessary for the classical DC OPF.

The bus and generation data for the DC OPF with losses are presented in Tables Annex-7 and Annex-8.

The losses are 12.26 MW, which represents 6% of the load.

TABLE ANNEX A-7 DC OPF RESULTS: GARVER NETWORK BUS DATA, WITH LOSSES

Bus	Load + Losses
#	P (MW)
1	21.9667
2	62.9686
3	13.1004
4	41.7898
5	62.4375
Total	202.2631

TABLE ANNEX A-8 DC OPF RESULTS: GARVER NETWORK GENERATION DATA, WITH LOSSES

Generator	Bus	Load + Losses
#	#	P (MW)
1	1	30.000
2	1	30.000
3	1	60.000
4	1	7.5998
5	3	37.3316
6	3	37.3316
Total		202.2631

TABLE ANNEX A-9 GARVER NETWORK MULTI PERIOD BUS DATA

1	2	3	4	5	6	7	8	9	10	11	12	13
bus_i	type	Pd	Qd	Gs	Bs	area	Vm	Va	Base KV	zone	V _{max}	V _{min}
1	3	80	0	0	0	1	1	0	6	1	1.1	0.9
2	1	240	0	0	0	1	1	0	6	1	1.1	0.9
3	2	40	0	0	0	1	1	0	6	1	1.1	0.9
4	1	160	0	0	0	1	1	0	6	1	1.1	0.9
5	1	240	0	0	0	1	1	0	6	1	1.1	0.9
6	2	0	0	0	0	1	1	0	6	1	1.1	0.9

The power of the generators was adjusted to meet the increase on loads and its growth over the periods under analysis.

TABLE ANNEX A-10 GARVER NETWORK MULTI PERIOD GENERATOR DATA

	1	2	3	4	5	6	7	8	9	10
#	bus	Pg	Qg	Qmax	Qmin	Vg	M Base	Status	Pmax	Pmin
1	1	50	0	0	0	1	100	1	50	0
2	1	50	0	0	0	1	100	1	50	0
3	1	50	0	0	0	1	100	1	50	0
4	3	60	0	0	0	1	100	1	60	0
5	3	100	0	0	0	1	100	1	100	0
6	3	100	0	0	0	1	100	1	100	0
7	3	100	0	0	0	1	100	1	100	0
8	6	150	0	0	0	1	100	1	150	0
9	6	150	0	0	0	1	100	1	150	0
10	6	150	0	0	0	1	100	1	150	0
11	6	150	0	0	0	1	100	1	150	0
12	2	500	0	0	0	1	100	1	500	0
13	4	500	0	0	0	1	100	1	500	0
14	5	500	0	0	0	1	100	1	500	0
15	1	500	0	0	0	1	100	1	500	0
16	3	500	0	0	0	1	100	1	500	0
17	6	500	0	0	0	1	100	1	500	0

TABLE ANNEX A-11 GARVER NETWORK MULTI PERIOD GENERATOR COST DATA

#	1	2	3	4	5(c2)	6(c1)	7c(0)
1	2	0	0	3	0	5	0
2	2	0	0	3	0	5	0
3	2	0	0	3	0	5	0
4	2	0	0	3	0	5	0
5	2	0	0	3	0	8	0
6	2	0	0	3	0	8	0
7	2	0	0	3	0	8	0
8	2	0	0	3	0	5	0
9	2	0	0	3	0	5	0
10	2	0	0	3	0	8	0
11	2	0	0	3	0	8	0
12	2	0	0	3	0	100	0
13	2	0	0	3	0	100	0
14	2	0	0	3	0	100	0
15	2	0	0	3	0	100	0
16	2	0	0	3	0	100	0
17	2	0	0	3	0	100	0

TABLE ANNEX A-12 GARVER NETWORK MULTI PERIOD BRANCH DATA

1 F bus	2 T bus	3 r	4 x	5 b	6 Rate A	7 Rate B	8 Rate C	9 Ratio	10 Angle	11 Status
1	2	0.1000	0.4	0	100	100	100	0	0	1
1	4	0.1500	0.6	0	80	80	80	0	0	1
1	5	0.0500	0.2	0	100	100	100	0	0	1
2	3	0.0500	0.2	0	100	100	100	0	0	1
2	4	0.1000	0.4	0	100	100	100	0	0	1
3	5	0.0500	0.2	0	100	100	100	0	0	1
2	6	0.0800	0.30	0	100	100	100	0	0	0
2	6	0.0800	0.30	0	100	100	100	0	0	0
2	6	0.0800	0.30	0	100	100	100	0	0	0
2	4	0.1000	0.30	0	100	100	100	0	0	0
5	6	0.1476	0.61	0	78	78	78	0	0	0
3	5	0.0500	0.20	0	100	100	100	0	0	0
3	5	0.0500	0.20	0	100	100	100	0	0	0
3	5	0.0500	0.20	0	100	100	100	0	0	0
4	6	0.0800	0.30	0	100	100	100	0	0	0
4	6	0.0800	0.30	0	100	100	100	0	0	0
4	6	0.0800	0.30	0	100	100	100	0	0	0
4	6	0.0800	0.30	0	100	100	100	0	0	0
4	6	0.0800	0.30	0	100	100	100	0	0	0
1	4	0.1500	0.60	0	80	80	80	0	0	0
1	5	0.0500	0.20	0	100	100	100	0	0	0
1	2	0.1000	0.40	0	100	100	100	0	0	0
2	3	0.0500	0.20	0	100	100	100	0	0	0

TABLE ANNEX A-13 LINE DATA FOR THE GARVER NETWORK EXPANSION PROBLEM

Br no	From bus	To bus	Resist. (pu)	React. (pu)	Cap. (MW)	Cost (10 ⁶ \$)
1	2	6	0,0800	0,0300	100	30
2	2	6	0,0800	0,0300	100	30
3	2	6	0,0800	0,0300	100	30
4	2	4	0,1000	0,4000	100	40
5	5	6	0,1476	0,6100	78	61
6	3	5	0,0500	0,2000	100	20
7	3	5	0,0500	0,2000	100	20
8	3	5	0,0500	0,2000	100	20
9	4	6	0,0800	0,3000	100	30
10	4	6	0,0800	0,3000	100	30
11	4	6	0,0800	0,3000	100	30
12	4	6	0,0800	0,3000	100	30
13	4	6	0,0800	0,3000	100	30
14	1	4	0,1500	0,6000	80	60
15	1	5	0,0500	0,2000	100	20
16	1	2	0,1000	0,4000	100	40
17	2	3	0,0500	0,2000	100	20

