UNIT COMMITMENT

USING

PARTICLE SWARM OPTIMIZATION

Thesis submitted in the partial fulfilment of requirement for the award of the Degree of

MASTER OF ENGINEERING

IN

POWER SYSTEMS AND ELECTRIC DRIVES

Submitted by

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "**Unit Commitment Using Particle Swarm Optimization**", in partial fulfilment of the requirements for the award of degree of Master of Engineering in *Power Systems and Electric Drives* submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala is an authentic record of my own work carried out under the supervision of Mr. Nitin Narang, Lecturer, and Dr. Sanjay K. Jain, Assistant Professor, EIED.

The matter in this report has not submitted for the award of any other degree of this you or any other university.

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ABSTRACT

An important criterion in power system operation is to meet the power demand at minimum fuel cost using an optimal mix of different power plants. Moreover, in order to supply electric power to customers in a secured and economic manner, thermal unit commitment is considered to be one of the best available options. It is thus recognized that the optimal unit commitment of thermal systems results in a great saving for electric utilities. Unit Commitment is the problem of determining the schedule of generating units subject to device and operating constraints.

The unit commitment has been identified for the thesis work. The formulation of unit commitment has been discussed and the solution is obtained by classical dynamic programming method. An algorithm based on Particle Swarm Optimization technique, which is a population based global search and optimization technique, has been developed to solve the unit commitment problem. The effectiveness of these algorithms has been tested on systems comprising three units and four units and compared for total operating cost.

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CHAPTER-1

INTRODUCTION

1.1 Overview

Unit commitment (UC) is a nonlinear mixed integer optimization problem to schedule the operation of the generating units at minimum operating cost while satisfying the demand and other equality and inequality constrains. The UC problem has to determine the on/off state of the generating units at each hour of the planning period and optimally dispatch the load among the committed units. UC is the most significant optimization task in the operation of the power systems. Solving the UC problem for large power systems is computationally expensive. The complexity of the UC problems grows exponentially to the number of generating units.

Several solution strategies have been proposed to provide quality solutions to the UC problem and increase the potential savings of the power system operation. These include deterministic and stochastic search approaches. Deterministic approaches include the priority list method, dynamic programming, Lagrangian Relaxation and the branch and- bound methods. Although these methods are simple and fast, they suffer from numerical convergence and solution quality problems. The stochastic search algorithms such as particle swarm optimization, genetic algorithms, evolutionary programming, simulated annealing, ant colony optimization and tabu search are able to overcome the shortcomings of traditional optimization techniques. These methods can handle complex nonlinear constraints and provide high quality solutions. This formulation drastically reduces the number of decision variables and hence can overcome the shortcomings of stochastic search algorithms for UC problems.

Due to simplicity and less parameter tuning, particle swarm optimization is used for solving the unit commitment problem. In this thesis we have to study the algorithm of particle Swarm optimization and formulate the algorithm for solving unit commitment using PSO. In the results we have to find the variation in the results of total operating cost of the system in the given time horizon and compare it with the results of the already existing method like dynamic programming.

1.2 Literature Review

In most of the interconnected power systems, the power requirement is principally met by thermal power generation. Several operating strategies are possible to meet the required power demand, which varies from hour to hour over the day. It is preferable to use an optimum or sub-optimum operating strategy based on economic criteria. In other words, an important criterion in power system operation is to meet the power demand at minimum fuel cost using an optimal mix of different power plants. Moreover, in order to supply high quality electric power to customers in a secured and economic manner, thermal unit commitment is considered to be one of the best available options. It is thus recognized that the optimal unit commitment of thermal systems results in a great saving for electric utilities. Unit Commitment is the problem of determining the schedule of generating units within a power system subject to device and operating constraints

Kerr *et al*. [1] have elaborated the need of unit commitment in the power system for economic point of view, discussed various aspects of unit commitment and procedure to formulate the unit commitment problem and its solution.

Hara *et al*. [2] have described a method of scheduling an integrated operation of a thermal power system. A cost function defined in which not only the operation cost of generating units but also system reliability considered. The criterion for economic operation defined to minimize the expected value of the cost function and, on the basis of this criterion; an equation which gives the optimum numbers of operating units and units for periodic overhaul can be obtained.

Lowery, [3] has determined the feasibility of using Dynamic Programming to solve the generating unit commitment problem. Results of the study showed that simple, straight forward constraints are adequate to produce a usable optimum operating policy. Also, required computer time to produce a solution is small; hence, the method is feasible.

Guy, [4] has used a constrained search technique is used to determine which units to shut down or start up in future hours to minimize system fuel costs, including start-up costs. Results in a generating unit schedule which meets system reliability requirements and yields minimum fuel costs.

Fang *et al.* [5] have compared the performance of four unit commitment methods, three of which are based on the dynamic programming approach. The results also showed that one type of unit commitment method may be preferred over others in terms of obtaining more economic schedules within reasonable computing times depending on the applications.

Lauer *et al.* [6] have concerned with the solution of large-scale unit commitment problems. A solution methodology has been developed for the optimization model that has two unique features. First, computational requirements grow only linearly with the number of units. Second, performance of the algorithm can be shown (rigorously) to actually improve as the number of units increases.

Lee *et al.* [7] have focussed industry attention on current problems faced by electric utility operators. It contains four "short note reports" from authors in different areas of the electric power industry. Unit commitment problems associated with uncertainty in loads, production costs, and in the face of increasingly difficult operational constraints are discussed.

Bosch *et al.* [8] have proposes decomposition and dynamic programming as techniques for solving the unit commitment problem, a high dimensional non-linear, mixed-integer optimization problem. Experiments indicate that the proposed methods locate in less time a better solution than many existing techniques.

Kusic *et al.* [9] have presented an approach to the problem of dispatch and unit commitment of wholly owned and commonly owned units.. Dynamic programming is used as the basic technique to determine an optimum schedule for start up and shutdown of available generating units in addition to unit base generation and production costs.

Snyder *et al.* [10] have discussed, when generating units must be evaluated and when they may be ignored. The heuristic procedures described in this paper are concerned with supplying all apriori information to the program thereby minimizing its execution time. Results are presented from field testing on a medium size utility. Composite generating unit formulation is described for the economic allocation of constrained fuel to a group of units.

Nieva *et al.* [11] have concerned with the thermal unit commitment problem for Large-Scale Power Systems. Results are given and discussed for very large and complex unit commitment problems.

Cohen *et al* [12] have described a new method which solves the unit commitment problem in the presence of fuel constraints. The method is being applied to a production-grade program suitable for Energy Management Systems applications.

Mukhtari *et al*. [13] have developed an expert system to assist power system operators in scheduling the operation of generating units. Numerical examples and test results show that this approach can obtain a better and operationally more acceptable unit commitment solution.

Lee [14] has presented a new method for short term thermal unit commitment. An algorithm based up on this new method has been developed, and tests of this algorithm have demonstrated satisfactory results. The computation time of this method is approximately linear with the number of hours in the unit commitment horizon.

Hobbs *et al*. [15] have discussed an approach which saves predecessor options was developed and implemented in an on-line energy management system. Results are given to demonstrate the benefits of the new algorithm.

Aoki *et al.* [16] have concerned with a method for solving a long-term unit commitment problem in a large scale power system. In order to overcome this defect, the authors develop a new algorithm based method variable metric method for dual maximization.

Tong *et al.* [17] have presented a new method for determining the unit-commitment schedule of a power system which operates under fuel utilisation constraints. Numerical results presented in this paper describe the usefulness and practicality of the proposed method.

Virmani *et al*. [18] have discussed the practical aspects of the Lagrangian Relaxation methodology for solving the thermal unit commitment problem.

Chowdhury *et al*. [19] have presented a probabilistic Schedules for continually changing loads in an interconnected system configuration for a specified period.

Handschin *et al*.[20] have described, a method for the unit commitment considering energy constraints obtained from a long-term optimisation.

Hussain [21] has presented the limitations of the existing UC program against the various constraints are overcome by applying simple techniques rather than spending time and money on ordering special new software. This objective is difficult to achieve with the existing software, but, together with other requirements.

Ruic *et al*. [22] have presented an original approach for solving extended unit commitment problem using the Lagrangian relaxation method.

Lee [23] have presented, a new approach for determining the priority order for thermal unit commitment. The addition can significantly improve the performance of this priority-order-based model without noticeable penalty in the computational requirements. In this paper, a mid-western utility system is used to illustrate the proposed approach.

Su *et al*. [24] have developed an, approach using fuzzy dynamic programming is proposed for the unit commitment of a power system. The effectiveness of the proposed approach is demonstrated by the unit commitment of Taiwan power system which contains **6** nuclear units, 48 thermal units, and 44 hydro units.

Ouyang *et al*. [25] have presented, a heuristic improvement of the truncated window dynamic programming (DP-VW) has been studied for the unit commitment application. An iterative process for the number of strategies saved in every stage is also incorporated to fine tune the optimal solution.

Mohamed *et al*. [26] have developed an expert system to assist operators in scheduling thermal generating units. Some of the complex operating constraints that are not violated frequently and/or are difficult to include in the unit commitment program are enforced by the expert system.

Ouyang *et al*. [27] have discussed a hybrid dynamic programming-artificial network algorithm (DP-ANN). The experimental results indicate that the proposed algorithm can significantly reduce the execution time of the traditional dynamic programming approach without degrading the quality of the generation schedule.

Sasaki *et al*. [28] have explored the possibility of applying the Hopfield neural network to combinatorial optimization problems in power systems, in particular to unit commitment. The proposed neural network could solve a unit commitment of 30 units over 24 periods, and results obtained are very encouraging.

Dasgupta *et al*. [29] have discussed the application of genetic algorithms to the objective of the optimal commitment is to determine the on/off states of the units in the system to meet the load demand and spinning reserve requirement at each time period, such that the overall cost of generation is minimised, while satisfying various operational constraints.

Ma *et al*. [30] have proposed a new fuzzy model for the unit commitment problem (UCP). A solution method for the proposed UCP model based on the genetic algorithms (GAs) is presented (FZGA). Numerical results show the superiority of solutions obtained compared to methods with traditional UCP models.

Baldick [31] have discussed a generalized version of the unit commitment problem that can treat minimum up- and down-time constraints, power flow constraints, line flow limits, voltage limits, reserve constraints, ramp limits, and total fuel and energy limits on hydro and thermal units. The author purpose an algorithm for this problem, based on Lagrangian decomposition, and demonstrates the algorithm with reference to a simple model system.

Maifeld *et al*. [32] have presented a new unit commitment scheduling algorithm. The proposed algorithm consists of using a genetic algorithm with domain specific mutation operators. Results showed the proposed algorithm finds good unit commitment schedules in a reasonable amount of computation time.

Li *et al*. [33] have introduced a new unit commitment method based on a de-commitment procedure for solving the power system resource scheduling problem. Comparisons of the proposed unit commitment method with the Lagrangian Relaxation (LR) approach and Fred Lee's Sequential Unit Commitment method (SUC) demonstrate the potential benefits of the proposed approach for power system operations planning.

Saneifard et *al*. [34] have discussed the application of fuzzy logic to the unit commitment problem is demonstrated. This method allows a qualitative description of the behaviour of a system, the system's characteristics, and response without the need for exact mathematical formulations It is demonstrated through a numerical example that a fuzzy logic-based approach achieves a logical and feasible economical cost of operation of the power system, which is the major objective of unit commitment.

Walsh *et al*. [35] have presented an augmented network architecture with a new form of interconnection between neurons giving a more general energy function containing both discrete and continuous terms. The new method also compares favourably with Lagrangian relaxation. Detailed results for a power system with thermal, hydro and pumped storage units are presented.

Ma *et al*. [36] have proposed an efficient algorithm for considering reactive power and voltage constraints in unit commitment. Test examples on the modified IEEE 30 bus system are presented to demonstrate the efficiency of the method.

Mantawy *et al*. [37] have presented a Simulated Annealing Algorithm (SAA) to solve the Unit Commitment Problem (UCP). New rules for randomly generating feasible solutions are introduced. The problem has two sub problems: a combinatorial optimization problem and a nonlinear programming problem. The former is solved using the SAA while the latter problem is solved via a quadratic programming routine. Numerical results showed an improvement in the solutions costs compared to previously obtained results.

Hung *et al*. [38] have proposed a constraint logic programming (CLP) algorithm to solve the thermal unit commitment (UC) problem in this paper. The results obtained are compared with those from the established methods of the dynamic programming (DP), the Lagrangian relaxation (LR) as well as the simulated annealing (SA).

Mantawy *et al*. [39] have presented, a new algorithm based on integrating genetic algorithms, tabu search and simulated annealing methods to solve the unit commitment problem. Results showed the superiority of the solutions obtained compared to genetic algorithms, tabu search and simulated annealing methods, and to two exact algorithms.

Juste *et al*. [40] have proposed the aim of finding a general method for solving the Unit Commitment (UC) problem. The proposed algorithm employs the Evolutionary Programming (EP) technique in which populations of contending solutions are evolved through random changes, competition, and selection. The practical implementation of that procedure yielded satisfactory results when the EP-based algorithm was tested on a reported UC problem previously addressed by some existing techniques such as Lagrange Relaxation (LR), Dynamic Programming (DP), and Genetic Algorithms (GAS). Numerical results for systems of up to 100 units are given and commented on.

Takriti *et al*. [41] have developed a technique for refining the unit commitment solution obtained from solving the Lagrangian. Our model is an integer program with nonlinear constraints. It can be solved to optimality using branch-and-bound. Numerical results indicate a significant improvement in the quality of the solution obtained.

Liang *et al*. [42] have represented an extended mean field annealing neural network approach is used for the short-term thermal unit commitment. The effectiveness of the proposed approach is demonstrated by thermal unit commitment of Taiwan power system. It is concluded from the results that the proposed approach is very effective in reaching proper unit commitment.

Richter *et al*. [43] have provided a price/profit-based UC formulation which considers the softer demand constraint and allocates fixed and transitional costs to the scheduled hours. The authors describe a genetic algorithm solution to this new UC problem and present results for an illustrative example.

Swarup *et al*. [44] have discussed the solution methodology of unit commitment (UC) using genetic algorithms (GA) is presented. Problem formulation, representation and the simulation results for a 10 generator-scheduling problem are presented.

