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Research Article

A Solution to Unit Commitment Problem via Dynamic Programming and Particle Swarm Optimization

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Abstract

The optimization problem while committing the units is minimizing the entire production cost, at the same time meeting the demand and fulfilling the equality and inequality limits. In order to supply adequate power to the consumers in a cost-effective and secured way the commitment of thermal units is the best option available. The commitment of generating units is done depending upon the prediction of upcoming demand. For getting a way out to the unit commitment problem there are numerous conventional and advanced programming practices used. For solving the deterministic problem the conventional dynamic programming algorithm is employed. In this paper DP is used to solve the unit commitment problem. In this paper Particle swarm optimization technique is used which is population based global searching optimization technique to solve the unit commitment problem, for committing the units optimally. It is arrived from the exploration on the bird and fish flocking movement behavior. For the straightforward implementation of the algorithm it is extensively used and rapidly developed and few particles are needed to be attuned. An algorithm was developed to attain a way out to the unit commitment problem using Particle Swarm Optimization technique. The effectiveness of the algorithm was tested on two test systems. The first system comprising of three units and the second system is an IEEE 30-bus system and the attained results using the two methods are compared for total operating cost.

Keywords: *Unit Commitment, Dynamic Programming, Particle Swarm Optimization Algorithm.*

1. Introduction

In the power system the load is not stable and it varies from hour to hour, day to day and reaches different peak values from one day to other day. At each period there will be distinct isolated load levels. So it is not worthwhile to run all the existing units all the time. It is essential to forecast the starting up of the units, connection of the units to the network, the order for shutting down the units and the time period for the units to be in off state (Vinod puri *et al*, 2012;Sivanagaraju, S, 2009). Today's energy shortage has made this forecasting task increasingly significant. In most of the unified power systems, the power obligation is predominantly met by thermal power generation. It results in excellent saving for electric utilities. While Scheduling the operation of the generating units at minimum operating cost at the same time fulfilling the equality and inequality limits is the optimization crisis involved in commitment of the units**.** The high dimensionality and combinatorial nature of the unit commitment problem curtails the attempts to develop any rigorous mathematical optimization method capable of solving the whole problem for any real-size system. For both deterministic and stochastic loads the unit commitment problem is applicable. The deterministic approach provides us definite and unique conclusions. However the faithful results are not obtained for stochastic loads. Nevertheless the constraints are changed into controlling constraints in stochastic models and then by any of the usual algorithms the formulation can be worked out. In state enumeration method the UC problem is solved by detailing all probable amalgamations of the generating units and then the combination that gives the smallest amount of the cost of operation is selected as the best possible solution (Sivanagaraju, S, 2009; Padhy, N.P, *et al*, 2004). While considering the priority list method for the committing the units, replication time and memory are saved, and it can also be pertained in a genuine power system. In contrast, the priority list method has shortcomings that consequence into suboptimal solutions since it won't consider each and every one of the possible combinations of generation (Padhy, N.P, *et al*, 2004). Dynamic programming is the one of the methodologies which gives optimal solution. To provide eminence solutions to the UC problem numerous solution approaches are proposed. These include autocratic and hypothetical search approaches (Padhy, N.P, *et al*, 2004; Vijay Kumar Shukla, *et al*, 2012). Autocratic approaches include the Priority List method (Senjyu, T, *et al*, 2003; Senjyu, T, *et al*, 2006), Dynamic Programming (Wood, A.

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J, 1996; Navpreet Singh Tung, *et al*, 2012; Saravanan, B, *et al*, 2013; Pang, C. K, *et al*, 1981; Muralidharan, S, *et al*, 2011), Lagrangian Relaxation (Virmani, S, *et al*, 1989) and the Branch and Bound methods. Even though the autocratic methods are simple and fast, they suffer from mathematical convergence and way out eminence problems. The hypothetical search algorithms such as particle swarm optimization (Kennedy, J, *et al*, 1995; Valle, Y, *et al*, 2008; Yuan, X, *et al*, 2009; Rama Krishna, P. V, *et al*, 2012; Kwang Y. Lee, *et al*, 2010; Lala Raja Singh, R, *et al*, 2010; Andries P, *et al*, 2007), genetic algorithms, evolutionary programming, and ant colony optimization are able to triumph over the limitations of conventional optimization methods**.** The new optimization technique explicitly the particle swarm optimization technique is employed to get a way out to the unit commitment problem in sort of acquiring minimum operating cost. The amount of decision variables is enormously reduced by this formulation. PSO is a popular optimization method outstanding to its minimalism, stoutness and reduced consumption of computing time attribute over other methods. Particle swarm optimization is used for solving the unit commitment problem due to straightforwardness and less parameter modification. This paper provides a detailed analysis of the unit commitment problem solution using Dynamic Programming method. In this paper an algorithm using PSO was developed for finding a solution to unit commitment problem.

