

THERMAL UNIT COMMITMENT USING HYBRID PARTICLE SWARM OPTIMIZATION

*A Thesis submitted in partial fulfillment of the requirements for the award of
degree of*

**Master of Engineering
In
Power Systems and Electric Drives**



Thapar University, Patiala

Submitted By
Ashutosh Kumar Yadav
Roll No. 801041005


Under the supervision of:
Mr. Nitin Narang
Assistant Professor
Electrical & Instrumentation Engineering
Department, Thapar University,
Patiala

July 2012
**Department of Electrical and Instrumentation
Engineering, Thapar University**
(Established under the section 3 of UGC act, 1956)
Patiala, 147004, Punjab, India

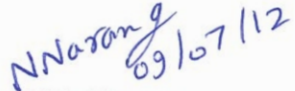
CERTIFICATE

I hereby certify that the work which is being presented in Thesis entitled, "**Thermal Unit Commitment Problem Using Hybrid Particle Swarm Optimization**", in partial fulfillment of the requirements for the award of degree of *Master of Engineering in Power Systems and Electric Drives* at Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Mr. Nitin Narang, Assistant Professor (EIED)**. The matter embodied in this thesis has not been submitted for the award of any other degree to any other university.


Date: 09/07/12



Ashutosh Kumar Yadav
Reg. No. (801041005)

This is to certify that above statement made by the candidate is correct and true to the best of my knowledge.


Mr. Nitin Narang
Assistant Professor (EIED)
Thapar University,
Patiala

Countersigned by


Dr. Smarajit Ghosh
Professor and Head (EIED)
Thapar University,
Patiala


Dr. S.K. Mohapatra
Dean (Academic Affair)
Thapar University,
Patiala

ACKNOWLEDGEMENT

Words are often less to reveal one's deep regards. With an understanding that work like this can never be the outcome of a single person, I take this opportunity to express my profound sense of gratitude and respect to all those who helped me through the duration of this work.

I would like express my gratitude and thanks to supervisor, **Mr. Nitin Narang, Assistant Professor**, Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, for his patient guidance and support throughout this work. It was an honour and privilege to work under him as a student. He also provides the help in technical writing and presentation style and I found his guidance to be extremely valuable.

I would also like to thanks **Mr. Nirbhaw Jap Singh, Assistant Professor**, Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, for his continuous support throughout the completion of thesis.

I would like to thanks **Dr. Smarajit Ghosh, Professor and Head**, Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, (Formerly known as Thapar Institute of Engineering and Technology, Patiala), for proving this opportunity to carry out Thesis work.

I am also thankful to my friends who devoted their valuable time for the successful completion of thesis. I express my feeling to all faculty and staff of EIED, Thapar University, Patiala for successful completion of thesis.

Last but not the least, thanks God for giving me a great family, friends and great teachers in all respect of life.

Ashutosh Kumar Yadav

Reg. No. 801041005

Email ID: 1985akyadav@gmail.com

ABSTRACT

In operational planning of power system, unit commitment problem (UCP) is important optimizing task. The UCP means to determine the optimal schedule of start-up or shutdown of generating units for scheduled period to meet the load demand. Unit commitment problem is two decision process of determining the commit/decommit of generating units and economic dispatch of electric power providing the satisfaction of all operating constraints i.e. power equality and inequality constraints and all other operating constraints so that operating cost be minimized. The unit commitment problem is multimodal and non-convex problem.

Various search technique has been applied to find optimal solution. In this thesis work hybrid particle swarm optimization has been applied to solve UCP. The particle swarm optimization has number of advantage but still it shows slow convergence characteristic near global optimal solution. In the proposed HPSO the property of simulated annealing for hill climbing has been hybridized with PSO. The proposed algorithm helps to explore the search area more effectively. Finally the HPSO algorithm is tested on two UCP and results has been compared with results reported in the literature.

Table of Contents

	Page No.
Certificates	i
Acknowledgement	ii
Abstract	iii
List of figures	vi
List of tables	vi
Chapter 1: Introduction	1-8
1.1 Introduction	1
1.2 Literature review	2
1.3 Author's contribution	8
1.4 Organization of the thesis	8
Chapter 2: Thermal Unit Commitment	9-15
2.1 Introduction	9
2.2 Constraints in unit commitment	9
2.2.1 Unit type	9
2.2.2 Spinning reserve	11
2.2.3 Thermal unit constraints	11
2.2.3.1 Minimum up time	11
2.2.3.2 Minimum down time	11
2.2.4 Crew constraints	11
2.3 Formulation of thermal unit commitment problem	12
2.3.1 Cost function	12
2.3.2 Constraints	14
2.3.2.1 Equality constraints	14
2.3.2.2 Inequality constraints	14
Chapter 3: Hybrid Particle Swarm Optimization	16-22
3.1 Introduction	16
3.2 Overview of particle and swarm	16
3.3 PSO as an optimization tool	17
3.4 Overview of PSO	17

3.5	Advantages and disadvantages of PSO	19
3.6	Hybrid PSO	21
Chapter 4:	Thermal Unit Commitment Using Hybrid PSO	23-31
4.1	Introduction	23
4.2	Formulation of thermal unit commitment problem	23
4.2.1	Cost function	23
4.2.2	Subjected to	24
4.2.2.1	Equality constraints	24
4.2.2.2	Inequality constraints	24
4.3	Unit scheduling for thermal unit commitment problem	25
4.3.1	Structure of individual for thermal unit commitment problem	25
4.3.2	Initialization of unit combination in population	25
4.3.3	Randomly generation of power	25
4.3.4	Priority list for unit scheduling	27
4.3.5	Spinning reserve constraints	27
4.3.6	Minimum up and down time constraints	28
4.3.7	Decommitment of excess unit	28
4.4	Calculation of objective function	29
4.5	Algorithm for thermal unit commitment problem using hybrid PSO	30
Chapter 5:	Results and Discussion	32-34
5.1	Introduction	32
5.2	Parameter setting	32
5.3	Comparison with techniques shows the effectiveness of applied method	32
Chapter 6:	Conclusion and scope of future work	35-35
6.1	Conclusion	35
6.2	Scope of work	35
Appendix		36-37
Appendix 1		36
Appendix 2		36
References		38-45

LIST OF FIGURES

	Page No.
Figure 2.1: Basic unit commitment	10
Figure 2.2: Start up cost of the thermal unit	13
Figure 3.1: The flow chart of the original PSO	20

LIST OF TABLES

	Page No.
Table 5.1: Parameter setting	32
Table 5.2: Comparison of total operating cost by different technique	33
Table 5.3: Load scheduling for four units and 8-hour by HPSO	33
Table 5.4: Load scheduling for ten units and 24-hour by HPSO	34

1.1 Introduction

In the operation of power system, more emphasis are put on enough generation of power is respect to meet the load demand. 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 problem [TUCP] 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 [UC] is the problem of determining the schedule of generating units within a power system subject to device and operating constraints. Unit commitment plays an important role in the economic operation of a power system. It is very significant optimization tasks, which determine the on/off status of the generating units over a scheduling period. Unit commitment problem divided into two parts, first part is the unit scheduled problem that determines on/off status of generating units in each time period of planning horizon and second is the economic load dispatch problem. So in TUCP, objective is the Minimize the operating cost which includes the starting cost and production cost and satisfied the all constraints [1]. Thermal unit commitment problem is subjected to several constraints that include minimum up-time and down-time, crew constraints, ramp rate limits, generation constraints, load balances, must-run units and spinning reserve constraints [2].

Unit commitment is a mixed-integer non-linear optimization problem. There are two types of approaches to solve the TUCP. First is Deterministic approaches include the priority list method, linear programming [LP] method, branch and bound [BAB] technique, lagrangian relaxation [LR], dynamic programming [DP] and second is the stochastic search approaches such as genetic algorithms [GA], evolutionary programming [EP], simulated annealing [SA], ant colony optimization [ACO], tabu search [TS] methods and particle swarm optimization [PSO] [3]. The PSO is a parallel evolutionary computation technique developed by Kennedy and Eberhart [4] based on the social behavior metaphor. A standard textbook on PSO, treating both the social and computational paradigms [5]. The PSO algorithm is initialized with a population of random candidate solutions, conceptualized as particles. Each particle is assigned a randomized velocity and is iteratively moved through the

problem space. It is attracted towards the location of the best fitness achieved so far by the particle itself and by the location of the best fitness achieved so far across the whole population (global version of the algorithm). The PSO always converges very quickly towards the optimal positions but may slow its convergence speed when it is near a minimum. For improving the PSO's performance near the optima, such as using an adaptive inertia weight [6, 7].

1.2 Literature Review

People use less electricity on Saturdays than on weekdays, less on Sundays than on Saturdays, and at a lower rate between midnight and about 7: 00 A.M. than during the day. Faced with this situation, electric utilities usually have fewer steam-electric generating units in service during lighter load periods. Unit commitment is the problem of optimal scheduling of the generating units during a specified time horizon. The committed units must meet the system load and reserve requirements at minimum operating cost, in addition to a variety of constraints [2]. The scheduling problem of UCP is to optimally allocate the load demand among the running units while satisfying the power balance equations and units operating limits [8]. Various researchers published lots of papers pertaining to the solution of thermal unit commitment. Kerr *et al.* [9] elaborated the need of UC in the power system for economic point of view and procedure to formulate the TUCP and its solution. Lauer *et al.* [10] have proposed a solution methodology, which developed for the optimization model of TUCP with two unique features as computational requirements grow only linearly with the number of units and performance of the algorithm can be rigorously to actually improve as the number of units increases. For solving the UCP, There are two types of approaches to solve the unit commitment problem. First is Deterministic approaches and second is the stochastic search approaches. Deterministic methods are simple and fast but it suffer from numerical convergence and solution quality problem. Stochastic methods can handle complex non-linear constraints and provide high quality solution but it suffers from the curse of dimensionality means when the number of generating units increases, computational time will be increased and quality of solution is poor [3]. Deterministic methods include the priority list method [11], BAB technique [12-14], dynamic programming [DP] [8, 15-17], and LR method [18-21]. Lee [11] has discussed, an optimal priority order depends not only upon the relative operational economics of the available units but also upon the system load variations. The computation time is approximately linear with the number of hours in the UC horizon. For N units and the total period of M intervals, the maximum number of possible

combination is $(2^N - 1)^M$, which can become a horrid number [8]. Turgen [12] suggested that the UCP is difficult for two reasons: first, the generating units usually have different running costs, so that the total production cost is a function of which units are kept on the line. Second, the production cost includes start-up costs that are influenced by the length of period units have been shut down. Turgeon [13] was presented a approach for determining the optimal TUCP to minimize the operating cost along with limitations that a unit should not started more than once a day and not more than two units of the same plant should be started up simultaneously. Dillon *et al.* [14] developed a method for determining the UC schedule for hydro-thermal systems extensions and modifications of the BAB method for Integer Programming. The shortcoming of BAB method is the exponential growth in the execution time with the size of UCP [1].

Dynamic programming has many advantages over the enumeration scheme, the chief advantage being a reduction in dimensionality of the problem [8]. Lowery [15] has determined the feasibility of using Dynamic Programming to solve the TUCP. Pang *et al.* [16] has described a truncated DP method for the commitment of thermal units over a period of up to 48 hours and satisfied various specified spinning reserve requirements and operating constraints. Pang *et al.* [17] proposed that significant potential savings can be achieved through the use of DP based methods for TUCP, but there is no assurance that they will yield optimal schedules. Li *et al.* [21] discussed that an approach based on de-commitment procedure for solving TUCP is comparison to DP method due to large computation time. Bertsekas *et al.* [18] described a solution methodology based on duality, Lagrangian relaxation and non-differentiable optimization that has two unique features. First, computational requirements typically grow only linearly with the number of generating units. Second, the duality gap decreases in relative terms as the number of units increases. Cohen *et al.* [19] have been described for solving the unit commitment and hydro scheduling problems as well as methods for solving the combined hydro-thermal scheduling problem. Virmani *et al.* [20] concentrated on the implementation aspects of the Lagrangian relaxation method applied to realistic and practical unit commitment problems. These above methods have only been applied to small UCP and have required major assumptions that limit the solution space and solution quality of LR depends on the method to update Lagrange multipliers [1].