ANNEX B - IEEE RTS NETWORK

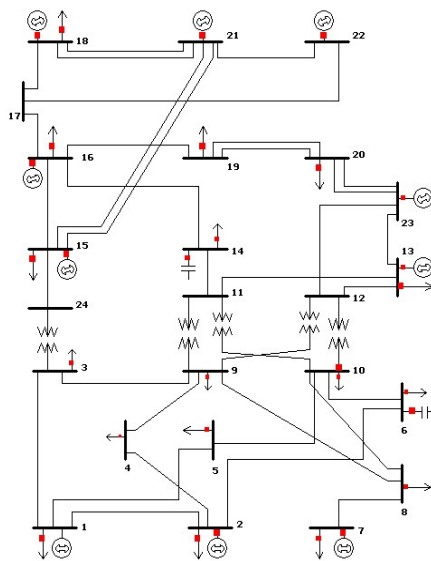


FIGURE ANNEX B-1 IEEE RTS NETWORK

TABLE ANNEX B-1 IEEE RTS NETWORK MULTI PERIOD BUS DATA

1	2	3	4	5	6	7	8	9	10	11	12	13
bus_i	type	Pd	Qd	Gs	Bs	Area	Vm	Va	Base KV	zone	V _{max}	V _{min}
1	2	324	39,6	0	0	1	1	1,075	138	1	1,10	0,92
2	2	291	36,0	0	0	1	1	1,075	138	1	1,10	0,92
3	1	540	66,6	0	0	1	1	0,000	138	1	1,10	0,92
4	1	220	27,0	0	0	1	1	0,000	138	1	1,10	0,92
5	1	213	25,2	0	0	1	1	0,000	138	1	1,10	0,92
6	1	408	50,4	0	0	1	1	0,000	138	1	1,10	0,92
7	2	375	45,0	0	0	1	1	1,075	138	1	1,10	0,92
8	1	513	63,0	0	0	1	1	0,000	138	1	1,10	0,92
9	1	525	64,8	0	0	1	1	0,000	138	1	1,10	0,92
10	1	585	72,0	0	0	1	1	0,000	138	1	1,10	0,92
11	1	0	0,0	0	0	1	1	0,000	230	1	1,10	0,92
12	1	0	0,0	0	0	1	1	0,000	230	1	1,10	0,92
13	2	0	97,2	0	0	1	1	1,025	230	1	1,10	0,92
14	1	745	70,2	0	0	1	1	0,000	230	1	1,10	0,92
15	1	582	115,2	0	0	1	1	1,025	230	1	1,10	0,92
16	2	951	36,0	0	0	1	1	1,025	230	1	1,10	0,92
17	1	300	0,0	0	0	1	1	0,000	230	1	1,10	0,92
18	2	999	122,4	0	0	1	1	1,025	230	1	1,10	0,92
19	1	543	66,6	0	0	1	1	0,000	230	1	1,10	0,92
20	1	384	46,8	0	0	1	1	0,000	230	1	1,10	0,92
21	2	0	0,0	0	0	1	1	1,025	230	1	1,10	0,92
22	2	0	0,0	0	0	1	1	1,025	230	1	1,10	0,92
23	3	0	0,0	0	0	1	1	1,025	230	1	1,10	0,92
24	1	0	0,0	0	0	1	1	1,000	230	1	1,10	0,92

TABLE ANNEX B-2 IEEE RTS NETWORK MULTI PERIOD GENERATOR DATA

#	1 Bus	2 Pg	3 Qg	4 Qmax	5 Qmin	6 Vg	7 M Base	8 Status	9 Pmax	10 Pmin
1	1	0	0	0	0	1	800	1	60	0
2	1	0	0	0	0	1	800	1	60	0
3	1	0	0	0	0	1	800	1	228	0
4	1	0	0	0	0	1	800	1	228	0
5	2	0	0	0	0	1	800	1	60	0
6	2	0	0	0	0	1	800	1	60	0
7	2	0	0	0	0	1	800	1	228	0
8	2	0	0	0	0	1	800	1	228	0
9	7	0	0	0	0	1	800	1	300	0
10	7	0	0	0	0	1	800	1	300	0
11	7	0	0	0	0	1	800	1	300	0
12	13	0	0	0	0	1	800	1	591	0
13	13	0	0	0	0	1	800	1	591	0
14	13	0	0	0	0	1	800	1	591	0
15	15	0	0	0	0	1	800	1	36	0
16	15	0	0	0	0	1	800	1	36	0
17	15	0	0	0	0	1	800	1	36	0
18	15	0	0	0	0	1	800	1	36	0
19	15	0	0	0	0	1	800	1	36	0
20	15	0	0	0	0	1	800	1	465	0
21	16	0	0	0	0	1	800	1	465	0
22	18	0	0	0	0	1	800	1	1200	0
23	21	0	0	0	0	1	800	1	1200	0
24	22	0	0	0	0	1	800	1	150	0
25	22	0	0	0	0	1	800	1	150	0
26	22	0	0	0	0	1	800	1	150	0
27	22	0	0	0	0	1	800	1	150	0
28	22	0	0	0	0	1	800	1	150	0
29	22	0	0	0	0	1	800	1	150	0
30	23	0	0	0	0	1	800	1	465	0
31	23	0	0	0	0	1	800	1	465	0
32	23	0	0	0	0	1	800	1	1050	0
33	19	0	0	0	0	1	800	1	591	0
34	4	0	0	0	0	1	800	1	300	0
35	17	0	0	0	0	1	800	1	1999	0
36	19	0	0	0	0	1	800	1	1999	0
37	20	0	0	0	0	1	800	1	1999	0
38	3	0	0	0	0	1	800	1	1999	0
39	5	0	0	0	0	1	800	1	1999	0
40	6	0	0	0	0	1	800	1	1999	0
41	8	0	0	0	0	1	800	1	1999	0

TABLE ANNEX B-3 IEEE RTS NETWORK MULTI PERIOD GENERATOR COST DATA

#	1	2	3	4	5(c2)	6(c1)	7c(0)
1	2	0	0	3	0	10,39	0
2	2	0	0	3	0	10,39	0
3	2	0	0	3	0	1,87	0
4	2	0	0	3	0	1,87	0
5	2	0	0	3	0	10,39	0
6	2	0	0	3	0	10,39	0
7	2	0	0	3	0	1,87	0
8	2	0	0	3	0	1,87	0
9	2	0	0	3	0	1,66	0
10	2	0	0	3	0	1,66	0
11	2	0	0	3	0	1,66	0
12	2	0	0	3	0	1,46	0
13	2	0	0	3	0	1,46	0
14	2	0	0	3	0	1,46	0
15	2	0	0	3	0	1,87	0
16	2	0	0	3	0	1,87	0
17	2	0	0	3	0	1,87	0
18	2	0	0	3	0	1,87	0
19	2	0	0	3	0	1,87	0
20	2	0	0	3	0	1,66	0
21	2	0	0	3	0	1,66	0
22	2	0	0	3	0	1,62	0
23	2	0	0	3	0	1,62	0
24	2	0	0	3	0	0,01	0
25	2	0	0	3	0	0,01	0
26	2	0	0	3	0	0,01	0
27	2	0	0	3	0	0,01	0
28	2	0	0	3	0	0,01	0
29	2	0	0	3	0	0,01	0
30	2	0	0	3	0	1,66	0
31	2	0	0	3	0	1,66	0
32	2	0	0	3	0	1,46	0
33	2	0	0	3	0	1,66	0
34	2	0	0	3	0	1000,00	0
35	2	0	0	3	0	1000,00	0
36	2	0	0	3	0	1000,00	0
37	2	0	0	3	0	1000,00	0
38	2	0	0	3	0	1000,00	0
39	2	0	0	3	0	1000,00	0
40	2	0	0	3	0	1000,00	0
41	2	0	0	3	0	1000,00	0

TABLE ANNEX B-4 IEEE RTS NETWORK MULTI PERIOD BRANCH DATA

1	2	3	4	5	6	7	8	9	10	11
F bus	T bus	r	x	b	Rate A	Rate B	Rate C	Ratio	Angle	Status
1	2	0,0130	0,0695	0,09222	175	175	175	0,0	0	1
1	3	0,2730	0,0560	0,01144	175	175	175	0,0	0	1
1	5	0,1090	0,4225	0,00458	175	175	175	0,0	0	1
2	4	0,1640	0,6335	0,00686	175	175	175	0,0	0	1
2	6	0,2485	0,9600	0,01040	175	175	175	0,0	0	1
3	9	0,1540	0,5950	0,00644	175	175	175	0,0	0	1
3	24	0,0000	0,4195	0,00000	400	400	400	0,6	0	1
4	9	0,1340	0,5185	0,00562	175	175	175	0,0	0	1
5	10	0,1140	0,4415	0,00478	175	175	175	0,0	0	1
6	10	0,0695	0,3025	0,49180	175	175	175	0,0	0	1
7	8	0,0795	0,3070	0,00332	175	175	175	0,0	0	1
8	9	0,2135	0,8255	0,00894	175	175	175	0,0	0	1
8	10	0,2135	0,8255	0,00894	175	175	175	0,0	0	1
9	11	0,0000	0,4195	0,00000	400	400	400	0,6	0	1
9	12	0,0000	0,4195	0,00000	400	400	400	0,6	0	1
10	11	0,0000	0,4195	0,00000	400	400	400	0,6	0	1
10	12	0,0000	0,4195	0,00000	400	400	400	0,6	0	1
11	13	0,0305	0,2380	0,01998	500	500	500	0,0	0	1
11	14	0,0270	0,2090	0,01758	500	500	500	0,0	0	1
12	13	0,0305	0,2380	0,01998	500	500	500	0,0	0	1
12	23	0,0620	0,4830	0,04060	500	500	500	0,0	0	1
13	23	0,0550	0,4325	0,01636	500	500	500	0,0	0	1
14	16	0,0250	0,1945	0,01636	500	500	500	0,0	0	1
15	16	0,0110	0,0865	0,00728	500	500	500	0,0	0	1
15	21	0,0315	0,2450	0,02060	500	500	500	0,0	0	1
15	21	0,0315	0,2450	0,02060	500	500	500	0,0	0	1
15	24	0,0335	0,2595	0,02182	500	500	500	0,0	0	1
16	17	0,0165	0,1295	0,01090	500	500	500	0,0	0	1
16	19	0,0150	0,1155	0,00970	500	500	500	0,0	0	1
17	18	0,0090	0,0720	0,14400	500	500	500	0,0	0	1
17	22	0,0675	0,5265	0,04424	500	500	500	0,0	0	1
18	21	0,0165	0,1295	0,01090	500	500	500	0,0	0	1
18	21	0,0165	0,1295	0,01090	500	500	500	0,0	0	1
19	20	0,0255	0,1980	0,01666	500	500	500	0,0	0	1
19	20	0,0255	0,1980	0,01666	500	500	500	0,0	0	1
20	23	0,0140	0,1080	0,00910	500	500	500	0,0	0	1
20	23	0,0140	0,1080	0,00910	500	500	500	0,0	0	1
21	22	0,0435	0,3390	0,02848	500	500	500	0,0	0	1

