

FACULDADE DE ENGENHARIA DA
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COMPUTAÇÃO EVOLUCIONÁRIA E LÓGICA DIFUSA APLICADAS AO PRÉ-
DESPACHO DE GERAÇÃO EM SISTEMAS COM FONTES RENOVÁVEIS

EVOLUTIONARY COMPUTING AND FUZZY LOGIC APPLIED TO
GENERATION SCHEDULING IN SYSTEMS WITH RENEWABLES

進化式演算法及模糊邏輯於擁有再生能源的系統中機組排程的應用

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ABSTRACT

The main objectives in the thesis are: to present a possible way to solve a unit commitment problem for an isolated network with renewable(wind) energy and incorporate the operator preference in determining the penetration of renewable energy.

The model of the unit commitment problem is constructed according to the network and data of an island (Crete, Greece). In the model, the objective function is to minimize the total cost, including operational costs and starting up/shutting down costs. The model also includes Power Balance Constraints, restriction of various generators, penetration limit of wind energy penetration, and minimum spinning reserve requirement.

After the formation of the mathematical model of the UC problem, a genetic algorithm is applied. Genetic algorithms are one of the branches in evolutionary computing which works similar to the evolutionary theory of Darwin. In fact, some special features of GA make them attractive in solving complex optimization problem. However, solutions obtained by GA may only be close to the optimal solutions. In order to obtain better solutions for the unit commitment problem, advanced genetic operators are introduced: Code Compression Technique, Niching method, Variation of Basic operator, and "Chromosome Repair and Neighborhood Digging". These operators focused on different aspects in improving the performance of a genetic algorithm when solving a unit commitment problem.

Additionally, with the flexibility of Genetic Algorithms, a new dispatch algorithm for fuzzy penetration of the wind energy was introduced. By using the fuzzy programming technique, this algorithm determined the wind energy penetration according to the preference of operators. In this thesis, the derivation of this dispatch method is shown.

The results of this work have been integrated in project CARE (EC DGXII JOULE PROJECT JOR3-CT96-0119)

摘要

本文的主要目的在：提出針對使用可再生能源的孤立電力系統中的機組排程(unit commitment，或譯發電排程)問題的一個可行的方法，同時，在決定可再生能源的引入量中加入操作人員的喜惡。這個機組排程問題的模型是根據一個島（克里特島，希臘）的電力網絡和數據來建立的。

在模型中的目標函數是把整體的發電成本降至最低，而當中包括運作的成本和發電機起動/關閉的花費。此外，電力平衡限制（Power balance constraints），不同種類發電機的操作條件，風力發電引入量的限制以及最低備轉容量要求等，也包括在此模型內。

在建立起機組排程問題的數學模型後，基因演算法（genetic algorithm,或譯遺傳演算法）便被應用於這一問題上。基因演算法是進化式演算法中（Evolutionary Computing)的一個分支，進化式演算法在運作上是近似於達爾文的進化理論的。事實上，基因演算法的特點對解決複雜的最佳化問題有很大的吸引力。不過，基因演算法所得到的答案可能只是接近最佳的答案。為了取得比較好的結果，因此加入了數個特別的模組（用於基因演算法中）：編碼壓縮技術，固定族群選擇法，基本參數的變動以及"基因修改及鄰近基因發掘"等。在為機組排程問題找尋答案時，這些模組從不同的方向改善基因演算法的表現。

另一方面，利用基因演算法擁有很大彈性的特點，加入新的經濟調度算法，來處理模糊風力發電引入量。應用模糊規劃理論，這個新的算法根據操作人員的喜惡找出適當的風力發電引入量。在這篇論文中，會介紹這一個調度算法的推演過程。

這一份工作的成果已加入一個歐洲聯盟 -- 被命名為 CARE 的計劃內。(EC DGXII JOULE PROJECT JOR3-CT96-0119)

RESUMO

Os objectivos fundamentais desta tese são: apresentar um novo modo de resolver o problema do pré-despacho de geração numa rede isolada com fontes renováveis (eólicas) e incorporar as preferências do operador na determinação do grau de penetração da produção renovável.

O modelo do problema de pré-despacho obedeceu às características e dados da rede da ilha de Creta (Grécia). Neste modelo, o objectivo é a minimização dos custos totais, incluindo operação e arranque/paragem. O modelo inclui restrições de balanço de energia, limites diversos relativos aos vários tipos de geradores, limites à penetração de geração eólica e mínimos a respeitar para reserva girante.

Ao modelo matemático do problema é aplicado um Algoritmo Genético (AG). Os AG constituem um dos ramos da Computação Evolucionária, que opera de forma similar à teoria da evolução de Darwin. De facto, algumas das suas características tornam-nos atractivos para a resolução de problemas complexos de optimização.

A fim de serem determinadas as melhores soluções para o problema do pré-despacho, foram introduzidos novos operadores genéticos: “Reparador Cromossómico” e “Mineração na Vizinhança”. Estes operadores conseguem, por mecanismos distintos, melhorar o desempenho do AG na solução do problema do pré-despacho.

Adicionalmente à flexibilidade dos AG, foi desenvolvido um novo algoritmo levando em conta limites difusos para a penetração da geração eólica. Com recurso à programação difusa, este algoritmo permite determinar ao nível de penetração conveniente de acordo com as preferências dos operadores. Nesta tese apresenta-se a dedução deste algoritmo.

Os resultados do trabalho descrito foram integrados no projecto CARE (EC DGXII JOULE PROJECT JOR3-CT96-0119).

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1. INTRODUCTION

In recent years, the operation of power systems has become more and more complex. The reasons for this increase come from different aspects: the increasing load demand and electrical energy dependency of the customers, the increasing number of components connected to the network, and the driving force towards the market environment, etc.... Due to these trends, the risks of the power system are increasing, thus the importance of security issues are also growing during operation. It is also important that the service quality is addressed and the cost of power generation needs to be reduced[5].

Faced with these new challenges, tradition ways of operating power system are becoming inadequate. Utilities need tools to assist the operation in order to deal with the new environment. Advanced control systems emerge as a tool in helping power system operation[5]. They provide adequate information to operators, such that the system can operate closer to the global optimal point. There are many application functions integrated into advanced control systems, however these functions are different from system to system.

Among the application functions of advanced control systems, Production Control specially deals with the control of the power generation. Its objectives are to minimise the cost of power generation with the desired quality and also satisfying the constraints of the system. The Production Control affects several distinct time periods and the corresponding Production Control functions are different.

Function	Time interval
Resource scheduling	Weeks – Year
Unit commitment	Hours – Day
Economic Dispatch Calculation	Minutes – Hour
AGC (Automatic Generation Control)	Seconds – Minutes
Local Control	Milliseconds – seconds

Unit commitment is one of the components in Production Control, as shown in the previous table[5]. It evaluates the scheduling of the generators within the forecasted load over the studied period. The general objectives of the unit commitment are to minimise the power generation cost and providing

that the constraints are satisfied[13]. The constraints for the unit commitment model are various and depend on the requirements of the system and the utilities.

The isolated power system network is slightly different from the ordinary power system network. In an isolated network, the network is separated from other networks. Due to this separation, there is no external source to feed the load, the security margin and spinning reserve need to be defined in specific manner to guarantee the desired level of operational safety. Nowadays, environmental protection is one of the important topics in our society, however, lack of natural resources is also another problem. Traditional thermal generators bring not only electrical energy but also pollution. With the increasing requirements toward environment protection, thermal generators work in a contradictory way with these requirements. Yet, another problem can occur with thermal generators in isolated networks. Due to their geographical location, fuel need to be transported, thus increasing the overall production costs.

Renewable energies (namely, wind) provide an alternative way to generate power. It is a clean and in some cases, low cost energy. The wind energy production not only reduces the cost of power generation but also causes indirectly reduction of the pollutant emitted by thermal generators. However, using wind generation still has many restrictions. Due to the random nature of the wind, the penetration of the wind power needs to be carefully studied to avoid stability problems and other perturbations.

With the introduction of wind generation, the application functions inside advanced control systems need to be adapted. The behaviour of the wind generation is slightly different from thermal generation. Thus, the unit commitment needs to change in order to deal with wind generation.

In this thesis, we will include the classical model of the unit commitment problem and we will advance further to include some rules (for generator start up) into the model. In this study, the unit commitment problem comes from an isolated network and the renewable energy source is widely used. Since we model our unit commitment in a classical approach, this model cannot be directly adopted and work under the market environment. Nevertheless, power system networks tend to become interconnect with other

networks and adopt to the market environment. However, isolated networks still exist due to the geographical limitation.

In the decision process of unit commitment, the wind power penetration needs to be considered. Generally, the penetration is a fixed specific value. In the thesis, we will try to reformulate the economic dispatch algorithm to determine the wind power penetration limit according to the preferences of the operators.

However, a unit commitment problem is hard to be solved mathematically. First, it involves a large number of integer (1/0) variables which causes many optimisation techniques failed. Second, a unit commitment problem generally has a high dimensionality in solution space. This is a great barrier to find the optimal solution by enumeration. Additionally, the realistic restrictions, sometimes, are difficult to be described by mathematical formulation, for instance, some thermal generators have several starting up procedures.

Thus, we employ Evolutionary Programming technique[3] (Genetic Algorithm) to solve our unit commitment problem. With its distinct characteristics, a Genetic Algorithm can ease the difficulties described above. However, the optimum of the solution of a Genetic Algorithm cannot be guaranteed and the solutions will have deviation too. Several genetic operators such as Deterministic Crowding Selection Scheme[10][11], Chromosome Repair and Neighbourhood digging, Dynamic Mutation Rate Adjustment, and Chromosome Compression Technique will be introduced. These operators aim at improving the solutions obtained by Genetic Algorithm and reduce the deviation of the solutions.

The main contributions of this thesis are:

- a. The demonstration of improvements in efficiency of GA by adopting a block structure for encoding chromosomes
- b. The demonstration of improvement in the quality of solutions by adopting neighbourhood search techniques and chromosome repair operators
- c. The development and successful test of a fuzzy dispatch model taking care of wind penetration constraints.

The thesis reports part of the work done for project CARE (EC DGXII-JOULE PROJECT JOR3-CT96-0119), an European Union research project. Based on the model described, we has prepared an unit commitment application that has been integrated in a EMS environment and is currently being operated in Greece by PPC – Public Power Generation (the Greek State Power Company), in the island of Crete.

2. OVERVIEW OF EVOLUTIONARY COMPUTING TECHNIQUES AND THEIR APPLICATION IN THE UNIT COMMITMENT/GENERATION SCHEDULING PROBLEM

2.1. Unit Commitment/Generation Scheduling Problem

In the daily operation of a power plant, unit commitment(UC) is an important decision step. It decides the operation of the generators in order to achieve the goal of meeting load. It is an important part in advanced control of the power system[5].

However, the UC problem is not easy to solve. Its variables are the mix of integer and continuous (where integer variables are the generators switch on / switch off variables and the continuous variables are the generation level of the generators)[13]. Due to the constraints of the UC, there is an increased difficulty in solving the problem. These constraints are limitations of the practical situation. Only with a model that includes these constraints, the solutions of the UC meet the requirements of the real world.

Target and constraints of the Unit Commitment

The classical target of UC is to minimise the total operation costs(generation, switching,...) , provided that the constraints are satisfied. Besides the operation cost, other targets can be defined, such as minimising NO_x and SO_x emission[16][29]. In this thesis, the UC problem is defined considering the following constraints :

- Power Balance Equation
- Spinning Reserve Requirement
- Technical limitation of various Generators (including renewable)
- Dynamic Security (Through the definition of limits to the penetration of wind generation)

A Classical Formulation

The following formulation can be developed for a period of 12,24 or even a 48 hours ahead. It neglects some second order issues like losses in the network, admitting that an adequate dispatch model will be correct (in real time) the solutions proposed by the UC model. However, these losses could be included in the model with simplicity, only at a cost of higher computing time.

Cost Function

$$\text{Minimize } \sum_{t=1}^T \sum_{i=1}^N C_i(P_{it}) + Sup_i(t) * (1 - U_{t-1}) * U_{it} + Sdown_i(t) * U_{t-1} * (1 - U_{it}) \quad (1)$$

Where T is the total time interval of UC

N is the total no of Generator

P_{it} is the Power Generation of the Generator G_i at interval t

$C_i(P_{it})$ is the Cost of Generation of Generator G_i at interval t

$Sdown_i(t)$ is the Cost for the Shut-down of Generator G_i at interval t

$Sup_i(t)$ is the Start-Up Cost of the Generator G_i at interval t. (Note: the Start-Up Cost for Generator G_i may have different cost according to the Start-up rules of the Generator.)

U_{it} is the status of Generator G_i at interval t

Constraints

I. Power Balance Equation

$$\sum_{i=1}^T P_{it} = L_t \quad \text{for } t=1, \dots, T \quad (2)$$

Where L_t is the load at the interval t

II. Spinning Reserve Requirement

$$\sum_{i=1}^T MP_{it} \geq L_t + L_t * S_p \quad \text{for } t=1, \dots, T \quad (3)$$

Where MP_{it} is the maximum possible Power Generation of Generator G_i at interval t.

In general, $MP_{it} \leq P_{i\max}$ this is due to 2 reasons:

- Ramping constraints of the unit, so $MP_{it} \equiv MP(t, P)$
- Availability of wind for Period t is excess of what is being used.

S_p is the Spinning Reserve (express in percentage of the Load)

III. Technical Limitation of the Thermal Generators

$$P_{i\min} \leq P_i \leq P_{i\max} \quad (4)$$

Where $P_{i\min}$ is the lower limit of Generator G_i

$P_{i\max}$ is the upper limit of Generator G_i

$$P_{it} \leq P_{(t-1)i} + R_i \quad \text{for } t=1..T \quad (5)$$

$$P_{it} \geq P_{(t-1)i} - R_i \quad \text{for } t=1..T \quad (6)$$

Where R_i is the ramp rate of the Generator G_i

$$D_i(t-1) \geq MUT_i * U_{i,t-1} * (1 - U_{it}) \quad \text{for } t=1..T \quad (7)$$

$$D_i(t-1) \geq MDT_i * U_{it} * (1 - U_{i,t-1}) \quad \text{for } t=1..T \quad (8)$$

Where $D_i(t)$ is the total time of the Generator G_i stayed in the current state (Up, Down)
 MUT_i is the Minimum Up Time of the Generator G_i
 MDT_i is the Minimum Down Time of the Generator G_i

- IV. Start-up Rule of the Generators
When Generators G_i Start
If **Rest Time of G_i < Warm Start-Up Cooling Time**
Generator G_i performs Hot Start up
 $Sup_i(t) = \text{Hot Start up Cost}$
If **Rest Time of G_i < Cold Start-Up Cooling Time**
Generator G_i performs Warm Start up
 $Sup_i(t) = \text{Warm Start up Cost}$
Otherwise
Generator G_i performs Cold Start up
 $Sup_i(t) = \text{Cold Start up Cost}$

Methodology

After having the formulation of the problem, it is necessary to select a proper method to solve this problem. In the previous studies [1], lots of different method has been developed to solve the UC problem.

- **Full Enumeration[1]** : This method is a simple method. It will try to search all the combination of the generators over the studied time horizon. However, when the number of the generators and studied time intervals increase, the number of the combination will increase rapidly. It is non-trivial to solve for a large system. (e.g. 5 generator schedule over 10 time intervals with yield $8.196e14$ combinations !!)

- **Dynamic-Programming Method**[1][30]: Proposed by Dr. Richard Bellman and his associates in the late 1950s[1]. It provided a systematic way to search the solution space. The main advantage of this method is : It can reduce the number of the computation and maintain the feasibility of the solution[1]. However, when using the dynamic-programming technique to solve the large scale UC problem, the dimension problem still exist and considerable memory is needed. In previous studies, many modified version of dynamic-programming method were proposed to solve the UC problem, such as : Extended differential dynamic programming[30], dynamic programming sequential combination (DP-TC), dynamic programming sequential combination (DP-SC), dynamic programming sequential truncated combination (DP-STC), Sequential Unit Commitment[30], stochastic dual dynamic programming (SDDP) [30]... etc.
- **Lagrange Relaxation Method** [1]: This method is based on the dual optimisation technique. The dual procedure will try to find the optimum by maximising the Lagrange multipliers[1]. It is a different approach by comparing with dynamic programming and full enumeration method. This method will not have the problem of the “curse of dimension”. But this method cannot guarantee that the solution given out is feasible. Furthermore, the convergence of this method might become unstable at the end and hence the process will never end. As Dynamic-Programming Method, there also exist various modified lagrange relaxation approaches, e.g. Augmented Lagrangian relaxation[28].

Other than the methods mentioned above, Branch-and-Bound method, Benders Decomposition[13], Expert System[25]approach and Evolutionary algorithm

techniques have also been used in solving the UC problem. In this thesis, genetic algorithm (one branch of evolutionary algorithm) will be adopted.

2.2. Application of Genetic Algorithm in Unit Commitment

Genetic Algorithm

A Genetic Algorithm (GA) is a computer-aided searching method. It is one of the branches in Evolutionary Computation(EC)[7]. Their working principle is based on the perceived performance of individuals evolution and is analogous to the evolution of a natural creature[7]. In nature, creatures (individuals) need to fight each other for the necessary resources mating. Generally, the fittest individuals will have better chance to survive and mate. However, some “lucky” individuals, regardless of their fitness, can also survive and contribute to the mating pool. Individuals tend to become fitter and fitter throughout evolution. There are several main categories in EC:

- Genetic Algorithm
- Evolution Strategies
- Evolutionary Programming
- Genetic Programming
- Classifier Systems
- Simulated Annealing EA

GAs were first developed by John Holland[3]. Because of its powerful searching ability, it is widely adopted in various applications nowadays. Along with this, it has immunity from the non-linear characteristics of the optimisation problem and the ability in finding good solution for the complex problem. In Figure 2, a simple algorithm of GA is shown.

Initially, a GA starts with a population of random chromosomes (individuals), which normally is a binary bit string. Chromosomes can also be constructed by non-binary bit strings, however, the performance of these GAs may become worse[3]. Indeed, chromosomes are the solutions of the studied optimisation problem. Some mechanisms/decoding methods are used to translate the chromosomes into solutions(like DNA inside the human body). In a GA, chromosomes are classified in accordance to their fitness. And, the fitness of a chromosome is calculated by a defined fitness function. In general, a fitness function is the objective function of a optimisation problem with the addition of the penalty costs whenever constraints of the problem violated. It should be emphasised that the fitness function is only used to evaluate the

payoff value of the chromosomes and it is independence from the GA. With this characteristic, the objective function of the optimisation problem can be very complex and highly non-linear.

In a GA, there are three basic genetic operators: Selection, Crossover, and Mutation. The selection operator is used to choose the suitable chromosomes for mating and entering next generation. There are several schemes in selection, e.g. roulette wheel selection, tournament selection scheme....etc. In a roulette wheel selection scheme, chromosomes are selected proportional to their fitness. With higher fitness, chromosomes get more chance to be selected[3]. The main idea of selection is to simulate the selection environment of nature.