As deterministic techniques have problems in solving large scale optimization problem so with the advancement of stochastic search approaches such as GA [22-27], EP [28], SA [29], ACO [30], TS methods [31] and PSO [1]. These stochastic search optimization methods attract much attention, because of their ability to search not only local optimal

solution but also global optimal solution and can easily deal with various difficult nonlinear constraints [1]. Dasgupta *et al.* [22] discussed the application of a GA to solve short-term UCP, i.e. deciding the commitment order of units for an entire day in advance. Maifeld *et al.* [23] have proposed algorithm consist of using a GA with domain specific mutation operators and easily accommodate any constraints. Kazarlis *et al.* [24] have discussed the disadvantage of GA algorithms has high execution time and optimality of the solution cannot be guaranteed. Senjyu *et al.* [25] introduced an approach based on GA which steps forward towards the optimal solution for UCP in respect to load demand in a suitable computational time. Senjyu *et al.* [26] is proposed a technique that leads to reduction of search space with unit integration technique for the solution of UCP with respect to load demand. Integer coded GA is proposed for solution to TUCP without penalty function for distortion of search space in less computational time discussed by Damousis *et al.* [27]. Juste *et al.* [28] have proposed algorithm employs the EP technique in which populations of contending solutions are evolved through random changes, competition, and selection respect to optimal solution of UCP. Mantawy *et al.* [29] provided a methodology for determining the feasible solutions to UCP, which results in considerable CPU time saving. Sum-im *et al.* [30] has proposed ACO algorithm to solve TUCP which are parallel search and optimization capabilities. Mantawy *et al.* [31] presented an application of the TS method to solve TUCP. Ebrahimi *et al.* [32] have presented the shuffled frog leaping to solve the UCP and minimum up/down-time constraints have been directly coded not using the penalty function method. However, these stochastic search methods require a considerable amount of computational time to find the near-global minimum especially for a large-scale UCP [1].

To reduce the search space and amount of computational time in large-scale UCP, hybrid methods combining stochastic search approaches and deterministic optimization methods [1]. Ouyang *et al.* [33] has presented a hybrid artificial neural network - dynamic programming for the short term UCP and savings in execution time. Orero *et al.* [34] proposed a combined GA-LR solution technique for UCP, allowing the modeling of virtually all the problem constraints and the combined procedure alleviates both the difficulties encountered in obtaining feasible solutions with the LR method and the excessive computation time and premature convergence problems of the GA method. Mantawy *et al.* [35] have proposed a hybrid algorithm (SA and TS methods) for the UCP and a basic advantage of the proposed algorithm is the high speed of convergence besides the high quality of solutions compared to those obtained by SA and TS methods. Cheng *et al.* [36] presented an application of a combined the GA's and LR method for the UCP and the

Lagrangian multipliers are updated by GA and improve the performance of Lagrangian Relaxation method in solving combinatorial optimization problems. Cheng *et al.* [37] solved the UCP by the annealing-genetic algorithm which incorporated the GA into the SA algorithm to improve the CPU time of the SA algorithm and the solution quality of GA. Nayak *et al.* [38] presented a hybrid approach, feedforward neural network and SA to solve the UCP and improved the optimal solution in the case of a multi-model objective function. Yamin *et al.* [39] have presented a hybrid model between GA and LR to solve the UCP and GA is used for update the Lagrange multiplier.

Padhy [40] observed that hybrid method performs better than individual methods for solving UCP. Ongsakul *et al.* [41] have proposed an enhanced adaptive Lagrangian relaxation which consists of adaptive LR and heuristic search and CPU times are small and increase linearly with the system size, which is favorable for large-scale implementation. Balci *et al.* [42] have combined PSO and LR to solve the UCP and CPU time of the other algorithms, hybrid method are five times faster than LR and seventeen times faster than GA. Sriyanyong *et al.* [43] proposed the hybrid method which incorporates the PSO into the LR method to update the Lagrange multipliers and improve the performance of LR method. Victoire *et al.* [44] have proposed a solution model for the UCP using fuzzy logic to address uncertainties in the problem. Liao *et al.* [45] have presented a hybrid chaos search immune algorithm/GA and fuzzy system method for solving short-term TUCP. Kumar *et al.* [46] developed a hybrid DP based Hopfield neural network approach to UCP and takes less CPU time. Rajan *et al.* [47] have presented an EP based SA method to the UCP and works only with feasible solutions generated based on heuristics, thus avoiding the computational burden entailed by the GA methods which first generate all feasible solutions and then purge the infeasible ones. A dynamic programming technique with a fuzzy and SA based unit selection procedure for the solution of UCP has been proposed by Patra *et al.* [48]. The curse of dimensionality of the DP technique is eliminated by minimizing the number of prospective solution paths to be stored at each stage of the search procedure.

Seki *et al.* [49] proposed a local search method to improve the feasible solution of LR method and search area has been reduced by considering one or two slacks generating units. Dieu and Ongsakul [50] have presented the hybrid technique with the combination of LR and augmented hopfield network (AHN). Solution to UCP has been achieved in three steps as the scheduling of generating units is performed by improved LR and optimal scheduling of generating units is achieved prevailing the satisfaction of all constraints and AHN performed

ELD. Optimum generation scheduling achieved by mixed binary real coded PSO considering reliability and spinning reserve constraints has been proposed by Wang and Singh [51]. Dudek [52] proposed adaptive SA technique to find the feasible optimal solution of UCP. Rajan [53] presented a hybrid technique comprising of EP and SA to improve the quality of UCP by feeding the commitment schedule outcome from EP to SA within the limitation of generating unit. Hadji and Vahidi [54] discussed a imperialistic competition algorithm method to converge the searching process towards the optimal solution by having imperialistic competition between each individual population. A Solution to UCP with the implementation of expert system (ES) and elite PSO (EPSO) leads the searching process towards the more feasible optimal solution proposed by Chen [55]. Handling of all the operating constraints is performed by ES and optimum generation scheduling is obtained by EPSO.

As modern random search techniques such as EP, ACS, GA, SA, ANN, TS as these techniques provide more feasible global optimal solutions [3]. Out of these random search techniques of optimization PSO is one of the fast convergence rate technique. Particle swarm optimization introduced by Kennedy and Eberhart [4, 56], is one of the modern random optimal search technique and robust in solving continuous non-linear optimization problems. The PSO generates high-quality solutions within shorter time duration and have more stable convergence characteristics than other stochastic methods [57]. Particle swarm optimization has been implemented to many power system problems, various researchers have presented the papers in concern to the applications of PSO in solving problems related with power system. Yoshida *et al.* [58] proposed that a mixed integer non linear programming of voltage and reactive power control solved by using PSO considering voltage security constraint. Economic load dispatch problem has been solved using PSO in less computational time and with fast convergence rate leads toward the optimal solution presented by Gaing [59]. Gallad *et al.* [60] discussed PSO for solving constrained ED with prohibited zone i.e. within the generating limits. Abido [61] proposed a PSO approach for the optimal time setting of power system stabilizer (PSS) to enhance the performance of PSS under loading and any disturbance conditions. Optimal generator maintenance scheduling in reasonable time has been achieved by PSO along with consideration of availability of resources and crew for the maintenance of generating units proposed by Koay and Srinivasan [62]. Musabi *et al.* [63] discussed that optimal selection of variable structure load frequency controller for a power system has been solved using PSO. Pancholi and Swarup [64] and Nireekshana *et al.* [65] proposed a PSO approach for optimal parameter setting of unified

power flow controller (UPFC) with objective function of net saving considering cost pertaining to energy loss and UPFC. Optimal reactive power dispatch has been achieved by using multiagent PSO making solution more optimized by fast interaction of agents and evolution mechanism of PSO in search space has been discussed by Zhao *et al.* [66].

Huang *et al.* [67] proposed that short term load forecasting has been achieved by parameter setting of autoregressive moving average exogenous variable model using PSO leads to day and week ahead load forecasting. To overcome the problem of premature convergence and local minima in unscented kalman filter and to improve the accuracy a dynamically inertia weight based modified PSO is implemented and proper estimation of harmonics in voltage source converter discussed by Dash and Mallick [68]. Lopez *et al.* [69] proposed an optimal supply area and location of electric power generation with biomass as fuel using binary PSO. A security constrained ELD is achieved by employing PSO with minimization of generating cost prevailing the satisfaction of all operating constraints has been presented by Ela *et al.* [70]. A global optimizer PSO has been employed to optimize the hyper parameters of least square vector machine for forecasting of gas content in transformer oil presented by Liao *et al.* [71]. Optimal power flow for efficient power system operation to minimize the operating cost, voltage stability enhancement achieved by using PSO has been presented by Abido [72] and Kim *et al.* [73].

In previous papers PSO is implemented for providing the solution to various problems related to power system. But PSO has some limitation of slow converge rate when search process reaches the local search area or optimal solution is near to searching point [74]. So hybrid PSO (HPSO) comes into picture to overcome the problem of slow convergence in local vicinity of optimal solution. Therefore some researchers published some papers pertaining to this. Naka *et al.* [75] proposed that a non continuous and non differential distribution state of power equipments i.e. static voltage compensator and static voltage reactor for estimation of load and generation output values within limits of distribution system using HPSO. Shunmugalatha and Slochanal [76] proposed an HPSO for incorporation of breeding and subpopulation process in PSO to estimate voltage stability, maximum loading limit and optimization of generating cost. Victoire and Jeyakumar [77] presented a HPSO and sequential quadratic programming technique for derivative free optimization solution to large scale EDP without considering the incremental fuel cost characteristics. Coelho and Lee [78] proposed a chaotic and gaussian PSO for more efficient dispatching of load in power system considering ramp rate and up and down power limits.

A multiobjective ELD leads to optimal solution using fuzzified PSO and minimization of operation cost and emission considering power security constraint proposed by Wang and Singh [79-80]. Liang *et al.* [81] discussed a fuzzy based PSO for optimal power flow considering error forecast for load and availability of wind and minimization of operation cost and real power losses. Moradi and Abdini [82] proposed a hybrid technique combination of GA and PSO for optimal location and sizing of diesel generator set on distribution system for the improvement in voltage stability. Gnanambal and Babulal [83] proposed a hybrid technique comprising of DE and PSO for determination of maximum loadability limit of power system and to overcome the disadvantage of both the individual techniques i.e. instability and stuck in local minima. So it's been concluded that to overcome the disadvantages of individual techniques, a hybridized techniques is recent development in the solving many practical problems associated with power system as easy to implement and less chances of failure to provide optimal solution.

1.3 Author's Contribution

Thermal unit commitment is categorized into generation scheduling and economic load dispatch problem. Thermal unit commitment is solved on the basis of priority list of generating units in respect to their average production cost within the limits of all the generating units and an hybrid PSO is implemented to solve the scheduling problem. Results of the proposed technique is compared with the results obtained from various optimization methods.

1.4 Organization of the Thesis

Thesis titled as "*Thermal Unit Commitment Using Hybrid Particle Swarm Optimization*" is divided into six chapters. Chapter one provides the detailed introduction on unit commitment along with literature review pertaining to the problem. Chapter two describes the formulation of thermal unit commitment problem. Chapter three deals with the explanation of HPSO technique and its algorithm. Chapter four presents the solution approach to the unit commitment problem using HPSO. Chapter five covers the discussion pertaining to results and chapter six summarize the conclusions and scope for further work.

2.1 Introduction

The unit commitment problem determines the combination of available generating units and scheduling their respective outputs to satisfy the forecasted demand with the minimum total production cost under the operating constraints enforced by the system for a specified period that usually varies from 24 hours to one week. The constraints to be satisfied are usually the status restriction of individual generating units, minimum up time, minimum down time, capacity limits, generation limit for the first and last hour, limited ramp rate, group constraint, power balance constraint, spinning reserve constraint, hydro constraint, etc [2]. The high dimensionality and combinatorial nature of the unit commitment problem curtail attempts to develop any rigorous mathematical optimization method capable of solving the whole problem for any real-size system. Nevertheless, in the literature, many methods using some sort of approximation and simplification have been proposed. The basic unit commitment logic or flow chart is given in fig. 2.1. In this flow chart only show which unit is start-up or shut-down with economically at that particular time interval [48].