TABLE ANNEX B-5 IEEE RTS NETWORK MULTI PERIOD BRANCH DATA (EXPANSION BRANCHES)

1 F bus	2 T bus	3 r	4 x	5 b	6 Rate A	7 Rate B	8 Rate C	9 Ratio	10 Angle	11 Status
3	24	0,0000	0,4195	0,00000	400	400	400	0,6	0	0
9	11	0,0000	0,4195	0,00000	400	400	400	0,6	0	0
10	11	0,0000	0,4195	0,00000	400	400	400	0,6	0	0
10	12	0,0000	0,4195	0,00000	400	400	400	0,6	0	0
1	5	0,1090	0,4225	0,00458	175	175	175	0,0	0	0
1	5	0,1090	0,4225	0,00458	175	175	175	0,0	0	0
2	4	0,1640	0,6335	0,00686	175	175	175	0,0	0	0
2	4	0,1640	0,6335	0,00686	175	175	175	0,0	0	0
2	6	0,2485	0,9600	0,01040	175	175	175	0,0	0	0
2	6	0,2485	0,9600	0,01040	175	175	175	0,0	0	0
6	10	0,0695	0,3025	0,49180	175	175	175	0,0	0	0
7	8	0,0795	0,3070	0,00332	175	175	175	0,0	0	0
7	8	0,0795	0,3070	0,00332	175	175	175	0,0	0	0
8	10	0,2135	0,8255	0,00894	500	500	500	0,0	0	0
11	13	0,0305	0,2380	0,01998	500	500	500	0,0	0	0
11	13	0,0305	0,2380	0,01998	500	500	500	0,0	0	0
14	16	0,0250	0,1945	0,01636	500	500	500	0,0	0	0
15	21	0,0315	0,2450	0,02060	500	500	500	0,0	0	0
15	24	0,0335	0,2595	0,02182	500	500	500	0,0	0	0
16	17	0,0165	0,1295	0,01090	500	500	500	0,0	0	0
16	17	0,0165	0,1295	0,01090	500	500	500	0,0	0	0
16	19	0,0150	0,1155	0,00970	500	500	500	0,0	0	0
17	18	0,0090	0,0720	0,14400	500	500	500	0,0	0	0
20	23	0,0140	0,1080	0,00910	500	500	500	0,0	0	0
11	13	0,0305	0,2380	0,01998	500	500	500	0,0	0	0
12	13	0,0305	0,2380	0,01998	500	500	500	0,0	0	0
11	14	0,0270	0,2090	0,01758	500	500	500	0,0	0	0
14	16	0,0250	0,1945	0,01636	500	500	500	0,0	0	0

ANNEX C - META-HEURISTIC MODELS

Meta-heuristic models usually adopted for applications to Power Systems are organized in trajectory meta-heuristics, evolutionary algorithms and swarm intelligence.

1. Trajectory meta-heuristics

Trajectory meta-heuristics use a single solution during the search process and the outcome is also a single optimized solution; most of trajectory meta-heuristics are extensions of simple iterative improvement procedures that incorporate techniques that enable the algorithm to escape from local optima; trajectory-based meta-heuristics include: hill climbing (HC), simulated annealing (SA), tabu search (TS) and greedy randomized adaptive search procedures (GRASP).

For having been somehow a source of inspiration in this thesis, SA and TS are briefly summarized.

Simulated Annealing (SA); SA is inspired by the physical chemistry process of annealing; annealing involves slowly heating and cooling materials to strengthen them; when cooling, annealing results in a global over time reduction in energy; locally, however, there may results in an increase in energy. SA is a variant of local search that allows some uphill moves to avoid becoming trapped in a local optimum; an improving local search move is always accepted while a worsening local search move is accepted according to a probability which depends on the relative deterioration in the evaluation function value, such that the worse a move is, the less likely it is to accept it; formally a move is accepted according to a probability distribution, known as the Metropolis distribution; SA is usually not very effective when used as stand-alone meta-heuristic; some references in this topic are (Romero, et al., 1996), (Gallego, et al., 1997), (Braga, et al., 2005).

Tabu-Search (TS); TS is an approach which seeks to avoid bad solutions which have already been explored; TS is characterized by the use of a flexible memory of the previously visited states, which guides the process in such a way that the search is not interrupted or disturbed when there are no movements that improve the current solution; this meta-heuristic avoids recently visited local optima, which have an attractive effect on the search trajectory, ensuring a more intelligent exploration as compared to traditional local search methods; some useful definitions on TS are: a) movement: an addition or removal of just one reinforcement in any stage t of the planning horizon, as long as the constraints are ensured; b) neighborhood of a sequence k : the set of sequences obtained through elementary modifications (movements) performed in the

present sequence; c) intensification/diversification: the process of defining the neighborhood and selecting the best neighbor to the next iteration; to intensify the search is to search the local area more thoroughly; to diversify the search is to force the search away from the current solution; d) length of tabu list: the length of the list signifies the balance between intensify/diversify; it defines how many iterations a reverse movement will stay in the list; TS is among the best performing meta-heuristics when it is applied with general strategies to balance intensification and diversification; TS is applied to many combinatorial problems (Silva, et al., 2011); more information and applications can be found in (Areiza, 1997), (Gallego, et al., 2000), (Silva, et al., 2001), (Sadegheih, et al., 2008), (Silva, et al., 2008), (Silva, et al., 2008).

2. Evolutionary Algorithms

Evolutionary Algorithms (EA); EA refers to a subset of the evolutionary computation (EC) that explore biological evolution mechanisms, as reproduction, mutation, recombination (crossover) and selection; several algorithms share these characteristics as Evolutionary Programming (EP), Genetic Algorithms (GA), Evolution Strategies (ES), Differential Evolution (DE) and Artificial Immune Systems (AIS); (Silva, et al., 2011).

Genetic Algorithms (GA); *“The GA analyzes, in an intelligent way, a very reduced number of proposed solutions with a strategy that allows finding high quality solutions. GAs work with a set of solutions, and not with a unique solution. This set of solutions is subject to a process of selection, recombination and mutation, and then a new population is generated. This new population is designated as the current population. The GA begins the process of optimization with an initial population and applies the genetic operators to find new generations. In GA, the following aspects should be specified: 1) the way in which the information is coded, which is fundamental in the determination of the algorithm quality; 2) the genetic parameters such as the population’s size and recombination and mutation rates; 3) the implementation of the genetic operators of selection, recombination and mutation; 4) the way in which the initial population is generated; and 5) the structure of new genetic operators and/or strategies that consider the particular characteristics of the problem.”* (Escobar, et al., 2004). More information can be found in (Reis, 2005), (Silva, et al., 2005), (Romero, et al., 2007), (Sadegheih, et al., 2008).

Evolution Strategies (ES); the $(\mu + \lambda)ES$ model includes μ parents and λ offsprings; ES use only the mutation operator; this operator consists in adding to the sequence k a normally distributed perturbation Z_t^k at all t stages of the planning horizon, as follows:

$$\tilde{S}_t^k = S_t^k + Z_t^k \quad (C.01)$$

$$Z_t^k = \sigma [N_{t1}(0,1)N_{t2}(0,1)...N_{tl}(0,1)...N_{tm}(0,1)] \quad (C.02)$$

In these expressions:

$\tilde{S}_t^k$ represents a new individual, after mutation of S_t^k ;

σ represents the mutation magnitude;

$N_{tl}(0,1)$ Corresponds to a normal distribution;

In the particular case of TEP, as the variables of the problem are discrete, a round functions needs to be applied to each element of the individuals; the best sequences between parent and offspring populations are chosen to survive to next generation using the selection operator; this model had been used with success in (Silva, et al., 2006), (Silva, et al., 2008), (Silva, et al., 2011);

Differential Evolution (DE); DE was introduced by Dong in 2006 (Dong, et al., 2006); with DE, at each generation, the offspring population is obtained by application of mutation and recombination operators; DE is based on arithmetical combinations of weighted difference among individuals; according to Silva, considering the TEP problem, the best results have been achieved with the following mutation rule:

$$X_t^k = Round[S_t^{r1} + F(S_t^{r2} - S_t^{r3})] \quad (C.03)$$

In this expression:

k is the selected individual;

t is the stage;

X_t^k corresponds to the k mutated individual in stage t ;

$r1, r2, r3$ and k are indices randomly chosen, where $r1 \neq r2 \neq r3 \neq k$

$S_t^{r1}, S_t^{r2}, S_t^{r3}$ are the respective selected individuals

F is the mutation operator

Round is a function that returns a rounded integer number.