Crossover and mutation are the main operators in generating new offspring. In a Crossover operator, two parent chromosomes will be selected randomly and a random point within the chromosome also will be determined. Then, the information up to the selected point, which is called crossover point, will be exchanged and two new chromosomes are obtained (As shown in Figure 1). In the figure, two chromosomes (10 bits) are selected as parents(CH1, CH2) and the crossover point is 6. After the crossover, the two new offspring (Ch1' , Ch2') will be generated. This type of Crossover is known as the Single Point Crossover and is widely used in simple genetic algorithm[3].

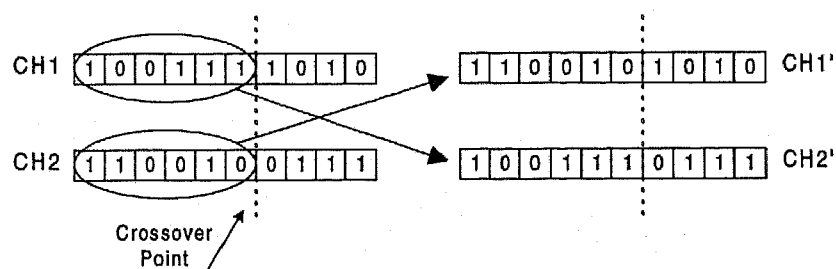


Figure 1 Single point crossover

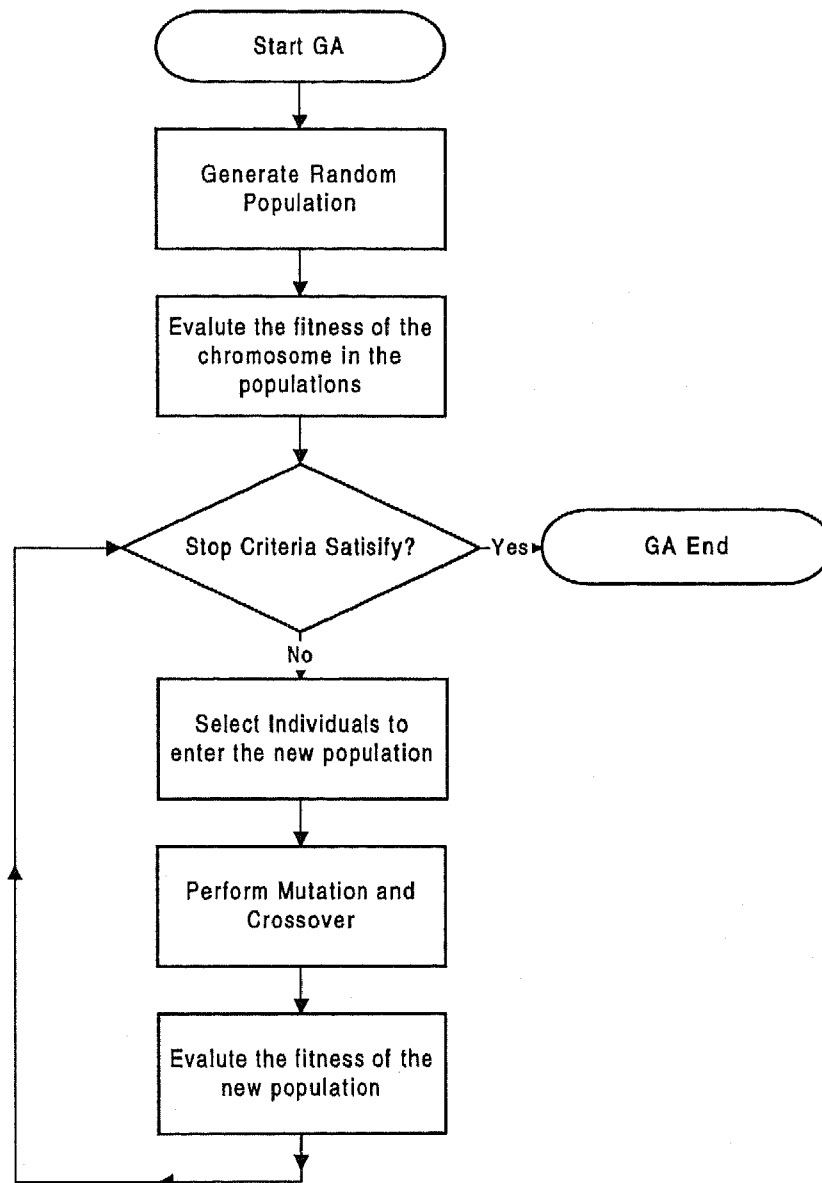


Figure 2 General Algorithm of GA

Another genetic operator for new chromosome generation is a Mutation Operation. It is the main source to introduce new genetic material into the population of a GA. In a GA, the mutation operator will simply flip the bits, means changing the bits from 1 to 0 or 0 to 1, of the chromosome with a low probability. This operator has the trend to prevent the possibility of ending the search in a local optimum[3].

The population will undergo the whole process for generations until the stopping criteria is reached. The stopping criteria can be dependent on the number of generations, the fitness of the ever-best chromosome, and the

median value of the population....etc. Generally, the number of generations acts as the stopping criteria for a GA.

By comparing GAs with other methods, they have several distinct characteristics:

- GAs code the parameters in a bit string and the meaning of the bits is completely transparent to the algorithm.
- GAs search the solutions in a parallel manner.
- Knowledge of the fitness function (or the objective function of the problem) is not needed. Even if the fitness function is non-linear, it will not affect the performance of GAs. It is because GAs only use them to calculate the fitness of the chromosome.
- The search of GAs are guided by probabilistic rules whereas other methods are guided by deterministic rules.

GA application in Unit Commitment

Due the characteristics of UC problems, they are not easily solved by a deterministic method, the intrinsic nature of GAs make them suitable to solve the UC problem. By comparing with the other methods, GAs have the following special characteristics:

1. GAs manipulate a binary bit chromosome and the UC problem mainly consists of binary variables (switch on / switch off)
2. GAs don't need knowledge about the objective function and constraints. They only use to calculate the fitness of chromosomes.

To use GAs in solving the optimisation problem, first of all, one needs to determine the method to encode the solutions into chromosomes. The way for encoding is arbitrary. However, there are 2 principles in encoding the chromosome which are stated in[3]:

Principle of meaningful building blocks:

The user should select a coding so that short, low-order schemata are relevant to the underlying problem and relatively unrelated to schemata over other fixed positions.

Principle of minimal alphabets:

The user should select the smallest alphabet that permits a natural expression of the problem.

Based on these principles, Figure 3 proposes a simple way to encode the UC problem.

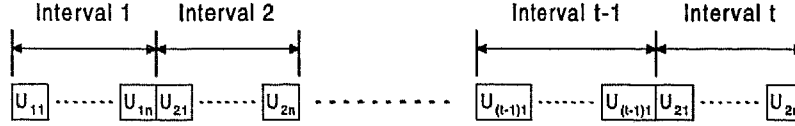


Figure 3 Coding method for Unit Commitment

In this encoding method, the state of all the generators, for a given time interval is grouped into one block. If there are t time intervals, the total number of blocks will be t blocks. With this kind of chromosome, the generator schedule can be represented directly.

Another issue in solving the UC problem by genetic algorithm, is the fitness calculation of a chromosome, or the schedule of the generators. For evaluating the fitness of a chromosome, the following procedures are needed:

1. Obtain each generator's schedule from decoding the chromosome with a specific scheme (decoding scheme).
2. Verify the constraints (Constraints I. - III.) of the model. Whenever the generator schedule violates any constraints, a penalty cost which is proportional to the degree of violation is added to the fitness of the chromosome.
3. Perform the economic dispatch routine for finding the production level of the committed generators (for all the time intervals). In the moment, for simplicity, the lambda search method [1] is used in the economic dispatch routine. However, advanced economic dispatch methods can be implemented for incorporating the network losses.
4. Calculate the Start-Up cost and the Shut down cost of the generator schedule in accordance to constraint IV.
5. Evaluate the operational cost of the generators with their power production level.

As a brief summary of the above fitness evaluation procedure, the following formula is the fitness function of the UC module.

$$\text{Fitness (Individul x)} = \sum_{t=1}^T \sum_{i=1}^N C_i(P_{it}) + Sup_i(t) * (1 - U_{t-li}) * U_{it} + Sdown_i(t) * U_{t-li} (1 - U_{it}) + \sum_{j=1}^J Penalty_j * VD_j \quad (9)$$

where J is the total no of constraints in the model
 VD_j is the violation degree of constraint j
 Penalty_j is the penalty cost for the violation of constraint j

The stopping criteria must also be provided to the algorithm. The algorithm will stop when a certain number of generations has been processed. Then, the generator schedule over a specific time horizon is determined. Thus, the UC model can be solved by using the algorithm shown in Figure 2.

The above scheme described for UC is simple, however, it is not suitable for practical use. It has difficulties with large number of generators and long time interval. Due to the increase in the length of the chromosome, the algorithm will need more time to converge. Moreover, the solutions of UC given out by genetic algorithm will have deviation (Run the same problem for several times, and find the average spread of the solution). It is important that the deviation of the solution is kept low, as it involves money. Several improvements should be made in order to overcome this problem.

3. OVERVIEW OF FUZZY DECISIONS AND FUZZY PROGRAMMING

3.1. Fuzzy Set

Imprecision and ambiguity exist everywhere in the natural world. In the world today, many types of information have a degree of uncertainty. Since the development of computers, they are widely used to predict, control and provide decisions for the real world. However, computers have difficulty in dealing with vague information. For example, does a computer understand the command like : “ Slightly decrease the temperature”? Probability and statistic theory can successfully model random events but vague information is not random and it is difficult to model it by using probability and statistic theory.

Fuzzy set theory (suggested by Dr. Lotfi Zadeh in 1965) provides a way to deal with the vagueness, imprecision and ambiguity information. Fuzzy set theory is a mathematical way to represent the uncertain nature of information. The following is the definition of a fuzzy set:

If X is a collection of objects denoted generically by x then a fuzzy set $\tilde{A}$ in X is a set of ordered pairs:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X\}$$

$\mu_{\tilde{A}}$ is the membership function that maps X to the membership space M and $\mu_{\tilde{A}}$ is the grade of membership of x in $\tilde{A}$. [6]

With the introduction of fuzzy sets, computers can deal with vague information. On the other hand, the decision maker can also deal with vague information and thus enhance the flexibility of the decision. The key concept of the fuzzy set theory is the introduction of “grade of membership” of the set. In the crisp set, elements either belong to the set or not belong to the set. e.g. Crisp set $C = \{\text{all the values between 5 and 6}\}$. This means that only the value greater than 5 and less than 6 will belong to Crisp set C and the other elements will not belong to X . The membership function of crisp set C is :

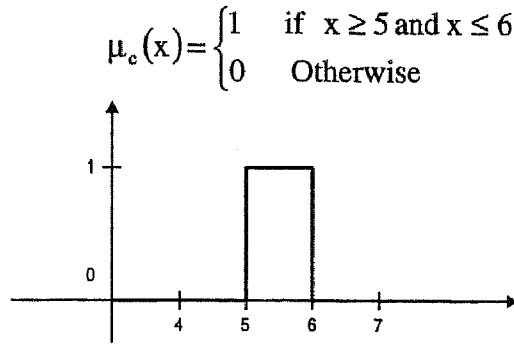


Figure 4 The membership function of crisp set C

In contrast to the crisp set, elements can partially belong to a fuzzy set. The elements belong to the set, to “some degree” (degree of membership). The membership function of the set will represent the degree of membership to the fuzzy set. e.g. fuzzy set $\tilde{A} = \{\text{all the values round 5 and 6}\}$. The membership function of $\tilde{A}$ is:

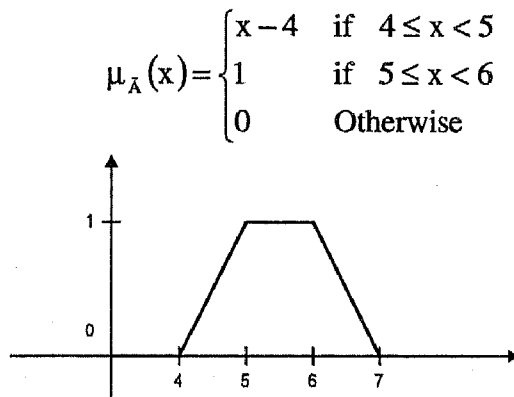


Figure 5 The membership function of Fuzzy set $\tilde{A}$

In the previous example, it is clearly shown that fuzzy sets can express the idea of “around”, whereas the crisp set cannot. Crisp set is one of the subsets of fuzzy set. By adjusting the membership function of the fuzzy set, a crisp set can be obtained. With the fuzzy set, linguistic concepts, vagueness and ambiguous information can be formulated and included into mathematical models.

3.2. Properties

The operation of fuzzy sets is similar to classical sets. However, with introduction of vagueness, some properties of the classical set are no longer

valid for fuzzy sets. In the following paragraph, the important properties of the fuzzy set will be shown and compared with the crisp set.

The set operations of the crisp sets are extended to the fuzzy sets. However, the operation of fuzzy sets is not exactly the same as in crisp sets. The set operation of Union, Intersection and Complement in fuzzy sets are defined as following.[4]

Union: $\mu_{\tilde{A} \cup \tilde{B}} = \max(\mu_{\tilde{A}}, \mu_{\tilde{B}})$

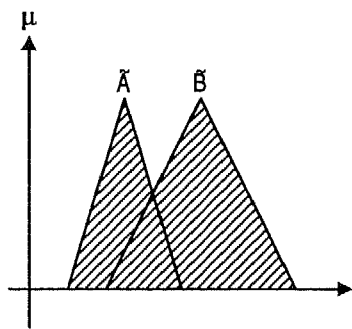


Figure 6 The Union of Fuzzy Set

Intersection: $\mu_{\tilde{A} \cap \tilde{B}} = \min(\mu_{\tilde{A}}, \mu_{\tilde{B}})$

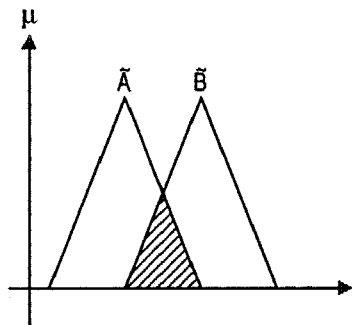


Figure 7 The Intersection of Fuzzy Set

Complement: $\mu_{\tilde{A}} = 1 - \mu_A$

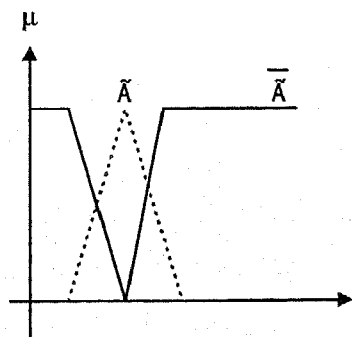


Figure 8 The Complement of Fuzzy Set

Despite the set operations, fuzzy sets also have equivalent properties to the crisp sets. The following is the common properties of fuzzy sets. For these properties, fuzzy sets have behaviour like the classical sets.

	Crisp Set	Fuzzy Set
Commutativity	$A \cup B = B \cup A$ $A \cap B = B \cap A$	$\tilde{A} \cup \tilde{B} = \tilde{B} \cup \tilde{A}$ $\tilde{A} \cap \tilde{B} = \tilde{B} \cap \tilde{A}$
Associativity	$A \cup (B \cap C) = (A \cup B) \cap C$ $A \cap (B \cup C) = (A \cap B) \cup C$	$\tilde{A} \cup (\tilde{B} \cap \tilde{C}) = (\tilde{A} \cup \tilde{B}) \cap \tilde{C}$ $\tilde{A} \cap (\tilde{B} \cup \tilde{C}) = (\tilde{A} \cap \tilde{B}) \cup \tilde{C}$
Distributivity	$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$ $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$	$\tilde{A} \cup (\tilde{B} \cap \tilde{C}) = (\tilde{A} \cup \tilde{B}) \cap (\tilde{A} \cup \tilde{C})$ $\tilde{A} \cap (\tilde{B} \cup \tilde{C}) = (\tilde{A} \cap \tilde{B}) \cup (\tilde{A} \cap \tilde{C})$
Idempotency	$A \cup A = A$ $A \cap A = A$	$\tilde{A} \cup \tilde{A} = \tilde{A}$ $\tilde{A} \cap \tilde{A} = \tilde{A}$
Identity	$A \cup \emptyset = A$ $A \cap X = A$ $A \cap \emptyset = \emptyset$ $A \cup X = X$	$\tilde{A} \cup \emptyset = \tilde{A}$ $\tilde{A} \cap X = \tilde{A}$ $\tilde{A} \cap \emptyset = \emptyset$ $\tilde{A} \cup X = X$
Transitivity	If $A \subseteq B \subseteq C$, then $A \subseteq C$	If $\tilde{A} \subseteq \tilde{B} \subseteq \tilde{C}$, then $\tilde{A} \subseteq \tilde{C}$
De Morgan's law	$\overline{A \cap B} = \overline{A} \cup \overline{B}$ $\overline{A \cup B} = \overline{A} \cap \overline{B}$	$\overline{\tilde{A} \cap \tilde{B}} = \overline{\tilde{A}} \cup \overline{\tilde{B}}$ $\overline{\tilde{A} \cup \tilde{B}} = \overline{\tilde{A}} \cap \overline{\tilde{B}}$

Remark: X is the universe of discourse

$\emptyset$ is the empty set

Although many properties of fuzzy sets are the same as the crisp sets, the excluded middle laws do not hold for the fuzzy sets. In the crisp sets,

$$A \cap \overline{A} = \emptyset$$

$$A \cup \overline{A} = X$$

By examining the Figure 8, it is clearly shown that the above laws do not exist in the fuzzy set, i.e.

$$\tilde{A} \cap \overline{\tilde{A}} \neq \emptyset$$

$$\tilde{A} \cup \overline{\tilde{A}} \neq X$$

3.3. Fuzzy Programming

Optimisation plays an important role in decision making. There already exist various different methods to find the optimal solution for certain problems and restrictions. In most of the methods, we need to identify the objective function and the restrictions of the problem. In the real world

optimisation problem, there are time when it is very difficult to identify the boundary of the problem. This is mainly due to the vagueness of information obtained from the real world, e.g. “the temperature of the room cannot be too high”. In addition, some types of constraints are considered “soft” constraints. They can be violated “slightly”, thus introducing flexibility into the optimisation problem. As we know, this kind of optimisation problem is difficult to be solved by the classical method. However, after adopting the concept of fuzziness, these kinds of constraints can be included into the optimisation problem. These “vague” and “soft” constraints can be modelled by using the fuzzy set concept. The solution of optimisation will be much better.

In the formulation of the classical optimisation process, we would like to find the optimal solution, x^* , which minimises (or maximise) the :

Objective function: $F(x)$ and

Subject to these constraints:

$$\begin{aligned} C_1 : G_1(x) &\leq b_1 \\ C_2 : G_2(x) &\leq b_2 \\ &\vdots \\ C_n : G_n(x) &\leq b_n \end{aligned}$$

In the this kind of optimisation problem, the solution space of the problem is bounded by all the constraints. Then the optimal solution, x^* is the one that achieves the minimum value of the objective function inside the solution space.