Sum-im. *et al*. [45] have discussed, an ant colony search algorithm(ACSA) to solve thermal unit commitment problem. ACSA is a new cooperative agents approach, which is inspired by the Observation of the behaviours of real ant colonies on the topic of ant trial formation and foraging methods. This proposed approach is tested and compared to conventional Lagrangian relaxation (LR), genetic algorithm (GA), Evolutionary programming (EP), Lagrangian relaxation and genetic algorithm (LRGA) on the 10 units system.

Sriyanyong *et al*. [46] have proposed Particle Swarm Optimization (PSO) combined with Lagrange Relaxation method (LR) for solving Unit Commitment (UC). The proposed approach employs PSO algorithm for optimal settings of Lagrange multipliers. The feasibility of the proposed method is demonstrated for 4 and 10unitsystems, respectively.

Samudi. *et al*.[47] have presents a new approach of particle swarm optimization (PSO) algorithm for short term hydro thermal scheduling (HTS) problems. The proposed algorithm is ideally suitable for hydro-thermal co-ordination problems, hydro economic dispatch problems with unit commitment, thermal economic dispatch with unit commitment problems and scheduling of hydraulically coupled plants.

1.3 Author's Contribution

The algorithms based on dynamic programming and Particle Swarm Optimization technique have been developed to obtain the solution of unit commitment problem. The effectiveness of these algorithms has been tested on various systems and the algorithms are compared for total operating cost.

1.4 Organization of The Thesis

This thesis titled as "*Unit Commitment Using Particle Swarm Optimization*" is divided into six chapters, the brief discussion are as follows

In chapter 1, a detailed introduction on unit commitment is given. The brief literature review is done for unit commitment and solution methodology. The author contribution and organisation of the thesis is also discussed.

The chapter 2, deals with the explanation of PSO technique and its algorithm.

This chapter 3 gives us the knowledge to solve the unit commitment problem using classical dynamic programming techinique.

In chapter 4, the formulation of algorithm to solve unit commitment using PSO is explained in detail with flow chat.

In chapter 5, the 3-units and 4-units, the unit commitment system is solved by having, the results obtained by dynamic programming and PSO based algorithms are compared for respective system

In chapter 6, summarize the conclusions and scope for further work.

CHAPTER 2

PARTICLE SWARM OPTIMIZATION

2.1 Introduction

Particle swarm optimization is a stochastic, population-based search and optimization algorithm for problem solving. It is a kind of swarm intelligence that is based on social-psychological principles and provides insights into social behaviour, as well as contributing to engineering applications. The particle swarm optimization algorithm was first described in 1995 by *James Kennedy and Russell C. Eberhart*. The techniques have evolved greatly since then, and the original version of the algorithm is barely used at present. Social influence and social learning enable a person to maintain cognitive consistency. People solve problems by talking with other people about them, and as they interacts their beliefs, attitudes, and behaviour changes, the changes could typically be depicted as the individuals moving toward one another in a socio-cognitive space.

2.2 Particle Swarm Optimization

The particle swarm simulates a kind of social optimization. A problem is given, and some way to evaluate a proposed solution to it exists in the form of a fitness function. A communication structure or social network is also defined, assigning neighbours for each individual to interact with a population of individuals defined as random guesses as the problem solutions is initialized. These individuals are candidate solutions and are also known as the particles, hence the name particle swarm. An iterative process to improve these candidate solutions is set in motion. The particles iteratively evaluate the fitness of the candidate solutions and remember the location where they had their best success. The individual's best solution is called the particle best or the local best. Each particle makes this information available to their neighbours. They are also able to see where their neighbours have had success. Movements through the search space are guided by these successes, with the population usually converging, by the end of a trial, on a problem solution better than that of non-swarm approach using the same methods.

The particle swarm optimization (PSO) algorithm is a population-based search algorithm inspired by the social behaviour of birds within a flock. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock, the aim of discovering patterns that govern the ability of birds to fly synchronously, and to suddenly change direction with a regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm. In PSO, individuals, referred to as particles, are "flown" through hyper dimensional search space. Changes to the position of particles within the search space are based on the social-psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience, or knowledge, of its neighbours. The search behaviour of a particle is thus affected by that of other particles within the swarm therefore PSO is the kind of symbiotic cooperative algorithm. The consequence of modelling this social behaviour is that the search process is such that particles stochastically return toward previously successful regions in the search space. The operation of the PSO is based on the neighbourhood principle as social network structure.

2.3 Particle Swarm Optimization Algorithm

A swarm consists of a set of particles, where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbours. Let $x_i(t)$ denotes the position of particle p_i in search space, at time step t. The position of p_i is then changed by adding a velocity $v_i(t)$ to the current position

The velocity vector drives the optimization process and reflects the socially exchanged information. Three different phases are differing in the extent of the social information exchange, which are detailed below. Form the basis of initial PSO algorithm. The phases are individual best, global best, local best

2.3.1 Individual Best

For this version, each individual compares its current position to its own best position, *xpbest,* only. This can be attempted through the following steps

1. Initialize the swarm, p_i *(t)*, of particles such that the position x_i *(t)* of each particle. $p_i(t)$ is random within the hyperspace, with $t = 0$.
2. Evaluate the performance of each particle, using its current position x_i *(t).*
3. Compare the performance of each individual to its best performance as

if $F(x_i(t)) < pbest_i$ then

$$pbest_i = F(x_i(t)) \qquad (2.1)$$

$$xpbest_i = x_i(t) \qquad (2.2)$$

4. Change the velocity vector for each particle using

$$v_i\,(t) = v_i\,(t - l) + p(xpbest_i - x_i(t) \qquad (2.3)$$

where p is a positive random number.

5. Move each particle to a new position.

$$x_i\,(t) = x_i(t - 1) + v_i(t) \qquad (2.4)$$

$$t = t + 1$$

6. Go to step 2, and repeat until convergence.

the farther away a particle is from its previously found best solution, the larger the change in velocity to return the individual toward its best solution. The upper limit of the random value *p* is a system parameter specified by the user. The larger the upper limit of *p*, the more the trajectory of the particles oscillates. Smaller values of *p* ensure smooth trajectories.

2.3.2 Global Best

The global best, *gbest,* of PSO reflects the star neighbourhood structure. The social knowledge used to drive the movement of particles includes the position of the best particle from the entire swarm. In addition, each particle uses its history of experiences in terms of its own best solution thus far. In this case the algorithm changes to:

1. Initialize the swarm, $p(t)$, of particles such that the position $x_i(t)$ of each particle .

$p(t)$ is random within the hyperspace, with $t = 0$.

2. Evaluate the performance of each particle, using its current position $x_i(t)$.
3. Compare the performance of each individual to its best performance thus far:

if $F(x_i(t)) < pbest_i$ then

$$pbest_i = F(x_i(t)) \quad (2.5)$$

$$xpbest_i = x_i(t) \quad (2.6)$$

4. Compare the performance of each particle to the global best particle:

if $F(x_i(t)) < xgbest$ then

$$xgbest = F(x_i(t)) \quad (2.7)$$

$$xgbest = x_i(t) \quad (2.8)$$

5. Change the velocity vector for each:

$$v_i(t) = v_i(t-l) + C_1(xpbest_i - x_i(t)) + C_2(xgbest - x_i(t)) \quad (2.9)$$

Where C_1 and C_2 are random variables. The second term above is referred to as the cognitive component, while the last term is the social component.

6. Move each particle to a new position:

$$x_i(t) = x_i(t-1) + v_i(t) \quad (2.10)$$

$$t = t + 1$$

7. Go to step 2, and repeat until convergence.

The further away a particle is from the global best position and its own best solution, the larger the change in velocity to move the particle back toward the best solutions.

2.3.3 Local Best

The local best, *xpbest* , reflects the circle neighbourhood structure. Particles are influenced by the best position within their neighbourhood, as well as their own past experience. Only steps 4 and 5 change by replacing *xgbest* with *xpbest.* While *xpbest* is slower in convergence than *xgbest, xpbest* results in much better solution and searches a larger part of the search space.

2.3.4 Fitness Calculation

The Step 2 to obtain *xgbest* and *xpbest* as discussed in sec 2.3.1 and 2.3.2 measures the performance of each particle. Here a function is used which measures the closeness of the corresponding solution to the optimum in evolutionary computing, this refers to the fitness function.

2.3.5 Convergence

The algorithms above continue until convergence has been reached. Usually, a PSO algorithm is executed for a fixed number of iterations, or fitness function evaluations. Alternatively, a PSO algorithm can be terminated if the velocity changes are close to zero for all the particles, in which case there will be no further changes in particle positions.

2.4 PSO System Parameters

PSO has shown to perform better on higher-dimensional problems. Standard PSO is influenced by six system parameters, namely the dimension of the problem, number of individuals, range of p, and upper limit on the maximum velocity, neighbourhood size and inertia weight. The influence of the upper limit has been discussed previously. Other system parameters are discussed below.

2.4.1 Dimension Of The Problem

Dimension of the problem deals with the variable or type of particle as the dimension of the problem increases the complexity also increases.

2.4.2 Number Of Individuals

The number of individual refer to the population size andit is depend up on the dimension of the problem

2.4.3 Range of p

Range of position is set to 1. As all the values are generated randomly and their values are between 0 and 1.

2.4.4 Maximum velocity, v_{max}

An upper limit is placed on the velocity in all dimensions. This upper limit prevents particles from moving too rapidly from one region in search space to another.

$$\text{If } v_i(t) > v_{max} \text{ then } v_i(t) = vmax, \tag{2.11}$$

$$\text{Or if } v_i(t) < -vmax \text{ then } v_i(t) = -vmax, \tag{2.12}$$

Where $v_i(t)$ is the velocity of particle p_i at time step t . Note that $v_{\max}$ does not place a limit on the position of a particle, only on the steps made in the hyper dimensional search space. v_{max} is usually initialized as a function of the range of the problem.

2.4.5 Neighbourhood size

The *xgbest* version is simply *xpbest* with the entire swarm as the neighbourhood. The *xgbest* is more susceptible to local minima, since all individuals are pulled toward that solution. The smaller the neighbourhood radius, and the more neighbourhoods can be used, the less susceptible PSO is to local minima. A larger part of search space is traversed, and no one solution has an influence on all particles. The more neighbourhoods there are, however. the slower the convergence.

2.4.6 Inertia weight

Improved performance can be achieved through application of an inertia weight applied to the previous velocity:

$$v_i(t) = w(j) * v_i(t - 1) + C_1(xpbest - x_i(t)) + C_2(x\,gbest - x_i(t)) \tag{2.13}$$

Where $w(j)$ is the inertia weight. The inertia weight controls the influence of previous velocities on the new velocity. Large inertia weights cause larger exploration of the search space, while smaller inertia weights focus the search on a smaller region. Typically, PSO is started with a large inertia weight, which is decreased over time.

According to the discussion in above sections, the following procedure can be used for implementing the PSO algorithm.

1. Initialize the swarm by assigning a random position in the problem search space to each particle.

2. Evaluate the fitness function for each particle and find out the pbest.

3. For each individual particle, compare the particle's fitness value with its *pbest*. If the current value is better than the *pbest* value, then set this value as the and the current particle's position, x_i, as p_i.

4. Identify the particle that has the best fitness value. The value of its fitness function is identified as *gbest* and its position as p_g.

5. Update the velocities and positions of all the particles using equation (2.9) and (2.13).

6. Repeat steps 2–5 until a stopping criterion is met (e.g., maximum number of iterations or a sufficiently good fitness value). The flow chart is given as under

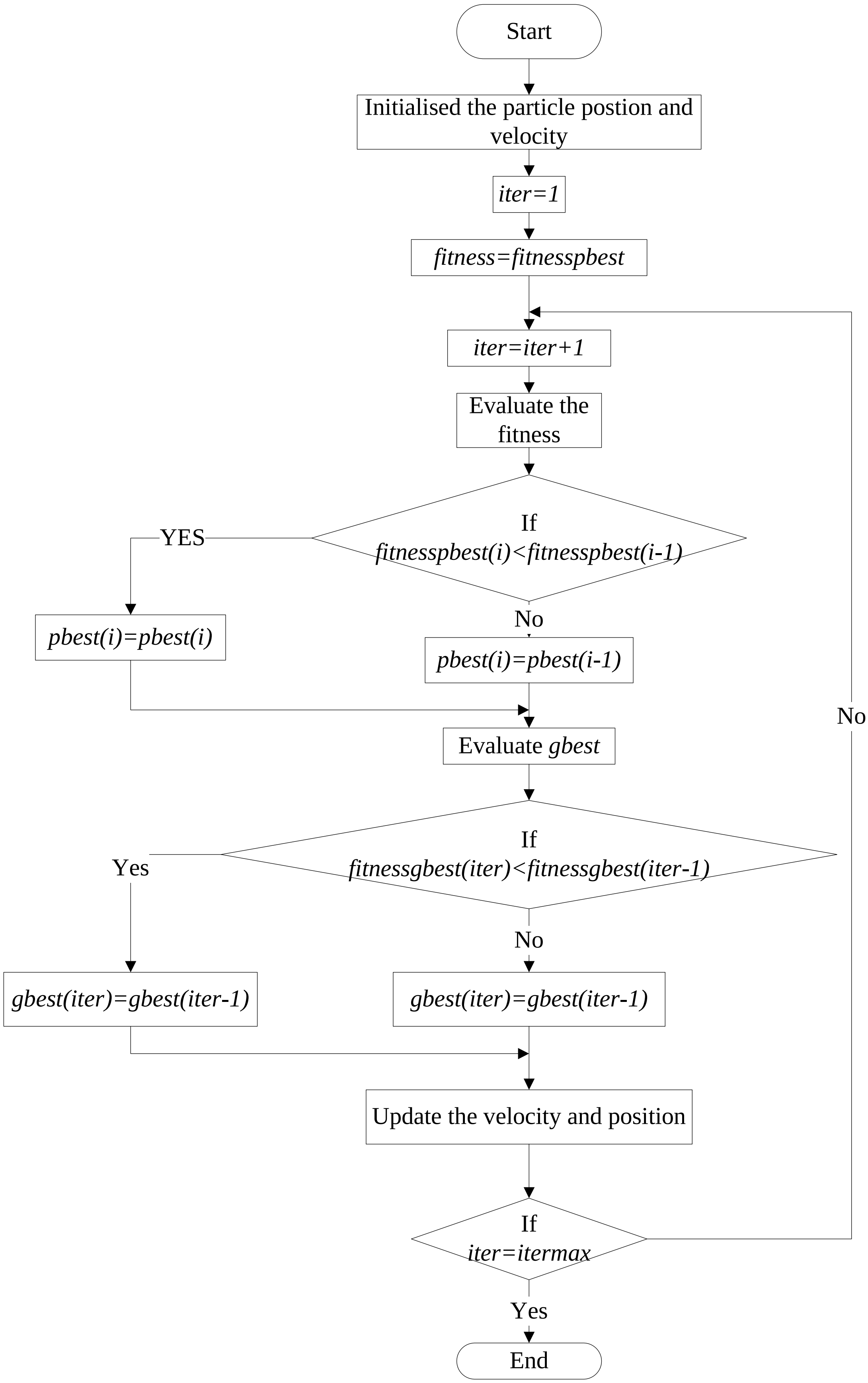


Fig. 2.4 *Basic PSO Algorithm.*

2.6 Test Example

The illustrative example, PSO is used for real life problems like in power system such as unit commitment, economic dispatch; hydrothermal scheduling etc. the unit commitment scheduling using PSO which is objective of thesis has been discussed in subsequent chapters. Here, the effectiveness of PSO is demonstrated through optimizing (minimizing) a test function. Expressed as

$$f(x) = \sum_{i=1}^{4} x_i^2 \tag{2.14}$$

Equality constraints are

$$x_1 + x_2 = 10 \tag{2.15}$$

$$x_3 + x_4 = 20 \tag{2.16}$$

While choosing different parameters

Dimension= 4

Population Size=1000

$C_1 = 2$

$C_2 = 2$

Iterations= 1000

Inertia constant= 0.9 to 0.4

The results to be obtained are

i) The fitness function should be minimizing or having optimal value.
ii) $x_1 + x_2 = 10$
iii) $x_3 + x_4 = 20$