The recombination operator works according to expression C.04; the recombination is done by the exchange between mutated and original individuals.

$$w_{tl}^k = \begin{cases} x_{tl}^k, & \text{if } (rand_l \leq CR) \text{ or } (l = \gamma) \\ s_{tl}^k, & \text{otherwise} \end{cases} \quad (C.04)$$

In this expression:

$rand_l$ is an uniform distribution (0,1) random variable;

γ is a branch randomly chosen among those eligible to receive reinforcements;

X_t^k corresponds to the k mutated individual in stage t;

CR is the recombination rate

w_{tl}^k is each position of the individual after the recombination operator

The recombination operator follows expression C.04, and compares the new individuals with the original ones from the parent population.

$$S^{k(new)} = \begin{cases} W^k, & \text{iff } (W^k) \leq f(S^k) \\ S^k, & \text{otherwise} \end{cases} \quad (C.05)$$

In this expression:

$S^{k(new)}$ is the k individual selected to the next generation;

$f(.)$ is the objective function

DE is different from other EA in this detail, as the selection operator performs a pair of comparisons (Rezende, et al., 2009), (Silva, et al., 2011).

Artificial Immune Systems (AIS); Artificial immune system is an area of research that bridges the disciplines of immunology, computer science and engineering; In 1994, Forrest et al. published a paper titled “Self – Non self Discrimination in a Computer” (Forrest, et al., 1994); since this paper was published, negative selection algorithm has attracted the attention of many researchers and practitioners and has been applied in numerous real world applications; although a diverse family of negative selection algorithms has been developed, the essential characteristics of the original negative selection algorithm introduced in this paper still remain; an important reference on AIS is (Castro, et al., 2002); a comprehensive and updated review of the recent advances in

AIS can be found in (Dasgupta, et al., 2011); Rezende et al. adopted AIS for a multistage transmission expansion planning (Rezende, et al., 2009), following one of the main algorithms presented in the literature, the CLONALG (Castro, et al., 2002); this algorithm is based on the following concepts: reproduction, hyper mutation, selection and receptor editing; to solve the TEP problem, Rezende described the sequence S_k as each antibody of the immune system; in addition, each element s_{il}^k refers to the reinforcement options and corresponds to a position of this antibody; $f(S_k)$ represents the total cost function in present value; the role of the reproduction operator is to clone antibodies, i.e. to perform identical copies; since n_{Ab} is the number of antibodies (sequences) and n_{clo} is the number of clones generated by each antibody S_k , after the application of this operator, there will be $G^{n_{Ab}}$ groups consisted of the original antibody S_k and its respective clones Cl^{ku} ;

$$G^k = \{S^k, Cl^{ku}\}, \text{ where } Cl^{ku} = S^k$$

$$\forall k \in \{1, 2, \dots, n_{Ab}\}; \forall u \in \{1, 2, \dots, n_{clo}\}$$
(C.06)

The hyper mutation operator aims to provide better quality antibodies. This process consists of adding a perturbation Z_t^k to each clone Cl^{ku} at all stages of the planning horizon, as follows:

$$\tilde{Cl}_t^{ku} = Cl_t^{ku} + Z_t^k$$
(C.07)

$$Z_t^k = \sigma [N_{t1}(0,1)N_{t2}(0,1)\dots N_{tl}(0,1)\dots N_m(0,1)]$$
(C.08)

In these expressions:

$\tilde{Cl}_t^{ku}$ represents a new antibody, after mutation of Cl_t^{ku} ;

σ represents the mutation magnitude;

$N_{il}(0,1)$ corresponds to a Gaussian distribution;

A rounding function must be applied to each position of the new antibodies, since the TEP reinforcements are discrete variables; after using the hyper mutation operator, the strategy adopted by the selection process is to keep the n_{Ab} best antibodies, from each group G^k (parent and its respective clones) to create a new group G^* ; the antibodies of the resulted group G^* are compared at each iteration; this step is represented by the

receptor editing that selects the best antibodies of group G^* in order to minimize $f(s_k)$; selection of identical antibodies is not allowed; at the end, the best and distinct n_{Ab} antibodies will evolve to the next generation, keeping the size of the initial population; this process ensures a better quality and diversified population for the next generation, since there will not be identical antibodies; TEP references on this algorithm are (Rezende, et al., 2009), and (Silva, et al., 2011).

3. Swarm Intelligence

Swarm Intelligence (SI); SI is the property of a system whereby the collective behavior of agents interacting locally with their environment cause coherent functional global patterns to emerge; SI provides a basis with which it is possible to explore problem solving without centralized control or the provision of a global model; the meta-heuristics included in this group, Particle Swarm Optimization (PSO) and Ant Colony optimization (ACO), are composed by a population of simple agents that interact with each other and with the environment; although the agents follow quite simple rules and there is no control structure responsible for guiding the behavior of the agents, the emergence of a global intelligent behavior is observed, unknown to individual agents.

Particle Swarm Optimization (PSO); PSO is originally attributed to Kennedy and Eberhart (Kennedy, et al., 1995) and was intended for simulating social behavior as a stylized representation of the movement of organisms in a bird flock or fish school; the book “Swarm Intelligence”, by Kennedy and Eberhart, describes many philosophical aspects of PSO and swarm intelligence (Kennedy, et al., 2001); an extensive survey of PSO applications is made by Poli (Poli, 2008); PSO is a computational method that iteratively try to improve a candidate solution with regard to a given measure of quality; More detailed information on this topic may be found in Chapter 4; an important reference in PSO application to TEP is (Jin, et al., 2007).

Ant Colony optimization (ACO); Ant colonies, as social insect societies, are distributed systems that, in spite of the simplicity of their individuals, present a highly structured social organization; because of this organization, ant colonies can accomplish complex tasks; ACO models derived from the observation of real ants’ behavior, and uses these models as inspiration for the design of new algorithms for the solution of optimization and distributed control problems; the main idea is that the self-organizing principles which allow the highly coordinated behavior of real ants can be exploited to coordinate populations of artificial agents that collaborate to solve computational problems (Dorigo, et al., 2004); according with Silva approach, in the TEP problem, each ant represents an attempt of finding a sequence, where the paths refer to the eligible branches to receive reinforcements (Silva, et al., 2011); an ant chooses to add reinforcements to the network, at each stage t of the planning horizon, through the following state transition rule:

$$c = \begin{cases} \operatorname{argmax}_{(i,j) \in T_t^k} \left\{ \tau(i,j)_t [\eta(i,j)]^\beta \right\}, & \text{if } q \leq q_0 \\ C, & \text{otherwise} \end{cases} \quad (\text{C.09})$$

In these expressions:

c indicates the selected reinforcement;

$\tau(0,1)_t$ corresponds to the pheromone trail laid on the branch (i,j); $\eta(0,1)_t$ represents the value of the heuristic function associated with branch (i,j);

β defines the importance of the heuristic function;

Argmax is the function that selects the maximum value for the result $\left[\tau(i,j)_t [\eta(i,j)]^\beta \right]$;

T_t^k is the set of branches that did not achieve the maximum number of reinforcements permitted;

q refers to a random number that follows a uniform distribution (0,1);

q_0 is a constant parameter $0 \leq q_0 \leq 1$;

C represents a random variable that follows a discrete distribution given by C.10, where $p_t^k(i,j)$ is the probability of choosing branch (i,j) to receive a reinforcement;

$$p_t^k(i,j) = \begin{cases} \frac{[\tau(i,j)_t [\eta(i,j)_t]^\beta]}{\sum_{t,u \in T_t^k} \left\{ \tau(t,u)_t [\eta(t,u)_t]^\beta \right\}}, & \text{if } (i,j) \in T_t^k \\ 0, & \text{otherwise} \end{cases} \quad (\text{C.10})$$

Two rules are used to update the pheromone trails (Silva, et al., 2011):

1. The local update rule is carried out while the sequences are being built up by the ants; the objective is to reduce the trails over the most relevant branches, avoiding the selection of the same reinforcements by all ants;
2. On the other hand, the global update rule is applied only when all ants have already finished their searches; this rule uses the information of the best sequence found by the ants to update the pheromone trails to the next algorithm iteration, that is, the search of a new group of ants; the objective is to increase the pheromone trails over the branches that have received reinforcements and reduce the trails over the least important branches, considering the configuration of the best sequence.

