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Artificial Intelligence for Transmission Expansion Planning in Sub-Saharan Africa.

M. Costeira da Rocha
EFACEC
South Africa

J. Tomé Saraiva
Fac. Engenharia Universidade Porto
Portugal

SUMMARY

Transmission networks are facing very demanding challenges in Sub-Saharan Africa: African utilities are focused on rural electrification, as the access to power is limited to 32 % of the overall population; load increase rates are very high; the connection of renewables and new bulk generation requires interconnection to already existing transmission grids, in some situations thousands of kilometers long; interconnectivity among Southern Africa Power Pool (SAPP) systems is very weak; the existing infra-structure requires improvement and maintenance. As a result of all these concerns, SAPP has already identified transmission expansion as one of the most important issues to be addressed on the next years in Southern Africa. It is also important to recognize that the connection of new generation plays an important role on interconnectivity amongst Sub-Saharan African countries, as relevant energy sources are typically located very far from the main consumers, and are often located in different countries. This is a quite different paradigm from that what is normally found in other continents.

Huge investment is needed to implement new transmission projects; and investors have to be identified outside the region. These investors require well established technical and stable legal frameworks. Both local stakeholders and investors need suitable dynamic tools to model the expansion of the systems. On these tools one has to take into account the complexity of the system on both space and time dimensions. Artificial intelligence based models, like Evolutionary Particle Swarm Optimization (EPSO) either real or discrete approach, have already been tested in real transmission networks, and may be also useful to plan the future Sub-Saharan transmission network. In this scope, this paper aims at describing a mathematical model to perform long term transmission expansion studies having a multiyear nature in order to identify the most adequate expansion plan while considering a number of criteria as the investment and operation costs, the reliability of operation and the uncertainties on loads.

KEYWORDS

Transmission Expansion Planning, Discrete Evolutionary Particle Swarm Optimization, Artificial Intelligence

Manuel.rocha@efacec.com

1. Transmission networks and electricity market

Economic growth forecast is usually considered as a relevant input for the investment on infrastructure. Sub-Saharan Africa economy doubled in size between 2000 and 2013, reaching a global GDP of $2.7 trillion. GDP *per capitae* increases slower, due to a relevant population growth, which is also one of the most relevant facts on infrastructure planning. The weakness of the Sub-Saharan energy system is considered as one of the main constraints for the economic development on a region under complex demographic and social challenges [1][2].

This region is rich in resources, with massive hydro potential in some countries, as DRC and Mozambique, excellent solar resource in vast areas, as in South Africa and Namibia, wind in coastal areas, and gas. In the last years the most important world gas discoveries occurred in Sub-Saharan Africa, with Mozambique appearing as a potential key player. The on-grid generation installed capacity in 2012 was 90 GW. The mix is dominated by coal (45%, mainly in South Africa) and hydro (22%). It is expected that gas penetration on the mix will increase during the next decade (with Nigeria, Angola and Mozambique).

The electricity market, considering both the resources and the demand, is very appealing, but it is also complex, as its development requires accessible and reliable physical infrastructures, coherent legal framework and political stability.

The main utilities of the region joint on the SAPP, Southern Africa Power Pool. The vision of the SAPP is to facilitate the development of a competitive electricity market in the SADC region. However, one has to keep in mind that South Africa is a dominant player on SAPP, as it accounts for 80 % of overall power demand.

One of the main electrical infra-structures in power systems are the transmission networks. These networks provide the physical support interconnecting distribution networks, big consumers and generation to the grid. They are also important when establishing electricity markets, as these are only possible to implement based on reliable and well-designed inter-country transmission networks.

2. Transmission Expansion Planning (TEP)

2.1. The importance of TEP modeling

During the last 20 years, power systems all over the world went through a process of liberalization and restructuring that determined changes at different levels. Apart from peculiarities that characterized this process in different countries, and particularly in Europe, 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 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 network 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, cross subsidies were common and final end user tariffs were typically determined using average approaches. The segmentation of the industry imposes 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. Transmission providers face a challenging task in preparing their expansion plans in view of this more decentralized and uncertain environment. 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.

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 corresponding tariffs, and the economic implications and constraints associated with the quality of electricity; TEP models are usually very complex[1].

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.