We can reformulate the optimisation problem with the introduction of fuzzy sets. The formulation of the problem will then become:

$$\begin{aligned} \text{Min } \phi &= F^t x \lesssim z \\ \text{Sub } Gx &\lesssim B \end{aligned}$$

According to [6], the optimisation problem can be reformulated by setting $A = \begin{pmatrix} F^t \\ G \end{pmatrix}$ and $D = \begin{pmatrix} z \\ B \end{pmatrix}$, such that, we can have the following equations:

$$Ax \lesssim D \text{ and } x \geq 0$$

As an analogy to the classical optimisation method, the membership function of the decision fuzzy set is the intersection of all the fuzzy sets.

$$\mu_D(x) = \min_i^{m+1} \mu_i(x)$$

where m is the total no of constraints.

Thus : $x^* = \text{Max}(\mu_D)$

The best solution of the fuzzy optimisation problem can be obtained. Suppose that the membership function of the constraints has the following form:

$$\mu_i(x) = \begin{cases} 1 & \text{if } (Ax)_i \leq B_i \\ 1 - \frac{(Ax)_i - B_i}{P_i} & \text{if } B_i < (Ax)_i \leq P_i \\ 0 & \text{if } (Ax)_i > P_i \end{cases}$$

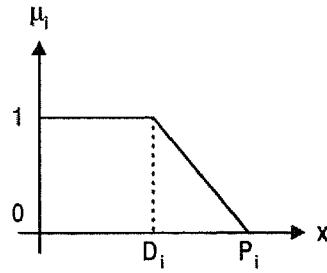


Figure 9 The membership function for Constraints

By the introduction of a new variable λ , the original fuzzy optimisation problem can be re-formulated as (details can be found in [6]):

Max λ

Sub: $\lambda P_i + (Ax)_i \leq D_i + P_i$ where $i = 1 \dots m+1$

$0 \leq \lambda \leq 1$ and $x \geq 0$

Therefore, the fuzzy optimisation problem is transformed back into a classical linear programming problem, which can be solved easily.

3.4. Conclusion

The fuzzy set theory provides a well defined mathematical representation of vagueness in the information, linguistic expressions, and ambiguous information which the classical set theory cannot represent properly. The fuzzy set theory classifies the elements with the “grade of membership” and the “degree of membership”, which is expressed in terms of the membership function of the fuzzy set.

The fuzzy set also has set operations, such as, union, intersection and complement. The union of the fuzzy sets are the maximum membership between the fuzzy sets. The intersection of the fuzzy sets are the minimum membership between the fuzzy sets. Actually, the crisp set is a special case of the fuzzy set with almost the same properties, except the excluded middle law.

With the introduction of the fuzzy set into the optimisation problem, the flexibility and adequacy are introduced. The fuzzy programming can be transformed into the classical LP problem with an additional variable. The classical LP program can be solved easily and thus the solution for the fuzzy programming can be obtained.

4. NEW MODEL FOR GENERATION DISPATCH WITH FUZZY WIND CONSTRAINTS

4.1. Introduction

In the unit commitment model, operational cost is needed to justify the performance of one proposed schedule (or chromosome). Thus, an economic dispatch routine is performed for every feasible chromosome. For simplicity, the dispatch procedure at the moment is based on the single bus model. With the known production levels of generators, the operational cost of the schedule can be evaluated. In addition, an indication of the ramping limits of the generators is indirectly supplied by the economic dispatch routine.

In our UC model, the amount of wind (renewable) energy penetration is considered. Since wind energy, generally, is a non-dispatchable source, it is controlled by switching wind generators either on or off. Along with this, the amount of the wind energy penetration is another important issue. The introduction of wind energy will bring the problem of dynamic security and instability. After studying the dynamic behaviour of the system, the utility can provide a penetration limit (intervals) to operators. Within the limit, operators can decide the level of wind production.

In this chapter, we will present a way to determine the degree of the wind energy penetration based on the fuzzy programming approach.

4.2. Dispatch Model

The mathematical formulation of the dispatch model with renewable energy can be expressed as following:

$$\begin{aligned}
 \text{Min } \phi_t &= \sum_{i=1}^N C_i(P_{gi}) \\
 \text{Subject to : } & \sum_{i=1}^N P_{gi} + W_t = L_t \\
 & P_i^{\min} \leq P_i \leq P_i^{\max} \\
 & W_t \leq \Pi_t \\
 & 0 \leq W_t \leq W_{\text{tav}}
 \end{aligned} \tag{10}$$

Where W_t is the wind energy penetration at time t
 W_{tav} is the maximum available wind energy at time t
 Π_t is the penetration of wind energy at time t

This is a general formulation of the economic dispatch including wind energy penetration. In this model, the objective is to minimise the total operational cost. Load is fed by the thermal generators and wind generators. Constraints are the limitations of generators and the limitation of wind generators. In this model, the resultant wind penetration will be close to the specific limit.

Now, instead of a fixed penetration guideline, an interval of penetration will be used. The original constraints can be expressed in a fuzzy way, i.e. :

$$W_t \lesssim \Pi_t$$

The membership of the this fuzzy constraint is expressed by using a linear function:

$$\mu_{W_t} = \begin{cases} 1 & \text{if } W_t \leq \Pi_t^{\min} \\ \frac{\Pi_t^{\max} - W_t}{\Delta \Pi_t} & \text{if } \Pi_t^{\min} \leq W_t \leq \Pi_t^{\max} \\ 0 & \text{if } W_t \geq \Pi_t^{\max} \end{cases}$$

Where $\Delta \Pi_t = \Pi_t^{\max} - \Pi_t^{\min}$

$\Pi_t^{\max}$ is the maximum allowable penetration amount

$\Pi_t^{\min}$ is the penetration guideline of the wind energy

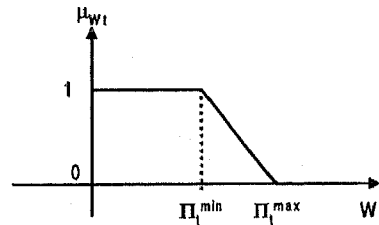


Figure 10 The membership function of wind energy penetration

The amount of wind generation penetration is expressed by a fuzzy set, and the $\Pi^{\min}$ is the penetration guideline and $\Pi^{\max}$ is the maximum allowable renewable energy. In many cases, by contract or by regulation, the dispatcher is forced to pay some compensation to private owners of wind parks if all available renewable energy is not utilised – meaning a loss for the private owners of such plants, based on unsold energy. Thus, a penalty cost C_w is introduced to represent the cost of not using all the available renewable energy. Then, the formulation for the dispatch model can be refined as following:

$$\text{Min } \phi_t = \sum_{i=1}^N C_i(P_{ti}) + C_w(W_{\text{lav}} - W_t)$$

$$\begin{aligned} \text{Subject to : } & \sum_{i=1}^N P_{ti} + W_t = L_t \\ & P_i^{\min} \leq P_i \leq P_i^{\max} \\ & W_t \leq \Pi_t \\ & 0 \leq W_t \leq W_{\text{lav}} \end{aligned}$$

(11)

Where C_w is the penalty cost for not using all available renewable energy

With the transformation of the fuzzy programming (which is mentioned in chapter 3). the dispatch model will become:

$$\text{Max } \mu$$

$$\text{Subject to : } g_1(P, \mu) = \sum_{i=1}^N C_i(P_{ti}) + C_w \left[W_{\text{lav}} - \left(L_t - \sum_{i=1}^N P_{ti} \right) \right] \leq \phi_t^{\max} - \mu \Delta \phi_t$$

$$g_2(P, \mu) = L_t - \sum_{i=1}^N P_{ti} \leq \Pi_t^{\max} - \mu \Delta \Pi_t$$

$$0 \leq L_t - \sum_{i=1}^N P_{ti} \leq W_{\text{lav}}$$

$$P_i^{\min} \leq P_i \leq P_i^{\max}$$

$$0 \leq \mu \leq 1$$

$$\text{note that : } L_t - \sum_{i=1}^N P_{ti} = W_t$$

(12)

Where $\Delta \phi_t = \phi_t^{\max} - \phi_t^{\min}$
 $\phi_t^{\max}$ and $\phi_t^{\min}$ is the operation cost
corresponding to the penetration amount $\Pi_t^{\min}$
and $\Pi_t^{\max}$

The membership function of the objective function ϕ_t is:

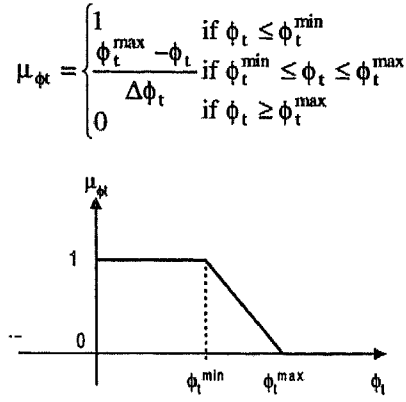


Figure 11 Membership function of the objective function ϕ

The above dispatch model can be solved by analogy to the ordinary economic dispatch problem. The following lagrangean function Λ can be built[1].

$$\Lambda = \lambda + \alpha g_1(P, \mu) + \beta g_2(P, \mu) \quad (13)$$

To derive the optimal solution of the model, the following condition should be satisfied.

$$\begin{aligned} \frac{\partial \Lambda}{\partial P_i} &= \alpha \frac{\partial C_i}{\partial P_i} + \beta, \forall i \\ \frac{\partial \Lambda}{\partial \mu} &= 1 + \alpha(C_{wr} \Delta \Pi_t + \Delta \phi_t) - \beta \Delta \Pi_t = 0 \\ \frac{\partial \Lambda}{\partial \alpha} &= g_1(P, \mu) = 0, \quad \frac{\partial \Lambda}{\partial \beta} = g_2(P, \mu) = 0 \end{aligned} \quad (14)$$

The first condition stipulates that all generators (except through affected by inequalities) should be working at constant marginal cost, given

by:

$$\frac{\partial C_i}{\partial P_i} = -\frac{\beta}{\alpha}, \forall i \quad (15)$$

With the last two condition, we can obtain the following equation to give λ :

$$\mu' = \frac{\phi_t^{\max} - \left\{ \sum_{i=1}^N C_i(P_{ti}) + C_w \left[W_{tav} - \left(L_t - \sum_{i=1}^N P_{ti} \right) \right] \right\}}{\Delta \phi_t}$$

$$\mu'' = \frac{\Pi_t^{\max} - \left(L_t - \sum_{i=1}^N P_{ti} \right)}{\Delta \Pi_t}$$
(16)

Furthermore, the constraints $0 \leq \lambda \leq 1$ and $0 \leq L_t - \sum_{i=1}^N P_{ti} \leq W_{tav}$ will lead to the constraints on λ'' :

$$\frac{\Pi_t^{\max} - W_{tav}}{\Delta \Pi_t} \leq \mu \leq 1$$
(17)

As we shall see, if the available renewable energy W_{tav} less than the $\Pi_t^{\min}$, it is not necessary to solve the fuzzy problem. If the available renewable energy W_{tav} is greater than the $\Pi_t^{\min}$, after solving the fuzzy problem, the optimal value of μ of the fuzzy problem can be obtained and thus gives out the amount of the renewable energy penetration.

The optimal μ of the dispatch problem is the value such that μ' is equal to μ'' , provided that all the constraints are satisfied. However, this is not easily be solved by the analytical method. A new algorithm similar to the ordinary economic dispatch algorithm will be used to solve for μ .

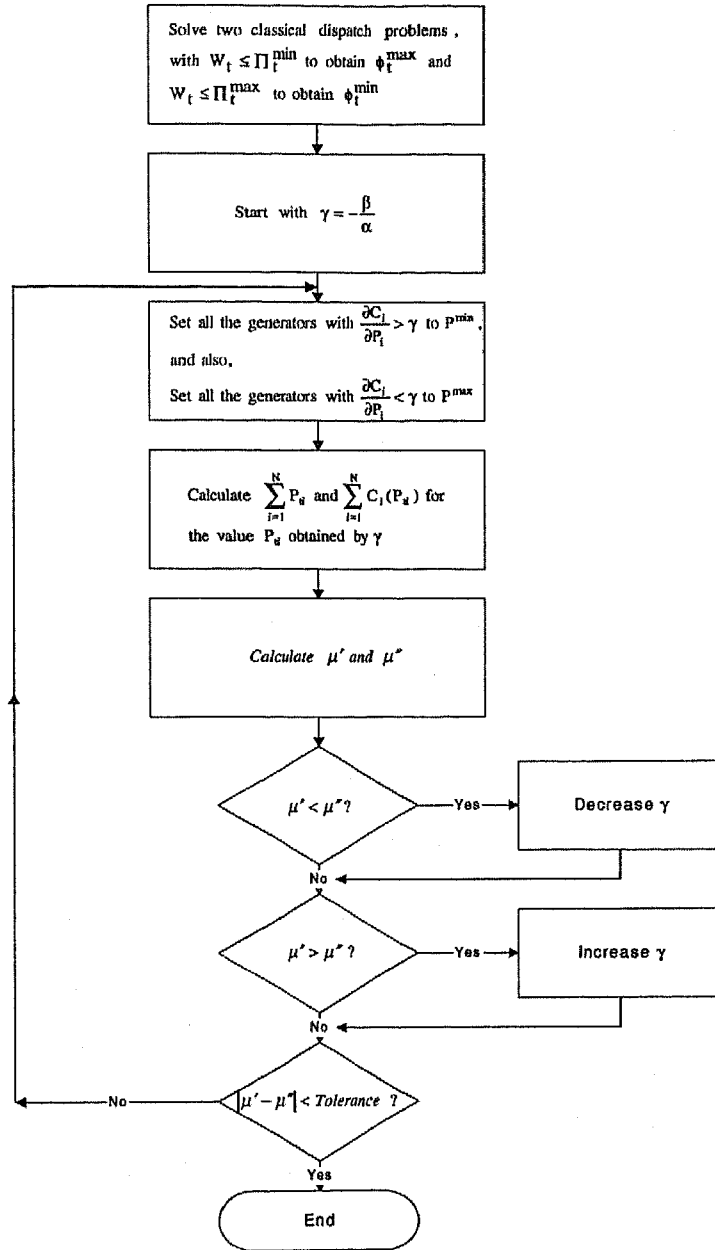


Figure 12 The algorithm for the pre-dispatch with renewable energy

Dispatch with Non-linear Fuzzy Constraints

In the previous evaluation, the membership function of the fuzzy constraints are expressed by a linear function. However, the preference of the decision makers (Operators) are not always consistent. The linear model is not adequate in some situations. In the following, we will try to modify the evaluation to accept another shape of the membership.

Now, suppose that the preference of the renewable constraints and the objective function can be expressed by quadratic equation. Then the membership function will be expressed as follows:

The membership function of the renewable energy generation:

$$\mu_{W_t} = \begin{cases} 1 & \text{if } W_t \leq \Pi_t^{\min} \\ f(W_t) & \text{if } \Pi_t^{\min} \leq W_t \leq \Pi_t^{\max} \\ 0 & \text{if } W_t \geq \Pi_t^{\max} \end{cases}$$

$$\begin{aligned} \text{where } f(W_t) &= a_1 W_t^2 + b_1 W_t + c_1 \\ f(\Pi_t^{\min}) &= 1 \\ f(\Pi_t^{\max}) &= 0 \\ f(W_t) &\geq 0 \quad \text{for } \Pi_t^{\min} \leq W_t \leq \Pi_t^{\max} \end{aligned}$$

(18)

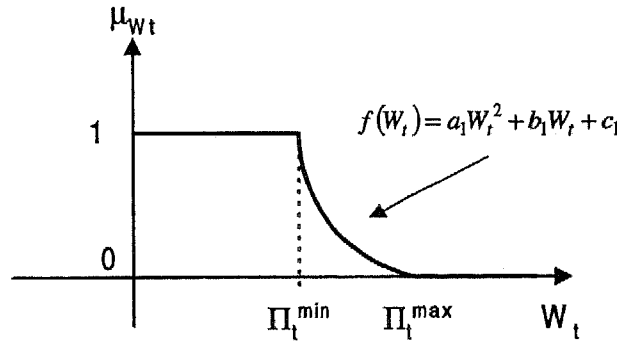


**Figure 13 Membership function of the renewable energy generation
(expressed in quadratic equation)**

And, the membership function of the objective function is:

$$\mu_{\phi_t} = \begin{cases} 1 & \text{if } \phi_t \leq \phi_t^{\min} \\ f(\phi_t) & \text{if } \phi_t^{\min} \leq \phi_t \leq \phi_t^{\max} \\ 0 & \text{if } \phi_t \geq \phi_t^{\max} \end{cases}$$

$$\begin{aligned} \text{where } f(\phi_t) &= a_2 \phi_t^2 + b_2 \phi_t + c_2 \\ f(\phi_t^{\min}) &= 1 \\ f(\phi_t^{\max}) &= 0 \\ f(\phi_t) &\geq 0 \quad \text{for } \phi_t^{\min} \leq \phi_t \leq \phi_t^{\max} \end{aligned}$$

(19)

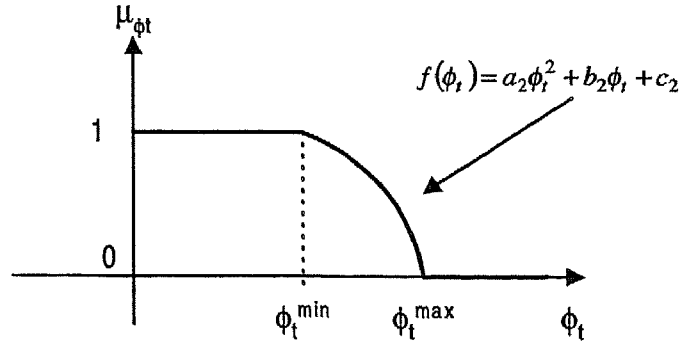


Figure 14 Membership function of the objective function (expressed in quadratic equation)

Although, the membership function of the fuzzy constraints is not the same, the procedure is similar. From Equation (11), we will obtain:

Max μ

$$\text{Subject to: } g_1(P, \mu) = \sum_{i=1}^N C_i(P_{ii}) + C_w \left[W_{tav} - \left(L_t - \sum_{i=1}^N P_{ii} \right) \right] - \phi_t \leq 0$$

$$g_2(P, \mu) = L_t - \sum_{i=1}^N P_{ii} + W_t \leq 0$$

$$0 \leq L_t - \sum_{i=1}^N P_{ii} \leq W_{tav}$$

$$P_i^{\min} \leq P_i \leq P_i^{\max}$$

$$0 \leq \mu \leq 1$$

(20)

Knowing that,

$$\mu = a_1 W_t^2 + b_1 W_t + c_1$$

$$W_t = \frac{-b_1 \pm \sqrt{b_1^2 - 4a_1(c_1 - \mu)}}{2a_1}$$

(21)

and

$$\mu = a_2 \phi_t^2 + b_2 \phi_t + c_2$$

$$\phi_t = \frac{-b_2 \pm \sqrt{b_2^2 - 4a_2(c_2 - \mu)}}{2a_2}$$

(22)

Substituting Equation (21) and (22) into (20), the entire model will become:

Max μ

$$\begin{aligned}
 \text{Subject to: } \quad & g_1(P, \mu) = \sum_{i=1}^N C_i(P_{ii}) + C_w \left[W_{lav} - \left(L_t - \sum_{i=1}^N P_{ii} \right) \right] - \frac{-b_2 \pm \sqrt{b_2^2 - 4a_2(c_2 - \mu)}}{2a_2} \leq 0 \\
 & g_2(P, \mu) = L_t - \sum_{i=1}^N P_{ii} + \frac{-b_1 \pm \sqrt{b_1^2 - 4a_1(c_1 - \mu)}}{2a_1} \leq 0 \\
 & 0 \leq L_t - \sum_{i=1}^N P_{ii} \leq W_{lav} \\
 & P_i^{\min} \leq P_i \leq P_i^{\max} \\
 & 0 \leq \mu \leq 1
 \end{aligned} \tag{23}$$

Once again, Equation (23) will be solved by constructing the lagrangean function which is the same as Equation (13). Furthermore, the procedure for solving the lagrangean function will be the same as Equation (14) and Equation(15). However, since $g_1(P, \mu)$ and $g_2(P, \mu)$ are not the same as in Equation (12), Equation (16) will need to change and become:

$$\begin{aligned}
 \mu' &= \frac{\left[2a_2 \sum_{i=1}^N C_i(P_{ii}) + 2a_2 C_w \left(W_{lav} - L_t + \sum_{i=1}^N P_{ii} \right) + b_2 \right]^2 - b_2^2 + 4a_2 c_2}{4a_2} \\
 \mu'' &= \frac{\left(2a_1 L_t - 2a_1 \sum_{i=1}^N P_{ii} + b_1 \right)^2 - b_1^2 + 4a_1 c_1}{4a_1}
 \end{aligned} \tag{24}$$

Then, the model can be solved by using the same algorithm shown in Figure 12, with μ' and μ'' in Equation (24).