With the developed program of PSO in Mat Lab while choosing the above function and parameters, the following results are found

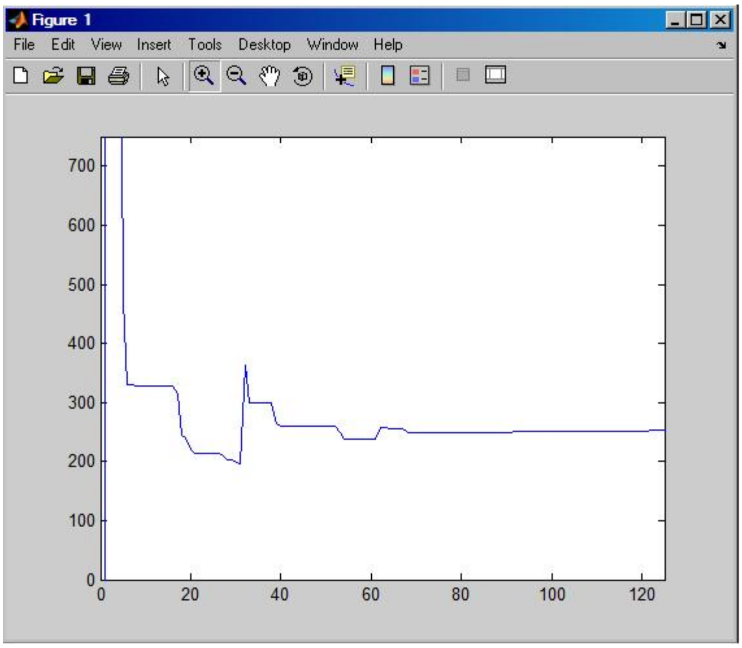


Fig .2.5 *fitness minimization graph*

In the Fig.2.5 it is found that the fitness of the function is varying at first and then it become constant at its optimal value. So the first result is effectively found.

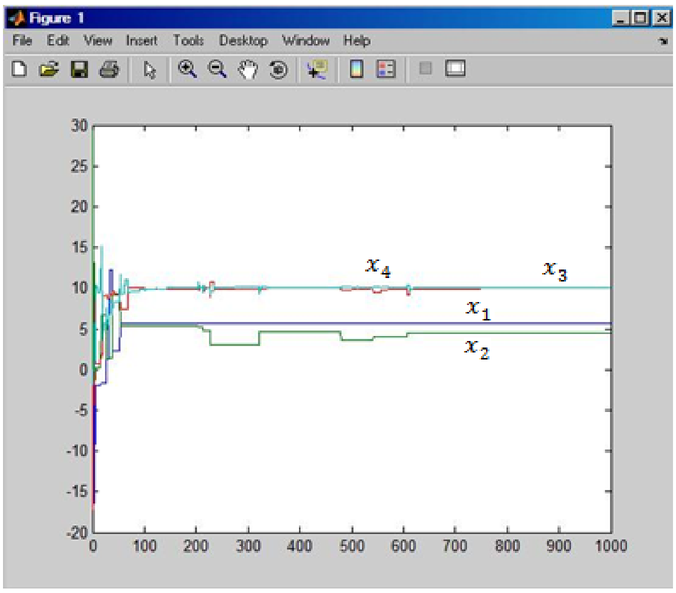
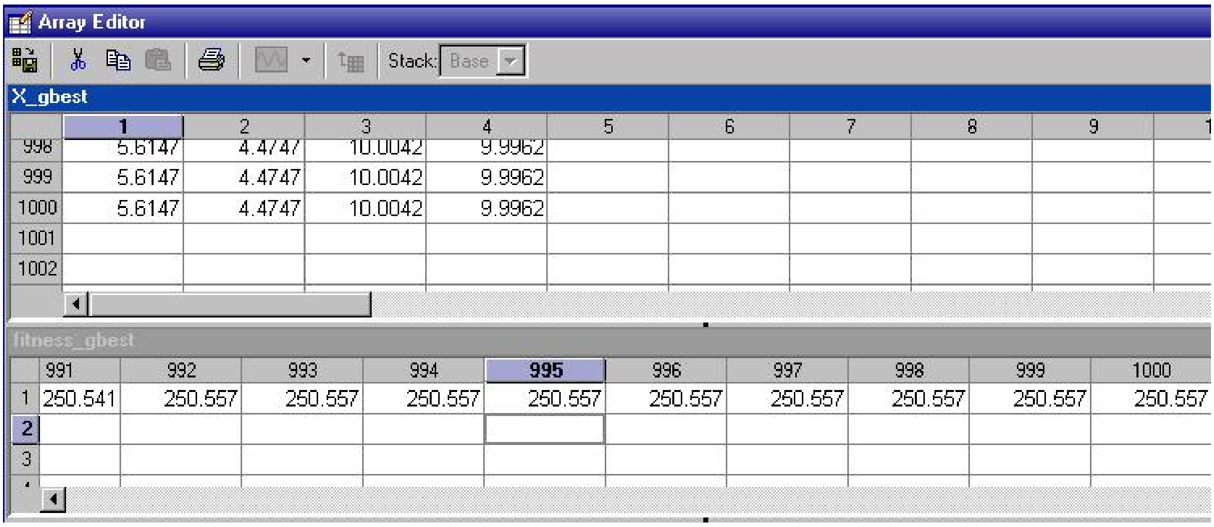


Fig.2.6 *Variation of the dimensions of the system*

In this Fig. 2.4 it is found that there is variation at the start and after that all the dimensions find their optimal value corresponding to optimal fitness of the function.



Array Editor

Stack: Base

X_gbest

	1	2	3	4	5	6	7	8	9
998	5.6147	4.4747	10.0042	9.9962					
999	5.6147	4.4747	10.0042	9.9962					
1000	5.6147	4.4747	10.0042	9.9962					
1001									
1002									

fitness_gbest

	991	992	993	994	995	996	997	998	999	1000
1	250.541	250.557	250.557	250.557	250.557	250.557	250.557	250.557	250.557	250.557
2										
3										

Table. 2.1 *Results of the global best and fitness global best*

This Table.2.1 gives us the direct results of all the dimension and corresponding their finesses. Hence it is verified that the PSO is a technique which is used to minimize any objective function or fitness function.

CHAPTER 3
UNIT COMMITMENT USING DYNAMIC PROGRAMMING

3.1 Introduction

Many utilities have daily load patterns which exhibit extreme variation between peak and off peak hours because people use less electricity on Saturday than on weekdays, less on Sundays than on Saturdays, and at a lower rate between midnight and early morning than during the day. If sufficient generation to meet the peak is kept on line throughout the day, it is possible that some of the units will be operating near their minimum generating limit during the off peak period. The problem confronting the system operator is to determine which units should be taken offline and for how long. In most of the interconnected power systems, the power requirement is principally met by thermal power generation. Several operating strategies are possible to meet the required power demand, which varies from hour to hour over the day. It is preferable to use an optimum or suboptimum operating strategy based on economic criteria. In other words, an important criterion in power system operation is to meet the power demand at minimum fuel cost using an optimal mix of different power plants. Moreover, in order to supply high-quality electric power to customers in a secured and economic manner, thermal unit commitment (UC) is considered to be one of best available options. It is thus recognized that the optimal UC of thermal systems, which is the problem of determining the schedule of generating units within a power system, subject to device and operating constraints results in a great saving for electric utilities. So the general objective of the UC problem is to minimize system total operating cost while satisfying all of the constraints.

Various approaches have been developed to solve the optimal UC problem. These approaches have ranged from highly complex and theoretically complicated methods to simple rule-of thumb methods. The scope of operations scheduling problem will vary strongly from utility to utility depending on their mix of units and particular operating constraints. The economic consequences of operation scheduling are very important. Since fuel cost is a major cost component, reducing the fuel cost by little as 0.5% can result in savings of millions of dollars per year for large utilities. A very important task in the operation of a power system concerns the optimal UC considering technical and economical constraints over a long planning horizon up to one year.

However, the generating companies (GENCOs) share of this remaining demand may difficult to predict since it will depend on how its price compares to that of other suppliers. The GENCO's price will depend on the prediction of its share of this remaining demand as that will determine how many units they have switched on. The UC schedule directly affects the average cost and indirectly the price, making it an essential input to any successful bidding strategy. There may be a tendency to think that maximizing the profit is essentially the same as minimizing the cost. This is not necessarily the case.

We have to remember that since we no longer have the obligation to serve the demand, the GENCOs may choose to generate less than the demand. This allows a little more flexibility and makes the problem complex in the UC schedules under the deregulated environment. Finally, the profit depends, not only on the cost, but also on revenue. If revenue increases more than the cost does, the profit will increase. So for the next-generation UC problem, researchers have to still play an important role. If the bid functions are non convex or non differentiable in nature, which is commonly seen in both regulated and deregulated power industry, then the above problem becomes complex. Further, the complexity increases if the competition is encouraged in both suppliers and buyers side including emission constraints. So it has been observed that the hybrid models, which are the combination of both classical and non classical methods, can handle the present day complex UC problem commonly seen within developed countries. With the available standard software products, electric utilities have to enhance, evolve, and upgrade or add new applications such as UC solutions for modern deregulated power industry in conjunction with energy management systems

3.2 Unit Commitment In Power System

The scope of the operations scheduling problem will vary strongly from utility to utility depending on their mix of units and particular operating constraints. The economic consequences of operations scheduling are very important. Since fuel cost is a major cost component, reducing the fuel cost by as little as 0.5 percent can result in savings of millions of dollar per year for large utilities. The time horizon of operations scheduling depends on a number of factors. Large steam units take several hours to start up and bring on-line. They also have minimum up and down-time constraints and start up costs which require that they be scheduled over a period of several days. The Schedule of the thermal units is also influenced by preventative maintenance schedules, nuclear refuelling schedules, or long-term fuel contracts which involve making decisions on a yearly or multi-year timeframe. Hydro scheduling also, in general, involves a yearly or multi-year time frame due to the large capacity of many hydro reservoirs. Many hydro or pumped hydro reservoirs have daily or weekly cycles. Typically the commitment and generating schedule is output on an hourly basis.

Although yearly or multi-year factors influence operations scheduling, the schedules actually produced are often useful for just several hours. This is because the scheduling requires forecast of many stochastic quantities such as loads, hydro inflows, and unit availabilities. If the actual values of these quantities differ greatly from the forecasts, then it is economical to resolve the operations scheduling problem. Since the determination of hourly hydro and thermal schedules over a period of several years is unrealistic and, As described above, unnecessary, past approach have developed a hierarchical approach to the overall operations scheduling problem .A typical hierarchy is shown in Fig 3.1

The Maintenance Scheduler solves for the time for preventive maintenance of the generating units. Typically, weekly schedules are generated over a period of one to three years. The Maintenance Scheduler coordinates with the long-Term Hydro Scheduler which produces hydro schedules over the same timeframe .This insures that the hydro energy is available, as needed, to replace units down for maintenance. The long-term maintenance and hydro schedules are inputs to the Unit Commitment and Short-Term Hydro Schedulers. Unit Commitment produces commitment and generation schedules for the thermal units while the Short-Term Hydro Scheduler produces generation schedules for the hydro units. The combined Unit Commitment and Short-Term Hydro scheduling problem often referred to as the Short-term hydro-thermal scheduling problem, produces hourly schedules over a period of several days.

Modern energy management systems often include unit commitment and, if appropriate, short-term hydro scheduling programs. These programs are run, at a minimum, daily to schedule the generating units of the systems. Differences between actual and forecasted loads, hydro inflows and unit availability will require that the implemented schedules differ from the ones generated by computer programs. Large errors between forecasted and actual data will often require that the unit commitment and hydro scheduling programs be rerun several times during a day. This paper will be mainly concerned with the shorter term aspects of operations scheduling. Methods for unit commitment and hydro scheduling will be described and in extensions to consider fuel constraints, losses, and transmission constraints will also be described. The operations scheduling methods that have been developed into production programs and which are based on optimization methods.