2.2. The network segmentation levels and algorithms

The first effort on TEP process has to do with the correct definition of its scope, even before using any model. One should proceed to a careful targeting of investments, which may be segmented in hierarchical levels: Hierarchical level 1 (HL1), that correspond to changes in the topology of the transmission system in respect to its structure; Hierarchical level 2, which correspond to changes in local nature network topology. One may say that HL1 is the structural level, and the one to be considered in TEP.

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. Heuristic methods evolve step-by-step generating, evaluating, and selecting solutions, with or without interacting with the planner. Taking advantage of the planers experience, the computational performance of heuristic approaches is usually better than that of mathematical methods.

In some cases, local searches are performed following rules defined by the planer. The solutions are classified according to these rules and consider information like technical, financial and service data. The process is stopped when no further improvement is possible on the best-found solution. Heuristic Tools include evolutionary algorithms and 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: 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 results

[1] This complexity is largely due to non-linear large models, with a significant computational burden, 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 algorithms could be fast and reliable.

demonstrate that evolutionary strategies found better sequences for TEP. A performance comparison of meta-heuristics to solve the dynamic (or multi-stage) transmission expansion planning problems is provided in [3]. As a result of these ideas, in this paper we describe the application to the TEP problem of a discrete version of EPSO combined with concepts as Fuzzy Numbers, Chaos and Lamarckism.

2.3. TEP in Sub-Saharan Africa

The connection of new generation plays an important role on interconnectivity amongst Sub-Saharan African countries, as relevant energy sources are typically located very far away from the main consumers, or even might be located in different countries[2]. The SAPP may assume a relevant coordination role on the planning of the electric power system among member utilities. It is also a forum on which regional solutions to electric energy problems are discussed and agreed [4].However, the reality is much more complex as Sub-Saharan state-owned utilities still need a deep reform, as several indicators reveal very poor performance when compared with those of other regions [1].

The planning of both generation and transmission is a complex topic anywhere in the world, and Sub-Saharan countries are not an exception. Even in South Africa, where the legal framework is more developed than in neighborhood countries, planning is a big challenge [5]. The provisions are dispersed in several Acts, Regulations, Licenses and Grid Code. Some authors, like Wilson and Adams [6], defend that *"… a theoretically integrated approach exists within the National Integrated Resource Plan (NIRP), under the jurisdiction of the National Energy Regulator of South Africa (NERSA). However, in practice it is apparent that the NIRP is largely irrelevant to ESKOM's planning, which is based on its own Integrated Strategic Electricity Plan (ISEP). It is appropriate that planning should be under the control of an independent body. …"*. On other countries, Grid Codes and Regulatory Independent Agencies are inexistent, which turns planning procedures even more difficult. Some countries adopted policies that also condition the procurement of local infrastructures, adding an additional constraint to the problem. It is the case of South Africa, with the Broad Based Black Economic Empowerment (BBBEE). There is nowadays a debate on BBBEE, if it is achieving its goal in correcting past injustices and opening up opportunities to black South Africans [7].

To implement new transmission projects huge investment are needed; and investors have to be identified outside the region. Both local and foreigner stakeholders and investors need suitable dynamic tools to model the expansion of the systems. On these tools one has to take into consideration the complexity of the system on both space and time dimensions. Some few models have been published focusing modeling system expansion in Sub-Saharan Africa. Rosnes and Vennemo developed a model for optimal expansion of generation, transmission and distribution in 43 country members of the four power pools in Sub-Saharan Africa, including the SAPP. This model was developed under different assumptions, with a horizon of 10 years [8].Nowadays more powerful tools and techniques may be adopted on tackling very complex models, as is the case of TEP.

3. Artificial intelligence for Transmission Expansion Planning

3.1. Introduction

Artificial intelligence based models, like Discrete Evolutionary Particle Swarm Optimization (DEPSO) [9], have already been tested in real transmission networks, and may be also useful on

[2] An example of such complex projects is the ZIZABONA project, involving Namibia, Zambia, Zimbabwe, Botswana and South Africa.

planning the Sub-Saharan transmission network of the future. These mathematical models are suitable to perform long term transmission expansion studies having a multiyear nature in order to identify the most adequate expansion plan while considering a number of criteria as the investment and operation costs, the reliability of operation, and the uncertainties on loads.