In the following, we will try to adopt a sigmoid function for the membership function of the fuzzy constraints in the dispatch model. Now, the membership function of the renewable penetration constraint and the objective function will be:

Renewable energy penetration:

$$\mu_{W_t} = \begin{cases} 1 & \text{if } W_t \leq \Pi_t^{\min} \\ f(W_t) & \text{if } \Pi_t^{\min} \leq W_t \leq \Pi_t^{\max} \\ 0 & \text{if } W_t \geq \Pi_t^{\max} \end{cases}$$

$$\text{where } f(W_t) = \frac{1}{1 + e^{-a_1(W_t - b_1)}}$$

(25)

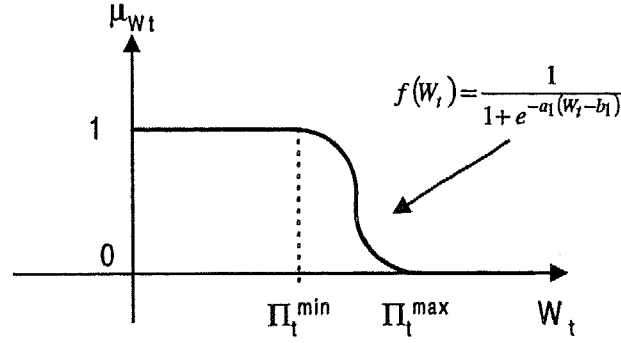


Figure 15 Membership function of the renewable energy generation (expressed in quadratic equation)

In the same manner, the membership function of the objective function will change to:

$$\mu_{\phi_t} = \begin{cases} 1 & \text{if } \phi_t \leq \phi_t^{\min} \\ f(\phi_t) & \text{if } \phi_t^{\min} \leq \phi_t \leq \phi_t^{\max} \\ 0 & \text{if } \phi_t \geq \phi_t^{\max} \end{cases}$$

$$\text{where } f(\phi_t) = \frac{1}{1 + e^{-a_2(\phi_t - b_2)}}$$

(26)

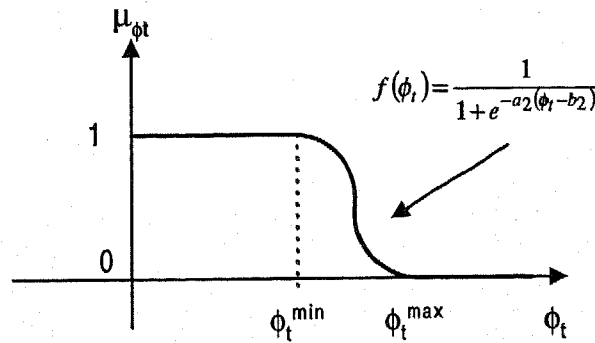


Figure 16 Membership function of the objective function (expressed in quadratic equation)

Although, the membership function is not the same as previous two models, the formulation is similar and the same procedure can be applied.

Firstly, with the membership function of renewable energy penetration (Equation (25)) and the objective function (Equation (26)), we could transform the original fuzzy optimisation problem (Equation (11)) into a crisp optimisation problem (Equation (29)) as previous modeled with Equation (27) and Equation (28):

$$\begin{aligned}\mu &= \frac{1}{1 + e^{-a_1(W_t - b_1)}} \\ W_t &= b_1 - \frac{\ln\left(\frac{1}{\mu} - 1\right)}{a_1}\end{aligned}\tag{27}$$

$$\begin{aligned}\mu &= \frac{1}{1 + e^{-a_2(\phi_t - b_2)}} \\ \phi_t &= b_2 - \frac{\ln\left(\frac{1}{\mu} - 1\right)}{a_2}\end{aligned}\tag{28}$$

Max μ

$$\begin{aligned}\text{Subject to: } g_1(P, \mu) &= \sum_{i=1}^N C_i(P_{ii}) + C_w \left[W_{lav} - \left(L_t - \sum_{i=1}^N P_{ii} \right) \right] - b_2 + \frac{\ln\left(\frac{1}{\mu} - 1\right)}{a_2} \leq 0 \\ g_2(P, \mu) &= L_t - \sum_{i=1}^N P_{ii} + b_1 - \frac{\ln\left(\frac{1}{\mu} - 1\right)}{a_1} \leq 0 \\ 0 &\leq L_t - \sum_{i=1}^N P_{ii} \leq W_{lav} \\ P_i^{\min} &\leq P_i \leq P_i^{\max} \\ 0 &\leq \mu \leq 1\end{aligned}\tag{29}$$

By constructing the largrangean function for Equation (29) as Equation (13) and solve as equation (14) and equation (15). We will get μ' and μ'' as following:

$$\mu' = \frac{1}{e^{a_2 \left[b_2 - \sum_{i=1}^N C_i (P_{ii}) - C_w \left(W_{lav} + \sum_{i=1}^N P_{ii} - L_t \right) \right]} + 1}$$

$$\mu'' = \frac{1}{e^{-a_1 \left(L_t - \sum_{i=1}^N P_{ii} - b_1 \right)} + 1}$$
(30)

Substituting μ' and μ'' in Equation (30) into the algorithm shown in Figure 12. The dispatch model with the sigmoid membership function can be solved.

Some Examples:

In the following example of the dispatch model, we have 5 generators in the system along with wind energy sources. The total production capacity of thermal generators is 111.25MW. Suppose that the load in a given time interval is 110MW and the available wind generation is 40MW. In addition, the guideline for the wind generation is not more than 20MW, and the maximum allowable wind generation is 30MW. In this case, the preference of the operators in regard to wind generation and the cost is linear, i.e.:

The membership function of the wind generation:

$$\mu_{W_t} = \begin{cases} 1 & \text{if } W_t \leq 20MW \\ \frac{30 - W_t}{(30 - 20)} & \text{if } 20MW \leq W_t \leq 30MW \\ 0 & \text{if } W_t \geq 30MW \end{cases}$$
(31)

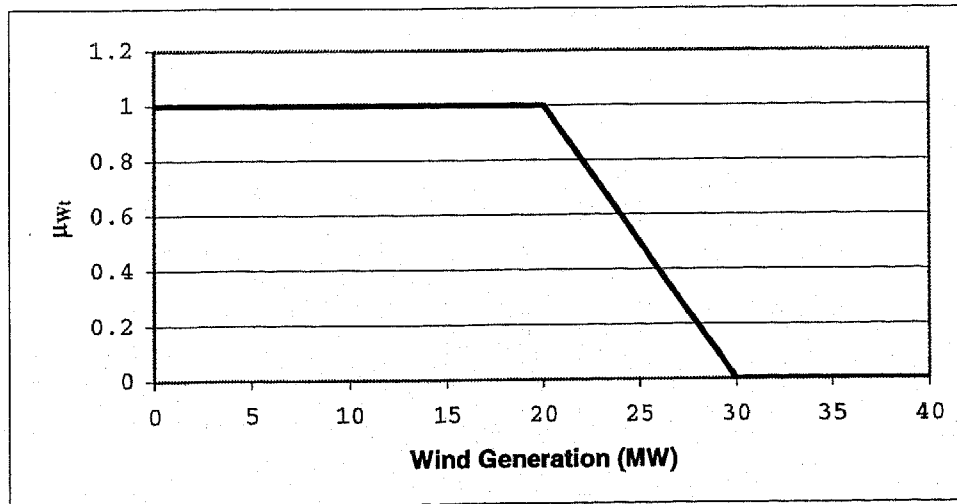


Figure 17 Membership function of wind generation (Equation (31))

On of the first steps for defining the membership function of the objective function, is to find out the maximum and minimum value of the objective function. With minimum wind power production(20MW), the objective function (operational cost) will reach its maximum. In the same manner, the minimum operational cost is the system operation with the maximum wind generation (30MW). Thus, the maximum and minimum value of the objective function are, in this example, 3673.209 and 2721.441 respectively

The membership of the objective function is:

$$\mu_{\phi} = \begin{cases} 1 & \text{if } \phi_t \leq \phi_t^{\min} \\ \frac{3673.209 - \phi_t}{(3673.209 - 2721.441)} & \text{if } \phi_t^{\min} \leq \phi_t \leq \phi_t^{\max} \\ 0 & \text{if } \phi_t \geq \phi_t^{\max} \end{cases} \quad (32)$$

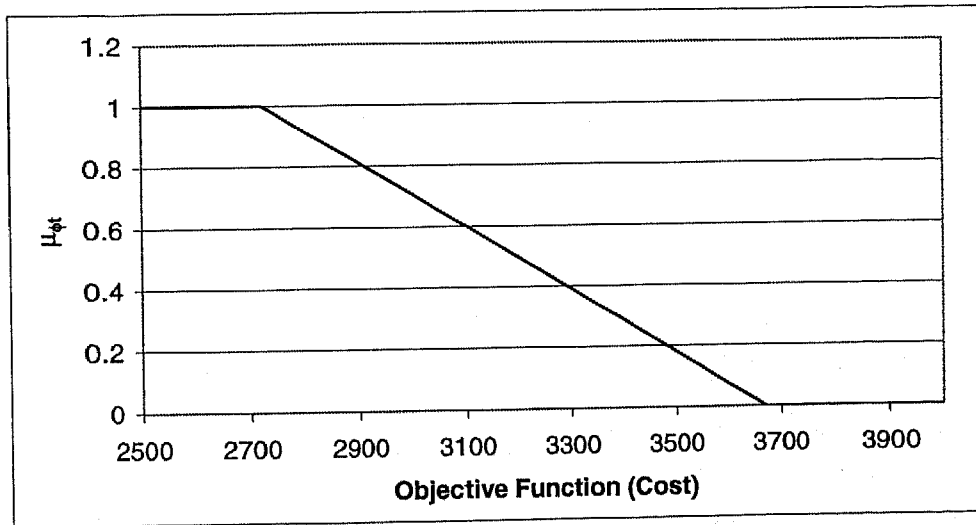


Figure 18 Membership function of the objective function (cost) (Equation (32))

With the algorithm showed in Figure 12, the result is:

Gen1	Gen2	Gen3	Gen4	Gen5	Gen6	Wind Generation
6.25	13.27	15.00	16.53	16.99	16.99	24.97

In the previous example, the preferences of the operators are natural for the wind generation and the objective function. Suppose that, our operators are conservative in the wind generation and they are generous in the production cost. We will try to model the membership function by means of a quadratic equation:

For the conservative membership function of wind generation, it is:

$$\mu_{W_t} = \begin{cases} 1 & \text{if } W_t \leq \Pi_t^{\min} \\ .01111W_t^2 - 0.655W_t + 9.66 & \text{if } \Pi_t^{\min} \leq W_t \leq \Pi_t^{\max} \\ 0 & \text{if } W_t \geq \Pi_t^{\max} \end{cases}$$

(33)

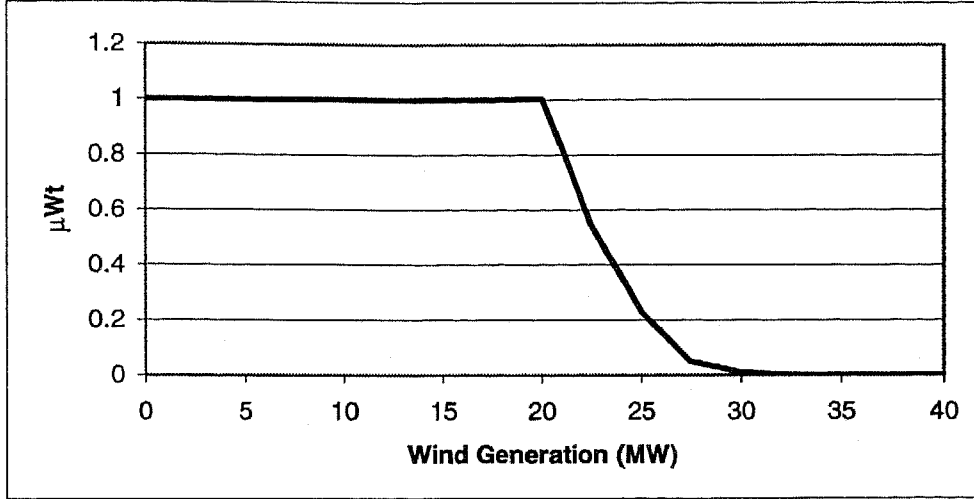


Figure 19 Membership function of the wind generation (Equation (33) conservative)

For the generous membership function of objective function (Cost), it

is:

$$\mu_{\phi_t} = \begin{cases} 1 & \text{if } \phi_t \leq \phi_t^{\min} \\ -1.149e^{-6}\phi_t^2 + 0.006295\phi_t - 7.623 & \text{if } \phi_t^{\min} \leq \phi_t \leq \phi_t^{\max} \\ 0 & \text{if } \phi_t \geq \phi_t^{\max} \end{cases}$$

(34)

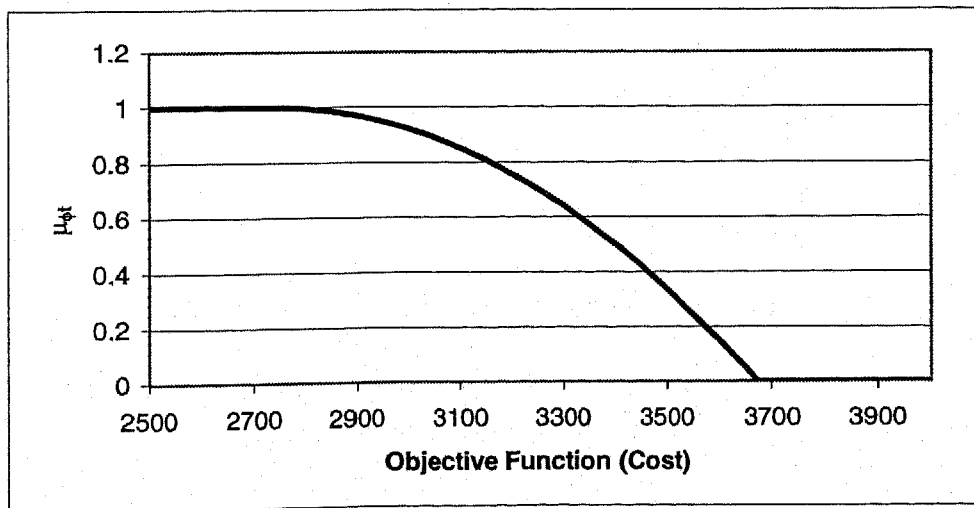


Figure 20 Membership function of the objective function (cost) (Equation (34) Generous)

By using the algorithm shown in Figure 12 and the Equation (24), the following result can be obtained:

Gen1	Gen2	Gen3	Gen4	Gen5	Gen6	Wind Generation
6.25	13.81	15.00	17.07	17.53	17.53	22.81

By comparing with the previous example, the wind generation in the last example is smaller. It is because, the membership function of the renewable generation is conservative.

In the final example, we will try to model the membership function of wind generation and the objective function (cost) by means of sigmoid functions.

Using a sigmoid function, the membership function of wind generation will become:

$$\mu_{W_t} = \begin{cases} 1 & \text{if } W_t \leq \Pi_t^{\min} \\ \frac{1}{1 + e^{0.91902(W_t - 25)}} & \text{if } \Pi_t^{\min} \leq W_t \leq \Pi_t^{\max} \\ 0 & \text{if } W_t \geq \Pi_t^{\max} \end{cases}$$

(35)

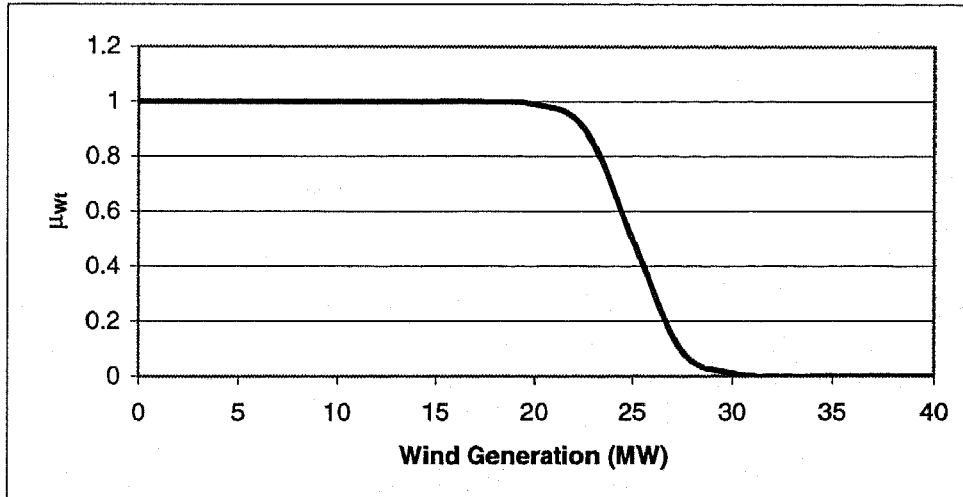


Figure 21 Membership Function of the renewable energy generation (Equation (35))

$$\mu_{\phi_t} = \begin{cases} 1 & \text{if } \phi_t \leq \phi_t^{\min} \\ \frac{1}{1 + e^{0.00966(\phi_t - 3197.325)}} & \text{if } \phi_t^{\min} \leq \phi_t \leq \phi_t^{\max} \\ 0 & \text{if } \phi_t \geq \phi_t^{\max} \end{cases}$$

(36)

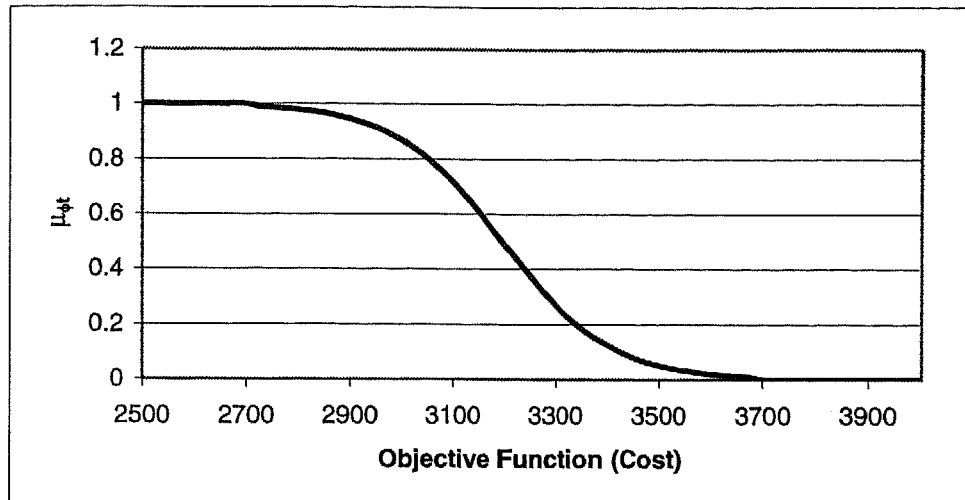


Figure 22 Membership function of the objective function (cost) (Equation (36))

With Equation (30), the following result can be obtained:

Gen1	Gen2	Gen3	Gen4	Gen5	Gen6	Wind Generation
6.25	13.27	15.00	16.53	16.99	16.99	24.97

The solution is similar to the solution obtained in the first example.