More details on how to use ACO can be found on (Rezende, et al., 2009) (Silva, et al., 2010), and (Silva, et al., 2011).

ANNEX D - DC OPF METHOD

This annex is based on a didactic text published in FEUP, written by Prof. Manuel Matos (Matos, 1999).

For a given network, with a set of generators to power a set of charges, and given a certain objective function, algorithms known as Optimal Power Flow aim at:

- a) Obtaining the so-called power dispatch, to know which generators should operate and how much power should be supplied by each of them;
- b) For this configuration of generation and load, know the power flow in the branches.

The most common objective functions may consider, inter alia, minimizing the active losses, minimizing costs, minimizing the number of enforcement actions to be taken in case of contingency, minimize the load cut (when shedding becomes necessary), or minimization of pollutants (environmental impact). This process is complex and nonlinear.

In particular case of network planning, it is usual to adopt linearized models, which are quicker to solve and sufficiently accurate for the planning requirements (Sanchez, et al., 2005). It is the case of the DC model we will adopt, in a version that includes the value of losses in the network. We will select an objective function to minimize production costs and power not supplied, using a method based on linear programming (Simplex).

Some simplifications are admitted in the DC model as valid:

- a) Resistance negligible;
- b) Admittance to ground negligible;
- c) Tension near the nominal value ($V \approx 1$ pu);
- d) Small angle differences between nodes.

The generation input power on the nodes is, by convention, positive. As a result, one may establish the concept of power injected at bus i as the difference between production and consumption.

The development of the nodal equations of the model can be made directly by the approaches to the general expressions.

$$P_i = \sum_{k \neq i} P_{ik} = \sum_{k \neq i} \frac{\theta_i - \theta_k}{X_{ik}}, (i = 1..n) \quad (D.01)$$

$$P_i = \theta_i \sum_{k \neq i} \frac{1}{X_{ik}} + \sum_{k \neq i} -\frac{\theta_k}{X_{ik}}, (i = 1..n) \quad (D.02)$$

where X_{ik} is line or transformer reactance in the branch between nodes i and k , and θ_i e θ_k are the angle shift in nodes i and k .

One can define

$$B'_{ii} = \sum_{k \neq i} \frac{1}{X_{ik}} \quad (D.03)$$

$$B'_{ik} = -\frac{1}{X_{ik}} \quad (i \neq k) \quad (D.04)$$

The expression above can be written in matrix form as follows:

$$P_i = \sum_{k \neq i} B'_{ik} \cdot \theta_k, i = 1..n \quad (D.05)$$

$$P = B' \cdot \theta \quad (D.06)$$

As the determinant of B' is zero, the system of equations is indeterminate, reflecting the fact that it is necessary to define the origin of the phases. Setting $\theta_{ref} = 0$, and eliminating one equation (generally corresponding to the reference bus, i.e. remove the B' line and column bus reference, and eliminate the corresponding element of the vectors P and θ), we obtain a solvable system of equations:

$$\hat{P} = \hat{B}' \cdot \hat{\theta} \quad (D.07)$$

One has now to solve the system of linear equations

$$\hat{\theta} = \hat{B}'^{-1} \cdot \hat{P} \quad (D.08)$$

to get the phase angles (in radians), which allows to calculate the values of the branches power flows through the expression (D.01).

In addition to the possibility of calculating the voltage phases and then the transit of active power in the branches, the DC model allows a direct relation between active power flow in branches and power on the buses.

Setting up:

$$Z' = \hat{B}'^{-1} \quad (D.09)$$

We will calculate:

$$\hat{\theta} = \hat{B}'^{-1} \cdot \hat{P} = Z' \cdot \hat{P} \quad (D.10)$$

Or

$$\theta_i = \sum_{j \neq \text{Ref}} Z'_{ij} \cdot P_j, i \neq \text{Ref} \quad (D.11)$$

Substituting the expression, it is possible to calculate the flow for all branches:

$$\begin{aligned} P_{ik} &= \frac{\theta_i - \theta_k}{X_{ik}} = \frac{\sum_{j \neq \text{Ref}} Z'_{ij} \cdot P_j - \sum_{j \neq \text{Ref}} Z'_{kj} \cdot P_j}{X_{ik}} \\ &= \frac{\sum_{j \neq \text{Ref}} Z'_{ij} - \sum_{j \neq \text{Ref}} Z'_{kj}}{X_{ik}} \cdot P_j, (i = 1..n) \end{aligned} \quad (D.12)$$

This expression is valid when i and k do not coincide with the reference bus.

Although the amendment is simple to make (as $\theta_i = 0$ or $\theta_k = 0$), for this purpose it is more convenient to define only $Z'_{\text{Ref}j} = 0$.

The joint consideration of all the previous equations can be expressed in matrix form as:

$$P_l = A \cdot \hat{P} \quad (D.13)$$

where A is called the matrix of sensitivities, as it indicates the sensitivity of flow in each branch to the variation of power injected in each node. Note that for a given network, the matrix A is not unique, as it depends on the considered bus reference.

The generic element of the matrix of sensitivities ($A_{l,j}$ or $A_{(i-k),j}$) relates the active power flow in line l, from i to k, with the power injected into node j, ie:

$$A_{l,k} = \frac{Z'_{ij} - Z'_{kj}}{X_{ik}} \cdot P_j, (i = 1..n) \quad (D.14)$$

This expression is valid if i and k coincide with the bus reference, if one sets $Z'_{Refj} = 0$.

ANNEX E - PAPER PRESENTED IN EEM 2011

Multiyear Transmission Expansion Planning using Discrete Evolutionary Particle Swarm Optimization

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Abstract - The objective of Transmission Expansion Planning (TEP) is to obtain a plan to expand or reinforce a transmission network that minimizes construction and operational costs while satisfying the requirement of delivering electricity safely and reliably to load centres along the planning horizon. This definition is quite simple, but the complexity of the problem and the impact on society transforms TEP on a challenging issue. The objective of this paper is the introduction of a new discrete approach to solve dynamic TEP, based on an improved version of the Evolutionary Particle Swarm Optimization (EPSO) meta-heuristic algorithm. The paper includes sections describing the Discrete EPSO (DEPSO), an enhanced approach of EPSO, the mathematical formulation of the problem, including the objective function and constraints, and the application of DEPSO to this problem. Finally, the use of the developed approach is illustrated using Case Studies based on the Garver network and on the IEEE 24 bus / 38 branch test system.

Keywords: dynamic transmission expansion planning, decision tools, heuristic techniques, discrete evolutionary particle swarm optimization.

Nomenclature

X^{it}	population in iteration it , including pt particles;
X_{pt}^{it}	particle pt in iteration it , including j projects taken from a specified list;
$X_{pt,j}^{it}$	integer variable with the value 0 if project j is not selected, with the value p if the project is selected to be commissioned in period p and with value $p+1$ if the project is delayed beyond the last period in the horizon;
$K_{pt,j}^{it,p}$	flag for iteration it , particle pt , and project j , taking the value 1 when $X_{pt,j}^{it} = p$
n_{pt}	number of particles in the population;
n_{pj}	number of projects in each particle;
np	number of periods in the horizon;
$niter$	maximum number of iterations;
it	iteration counter;
V_{pt}^{it}	velocity vector of particle pt in iteration it ;
b_{pt}	best solution found for particle pt in previous iterations;
b_G^*	best global: best overall solution ever found by the swarm in its past life, that is in all iterations; The symbol $*$ means that the variable undergoes mutation
w_{pt}^{it*}	weights conditioning the mutation of particle pt in iteration it ; $t = 1$: inertia; $t = 2$: memory; $t = 3$: cooperation;
w_4^{it*}	weights conditioning the mutation of the best global particle in iteration it ;
p	communication factor;
k_a	constant used on the Lamarckian evolutionary process, set to np ;

k_b	constant controlling the mutation of the particles on the Lamarckian evolutionary process, $k_b \in [0,1]$;
k_c	constant controlling the mutation of the best global particle, $k_c \in [0,1]$;
IC_j	investment cost of project j , (€);
ir, if	interest and inflation rates;
$max\ prj$	maximum number of projects admitted per period;
OC_{pt}	operational cost associated to particle pt ;
α_y	penalty factors assigned to the evaluation function of a particle;
c_k	generation cost;
Pg_k, Pl_k	generation and load at node k ;
G	penalty assigned to PNS in DC OPF studies;
abk	sensitivity coefficient relating the active flow in branch b with the injected power in node k ;
Pg_k^{min}, Pg_k^{max}	minimum and maximum generation in node k ;
P_b^{min}, P_b^{max}	minimum and maximum flows in branch b ;
$PNS(N)_p$ and $PNS(N-1)_p$	power not supplied in period p , for the intact system, when all components are available, and for $N-1$ contingencies.