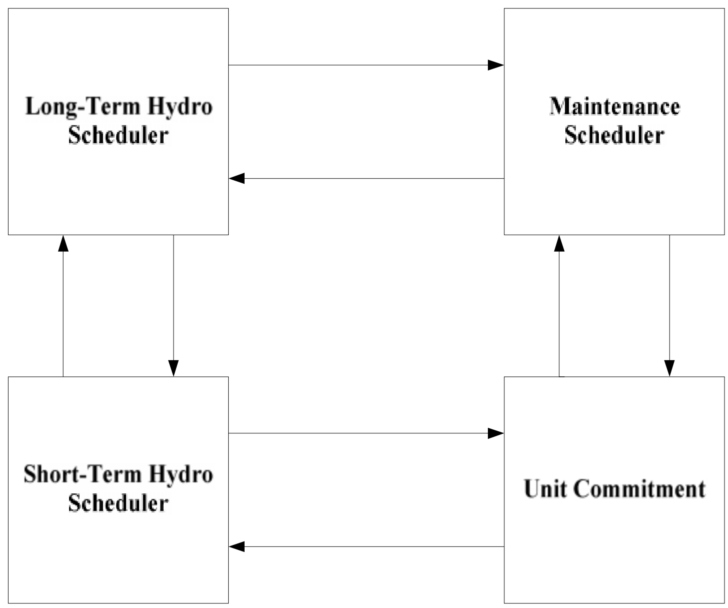


Fig 3.1. *The typical hierarchy for overall operation of scheduling problem***.**

3.3 Unit Commitment Under Deregulated Power Industry

Since the mid-1980s, the electrical power-supply industry around the world has experienced a period of rapid and critical changes regarding the way electricity is generated, transmitted, and distributed. The need for more efficiency in power production and delivery has led to privatization, restructuring, and, finally, deregulation of the power sectors in several countries traditionally under control of federal and state governments. Many countries like England, the U.S., Canada, Australia, New Zealand, Chile, Argentina, Peru, Colombia, and Scandinavian are already exercising with the deregulated electricity industry.

Though there have been some pitfalls here and there, the end users of the system are enjoying the fruits of the deregulated electricity industry tree. So it is the high time for both the developed and developing countries to modify or replace their traditional algorithms based on the requirements of the modern power industry. In any restructured or deregulated power industry, the pool implements a power action based on a UC model. Suppliers submit their bids to supply the forecasted daily inelastic demand.

Each bid consists of a cost function and a set of parameters that define the operative limits of the generating unit. After the pool solves the UC problem, the system marginal price is determined for each time period. The system marginal price is nothing but the maximum average cost among the scheduled generators. Several scheduling and pricing concerns have been raised with the use of UC models to conduct power pool auctions.

It is reported that the cost minimization model does not always lead to lower prices when they are defined as maximum average costs. Cost suboptimal solutions that result in lower prices may exist and, therefore, the applicability of cost minimization UC models for power pool auctions is questioned.

3.4 Consideration Used In Unit Commitment

Utilities have daily and weekend load variation that may vary by more than 200% from peak-hour load demand through early morning load valley hours. If all the generating equipment that is on-line for the entire day, then many of these units would be operating at their minimum power limits during the early morning valley hours. Rather than run many of these units at minimum power, it may be more economical to shut these units to be shut down overnight.

Consequently, economic decisions must be made as to the selection of units to be shut down, the hour of day they are to be shut down and the hour of the following day that they are to be started up again. In addition to the economic considerations for shut down, other considerations must be reviewed that relate to utility operation policies, physical operating constraints of the units, and utility system reliability. All these considerations enter into the analysis of unit commitment.

3.4.1 Economic Consideration Of Unit Commitment

A fundamental principle in developing a preliminary commitment is that the most economic operation tends to result when the fewest number of units are online. This can be illustrated by considering the operating cost per megawatt hour versus the electrical power output characteristic of thermal units, as illustrated in the Fig 3.2

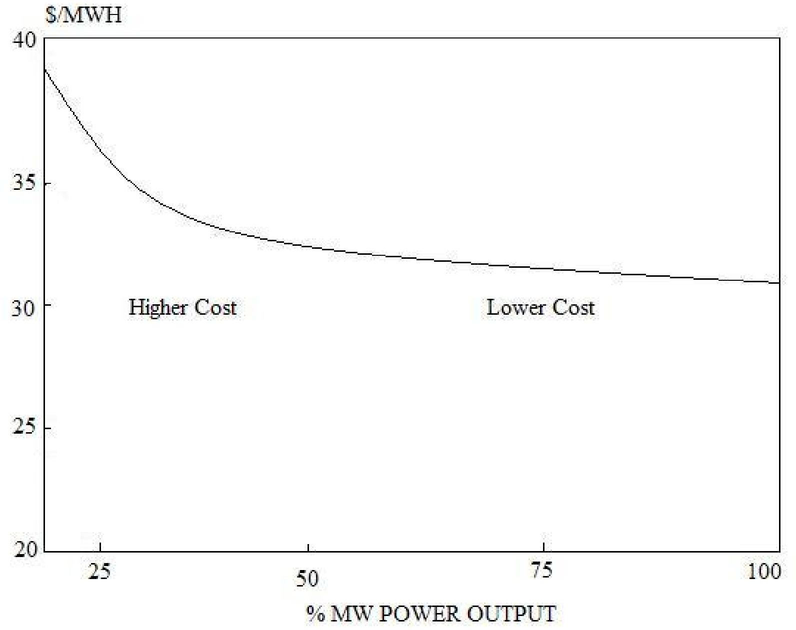


Fig. 3.2 *Thermal unit average operating cost*

The average operating cost per megawatt-hour is the product of cost of fuel times the average heat rate plus variable operation and maintains costs. Power is more expensive to generate per kilowatt-hour when the unit operates at low-power output than when it operates at higher output. A power system with many generating units could operate all of them to serve every load demand. Since the sum of power output from all of the generators must equal the load, many of the generating units could be operating at low-power output , which result in low operating cost, as noted in figure . Alternatively, the power system could start up only enough generating units to meet the load. In this case, all of the generating units are operating at the lower cost region of the figure. In this case the total average operating costs are lower. Thus the minimum operating costs commitment policy is to commit the minimum amount of capacity for service.

Having illustrated that commitment with a minimum number of units tends to be most economical, we must now decide which units are the best ones to commit for each hour. As a preliminary step, a commitment priority list is developed that ranks the units' full-load hourly fuel cost per mega watt. For a given hour the priority list is reviewed, in order from lowest to highest $/MWh, committing enough units to serve the load. Refinement to this preliminary commitment will make it more economical. An economic refinement that may be used to this preliminary commitment is to decrease the total unit start up costs, the costs associated with bringing units from down to operating conditions. Start-up costs are associated with supplying energy to bring the unit to operating condition.

3.4.2 Reliability Considerations Of Unit Commitment

In addition to economic, it is important to ensure that there will be sufficient generation online to meet load demand during fault as well as normal situations, such as generating unit forced outages, transmission line outages and interconnection emergency. One of the first tasks in real-time unit commitment is to accurate models for projecting future load demand. Models are generally required for three time spans

i) **Several hours in advance**: - the several hour projection is useful for trimming an established unit commitment schedule

ii) **1-2 days in advance: -** 1or 2 day projection aids in establishing unit start up and shut down cost schedule.

iii) **1 week in advance:-**the load projection one week in advance is useful in scheduling any hydro unit on the system.

With the load forecast and hydro generation schedules established, the thermal unit commitment can be planned to ensure system reliability

3.5 Constraints in Unit Commitment

Many constraints can be applied on the unit commitment problem. Each individual power system, power pool, reliability council, may impose different rules on the scheduling of units, depending on the generation.

3.5.1 Unit Type

The thermal units are usually divided into the following unit types: must-run units, cycling units, and peakers. Must-run units are those units that must be on-line, if available, due to operating constraints, reliability requirements, or economic considerations. Cycling units are units that can cycle on and off and are subject to minimum up and down-time constraints. Both must-run and cycling units are dispatched economically between their minimum and maximum limits. Peakers are units (usually gas turbines) that can start up quickly and are typically not subject to minimum up- or down-time constraints. Many utilities require that peakers, when dispatched, operated their upper generating limit.

3.5.2 Spinning Reserve

Spinning reserve describes the total amount of generation available from all unit synchronized (i.e. spinning) on the system, minus the present load supplied and losses being incurred. Spinning reserve must be carried out in such a way that the loss of one or more units does not cause too far a drop in system frequency. Spinning reserve must obey certain rules which will specify that reserve must be capable of making up the loss of most heavily loaded unit in a given period of time. Reserve requirement also calculated as a function of the probability of not having sufficient generation to meet the load, by making people.

3.5.3 Thermal Unit Constraints

Thermal units usually require a crew to operate them, especially when turned on and turned off. A thermal unit can undergo only gradual temperature changes, which in turn translates into a time period of some hours that are required to bring the unit “online”. As a result of such restrictions various constraints arise, in the operation of a thermal plant, such as:

3.5.3.1 Minimum up time*:* once the unit is running, it cannot be turned off immediately.

$$T_{i,j}^{on} > T_i \text{ minimum up time (in hours)} \qquad (3.1)$$

3.5.3.2 Minimum down time*:* once the unit is decommitted, there is a minimum time before it can be recommitted.

$$Tij^{off} > T_i \text{ minimum down time (in hours)} \qquad (3.2)$$

3.5.4 Crew constraints

If a plant consists of two or more units, they cannot both be turned on at the same time since there are not enough crew members to attend both units at the start up. In addition, a certain amount of energy must be expended to bring the unit online as the temperature and pressure of the thermal unit are required to move slowly, this energy does not result in any MW generation from the unit and is brought into the unit commitment problem as a “start-up cost.” The start-up cost can vary from a maximum “cold-start” value to a much smaller value, if the unit was only turned off recently and is still relatively close to operating temperature. There are two approaches for treating a thermal unit during its down period. The first approach allows the unit’s boiler to cool down and then heat back, it upto the operating temperature, in time for a scheduled turn on. The second approach (called banking) requires that sufficient energy should be given to the boiler to just maintain operating temperature. The costs for the two are compared so that, if possible, the best approach (cooling or banking) can be chosen.

Start up cost when cooling is given by

$$C_c\ (1 - e^{-t/\alpha}) \times F + C_f \tag{3.3}$$

Where,

C_c = cold-start cost (MBtu)

F = fuel cost

C_f = fixed cost (includes crew expense, maintenance expenses) (in R)

α = thermal time constant for the unit

t = time (h) the unit was cooled

Start-up cost when banking is given by

$$C_c\ (1 - e^{-t/\alpha}) \times F + C_t \tag{3.4}$$

Where C_t = cost (MBtu / h) of maintaining unit at operating temperature

Up to a certain number of hours, the cost of banking will be less than the cost of cooling. Due to, maintenance or unscheduled outages of various equipment in the plant; the capacity limits of thermal units may change frequently, this must also be taken into account in unit commitment.

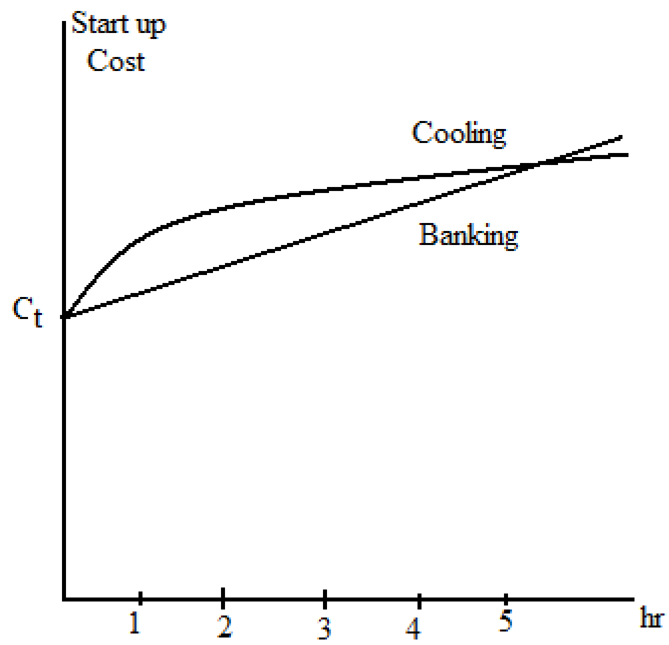


Fig. 3.3 *Start up cost of the thermal unit*

3.5.5 Other Constraints

There are other constraints which are also consider in the unit commitment problem

a) Hydro-constraint

Unit commitment cannot be completely separated from the scheduling of hydro units whereas it can be assumed that the hydro thermal scheduling can be separated from the unit commitment problem. But we cannot assess that the result will be an optimal solution.

b) Must run

For voltage support on the transmission network or for such purposes as supply of steam for uses outside the steam plant itself, some units are given a must-run status during certain times of the year.

c) Fuel constraint

A system in which some units have limited fuel, or else have constraints that require them to burn a specified amount of fuel in a given time, presents a most challenging unit commitment problem

d) Fuel cost computation

Fuel cost in unit commitment problem may be divided into two categories: the transitional cost and production or generation cost. Generally the transitional cost is the cost associated with the starting of the unit and it may also include shut down cost. The production cost is the fuel cost required to meet the load. It depends on the unit loading, heat rate and fuel price. Computation of these costs is given below:

e) Transitional Cost

The shutting down of units are not associated with cost, normally but a provision can be made to include shutdown costs in the computation of total cost. A constant cost may be specified for each unit as the shut down cost. This cost is taken to be independent of the length of time; the unit has been running before the shutdown. In the unit commitment problem usually some form of start up cost is considered. A simple practice is to assume a constant cost irrespective of the unit down time.

However, in order to provide a more accurate measure of the actual cost involved, a time dependent start up cost is required. The start up cost is expected to be dependent on the temperature of the unit considered and hence on it's down time. Since the cooling rate of a unit is approximately exponential, an exponential start up cost curve is generally accepted though other forms of cost curve may also be used. It will be more economical to keep the unit in hot standby instead of shutting it down completely. The choice between shutdown and hot standby will depend on the two cost curves and the length of time, a unit is kept out-of-service. Generally, a constant fuel rate is required to maintain the boiler temperature and pressure, and thus the standby cost curve may be assumed to be a linear function of the shutdown time. As a result of this, a unit will be allowed to cool or be in hot standby as determined by the lower of the start up and hot standby costs

f) Production cost

$$F(P_i)= a_i + b_i P_i + C_i P_i^2 \qquad (3.5)$$

Where $P_{i,t}$ is the Power generation (in MW) of unit i , at hour t and a_i , b_i , c_i are the fuel cost of coefficients. The production cost is the cost of the fuel required by a given set of on-line generating units to meet the load demand in the system. Since the overall objective of the unit commitment problem is to minimize the overall total cost, hence the production cost should also get minimized as well.