2.2 Constraints in Unit Commitment

Depending on the nature of power system under study, the UCP is subjected to many constraints, the main constraints pertaining to UCP are power balance constraints and spinning reserve constraints. The other constraints include the thermal constraints, fuel constraints, security constraints etc. [2].

2.2.1 Unit Type

The thermal units are usually divided into the following unit types: must-run units, cycling units, and peak load unit. Generally in power system, some of the units are given a must run status in order to provide voltage support for the network. 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. Peak load units are those generating units which are capable to serve the load demand in case of any sudden increase in load demand and these are able to start up in less possible time, usually gas turbines generating unit serves the motive of peak load units [8].

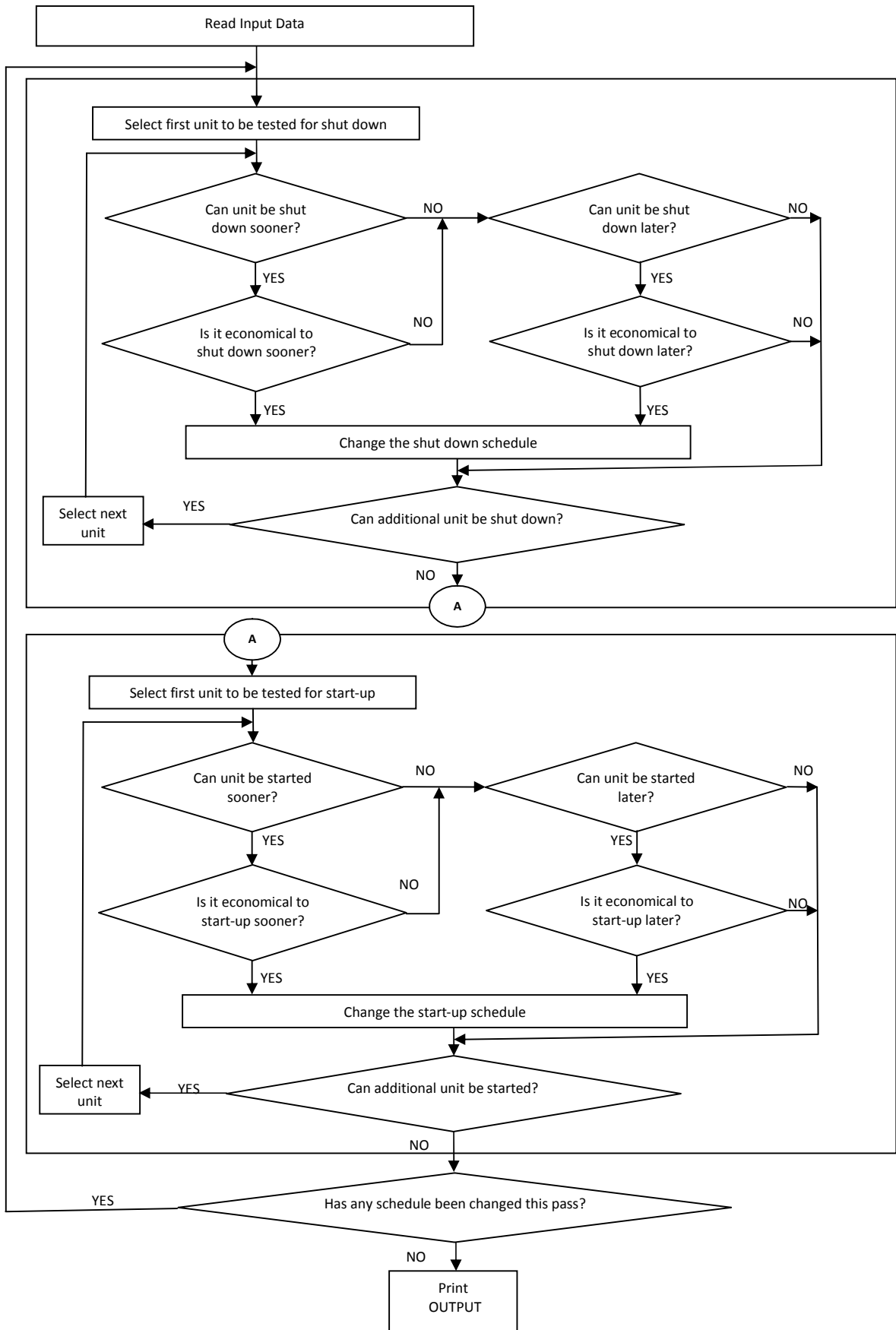


Fig. 2.1 Basic Unit Commitment

2.2.2 Spinning Reserve

The spinning reserve is the amount of extra real power generation available from all synchronized units to serve the load demand in case of any fault or sudden tripping or maintains of any generating units. 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 [16].

2.2.3 Thermal Unit Constraints

The temperature and pressure of the thermal units vary very gradually and units must be synchronized before they are brought online. 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 [16]:

2.2.3.1 Minimum up time:

Once the unit is running, it cannot be turned off immediately. It means that generating unit cannot turn off immediately, it needs some time to reach the off state [43].

$$T_{i,t}^{on} \geq MUT_i \quad (2.1)$$

where $T_{i,t}^{on}$ = Continuously on time duration for i^{th} unit upto time t

MUT_i = Minimum up-time for i^{th} unit

2.2.3.2 Minimum down time:

Once the unit is decommitted, there is a minimum time before it can be recommitted. It means that generating unit cannot turn on immediately; it needs some time to reach the committed state.

$$T_{i,t}^{off} \geq MDT_i \quad (2.2)$$

where $T_{i,t}^{off}$ = Continuously off time duration for i^{th} unit upto time t

MDT_i = Minimum down-time for i^{th} unit

2.2.4 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 up to the operating temperature, in time for a scheduled turns on [8].

Start up cost when cooling is given by

$$C_c \left(1 - e^{-\frac{t}{\alpha}}\right) \times F + C_f \quad (2.3)$$

where C_c = cold-start cost

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

F = fuel cost

α = thermal time constant for the unit

t = time (h) the unit was cooled

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 banking is given by

$$C_c \left(1 - e^{-\frac{t}{\alpha}}\right) \times F + C_t \quad (2.4)$$

where C_t = Cost 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. The variation of starting cost with starting at cooling or banking shown in fig. 2.2.

2.3 Formulation of Thermal Unit Commitment Problem

2.3.1 Cost Function

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 is a quadratic function of the generator power output [3, 49].

The total operating costs is the sum of the production costs and the start-up costs. The generator start-up cost depends on the time the unit has been switched-off prior to the start up. The start-up cost at any given time is assumed to be an exponential cost curve.

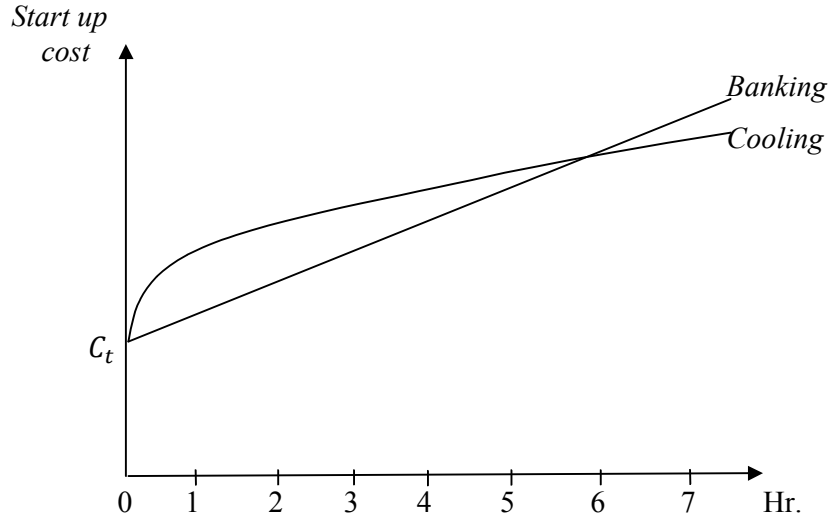


Fig. 2.2 Start up cost of the thermal unit

Cost function is minimizing the total operating cost, subject to a number of system and unit constraints [3].

$$OC_T = \sum_{t=1}^T \sum_{i=1}^N PC_{i,t} \times U_{i,t} + SC_{i,t} \times (1 - U_{i,t-1}) \times U_{i,t} \quad (2.5)$$

where

$$PC_{i,t} = a_i + b_i \times P_{i,t} + c_i \times P_{i,t}^2 \quad (2.6)$$

and

$$SC_{i,t} = \begin{cases} F_{hs,i} & \text{if } MDT_i \leq T_{i,t-1}^{off} \leq MDT_i + T_{co,i} \\ F_{cs,i} & \text{if } T_{i,t-1}^{off} > MDT_i + T_{co,i} \end{cases} \quad (2.7)$$

a_i, b_i, c_i = Unit cost coefficients for i^{th} unit

$F_{hs,i}$ = Hot start up cost for i^{th} unit

$F_{cs,i}$ = Cold start up cost for i^{th} unit

MDT_i = Minimum down time for i^{th} unit

N = No. of units

OC_T = Total operating costs for the scheduling period

$PC_{i,t}$ = Production cost of i^{th} unit at time t

$P_{i,t}$ = Generated power by i^{th} unit at time t

$SC_{i,t}$ = Starting cost for i^{th} unit at time t

$T_{co,i}$ = Cold start up time for i^{th} unit

T = Scheduling period

$U_{i,t}$ = Binary variable to indicate the on/off state of i^{th} unit at time t

$$U_{i,t} = \begin{cases} 1 & \text{if } i^{th} \text{ unit is committed at time } t \\ 0 & \text{otherwise} \end{cases}$$

The overall objective is to minimize operating cost subject to a number of system and unit constraints.

2.3.2 Constraints

There are two types of constraints in TUCP [1].

1) Equality constraints

2) Inequality constraints

2.3.2.1 Equality Constraints

Power balance constraint

The total generated power at each hour must be equal to the load demand of the corresponding hour [25].

$$\sum_{i=1}^N P_{i,t} \times U_{i,t} = P_{d,t} \quad (2.8)$$

where $P_{d,t}$ = Power demand and transmission loss at particular time t

$P_{i,t}$ = Generated power at time t by i^{th} unit

2.3.2.2 Inequality Constraints

Spinning reserve constraint

For reliable operation, the power system has to maintain a certain megawatt capacity as spinning reserve [38].

$$\sum_{i=1}^N P_i^{\max} U_{i,t} \geq P_{d,t} + R_t \quad (2.9)$$

where P_i^{\max} = Maximum generated power by i^{th} unit

R_t = Spinning reserve power at time t

Generation limit constraint

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

$$P_i^{\min} \leq P_{i,t} \leq P_i^{\max} \quad (2.10)$$

where P_i^{\min} = Minimum generated power by i^{th} unit

$P_{i,t}$ = Generated power at time t by i^{th} unit

Minimum up time constraints

A unit must be on for a certain number of hours before it can be shut down.

$$T_{i,t}^{on} \geq MUT_i \quad (2.11)$$

where $T_{i,t}^{on}$ = Continuously on time duration for i^{th} unit upto time t

MUT_i = Minimum up-time for i^{th} unit

Minimum down time constraints

A unit must be off for a certain number of hours before it can be brought online.

$$T_{i,t}^{off} \geq MDT_i \quad (2.12)$$

where $T_{i,t}^{off}$ = Continuously off time duration for i^{th} unit upto time t

MDT_i = Minimum down-time for i^{th} unit

Unit initial status

The initial unit states at the start of the scheduling period must be taken into account.

All the generators are assumed to be connected to the same bus supplying the total system demand. Therefore, the network constraints are not taken into account.