4.3. Conclusion

Renewable energy is a clean, cheaper way of power generation, however, the wind generation is a non-dispatchable source. The dispatcher can only switch on / switch off the generators. Although the renewable energy has merit in environmental impact and is cost effective, it will bring about dynamic security problems in the power system. Hence, utilities set a guideline for amount of the renewable energy penetration.

Generally, the guideline for the penetration is a “soft” constraint. This is done in this way because it is difficult to define an “exact” limit for wind penetration, which depends on the possible disturbances or contingencies and their probability of occurrence. In addition, the simulations needed to establish such limits require the integration of system differential equations in the time domain, which is not practical for on-line real time applications. It is desired that the dispatch procedure can accept this kind of “soft” constraint and determine the solution in a flexible way. In addition, the penalty cost for not using available renewable energy is also desired to account in the dispatch model.

In this chapter, the ordinary dispatch model is reformulated to incorporate the wind penetration and the introduction of penalty costs for the unused available renewable energy. By expressing the penetration guideline into a fuzzy constraint, the model can find the dispatch result flexibly. With the fuzzy programming technique, the dispatch model can be transformed back to a classical mathematical programming. By using the Lagrangian method, the whole model can be solved by finding solution to make two equation equal. Thus, a algorithm similar to the classical economic dispatch algorithm is proposed.

5. NEW MODEL FOR UNIT COMMITMENT/GENERATION SCHEDULING

5.1. Introduction

In a previous chapter (chapter 2), we briefly introduced the principle of a simple Genetic Algorithm and also a way in solving a unit commitment by using a Genetic Algorithm. In that section, the procedures for evaluating the fitness value of a feasible candidate is established and a straight forward way in encoding the chromosome. With these information, a genetic algorithm is capable in finding the solution for a unit commitment problem. However, with some rough tests, we discover that a simple Genetic Algorithm is not suitable for attacking a unit commitment problem with high dimension. Some modifications and problem specific operators are added to improve the performance of a simple Genetic Algorithm in a unit commitment problem. As other pioneers in adopting GA for unit commitment problems[13][14][15][16][17][18], in this work, we introduce some specific operators in our Genetic Algorithm. They are:

- Code Compression Technique
- Niching Method – Deterministic Crowding Selection Scheme
- Chromosome Repair and Neighbourhood Digging
- Variation of Basic Operators

The introduced operators improve the algorithm in different aspects. The first one, “Code Compression Technique”, aims at reducing the dimension of a unit commitment problem. “Niching Method” and “Variation of Basic Operators” focus on the behaviour of a simple Genetic Algorithm. The last operator, “Neighbourhood Digging and Chromosome Repair”, is an operator for the unit commitment problem. By using knowledge about the unit commitment problems, this operator assist the algorithm consistently locating good solutions.

5.2. Code Compression Technique

To use the GA to solve the optimisation problem, encoding the solution of the problem into the chromosomes is a main step. How to encode the solution is flexible, however, an adequate coding method is the key to the success of the problem. In chapter 2, we have stated the principles for chromosome coding, which are guidelines for defining the encoding method. Furthermore, the encoding of the chromosome should be relevant to the actual problem and should avoid unnecessary parameters.

In Chapter 2, we also proposed a simple encoding scheme for the unit commitment problems. This scheme satisfies the principles of the chromosome coding. However, this encoding method will lead to a long chromosome. The size of the chromosome by using the direct encoding method is the product of the no. of generators and the no. of the time intervals. Suppose we have 15 generators and the time intervals in consideration are 48. By using the direct encoding method, the chromosome size will be $48 \times 15 = 720$ bits! This is really a long chromosome, and therefore long computation time.

Thus, a coding compression technique is developed to reduce the length of the chromosome; actually, this technique is another way to encode the solution of the UC problem. This method takes advantage of the characteristics of the UC solution. During the operation, usually, generators will not switch on / switch off frequently. They (generators) will only be switched on/ off when necessary. For a period of 48 hours, the state of the generators only change a few times (Actually, generators changing their states frequently is not desirable). In addition, due to the technical limitation of the generators, their states can only have several changes in 48 hours. However, the direct encoding method proposed in Chapter 2, generator is permitted to change its states frequently (the no. of changes can equal to the total no of study periods), i.e. 1 generator can have 48 changes in the 48 hours. Thus, many variables are redundant. These redundant variables increase the length of the chromosome and also bring many infeasible solutions. Considerable computation time is wasted on processing the infeasible solutions.

In contrast to the direct encoding method, the new encoding method will avoid the algorithm processing infeasible chromosome. The new encoding method makes use of characteristics in the UC solution. In the new encoding method, a set of the generator states represents not only a time step, but several successive time steps. The following is the scheme of the new encoding method.

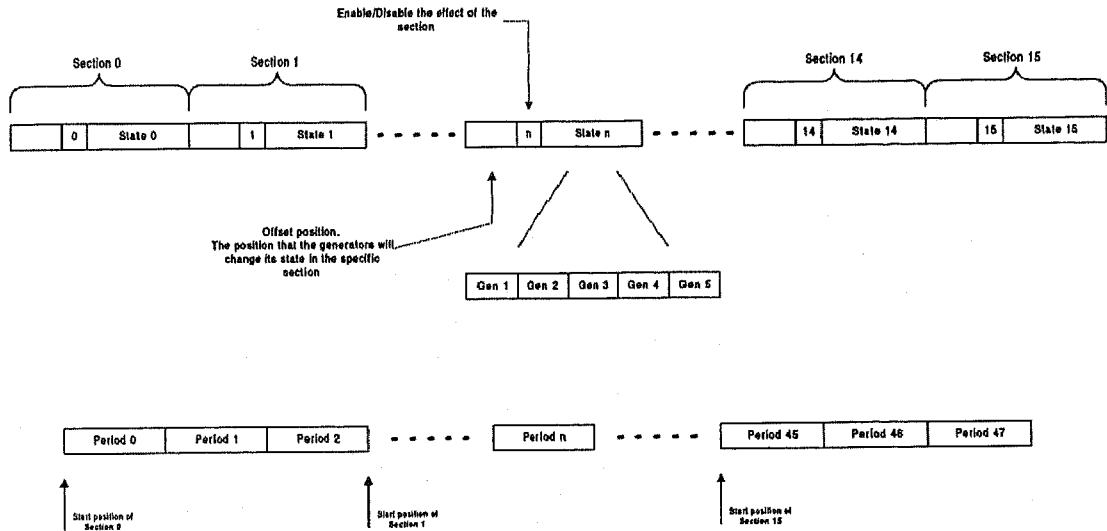


Figure 23 The new encoding method for chromosome

In the figure 13, the chromosome for UC problem with 48 hour intervals and 5 generators is shown. We divide the 48 time steps into 16 blocks (i.e. 3 time steps constitute 1 block) and each block has its corresponding variables in the chromosome. Thus, there are also 16 sections in the chromosome. In the chromosome, each section will contain three parts, they are: the generators states, section enable/disable variable and the offset position. The enable / disable variable is used to disable all of the section. If one section is disabled, the generators state for the corresponding block will be the same as the last time step of the previous block. The generators states contain all the states for the corresponding block and those states will take effect according to the offset position. Every block has a fixed position within the UC schedule. The offset position indicates where the information carried by the block takes place. Suppose the UC schedule has 48 time intervals and is divided by 12 blocks. Then each block includes only one change of schedule

during 4 time intervals. If the offset position value of a block is 3, then the change of the schedule will take place at the third interval of the block.

With this new coding method for the chromosome, the length of the chromosome is reduced dramatically. As seen previously, if we have a UC problem that schedule 5 generators over 48 time steps, the length of the chromosome will become $(2+5+1)*16 = 128\text{bits}$ (In one section, 5 bits for 5 generators, 1 bit for enable / disable, and 2 bit for the offset position). For the direct encoding method, the chromosome length will become $5*48 = 240\text{bits}$. The chromosome length of the new method is almost half of the direct encoding method.

However, the selection of the number of sections is important. It can affect the length of the chromosome and the solution of the UC. If the number of sections is too small, many possible solution of the UC will be disregarded. If the number of section is too large , the length of the chromosome will be long. In previous example, we choose 16 sections for 48 time steps, i.e. 3 time steps is aggregated together.

The following table is the chromosome length with different number of sections. (48 time steps and 17 generators

Number. of sections	Offset bit	Total length of the chromosome
24	1	$(17+1+1)*24=456$ bits
16	2	$(17+1+2)*24=320$ bits
12	3	$(17+1+3)*12=252$ bits
8	3	$(17+1+3)*8=168$ bits
6	3	$(17+1+3)*6=126$ bits

(note: the direct method need 816 bits)

5.3. Niching Method – Deterministic Crowding Selection Scheme[10]

UC problem is a “Hard” optimisation problem. It is due to its high dimension space domain and its highly non linear characteristics. In the previous section, we suggested a way to compress the length of the chromosome such that the search space can be reduced. However, we find out that when we use a simple genetic algorithm (described in Chapter 2 – SGA) to solve the UC problem, the solution given out by SGA is not good enough. Firstly, the other solutions given out are very similar to the best solution given

out by the SGA. When we tried to run the SGA for the same UC problem in several times, solutions have a great deviation. Since the deviation is large, it is desired to reduce it.

Due to the nature of the SGA; the above result is normal. It is known that[10] the SGA are suitable for finding the optimal solution for a unimodal function. However, for a multimodal function like the UC problem, the SGA will have difficulties in identifying the multi-optimal of the function. In our UC problem, as described above, we not only need the optimal solutions but also the sub-optimal solutions. Adopting the niching method in the SGA is one of the ways to overcome this problem.

The Niching method is developed to reduce the genetic drift effect (the loss of alternative solutions due to random fluctuation) of the SGA. This method will try to maintain the diversity of the population of the genetic algorithm, in such a way that the GA can investigate many peaks in parallel. Niching method is analogous to a natural ecosystem. In nature, different species can live in the same environment. Each species is a group of individuals, that have similar biological features, and they can only be interbred with the individuals among the group. Moreover, a niche is a subspace in the environment (search space), where several different groups of species can live. Niching method tries to achieve and maintain the different niches in the population. Actually, a niche is an optimum of the population. Maintaining different niches means maintaining different optima in the population.

Deterministic Crowding Selection (DC) scheme (Mahfoud, 1995) is an improvement from the De Jong's crowding method. The crowding method is a modification of the selection scheme. Originally, the selection scheme (tournament or roulette wheel selection) will select the chromosomes to enter the new generation according to the fitness of the chromosome. The higher fitness chromosomes can survive and enter the new generation and the lower fitness chromosomes will vanish. In contrast to the traditional selection scheme[3], the crowding method will only replace the similar chromosome in the population. It works by selecting randomly a portion of chromosomes in the population. This portion[10] of chromosomes will undergo mutation and crossover. Then, a sample of the chromosomes in the original population will

be chosen to be replaced by the new offspring. The new offspring will replace the most similar chromosome in the sample. The similarity of the chromosomes is measured by their Hamming distance.

Deterministic Crowding works similarly to the crowding method. It randomly pairs all the individuals in the population. Every pair of chromosomes is regarded as parents ($n/2$ pairs of parents). Each pair of parents will perform crossover and mutation and will produce two offspring. Each offspring will compete with one of their parents. The distance between the parents and the offspring will be calculated. The opponents of the selection tournament will be selected according to their closeness. For example, suppose there is a pair of chromosomes (parents), Parent 1 and Parent 2. After the process of crossover and mutation, two offspring will be generated, Child 1 and Child 2. In fact, only two sets of selection tournament exist, either Parent 1 against Child 1, Parent 2 against Child 2 or Parent 1 against Child 2, Parent 2 against Child 1. The distance of either set of the tournament will be calculated. The selection method in DC is according to their fitness. The more close set of tournaments will be performed. Higher Fit chromosomes will take the place of the Lower Fit chromosome and enter the next generation. As described in [10], the crossover rate of the DC is simply set to 1. This is because DC is an elitist method and if the child is less fit than the parent, the child will never entered the new generation. The following is the block diagram of the deterministic crowding selection scheme.

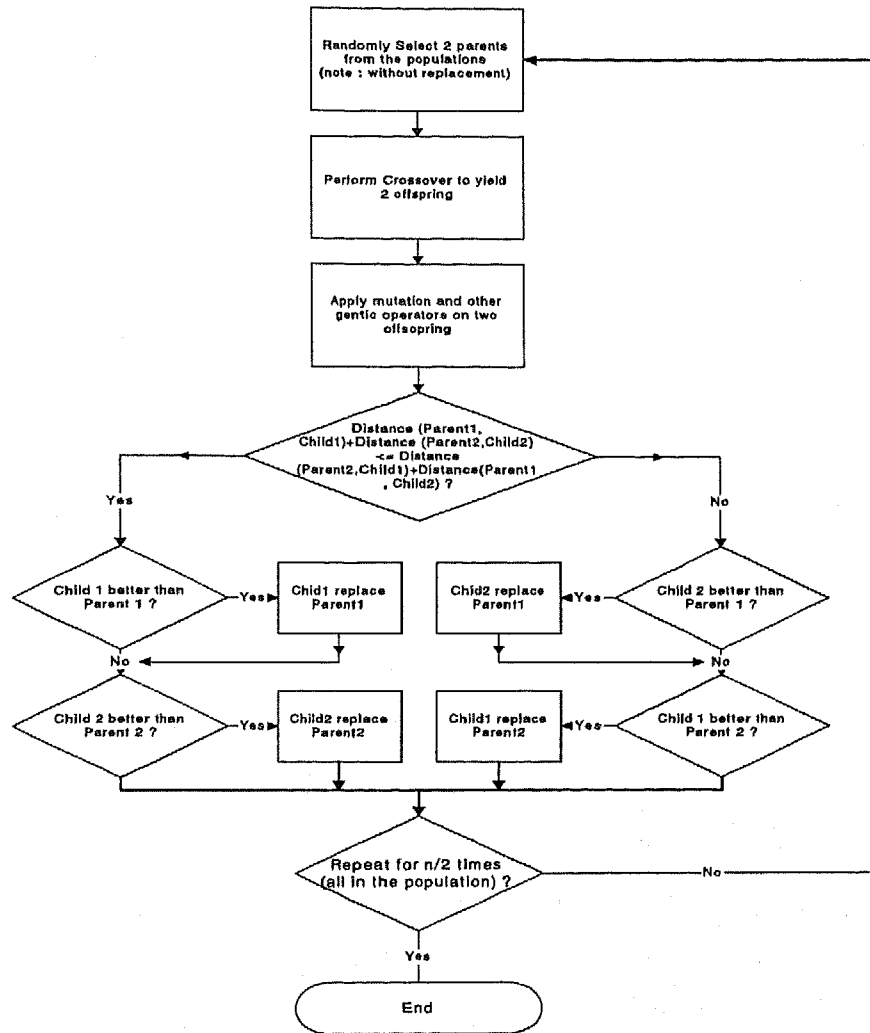


Figure 24 Algorithm of Deterministic Crowding Method

In the algorithm of the DC, we need to evaluate the closeness between the parents and the offspring and this distance is used as a criteria for selecting the opponents in the selection tournament. The similarity of the chromosome can be measured by genotypic similarity or phenotypic similarity.

Genotypic similarity is generally related to the bit string representation of the chromosome. It is calculated by counting the number of different bits between the individuals. Then, the number of different bit is the distance between the two individuals. Generally, the genotypic similarity is the Hamming distance between the two individuals. Suppose, for example, that we have two individuals, Parent1 and Child1, with chromosomes strings 10110 and 00111 respectively. So, the genotypic distance between Parent1 and Child1 is 2.

Phenotypic similarity is yet, another way to measure the closeness of individuals. Unlike the genotypic way, the phenotypic similarity uses the decoded parameter of the chromosomes to evaluate the distance. Adopting the previous example, the decoded value for Parent1 becomes 22 (the binary value of 22 is 10110) and the decoded value for Child1 becomes 7. So, the phenotypic similarity of Parent1 and Child1 is 15 (22-7).

Since there are two ways to define the closeness of the chromosomes in the algorithm of DC, in our unit commitment. We would like to determine which is the appropriate scheme for our problem, thus, we performed some tests with these two different schemes. The tests are performed in 30 runs for each method, with the same set of data with a random seeds.

	Genotypic Similarity	Phenotypic Similarity
Means	61154.080	65746.517
Standard Deviation	1853.010	4207.237
Standard Deviation Percentage	3.030%	6.399%

In the above table, we see that using the genotypic distance to measure the closeness of the chromosomes in DC, can yield better solution. Actually, this is due to the special coding method adopted in the unit commitment problem. In our coding method, every bit has the same significance regardless of the location in the chromosome. According to the method of measuring the Hamming distance, each bit inside the chromosomes is the same and thus is appropriate for our coding. On the other hand, in phenotypic similarity measuring method, each bit inside the chromosome has different importance.

In the unit commitment problem, it is desired to obtain more than 1 solution and operators can have more information for deciding. In genetic algorithms, it is possible to obtain more than 1 solution and this is an advantage over traditional methods. However, the simple genetic algorithm has some difficulties in dealing with multi-modal objective function (unit commitment). The Deterministic Crowding selection scheme is introduced into the genetic algorithm to improve the genetic algorithm.

5.4. Chromosome Repair and Neighbourhood Digging

In the previous section, a Niching method is introduced into the genetic algorithm to improve the performance of the genetic algorithm. One of the Niching methods – Deterministic Crowding Selection Scheme (DC) is adopted. The purpose of DC is to maintain the diversity of the population in the GA. The uses of the DC can improve the result of the UC obtained by GA.

“Chromosome Repair and Neighbourhood Digging” (ND) is introduced to further improve the performance of the GA. In contrast to DC, ND will introduce diversity to the population. This genetic operator is built for the UC problem as an addition.