3.6 Formulation of Unit Commitment

The objective of the UC problem is to minimize the total operating costs subjected to a set of system and unit constraints over the scheduling horizon. It is assumed that the production cost, PC_i for unit '*i*' at any given time interval is a quadratic function of the generator power output, p_i.

$$PC_i = a_i + b_i p_i + c_i p_i^2 \tag{3.6}$$

Where a_i, b_i, ci are the unit cost coefficients. The generator start-up cost depends on the time the unit has been switched off prior to the start up, T_{off}. The start-up cost SC_i at any given time is assumed to be an exponential cost curve.

$$SC_i = \sigma_i + \delta_i\{1 - e^{\left(\frac{-T_{off,i}}{\tau_i}\right)}\} \tag{3.7}$$

Where σ_i is the hot start-up cost, δ_i the cold start-up cost and τ_i is the cooling time constant.

The total operating costs, OC_T for the scheduling period T is the sum of the production costs and the start-up costs.

$$OC_T = \sum_{t=1}^{T}\sum_{i=1}^{N} PC_{i,t}U_{i,t} + SC_{i,t}(1 - U_{i,t-1})U_{i,t} \tag{3.8}$$

Where $U_{i,t}$ is the binary variable to indicate the on/off state of the unit i at time t. $U_{i,t}$ =1 if unit i is committed at time t, otherwise $U_{i,t}$=0.

The overall objective is to minimize OC_T subject to a number of system and unit constraints. All the generators are assumed to be connected to the same bus supplying the total system demand. Therefore, the networks constraints are studied above are as follows briefly.

3.6.1 Power Balance Constraint

The total generated power at each hour must be equal to the Load of the corresponding hour, D_t.

$$\sum_{i=1}^{N} p_{i,t} U_{i,t} = P_{D_t} \tag{3.9}$$

3.6.2 Power Generation Limits

The generation of the unit is under its minimum and maximum limit

$$p_i^{min} \leq p_{i.t} \leq p_i^{max} \tag{3.10}$$

3.6.3 Minimum Up Time

This constraint signifies the minimum time for which a committed unit should be turned off and removed from online.

$$T_{i,t}^{on} \geq MUT_i \tag{3.11}$$

3.6.4 Minimum Down Time

This constraint signifies the minimum time for which a de-committed unit should be turned on and brought on-line.

$$T_{i,t}^{off} \geq MDT_i \tag{3.12}$$

3.6.5 Spinning Reserve Constraints

Spinning reserve is the term used to describe the total amount of generation available from all the units synchronized on the system minus the present load plus losses being incurred. Spinning reserve must be carried so that the loss of one or more units does not cause too far a drop in system frequency

$$\sum_{i=1}^{N} p^{\max}{}_{i,t} U_{i,t} \geq P_{D_t} + R_t \tag{3.13}$$

3.7 The Algorithm Of Unit Commitment

i) Make the required combination of n no of generators

Combination = 2^n-1

ii) Select the feasible combination according to the given load.

iii) Calculate the combination having least production cost.

iv) Compute total cost, and do for all states.

v) Save lowest cost strategies.

vi) Trace optimal schedule

The flow chart of unit commitment is studied as under

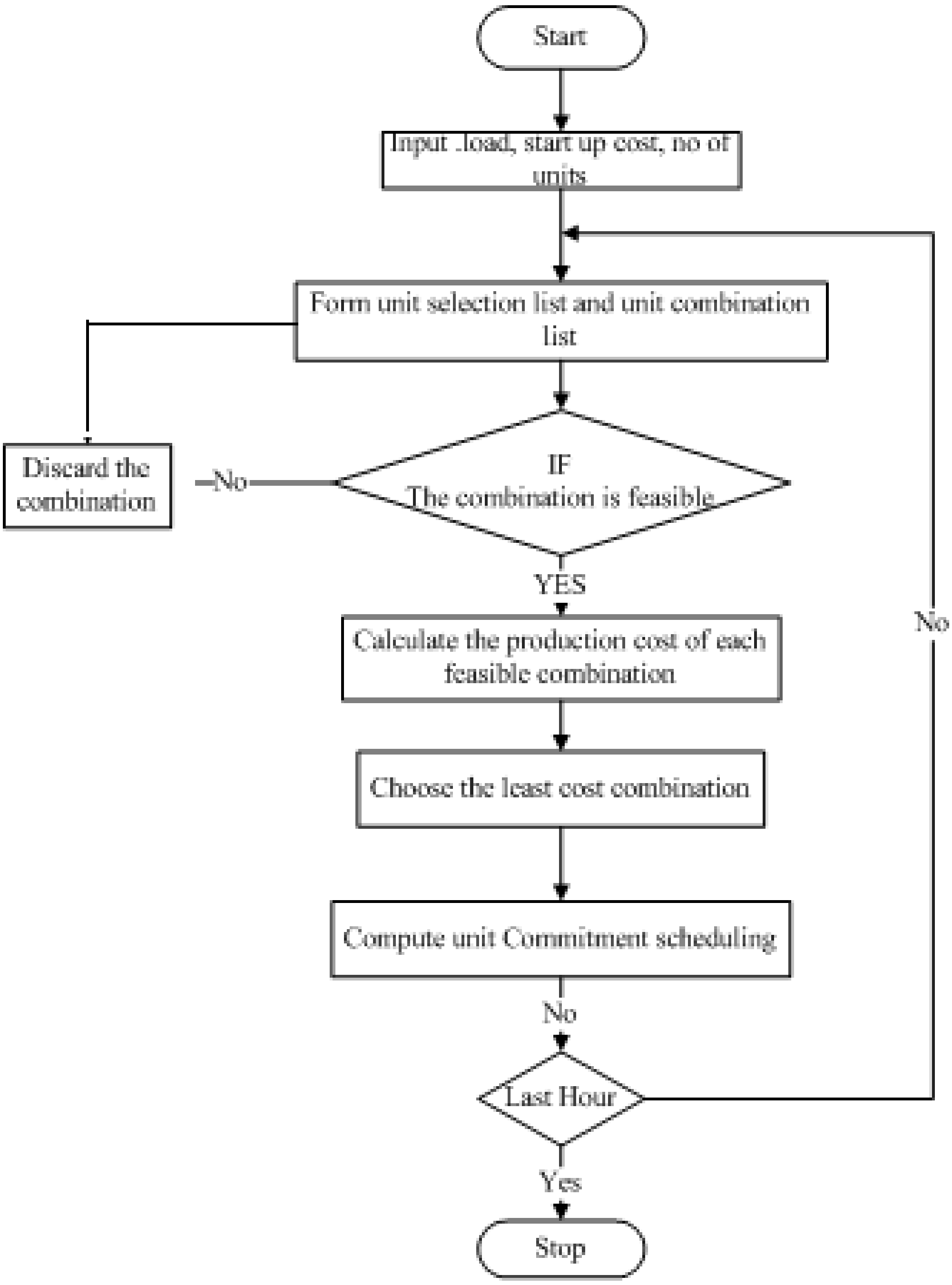


Fig .3.4 *Flow chart to solve Unit Commitment problem*

3.8 Dynamic Programming.

There are several approaches to implement an optimization procedure. One approach is an exact mathematical optimization procedure called "*dynamicprogramming.*" In mathematics and computer science, dynamic programming is a method of solving problems that exhibit the properties of overlapping sub problems and optimal substructure (described below). The method takes much less time than naive methods.

The term was originally used in the 1940s by Richard Bellman to describe the process of solving problems where one needs to find the best decisions one after another. By 1953, he had refined this to the modern meaning. The field was founded as a systems analysis and engineering topic that is recognized by the IEEE. Bellman's contribution is remembered in the name of the Bellman equation, a central result of dynamic programming which restates an optimization problem in recursive form. A Bellman equation (also known as a dynamic programming equation), named after its discoverer, Richard Bellman, is a necessary condition for optimality associated with the mathematical optimization method known as dynamic programming.

The word "*programming*" in "*dynamic programming*" has no particular connection to computer programming at all, and instead comes from the term "mathematical programming", a synonym for optimization. Thus, the "program" is the optimal plan for action that is produced. For instance, a finalized schedule of events at an exhibition is sometimes called a program.

Optimal substructure means that optimal solutions of sub problems can be used to find the optimal solutions of the overall problem. For example, the shortest path to a goal from a vertex in a graph can be found by first computing the shortest path to the goal from all adjacent vertices, and then using this to pick the best overall path, as shown in Figure In general, we can solve a problem with optimal substructure using a three-step process:

1. Break the problem into smaller sub problems.
2. Solve these problems optimally using this three-step process recursively.
3. Use these optimal solutions to construct an optimal solution for the original problem.

The sub problems are, themselves, solved by dividing them into sub-sub problems, and so on, until we reach some simple case that is solvable in constant time

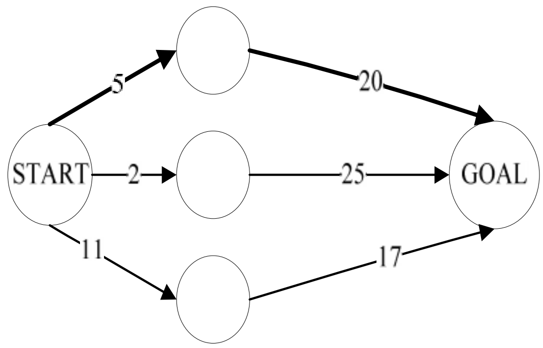


Fig .3.5 *Finding the shortest path in a graph using optimal substructure; a straight line indicates a single edge; a wavy line indicates a shortest path between the two vertices it connects (other nodes on these paths are not shown); the bold line is the overall shortest path from start to goal.*

3.8.1 Dynamic programming approaches:

a) Top-down approach:

The problem is broken into sub problems, and these sub problems are solved and the solutions remembered, in case they need to be solved again. This is recursion and memorization combined together.

b) Bottom-up approach:

All sub problems that might be needed are solved in advance and then used to build up solutions to larger problems. This approach is slightly better in stack space and number of function calls, but it is sometimes not intuitive to figure out all the sub problems needed for solving the given problem

3.8.2 Example on Deterministic Finite-State Problems:

Scheduling problem : Find optimal sequence of operations A, B, C, D.A must precede B, and C must precede D, in Fig .3.6. Given start up cost *SA* and *SC*, in Fig .3.7and setup transition cost *Cmn* from operation *m* to operation *n*

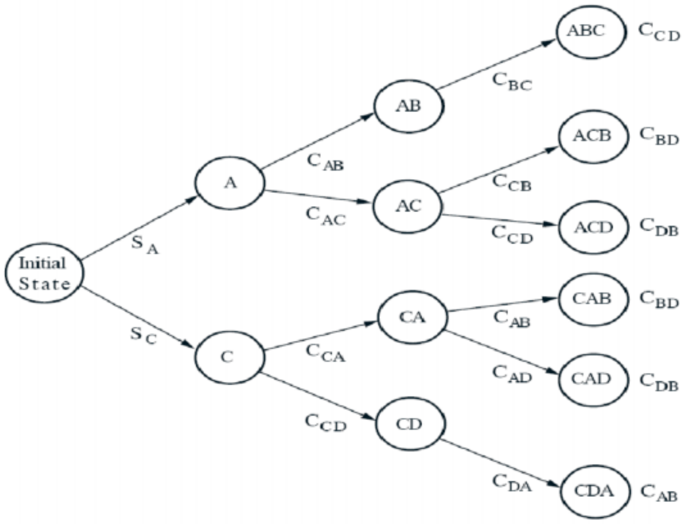


Fig .3.6 *Optimal sequence of operations*

Solution:-

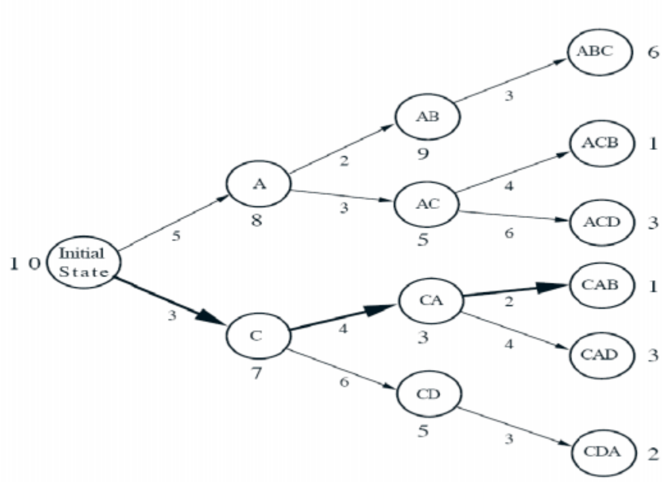


Fig .3.7 *Represent a unit shipment cost*

This is a one dimension problem which represent a unit shipment cost the values in the arc is the cost and the node represents the states.

1. State 1= min (5,3) = 3

   Selection of state 1=C

   Solution of state 1= initial state to C

2. State 2= state 1+min(4,6)=3+4

Selection of state2=CA

Solution of state 2= initial state - C - CA

3. State 3= state2+min(2,4)=7+2=9
   Selection of state 3=CAB
   Solution of the state 3= initial state - C - CA- CAB.
   Final solution is(initial state - C - CA- CAB.)
   The minimum cost is= 3+4+2=9.

3.9 Unit Commitment Solution Using Dynamic Programming

Dynamic programming acts as an important optimization technique with broad application areas. It decomposes a problem into a series of smaller problems, solves them, and develops an optimal solution to the original problem step-by-step. The optimal solution is developed from the sub problem recursively. In its fundamental form, the dynamic programming algorithm for unit commitment problem examines every possible state in every interval. Some of these states are found to be infeasible and hence they are rejected instantly. But even, for an average size utility, a large number of feasible states will exist and the requirement of execution time will stretch the capability of even the largest computers. Hence many proposed techniques use only some part of simplification and approximation to the fundamental dynamic programming algorithm.