I. INTRODUCTION

A dynamic, or multiyear, TEP model aims at determining the timing, the type and the location of the new transmission facilities that should be added to an existing network along a planning horizon in order to ensure an adequate transmission capacity taking into account future generation options and load requirements, in a long-term horizon. Even though this definition is quite clear, the complexity of the problem and the impact on society transform TEP on a challenging issue. On the legal and regulatory side, the European Parliament and the European Council approved the Directive 2003/54/CE, establishing common rules for the internal electricity market. TEP is clearly identified as a major responsibility of TSOs, given that they should ensure the long-term ability of the system to meet reasonable demands for the transmission of electricity. More recently, the Commission Regulation (EU) No 838/2010 of 23 September 2010, defined the guidelines to the inter-transmission system operator compensation mechanism associated with cross-border flows of electricity, to be carried out by the Agency for the Co-operation of Energy Regulators. In line with these concerns, this paper details a multiyear dynamic model for the TEP. This optimization problem has a mixed integer nature that justifies the use of an enhanced version of EPSO, in which we

included mechanisms specifically designed to address discrete problems turning it into DEPSO. Apart from this introductory section, this paper is structured as follows. Section II reviews several approaches to the TEP as well as metaheuristics. Section III details the mathematical formulation of the TEP and describes the application of the DEPSO to this problem. Finally, Section IV includes two Case Studies based on the Garver Network and on the IEEE 24 bus / 38 branch test system and Section V presents the most relevant conclusions.

II. LITERATURE REVIEW

A. Transmission Expansion Planning

The objective of TEP problem is to determine the timing, the type and the location of new transmission elements to add to a transmission network along a planning horizon. These elements should be selected so that the resulting network is able to accommodate future generation additions as well as the forecasted demand evolution under a specified reliability level. The literature on TEP is vast and [1, 2] enumerate and classify publications on this problem. In the next paragraphs we will briefly address some of the key features of TEP.

In the first place, it is important to distinguish between static and dynamic formulations. Static formulations as the ones in [3, 4] are approaches in which the years in the horizon are treated in a separate and sequential way. This means that one solves consecutively planning problems for each year in the horizon and the additions identified in a particular year are assumed as available in posterior periods. The final plan just corresponds to the addition of a number of partial plans. This solution strategy loses the global view that should exist over the problem, in the sense that the solution of a true multiyear problem will not, in general be the same as the collection of the partial individual year plans. In this sense, [5, 6] describe multiyear approaches of the TEP problem. Given the complexity of the fully integrated problem, several authors proposed simplifications based for instance in series of static sub problems leading to formulations often termed as pseudo-dynamic procedures, as the ones in [7, 8].

TEP models use several optimization techniques including classical optimization methods, dynamic and quadratic programming, mix-integer and decomposition techniques and metaheuristics. In this scope, [3, 9] use Genetic and Evolutionary algorithms, Simulated Annealing is used in [6, 10], Tabu Search is adopted in [3, 11], Expert Systems are used in [4, 12] and [8] details the use of Greedy Randomized Procedures. Finally, the operation and the expansion planning of power systems is more than ever before contaminated by uncertainties and [13 - 15] detail some approaches to the TEP using probabilistic and fuzzy set models.

B. Evolutionary algorithms and particle swarms

Metaheuristic methods go step-by-step generating, evaluating, and selecting solutions, with or without interacting with the planner [1]. Taking advantage of the planners experience, the computational performance of metaheuristic methods is usually better than that of mathematical methods. Meta heuristics include a large number of approaches but in

this section we will focus on evolutionary algorithms and on particle swarm optimization. Evolutionary algorithms are usually organized in the following steps: initialize a random population P of μ elements; repeat reproduction (by recombination and/or mutation), evaluation, selection and test, until test (for termination criteria is valid, based on fitness, on number of generations or other criteria) is positive. Evolutionary computation offers several advantages [16], namely its conceptual simplicity, broad applicability, outperform classic methods on real problems, potential to use knowledge and hybridize with other methods, parallelism, robust to dynamic changes and capability for self-optimization.

The particle swarm optimization (PSO) was proposed by Kennedy in 1995, based on the parallel exploration of the search space by a swarm [17]. The swarm is a set of particles, and each particle is a possible solution. These particles proceed through the search space, that is, the space where feasible solutions can be found. PSO has many key advantages over other optimization techniques. Among others, it is a derivative-free algorithm unlike many conventional techniques, it is flexible to form hybrid tools together with other optimization techniques, it is less sensitive to the nature of the objective function, i.e., convexity or continuity, it is able to escape from local minima, it is easy to implement and program, it is adequate to handle objective functions with stochastic nature and it is not dependent on a good initial solution. More detailed information about PSO applications in power systems can be found in [18]. The first discrete PSO approach was proposed by Kennedy and Eberhart for binary-valued solution elements. Al-kazemi and Mohan [19] introduced another PSO, whose particles are influenced alternatively by their own best position and by the best position among their neighbours. Other researchers proposed different approaches that proved adequate for some particular problems, but the implementation complexity turned difficult their dissemination to other applications.

In 2002 Miranda and Fonseca [20] introduced EPSO, joining the best features of both particle swarm methods and evolutionary algorithms. EPSO focuses in regions of the search space where one can find better contributions for the solution, instead of conducting a blind sampling of the space. It was adopted the general scheme of the movement rule of PSO. The evolutionary flavor is given by the self-adaptive mechanism to determine the best values to the weight terms. The off-springs are generated by recombination of the particles, following the recombination rules (1) and (2).

$$X_{pt}^{it+1} = X_{pt}^{it} + V_{pt}^{it+1} \quad (1)$$

$$V_{pt}^{it+1} = w_{pt,1}^{it*} V_{pt}^{it} + w_{pt,2}^{it*} (b_{pt} - X_{pt}^{it}) + w_{pt,3}^{it*} (b_G^* - X_{pt}^{it}) p \quad (2)$$

In this work, we adopted an EPSO based approach instead of PSO or other metaheuristic, since it performs better when dealing with very complex problems, as it is detailed in [20].

III. MULTIYEAR TEP FORMULATION WITH DEPSO

A. Discrete Evolutionary Particle Swarm Optimization

The discrete EPSO used in this paper is a new approach of the EPSO model able to tackle problems with non-continuous

and integer search spaces. Its main characteristics will now be detailed. The population is characterized by the number of particles npt , the number of projects npj , and the number of possible periods in the horizon, np . Each particle is a possible solution to the problem. The main differences between this approach and classical EPSO are: the elements in the particles are integers, the mutation rules are different and the Lamarckian evolution concept is introduced. However, DEPSO includes the same blocks of classic EPSO, as follows.