2. Formulation of Unit Commitment Problem

The intent of the UC problem is minimizing the total operating cost in order to meet the demand. It is assumed that the production cost, PC_j for unit 'j' in a given time interval is a quadratic function of the output power of the generator, P_j.

$$F_j(P_j) = a_j P_j^2 + b_j P_j + c_j \quad (1)$$

Where a_j, b_j, c_j are the corresponding unit's cost coefficients. For the scheduling period 'T' the sum of the production cost's obtained from the corresponding committed units gives the total operating cost, OC_T.

$$OC_T = \sum_{t=1}^{T} \sum_{j=1}^{N} PC_{j,t} U_{j,t} \quad (2)$$

Where $U_{j,t}$ is a binary variable to signify the on/off status of the unit 'j' at time t. The objective is to lessen OC_T subjected to a number of constraints. The assumption is that the total system demand is supplied by all the generators connected to the same bus. The following constraints are included:

2.1Power Balance Constraint

The total generated power and load at corresponding hours must be equal.

$$\sum_{j=1}^{N} P_{j,t} U_{j,t} = P_D \quad (3)$$

2.2Power Generation Limits

The generated power of a unit should be within its minimum and maximum power limits.

$$P_{jmin} \leq P_j \leq P_{jmax} \quad (4)$$

3. Dynamic Programming Method

The basis for Dynamic Programming (DP) is the theory of optimality elucidated by Bellman in 1957. This method can be used to explain crises in which many chronological conclusions are to be taken in defining the optimum operation of a system, which consists of distinct number of stages. The searching may be in forward or backward direction**.** (Wood, A. J, 1996; Navpreet Singh Tung, *et al*, 2012). Within a time period the combinations of units are known as the states. In Forward DP a excellent economic schedule is obtained by commencing at the preliminary stage amassing the total costs, then retracing from the combination of least accumulated cost starting at the last stage and finishing at the initial stage. The stages of the DP problem are the periods of the study horizon. Each stage usually corresponds to one hour of operation i.e., combinations of units steps forward one hour at a time, and arrangements of the units that are to be scheduled are stored for each hour. Finally, by backpedaling from the arrangement with smallest amount of total cost at the final hour throughout the finest path to the arrangement at the preliminary hour the most economical schedule is acquired (Saravanan, B, *et al*, 2013; Pang, C. K, *et al*, 1981). The estimation of each and every combination is not convenient evidently. Additionally, several of the combinations are prohibited due to insufficient existing capacity. The step by step procedure for dynamic programming approach is as follows**:**

1) Start randomly by considering any two units.
2) Assemble the collective output of the two units in the form of discrete load levels.
3) Determine the most economical combination of the two units for all the load levels. It is to be observed that at each load level, the economic operation may be to run either a unit or both units with a certain load sharing between the two units.
4) Obtain the more cost-effective cost curve for the two units in discrete form and it can be treated as cost curve of single equivalent unit.
5) Add the third unit and the cost curve for the combination of three units is obtained by repeating the procedure.
6) Unless all the existing units are considered the procedure is repeated.

The benefit of this method is that having the best way of running N units, it is simple to find out the best way for running N + 1 units. The DP approach is based on the subsequent recurring equation**.**

$$F_M(P) = \min[f_M(Q) + F_{M-1}(P - Q)] \quad (5)$$

Where $F_M(P)$ is the minimum cost in Rs. /hr of generation of P MW by M generating units. $f_M(Q)$ is the cost of generation of Q MW by Mth unit. $F_{M-1}(P - Q)$ is the minimum cost of generation of (P-Q) MW by the remaining (M -1) units**.** In its elemental form, the dynamic programming algorithm for unit commitment problem inspects every possible state in every interval. The dimensionality of the problem is significantly declined which is the chief advantage of this technique. The postulations for structuring the step by step procedure for dynamic programming method are tracked below:

1) A state consists of a group of units with only precise units in service at a time and the remaining off-line.
2) While the unit is in off state the start-up cost of a unit is independent of the time specifically it remains fixed.
3) For closing the unit there will be no cost involved.
4) The order of precedence is firm and a small quantity of power must be in operation in each interval**.**

The flow chart for DP method is shown in Fig. 1

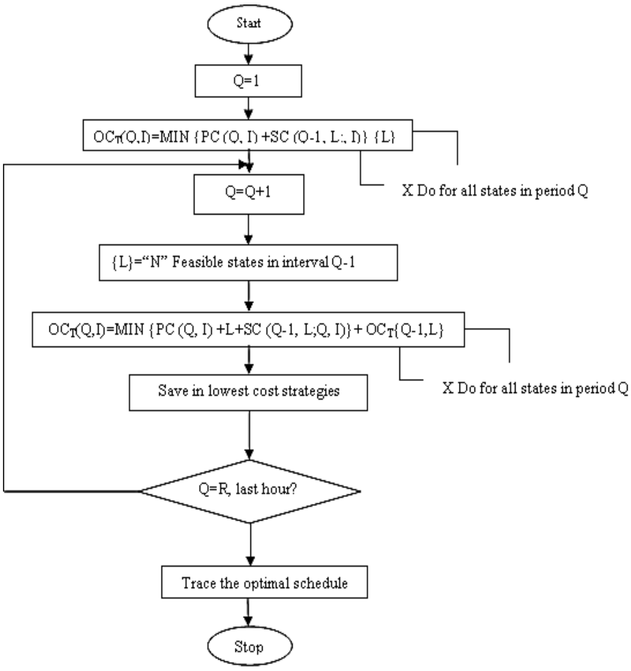

Fig.1 Flow chart for Dynamic Programming method

The major competent cost-effective combination of units can be well determined using the recursive relation**.** Considerable computational saving can be attained by using this method. It is not obligatory to solve the co-ordination equations. The total figure of units accessible, their individual cost characteristics and load cycle are supposed to be known. Only when the operations at the earlier stages are not affected by the decisions at the later stages this method is appropriate.

4. Particle Swarm Optimization

It is a stochastic, population based search and optimization technique like many other bio-inspired algorithms. Swarm intelligence is the basis for this efficient evolutionary computational procedure. James Kennedy and Russell Eberhert developed it in 1995 (Kennedy, J, *et al*, 1995; Valle, Y, *et al*, 2008). Fish schooling and bird flocking are the two explicit insights for this method. For an ample mixture of search and optimization crises it has been applied effectively. In PSO, entities converse either straightly or tortuously with one another. It is a straightforward technique and necessitates less parameter. It emulates the human (or insects) social behavior**.** The entities in the population are named as particles (Yuan, X, *et al*, 2009; Rama Krishna, P. V, *et al*, 2012). Each particle in the swarm stands for a feasible way out to the existing problem of optimization. The conventions for the particle movement throughout the space are made-up from the simple flocking rules. If a particle discovers capable innovative solution, all supplementary particles will move closer to it, by more systematically searching the solution space (Lala Raja Singh, R, *et al*, 2010). Individuals interrelate with one another while learning from their individual knowledge, and slowly the population entities shift into superior areas of the problem space. The fitness values of all the individuals are estimated by the fitness function which is to be optimized.

As an optimization tool, PSO provides a population based exploring process in which individuals alter their location with time. The flying of the particles is directed by their velocities. In the investigation each particle memorizes its own best location found so far. This location is called the personal best and is denoted by P_{best}. Additionally amongst the P_{best} values acquired the best fitness is specified by merely one particle, which is called the global best, denoted by G_{best} (Rama Krishna, P. V, *et al*, 2012). The updating of particle's position as well as the velocity must be done. According to the fitness values of the restructured individuals the P_{best} and G_{best} locations are restructured. The regulation in the direction of P_{best} and G_{best} locations by the particle swarm optimizer is theoretically analogous to the crossover operation employed by genetic algorithms. The update equations for the velocity and position are given by

$$V_i^{t+1} = V_i^t + c_1 r_1^t (P_{besti}^t - x_i^t) + c_2 r_2^t (G_{best}^t - x_i^t) \quad (6)$$

$$x_i^{t+1} = x_i^t + V_i^{t+1} \quad (7)$$

c_1, c_2: acceleration coefficients
x: The location of the particle,
r_1, r_2: Two independently engendered evenly dispersed random numbers between 0 and 1.
W: inertia weight.
V_i^t : The particle's rapidity (velocity) in ith dimension.
For updating the velocities in PSO, a particle is persuaded by its P_{best} and G_{best} positions. The searching of the

optimum solution is done by regulating the flight of the particle towards its P_{best} and G_{best} locations.