CHAPTER 3

HYBRID PARTICLE SWARM OPTIMIZATION

3.1 Introduction

A random search technique leads to the global optimal solution inspired by choreography of a bird flock come into existence i.e. particle swarm optimization (PSO) proposed by Kennedy and Eberhart in 1995, on based on swarm intelligence as in case of swarm of bees and fish. Swarm intelligence is powerful tool that have distributed behavior [4]. In a flock of birds or a school of fish, if one individual finds a good way to move for the food or protection, other members in the swarm follow its movement promptly. This process can be modeled by a swarm of particles moving in the multidimensional search space, each of which has a position and a velocity. These particles flying across the hyperspace, record the best positions which they have ever encountered. Members of a swarm adjust their velocities and positions by communicating desirable positions to one another [6].

3.2 Overview of Particle and Swarm

Five principles of swarm intelligence in various models for applications in artificial life [84] are discusses in brief as under.

- *Quality principle:* In respect to this principle, population should meet all the quality standard in the environment.
- *Proximity Principle:* The population should be able to carry out simple space and time computation with respect to this principle.
- *Principle of diverse response:* A location to resources for all the population should not lie along excessively narrow lines to insure orderly response to the environment.
- *Principle of stability:* Population should not change its behaviour upon every fluctuation of the environment as it does not produce a worthwhile return for the investment.
- *Principle of adaptability:* Rewards in terms of return on the investment, population should change a behavioural mode in respect to this.

3.3 PSO as an Optimization Tool

As modern random search techniques such as EP, ACS, GA, SA, ANN, TS etc. as these techniques provide more feasible global optimal solutions [3]. Out of these random search techniques of optimization PSO is one of the fast convergence rate techniques. PSO can be used as an effective optimization tool to handle the optimization problems which cannot be easily solved by the traditional analytical approaches. As an optimizer, PSO provides a population-based search procedure. Each single particle can be assumed as a “bird” in the search space. Particles flying in the multidimensional space adjust their position based on both its own experience and that of their neighboring companions. In this way, PSO combines local search with global search for balancing the exploration and exploitation [4]. To adjust its flying speed and direction, an individual can learn from its past experiences. Therefore, all the individuals in the swarm can quickly converge to near-optimal geographical positions with well-preserved population density distribution by observing the behavior of the flock and memorizing their flying histories [56].

PSO is considered as an evolutionary computation approach as there are many common characteristics between evolutionary algorithms and PSO such as [43]:

- 1) It is initialized with a population of random solutions.
- 2) It searches for the optimum values by updating generations.
- 3) The adjustments of individuals are analogous to real value crossover operation in evolutionary algorithms.
- 4) Objective evaluation is evaluated by objective functions.

Comparing with evolutionary algorithms, PSO’s information sharing mechanism is significantly different. In EAs, individuals share their information with each other by crossover and the whole population moves like one group towards an optimal point. In PSO, only global best position provides the information to other individuals to adjust their speeds. It is a one-way information sharing mechanism. The entire population follows the movement of the best individual and converges to a *near-optimal* solution quickly [70].

3.4 Overview of PSO [56]:

Let P and V denote a particle’s coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. Therefore, the particle is represented as $P_{j,i,t} = [P_{j,i,1} \ P_{j,i,2} \ \dots \ P_{j,i,T}]$ in the $K \times N$ dimensional space. The best previous position of

each particle is recorded and represented as $P_{j,i,t}^{best} = [P_{j,i,1}^{best} \quad P_{j,i,2}^{best} \quad \dots \quad P_{j,i,T}^{best}]$ in the $K \times N$ dimensional space and called the local best position. The index of the best particle among all the particles in the group is represented by the $G_{i,t}^{best} = [G_{i,1}^{best} \quad G_{i,2}^{best} \quad \dots \quad G_{i,T}^{best}]$ and called the global best position. The rate of the velocity for particle is represented as $V_{j,i,t} = [V_{j,i,1} \quad V_{j,i,2} \quad \dots \quad V_{j,i,T}]$.

The modified velocity and position of each particle can be calculated using the current velocity and distance from local best position to global best position as shown in the following formulas:

$$V_{j,i,t}^{new} = w \times V_{j,i,t} + C_1 \times rand() \times (P_{j,i,t}^{best} - P_{j,i,t}) + C_2 \times rand() \times (G_{i,t}^{best} - P_{j,i,t}) \quad (3.1)$$

$$P_{j,i,t}^{new} = P_{j,i,t} + V_{j,i,t}^{new} \quad (j = 1, 2, \dots, K; i = 1, 2, \dots, N; t = 1, 2, \dots, T) \quad (3.2)$$

where K = number of particles in a group

N = Number of members in a particle

T = Time period of members

w = Inertia weight factor

C_1 and C_2 = Acceleration constant

$V_{j,i,t}^{new}$ = New velocity of i^{th} member of j^{th} particles at time interval t

$$V_i^{\min} \leq V_{j,i,t}^{new} \leq V_{j,i,t}^{\max}$$

$P_{j,i,t}^{new}$ = New position of i^{th} member of j^{th} particles at time interval t

rand ()= Uniform random values in the range [0, 1]

$V_{j,i,t}$ = Current velocity of i^{th} member of j^{th} particles at time interval t

$P_{j,i,t}$ = Current position of i^{th} member of j^{th} particles at time interval t

$P_{j,i,t}^{best}$ = Local best position of i^{th} member of j^{th} particles at time interval t

$G_{i,t}^{best}$ = Global best position of i^{th} member at time interval t

In the above procedures, the parameter $V_{j,i,t}^{\min}$ determined the resolution with which regions are to be searched between the present position and target position. If $V_{j,i,t}^{\max}$ is too high, particles might fly past good solution. If $V_{j,i,t}^{\max}$ is too small, particles may not explore sufficiently beyond local solutions [56].

The constant C_1 and C_2 represent the weighting of the stochastic acceleration terms that pull each particle towards the local best position and global best position. Low values allow particles

to roam far from the target regions before being tugged back. On other hand, high values result in abrupt movement towards, or past, target regions [7].

Suitable selection of inertia weight w provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. In general, the inertia weight w is set according to the following formula [6]:

$$w = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{IT_{\max}} \right) \times IT \quad (3.3)$$

where IT_{\max} = maximum number of iteration

IT = Current number of iteration

w_{\max} = Maximum inertia weight

w_{\min} = Minimum inertia weight

Stochastic optimization algorithm can be stopped by various available criterion, such as tolerance, number of function evaluations and the maximum number of iterations. Global best position is the optimum solution. Basic PSO flow chart is in fig. 3.1.

3.5 ADVANTAGES AND DISADVANTAGES OF PSO

A PSO is considered as one of the most powerful methods for resolving the non-smooth global optimization problems and has many advantages as compared to other heuristic optimization techniques, which are as follow:

- PSO is a derivative-free technique just like as other heuristic optimization techniques.
- PSO is easy in its concept and coding implementation.
- PSO is less sensitivity to the nature of the objective function compared to the conventional mathematical approaches and other heuristic methods.
- PSO has limited number of parameters including only inertia weight factor and two acceleration coefficients [6].
- PSO seems to be somewhat less dependent of a set of initial points compared to other evolutionary methods, implying that convergence algorithm is robust.

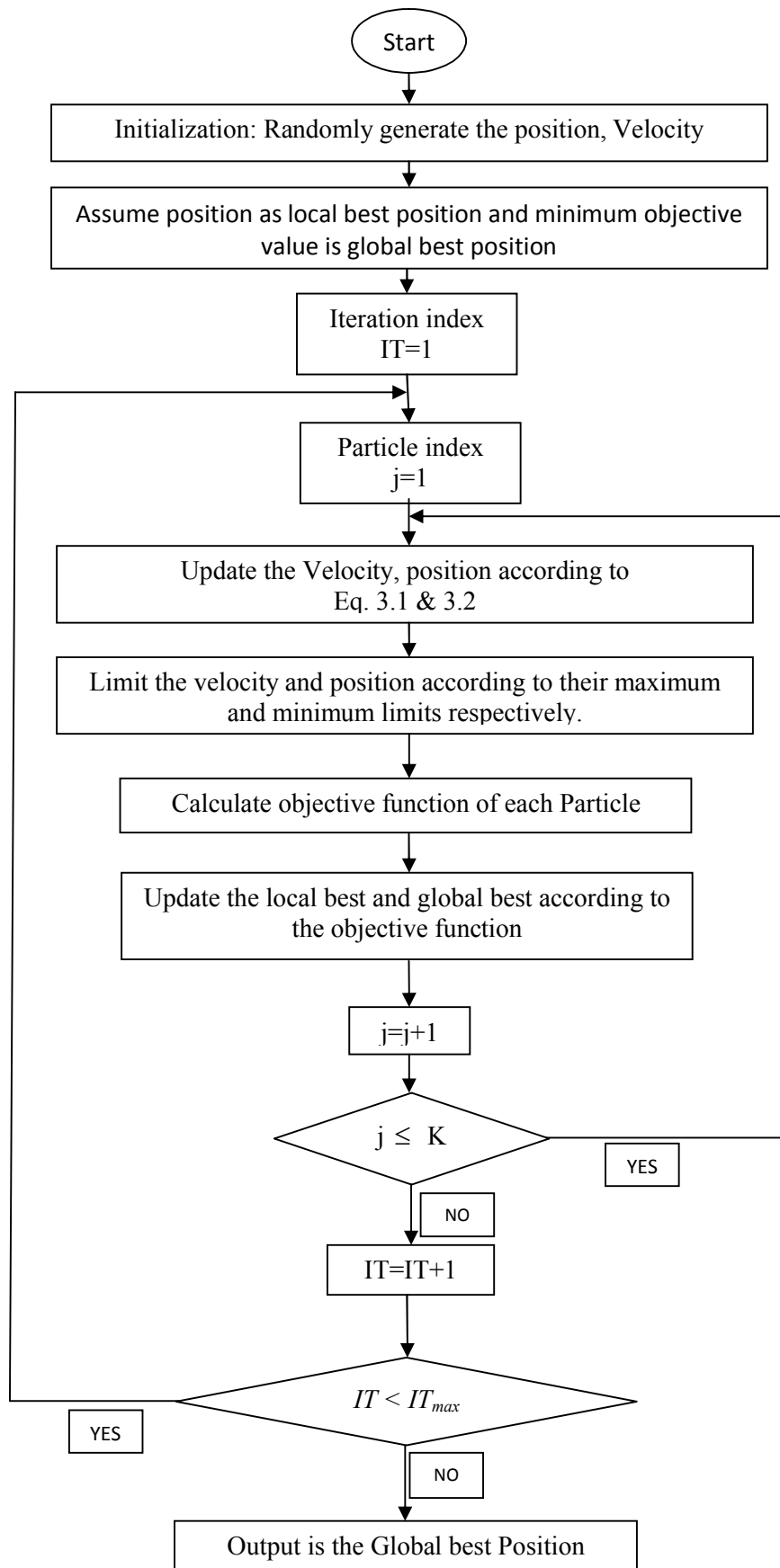


Fig. 3.1 The Flowchart of the original PSO

- PSO techniques can generate high-quality solutions within shorter calculation time and stable convergence characteristics [43].

PSO is implemented for providing the solution to various problems related to power system. But PSO has some limitation of slow converge rate when search process reaches the local search area or optimal solution is near to searching point [74]. So hybrid PSO (HPSO) comes into picture to overcome the problem of slow convergence in local vicinity of optimal solution.

3.6 Hybrid PSO

Even though there are numerous variants for the PSO algorithm, premature is still the main disadvantage of the PSO. In most of the variants and the original form, particles in a swarm only could learn from the local best position and global best position. This strategy would lead to the simplification of the swarm. Lacking of diversity of the population, particularly during the latter stages of the process, is the substantial factor for the convergence of particles to local optimum solutions prematurely. To improve the global search ability in the PSO algorithm of the optimization by keeping diversity of the population. Randomization is widely used in most evolutionary optimization algorithm, such as genetic algorithm and simulated annealing algorithm, to guide the method to avoid local optima [43].

The idea of simulated annealing algorithm is to allow hill-climbing moves, so that the algorithm can escape from local optima. It makes a hill-climbing move over the worse alternative with a probability that depends on the difference of the objective value between two positions. This idea is adopted in our novel strategy [29].