Replication: in each iteration the population is cloned twice;

Mutation of weights: the three weights (inertia, memory and cooperation) are subjected to mutation as indicated in (3);

$$w_{pt,j,t}^{it+1*} = \left(0.5 + rand() - \frac{1}{1 + \exp(-w_{pt,j,t}^{it*})} \right) \quad (3)$$

Mutation of the best global particle: the global best particle is a vector, whose positions are mutated only when randomly generated numbers $N \in [0,1]$ take values less than $k_c \in [0,1]$. The weights are updated by (3) and the mutation of particle bg is obtained by (4);

$$b_{Gj}^* = b_{Gj} + round(2 \cdot w_4^{it*} - 1) \quad (4)$$

Recombination: we adopted the same expressions of the classic EPSO, which we round up to integers. When the particles exceed the search space boundaries, they are returned to the search space, either being placed on the edge or in a contiguous position, (5, 6);

$$X_{pt,j}^{it} = 0 - round(rand()) \quad (5)$$

$$X_{pt,j}^{it} = np + 1 - round(rand()) \quad (6)$$

Recombination by Lamarckian evolution: when the velocity of a particle is zero, a Lamarckian evolution of that particle is promoted, using (7). The particle only sees some of his positions mutated, those when randomly generated numbers $N \in [0,1]$ take values less than k_b ; k_a is set to $nper$.

$$V_{pt,j}^{it} = round \left(2 \cdot k_a \cdot \left(0.5 + rand_1() - \frac{1}{1 + \exp(-rand_2())} \right) - k_a \right) \quad (7)$$

If one wants to have a completely symmetric probability, $rand_2()$ has to be changed by 0. When there one need to favor the anticipation of the projects, the adoption of a normal randomly generated number is more suitable. In our tests we have adopted $\exp(0)$ instead of $\exp(rand_2())$.

Selection: at each position of the population survives the clone whose fitness is better than the best particle of the same position. The best global will be updated if some of the best particles has best fitness.

B. TEP modeling

1) Investment plan project list and population

We have started modeling TEP by defining an investment plan project list, based on npj projects (including new lines and transformers), and a time frame, based on np periods, typically associated to yearly stages. The list of possible

projects may include not only new lines to establish in new corridors, but also lines to install in existing corridors. A solution X_{pt} corresponds to an expansion plan and it includes a number of projects selected among the mentioned list that have to be ready for service in each time frame period. The first population X , with npt particles, is randomly generated and it corresponds to a matrix with $npt \times npj$ dimension.

2) Mathematical model of TEP

The formulation of the TEP model is given by (8-12). This problem aims at minimizing the objective function (8) that includes operation and investment costs along the horizon referred to the initial year. The feasibility of solutions and their operational cost, in particular PNS, are evaluated running a DC Optimal Power Flow for each period. In each period the network integrates the installations commissioned previously and the forecasted demand.

$$\min CostX_{i,iter} = \sum_{p=0}^{nper+1} \left[\sum_{j=1}^{npj} IC_j \cdot K_{ij}^p + OC_i \right] / (1+ir)^p \quad (8)$$

Subjected to:

$$\text{Physical constraints (power flow and generator limits);} \quad (9)$$

$$\text{Financial constraints (global and period constraints);} \quad (10)$$

$$\text{Power not supplied and reliability constraints} \quad (11)$$

$$pt = 1, 2, \dots, npt; it = 1, 2, \dots, niter \quad (12)$$

The objective function (8) is subjected to physical constraints, namely associated to the capacity of the generators and of the available branches, to financial constraints and also to quality of service minimum requirements, for instance expressed by maximum amounts of PNS in N and in $N-1$ regimes.

3) Operation costs and constraints

The operation cost is estimated solving a DC OPF algorithm formulated by (13 – 17).

$$\min f = \sum c_k \cdot Pg_k + G \cdot \sum PNS_k \quad (13)$$

Subject to:

$$\sum Pg_k + \sum PNS_k = \sum Pl_k \quad (14)$$

$$Pg_k^{\min} \leq Pg_k \leq Pg_k^{\max} \quad (15)$$

$$PNS_k \leq Pl_k \quad (16)$$

$$P_b^{\min} \leq \sum a_{bk} \cdot (Pg_k + PNS_k - Pl_k) \leq P_b^{\max} \quad (17)$$

While doing this, network and generator limit constraints are enforced but if transmission capacity is insufficient then PNS will be non zero thus increasing the value of the objective function (13). This means that using this strategy were are inherently penalizing particles that are not adequate in terms of being able to connect adequately generation and demand. On the other hand, this formulation assumes that the network is lossless. In order to increase the realism of the model, this DC-OPF was enhanced to include an estimate of transmission losses according to the scheme in Table I. The convergence of this iterative process is usually reached in less than 5 iterations. At the end of it, we get the generation cost, the level of losses and the eventual non zero value of PNS for the entire system, $PNS(N)$. If the level of losses exceeds a reference value, then this particle is penalized with a term α_1

in the fitness function and if the PNS(N) is not zero, then the penalty term α_2 is introduced in the fitness function.

TABLE I
PROCEDURE DC-OPF WITH LOSSES

Procedure DC-OPF with Losses	
i)	Run an initial dispatch using (13-17);
ii)	Compute voltage phases using the DC model;
iii)	Estimate active losses in branch m-n using (18). In this expression, g_{mn} is the conductance of branch m-n and θ_{mn} is the phase difference across this branch;
	$Loss_{mn} \approx 2 \cdot g_{mn} \cdot (1 - \cos \theta_{mn})$ (18)
iv)	Add half of the losses in branch m-n to the original loads in nodes m and n. Run a new dispatch using (13-17) and update voltage phases;
v)	End if the difference of voltage phases in all nodes is smaller than a specified threshold. If not, return to iii).

Each of the projects is characterized by its investment cost. Then when a project is selected for a particular period, its investment cost is referred to the period 0, using an interest rate adequate to the risk of this type of investment. We also considered two kinds of financial constraints. The first one corresponds to the maximum number of projects that can be implemented per period. This limitation arises due to financial or operational reasons and if it violated we consider a penalty term α_3 in the fitness function. The second one corresponds to the maximum investment value over the entire horizon and it models a global financial constraint. If it is violated, then a penalty term α_4 is included in the fitness function.

Regarding the reliability, the developed approach penalizes plans in which the PNS is non-zero for network configurations associated to N-1 contingencies. It would also be possible to include penalties for a selected number of N-2 contingencies following the indications in the Grid Codes of several countries. This evaluation can be modified, extending the number of configurations to analyze or, in the limit, to run a Monte Carlo simulation for every particle. This would obviously lead to a dramatic increase of the computation time. The penalties over PNS (N-1) are made using the term α_5 .

4) Fitness Function

Considering the objective function (8) plus the five penalty terms mentioned above, we formulate the fitness function, used to evaluate the particles using (19).

$$CostX_{i,iter} = \sum_{p=0}^{nper+1} \left[\sum_{j=1}^{nproj} IC_j \cdot K_{ij}^p + OC_i \right] / (1+ir)^p + \sum_{y=1}^5 \alpha_y \quad (19)$$

C. Further details on the developed model

1) The number of periods and the number of states

Projects may take the state corresponding to the period when they are considered complete and available. In addition to these states, two more are possible, corresponding to situations of non-implementation of a particular Project: either the possibility of not being chosen, or the possibility of being postponed beyond the periods under review. So, $np+2$ possible states are considered. For example, in a four period analysis we have 6 states: 0, which corresponds to not choosing the Project, 1..4, the period in which the Project can

be completed, and 5, corresponding to the postponement of the Project. This means that $X_{pt,j}^{it} \in [0,5]$.

2) Local search by Lamarckian evolution

The described DEPSO is boosted by a local search procedure conducted nearby the best solutions ever founded. Thus we create a new population on which we run an additional search. This population will result either from the evolution of clones of the best global or from a randomly selected particle among the best population. The Lamarckian evolution is also promoted using (7).

3) Evaluation process

In order to spare computation time, we also considered that it is not necessary to test particles that are already known, either as previous best globals, or because that belong to the best population. When penalizing particles that are already known, it is possible to spare time and accelerate the search. This will increase the diversity in the population and will reduce the risks the premature convergence to local minima.

IV. CASE STUDIES

A. Introduction

The developed model was applied to two the well-known networks: the Garver Network and to the IEEE 24 RTS. To make results easier to compare with results available in the literature, we chose a fitness function based only on the value of the investment, without considering losses. When indicated, PNS(N-1) constraints were considered.

B. Garver Network

In the first test we used the Garver network, with six buses and six lines. This network should be expanded from the original situation to the demand levels defined in [21]. Table II indicates a list of 17 projects based on several publications using this network. Using this network we ran two types of studies: a single period test and a planning exercise that includes a planning horizon with four periods.

The solution we got for the single period analysis was the same as that found in the literature: branch 3-5, 1 line; branch 4-6, 3 new lines. The algorithm was run 100 times with populations of 10, 20, 30 and 50 particles. The performance of developed DEPSO was remarkable, given that convergence was obtained for a very small number of iterations, even for populations of 10 particles. For populations with at least 20 particles in 98% of cases the optimal solution was found in less than 10 iterations.