4.1Particle swarm optimization fundamental algorithm

1. Preliminarize the swarm by conveying a random position in the problem search space to each particle.
2. Using the current location of each particle the fitness function is evaluated to find out the P_{best}.
3. Compare the particle's fitness value with its P_{best} for each individual particle. If the existing value is superior to the P_{best} value, then place this value as the P_{best} and the recent position of the particle x_i as p_i.
4. The particle having the best fitness value among the P_{best} values is identified. The fitness function value is recognized as G_{best} and its location as p_g..
5. Now the velocities and positions are updated for all the particles.
6. Until an ending condition is met i.e., maximum number of iterations or a sufficiently good fitness value is obtained the steps 2-5 are repeated.

4.2 PSO Algorithm Parameters

The performance of the PSO algorithm is influenced by a number of parameters (Umarani, R, *et al*, 2010).Some of these parameter's values and their selections for any given optimization problem, have large impact on the effectiveness of the PSO method and other parameters have small or no consequences**.** The fundamental parameters of the PSO algorithm are swarm size or number of particles or population size, number of iterations, velocity components, acceleration coefficients and inertia weight exemplified below.

4.2.1 Population size

The number of particles 'n' in the swarm is defined as population size or swarm size. A huge swarm engenders to cover larger parts of the search space per iteration. Reduction in number of iterations is done by considering a large number of particles needed to acquire an excellent optimization result (Umarani, R, *et al*, 2010; Andries P, *et al*, 2007). The computational complexity per iteration is increased by considering huge amounts of particles in contrast and is additionally time consuming. Most of the PSO implementations use an interval of $\mathbf{n \in [20, 60]}$ for the swarm size which is proved from a number of experimental studies.

4.2.2 Number of iterations

To obtain a good result the number of iterations required is crisis-dependent. The search process might be prematurely stopped by considering too lesser number of iterations, while too large number of iterations results in redundant supplementary computational complication and more time is needed.

4.2.3 Velocity equation constituents

For updating particle's velocity, the velocity components are very essential (Andries P, *et al*, 2007). By means of the global best and individual best values of each the particle, the i^{th} particle velocity in the j^{th} dimension is restructured according to the (6). There are three terms in the particle's velocity equation.

1. The first term V_{ij}^t is called inertia component. It affords a remembrance of the prior direction of flight that means movement in the abrupt past. This term represents as an impetus which avoids to considerably changing the path of the particles and to bias towards the existing path.
2. The second term $c_1 r_{1j}^t \left[P_{best,i}^t - x_{ij}^t\right]$ is called cognitive component. The performance of the particles is assessed relative to past performances by this term. It seems to be like an individual memory of the best position of the particle. The result of this component corresponds to the affinity of individuals to return to positions that fulfilled them mainly in the earlier period.
3. The third term is $c_2 r_{2j}^t [G_{best} - x_{ij}^t]$ called social component which assesses the performance of the particles comparative to a cluster of particles or neighbors. The effect of this component is that each and every particle flies towards the best position found by the neighborhood of the particle.

4.2.4 Acceleration coefficients

The acceleration coefficients c_1 and c_2, collectively with the arbitrary values r_1 and r_2, retain the stochastic authority of the cognitive and social components of the particle's velocity correspondingly. The constant c_1 conveys a great deal of assurance a particle has in itself, while c_2 conveys a great deal of assurance a particle has in its neighbors.