3.2. Discrete Evolutionary Particle Swarm Optimization (DEPSO)

The classical Particle Swarm Optimization (PSO) was proposed by Kennedy in 1995, based on the parallel exploration of the search space by a swarm, a set of “particles”, the solutions or alternatives, which are transformed along the process [10]. The particles proceed through the search space, that is, the space integrating feasible solutions. Each particle coordinates are associated with two vectors, its position X_i and its velocity V_i, where i is the particle position in the swarm. When exploring the search space, the particles movement is influenced by three elements: its own position, the position of the best particle ever found on its position and the best particle ever found on the swarm. PSO has many key advantages over other optimization techniques like: 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 has less parameters to adjust unlike other evolutionary techniques; it has the ability to escape from local minima; it is easy to implement and program; it can handle objective functions with stochastic nature; it does not require a good initial solution to start the iterative process. More detailed information about PSO applications in power systems can be found in [11, 12].

In 2002 Miranda and Fonseca [13] introduced the Evolutionary Particle Swarm Optimization (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. In [14] it was adopted the general scheme of the movement rule of PSO according to which the new particles are a combination of four particles: its direct ancestor, the ancestor of its ancestor, a distant past best ancestor and the current global best of the swarm. This recombination rule pushes the population towards the optimum. The evolutionary flavor is given by the self-adaptive mechanism to determine the best values to the weight terms. As in PSO, vectors represent possible solutions in EPSO.

The off-springs are generated by recombination of the particles, which can be modelled by the rules specified by (1) and (2). This movement is illustrated in Figure 1.

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{1}$$

$$V_i^{k+1} = W_{i1}{*}.X_i^k + W_{i2}{*}\,(b_i - X_i^k) + W_{i3}{*}.(b_G{*} - X_i^k).p \tag{2}$$

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 *inertia* term
$W_{i2}*$	weight conditioning the *memory* term
$W_{i3}*$	weight conditioning the *cooperation* term
$W_{i4}*$	weight conditioning the *best global* particle
P	communication factor

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.

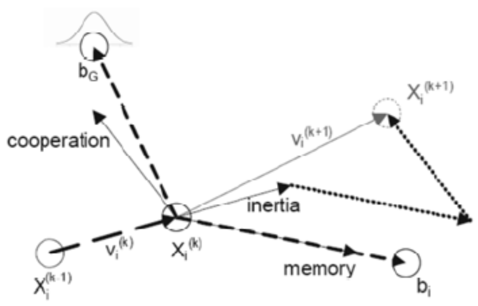

Figure 1 - EPSO Movement Rule (Source:[14])

The communication factor P is a diagonal matrix affecting all dimensions of a particle, containing binary variables of value 1 with probability p and value 0 with probability (1-p). The p value controls the flow of information within the swarm and is 1 in classical formulations. The symbol * indicates that the parameter will undergo mutation. Mutation is a relevant operation because it can provide extra chances for the swarm to escape from local minima and also the necessary focus and zoom in the optimum when the inertia and memory weights are reduced and the cooperation weight is larger. Reference [15] provides results that demonstrate the superior performance of EPSO.

The DEPSO 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, each one representing a possible solution for the problem, the number of positions in a particle, which means the number of projects that are included in an expansion plan project list and the number of possible states in each particle position, representing the period when each project would enter in service. The main difference between this approach and classical EPSO is that the elements in this particle are integers, instead of real numbers.

DEPSO follows the same structure of classic EPSO, and the algorithm is organized as follows.
- Replication: the population is cloned twice;
- Mutation of weights: as in the classical EPSO approach, there are three weights that are subjected to mutation: inertia, memory and cooperation. The mutation is performed through a sigmoid function[3] as indicated in (3);

$$w_{pt,j,t}^{it+1*} = \left(0.5 + rand() - \frac{1}{1 + \exp\left(- w_{pt,j,t}^{it*} \right)} \right) \quad (3)$$

[3] The sigmoid function 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. 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 algorithm (no intermediate conversions needed).