The four periods test was designed with the following assumptions: load increase of 5% per period; fixed investment costs (for the sake of simplicity, it was considered that the effect of technological and market competitiveness outweighed the effect of inflation and capital discount rates); lines available from the year of entry into service (network configuration, and the corresponding power flow, for subsequent years depend on previous years configuration). Several solutions were identified with the same fitness value, which corresponds to an investment of 160 M\$.

TABLE II
Line data for the Garver network expansion problem.

Branch no	From bus	To bus	Resist. (pu)	React. (pu)	Cap. (MW)	Cost (10 ⁶ \$)
1	2	6	0,0800	0,0300	100	30
2	2	6	0,0800	0,0300	100	30
3	2	6	0,0800	0,0300	100	30
4	2	4	0,1000	0,4000	100	40
5	5	6	0,1476	0,6100	78	61
6	3	5	0,0500	0,2000	100	20
7	3	5	0,0500	0,2000	100	20
8	3	5	0,0500	0,2000	100	20
9	4	6	0,0800	0,3000	100	20
10	4	6	0,0800	0,3000	100	30
11	4	6	0,0800	0,3000	100	30
12	4	6	0,0800	0,3000	100	30
13	4	6	0,0800	0,3000	100	30
14	1	4	0,1500	0,6000	80	60
15	1	5	0,0500	0,2000	100	20
16	1	2	0,1000	0,4000	100	40
17	2	3	0,0500	0,2000	100	20

In some cases the solution to four periods complements the solution obtained for the single period run with two more lines (ex. period 1: 2-6, (1 line); 3-5 (1); 4-6 (3), 1-5 (1)). Other solutions are different from what was obtained for the single period (ex. period 1: 2-6 (1); 3-5 (1); 4-6 (1); 1-5 (1); Period 3: 4-6 (1); Period 4: 3-5 (1)). As for the single period test mentioned before, the algorithm was run 100 times with populations of 10, 20, 30, 50 and 80 particles. The 10 particles population showed a larger convergence difficulty, but in 94% of cases it reached the optimum in 100 iterations. Using populations of 30 particles one reaches the optimum in 95% of cases after 42 iterations, while with 80 particles we get similar results in 20 iterations. These results are shown in Figure 1.

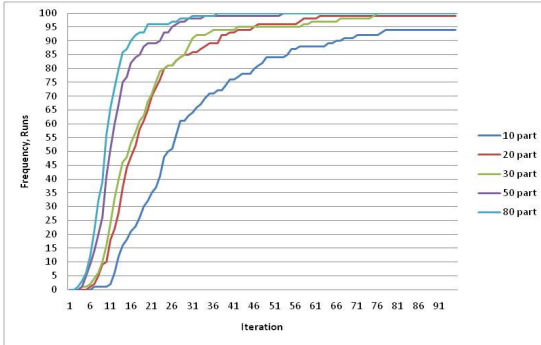


Fig. 1 Convergence in Garver Network test, 4 periods.

Finally, Figure 2 compares the results obtained using the EPSO reported in [9] and the developed DEPSO. In each test 100 runs were performed with 10, 30, 50, 80 and 100 particles. This figure shows the frequency of the best fitness for 25, 50 and 100 iterations. DEPSO has better performance than the classical EPSO and is able to escape from local minimum.

C. IEEE 24 Network

The IEEE RTS has 24 nodes, 35 lines and 32 generators and its original data can be found in [22].

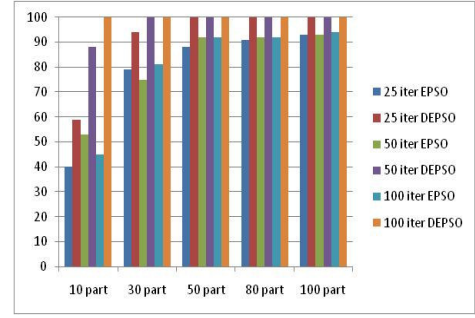


Fig. 2 – Comparison between the EPSO and DEPSO.

In order to obtain a more stressed network and in line with other recent research works, the demand was set at 8,550 MW and the installed generation capacity is 10,215 MW, 3 times more than the original values in [22]. The list of possible projects is shown in Table III. The dimension of the search space has $3^{28} = 22,8 \times 10^{12}$ positions, for a single period, and $6^{28} = 6,1 \times 10^{21}$ positions, for a four period analysis. The update of costs to period 0 was made at a 10% rate per period. The solutions which did not respect either the physical constraints, or $PNS(N) > 0$, or $PNS(N-1) > 0\%$ of the load, were penalized as indicated in Section III.B.

TABLE III
List of projects for the IEEE network expansion problem.

Branch no	From bus	To bus	Resist. (pu)	React. (pu)	Cap. (MW)	Cost (10 ⁶ \$)
1	3	24	0,0000	0,4195	400	500
2	9	11	0,0000	0,4195	400	500
3	10	11	0,0000	0,4195	400	500
4	10	12	0,0000	0,4195	400	500
5	1	5	0,1090	0,4225	175	220
6	1	5	0,1090	0,4225	175	220
7	2	4	0,1640	0,6335	175	330
8	2	4	0,1640	0,6335	175	330
9	2	6	0,2485	0,9600	175	500
10	2	6	0,2485	0,9600	175	500
11	6	10	0,0695	0,3025	175	160
12	7	8	0,0795	0,0032	175	160
13	7	8	0,0795	0,0032	175	160
14	8	10	0,2135	0,8255	175	430
15	11	13	0,0305	0,2389	500	660
16	12	13	0,0305	0,2380	500	660
17	14	16	0,0250	0,1945	500	540
18	15	21	0,0315	0,2450	500	680
19	15	24	0,0335	0,2595	500	720
20	16	17	0,0165	0,1295	500	360
21	16	17	0,0165	0,1295	500	360
22	16	19	0,0150	0,1150	500	320
23	17	18	0,0090	0,0720	500	200
24	20	23	0,0140	0,1080	500	300
25	11	13	0,0305	0,2380	500	660
26	12	13	0,0305	0,2380	500	660
27	11	14	0,0305	0,2380	500	580
28	14	16	0,0250	0,1945	500	540

In the single period exercise, the fitness function considered the investment costs, no limit was imposed on the number of

projects to be added, losses were not considered and the constraint $PNS(N-1) > 0\%$ of the load was not considered. We performed 20 tests of 1000 iterations each, with 10, 30 and 100 particles. The best solution ever found has a fitness of 1954,55 M€ and it includes two new transformers (9/11; 10/11) and three new lines (2/4, 6/10 and 11/13). The most frequent fitness value that was found was 1963,64 M€, and it corresponds to three different solutions: one solution with frequency 1/20 (new lines 6/10; 7/8(2); 16/17(2); 20/23; 11/13), one solution with frequency 4/20 (new lines: 2/4(2); 2/6; 6/10; 7/8(2); 16/19; 17/18) and one solution with frequency 15/20 (new lines: 1/5; 6/10; 7/8(2); 20/23; 11/13). Regarding the performance of the algorithm, with a population of 30 particles, the plans with a fitness of 1963,64 M€ are obtained in 95% of the cases. If the number of particles is increased to 100, then running 600 iterations is enough to obtain the mentioned fitness in 100% of the cases.

On the four period analysis, we admitted that the demand evolves by 5% per period and we considered two new generators to cope with the demand increase: one in bus 4 (300 MW, similar to the generators in bus 7), and another in bus 19 (591 MW, similar to the generator in bus 13). The fitness only included investment costs, the estimate of losses was not considered and we imposed a limit of 6 projects per period. Reliability was evaluated with $PNS(N)$ and $PNS(N-1)$ for branch contingencies. The best solution ever found has a fitness of 3.345,6 M€, and it was obtained with a run with 100 particles, in 694 iterations and includes: in period 1, one new transformer (10/12) and five new lines (6/10; 7/8; 11/13; 14/16; 15/21); in period 2 one new line (11/13); in period 3 one new line (7/8) and in period 4 one new line (2/4).

V. CONCLUSIONS

This paper proposes a discrete approach of evolutionary particle swarm optimisation to solve a Multiyear Transmission Expansion Planning. The results demonstrate that it is an accurate model, and allows the identification of good quality solutions with less particles and less iterations when compared with classical particle swarm optimization algorithms. Future developments include the test of seeding procedures in order to reduce the computation time and testing this approach to real sized transmission systems.

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ANNEX F - PAPER PRESENTED IN PSCC 2011