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Multi-Area Unit Commitment Using Hybrid Particle Swarm Optimization Technique with Import and Export Constraints

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Abstract

This paper presents a novel approach to solve the Multi-Area unit commitment problem using particle swarm optimization technique. The objective of the multi-area unit commitment problem is to determine the optimal or a near optimal commitment strategy for generating the units. And it is located in multiple areas that are interconnected via tie lines and joint operation of generation resources can result in significant operational cost savings. The dynamic programming method is applied to solve Multi-Area Unit Commitment problem and particle swarm optimization technique is embedded for computing the generation assigned to each area and the power allocated to all committed unit. Particle Swarm Optimization technique is developed to derive its Pareto-optimal solutions. The tie-line transfer limits are considered as a set of constraints during the optimization process to ensure the system security and reliability. Case study of four areas each containing 26 units connected via tie lines has been taken for analysis. Numerical results are shown comparing the cost solutions and computation time obtained by using the Particle Swarm Optimization method is efficient than the conventional Dynamic Programming and Evolutionary Programming Method.

Keywords: Multi-Area Unit Commitment, Evolutionary Programming, Dynamic Programming Method, Particle Swarm Optimization Method

1. Introduction

In an interconnected system, the objective is to achieve the most economical generation that could satisfy the local demand without violating tie-line capacity constraints. Due to inter-area transmission constraints, multi-area unit commitment problems (MAUC) are very complicated when compared with single-area unit commitment problems. Research explores that the application of these existing single-area unit commitment to multi-area unit commitment problem is required [1–4].

Furthermore, unit commitment is treated, as separately from the economic dispatch, the linear fuel cost curve may be an expensive operation schedule or a violation of spinning reserve requirements. In multi-area systems, local generations are not equal to local load demands. Areas with lower fuel cost units may generate more power than their demand and export the excessive energy to the deficient areas; likewise, areas with higher fuel cost units will generate less power than their demand and import the additional energy from other areas with surplus capacity. So, the unit commitment of an area should comply with the local generation as well as the local load demand. References [5–11] provide comprehensive study on multi-area scheduling by relating unit commitment and economic dispatch with tie-line constraints. The following paragraph discusses some of the method, which is adopted in the multi-area unit commitment problem and their implications.

There are some drawbacks in implementing the simple priority list method for unit commitment. Although the technique was fast, the results are far from optimal, especially when there are massive on/off transitions. Another difficulty is in which did not deal with topological connections in a multi-area system as it considered export/import limitations, which would cause infeasible solutions in many applications. Another approach [6] overcame the previous difficulties. It considered the topological constraints and enhanced unit commitment with economic dispatch .The λ iteration method takes excessive time in finding the optimal solution in large-scale power systems and the speed of the algorithm required some improvement. In the iterative procedure between unit commitment and economic dispatch, there is a need to adjust the unit commitment according to the required area generation. If we use Dynamic Programming Sequential Combination (DP-SC) for unit commitment in a power pool, the search for an optimal solution is very time consuming. If we adopt the priority list method, there may be a solution gap between the resultant schedule and the actual economic operation schedule. If we repeat the process, we may reduce the operation cost, but it will demand a longer execution time. The DP-SC method is used for unit–commitment problem in an interconnected area and particle swarm optimization technique is embedded for assigning generation to each area and modifying the economic dispatch schedule.

In this paper, we propose a more efficient approach to the multi-area generation dispatch problem. The proposed technique is used to improve the speed and reliability of the optimal search process. Instead of using λ iteration method in assigning power generation to each area, we used particle swarm optimization to find the optimal allocation of power generation in each area and entire system. Using particle swarm optimization techniques in each area and entire system, we can save time in performing the economic dispatch and operating cost.

The meta-heuristic methods [12–19] are iterative techniques that can search not only local optimal solutions but also a global optimal solution depending on the problem domain and time limit. In the meta-heuristic methods, the techniques frequently applied to the UC problem are genetic algorithm (GA), tabu search (TS), evolutionary programming (EP), simulated annealing (SA), particle swarm optimization (PSO), etc. They are general-purpose search techniques based on the principles inspired from the genetic and evolution mechanisms observed in natural systems and populations of living beings. These methods have the advantage of searching the solution space more thoroughly. The main difficulty is their sensitivity to the choice of parameters.