4.2.5 Inertia weight

The inertia weight, denoted by 'w', is considered to substitute V_{max} by amending the influence of the prior velocities in the process, i.e. it straightens the impetus of the particle by replicating on the involvement of the previous velocity (Andries P, *et al*, 2007). The inertia weight can be employed either as a rigid value or vigorously altering values. At every step the inertia weight 'w' is multiplied with the velocity of the previous time step, i.e. V_i^t. Consequently, in the gbest PSO, the velocity equation of the particle *i* with the inertia weight in j^{th} dimension is modified from equation (6) to (8)

$$V_{ij}^{t+1} = wV_{ij}^t + c_1 r_{1j}^t \left[P_{best,i}^t - x_{ij}^t\right] + c_2 r_{2j}^t [G_{best}^t - x_{ij}^t] \quad (8)$$

5. Unit Commitment Using PSO

For solving the unit commitment problem the subsequent steps are used in the PSO procedure (Vinod puri *et al*, 2012):

1. A populace of particles p_i and additional variables are initialized. All particles are typically generated arbitrarily within acceptable range $P_{jmin} \leq P_j \leq P_{jmax}$ where P_j represents the power generated by j^{th} unit in the power system.
2.The parameters for instance figure of particles, the dimension of population, primary and ultimate inertia weight, particle's speed i.e., velocity, number of iterations etc.
3. The fitness function for the population is estimated.

$$OC_T = \sum_{t=1}^{T}\sum_{j=1}^{N} PC_{j,t}U_{j,t} \quad (9)$$

WherePC_j is$PC_j = a_j + b_jP_j + c_jP_j^2$. Each individual's fitness value is compared with its P_{best}. The finest fitness value amongst the P_{best} values is denoted as G_{best}.
4. Modify the individual's velocity V_i of each individual using the equation

$$V_i^{t+1} = wV_i^t + c_1r_1^t\left[P_{best,i}^t - x_i^t\right] + c_2r_2^t\left[G_{best}^t - x_i^t\right] \quad (10)$$

5. Revise the individual's position xi using

$$x_i^{t+1} = x_i^t + V_i^{t+1} \quad (11)$$

6. If each individual's estimation value is better than the prior P_{best}, the present value is located as P_{best}. If the finest P_{best} is superior to G_{best} the value is taken as G_{best}.
7. If the termination criteria i.e., the number of iterations attains the utmost value then go to step 8, else go to step 3.
8. Evaluate the total cost, power distribution between the units, number of units committed.
9. The individual that engenders the newest G_{best} is the best possible power generated by each unit with the least total generation cost.

The advantages (benefits) of PSO technique are:
1. It can be simply planned and customized with fundamental arithmetic and logical functions.
2. It is economical in terms of calculation time and remembrance.
3. It necessitates tuning of fewer parameters.
4. It is capable of being incorporated easily with other optimization tools to shape hybrid ones.
5. It is less susceptible to a superior premature solution because it is a population – based method

The flow diagram for Particle Swarm Optimization applied to unit commitment is shown in Fig.2