In the process of the PSO algorithm, particles in the swarm would come together at a step. And then, according to the traditional moving strategy, it must be difficult for particles to escape from the accumulation point. We consider that particles with similar objective value are close to each other. After that, the algorithm would lose its global search ability. To keep the diversity of the swarm, a random position is introduced to guide the flying of particles with a probability that depends on the difference of the objective between the particles with the maximum absolute objective value and the minimum one. The probability is defined as follows [85]:

$$P(\Delta f) = \exp\left(\frac{Fit^{\min} - Fit^{\max}}{e + Fit^{\min}}\right) \quad (3.4)$$

where $P(\Delta f)$ = probability for objective function

Fit^{\max} = maximum absolute objective value of the current swarm

Fit^{\min} = minimum absolute objective value of the current swarm

e = a small positive value.

The procedure for the Hybrid PSO (HPSO) method is as follows.

Step 1: Initialize the velocity, position, local best position and global best position.

Step 2: Set $IT=1$

Step 3: Evaluate the objective function

Step 4: Update the local best position and global best position

Step 5: Calculate the probability of mutation with the maximum absolute value and the minimum absolute value according to Eq. (3.4).

Step 6: if $rand() < P(\Delta f)$, then

6 (a): if $IT < IT_{\max}$, then

$$New\ Global\ best\ position = rand() \times (P_i^{\max} - P_i^{\min}) + P_i^{\min}$$

if $Objective\ Value_{at\ global\ best\ position} > Objective\ Value_{at\ new\ global\ best\ position}$, then

Global best position = new global best position

otherwise

$$New\ Local\ best\ position = rand() \times (P_i^{\max} - P_i^{\min}) + P_i^{\min}$$

if $Objective\ Value_{at\ local\ best\ position} > Objective\ Value_{at\ new\ local\ best\ position}$, then

Local best position = new local best position

Step 7: Calculate the inertia weight according to Eq. (3.3).

Step 8: calculate the new velocity according to Eq. (3.1).

Step 9: update the position according to Eq. (3.2).

Step 10: If $IT < IT_{\max}$, $IT = IT + 1$ and return to step 3. Otherwise, global best is the optimum solution.

CHAPTER 4

THERMAL UNIT COMMITMENT USING HYBRID PSO

4.1 Introduction

Unit commitment problem (UCP) 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 constraints. The UCP 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. Unit Commitment is the most significant optimization task in the operation of the power systems. Solving the UCP for large power systems is computationally expensive. The complexity of the UC problems grows exponentially to the number of generating units [2].

There are many methods to solve the UCP [56]. The algorithm to solve unit commitment problem is discussed in detail in this chapter. The unit commitment problem is solved by hybrid particle swarm optimization (HPSO).

Unit commitment problem can be divided into two parts, first part is the unit scheduled problem that determines on/off status of generating units in each time period of planning horizon and second is the economic load dispatch problem. So in unit commitment problem, objective is to minimize the operating cost which includes the starting cost and production cost and satisfied the all equality and inequality constraints. The standard UCP is subjected to several constraints that include minimum up-time and down-time, crew constraints, ramp rate limits, generation constraints, load balances, must-run units and spinning reserve constraints [1, 2].

4.2 Formulation of Thermal Unit Commitment Problem

4.2.1 Cost Function

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 is a quadratic function of the generator power output [3, 49].

The total operating costs is the sum of the production costs and the start-up costs. The generator start-up cost depends on the time the unit has been switched-off prior to the start up. The start-up cost at any given time is assumed to be an exponential cost curve.

Cost function is minimizing the total operating cost, subject to a number of system and unit constraints [1].

$$OC_T = \sum_{t=1}^T \sum_{i=1}^N PC_{i,t} \times U_{i,t} + SC_{i,t} \times (1 - U_{i,t-1}) \times U_{i,t} \quad (4.1)$$

where

$$PC_{i,t} = a_i + b_i \times P_{i,t} + c_i \times P_{i,t}^2 \quad (4.2)$$

and

$$SC_{i,t} = \begin{cases} F_{hs,i} & \text{if } MDT_i \leq T_{i,t-1}^{off} \leq MDT_i + T_{co,i} \\ F_{cs,i} & \text{if } T_{i,t-1}^{off} > MDT_i + T_{co,i} \end{cases} \quad (4.3)$$

The overall objective is to minimize the total operating cost subject to a number of system and unit constraints.

2.3.2 Subjected To:-

2.3.2.1 Equality Constraints

Power balance constraint

The total generated power at each hour must be equal to the load demand of the corresponding hour [25].

$$\sum_{i=1}^N P_{i,t} \times U_{i,t} = P_{d,t} \quad (4.4)$$

2.3.2.2 Inequality Constraints

Spinning reserve constraint

For reliable operation, the power system has to maintain a extra capacity as spinning reserve [38].

$$\sum_{i=1}^N P_i^{\max} U_{i,t} \geq P_{d,t} + R_t \quad (4.5)$$

Generation limit constraint

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

$$P_i^{\min} \leq P_{i,t} \leq P_i^{\max} \quad (4.6)$$

Minimum up time constraints

A unit must be on for a certain number of hours before it can be shut down.

$$T_{i,t}^{on} \geq MUT_i \quad (4.7)$$

Minimum down time constraints

A unit must be off for a certain number of hours before it can be brought online.

$$T_{i,t}^{off} \geq MDT_i \quad (4.8)$$

Unit initial status

The initial unit states at the start of the scheduling period must be taken into account.

All the generators are assumed to be connected to the same bus supplying the total system demand. Therefore, the network constraints are not taken into account.

4.3 Unit Scheduling for Thermal Unit Commitment Problem

Thermal Unit commitment problem can be dividing into two parts, first part is determining the on/off status of generating units in each time period of planning horizon and second is the unit scheduling problem [1].

4.3.1 Structure of individual for Thermal Unit Commitment Problem

Each population has two dimensions, one dimension for number of units (N) and second for time horizon (T). So, the on-off schedule of the units is stored as an integer-matrix U with dimension (N x T). A matrix representation of a population is shown as follow:

$$U = \begin{bmatrix} u_1^1 & u_1^2 & \dots & u_1^T \\ u_2^1 & u_2^2 & \dots & u_2^T \\ \vdots & \vdots & \vdots & \vdots \\ u_N^1 & u_N^2 & \dots & u_N^T \end{bmatrix} \quad (4.9)$$

4.3.2 Initialization of Unit Combination in population

A set of unit combination is created at random. For the complete K population, the candidate solution of each particle is randomly initialized. The position of each particle is generated using a uniform distributed random number.

$$U = \begin{cases} 1 & \text{if random number is greater than 0.5} \\ 0 & \text{otherwise} \end{cases} \quad (4.10)$$

Unit combination has three dimensions because population dimension will be introducing (K). So, the on-off schedule of the units is stored as an integer-matrix U with dimension (K x N x T). A matrix representation of a particle with population is shown as follow:

$$U = \begin{bmatrix} \begin{bmatrix} u(1,1,1) & u(1,1,2) & \dots & u(1,1,T) \\ u(1,2,1) & u(1,2,2) & \dots & u(1,2,T) \\ \vdots & \vdots & \vdots & \vdots \\ u(1,N,1) & u(1,N,2) & \dots & u(1,N,T) \end{bmatrix} \\ \begin{bmatrix} u(2,1,1) & u(2,1,2) & \dots & u(2,1,T) \\ u(2,2,1) & u(2,2,2) & \dots & u(2,2,T) \\ \vdots & \vdots & \vdots & \vdots \\ u(2,N,1) & u(2,N,2) & \dots & u(2,N,T) \end{bmatrix} \\ \vdots \\ \begin{bmatrix} u(K,1,1) & u(K,1,2) & \dots & u(K,1,T) \\ u(K,2,1) & u(K,2,2) & \dots & u(K,2,T) \\ \vdots & \vdots & \vdots & \vdots \\ u(K,N,1) & u(K,N,2) & \dots & u(K,N,T) \end{bmatrix} \end{bmatrix} \begin{matrix} (j = 1,2,\dots,K; i = 1,2,\dots,N; \\ t = 1,2,\dots,T) \end{matrix} \quad (4.11)$$

where $u(j, i, t)$ = unit on/off status of i^{th} unit at time t for j^{th} population

K= population

N= number of generating units

T= time period for scheduling

4.3.3 Randomly generation of power

Initial velocity and power (position) are generated by random uniform number, which lies between its maximum and minimum value respectively. Expression of velocity and power are as follow:

$$V_{j,i,t} = V_i^{\min} + rand() \times (V_i^{\max} - V_i^{\min}) \quad (j = 1,2,\dots,K; i = 1,2,\dots,N; t = 1,2,\dots,T) \quad (4.12)$$

$$P_{j,i,t} = P_i^{\min} + rand() \times (P_i^{\max} - P_i^{\min}) \quad (4.13)$$

where $rand()$ = Uniformly distributed random values in the range [0, 1].

V_i^{\min} and V_i^{\max} = Minimum and maximum value of velocity respectively.

P_i^{\min} and P_i^{\max} = Minimum and maximum value of power respectively.

4.3.4 Priority list for unit-scheduling

Priority list is created according to each unit parameters. Cost per produced unit, of a unit at its maximum output power usually is less than that at other output power levels. Priority list is based on fuel cost obtained from the average fuel cost of each unit operating at its maximum output power [11]. The average full-load cost λ of a unit is defined as the cost per unit of power (\$/MW) when the unit is at its full capacity [1]. When the fuel cost of unit is given by Eq. (4.2), λ can be expressed as

$$\lambda_i = \frac{PC_i(P_i^{\max})}{P_i^{\max}} = \frac{a_i}{P_i^{\max}} + b_i + c_i \times P_i^{\max} \quad (4.14)$$

The units are ranked by their λ in ascending order. Thus, the priority list of units will be formulated based on the order of λ_i , in which a unit with the lowest λ_i will have the highest priority to be dispatched.

4.3.5 Spinning reserve constraints

The obtained primary unit-scheduling may not satisfy the spinning reserve constraints (4.5). Therefore, the spinning reserve violations are repaired by heuristic search. The procedure for repairing the spinning reserve violations in primary unit-scheduling is as follows [22]:

Step 1. Set $j = 1$.

Step 2. Set $t = 1$.

Step 3. For all uncommitted units at hour t , calculate the average full-load cost λ_i using Eq. (4.14). Sort them in ascending order of λ_i to obtain a unit scheduling list $S(\lambda_i)$.

Step 4. The amount of excessive spinning reserve at each hour is calculated by

$$Z_{j,t} = \sum_{i=1}^N U_{j,i,t} \times P_i^{\max} - P_{d,t} - R_t \quad (4.15)$$

Step 5. If $Z_{j,t} \geq 0$, go to step 6;

Step 6. Commit an uncommitted unit in $S(\lambda_i)$ with the lowest λ_i , one unit at a time until the spinning reserve constraint is satisfied.

Step 7. If $t < T$, $t = t + 1$ and return to step 3.

Step 7. If $j < K$, $j = j + 1$ and return to step 2. Otherwise, stop.

4.3.6 Minimum up and down time constraints

Since the obtained unit schedule may not satisfy the minimum up/down time constraints, a heuristic search algorithm is required to repair any violations of these constraints. The continuously on/off times of the i^{th} unit up to hour t are calculated as follows [24]:

$$T_{j,i,t}^{on} = (1 + T_{j,i,t-1}^{on}) \times U_{j,i,t} \quad (4.16)$$

$$T_{j,i,t}^{off} = (1 + T_{j,i,t-1}^{off}) \times (1 - U_{j,i,t}) \quad (4.17)$$

where $T_{j,i,t}^{on}$ = continuously on time for i^{th} unit upto time t for j^{th}

$T_{j,i,t}^{off}$ = continuously off time for i^{th} unit upto time t for j^{th}

The procedure to repair violations of the minimum up/down times constraints are as follows:

Step 1: Calculate the duration on and off times of all units for the whole schedule time horizon using Eq. (4.16) & (4.17).

Step 2: Set $j = 1$.

Step 3: Set $t = 1$.

Step 4: Set $i = 1$.