The main function of the ND, as its name indicates, is to try to repair the unfeasible chromosome and explore the neighbourhood of the chromosome. This genetic operator is based on the idea of modifying the chromosome artificially. When we examine chromosomes (either feasible or unfeasible one), some of them can be improved by making a slight modification of the chromosome. However, GA sometime cannot determine this modification even though the modification is so obvious to us, this is mainly due to the nature of the GA. Generally, GA does not have the information about the objective function and the search space of the problem. The GA just modifies the chromosomes by mutation and crossover. This is the merit of the GA, as mentioned above, because some constraints / objective functions are difficult to express in formulas. Actually, mutation and crossover are stochastic processes and by some chance (bad luck), it cannot identify the same obvious modification. (Actually every bit is the same for GA). Lack of information about the studied problem is the main reason why the GA cannot identify the better neighbours of the chromosomes. ND is developed based on the observation of this phenomenon.

This genetic operator (ND) will try to help GAs to improve the chromosome in the population. In ND, some information of the problem is included to examine the chromosome. Information is expressed as a rule based in ND. The rules will examine the selected chromosome and give a suggestion to make an improvement. Then, the original chromosome will be replaced by the new chromosome which is, of course, better than the original one. If the rules in ND cannot find the better chromosome in the neighbourhood, then the

original chromosome will be kept. In fact, the change made by ND is small and only 1 bit different from the original chromosome. The change is similar to a mutation occur in the chromosome. However, this mutation will always occur in the correct place and always improve the chromosome.

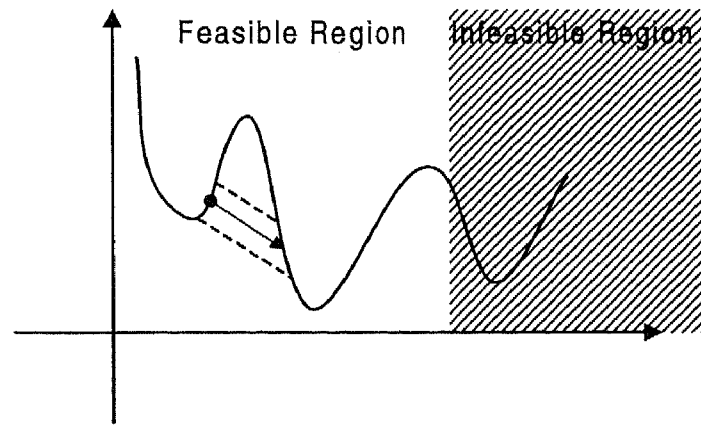


Figure 25 The conceptual diagram for neighborhood digging

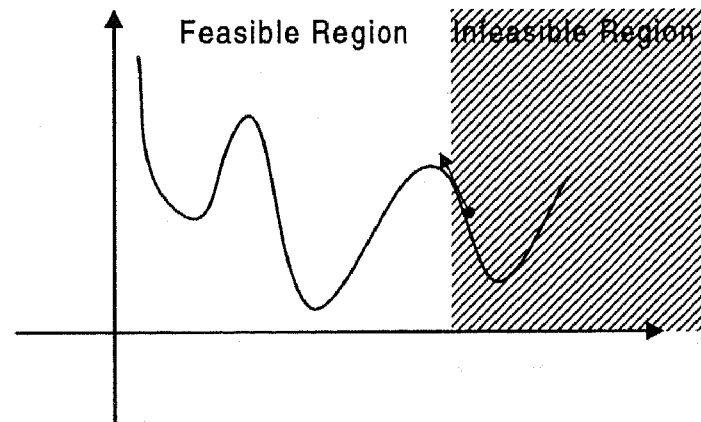


Figure 26 The conceptual diagram for chromosome repair

Rules play an important role in ND, they guide the algorithm to explore the neighbour chromosomes. The rules are built by the nature of the UC problem and the characteristics of the chromosome. With the rules, the ND can explore the better neighbourhood. The rules are defined according to some basic procedures that may reduce the cost of the schedule. The following rules are adopted in our UC module:

- Make a generator operate continually
- Postpone / Delay (within a block of the compression technique) the generators start up / shut down

- Switch off / Switch on a generator

While processing the ND operators, the neighbourhood will be searched according to the previous rules.

As described above, the ND will act according to the rules in exploring the neighbourhood of the individual. Once a better chromosome is found, the new and more fit chromosome will take the place of the original and enter the population. The same procedure applies for the unfeasible individuals. When a feasible individual is found during the exploration of the original unfeasible chromosome, the new and feasible chromosome will take the place of the original. Thus, the unfeasible individuals may turn into a feasible individual after the ND routine.

ND is not suitable to be performed frequently, due to the following points. Firstly, the ND routine consumes valuable computation time during identification of the new chromosome. Secondly, the ND will interfere with the processes of the genetic algorithm by modifying the individuals artificially. If the ND is performed too frequently, the solution obtained by GA will become worse. Thus, in the UC module, the ND operator will be performed only in specific generation and the chromosomes will be selected randomly from the population to be submitted to the operator.

5.5. Variation of Basic Operators

Despite the ND operators described in the previous section, there is a common way to introduce diversity into GA. That is achieved by varying the rate of mutation in the mutation operator. As commonly known, a mutation operator is one of the main sources of introducing diversity into the population. In the beginning, the mutation rate will be kept low. Then, when the best chromosomes have not changed for several generation, the mutation rate will increase slightly in order to help the GA jump out of the local optimal.

5.6. CARE Project

The CARE project aims at building a global control system for a power system with large penetration of renewable energy. This project is supported by the European Union JOULE-THERMIE research program. The project is developed under the frame of JOULE III project "CARE" (N° JOR3-CT96-

0119) : “Advanced control advice for power systems with large integration of renewable energy sources”. The control system developed by this project is designed to provided advice on the optimal operation strategy for a medium sized isolated network with large penetration of renewable energy.

In an isolated network, the operation of the system must be determined carefully to avoid instability of the system. Furthermore, the integration of renewable energy is another main concern. With large scale penetration of renewable, the impact on the power system is considerable.

The CARE system is developed with focus on dynamic stability of the power system and the proposed some preventive control measures to operators. The trust in increased security and reliability of the system will allow for increases in the penetration of renewable energy.

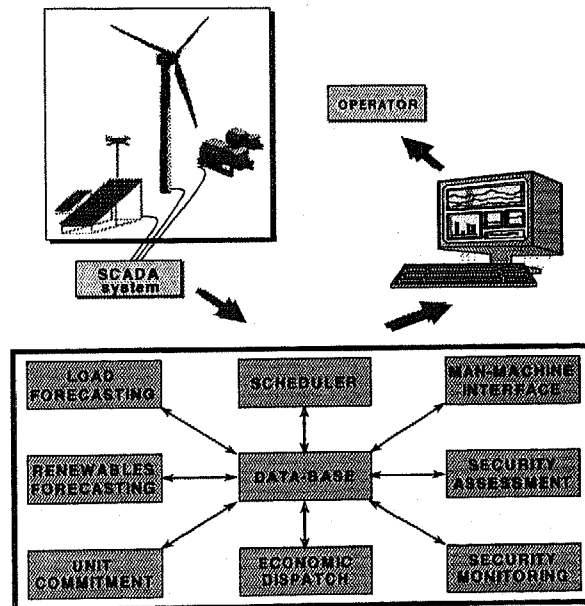


Figure 27 The Architecture of the CARE system (Picture taken from the report of CARE)

In the CARE system, advanced routines of control systems are included, namely:

- Short term load and renewable forecast
- Unit Commitment
- Economic Dispatch
- Security Assessment
- Security monitoring

These modules are delivered by a consortium of research institutions and companies from several countries. They are:

- France (ARMINES)
- Greece (NTUA, Univ. of Crete and Thessaloniki)
- Portugal (INESC)
- UK (UMIST and RAL)

In Figure 28, the simple diagram of the co-operation between modules are shown.

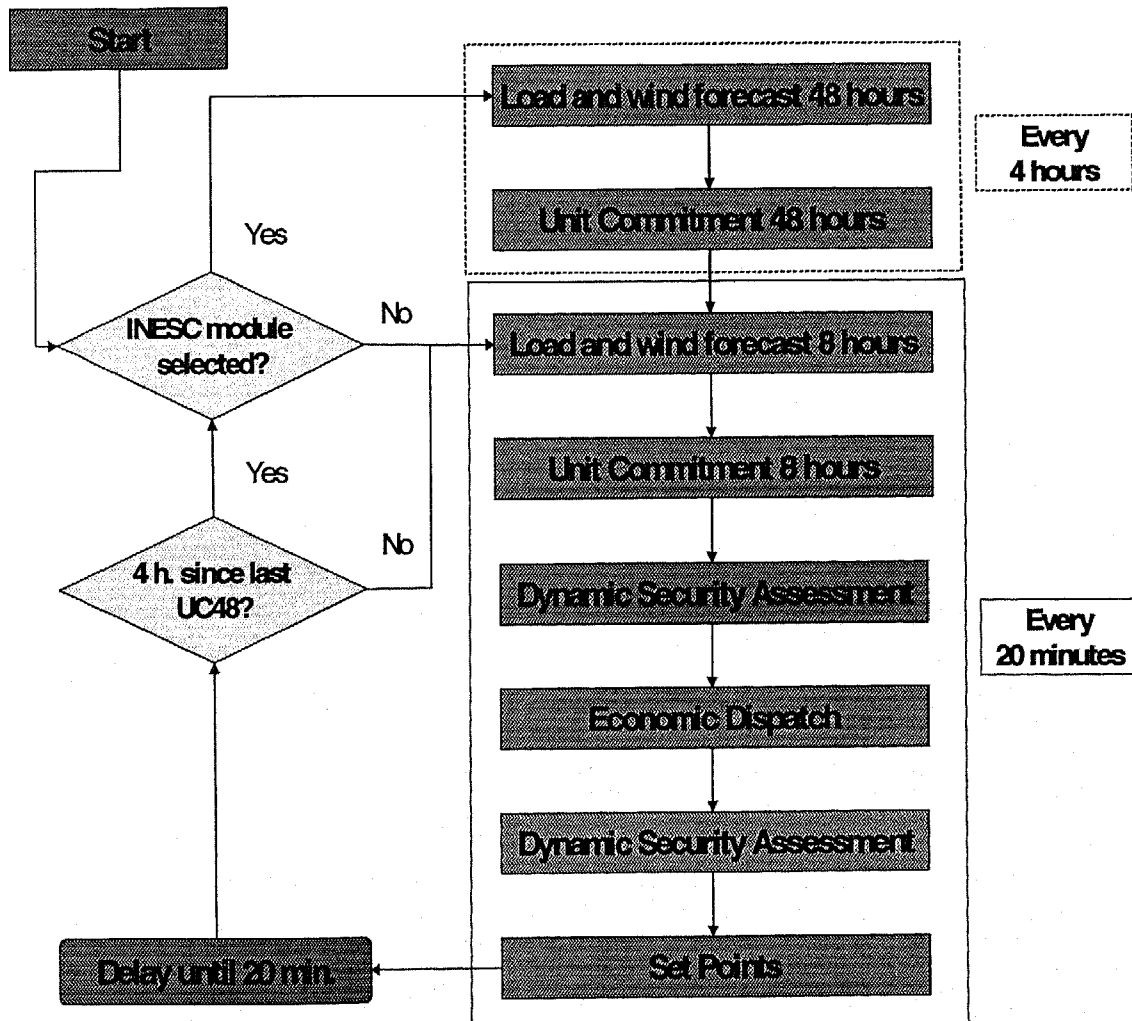


Figure 28 The Algorithm of the main operation of the CARE system (Picture taken from the report of CARE)

5.7. Conclusions

Genetic algorithms are powerful tools for solving the optimisation problem. However, the simple genetic algorithm is not able to solve a multi-modal optimisation problem. It can only deal with the uni-modal optimisation problem. Unfortunately, most of the practical problems are of the multi-modal type. Since unit commitment problems are multi-modal too, a simple genetic algorithm has difficulties in searching the solution for a UC problem. The aim of unit commitment is to provide an operation strategy to the system operators. It is desired that several alternatives are given out and the operators can choose among them. Thus, a niching technique is introduced to the genetic algorithm. The Niching technique is developed in order to preserve the diversity of the population, in such a way that the multi-optima of the multi-modal problem can be explored. Among different Niching method, Deterministic Crowding scheme, which is developed from the standard crowding scheme by Smir W. Mahfound[10], is employed to improve the performance of a genetic algorithm. Based on the principle that the new elements replace the similar parent, Deterministic Crowding preserve the diversity within the population and can locate different optima of a problem. It is suitable for solving the multi-modal optimisation problem, like unit commitment.

In this chapter, we also proposed a way to reduce the length of the chromosome of the genetic algorithm. The direct coding method of the unit commitment problem will lead to a very long chromosome and this is not feasible when solved using a GA. Thus, we proposed a compressed technique to encode the chromosome of a unit commitment problem. Thus, the new coding method will reduce the redundancy in the encoding scheme, and in such a way , the length of the chromosome can be reduced.

Finally we introduced the “chromosome repair and neighbourhood digging” technique. It will try to examine the chromosome in the population and attempt to correct the infeasible chromosomes or improve these chromosomes. The change taking place will be slight(only 1 bit will be changed). It is similar to a mutation operator but the location of the mutation is always correct to improve the chromosome. In addition, the dynamic mutation rate adjustment is used in the mutation operator.

Our unit commitment model is one of the module included in the CARE system. This CARE system was tested in the power network of Crete in Greece, operated by PPC – Public Power Corporation, the national utility of Greece, and received approval and praise from the operators and the company. This approval was expressed publicly in a special workshop organised by EU – European Union, Devoted to the CARE System[35].

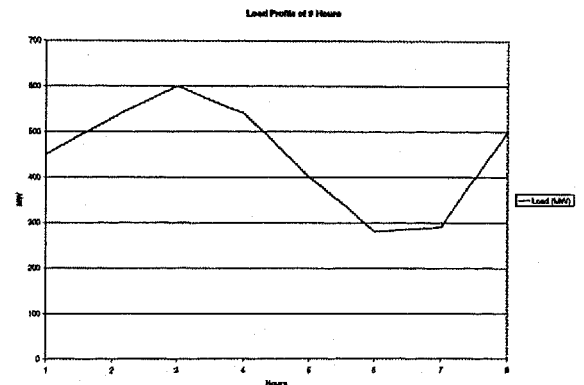
6. CASE STUDIES

6.1. Example 1

In the first example, the unit commitment problem is taken from reference[1]. The objective of the problem is to minimize the total cost of the schedule. In this problem, 4 generators are to be committed to serve the load of 8 hours. The total cost includes operation cost and the start-up cost of the generators. The operation cost of each generator is described by an linear equaiton. The start up cost of the generator depends on the rest time of the generator. Two start up modes are defined : hot start-up and cold start-up , which correspond to different start-up costs. In the operation of the generator, the output power needs to be within the minimum and the maximum value. In addition, the rest time of the generator should be greater than its Minimum Down Time and the generator is obliged to operate above its Minimum Up Time. The follwing tables are : the 8 hours load profile of the problem, the characteristic and initial conditions of the generators.

The 8 hours load profile

Hour	Load (MW)
1	450
2	530
3	600
4	540
5	400
6	280
7	290
8	500



Unit	Output Power (MW)		Incremental Heat Rate (Btu/kWh)	No-Load Cost (R/h)	Full-Load Ave. Cost (R/mWh)	Minimum Times(h)	
	Max	Min				Up	Down
1	80	25	10440	213.00	23.54	4	2
2	250	60	9000	585.62	20.34	5	3
3	300	75	8730	684.74	19.74	5	4
4	60	20	11900	252.00	28.00	1	1

Unit	Initial Conditions	Start Up Costs		
	Hours [Off-line(-)/On-line(+)]	Hot (R)	Cold (R)	Cold Start (h)
1	-5	150	350	4
2	+8	170	400	5
3	+8	500	1100	5
4	-6	0	0.02	0

In the reference[1], 3 kinds of methods are used to solve this example. These method are: Priority order method, compete enumeration method and the forward dynamic-programming method. The results are summarized in the following table.

Methods	Total Cost (R)
Priority order. Up and down times neglected	73439
Enumeration with 4 strategies saved. Up and down times neglected	73274
Dynamic programming with Up and down times observed	No Solution
With 4 strategies saved	
With 8 strategies saved	
With 10 strategies saved	

The above example was also solved by our UC module. The 5 best solutions are kept when solving this example. Constraints are the same as stated in the example, and the minimum up and down time are observed.

The following table display the 5 best solutions obtained by the UC module in a single run of the module.

Solution	Cost
The Best	74005
2 nd Best	74018
3 rd Best	74110
4 th Best	74397
5 th Best	74478

And the schedule of the Best solution:

Hours	Unit1	Unit2	Unit3	Unit4
1	0	150	300	0
2	25	205	300	0
3	50	250	300	0
4	25	215	300	0
5	80	0	300	20
6	0	0	280	0
7	0	0	290	0
8	0	200	300	0

Running the same uc module for 10 times with the same data, the following results are obtained:

Runs	Best Cost
1 st	74018
2 nd	74005
3 rd	74005
4 th	74005
5 th	74005
6 th	74005
7 th	74005
8 th	74005
9 th	74005
10 th	74110

For this example, all the results obtained by using our UC module are better than the results obtained in reference[1]; in addition, the solution obtained by the reference is also included. From the table of 5 best solutions, we could find out that the best solution is 74005 and the solution obtained by the reference is the 3rd solution (74110) in that run.

6.2. Example 2

In the second example, the problem is also taken from the other publication[13]. In the reference, genetic algorithm is used to solved the problem. Furthermore, the authors tried to compare their results with the other well-known methods. As the approaches of our UC module are similar and they have the results with the other method, we chose their testing problem as an example.

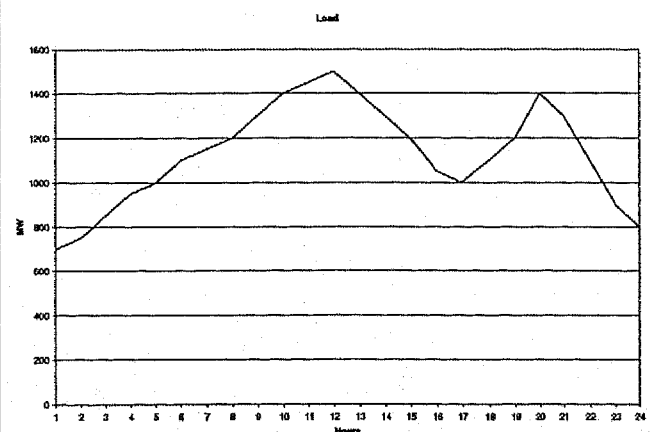
This example consists of 2 unit commitment problem. In the first problem, 10 generators need to be scheduled over the loads of 24 hours (1 hour interval) . The data of the generators are listed in the following table. For the second problem, the first 10 units are the same as the first problem and the other are duplicated. Furthermore, the load demand is simply doubled from the first problem.

The following tables summarize the load and the generators characteristics (including the initial conditions) for the first unit commitment problem.