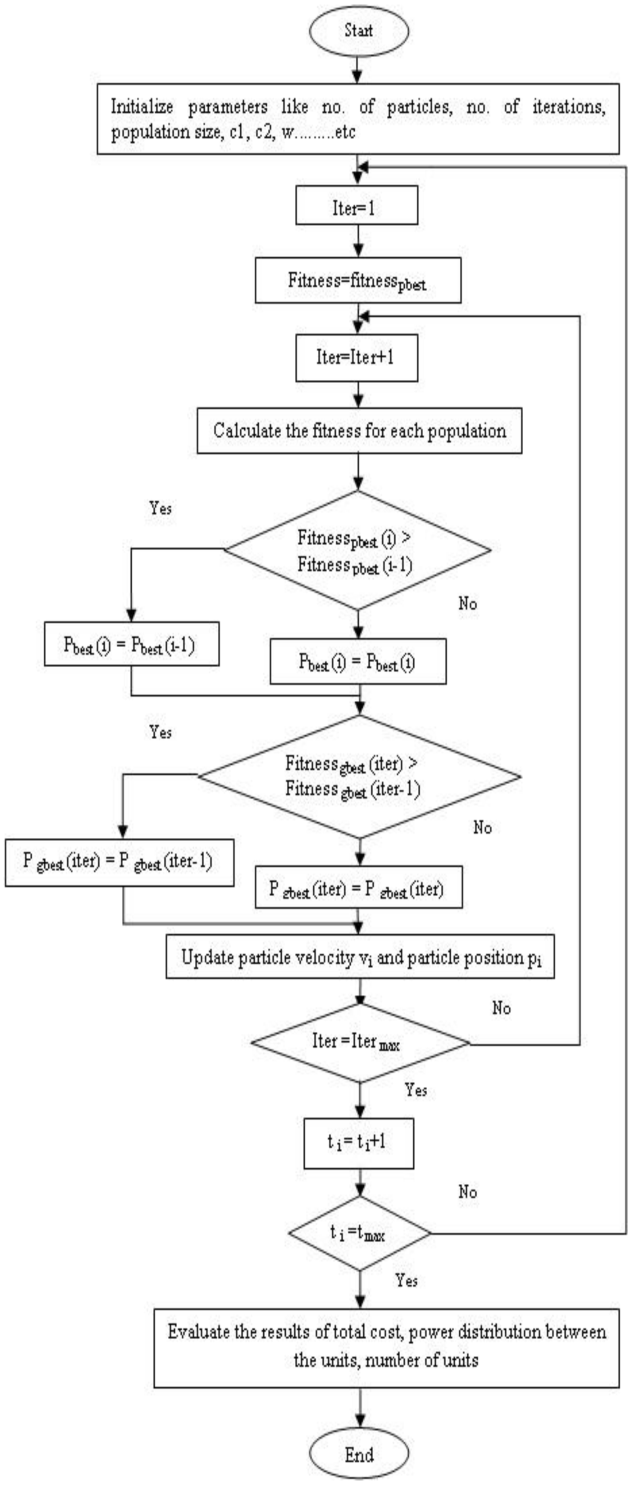

Fig.2 Flow chart for PSO applied to unit commitment

Table 1 Data pertaining to the units for test system 1

Unit	Min(MW)	Max(MW)	a($/MW^{2}H)	b($/MWH)	c($/H)
1	100	600	0.001562	7.92	561
2	100	400	0.001940	7.85	310
3	50	200	0.004820	7.97	78

Table 2 Load data for test system 1

Hour	1	2	3	4	5	6	7	8	9	10	11	12
load	1200	1200	1150	1100	1000	900	800	600	550	500	500	500
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load	500	500	600	800	850	900	950	1000	1050	1100	1200	1200

Table 3 Unit Commitment using Dynamic Programming

S.no	LOAD	UC	Allocation of load between the units			Total Cost($)
			P1	P2	P3	
1	1200	1 1 1	600	400	200	11500.52
2	1200	1 1 1	600	400	200	11500.52
3	1150	1 1 1	550	400	200	11014.705
4	1100	1 1 1	550	400	150	10531.855
5	1000	1 1 1	460.8794	389.1205	150	9583.2395
6	900	1 1 1	405.4825	344.5174	150	8655.9138
7	800	1 1 0	450	350	0	7736.455
8	600	1 0 0	600	0	0	5875.32
9	550	1 0 0	550	0	0	5389.505
10	500	1 0 0	500	0	0	4911.5
11	500	1 0 0	500	0	0	4911.5
12	500	1 0 0	500	0	0	4911.5
13	500	1 0 0	500	0	0	4911.5
14	500	1 0 0	500	0	0	4911.5
15	600	1 0 0	600	0	0	5875.32
16	800	1 1 0	450	350	0	7736.455
17	850	1 1 1	405.4825	344.5174	0	8197.1638
18	900	1 1 1	405.4825	344.5174	150	8655.9138
19	950	1 1 1	433.1810	366.8189	150	9117.4134
20	1000	1 1 1	460.8794	389.1205	150	9583.2395
21	1050	1 1 1	500	400	150	10053.85
22	1100	1 1 1	550	400	150	10531.855
23	1200	1 1 1	600	400	200	11500.52
24	1200	1 1 1	600	400	200	11500.52
			Total operating cost			199097.7838

Table 4 Parameters for PSO

Parameter	Value
Population size	50
Number of iterations	500
Cognitive constant, c1	2
Social constant, c2	2
Inertia weight, W	0.3-0.95