Step 5: If $U_{j,i,t} = 0$ and $U_{j,i,t-1} = 1$, then

5(a) If $T_{j,i,t-1}^{on} < MUT_i$, then $U_{j,i,t} = 1$

5(b) If $(t + MDT_i - 1 \leq T)$ and $(T_{j,i,t+MDT_i-1}^{off} < MDT_i)$, then $U_{j,i,t} = 1$

5(c) If $(t + MDT_i - 1 > T)$ and $(\sum_{m=t}^T U_{j,i,m} > 0)$, then $U_{j,i,t} = 1$

Step 6: Update the duration on/off times for the i^{th} unit using Eq. (4.16) & (4.17).

Step 7: If $i < N$, $i = i + 1$ and return to step 5.

Step 8: If $t < T$, $t = t + 1$ and return to step 4.

Step 9: If $t < T$, $t = t + 1$ and return to step 3. Otherwise, stop.

4.3.7 Decommitment of excess units

Repairing the minimum up and down time constraints can lead to excessive spinning reserves, which is not desirable due to the high operation cost. In a heuristic search algorithm based on a priority list to decommit the redundant units due to the minimum up and down time repairing, thereby reducing the operating cost. Starting from the committed units with the lowest

priority list (the highest average operating cost), the algorithm determines units that can be decommitted without violating the minimum up and down time and spinning reserve constraints until no unit can be decommitted. So very important point in this process, the spinning reserve and minimum up and down time constraints must be checked before decommitting a unit [1].

Procedure for decommitment of excessive units is as follows:

Step 1: Set $j=1$.

Step 2: Set $t = 1$.

Step 3: Calculate the average full-load cost λ_i of each committed unit in hour t and sort the units in the descending order of λ_i to obtain a unit scheduling list $S(\lambda_i)$. Let the first unit in $S(\lambda_i)$ be $CU_{j,t}$.

Step 4: The amount of excessive spinning reserve at hour t is calculated by

$$Z_{j,t} = \sum_{i=1}^N U_{j,i,t} \times P_i^{\max} - P_{d,t} - R_t \quad (4.18)$$

Step 5: If $Z_{j,t}$ is less than the maximum generation power of $CU_{j,t}$, go to step 7.

Step 6: If decommitting $CU_{j,t}$ does not violate its minimum up/down time constraint, decommit $CU_{j,t}$ and update on/off status for all units.

Step 7: Delete $CU_{j,t}$ from $S(\lambda_i)$.

Step 8: If $S(\lambda_i)$ is not empty, let $CU_{j,t}$ be the first unit in $S(\lambda_i)$ and return to step 3.

Step 9: If $t < T$, $t = t + 1$ and return to step 3.

Step 10: If $j < K$, $j = j + 1$ and return to step 2. Otherwise, stop.

4.4 Calculation of objective function

Objective function is minimizing the total operating cost, which include the production cost and starting cost. The procedure of calculate the objective function is as follow:

Step 1: Calculate the on and off time duration from Eq. (4.12) & (4.13).

Step 2: Set $t=1$

Step 3: Set $i=1$

Step 4: Calculate the error

$$error_{j,t} = \left(\sum_{i=1}^N P_{j,i,t} - P_{d,t} \right)^2 \quad (j = 1, 2, \dots, K; i = 1, 2, \dots, N; t = 1, 2, \dots, T) \quad (4.19)$$

$$error_j = \sum_{t=1}^T error_{j,t} \quad (4.20)$$

Step 5: Calculate the production cost from Eq. (4.2).

Step 6: Calculate the starting cost from Eq. (4.3).

Step 7: Calculate objective function

$$F_j = \sum_{t=1}^T \sum_{i=1}^N PC_{j,i,t} \times U_{j,i,t} + SC_{j,i,t} \times (1 - U_{j,i,t-1}) \times U_{j,i,t} + M \times error_j \quad \left(\begin{array}{l} j=1,2,\dots,K; \\ i=1,2,\dots,N; \\ t=1,2,\dots,T \end{array} \right) \quad (4.21)$$

where M=A extreme penalty factor

Step 8: If $i < N$, $i = i + 1$ and return to step 4.

Step 9: If $t < T$, $t = t + 1$ and return to step 3. Otherwise, stop.

4.5 Algorithm for Thermal Unit Commitment using Hybrid PSO

Step 1: Read data; viz. Cost coefficient (a_i , b_i , c_i), P_i^{\max} , P_i^{\min} , PSO constant, and unit commitment constant.

Step 2: Initialization unit combination as in Section (4.3.2).

Step 3: Calculate priority list of units according to each unit parameters as in Section (4.3.4).

Step 4: Modify unit's status of unit combination satisfying spinning reserve constraints as in Section (4.3.5).

Step 5: Repair unit's status of unit combination satisfying minimum up/down time violations as in Section (4.3.6).

Step 6: Decommit units of each hour to reduce excessive spinning reserve constraints and also repairing the minimum up/down times constraints as in Section (4.3.7).

Step 7: Randomly generate the velocity and position as by Eq. (4.12) & (4.13) respectively.

Step 8: Find the objective values Eq. (4.21) and set as cost is F_j^{best} and set $P_{j,i,t}^{best} = P_{j,i,t}$ and minimum objective value is set as a global value and its particles is set a $G_{i,t}^{best}$.

Step 9: Iteration start set IT=1

Step 10: Calculate the probability of mutation with the maximum absolute value and the minimum absolute value according to Eq. (3.4)

Step 11: If $[rand() < P(\Delta f)]$, then

11(a): If $IT < IT_{\max}$, then $G_{i,t}^{best}$ is changed as follow.

$$G_{i,t}^{bestnew} = P_i^{\min} + rand() \times (P_i^{\max} - P_i^{\min}) \quad (4.22)$$

If $F(G_{i,t}^{best}) > F(G_{i,t}^{bestnew})$ according to Eq. (4.21), then

$$G_{i,t}^{best} = G_{i,t}^{bestnew} \quad (4.23)$$

otherwise, $P_{j,i,t}^{best}$ is changed as follow.

$$P_{j,i,t}^{bestnew} = P_i^{\min} + rand() \times (P_i^{\max} - P_i^{\min}) \quad (4.24)$$

If $F(P_{j,i,t}^{best}) > F(P_{j,i,t}^{bestnew})$ according to Eq. (4.21), then

$$P_{j,i,t}^{best} = P_{j,i,t}^{bestnew} \quad (4.25)$$

Step 12: Calculate the inertia weight according to Eq. (3.3).

Step 13: Calculate the new velocity using Eq. (3.1).

13(a): If $(V_{j,i,t}^{new} > V_i^{\max})$ THEN update $(V_{j,i,t}^{new} = V_i^{\max})$.

13(b): If $(V_{j,i,t}^{new} < V_i^{\min})$ THEN update $(V_{j,i,t}^{new} = V_i^{\min})$.

Step 14: Calculate the new position using Eq. (3.2).

14(a): If $(P_{j,i,t}^{new} > P_i^{\max})$ THEN update $(P_{j,i,t}^{new} = P_i^{\max})$.

14(b): If $(P_{j,i,t}^{new} < P_i^{\min})$ THEN update $(P_{j,i,t}^{new} = P_i^{\min})$.

Step 15: Calculate the new objective value by Eq. (4.21) and set as cost is F_j^{new}

Step 16: If $(F_j^{new} < F_j^{best})$ THEN set $(F_j^{best} = F_j^{new})$ and $(P_{j,i,t}^{best} = P_{j,i,t}^{new})$

Step 17: Calculate the minimum objective value of F_j^{best} and set F^{\min} and position according to

F^{\min} is set as $G_{i,t}^{best}$.

Step 18: If $IT < IT_{\max}$, $IT = IT + 1$ and return to step 10. Otherwise, STOP and F^{\min} & $G_{i,t}^{best}$ give the optimum output.

5.1 Introduction

The previous chapters that have been studied provide the complete knowledge of thermal unit commitment problem and its formulation using Hybrid particle swarm optimization. The algorithms of hybrid particle swarm optimization, which are presented in chapter 4, have been applied for solving thermal unit commitment problem. In this section, two cases are studied to illustrate the effectiveness of the proposed method in terms of its solution quality. The spinning reserve is assumed to be 10% of the load demand. The first system consists of four generating units, 8-hr scheduling periods while the second system consists of ten generating units, 24-hr scheduling periods. Production fuel cost function of each generator is estimated into quadratic form. Test data is given in appendix-1 and appendix-2 [27].

5.2 Parameter Setting

In the research work, proposed algorithm based on HPSO carried out to solve TUCP. To find the optimal solution, program is run at different value of acceleration constants (C_1 and C_2), inertia weight (w), which is depends on maximum and minimum value of inertia weight (W_{max} and W_{min}) and e which is a small positive value. Inertia weight is also depends on maximum iteration value (IT_{max}). The program is run for different value of C_1 , C_2 , W_{max} , W_{min} , e and IT_{max} , minimum operating cost is achieved at following values of these parameter, which is given in table 5.1.

Table 5.1 Parameter Setting

C_1	C_2	W_{max}	W_{min}	IT_{max}	e
1.5	2.5	0.9	0.4	1000	0.8

5.3 Comparison with techniques shows the effectiveness of applied method

To show the effectiveness of the hybrid PSO method, two systems are investigated. For each problem results are compared with results of PSO method and DP method. Comparison of total operating cost achieved by different technique is given in table 5.2.

Table 5.2 comparison of total operating cost by different technique

	Operating cost for 4 Units, 8-hour scheduling	Operating cost for 10 Units, 24-hour scheduling
DP	73439*	-
PSO	75434	575559
HPSO	75384	575228

(*) Minimum up and minimum down times constraints are neglected.

Results calculated using HPSO in comparison of PSO and DP is found more satisfactory and all constraints are satisfied. The powers generated by different generating units are given in table 5.3 for four generating units and in table 5.4 for ten generating units.

Test System 1

Four generating units are to be committed to serve 8-hr load pattern. Data on the generating units and load pattern are contained in appendix-1. Results are obtaining from DP, PSO and hybrid PSO. In table 5.3, power generating by each unit at particular hour is given by HPSO.

Table 5.3 Load scheduling for four units and 8-hours by HPSO

Hour	Load (MW)	Unit number			
		1	2	3	4
1	450	253.9444	196.0463	0	0
2	530	254.9908	250	25	0
3	600	209.9897	250	80	60
4	540	300	214.9901	25	0
5	400	261.4101	113.5816	25	0
6	280	219.992	60	0	0
7	290	205.0027	84.9887	0	0
8	500	271.1267	228.8652	0	0

Test System 2

Ten generating units are to be committed to serve 24-hr load pattern. Data on the generating units and load pattern are contained in appendix-2. Results are obtaining from

PSO and hybrid PSO. In table 5.4, power generating by each unit at particular hour is given by HPSO.

Table 5.4 Load scheduling for ten units and 24-hours by HPSO

Hour	Load MW	Unit number										
		1	2	3	4	5	6	7	8	9	10	
1	700	357.3112	342.6855	0	0	0	0	0	0	0	0	0
2	750	417.7047	332.2841	0	0	0	0	0	0	0	0	0
3	850	455	308.5294	0	86.40083	0	0	0	0	0	0	0
4	950	390.0371	312.5746	130	117.4434	0	0	0	0	0	0	0
5	1000	455	333.0032	113.0556	98.90036	0	0	0	0	0	0	0
6	1100	345.8946	341.9176	125.6202	128.1898	158.3647	0	0	0	0	0	0
7	1150	455	340.895	124.9892	119.0289	110.0682	0	0	0	0	0	0
8	1200	373.7447	455	112.3666	113.3546	145.5439	0	0	0	0	0	0
9	1300	455	368.316	92.10834	106.5999	152.0525	62.7276	63.18403	0	0	0	0
10	1400	434.4284	455	104.1227	130	137.7486	63.0605	65.66188	10	0	0	0
11	1450	418.4304	455	130	130	136.0362	74.1932	85	11.3234	0	10	10
12	1500	455	333.876	124.6244	119.947	162	80	79.04258	42.0671	48.4006	55	55
13	1400	368.9452	455	122.7201	121.7844	156.5447	80	85	10	0	0	0
14	1300	404.7179	455	96.51276	110.6883	152.4707	23.7101	56.88844	0	0	0	0
15	1200	363.1637	455	120.2661	117.4973	144.0585	0	0	0	0	0	0
16	1050	455	224.308	105.4207	130	135.3648	0	0	0	0	0	0
17	1000	175.1722	455	108.3318	130	131.4507	0	0	0	0	0	0
18	1100	302.071	416.408	101.4373	118.0713	162	0	0	0	0	0	0
19	1200	455	354.8076	122.6235	116.9871	150.5471	0	0	0	0	0	0
20	1400	455	435.8497	130	111.9499	162	70.1015	25	10	0	0	0
21	1300	455	354.8296	108.7111	130	162	64.4521	25	0	0	0	0
22	1100	378.0001	455	0	0	162	80	25	0	0	0	0
23	900	455	328.4558	0	0	116.481	0	0	0	0	0	0
24	800	455	344.9764	0	0	0	0	0	0	0	0	0

Results of HPSO are more satisfactory than DP and PSO. All constraints of TUCP are satisfied in HPSO algorithm.