Dynamic programming has many advantages over the enumeration scheme. The chief advantage of this technique is the reduction in the dimensionality of the problem. Suppose we have found units in a system and any combination of them could serve the single load. A maximum of 2N-1 combinations are available for testing. The imposition of priority list, arranged in order of the full load average cost rate would result in a theoretically correct dispatch and commitment only if

1. No load costs are zero.

2. Unit input-output characteristics are linear between zero output and full load.

3. There are no other restrictions.

4. Start-up costs have a fixed amount.

In dynamic programming algorithm:

1. A state consists of an array of units with only specified units operating at a time and rest off-line.

2. The start-up cost of a unit is independent of the time it has been off-line (i.e., it is a fixed amount).

3. There are no costs for shutting down a unit.

4. There is a strict priority order, and in each interval a specified minimum amount of capacity must be operating.

A feasible state is one in which the committed units can be supply the required load and that meets the amount of capacity at each period The dynamic programming algorithm can be run backward in time starting from the final hour to be studied, back to the initial hour. Conversely, we have set the algorithm to run forward in time from the initial hour to the final hour. DP approach has distinct advantages in solving generator unit commitment. For example, if the start-up cost of a unit is a function of time it has been off-line (i.e., its temperature), then a dynamic programming approach is more suitable since the previous history of the unit can be computed at each stage. There are other practical reasons for going for D.P. The initial conditions are easily specified and the computations can go forward in time as long as required. The flowchart for the Dynamic programming approach to Unit commitment problem is given below in Fig 3.8.

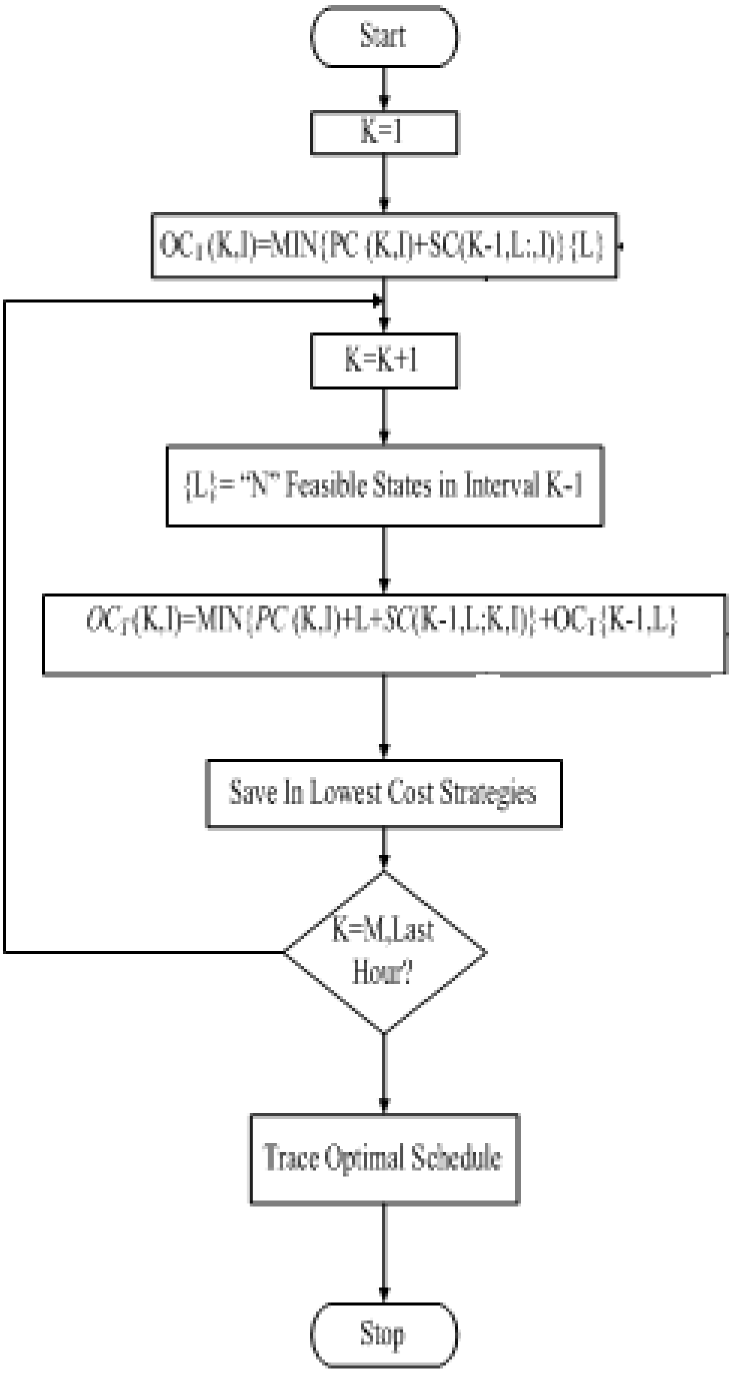


Fig .3.8 *Unit commitment by dynamic programming.*

CHAPTER 4
UNIT COMMITMENT USING PARTICLE SWARM OPTIMIZATION

4.1 Introduction

As explained, Unit commitment (UC) is a nonlinear mixed integer optimization problem to schedule the operation of the generating units at minimum operating cost while satisfying the demand and other equality and inequality constrains. The UC problem has to determine the on/off state of the generating units at each hour of the planning period and optimally dispatch the load and reserve among the committed units. UC is the most significant optimization task in the operation of the power systems. Solving the UC problem for large power systems is computationally expensive. The complexity of the UC problems grows exponentially to the number of generating units.

There are many methods to solve the unit commitment but here we are choosing particle swarm optimization. The algorithm to solve unit commitment problem is discuss in detail in this chapter. Here the generating units are behaving like dimension of the system, in PSO. The position or the value of the generating unit generated randomly between the upper and lower limit. After that, these values are updating till the optimization level reached.

Here the unit commitment problem is solved by PSO (Particle Swarm Optimization). The formulation and algorithm is simple and required less parameter tuning and thus poised to overcome various shortcomings of traditional and other stochastic search and optimization technique.

4.2 Problem Formulation

The problem formulation is already study in chapter 3, here we explain the formulation in brief the objective of the UC problem is to minimize the total operating costs subjected to a set of system and unit constraints.

$$PC_i = a_i + b_i p_i + c_i p_i^2 \tag{4.1}$$

Where a_i, b_i, ci are the unit cost coefficients.

$$SC_i = \sigma_i + \delta_i \{1 - e^{\left(\frac{-T_{off,i}}{\tau_i}\right)}\} \tag{4.2}$$

Where σ_i is the hot start-up cost, δ_i the cold start-up cost and τ_i is the cooling time constant.

The total operating costs, OC_T for the scheduling period T is the sum of the production costs and the start-up costs.

$$OC_T = \sum_{t=1}^{T} \sum_{i=1}^{N} PC_{i,t} U_{i,t} + SC_{i,t} (1 - U_{i,t-1}) U_{i,t} \tag{4.3}$$

Where $U_{i,t}$ is the binary variable to indicate the on/off state of the unit i at time t. $U_{i,t}$ =1 if unit i is committed at time t, otherwise $U_{i,t}$=0.

The overall objective is to minimize OC_T subject to a number of system and unit constraints. All the generators are assumed to be connected to the same bus supplying the total system demand. Therefore, the network constraints are as follows

4.2.1 Power balance constraint

$$\sum_{i=1}^{N} p_{i,t} U_{i,t} = P_D \tag{4.4}$$

4.2.2 Spinning reserve constraint

$$\sum_{i=1}^{N} p_{i,t} U_{i,t} \geq P_D + R_t \tag{4.5}$$

4.2.3 Generation limit constraint

$$p_i^{min} \leq p_{i.t} \leq p_i^{max} \tag{4.6}$$

4.2.4 Minimum up/down time constraints

$$T_{i,t}^{on} \geq MUT_i \tag{4.7}$$

$$T_{i,t}^{off} \geq MDT_i \tag{4.8}$$

The initial unit states at the start of the scheduling period must be taken into account. Where p_i^{min} & p_i^{max} are the minimum and maximum generation limit of the i^{th} unit, T_i^{on} & T_i^{off} represents the duration during which the i^{th} unit is continuously on and off respectively and MUT_i & MDT_i are the minimum up-time and down-time respectively.

4.3 Particle Swarm Optimization For Solving Unit Commitment Problem

The Particle swarm optimization (PSO) has been briefed in chapter 2. PSO is a population based searching algorithm. This approach simulates the simplified social system such as fish schooling and birds flocking. PSO is initialized by a population of potential solutions called particles. Each particle flies in the search space with a certain velocity. The particle's flight is influenced by cognitive and social information attained during its exploration. It has very few tuneable parameters and the evolutionary process is very simple. It is capable of providing quality solutions to many complex power system problems. One such problem is the unit commitment of thermal units in the power system. PSO is used to minimize the total operating cost by committing those optimal combinations of the units which satisfy the constraints and gives the minimum cost corresponding to that combination.

Our main aim is to minimise the operating cost, so we are using the ALM method for handling equality and in equality constraints. In this problem the up and down time of the units are not taken into consideration. the algorithm for UC is detailed as follows

4.3.1 Algorithm

The following steps are used by the PSO technique to solve the unit commitment problem

1. Initialize a population of particles p_i and other variables. Each particle is usually generated randomly with in allowable range.

$$upper\ limit \geq p_i \geq lower\ limit \quad (4.9)$$

Here p_i represented as i^{th} unit in the power system.

2. Initialize the parameters such as the size of population, initial and final inertia weight, random velocity of particle, acceleration constant, the max generation, Lagrange's multiplier (λ_i), etc.

3. Calculate the fitness of each individual in the population using the fitness function or cost function.

$$OC_T = \sum_{t=1}^{T} \sum_{i=1}^{N} PC_{i,t} U_{i,t} + SC_{i,t}(1 - U_{i,t-1}) U_{i,t} \quad (4.10)$$

Where $PC_{i,t}$ is represented as

$$PC_i = a_i + b_i p_i + c_i p_i^2 \quad (4.11)$$

With equality constraint as

$$\sum_{i=1}^{N} p_{i,t} U_{i,t} = P_D \quad (4.12)$$

Where P_i is the i^{th} generators and P_D is the load or demand.

And inequality constraints as

$$p_i^{min} \leq p_i \leq p_i^{max} \quad (4.13)$$

4. Compare each individual's fitness value with its *pbest*. The best fitness value among *pbest* is denoted as *gbest*.

5. Modify the individual's velocity v_{id} of each individual p_i as

$$v_i^{(t)} = v_i^{(t-1)} + C_1 * \text{rand}() * (p_{pbesti} - p_i^{(t)}) + C_2 * \text{rand}() * (p_{gbest} - p_i^{(t)}) \quad (4.14)$$

6. Modify the individual's position p_i as

$$p_i^{(t)} = p_i^{(t-1)} + p_i^{(t)} \quad (4.15)$$

where i is the i^{th} unit and t is the hour.

7. If the evaluation value of each individual is better than the previous p*pbest* , the current value is set to be *ppbest.* If the best *ppbest* is better than *pgbest* the value is set to be *pgbest.*

8. Modify the λ and α for each equality and Inequality constraint

For Inequality Constraint

$$\alpha=max(inequality\ constraint,-\lambda(iter-1)/(2*r)) \qquad (4.16)$$

$$\lambda(iter)=\lambda(iter-1)+(2*r*\alpha) \qquad (4.17)$$

For equality Constraint

$$\lambda\ (iter)=\lambda(iter-1)+(2*r*((equality\ constraint)) \qquad (4.18)$$

9. Minimise the fitness function using PSO method for the number of units running at that time.

10. If the number of iteration reaches the maximum then go to step 11. Otherwise go to step 3.

11. The individual that generates the latest is the optimal generation power of each unit with the minimum total generation cost.

The flow chart of the above mention steps is developed as under.

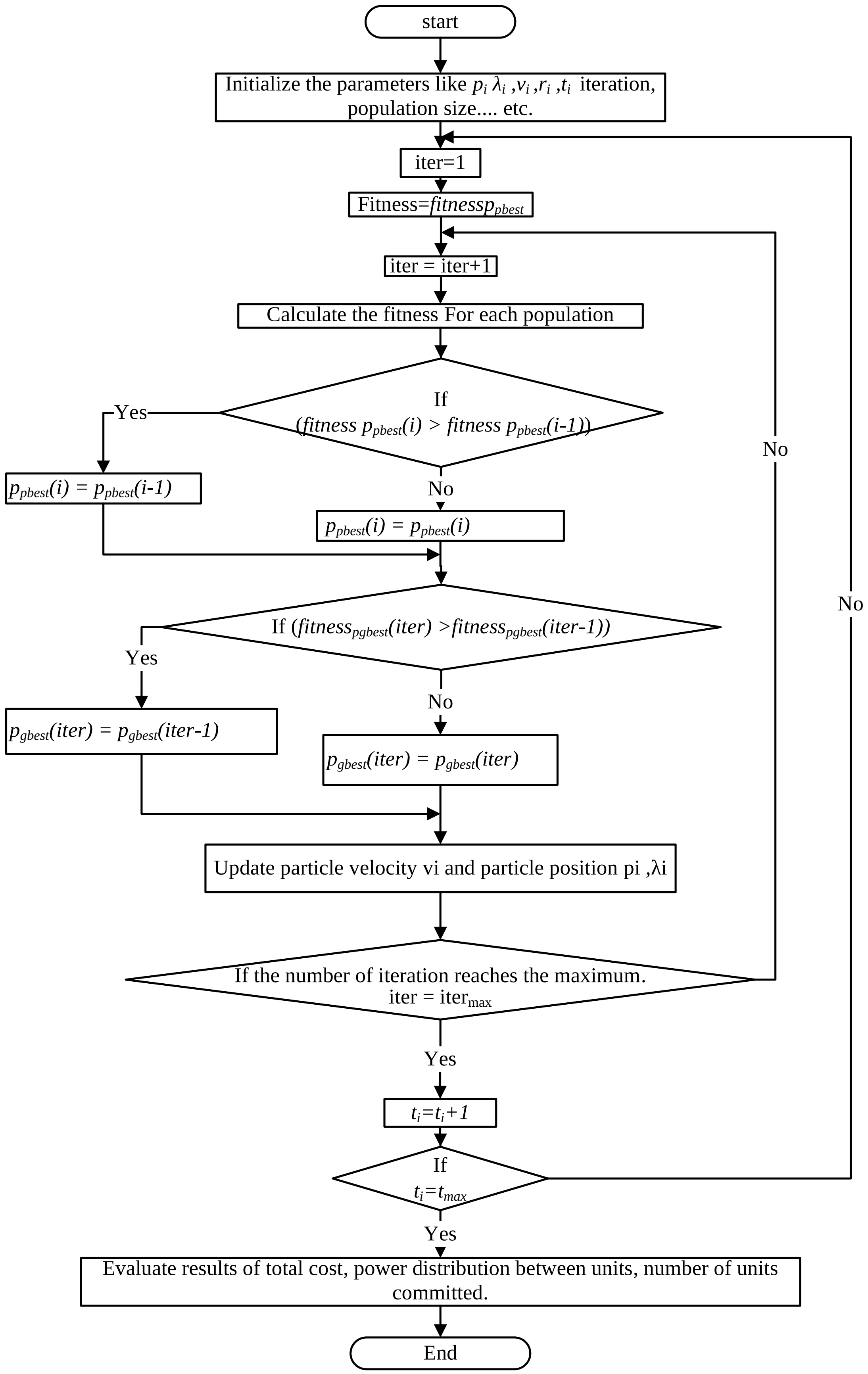


Fig .4.1 *Flow chart for solving unit commitment using PSO*

CHAPTER 5

RESULT AND DISSCUSSION

5.1 Introduction

The previous chapters that have been studied, provide the complete knowledge of unit commitment problem and its formulation using particle swarm optimization and dynamic programming. The algorithms of dynamic programming and particle swarm optimization, which are presented in chapter 3 and chapter 4 respectively, have been applied for solving unit commitment. The performance has been studied for three generator and four generator test data. The results for the respective systems are discussed as -

5.2 Test System 1

Three units are to be committed to serve 15-h load pattern. Data on the units and load pattern are contained in the given Table 5.1. The details of fuel cost components, initial conditions and load pattern are given in Table 5.1(a), 5.1(b) and 5.1(c) respectively.