In this paper, section one introduces that the mathematical model of the multi-area unit commitment problem. In the problem formulation, DP method is used for committing the unit in each area and λ iteration method is used for importing and exporting power to other area and minimizes the operating cost. Furthermore, tie-line transfer capacities and area spinning reserve requirements are also incorporated in order to ensure system security and reliability. The Reserve-sharing scheme is used to enable the area without enough capacity to meet its reserve demand. The objective of MAUC, constraints and conditions of optimal solution are also discussed in this section. Section 3 and 4 explains the EP and PSO algorithm adopted for importing and exporting power to other area. Section 5 gives the results of a case study each one based on a four-area system. A four-area IEEE test power system [6] is then used as an application example to verify the effectiveness of the proposed method through numerical simulations. A comparative study is also made here to illustrate the different solutions obtained based on conventional, EP and PSO methods. Conclusions are presented in the last section.

2. Problem Formulation

The cost curve of each thermal unit is in quadratic form

$$F(Pg_i^k) = a_i^k (Pg_i^k)^2 + b_i^k (Pg_i^k) + c_i^k \text{ :\$/hr k=1 } N_A \tag{1}$$

The incremental production cost is therefore

$$\lambda = 2a_i^k Pg_i^k + b_i^k \tag{2}$$

or

$$Pg_i^k = \lambda - b_i^k \;/ 2a_i^k \tag{3}$$

The start up cost of thermal unit is an exponential function of the time that the unit has been off

$$S(X_{i,j}^{off}) = A_i + B_i(1 - e^{X_{i,j}^{off}}) \tag{4}$$

2.1. Multi-Area Unit Commitment

The objective function for the multi-area unit commitment is to minimize the entire power pool generation cost as follows:

$$\min_{I,P} \sum_{k=1}^{N_A} \sum_{j=1}^{t} \sum_{i=1}^{N_k} [I_{i,j}^k F_j^k (Pg_{i,j}^k) + I_{i,j}(1 - I_{i,j-1}) S_i (X_{i,j-1}^{off})] \tag{5}$$

and the following constraints are to be met for optimization

1) System power balance constraints

$$\sum_k Pg_j^k = \sum_k D_j^k + W_j ; j = 1.......t \tag{6}$$

where $\sum_k Pg_j^k = \sum_k Pg_{i,j}^k$

2) Spinning reserve constraints in each area

$$\sum_i \overline{Pg_i^k} \geq D_j^k + R_j^k + E_j^k - L_j^k \text{ ;j=1...t} \tag{7}$$

3) Generation limits of each unit

$$\underline{Pg_j^k} \leq Pg_{i,j}^k \leq \overline{Pg_j^k} \text{ ;i=1...}N_k\text{;j=1...t;k=1...}N_A \tag{8}$$

4) Minimum Up and Down time constraints

$$(X_{i,j-1}^{off} - T_i^{on}) * (I_{i,j-1} - I_{i,j}) \geq 0 \quad (9)$$

$$(X_{i,j-1}^{off} - T_i^{off}) * (I_{i,j-1} - I_{i,j}) \geq 0 \quad (10)$$

To decompose the problem in Equation (5), it is re-written as

$$\min_{P} \sum_{j=1}^{t} [F(Pg_{i,j})] \quad (11)$$

where

$$F(Pg_{i,j}) = \sum_{k=1}^{N_k} F^k(Pg_{i,j}^k) \quad (12)$$

subject to the constraints of Equation (6) and (8) and following constraints.