CHAPTER 6

CONCLUSION AND SCOPE FOR FUTURE WORK

6.1 Conclusion

A hybrid particle swarm optimization (HPSO) algorithm is implemented to solve thermal unit commitment problem (TUCP). It is having advantage of to find the global optimal solution with high convergence rate due to hybridization of hill climbing property of simulated annealing with particle swarm optimization. Thermal unit commitment problem has been solved for four and ten generating units in respect to load demand using HPSO algorithm. Result obtains using proposed technique is outperform in comparison to DP and PSO.

6.2 Scope for Future Work

Scope of work after implementation TUCP using HPSO is summarized as:

- Several inaccuracies and uncertainties in the input information like cost coefficient, transmission loss coefficient that can be formulates the stochastic model. It can be converted to its equivalent deterministic model and HPSO can be solved the TUCP.
- This technique can be hybridized with differential evolution (DE), biogeography based optimization (BBO) and artificial immune system.

APPENDIX

APPENDIX 1:

1. Input data for four generating units and 8-hour scheduling.

	Unit 1	Unit 2	Unit 3	Unit 4
P^{\max} (MW)	300	250	80	60
P^{\min} (MW)	75	60	25	20
a (\$/h)	684.74	585.62	213.00	252.00
b (\$/MW h)	16.83	16.95	20.74	23.60
c (\$/MW ² h)	0.0021	0.0042	0.0018	0.0034
min up time (h)	5	5	4	1
min down time(h)	4	3	2	1
Hot start cost(\$)	500	170	150	0
Cold start cost(\$)	1100	400	350	0.02
Cold start hrs(h)	5	5	4	0
Initial status(h)	8	8	-5	-6

2. Load Demand for 8-Hour

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

APPENDIX 2:

1. Input data for ten generating units and 24-hour scheduling.

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
P^{\max} (MW)	455	455	130	130	162
P^{\min} (MW)	150	150	20	20	25
a (\$/h)	1000	970	700	680	450
b (\$/MW h)	16.19	17.26	16.60	16.50	19.70
c (\$/MW ² h)	0.00048	0.00031	0.002	0.00211	0.00398
min up time (h)	8	8	5	5	6
min downtime(h)	8	8	5	5	6
Hot start cost(\$)	4500	5000	550	560	900
Cold start cost(\$)	9000	10000	1100	1120	1800

Cold start hrs(h)	5	5	4	4	4
Initial status(h)	8	8	-5	-5	-6

	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P^{\max} (MW)	80	85	55	55	55
P^{\min} (MW)	20	25	10	10	10
a (\$/h)	370	480	660	665	670
b (\$/MW h)	22.26	27.74	25.92	27.27	27.79
c (\$/MW² h)	0.00712	0.00079	0.00413	0.00222	0.00173
min up time (h)	3	3	1	1	1
min downtime(h)	3	3	1	1	1
Hot start cost(\$)	170	260	30	30	30
Cold start cost(\$)	340	520	60	60	60
Cold start hrs(h)	2	2	0	0	0
Initial status(h)	-3	-3	-1	-1	-1

2. Load Demand for 24-Hour.

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

REFERENCES

- [1] Yuan, X., Nie,H., Su, A., Wang, L. and Yuan,Y., “*An improved binary particle swarm optimization for unit commitment problem*”, Expert Systems with Applications, Vol. 36, No. 4, pp. 8049-8055, 2008.
- [2] Hobbs, W.J., Hermon, G., Warner S. and Sheble, G.B., “*An enhanced dynamic programming approach for unit commitment*”, IEEE Power Engineering Review, Vol. 3, No. 3, pp. 1201- 1205, Aug. 1988.
- [3] Pappala,V.S. and Erlich, I., “*A new approach for solving the unit commitment problem by adaptive particle swarm optimization*”, IEEE Trans. on Power Syst., pp. 1-6, 2008.
- [4] Kennedy, J. and Eberhart, R.C., “*Particle swarm optimization*”, in: Proc. IEEE Conf. on Neural Networks, IV, Piscataway, NJ, pp. 1942–1948, 1995.
- [5] Kennedy, J., Eberhart, R.C. and Shi, Y., “*Swarm intelligence*”, Morgan Kaufmann Publishers, San Francisco, CA, pp. 1, 2001.
- [6] Shi, Y. and Eberhart, R., “*A modified particle swarm optimizer*”, IEEE, pp. 69-73, 1998.
- [7] Shi, Y. and Eberhart, R.C., “*Empirical study of particle swarm optimization*”, IEEE, pp. 1945-1950, 1999.
- [8] Wood, A.J. and Wollenberg, B., “*Power generation, operation and control*”, second edition, John Wiley, New York, 1996.
- [9] Kerr, R.H., Scheidt, J. L., Fontana, A. J. and Wiley, J. K., “*Unit commitment*”, IEEE Trans. on Power Apparatus and Syst., Vol. PAS-85, No. 5, pp. 417-421, May 1966.
- [10] Lauer, G.S., N. R. Sandell, Jr., Bertsekas and T.A. Posbergh, “*Solution of large scale optimal unit commitment problem*”, IEEE Trans. on Power Apparatus and Syst., Vol. PAS 101, No. 1, pp. 79-96, Jan. 1982.
- [11] Lee, F.N., “*Short-term thermal unit commitment - a new method* ”, IEEE Trans. on Power Syst., Vol. 3, No. 2, pp. 421-428, May 1988.
- [12] Turgeon, A., “*Optimal unit commitment*”, IEEE Trans. on Automatic Control, Vol. 23, No. 2, pp. 223–227, 1977.
- [13] Turgeon, A., “*Optimal scheduling of thermal generating units*”, IEEE Trans. on Automatic Control, Vol. 23, No. 6, pp. 1000–1005, 1978.

- [14] Dillon, T. S., “*Integer programming approach to the problem of optimal unit commitment with probabilistic reserve determination*”, IEEE Trans. on Power Apparatus and Syst., Vol. 97, No. 6, pp. 2154–2164, 1978.
- [15] Lowery, P. G., “*Generating unit commitment by dynamic programming*”, IEEE Trans. on Power Apparatus And Syst., Vol. PAS-85, No. 5, pp. 422-426, May 1966.
- [16] Pang, C. K., and Chen, H. C., “*Optimal short-term thermal unit commitment*”, IEEE Trans. on Power Apparatus and Syst., Vol. 95, No. 4, pp. 1336–1342, 1976.
- [17] Pang, C. K., Sheble, G. B., And Albuyeh, F., “*Evaluation of dynamic programming based methods and multiple area representation for thermal unit commitments*”, IEEE Trans. on Power Apparatus and Syst., Vol. 100, No. 3, pp. 1212–1218, 1981.
- [18] Bertsekas, D. P., Lauer, G. S., Sandell, N. R., Jr., and Posbergh, T. A., “*Optimal short-term scheduling of large-scale power systems*”, IEEE Trans. on Automatic Control, Vol. 28, No. 1, pp. 1–11, 1983.
- [19] Cohen, A., and Sherkat, V., “*Optimization-based methods for operations scheduling*”, Proceedings of IEEE, Vol. 75, No. 12, pp. 1574–1591, 1987.
- [20] Virmani, S., Adrian, E.C., Imhof, K. and Muhhejee, S., “*Implementation of a lagrangian based unit commitment problem*”, IEEE Trans. on Power Syst., Vol. 4, No. 4, pp. 1373-1384, Oct. 1989.
- [21] Li, C. and Johnson, R. B., “*A new unit commitment method*”, IEEE Trans. on Power Syst., Vol. 12, No. 1, pp.113-119, Feb. 1997.
- [22] Dasgupta, D. and McGregor, D. R., “*Thermal unit commitment using genetic algorithm*”, IEE Proc. on Gener. Transm. Distrib., Vol. 141, No. 5, pp. 459-465, Sept. 1994.
- [23] Maifeld, T.T. and Sheble, G.B., “*Genetic-based unit commitment algorithm*”, IEEE Trans. on Power Syst., Vol. 11, No. 3, pp. 1359-1370, Aug. 1996.
- [24] Kazarlis, S.A., Bakirtzis, A.G., and Petridis, V., “*A genetic algorithm solution to the unit commitment problem*”, IEEE Trans. on Power Syst., Vol. 11, No. 1, pp. 83–92, 1996.
- [25] Senjyu, T., Yamashiro, H., Uezato, K., and Funabashi, T., “*A unit commitment problem by using genetic algorithm based on unit characteristic classification*”, Proc. IEEE/Power Engineering Society Winter Meeting, Vol. 1, pp. 58–63, 2002.
- [26] Senjyu, T., Yamashiro, H., Uezato, K., and Funabashi, T., “*Fast solution technique for large-scale unit commitment problem using genetic algorithm*”, IEE Proc. on Gener. Transm. Distrib., Vol. 150, No. 6, pp. 753–760, 2003.

- [27] Damousis, I.G., Bakirtzis, A.G., and Dokopoulos, P.S., “*A solution to the unit commitment problem using integer-coded genetic algorithm*”, IEEE Trans. Power Syst., Vol. 19, No. 2, pp. 1165–1172, 2004.
- [28] Juste, K.A., Kita, H., Tanaka, E., and Hasegawa, J., “*An evolutionary programming solution to the unit commitment problem*”, IEEE Trans. on Power Syst., Vol. 14, No. 4, pp. 1452–1459, 1999.
- [29] Mantawy, A.H., Abdel-Magid, Y.L., and Selim, S.Z., “*An simulated annealing algorithm for unit commitment*”, IEEE Trans. on Power Syst., Vol. 13, No. 1, pp. 197–204, 1998.
- [30] Sum, I.T. and Ongsakul, W., “*Ant colony search algorithm for unit commitment*”, Industrial Technology, IEEE International Conference, Vol. 1, pp. 72 -77, Dec. 2003.
- [31] Mantawy, A.H., Abdel-Magid, Y.L., and Selim, S.Z., “*A unit commitment by tabu search*”, IEE Proc. on Gener. Trans. Distrib., Vol. 145, No. 1, pp. 197–204, 1998.
- [32] Ebrahimi, J., Hosseinian, S.H. and Gharehpetian, G.B., “*Unit commitment problem solution using shuffled frog leaping algorithm*”, IEEE Trans. On Power Syst., Vol. 26, No. 2, pp. 573-581, May 2011.
- [33] Ouyang, Z. and Shahidehpour, S.M., “*A hybrid artificial neural network-dynamic programming approach to unit commitment*”, IEEE Trans. on Power Syst., Vol. 7, No. 1, pp. 236-242, Feb. 1992.
- [34] Orero, S.O. and Irving, M.R., “*A combination of the genetic algorithm and lagrangian relaxation decomposition techniques for the generation unit commitment problem*”, Electric Power Syst. Research, Vol. 43, No. 3, pp. 149-156, March, 1997.
- [35] Mantawy, A.H., Magid, Y.L.A. and Selim, S.Z., “*A new simulated annealing-based tabu search algorithm for unit commitment*”, IEEE, pp. 2432-2437, 1997.
- [36] Cheng, C.P., Liu, C.W. and Liu, C.C., “*Unit commitment by lagrangian relaxation and genetic algorithms*,” IEEE Trans. Power Syst., Vol. 15, No. 2, pp. 707–714, May 2000.
- [37] Cheng, C.P., Liu, C.W. and Liu, C.C., “*Unit commitment by annealing-genetic algorithm*”, I.J. of Electrical Power and Energy Syst., Vol. 24, No. 3, pp. 149-158, 2002.
- [38] Nayak, R. and Sharma, J.D., “*A hybrid neural network and simulated annealing approach to the unit commitment problem*”, Computers and Electrical Engineering, Vol. 26, No. 6, pp. 461-477, 2000.