Table 5.1 (a) Fuel cost components

Units	Max (MW)	Min (MW)	No-Load Cost (R/h)	Full load Ave.Cost (R/mWh)	Minimum Up time (h)	Minimum Down Time (h)	Fuel cost component		
							Ai (R/h)	bi (R/MWh)	ci (R/MW^2h)
1	**600**	**150**	**213.00**	**9.79**	**4**	**2**	**561**	**7.92**	**0.001562**
2	**400**	**100**	**585.62**	**9.48**	**5**	**3**	**310**	**7.85**	**0.00194**
3	**200**	**50**	**684.74**	**11.188**	**5**	**1**	**93.6**	**9.564**	**0.005784**

Table 5.1(b) Initial conditions

Unit	Initial condition	Start up cost hot	Start up cost cold	Cold start Time(h)
1	**-5**	**150**	**350**	**4**
2	**8**	**170**	**400**	**5**
3	**8**	**500**	**1100**	**5**

Table 5.1(c) Load pattern

Hour	1	2	3	4	5	6	7	8
Load	1200	1150	1100	1050	1000	950	900	850
Hour	9	10	11	12	13	14	15	
Load	800	750	700	650	600	550	500	

TABLE 5.1: *-3- Units characteristics, load pattern, and initial status of the unit.*

5.2.2 Dynamic Programming Results

The results obtained for the test system1 using dynamic programming are summarized below in Table.5.2

S.No	Load	Unit combination selected	Distribution of load among the units			Total Operating cost$\times 10^4$ (R)
1	1200	1 1 1	600	400	200	13848.96
2	1150	1 1 1	600	400	150	25152.48
3	1100	1 1 1	600	400	100	35938.69
4	1050	1 1 1	600	400	50	46225.05
5	1000	1 1 0	600	400	0	55915.61
6	950	1 1 0	550	400	0	65401.29
7	900	1 1 0	500	400	0	74520.47
8	850	1 1 0	450	400	0	83401.31
9	800	1 1 0	400	400	0	91591.83
10	750	1 1 0	350	400	0	99437.15
11	700	1 1 0	350	400	0	106581.62
12	650	1 1 0	250	400	0	112981.24
13	600	1 1 0	200	400	0	118996.72
14	550	1 1 0	150	400	0	124632.96
15	500	1 1 0	150	350	0	128832.41
Total Operating Cost						128832.41

TABLE .5.2 *Result of 3-units, unit commitment problem using Dynamic Programming*

5.2.3 PSO Results

The results obtained from PSO are detailed in Table 5.3 for tree generator system. Correspondingly, the variation of fitness and Xgbest are shown in Fig. 5.1 and Fig. 5.2 respectively. The total operating cost is calculated, the unit combination selected in each hour and the distribution of load among each unit. From Fig (5.1), it is concluded that at first there is variation in the operating cost (fitnessgbest) and after some iteration the operating cost is set to its optimal point. i.e. The operating cost is minimized. Same is the case with Fig (5.2), there are three units i.e. $Unit_1$, $Unit_2$, $Unit_3$. As these are denoted by Xgbest1, Xgbest2, Xgbest3, the behaviour of these three units are also varying at first and then these are set to their optimal point.

S.No	Load	Unit combination selected	Distribution of load among the units	Total Operating cost$\times 10^4$ (R)
1	1200	1 1 1	603.9896 399.5993 198.1366	13704.6339
2	1150	1 1 1	601.5616 400.5913 150.6513	25008.6212
3	1100	1 1 1	591.0499 398.3093 110.6391	35763.5278
4	1050	1 1 1	589.3339 393.5762 67.5547	45997.1254
5	1000	1 1 0	598.918 400.9325 0	55637.0474
6	950	1 1 0	549.9872 400.0272 0	64786.9488
7	900	1 1 0	505.8089 394.8238 0	73458.9761
8	850	1 1 0	456.5077 391.9949 0	81659.2328
9	800	1 1 0	416.9848 383.22 0	89395.5607
10	750	1 1 0	408.8343 340.5459 0	96670.1498
11	700	1 1 0	373.684 325.8019 0	103487.3111
12	650	1 1 0	350.6772 299.3466 0	109851.2888
13	600	1 0 0	600.0123 0 0	115726.6111
14	550	1 0 0	550.0049 0 0	121116.111
15	500	1 0 0	500.0048 0 0	126027.6111
Total Operating Cost				126027.6111

TABLE .5.3 *Result of 3-units, unit commitment problem using PSO*

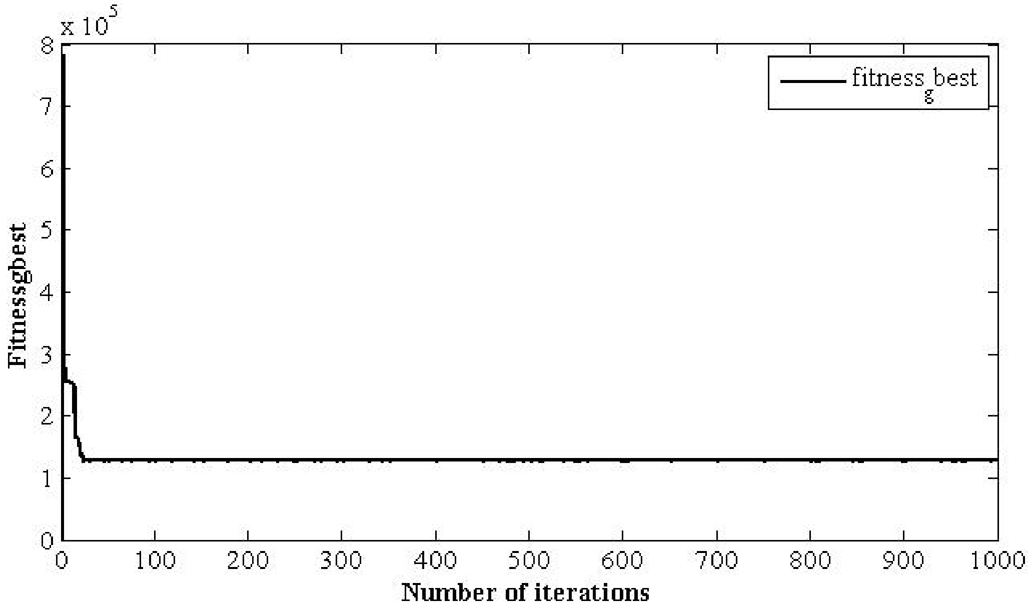


Fig 5.1 *Variation of fitness global best (Total Operating Cost)*

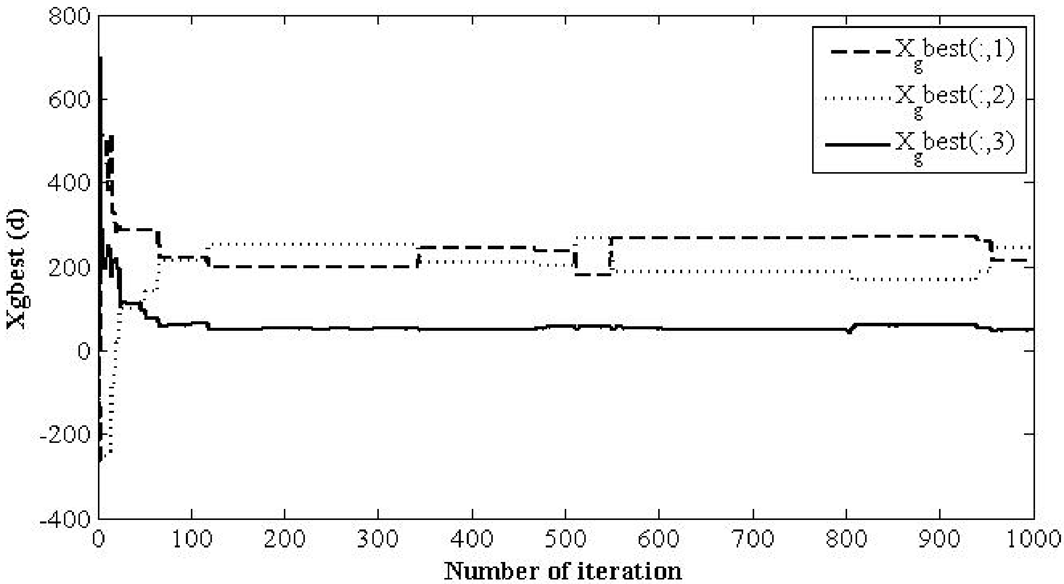


Fig 5.2 *Variation of Xgbest (Generating Units)*

5.3 Test System 2

Four units are to be committed to serve an 8-h load pattern. The details of unit characteristics, fuel cost components, initial conditions and load pattern are given in Table 5.4(a), 5.4(b), 5.4(c), 5.4(d) respectively.

TABLE 5.4(a) Unit characteristics

Units	Max (MW)	Min (MW)	Incremental cost (R/MWh)	No-Load Cost (R/h)	Full load Ave.Cost (R/MWh)	Min.Up time (h)	Min. Down Time (h)
1	80	25	20.88	213.00	23.54	4	2
2	250	60	18.00	585.62	20.34	5	3
3	300	75	17.46	684.74	19.74	5	1
4	60	20	23.80	252.00	28.00	1	1

TABLE 5.4(b) Fuel cost component

Fuel cost component		
ai (R/h)	bi (R/MWh)	Ci (r/MW^2h)
684.74	16.83	.0021
585.62	16.95	0.0042
213	20.74	.0018
252	23.60	.0034

TABLE 5.4(c) Fuel cost component

Unit	Initial condition	Start up cost Hot (R)	Start up cost Cold (R)	Cold start Time(h)
1	-5	150	350	4
2	8	170	400	5
3	8	500	1100	5
4	-6	0	0.02	0

TABLE 5.4(c) Load pattern

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

TABLE 5.4: - 4 -*Units characteristics, load pattern, and initial status of the units.*

5.3.2 Dynamic Programming Results

The results obtained for the test system2 using dynamic programming are summarized below in Table.5.5

S.No	Load (MW)	Unit combination selected	Distribution of load among the units(MW)	Total production cost× 10^4 (R)
1	450	0 1 1 0	0 150 300 0	10708.36
2	530	0 1 1 0	0 230 300 0	21356.72
3	600	0 1 1 1	50 250 300 0	33807.08
4	540	0 1 1 0	0 240 300 0	44635.46
5	400	0 1 1 0	0 100 300 0	52943.82
6	280	0 0 1 0	0 0 280 0	58517.36
7	290	0 0 1 0	0 0 290 0	64265.50
8	500	0 1 1 0	0 200 300 0	74773.86
Total Operating Cost				74773.86

TABLE 5.5 *Result of 4-units system using Dynamic programming*

5.3.3 PSO Results

Results are coming according to given data for the four generator unit commitment problem. Here the total operating cost is calculated, the unit combination selected in each hour and the distribution of load among each unit.

S.No	Load (MW)	Unit combination selected	Distribution of load among the units(MW)	Total production cost× 10^4
1	450	0 1 1 0	0 150.614 298.9599 0	10645.3544
2	530	0 1 1 0	0 230.154 299.8036 0	21274.5187
3	600	0 1 1 1	0 253.054 306. 35 40.0609	33721.4399
4	540	0 1 1 0	0 239.7138 300.635 0	44539.7219
5	400	0 1 1 0	0 125.0072 274.8632 0	52781.5693
6	280	0 0 1 0	0 0 279.9979 0	58343.343
7	290	0 0 1 0	0 0 290.0055 0	64085.3994
8	500	0 1 1 0	0 199.4972 299.8515 0	74551.818
Total Operating Cost				74551.818

TABLE .5.6 *Result of 4-units system using PSO*

It is seen from the Table 5.6 that the total operating cost in this case is minimum as compared to the results obtained as seen in the Table 5.5 in case of dynamic programming Now, in Fig5.4. As at first the there is variation in the operating cost of the four units, but after few iteration the operating cost is minimized as it is set to its optimal point. In Fig 5.4 Units (Xbgest) also shows the random behaviour at first then they also reach their optimal point.