5) Export/Import constraints

$$\sum_i Pg_{i.j}^k \leq D_j^k + E_{j\max}^k \quad (13)$$

$$\sum_i Pg_{i,j}^k \geq \sum_k D_j^k - L_{j\max}^k \quad (14)$$

$$\sum_i E_j^k - \sum_k L_j^k + W_j = 0 \quad (15)$$

6) Area generation limits

$$\sum_i Pg_{i,j}^k \leq \sum_i \overline{Pg_i^k} - R_j^k \;; k = 1 \ldots N_A \;; j = 1 \ldots t \quad (16)$$

$$\sum_i Pg_{i,j}^k \geq \sum_i \underline{Pg_i^k} \;; k = 1\, N_A \;; j = 1 \ldots t \quad (17)$$

Each $F^k(Pg_{i,j}^k)$ for $k = 1 \ldots, N_A$ is represented in the form of schedule tables, which is the solution of the mixed variables optimisation problem

$$\min_{I,P} \sum_i [I_{i,j}^k F_i^k(Pg_{i,j}^k) + I_{i,j}(1 - I_{i,j-1}) S_i(X_{i,j}^{off})] \quad (18)$$

Subject to constraints of Equation (7), (9-10) and initial on/off condition of each unit.

The multi-area unit commitment problem is solved by Dynamic Programming Sequential Combination (DP-SC) method to form the optimal generation scheduling approach. Among the available generating units in the interconnected multi-area system and the proposed method sequentially identifies, via a procedure that resembles bidding, the most advantageous units to commit until the multi-area system obligations are fulfilled and this method has been explained [13].

2.2. Multi-Area Economic Dispatch

The objective of Multi-area Economic Dispatch (MAED) is to determine the allocation of generation of each unit in the system and power exchange between areas so as to minimize the total production cost. The lamda–iteration method is implemented in the MAED to include area import and export constraints and tie-line constraints [15]

The objective is to select λ_{sys} every hour to minimize the operation cost.

$$Pg_j^k = D_j^k + E_j^k - L_j^k \quad (19)$$

where $Pg_j^k = \sum_{i=1}^{N_k} Pg_{i,j}^k$

Since the local demand D_j^k is determined in accordance with the economic dispatch within the pool , changes of P_{gj}^k will cause the spinning reserve constraint of Equation (7) to change accordingly and redefine Equation(18).

In this study, the iterative equal incremental cost method (λ method) was used to solve Equation (11) and serve as a coordinator between unit commitments in various areas. With the λ iteration, the system would operate at an optimal point if λ for each unit is equal to a system incremental cost λ_{sys} .Units may operate in one of the following modes when commitment schedule and unit generation limits are encountered:

1) Coordinate mode: The output of unit i is determined by the system incremental cost

$$\lambda_{\min,i} \leq \lambda_{sys} \leq \lambda_{\max,i} \quad (20)$$

2) Minimum mode: Unit i generation is at its minimum level.

$$\lambda_{\min,i} > \lambda_{sys} \quad (21)$$

3) Maximum mode: Unit i generation is at its maximum level.

$$\lambda_{\max,i} < \lambda_{sys} \quad (22)$$

4) Shut down mode: Unit i *is* not in operation, $Pg_i = 0$.

Besides limitations on individual unit generations, in a multi-area system, the tie-line constraints in Equation (9), (10) and (14) are to be preserved. The operation of each area could be generalized into one of three modes as follows:

Area coordinate mode

$$\lambda^k = \lambda_{sys} \quad (23)$$

$$D_j^k - L_{\max}^k \leq \sum_i P_{i,j}^k \leq D_j^k + E_{\max}^k \quad (24)$$

or

$$-L_{\max}^k \leq \sum_i Pg_{i,j}^k - D_j^k \leq E_{\max}^k \quad (25)$$

a. Limited export mode

When the generating cost in one area is lower than the cost in the remaining areas of the system, that area may generate its upper limit according to Equation (13) or (16), therefore,

$$\lambda^k < \lambda_{sys} \tag{26}$$

λ^k is the optimal equal incremental cost which satisfies the generation requirement in each area k.

b. Limited import mode

An area may reach its lower generation limit according to Equation (14) or (17), because of the higher generation costs.

$$\lambda^k_{\min} > \lambda_{sys} \tag{27}$$

The proper generation schedule in multi-area will result by satisfying tie-line constraints and minimizing the system generation cost.