- [39] Yamin, H.Y. and Shahidepour, S.M., “*Unit commitment using a hybrid model between lagrangian relaxation and genetic algorithm in competitive electricity markets*”, Electric Power syst. Research, Vol. 68, No. 2, pp. 83-92, 2004.
- [40] Padhy, N.P., “*Unit commitment using hybrid models: a comparative study for dynamic programming, expert system, fuzzy system and genetic algorithms*”, I.J. of Electrical Power and Energy Syst., Vol. 23, No. 8, pp. 827-836, 2000.
- [41] Ongsakul, W. and Petcharaks, N., “*Unit commitment by enhanced adaptive lagrangian relaxation*”, IEEE Trans. on Power Syst., Vol. 19, No. 1, pp. 620–628, Feb. 2004.
- [42] Balci, H.H. and Valenzuela, J.F., “*Scheduling electric power generators using particle swarm optimization combined with the lagrangian relaxation method*”, I.J. Application Math. Computer Science, Vol. 14, No. 3, pp. 411–421, 2004.
- [43] Sriyanyong, P. and Song, Y.H., “*Unit commitment using particle swarm optimization combined with lagrange relaxation*”, IEEE Power Engineering Society General Meeting, Vol. 3, pp.2752-2759, June 2005.
- [44] Victoire,T.A.A. and Jeyakumar, A. E., “*A tabu search based hybrid optimization approach for a fuzzy modeled unit commitment problem*”, Electric Power Syst. Research, Vol. 76, No. 6-7, pp. 413–425, 2006.
- [45] Liao, G.C. and Tsao, T.P., “*Using chaos search immune genetic and fuzzy system for short-term unit commitment algorithm*”, I.J. of Electrical Power and Energy Syst., Vol. 28, No. 1, pp. 1-12, 2006.
- [46] Kumar, S.S. and Palanisamy, V., “*A dynamic programming based fast computation hopfield neural network for unit commitment and economic dispatch*”, Electric Power Syst. Research, Vol. 77, No. 8, pp. 917-925, 2007.
- [47] Rajan, C.C.A. and Mohan, M.R., “*An evolutionary programming based simulated annealing method for the unit commitment problem*”, I.J. of Electrical Power and Energy Syst., Vol. 29, No. 7, pp. 540-550, 2007.
- [48] Patra, S., Goswami, S.K. and Goswami, B., “*Fuzzy and simulated annealing based dynamic programming for the unit commitment problem*”, Expert System with Applications, Vol. 36, No. 3, pp. 5081-5086, 2009.
- [49] Seki, T., Yamashita, N. and Kawamoto, K., “*New local search methods for improving the lagrangian-relaxation-based unit commitment solution*”, IEEE Trans. on Power Syst., Vol. 25, No. 1, pp. 272-283, Feb. 2010.

- [50] Dieu, V.N., and Ongsakul, W., “*Augmented lagrange hopfield network based lagrangian relaxation for unit commitment*”, I.J. of Electrical Power and Energy Syst., Vol. 33, No. 3, pp. 522-530, March 2011.
- [51] Wang, L. and Singh, C., “*Unit commitment considering generator outages through a mixed-integer particle swarm optimization algorithm*”, Applied Soft Computing, Vol. 9, No. 3, pp. 947-953, June 2009.
- [52] Dudek, G., “*Adaptive simulated annealing schedule to the unit commitment problem*”, Electric Power Syst. Research, Vol. 80, pp. 465-472, 2010.
- [53] Rajan, C.C.A., “*Hydro-thermal unit commitment problem using simulated annealing evolutionary programming approach*”, I.J. of Electrical Power and Energy Syst., Vol. 33, No. 4, pp. 939-946, April 2011.
- [54] Hadji, M.M. and Vahidi, B., “*A Solution to the Unit Commitment Problem Using Imperialistic Competition Algorithm*”, IEEE Trans. on Power Syst., Vol. 27, No. 1, pp. 117-124, February 2012.
- [55] Chen, P.H., “*Two-level hierarchical approach to unit commitment using expert system and elite PSO*”, IEEE Trans. on Power Syst., Vol. 27, No. 2, pp. 780-789, May 2012.
- [56] D. P. Kothari and J. S. Dhillon, “*Power System Optimization*”, Second Edition, PHI learning Private limited, 2011.
- [57] Padhy, N.P., “*Unit Commitment—A Bibliographical Survey*”, IEEE Trans. on Power Syst., Vol. 19, No. 2, PP. 1196-1205, May 2004.
- [58] Yoshida, H., Kawata, K., Fukuyama, Y., Takayama, S. and Nakanishi, Y., “*A particle swarm optimization for reactive power and voltage control considering voltage security assessment*”, IEEE Trans. on Power Syst., Vol. 15, No. 4, pp. 1232-1239, Nov. 2000.
- [59] Gaing, Z. L., “*Particle swarm optimization to solving the economic dispatch considering the generator constraints*”, IEEE Trans. on Power Syst., Vol. 18, No. 3, pp. 1187-1195, Aug. 2003.
- [60] El-Gallad, A., El-Hawary, M., Sallam, A. and Kalas, A., “*Particle swarm optimizer for constrained economic dispatch with prohibited operating zones*”, IEEE Canadian Conference on Electrical & Computer Engineering, pp. 78-81, 2002.
- [61] Abido, M. A., “*Optimal Design of Power-System Stabilizers Using Particle Swarm Optimization*”, IEEE Trans. on Energy Conversion, Vol. 17, No. 3, pp. 406-413, Sept. 2002.

- [62] Koay, C.A. and Srinivasan, D., “*Particle swarm optimization-based approach for generator maintenance scheduling*”, IEEE, pp. 167-173, 2003.
- [63] Al-Musabi, N.A., Al-Harnouz, Z.M., Al-Duwaish, H.N. and Al-Baiyal, S., “*Variable structure load frequency controller using particle swarm optimization technique*”, IEEE, pp. 380-383, 2003.
- [64] Pancholi, R.K. and Swarup, K.S., “*Particle swarm optimization for security constrained economic dispatch*”, IEEE, pp. 7-12, 2004.
- [65] Nireekshana, T., Rao, G.K. and Raju, S.S.N., “*Incorporation of unified power flow controller model for optimal placement using particle swarm optimization technique*”, IEEE, pp. 209-214, 2011.
- [66] Zhao, B., Guo, C.X. and Cao, Y.J., “*A multiagent-based particle swarm optimization approach for optimal reactive power dispatch*”, IEEE Trans. on Power Syst., Vol. 20, No. 2, pp. 1070-1078, May 2005.
- [67] Huang, C.M., Huang, C.J. and Wang, M.L., “*A particle swarm optimization to identifying the ARMAX model for short-term load forecasting*”, IEEE Trans. On Power Syst., Vol. 20, No. 2, pp. 1126-1133, May 2005.
- [68] Dash, P.K. and Mallick, R.K., “*Accurate tracking of harmonic signals in VSC-HVDC systems using PSO based unscented transformation*”, I.J. of Electrical Power and Energy Syst., Vol. 33, No. 7, pp. 1315-1325, Sept. 2011.
- [69] Lopez, P.R., Gonzalez, M.G., Reyes, N.R. and Jurado, F., “*Optimization of biomass fuelled systems for distributed power generation using particle swarm optimization*”, Electric Power Syst. Research, Vol. 78, No. 8, pp. 1448–1455, Aug. 2008.
- [70] El-Ela, A.A.A., Fetouh, T., Bishr, M.A. and Saleh, R.A.F., “*Power systems operation using particle swarm optimization technique*”, Electric Power Syst. Research, Vol. 78, No. 11, pp. 1906–1913, Nov. 2008.
- [71] Liao, R., Zheng, H., Grzybowski, S. and Yang, L., “*Particle swarm optimization-least squares support vector regression based forecasting model on dissolved gases in oil-filled power transformers*”, Electric Power Syst. Research, Vol. 81, No. 12, pp. 2074–2080, Dec. 2011.
- [72] Abido, M.A., “*Optimal power flow using particle swarm optimization*”, I.J. on Electrical Power and Energy Syst., Vol. 24, No. 7, pp. 563-571, Oct. 2002.
- [73] Kim, J.Y., Mun, K.J., Kim, H.S. and Park, J.H., “*Optimal power system operation using parallel processing system and PSO algorithm*”, I.J. of Electrical Power and Energy Syst., Vol. 33, No. 8, pp. 1457–1461, Oct. 2011.

- [74] Arya, L.D., Titare, L.S. and Kothari, D.P., “*Improved particle swarm optimization applied to reactive power reserve maximization*”, I.J. Electrical Power and Energy Syst., Vol. 32, No. 5, pp. 368–374, June 2010.
- [75] Naka, S., Genji, T., Yura, T. and Fukuyama, Y., “*Distribution state estimation considering nonlinear characteristics of practical equipment using hybrid particle swarm optimization*”, IEEE, pp. 1083-1088, 2000.
- [76] Shunmugalatha, A. and Slochanal, S.M.R., “*Optimum cost of generation for maximum loadability limit of power system using hybrid particle swarm optimization*”, I.J. Electrical Power and Energy Syst., Vol. 30, No. 8, pp. 486–490, Oct. 2008.
- [77] Victoire, T.A.A. and Jeyakumar, A.E., “*Hybrid PSO–SQP for economic dispatch with valve-point effect*”, Electric Power Systems Research, Vol. 71, No. 1, pp. 51–59, Sept. 2004.
- [78] Coelho, L.D.S. and Lee, C.S., “*Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches*”, I.J. Electrical Power and Energy Syst., Vol. 30, No. 5, pp. 297–307, June 2008.
- [79] Wang, L. and Singh, C., “*Environmental/economic power dispatch using a fuzzified multi-objective particle swarm optimization algorithm*”, Electric Power Syst. Research, Vol. 77, No. 12, pp. 1654–1664, Oct. 2007.
- [80] Wang, L. and Singh, C., “*Balancing risk and cost in fuzzy economic dispatch including wind power penetration based on particle swarm optimization*”, Electric Power Syst. Research, Vol. 78, No. 8, pp. 1361–1368, Aug. 2008.
- [81] Liang, R.H. Tsai, S.R., Chen, Y.T. and Tseng, W.T., “*Optimal power flow by a fuzzy based hybrid particle swarm optimization approach*”, Electric Power Syst. Research, Vol. 81, No. 7, pp. 1466–1474, July 2011.
- [82] Moradi, M.H. and Abedini, M., “*A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems*”, I.J. Electrical Power and Energy Syst., Vol. 34, No. 1, pp. 66–74, Jan. 2012.
- [83] Gnanambal, K. and Babulal, C.K., “*Maximum loadability limit of power system using hybrid differential evolution with particle swarm optimization*”, I.J. Electrical Power and Energy Syst., Vol. 43, No. 1, pp. 150–155, Jan. 2012.
- [84] Millonas, M.M., “*Swarms, phase transitions and collective intelligence*”, Complex Systems Group, Theoretical Division and centre for non-linear studies, MS.B258. Los

Alamos National Laboratory, Los Alamos, NM87545 and Santa Fe Institute, Santa, NM, pp. 1-32.

- [85] Zhou, D., Gao, X., Liu, G., Mei, C., Jiang, D. and Liu, Y., “*Randomization in particle swarm optimization for global search ability*”, *Expert Systems with Applications*, Vol. 38, No. 12, pp. 15356-15364, Nov.-Dec. 2011.