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
$P_{\max}$	455	455	130	130	162
$P_{\min}$	150	150	20	20	25
$a(\$/h)$	1000	970	700	680	450
$b(\$/MWh)$	16.19	17.26	16.60	16.50	19.70
$c(\$/MW^2h)$	0.00048	0.00031	0.002	0.00211	0.00398
Min Up Time (h)	8	8	5	5	6
Min Down Time (h)	8	8	5	5	6
Hot Start Cost (\$)	4500	5000	550	560	900
Cold Start Cost (\$)	9000	10000	1100	1120	1800
Cold Start Hours (h)	5	5	4	4	4
Initial Status	8	8	-5	-5	-6

	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
$P_{\max}$	80	85	55	55	55
$P_{\min}$	20	25	10	10	10
$a(\$/h)$	370	480	660	665	670
$b(\$/MWh)$	22.26	27.74	25.92	27.27	27.79
$c(\$/MW^2h)$	0.00712	0.0079	0.00413	0.00222	0.00173
Min Up Time (h)	3	3	1	1	1
Min Down Time (h)	3	3	1	1	1
Hot Start Cost (\$)	170	260	30	30	30
Cold Start Cost (\$)	340	520	60	60	60
Cold Start Hours (h)	20	2	0	0	0
Initial Status	-3	-3	-1	-1	-1

Hour	Demand (MW)	Hour	Demand (MW)
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800



In the reference, the same problems (Problem 1 and Problem 2) are tested by using Dynamic Programming, Lagrange relaxation method and Genetic Algorithm. According to their report, they had some difficulty in the DP solution in modelling time-dependent constraints. So, they only presented the DP result for the 10 generators unit commitment problem. The following results are included in the reference[13]:

Units	DP solution	Largrangian Relaxtion Solution	GA solution	
			Best	Worst
10	565825	565825	565825	570032
20	-	1130660	1126243	1132059

By using our UC module to solve the problem 1 and problem 2 (10 units and 20 units), we obtained the following results.

	First Problem (10 Units)	Second Problem (20 Units)
1 st run	556319	1115523
2 nd run	554479	1118686
3 rd run	553592	1115590
4 th run	556566	1117543
5 th run	557318	1117944
6 th run	557557	1119373
7 th run	556715	1122147
8 th run	555576	1120620
9 th run	555693	1119521
10 th run	554189	1120154
Average	555800	1118710
Deviation	0.23%	0.18%
Worst	557557	1122147
Best	553592	1115523

From the results above, we can find that all the solutions obtained by our UC module are better than the realties shown in the reference (including the resets obtained by using Dynamic Programming and Lagrange Relaxation Method.

6.3. Example 3

In the example, the power system of Crete (one of the island in Greece) will be used as an example. The power system in Crete is an isolated network, which consists of 17 various generator units, including diesel

generators, gas turbines and steam engines. In addition, wind energy generation is widely used in this system (note: in this testing example, the limit of the wind generation is fixed).

In this example, the studied time horizon is 48 hours with 1 hour time interval. Furthermore, the minimum reserve and the ramping constraints were included. In this example, parameters of some genetic operators will be changed in order to investigate the influence in the output result.

The following is the characteristics and the initial conditions of the example system.

	Steam1	Steam2	Steam3	Steam4	Steam5
$P_{\max}$ (MW)	4	7	7	13	16
$P_{\min}$ (MW)	6.25	15	15	25	25
Load Change Rate(MW/min)	0.6	0.1	0.1	0.1	0.1
a(Kdra/h)	0	0	0	0	0
b(Kdra/MWh)	18.64	13.53	13.53	12.13	11.21
c(Kdra/MW ² h)	-16.14	7.13	7.13	7.0	10.82
Shut Down Time (min)	10	90	90	25	20
Shut Down Cost (kDra)	10.12	151.8	151.8	69	50.6
Hot Start Cost (kDra)	80.406	331.2	331.2	276	177.1
Hot Start Time (min)	72	165	165	132	60
Warm Cooling Time (min)	240	240	240	480	480
Cold Start Cost (kDra)	282.17	596.825	596.825	668.44	822.75
Cold Start Time (min)	288	300	300	320	512
Cold Cooling Time (min)	2100	1440	1440	2400	3000
Initial Generation (MW)	4	7	7	13	16
Initial Status (Min)	+230	+320	+320	+420	+230

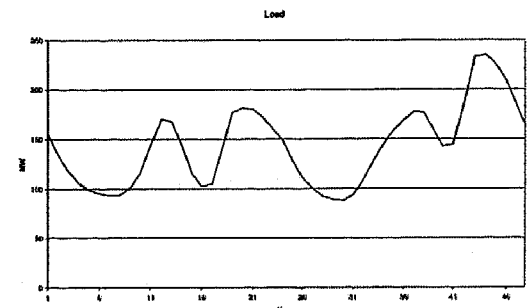
	Steam6	Gas1	Gas2	Diesel1	Diesel2
$P_{\max}$ (MW)	4	3	3	3	3
$P_{\min}$ (MW)	6.25	14.5	14.5	12.25	12.25
Load Change Rate(MW/min)	0.6	2	2	2	2
a(Kdra/h)	0	0	0	0	0
b(Kdra/MWh)	18.64	29.76	29.76	8.60	8.60
c(Kdra/MW ² h)	-16.14	206.42	203.42	1.77	1.77
Shut Down Time (min)	10	20	20	8	8
Shut Down Cost (kDra)	10.12	8.364	8.364	9.2	9.2
Hot Start Cost (kDra)	80.406	52.28	52.28	33.12	33.12
Hot Start Time (min)	72	13.25	13.25	31	31
Warm Cooling Time (min)	240	-	-	-	-
Cold Start Cost (kDra)	282.17	-	-	-	-
Cold Start Time (min)	288	-	-	-	-
Cold Cooling Time (min)	2100	-	-	-	-
Initial Generation (MW)	4	3	3	3	3
Initial Status (Min)	+230	-200	-200	+200	+200

	Diesel3	Diesel4	GT1	GT4	GT5
$P_{\max}$ (MW)	3	3	3	3	3
$P_{\min}$ (MW)	12.25	12.25	16.2	24	36
Load Change Rate(MW/min)	2	2	2	2	2
a(Kdra/h)	0	0	0	0	0
b(Kdra/MWh)	8.60	8.60	30	31	30
c(Kdra/MW ² h)	1.77	1.77	203.42	203.42	203.42
Shut Down Time (min)	8	8	20	20	20
Shut Down Cost (kDra)	9.2	9.2	8.364	8.364	8.364
Hot Start Cost (kDra)	33.12	33.12	52.275	60	52.275
Hot Start Time (min)	31	31	9	5.5	11
Warm Cooling Time (min)	-	-	-	-	-
Cold Start Cost (kDra)	-	-	-	-	-
Cold Start Time (min)	-	-	-	-	-
Cold Cooling Time (min)	-	-	-	-	-
Initial Generation (MW)	3	3	3	3	3
Initial Status (Min)	+200	+200	-200	+200	+200

	GT6	GT7
$P_{\max}$ (MW)	3	3
$P_{\min}$ (MW)	37	16.2
Load Change Rate(MW/min)	2	2
a(Kdra/h)	0	0
b(Kdra/MWh)	31.5	30.5
c(Kdra/MW ² h)	200	205
Shut Down Time (min)	20	20
Shut Down Cost (kDra)	8.364	8.364
Hot Start Cost (kDra)	52.275	51
Hot Start Time (min)	10	10
Warm Cooling Time (min)	-	-
Cold Start Cost (kDra)	-	-
Cold Start Time (min)	-	-
Cold Cooling Time (min)	-	-
Initial Generation (MW)	3	3
Initial Status (Min)	-200	-200

The 24 hours load profile is:

Hour	Demand (MW)	Hour	Demand (MW)
1	156	25	129.5
2	135.4	26	111.7
3	118.7	27	99.8
4	106.2	28	92.3
5	98.8	29	88.8
6	95	30	87.9
7	93.8	31	93.7
8	93.7	32	108.1
9	101.1	33	126.9
10	115.9	34	144.4
11	143.9	35	158.9
12	170.4	36	169
13	167.9	37	177.7
14	142.7	38	176.7
15	114.9	39	159.6
16	102.8	40	143
17	105	41	144.2
18	139.1	42	186.1
19	176.8	43	233.1
20	181.7	44	234.9
21	179.9	45	225.7
22	172.4	46	209.3
23	160.6	47	186.1
24	149.4	48	164.6



In this example, the wind penetration limited is fixed and all the wind generations are used. The required minimum system reserve is set as 110% of the load and maximum system capacity needs to account for the ramping rate of the generators.

The effect of the number of block in coding the chromosome

In encoding the solutions to the chromosomes, a compression technique is used. Generally, this method groups several time intervals into a section/block. Within the time intervals, generators only can change their states once. This results in reducing the sizes of the chromosome and eliminates some infeasible solutions. By changing the number of blocks in the compression technique, the following results are obtained.

Block No	48	24	16	12	6	3	2
Average Cost	87512.9	87228.5	87882.7	87631.9	89695.7	93816.9	94053.5
Percentage of Deviation	0.886	0.602	0.413	0.321	1.059	0.000	0.000

The above results summarize the effect of the number of block in the chromosome coding method. In the coding method, the no of blocks corresponds to the no. of intervals that will group together. Within the time intervals of the block, generators can only change their states once.

Block No.	No. of hours grouped together
48	1
24	2
16	3
12	4
6	8
3	12
2	24

The results shows that the average costs of the first 4 test groups (no. of block: 48, 24, 16 and 12) are similar. However, start from the 5th group (no. of block: 6), the average cost start increasing.

By examining the compression technique, we find that when the number of blocks decreases, more time intervals will group together. Generators can only change their state once within a block. The more time intervals group together, the longer the generators will operator / rest. As we know, some expensive generators are only used for supplying the peak load. If these kind of generators keep on working for a long period, the total operation cost will increase. The results show that the adequate number of blocks is, beyond 12 which corresponds to 4 hours in this example.

Population size against the no. of generations

In Genetic Algorithm, population size and the number of generations are two of the parameters affecting the overall performance. The population size assigns the number of individuals to exist in a population and this represents how many parallel processes will perform in Genetic Algorithm. The number of generations specifies how many generations a GA will develop

and this parameter acts as the stopping criteria of the GA. Both parameters will affect the either solutions and the processing time. If the population size becomes smaller, the individuals in a population become less in number and the diversity of the population will reduce too. With less diversity in GA, more chance of trapping in local optimal. In contrast, with less individuals inside a population, the time for fitness evaluation will reduce and thus speed up the overall computing time of the algorithm. The generation number has the similar effect as population size. With smaller number of generations, GA has not enough time to converge. But, the larger the generation no, the longer time will need to complete the process. The following table shows the result when the population size and the no. of generation vary.

			Population Size					
			50	100	200	400	600	1200
No. of Generations	2400	Average	88837.2					
		Stdev Per.	1.816					
	1200	Average		87597.4	87582.6			
		Stdev Per.		0.517	0.281			
	600	Average			87613.7			
		Stdev Per.			0.337			
	300	Average			88596.6	88610.3		
		Stdev Per.			0.544	0.734		
	200	Average					89573.4	
		Stdev Per.					0.583	
	100	Average						91802.9
		Stdev Per.						1.596

In the above results, the test in the main diagonal has the same computation time. We can find that the average cost is better for the 2nd and 3rd test (100 populations and 1200 generations, 200 populations and 600 generations). Some addition tests are performed, we try to double and half the no. of generations while fixing the population size at 200. We find that with higher no. of generation, the deviation of the solution is decrease, in contrast, the deviation is increasing. It should be pointed out that longer time is needed for more no. of generation.

Effect of Chromosome Repair and Neighbourhood Digging

In this section, the effect of the Chromosome Repair and Neighbourhood Digging is investigated. The following table shows the results obtained by changing the rate of performing the ND routine and the probability for choosing the individuals undergo the ND process.

			Probability for choosing Chromosome during ND			
			No ND	0.3	0.6	0.9
Rate of performing ND*	20	Average Cost	88850.18	87929.02	87633	87506.12
		Stdev Per.	1.045	0.886	0.365	0.582
	40	Average Cost		87884.55	87595.74	87647.94
		Stdev Per.		0.746	0.271	0.366
	60	Average Cost		88111.35	87739.48	87779.31
		Stdev Per.		0.871	0.513	0.438

* Note: This shows how frequent the ND will perform. (ND performs every 20, 40, 60 generations)

The above results show the effect of the ND is searching the solutions for genetic algorithm. First of all, we can find that the ND routine can improve the performance of the UC module and also reduce the deviation of the solutions obtained. It will become clear when comparing the results with ND and the results without ND. The average cost without ND and also the result deviation is the worst within the table.

Inside the table of the ND, we can investigate some characteristics of the ND routine. As we mentioned before, the ND routine will perform in a specified rate and randomly select the individuals that undergo the process. In the table, UC routine will perform in a rate of 20, 40 and 60 generation; furthermore, the probability in selecting the individuals will be 0.3, 0.6 and 0.9. In fact, the processing time of the UC module is closely related to the rate and the probability of performing ND. More frequently and more individuals undergo the ND process, the more time is needed for the UC module. Thus, the rate of 60 generation and 0.3 probability for the ND (result in lower corner) will consume less time by comparing with the one that has the rate of 20 generations and 0.9 probability (result in upper left corner) for the ND routine. It seems that higher rate and probability can improve the output solution of the UC module. However, as the ND will distribute the process of the genetic algorithm and with perform ND more frequent and higher

proportion of the population, it may lead to a contrary result. This can be seen by comparing the results of the first row which corresponds to perform ND every 20 generations, with the results of the second row (perform ND every 40 generations). All results of the latter are superior to the previous. From the results, it shows that performing the ND routine every 40 generations and with 60% of the population undergoing the ND process is adequate for our UC module. The following chart is the solution from one of the runs for this example problem. In the sample run, the number of blocks for the compression technique is 12 and the ND routine is performed every 40 generations and with probability 0.6 in choosing the individuals. In addition, 200 individuals are in the population and the whole module will perform 600 generations.

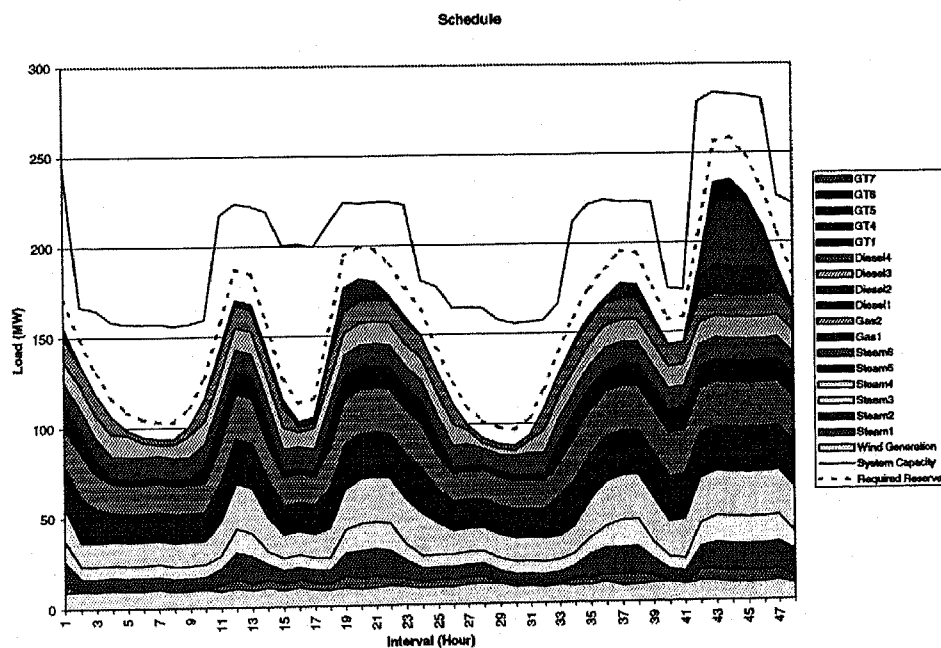


Figure 29 Solution schedule for example 3

The total cost of the above schedule is 87476.6 kDra. In the bottom of the schedule is the portion of wind generation, and then is the generation of the other thermal generators (steam, gas, diesel, etc...). The dot line is the required reserve for the schedule and the line beyond the dot line is the actual capacity of the system (note that, the system capacity is calculated with the consideration of the ramping constraint of the generators).

6.4. Example 4

In this example, the problem is similar to the previous example. However, some alterations are made. This UC problem is invented to test the performance of our UC module with the new dispatch algorithm. The generator data in this example is similar to the Example 3, the only difference is that while the cost is represented by a quadratic equation and in Example 3, the cost of the generator is represented by means of a linear equation. Furthermore, the load profile is also the same as the previous example. The following are the characteristics, initial condition and the load of the generators.

	Steam1	Steam2	Steam3	Steam4	Steam5
$P_{\max}$ (MW)	4	7	7	13	16
$P_{\min}$ (MW)	6.25	15	15	25	25
Load Change Rate(MW/min)	0.6	0.1	0.1	0.1	0.1
a(Kdra/h)	1	1	1	1	1
b(Kdra/MWh)	18.64	13.53	13.53	12.13	11.21
c(Kdra/MW ² h)	-16.14	7.13	7.13	7.0	10.82
Shut Down Time (min)	10	90	90	25	20
Shut Down Cost (kDra)	10.12	151.8	151.8	69	50.6
Hot Start Cost (kDra)	80.406	331.2	331.2	276	177.1
Hot Start Time (min)	72	165	165	132	60
Warm Cooling Time (min)	240	240	240	480	480
Cold Start Cost (kDra)	282.17	596.825	596.825	668.44	822.75
Cold Start Time (min)	288	300	300	320	512
Cold Cooling Time (min)	2100	1440	1440	2400	3000
Initial Generation (MW)	4	7	7	13	16
Initial Status (Min)	+230	+320	+320	+420	+230

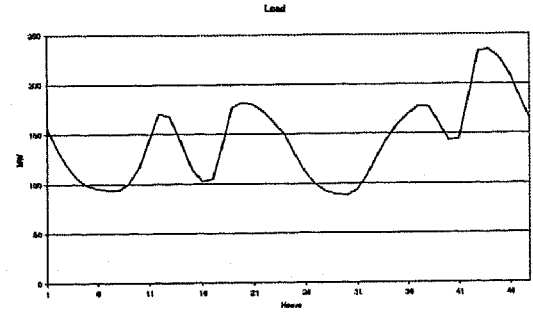
	Steam6	Gas1	Gas2	Diesel1	Diesel2
$P_{\max}$ (MW)	4	3	3	3	3
$P_{\min}$ (MW)	6.25	14.5	14.5	12.25	12.25
Load Change Rate(MW/min)	0.6	2	2	2	2
a(Kdra/h)	1	1	1	1	1
b(Kdra/MWh)	18.64	29.76	29.76	8.60	8.60
c(Kdra/MW ² h)	-16.14	206.42	203.42	1.77	1.77
Shut Down Time (min)	10	20	20	8	8
Shut Down Cost (kDra)	10.12	8.364	8.364	9.2	9.2
Hot Start Cost (kDra)	80.406	52.28	52.28	33.12	33.12
Hot Start Time (min)	72	13.25	13.25	31	31
Warm Cooling Time (min)	240	-	-	-	-
Cold Start Cost (kDra)	282.17	-	-	-	-
Cold Start Time (min)	288	-	-	-	-
Cold Cooling Time (min)	2100	-	-	-	-

Initial Generation (MW)	4	3	3	3	3
Initial Status (Min)	+230	-200	-200	+200	+200

	Diesel3	Diesel4	GT1	GT4	GT5
$P_{\max}$ (MW)	3	3	3	3	3
$P_{\min}$ (MW)	12.25	12.25	16.2	24	36
Load Change Rate(MW/min)	2	2	2	2	2
a(Kdra/h)	1	1	1	1	1
b(Kdra/MWh)	8.60	8.60	30	31	30
c(Kdra/MW ² h)	1.77	1.77	203.42	203.42	203.42
Shut Down Time (min)	8	8	20	20	20
Shut Down Cost (kDra)	9.2	9.2	8.364	8.364	8.364
Hot Start Cost (kDra)	33.12	33.12	52.275	60	52.275
Hot Start Time (min)	31	31	9	5.5	11
Warm Cooling Time (min)	-	-	-	-	-
Cold Start Cost (kDra)	-	-	-	-	-
Cold Start Time (min)	-	-	-	-	-
Cold Cooling Time (min)	-	-	-	-	-
Initial Generation (MW)	3	3	3	3	3
Initial Status (Min)	+200	+200	-200	+200	+200

	GT6	GT7
$P_{\max}$ (MW)	3	3
$P_{\min}$ (MW)	37	16.2
Load Change Rate(MW/min)	2	2
a(Kdra/h)	1	1
b(Kdra/MWh)	31.5	30.5
c(Kdra/MW ² h)	200	205
Shut Down Time (min)	20	20
Shut Down Cost (kDra)	8.364	8.364
Hot Start Cost (kDra)	52.275	51
Hot Start Time (min)	10	10
Warm Cooling Time (min)	-	-
Cold Start Cost (kDra)	-	-
Cold Start Time (min)	-	-
Cold Cooling Time (min)	-	-
Initial Generation (MW)	3	3
Initial Status (Min)	-200	-200

Hour	Demand (MW)	Hour	Demand (MW)
1	156	25	129.5
2	135.4	26	111.7
3	118.7	27	99.8
4	106.2	28	92.3
5	98.8	29	88.8
6	95	30	87.9
7	93.8	31	93.7
8	93.7	32	108.1
9	101.1	33	126.9
10	115.9	34	144.4
11	143.9	35	158.9
12	170.4	36	169
13	167.9	37	177.7
14	142.7	38	176.7
15	114.9	39	159.6
16	102.8	40	143
17	105	41	144.2
18	139.1	42	186.1
19	176.8	43	233.1
20	181.7	44	234.9
21	179.9	45	225.7
22	172.4	46	209.3
23	160.6	47	186.1
24	149.4	48	164.6



In this example, the wind energy penetration is not a fixed limit. Instead, the penetration limit is defined by an Interval, which is from 10% of the load to 15% of the load. The information of the wind generation comes from the wind forecasted module. As the example 3, the spinning reserve of the schedule need to be 10% of the total load.