2.3. Tie-Line Flow of Four Areas

An economically efficient area may generate more power than the local demand, the excess power will be exported to the other areas through the tie-lines. As shown in Fig. 1, assume area 1 has excess power, the line flows would have directions from area 1 to other areas, and the maximum power generation for area 1 would be the local demand in area 1 plus the sum of all the tie-line capacities connected to area 1. If we fix the area 1 generation at its maximum level, then the maximum power generation in area 2 could be calculated in a similar way to area 1.

Since tie-line imports power at its maximum capacity, this amount should be subtracted from the generation limit of area 2. According to the system power balance equation some areas must have a power generation deficiency, and require generation imports. The minimum generation level of these areas is the local demand, minus all the connected tie-line capacities. If any of these tie lines is connected to an area with higher deficiencies, then the flow directions should be reversed. The tie-line flow details of four area and directional matrix were presented in [9].

Directional matrix: It indicates power flow direction from one area to another area.

$D_{l,k}$ = [1 when line flows from l to k l >k [-1 when line flows from k to l

$D_{l,l} = 0, D_{l.k} = -D_{k,l}$ initial $D_{l.k}$ are zero

3. Evolutionary Programming Method

3.1. Introduction

EP is a mutation-based evolutionary algorithm applied to discrete search spaces. D. Fogel (Fogel, 1988)] extended the initial work of his father L. Fogel (Fogel, 1962) [15–18] for applications involving real-parameter optimization problems. Real-parameter EP is similar in prin

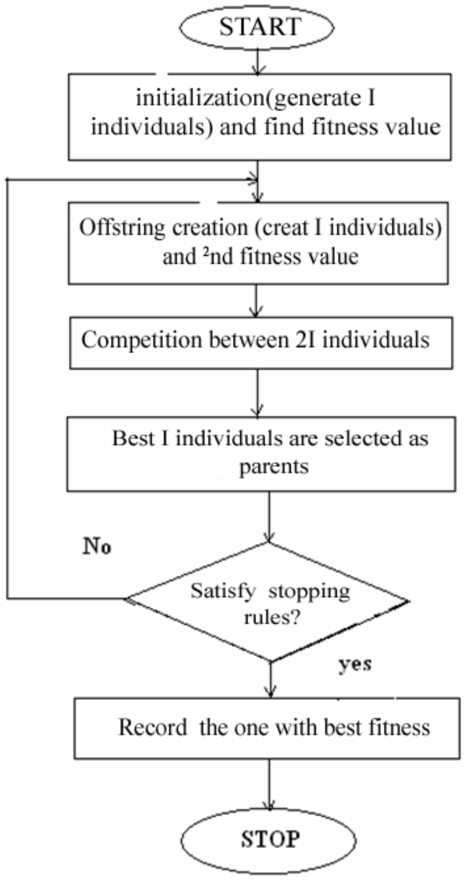

Figure 1. Flow chart for evolutionary algorithm.

ciple to evolution strategy (ES), in that normally distributed mutations are performed in both algorithms. Both algorithms encode mutation strength (or variance of the normal distribution) for each decision variable and a self-adapting rule is used to update the mutation strengths. Several variants of EP have been suggested (Fogel, 1992).

3.2. Evolutionary Programming Algorithm

The original Evolutionary Programming involved evolving populations of extending algorithms to develop artificial intelligence [17]. In this technique a strong behavioral link is sought between each parent and its offspring, at the level of the species.Fig.1 shows e general scheme of the EP algorithm.

3.3. Implementation of Evolutionary Algorithm for Multi-Area Unit Commitment Problem

Step (1): Read in unit data, tie-line data, demand profile.

Step (2): Perform the dynamic programming to get the initial commitment schedule for each area.