Table 5 Unit Commitment using PSO

S.no	LOAD	UC	Allocation of load between the units			Total Cost($)
			P1	P2	P3	
1	1200	1 1 1	600	400	200	11500.52
2	1200	1 1 1	600	400	200	11500.52
3	1150	1 1 1	570.354	400	179.6458	11012.0512
4	1100	1 1 1	532.5916	400	167.4083	10529.9199
5	1000	1 1 1	461.5	363.6	174.9	9588.892
6	900	1 1 1	444.6	345.7	109.6	8655.9933
7	800	1 1 1	381.3	302.1	116.7	7740.2747
8	600	0 1 1	0	400	200	5625.2
9	550	1 0 1	426.8	0	123.1	5357.9345
10	500	0 1 1	0	364.4	135.5	4674.5788
11	500	0 1 1	0	364.4	135.5	4674.5788
12	500	0 1 1	0	364.4	135.5	4674.5788
13	500	0 1 1	0	364.4	135.5	4674.5788
14	500	0 1 1	0	364.4	135.5	4674.5788
15	600	0 1 1	0	400	200	5625.2
16	800	1 1 1	381.3	302.1	116.7	7740.2747
17	850	1 1 1	414	296	140.1	8200.3796
18	900	1 1 1	444.6	345.7	109.6	8655.9933
19	950	1 1 1	416.4	386.6	146.8	9116.3512
20	1000	1 1 1	461.5	363.6	174.9	9588.892
21	1050	1 1 1	511	387	152	10055.2941
22	1100	1 1 1	532.5916	400	167.4083	10529.9199
23	1200	1 1 1	600	400	200	11500.52
24	1200	1 1 1	600	400	200	11500.52
			Total operating cost			197397.5459

Table 6 Comparison of two methods for test system 1

Method	Total operating cost
Particle Swarm Optimization	**197397.5459**
Dynamic Programming	199097.7838

Table 7 Data for test system 2

Unit	Min(MW)	Max(MW)	a($/MW^{2}H)	b($/MWH)	c($/H)
1	50	200	0.0037	2.0000	0
2	20	80	0.0175	1.7500	0
3	15	50	0.0625	1.0000	0
4	10	35	0.0083	3.2500	0
5	10	30	0.0250	3.0000	0
6	12	40	0.0250	3.0000	0

Table 8 Unit Commitment result for test system 2

Method	UC schedule	Allocation of load among the units						Total cost($)
		P1	P2	P3	P4	P5	P6	
PSO	111100	196.1964	50.2045	19.0928	17.9063	0	0	**769.5164**
Dynamic programming	111000	186.768	46.6311	50	0	0	0	828.511

6. Results and Discussion

6.1 Test system 1

Three units are to be considered to serve 24-h load pattern. Data concerning the units and load pattern is given in tables 1 and 2.

A comparison of total operating cost using the two discussed methods is done. The optimum parameters for the implementation of PSO are shown in Table 4. Tables 3 and 5 represent the results for unit commitment problem via Dynamic Programming method and Particle swarm optimization method. The first column represents the hour. The second column represents the load corresponding to the hour, the third column represents the commitment of units i.e., the units committed for the load. P1, P2, P3 represent the power generation from units 1, 2 and 3. The fourth column represents the allocation of load among the units and the last column represents the total cost obtained by committing the units. The last row in tables 3 and 5 represents the total operating cost obtained for 24-h load cycle. Table 6 gives the Comparison of the two methods for total operating cost. From the last column of the table 6 it is shown that the total operating cost obtained using the Particle Swarm Optimization method is minimum compared to DP method.

6.2 Test system 2

In this an IEEE standard 30-bus system with 6 generator units is taken (Rahmat, N, *et al*, 2013). The data for test system is given in table 7. The result obtained for the system using DP and PSO methods for a load of 283.4MW is shown in Table 8. The first column in the table indicates the method used for solving the UC problem. The second column indicates the scheduling of the units for the load given. The third column indicates the allocation of load among the units.P1, P2, P3, P4, P5, P6 represent the power generation from corresponding units 1, 2,3,4,5 and 6. The last column gives the total cost attained by committing the units. From the last column of the table 8 it is shown that the total operating cost obtained using the Particle Swarm Optimization method is minimum compared to DP method.

Conclusion

The optimal unit commitment of thermal systems resulted in enormous saving for electrical utilities. The formulation of unit commitment was discussed and the solution is obtained using the Dynamic Programming and Particle Swarm Optimization methods. The results obtained from these methods are compared. It is found that the total operating cost obtained from the solution of unit commitment using particle swarm optimization is minimum compared to the outcomes obtained using the Dynamic Programming method.

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