Firstly, we perform the UC module with the data of the problem. The penalty cost for not using the wind energy is 200 Kdra/MWh. Assume that the preference of the operator is "NORMAL" for wind penetration and also "NORMAL" for the cost of the schedule. Thus, the membership function of the wind penetration and the cost of the dispatch will be:

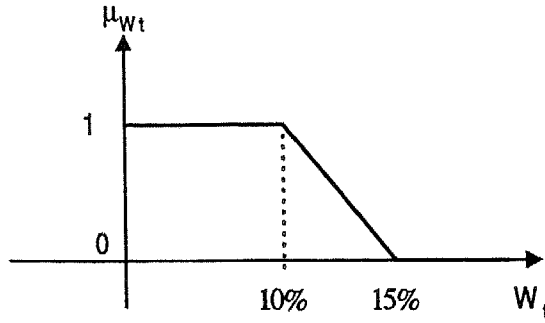


Figure 30 "NORMAL" membership function for wind energy penetration

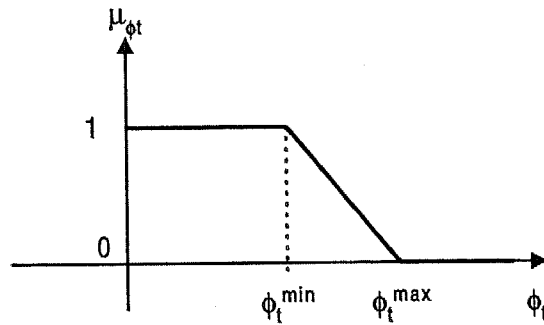


Figure 31 "NORMAL" membership function for the operation cost

With all the data of the unit commitment problem and the preference of the operator, our UC module with the new dispatch problem find the following solution:

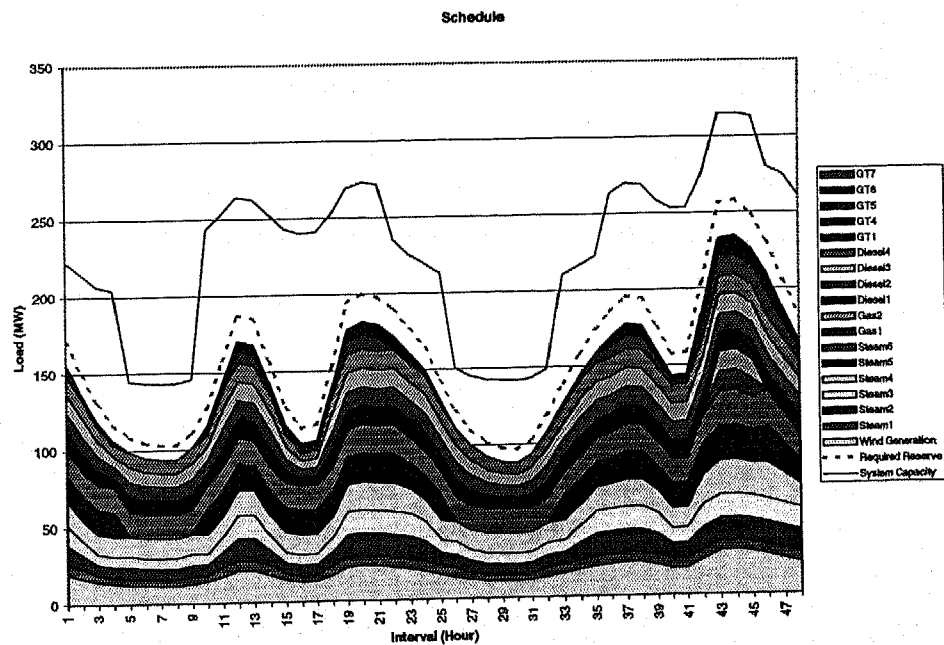


Figure 32 Solution schedule with "NORMAL" preference of wind and operation cost

The total operation cost for this schedule is 169917.8 Kdra. The minimum requirement of the reserve is satisfied. The following table are the percentage of the wind energy penetration in each time intervals:

Hour	1	2	3	4	5	6
Wind P. Percent.	12.41	12.39	12.12	12.40	12.33	12.45
Hour	7	8	9	10	11	12
Wind P. Percent.	12.34	12.49	12.37	12.36	12.21	12.24
Hour	13	14	15	16	17	18
Wind P. Percent.	12.32	12.36	12.42	12.29	12.59	12.26
Hour	19	20	21	22	23	24
Wind P. Percent.	12.50	12.53	12.47	12.45	12.40	12.30
Hour	25	26	27	28	29	30
Wind P. Percent.	12.41	12.32	12.41	12.32	12.50	12.44
Hour	31	32	33	34	35	36
Wind P. Percent.	12.48	12.27	12.25	12.37	12.33	12.26
Hour	37	38	39	40	41	42
Wind P. Percent.	12.47	12.41	12.46	12.28	12.45	12.51
Hour	43	44	45	46	47	48
Wind P. Percent.	12.45	12.43	12.46	12.38	12.42	12.54

From the table, we can find that with the "NORMAL" preference about the wind penetration and the cost function, the wind penetration will be around 12% – 12.5%.

Now, we want to change the preference of the operator about the wind energy penetration and the cost function. The new operator has a different point of view in the operation. He don't like risk and he want to operate the system in a safe manner. His preference of the wind penetration is "RISK AVERSION" . However, he is not very care about the operation cost and the he is "GENEROUS" for the operation cost. With this information, the following schedule will obtain.

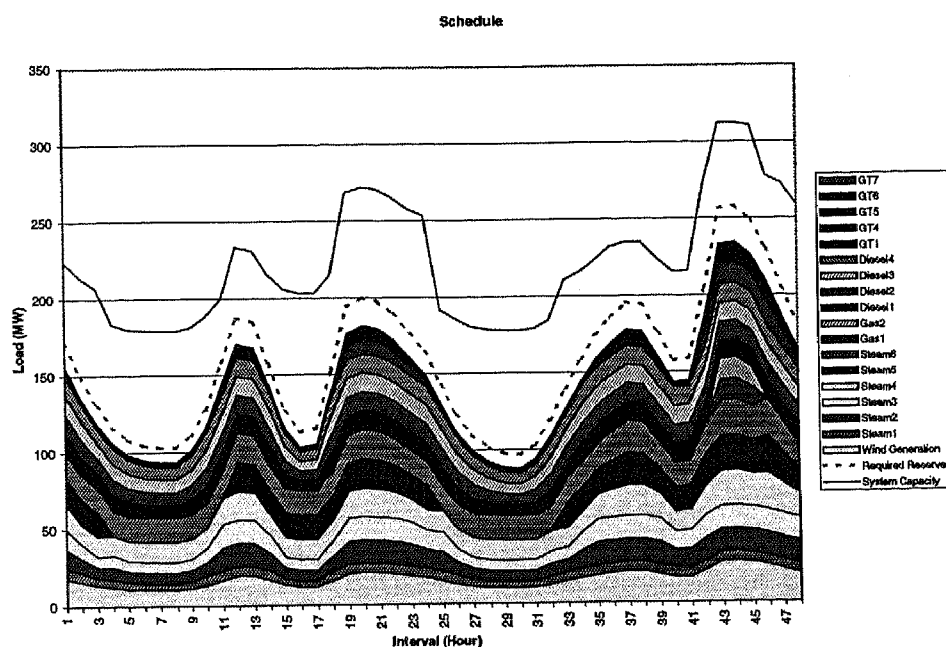


Figure 33 Solution schedule with “RISK AVERSION” wind penetration and “GENEROUS” operation cost

The total cost of the schedule obtained by the UC module is 173481.3kDra which is more expensive than the previous test (an increase of about 2%). As we can find that from the following table, which summarizes the wind penetration in all the time intervals, the wind penetration is less than the previous test. The penetration is around 11% - 11.5% of the load. This is the reflection of the “RISK AVERSION” attitude of the operator. The following table summarize the percentage of the wind energy penetration

Hour	1	2	3	4	5	6
Wind P. Percent.	11.44	11.34	11.33	11.44	11.35	11.37
Hour	7	8	9	10	11	12
Wind P. Percent.	11.31	11.24	11.45	11.40	11.43	11.41
Hour	13	14	15	16	17	18
Wind P. Percent.	11.29	11.22	11.46	11.40	11.35	11.34
Hour	19	20	21	22	23	24
Wind P. Percent.	11.41	11.47	11.45	11.40	11.46	11.43
Hour	25	26	27	28	29	30
Wind P. Percent.	11.44	11.20	11.42	11.22	11.38	11.42
Hour	31	32	33	34	35	36
Wind P. Percent.	11.20	11.30	11.42	11.36	11.33	11.43
Hour	37	38	39	40	41	42
Wind P. Percent.	11.30	11.41	11.37	11.42	11.39	11.34
Hour	43	44	45	46	47	48
Wind P. Percent.	11.40	11.37	11.45	11.43	11.33	11.26

7. CONCLUSIONS

In advanced control of the power system, Production Control suggests the suitable strategies for energy production. These strategies need to be economic, secure and satisfy the required service quality. Unit Commitment is one of the modules in Production Control, which plans the generators operation in hours/days horizon.

In Unit commitment modules, the main objective is to minimise the production cost (fuel cost and the cost for generators start-up and shutdown) while feeding the load according to the forecasted power consumption. other requirements / restrictions are added to the module in such a way that the strategy plan given out conforms to the needs of efficient, economy and secure operation.

The most common constraints to the UC problem are : the Power Balanced in the system, the technical limitations of the generators, spinning reserve requirement and additional constraints such as: the limitations on the emissions of pollutants[15], limitation of the crew in the power plants, the security evaluation of the system, contract limitations of the utility ... etc. The constraints adopted in the UC model are highly dependent on the utility. In our UC model, the studied system is an isolated network (on an island) which has traditional thermal generators and renewable energy source. The objective is to obtain a economic generator schedule with respect to common constraints such as the Power Balance Equation (with the forecast load), Minimum Reverse Requirement, Technical limitation of Generators and some dynamic security (definition of the limits to the penetration of the wind generation).

However, there exists many problems in solving a unit commitment problem. In general, its decision variables are discrete (0/1 integer) and non-linear solution space. On this other side, high dimensionality solution space increases the difficulties and requirements of the solving technique.

Under the effort of many pioneers, many methods are used in solving UC problem: Full Enumeration, Dynamic Programming Technique, and Lagrange Relaxation method. However, these methods have their inherent limitation for solving the UC problem. Full Enumeration tries all the combinations of the UC problem and finds the solution. The solution given out

by the full enumeration method will be the optimal solution, but this method will consume a considerable computation time even for a very small UC problem. Dynamic Programming technique are widely used methods in solving the UC problems; and there are several variations for this method. It works by decomposing the UC problem into time steps and thus reducing the computational work load dramatically by comparing with the Enumeration method. However, for a big UC problem, Dynamic Programming will still have to face the “curse of dimensionality”[30]. The solution obtained by Dynamic programming may not be the optimal of the problem but the solution is closed enough to the optimal. By contrasted with the above method, Lagrange Relaxation technique works based on the dual optimisation approach. This method doesn’t had the problem of the dimensionality. However, the Lagrange Relaxation technique cannot guarantee the optimality of the solution will be obtained.

In this thesis, we introduce a genetic algorithm for solving the UC problem. The Genetic Algorithm works based on the evolutionary theory of Darwin, by encoding the UC problem into a chromosome. Since the Genetic Algorithm doesn’t need the information about the objective function nor the solution spaces for the problem. The non-linear constraints can easily be introduced. A Genetic algorithm works in a different way from the other methods, by directly coding the parameter set from a population of points. Using the payoff information of the objective function, the method is immune from the non-linearity of the objective function, in addition, the search in genetic algorithm will be guided by the probability transition rule.

The operational costs of the UC schedule is defined as the fitness function for the chromosomes. By introducing a penalty into the fitness of the chromosome, various constraints can be included into the chromosome evolution. Under the genetic operator, Crossover, Mutation and Selection, a UC schedule will be obtained.

Since the integration of the renewable energy into the isolated network is needed, in our UC model, the security issue of the system must be taken into the consideration. For our unit commitment model, the renewable energy integration will be according to a general guideline. Since this integration guideline is flexible, the wind energy integration can violate it slightly in

order to achieve the better solution, however, renewable integration cannot exceed a maximum penetration limit.

In order to introduce the flexibility into the UC problem and integrate the renewable energy in a economic way, in this thesis, we introduce the fuzzy concept to deal with this kind of constraint. As we know, fuzzy set theory is one of best theories in dealing with vague or soft constraints. We make use of the concept of the fuzzy programming and reformulate the economic dispatch problem. In such a way that the level of wind penetration can be determined in a flexible way. With the introduction of various membership functions, the dispatch routine can determine the limits of wind penetration.

In addition, this thesis also introduces several genetic operators into the genetic algorithm. These genetic operators enhance the searching ability of the genetic algorithm in order to ease the difficulties of the UC problem. We introduce a compression technique, which is used to reduce the resulting length of the chromosome. This technique can reduce the number of infeasible solutions and thus speed up the process of the genetic algorithm and improve the quality of the solution found. A niching technique is also used in the genetic algorithm. Among various niching scheme, Deterministic Crowding scheme is introduced. This scheme is advocated by Samir W. Mahfoud who developed this scheme from the standard Crowding scheme. With the Deterministic Crowding, Genetic Algorithm is capable of exploring different optima in a multi-modal optimisation problem, such as the UC problem. This scheme will try to preserve the diversity of the population and in addition, avoid fit chromosomes spread around and dominate the whole population of the Genetic algorithm. This scheme has already proved to have the ability to solve the multi-modal optimisation problem in literature.

Other than the two modifications mention in the above paragraph, the dynamic mutation rate adjustment and “Chromosome Repair and Neighbourhood Digging” operators are also introduced. Dynamic mutation rate adjustment defined as, the adjust of the mutation rate dynamically whenever the ever best solution obtained have changed for several generations. Chromosome Repair and Neighbourhood Digging are trial operators, which aims at recovering the infeasible chromosome into feasible and also improving the already feasible chromosomes. The effect of the

Chromosome Repair and Neighbourhood Digging is similar to the mutation operator but, unlike the mutation operator, the location of bit changed will always improve the chromosome. This operator will only take place in some specific generation and only take effect in certain chromosomes (which is selected in randomly).

The European Funded project “CARE” aims at developing an advanced control system , which provides optimal strategies for the system operators in the medium or large scale isolated network with renewable energy. The UC module developed are one of the functions included in the CARE system.

In this Unit Commitment module, wind generation is included. The dispatch model is used to determine the limit for the wind generation penetration according to the preference of the operator. Furthermore, additional constraints can be adopted into the model by means of adding penalty to the fitness of the chromosome. Special techniques are added such as the compression coding technique, chromosome repair and neighbourhood digging, dynamic mutation rate adjustment and Deterministic Crowding Selection Scheme (Niching).

Future Paths...

The UC module developed in this thesis provides an way to solve the unit commitment problems. Nevertheless, there are many restrictions in this module and additional effort is needed to improve on its weak points. Firstly, the model of the UC module is made under a classical point of view. Under the marketing environment, our UC module cannot be adopted directly. It is also important that our approaches focus on the isolated network and hasn't considered the interconnected power exchanged. Secondly, our UC module cannot guarantee the output solution. The solution given out may not be the optimal but second or close to the optimal solution. Besides, when performing the UC module for several runs with the same data, deviations exist within solutions of several runs. Special genetic operators can reduce the deviations, however, deviations still exist. Problem dimension is an important problem in unit commitment. In our UC module, by using a genetic algorithm, the problem is not severe. Nevertheless, larger dimension unit commitment

problems will lead to an increase in computation time, worse output solutions, and higher deviations in the solutions. Finally, the new economic dispatch model needs more computation time in comparison with the classical economic dispatch model. It is specially important for the on-line advanced control system. In addition, the operator preference indication in the new dispatch model is limited. We can see that, the acceptable membership function for the preference for the new dispatch model has limitation. For example, preference cannot expressed by a third / fourth (or even higher) order polynomial equation.

The Future development of our UC module can summaries as following:

- Defining the model in such a way that can work under market environment
- Addition constraints, such as: Crew Constraint, network losses, Security Evaluation, Environmental Consideration.
- Interconnecting Power and Hydro Power Reservoir
- Reliable technique for finding the optimal solution for the model in an acceptable computation time
- Co-ordination with the on-line Dynamic Security Assessment module
- Consider the schedule of the Reactive Power
- Reduce the computation effort for the new dispatch model
- Increase the preference level for the new dispatch model and accept different kinds of membership function

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