Step (3): Initialization of parent population. The initial parent population of size Np is randomly generated for committed unit in each area:

1) To generate the initial parent population

$$I_p = \left[(p_{g1}^{kp} .... p_{gN}^{kp})\right]; k = 1,2,3,4 \;\&\; p = 1,2...N_p; \quad (28)$$

2) To calculate the fuel cost for each population using Equation (1)

$$FC_p^K = [(a(Pg_1^{kp})^2 + b(Pg_1^{kp}) + c); k = 1,2,3,4 \;\&\; p = 1,2...N_p \quad (29)$$

3) To calculate the start up cost for each population using Equation (4)

4) To calculate the production cost Production

$$\text{cost}= FC_p^k + SC_p^k \quad (30)$$

5) To calculate the fitness function for each parent of population

$$F_P = FC_P^K + SC_P^K + K(\sum_{i=1}^{Nk} PG_i^{kp} - D_j^k) \quad (31)$$

The values of the penalty factor is chosen such that if there are any constraints violations then the fitness function value corresponding to that parent will be ineffective.

Step (4): Mutation

1) To generate an offspring population Io of size from Np from each parent Ip

$$I_O = [(Pg_1^{ko} .... Pg_N^{ko}); k = 1,2,3,4; 0 = 1.....N_p \quad (32)$$

generated as

$$Pg_i^{KO} = Pg_i^{KO} + N(0, \sigma^2 Pg_i^K); i = 1,2......N$$

Similarly all Pg_i is generated for all areas subjected to

$$\text{Pg}_i^{ko} = \text{Pg}_{i,\min}\;;\ \text{if}\ \text{Pg}_i^{ko} < \text{Pg}_{i,\min}$$

$$\text{Pg}_i^{ko} = \text{Pg}_{i,\max}\;;\ \text{if}\ \text{Pg}_i^{KO} > \text{Pg}_{i,\max} \quad (33)$$

$N(0,\sigma^2)$ represents a normal random variable with zero mean and standard deviation

$$\sigma_{Pg_i} = \beta * (F_{pi} / F_{\max}) * (\sigma_{ij,\max} - \sigma_{ij,\min}) \quad (34)$$

where β is scaling factor, F_{pi} is the value of fitness function corresponding to I_i and $F_{\max}$ is the maximum fitness function value among parent population

2) To compute the fitness value corresponding to each offspring using Equation (31)

Step (5): (competition and selection). The 2*I* individuals compete with each other for selection using Equation (6). A weight value W_i is assigned to each individual as follows:

$$W_i = \sum_{t=1}^{I} W_t \quad (35)$$

$$W_t = \{1, if \quad u < (f_t / f_t + f_i)$$

$$W_t = \{0, otherwise \quad (36)$$

where f_t is the fitness of the i^{th} competitor randomly selected from 2*I* individuals and *u* is a uniform random number ranging over [0, 1].While computing the weight for each individual, it is ensured that each individual is selected only once from the combined population. Even though relative fitness values are used during the process of mutation, competition and selection, it leads to slow convergence. This is because the ratio $f_t/(f_t + f_i)$ is always around 0.5 without uniform distribution between 0 and 1.Hence, the following strategy is followed in this paper to assign weights:

$$W_t = \{1, if \;\; f_t/(f_t + f_i) > 0.5 \quad (37)$$

$$W_t = \{0, otherwise$$

This weight assignment is found to yield proper selection and good convergence. When all the 2*I* individuals obtain their weights, they are ranked in descending order and the first *I* individuals are selected as parents along with their fitness values for next generation.

Steps (4) and Steps (5) are repeated until there is no appreciable improvement in the minimum fitness value.

Step (6): Optimum generation schedule is obtained for four areas using minimum fitness value. Check area generation with local demand

Step (7): Areas with lower fuel cost may export the excessive generation to other areas with higher fuel cost (deficiency areas) with tie line limit.