- Mutation of best global: the global best particle is a vector, whose positions are mutated only when randomly numbers uniformly generated in the interval [0.1] take values less than k_c € [0,1] . The weights are updated by (3) and the mutation of particle b_G is obtained by (4);

$$b_{Gj}^{*} = b_{Gj} + round\left(2.w_4^{it*} - 1\right) \quad (4)$$

- Recombination: we adopted the same expressions of the classic EPSO, which we round up to integers. Accordingly, we shall not consider a continuous velocity spectrum, but jumps from one admissible position to another admissible position in the search space. 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, according to a random generation (5 and 6);

$$X_{pt,j}^{it} = 0 + round(rand()) \quad (5)$$

$$X_{pt,j}^{it} = np + 1 - round\left(rand\,()\right) \quad (6)$$

- Recombination by Lamarkian evolution: when the velocity of a particle is zero, meaning that it will not move, it is promoted a Lamarckian evolution of that particle using (7). In this particular evolution the particle only sees some of his positions mutated, those when random numbers uniformly generated in the interval [0.1] take values less than kb; k_a is set to nper.

$$V_{pt,j}^{it} = round\left(2.ka.\left(0.5 + rand_1() - \frac{1}{1+\exp(-rand_2())}\right) - ka\right) \quad (7)$$

- Selection: at each position of the population survives the clone whose fitness is better than the best article of the same position. The best global is updated if some of the best particles has best fitness.

This model is boosted by local search nearby the best solutions ever founded. When a particle has a good fitness, it is assumed that other particles in their vicinity may be of interest. Thus we create a new population on which we run an additional search. This population will result from the evolution of clones of the best global or a randomly selected particle among the best population. The Lamarkian evolution is also promoted using (7).

Numerous tests were conducted to compare the performance of this approach with conventional EPSO approaches. The results were very promising given that the new approach was able to escape from local minima in more than 95% of the analyzed cases and also because it was possible to identify good solutions with less iterations and smaller populations than previously.

3.3. TEP modeling using DEPSO

TEP modeling using DEPSO starts by defining an investment plan project list, based on P_r projects, and a time frame, based on P_e periods, is defined by the following information: origin bus, destination bus, technical data and investment. A solution X_i of the TEP problem corresponds to a plan that includes a number of projects selected among this list as well as their location in the time frame. The search space under analysis is discrete and integer. It typically includes a large number of possible alternative plans, given by P_eP_r.

The general formulation of the TEP is given by (8-11).

Min Cost (Xi) = Investment (Xi) + Oper. cost (Xi)+ α_i (8)
Subject to:
Physical constraints (generation; power flow limitations); (9)
Financial constraints (global and period constraints); (10)
Quality of service constraints (reliability) (11)

The list of possible projects mentioned in a) can include, not only new lines to establish in new corridors, but also lines to install in existing corridors or projects associated with the upgrade of the capacity of existing lines, for example increasing the voltage level. Each of these projects is characterized by its investment cost and period. Then if a particular project is selected for a particular period, its investment cost is referred to the period 0, using an interest rate appropriate to the risk of this type of investment. Operation Costs are evaluated solving a linearized DC_OPF problem. While doing this, network and generator limit constraints are enforced. However, if transmission or generation capacity is insufficient, then the power not supplied (PNS) will be non-zero, thus increasing the value of the objective function. This means that using this strategy, we are inherently penalizing particles that are not adequate in terms of being able to connect properly 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. The objective function (08) 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. Failure to comply with the constraints set leads the solutions to be penalized, with the penalty terms α_i: if the level of losses exceeds a reference value; if the PNS(n) is not zero; if maximum number of projects per period is exceeded; if investment value over the entire horizon is exceeded; if the PNS (n-1) is not zero.

3.4. Multiyear TEP model considering load uncertainties

Several TEP data is actually affected by uncertainties: load demand evolution, generation costs, new generation (technology, location, year), 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 Saraiva introduced in 1990 the first DC and AC models admitting that at least one generation and demand are modeled by fuzzy numbers [16]. 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 Saraiva describe the formulations and the solution algorithms developed to model 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 [17]. 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 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 just focus on the uncertainties affecting the loads, within a range of +/- 5%. In order to also simplify the model, without compromising its validity, the uncertainty of the loads is modelled by a triangular membership function. For illustration purposes, when combining the uncertainties affecting two loads we obtain the polygon shown in Figure 2. The combination of two loads affected by uncertainty results in a pyramid. The point of maximum membership corresponds to the coordinates (A2, B2). If, for 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 ((A1, B1) - (A2, B2)) and the edge ((A2, B2) - (A4, B4)). That is, to study the uncertainty affecting the loads, and under these assumptions, it is enough to study points that lie along these two edges.

Regarding this simplification, it should be noted that when analyzing the performance of a 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.