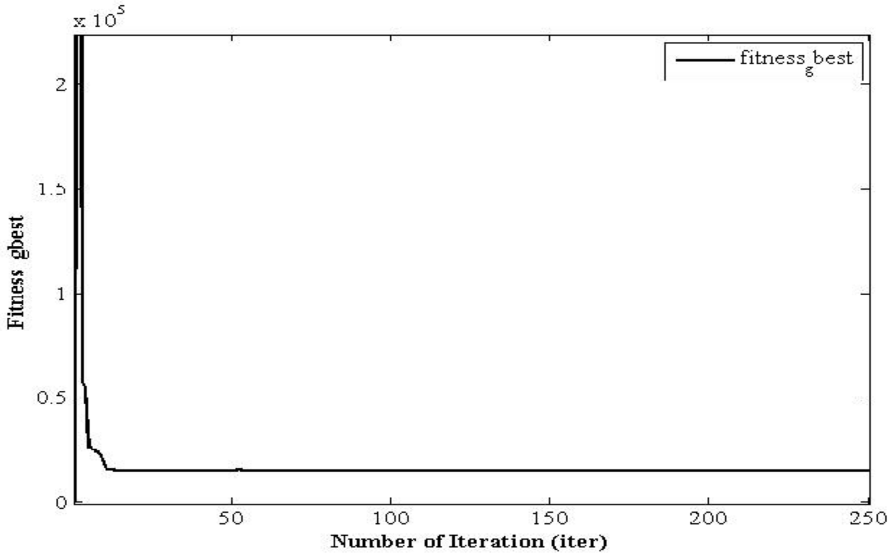


Fig 5.3 Variation of Fitness global best (Total Operating Cost)

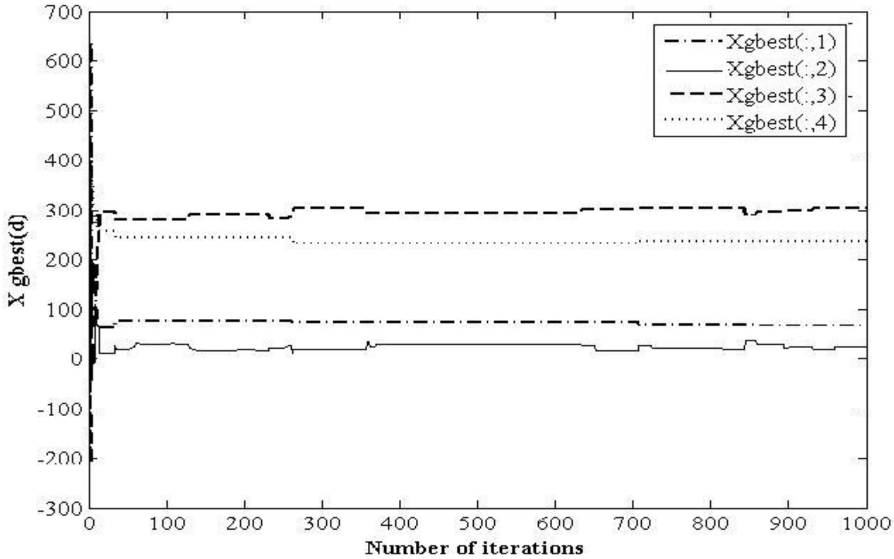


Fig 5.4 Variation of X global best (Generation Units)

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE

6.1 Conclusions

It is recognized that the optimal unit commitment of thermal systems results in a great saving for electric utilities. Unit Commitment is the problem of determining the schedule of generating units subject to device and operating constraints. The formulation of unit commitment has been discussed and the solution is obtained by classical dynamic programming method. An algorithm based on Particle Swarm Optimization technique, which is a population based global search and optimization technique, has been developed to solve the unit commitment problem. The effectiveness of these algorithms has been tested on systems comprising three units and four units and compared for total operating cost. It is found that the result obtained from the unit commitment using particle swarm optimization are minimum than the results obtained from classical Dynamic programming.

6.2 Scope of Future Work

The unit commitment schedule can be formulated for units like hydro power generation units, nuclear power generation units , wind power generation units, solar power generation units etc.

The methodology to increase the computation speed of particle swarm optimization can be evolved to solve the large unit commitment problem.

REFERENCES

[1] R. H. Kerr, J. L. Scheidt, A. J. Fontana and J. K. Wiley, "*Unit Commitment*", IEEE Transactions on Power Apparatus And Systems.vol. PAS-85, No. 5, pp. 417-421. May 1966.

[2] K. Hara, M. Kimura and N. Honda, "*A Method for Planning Economic Unit Commitment and Maintenance of Thermal Power Systems*", IEEE Transaction on Power Apparatus And Systems, vol. PAS-85, NO.5 , pp.421-436. May 1966

[3] P. G. Lowery, "*Generating Unit Commitment by Dynamic Programming*", IEEE Transaction on Power Apparatus And Systems, vol. PAS-85, No. 5, pp. 422-426. May 1966.

[4] J. D. Guy. "*Security Constrained Unit Commitment*". IEEE Transactions on Power Apparatus and Systems, vol. 90, pp. 1385-1389, May/June 1971.

[5] C. K. Fang, G. B. Sheble and F. Albu, "*Evaluation Of Dynamic Programming Based Methods And Multiple Area Representation For Thermal Unit Commitments*", IEEE Transactions on Power Apparatus and Systems. vol. 100, No. 3, pp. 1212-1218, Mar. 1981.

[6] G. S. Lauer, N. R. Sandell, Jr., Bertsekas and T.A. Posbergh, "*Solution Of Large Scale Optimal Unit Commitment Problem*". IEEE Transactions on Power Apparatus and Systems, vol. 101, pp. 79-96, Jan. 1982.

[7] K.D. Lee, R.H. Vierra, G.D. Nagel and R.T. Jenkins, "*Problems Associated With Unit Commitment In Uncertainty*", IEEE Transactions on Power Apparatus and Systems, vol. 104, No. 8, pp.2072-2078, Aug.1985.

[8] P.PJ van den Bosch and G. Honderd, "*A Solution Of The Unit Commitment Problem Via Decomposition And Dynamic Programming*", IEEE Transactions on Power Apparatus and Systems, vol. 104, pp. 1684-1690, July 1985.

[9] G. L. Kusic and H. A. Putnam, "*Dispatch And Unit Commitment Including Commonly Owned Units*", IEEE Transactions on Power Apparatus and Systems, vol. 104. pp. 2408-2412. Sep. 1985.

[10] Walter L. Snyder. Jr., H. David Powell, Jr. and John C. Rayburn, "Dynamic Programming Approach To Unit Commitment", *IEEE Transaction on Power* System. vol. 2, pp. 339-347. May 1987.

[11] R. Nieva, A. lnda and I. Guillen, "*Lagrangian Reduction Of Search-Range For Large-Scale Unit Commitment*", IEEE Transaction on Power System, vol. 2, pp. 465-473. May 1987.

[12] A .I. Cohen and S.H. Wan," *A Method For Solving The Fuel Constrained Unit Commitment Problem*", IEEE Transaction on Power System, vol.2, pp. 608-614, Aug. 1987.

[13] S. Mukhtari, J. Singh and B. Wollenberg, "*A Unit Commitment Expert System*", IEEE Transaction on Power System, vol. 3, No. I, pp. 272-277. 1988.

[14] Fred. N. Lee, "*Short-Term Thermal Unit Commitment - A New Method* ", IEEE Transaction on Power System, vol. 3, pp. 421-428, May 1988.

[15] Walter J. Hobbs, Gary Hermon, Stephen Warner and Gerald B. Sheble, "*An Enhanced Dynamic Programming Approach For Unit Commitment* ", IEEE Power Engineering Review, pp.70. Aug. 1988.

[16] K. Aoki, M. Itoh, T. Satoh, K. Nara and M. Kanezashi, "*Optimal Long-Term Unit Commitment In Large Scale Systems Including Fuel Constrained Thermal And Pumped Storage Hydro*", IEEE Transaction on Power System, vol. 4, pp. 1065-1073, Aug 1989.

[17] S. K. Tong and Shahidehpour, "*Combination Of Lagrangian-Relaxation And Linear-Programming Approaches For Fuel-Constrained Unit Commitment Problems*". IEE Proc.- Gener. Tansnm. Distrib., vol. 136, Pt. C. pp.162-174, May 1989.

[18] Sudhir Virmani, Eugene C. Adrian, Karl Imhof and Shishir Muhhejee, "*Impleme-ntation Of A Lagrangian Based Unit Commitment Problem*", IEEE Transaction on Power System, vol. 4, pp. 1373-1384 Oct. 1989.

[19] N. Chowdhury and R. Billinton, "*Unit Commitment In Interconnected Generating System Using A Probabilistic Technique*", IEEE Transaction on Power System, vol. 5, pp. 1231-1238. Nov. 1990.

[20] E. Handschin and Slomski. "*Unit Commitment In Thermal Systems With Long-Term Energy Constraints*". *IEEE Transaction on PowerSystem*, vol. 5, pp. 1470.1477. Nov. 1990.

[21] Khadim Hussain, "*Solution Method For Unit Commitment Limitations And Utility Constraints*". IEEE Computer Applications in Power, pp.16-20, Jan. 1991.

[22] Slobodan Ruic and Nikola Rajakovic, "*A New Approach For Solving Extended Unit Commitment Problem*", IEEE Transaction on Power System, vol.6, pp. 269-275, Feb. 1991.

[23] Fred N. Lee. "*The Application Of Commitment Utilization Factor (CUF) To Thermal Unit Commitment*", IEEE Transaction on Power System, vol. 6, pp. 691-698. May 1991.

[24] Chung-Ching Su and Yuan-Yih Hsu. "*Fuzzy Dynamic Programming : An Application To Unit Commitment*", IEEE Transaction on Power System, vol.6, pp. 1231-1237, Aug. 1991.

[25] Z. Ouyang and S.M. Shahidehpaur, "*An Intelligent Dynamic Programming For Unit Commitment Application*", IEEE Transaction on Power System, vol. 6, pp. 1203-1209, Aug. 1991.

[26] Md-Sayeed Salam abdul-Razak Hamdan and Khalid Mohamed Nor, "*Integrating An Expert System Into A Thermal Unit- Commitment Algorithm*", IEE Proceedings-C,vol.138, pp.553-559, Nov. 1991.

[27] Z. Ouyang and S.M. Shahidehpour, "*A Hybrid Arificial Neural Network-Dynamic Programming Approach To Unit Commitment*",IEEE *Transaction on Power System,* vol. 7, pp. 236-242. Feb. 1992.

[28] H. Sasaki, M. Watanak and R. Yokoyama, "*A Solution Method Of Unit Commitment By Artificial Neural Networks*", IEEE Transaction on Power System. vol. 7, pp. 974-981, Aug. 1992.

[29] D. Dasgupta and D. R. McGregor. "*Thermal Unit Commitment Using Genetic Algorithm*", IEEE Proc.-Gener. Transm. Distrib., vol. 141, pp.459-465, Sept. 1994.

[30] X. Ma, A. A. El-Keib, R. E. Smith and H. Ma, "*A Genetic Algorithm Based Approach to Thermal Unit Commitment of Electric Power Systems*". Electric Power System Research, vol. 34, pp. 29-36. 1995.

[31] Ross Baldick, "*The Generalized Unit Commitment Problem*': IEEE Transaction on Power System, vol. 10, pp. 465-475, Feb. 1995.

[32] Tim T. Maifeld and Gerald B. Sheble, "*Genetic-Based Unit Commitment Algorithm*", *IEEE Transaction on Power* System, vol. 11,pp. 1359-1370, Aug. 1996

[33] C. Li and R. B. Johnson, "*A New Unit Commitment Method*", IEEE PES Summer Meeting, 1996 .

[34] Seyedrasoul Saneifard, Nandipuram R. Prasad and Howard A. Smolleck, " *A Fuzzy Logic Approach To Unit Commitment*", IEEE Transaction *on Power* System, vol. 12, pp. 988-995, May. 1997.

[35] M.P. Walsh and M.J.O. Mallry,"*Augmented Hopfield Network For Unit Commitment And Economic Dispatch*", IEEE *Transaction on Power System,* vol. 12, pp. 1765-1774, Nov. 1997.

[36] H. Ma and S. M. Shahidehpour, " Decomposition Approach to *Unit Commitment with Reactive Constraints*", IEE Pro.-Gener. Trans. Distrib., Vol. 144, No. 2, pp. 113-117, March 1997.

[37] A.H. Mantawy, Youssef L. Abdel-Magid and Shokri Z. Selim. "*A Simulated Annealing Algorithm For Unit Commitment*", *IEEE Transaction on Power System,* vol. 13, pp. 197-204, Feb. 1998

[38] Kun-Yuan Hung, Hong -Tier Yang and Ching - Lien Hung, "*A New Thermal Unit Commitment Approach Using Constraint Logic Programming*", *IEEE Transaction on Power* System, vol. 13. pp. 936-945. Aug. 1998

[39] A.H. Mantawy. Yousnef L. Abdel-Magid and Shakri Z. Selim," *Intepting Genetic Algorithms, Tabu Search And Simulated Annealing For The Unit Commitment Problem*", *IEEE* Transaction *on Power* System, vol. 14, pp. 829-836. Aug. 1999.

[40] K.A. Juste, H. Kita, E. Tanaka and J. Hasegawa, "*An Evolutionary Programming Solution To The Unit Commitment Problem*". IEEE Transactions on Power System, vol. 14, pp. 1452.1459, Nov. 1999

[41] Samer Takriti, and John R. Birge, "*Using Integer Programming To Refine Lagrangian -Based Unit Commitmnt Solutions*", IEEE Transactions on Power Systems, vol. 15, pp. 151-156, Feb. 2000.

[42] R.H. Liang. and F.C. Kang, "*Thermal Generating Unit Commitment Using An Extended Mean Field Annealing Neural Network*, *IEE Proc.On Gener. Transm. Distrib.,* vol. 147, pp. 164.170, May 2000

[43] Charles W. Richter, Jr., and Gerald B. Sheble, "*A Profit-Based Unit Commitment For The Competitive Environment*", IEEE Transactions on Power Systems, vol. 15, pp. 715.721, May 2000.

[44] K.S. Swarup and S. Yamashiro, "*Unit Commitment Solution Methodology Using Genetic Algorithm*", IEEE Transaction on Power System, vol. 17, pp. 87-91, Feb. 2002

[45] Sum-im. T. and Ongsakul .W., "*Ant colony search algorithm for unit commitment*", Industrial Technology, IEEE International Conference , vol 1, p p.72 -77, Dec. 2003.

[46] Sriyanyong , P.; Song, Y.H., "*Unit commitment using particle swarm optimization combined with Lagrange relaxation*", IEEE Power Engineering Society General Meeting, vol 3, p p.2752-2759, June. 2005.

[47] Samudi.C., Das. G.P., Ojha. P.C., Sreeni.T.S. and Cherian. S.,"*HydroThermal Scheduling Using Particle Swarm Optimization*", IEEE/PES Transmission and Distribution Conference and Exhibition, p p.1-5, April. 2008