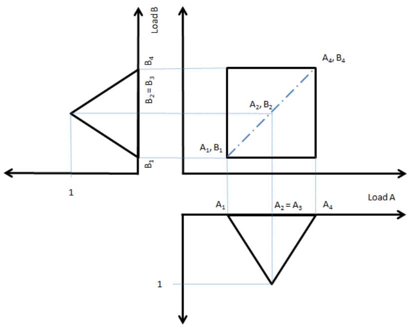

Figure 2 - Combination of two triangular fuzzy loads

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 only considering 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 point associated to the minimum load combination and to the point of maximum load combination.

The assessment of multiyear TEP considering uncertainties can be made by adopting the same expression (8) listed before, but considering an additional penalty factor when the solution (obtained for the deterministic load) affected by uncertainty originate non-null values for the power not supplied. If power not supplied is non-null the particle will be penalized and will hopefully evolve while enforcing all problem constraints (9-11).

At the end of the evaluation process a set of possible solutions is obtained, 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. 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. Once analyzed all the particles affected by the specified load uncertainties, a set of solutions to the problem is obtained.

3.5. Case Study – IEEE 24 bus Reliability Test System

The IEEE RTS network has 24 nodes, 35 lines and 32 generators. 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. The list of possible projects on the expansion planning included 28 new projects, in which four projects correspond to the installation of new transformers.

For a single period analysis the search space has $3^{28} = 2{,}29 \times 10^{13}$ positions. The fitness has considered the investment cost, no limit was imposed for the number of projects to be added. A set of 20 tests, 1000 iterations each, with 10, 30 and 100 particles were performed. One has to keep in mind that with 1000 iterations and a population of 30 particles only 90.000 solutions are tested, in a search space with $2{,}29 \times 10^{13}$ possible solutions. The best solution ever found has 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). With populations of 30 particles the success frequency was of 95% of the cases.

On the four periods analysis the same list of possible projects was adopted. For these tests, and to cope with the demand increase of 5% a year, two new generators were added. The search space for a four period analysis has $6^{28} = 6{,}14 \times 10^{21}$ positions. The best solution found 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 and five new lines; in period 2 one new line; in period 3 one new line and in period 4 one new line.

Multi period test results were also compared with single period test results. With this purpose, additional tests with larger populations and more iteration were performed. As can be seen in Figure 3, 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).

On Table 1 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.

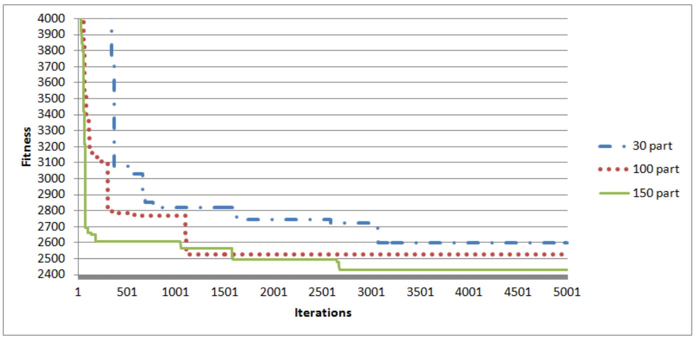

Figure 3 – Deterministic multi-period test fitness evolution with 30, 100 and 150 particles.

Among the single period and multi-period solutions one finds significant differences as indicated in Table 1: 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 singe period solution are included in the multi-period solution: 3/24, 10/12, 2/6, 11/13 and 11/23.

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.

When considering uncertainties on the four period analyses, the same list of possible projects on the expansion planning was adopted. The uncertainty in each load is modeled using a fuzzy number with a triangular membership function. It should be noted that point of 100% corresponds to the deterministic solution, already mentioned previously. All particles were tested by assessing the PNS (n-1) with the fuzzy load.

Table 1 – Deterministic expansion plans for the single and multi-period analysis.

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	11/23
		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

From the results we observe the following: the solutions that include transformer 3/24 display poor quality in the presence of load uncertainties; some solutions that have identified the exclusion of certain lines (such as 1/5 and 11/23, which interconnect generating buses with relevant loads) also show poor quality, being very sensitive to load variations; only 19% of the 100 solutions that integrate the final 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 worse fitness, namely solutions having larger investment cost.

4. Conclusions

We present in this paper a dynamic or multiyear TEP model, based on heuristic DEPSO. 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 an estimation 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 constraints, 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, load uncertainty is then considered, 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. 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.

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