4. Particle Swarm Optimization

Particle swarm optimization (PSO) is inspired from the collective behavior exhibited in swarms of social insects [19]. It has turned out to be an effective optimizer in dealing with a broad variety of engineering design problems. In PSO, a swarm is made up of many particles, and each particle represents a potential solution (i.e., individual). A particle has its own position and flight velocity, which are adjusted during the optimization process based on the following rules:

$$V_i^{P+1} = \omega * V_i^P + C_1 * rand() * (P_{bi}^{KP} - P_i^{KP}) + C_2 * rand() * (P_{gi}^{KP} - P_i^{KP}) \quad (38)$$

$$P_i^{KP} = P_i^{KP} + V_i^{P+1} \quad (39)$$

where V_{t+1} is the updated particle velocity in the next iteration, V_t is the particle velocity in the current iteration, ω is the inertia dampener which indicates the impact of the particle's own experience on its next movement, $C_1 * rand$ represents a uniformly distributed number within the interval [0, $c1$], which reflects how the neighbours of the particle affects its flight, P_{bi}^{KP} is the neighbourhood best position, V_i^P is the current position of the particle and $C_2 * rand$ represents a uniformly distributed number within the interval [0, $c2$], which indicates how the particle trusts the global best position, P_{gi}^{KP} is the global best position, and V_i^{P+1} is the updated position of the particle. Under the guidance of these two updating rules, the particles will be attracted to move towards the best position found thus far. That is, the optimal solutions can be sought out due to this driving force.

The major steps involved in Particle Swarm Optimization approach are discussed below:

1) Initialization

The initial particles are selected randomly and the velocities of each particle are also selected randomly. The size of the swarm will be (Np x n), where Np is the total number of particles in the swarm and 'n' is the number of stages.

2) Updating the Velocity

The velocity is updated by considering the current velocity of the particles, the best fitness function value among the particles in the swarm. The velocity of each particle is modified by using Equation (28)

The value of the weighting factor ω is modified by following Equation (40) to enable quick convergence.

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) / iter_{\max} * iter \quad (40)$$

The term $\omega < 1$ is known as the "inertia weight" and it is a friction factor chosen between 0 and 1 in order to determine to what extent the particle remains along its original course unaffected by the pull of the other two terms. It is very important to prevent oscillations around the optimal value.

3) Updating the Position

The position of each particle is updated by adding the updated velocity with current position of the individual in the swarm

4.1. Algorithm of Particle Swarm Optimization

The step by step procedure to compute the global optimal solution is followed.

Step (1): Initialize a population of particles with random positions and velocities on d dimensions in the problem space.

Step (2): For each particle, evaluate the desired optimization fitness function in the variables.

Step (3): compare particles fitness evolution with particles $Pbest$. If current value is better then $Pbest$, then set $Pbest$ value equal to the current value, and the $Pbest$ location equal to the current location in the dimensional space.

Step (4): Compare fitness evaluation with the populations overall previous $Pbest$. If current value is better than $gbest$, then reset to the current particles array index and value.

Step (5): Change the velocity and position of the particle according to Equations (38) and (39) respectively.

Step (6): Loop to step 2 until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations.

4.2. Implementation of Particle Swarm Optimization Algorithm for Multi-Area Unit Commitment

The various steps of the PSO algorithm are given below for solving multi area unit commitment problem:

Step (1): Read in unit data, tie-line data, load demand profile.

Step (2): Perform the dynamic programming to get the initial commitment schedule for each area.

Step (3): Initialization of particle .The initial particle of size Np is generated randomly for committed unit in each area :

1) Calculate the initial particle population

$$I_p = [(P_1^{kp} \ldots\ldots P_2^{kp}); k = 1,2,3,4 : p = 1\ldots\ldots N_p \quad (41)$$

2) Calculate the fuel cost for each particle using Equation (1)

$$FC_p^k = [(a(P_1^{kp})^2 + b(P_1^{kp}) + c); k = 1,2,3,4; p = 1,2\ldots N_p \quad (42)$$

3) Calculate start up cost of each particle using Equation (4)

4) Calculate the production cost Production

$$\text{Cost} = \text{FC}_\text{p}^\text{k} + SC_p^k \quad (43)$$

5) Calculate the fitness function for each particle of population

$$F_p = \text{FC}_\text{p}^\text{k} + SC_p^k + k(\sum_{i=1}^{N_k} P_i^{kp} - D_j^k) \quad (44)$$

6) To calculate the $Pbest$ by using fitness function values, If current value is better then previous $Pbest$,then set $Pbest$ value equal to the current value and compute $gbest$ if current value is.

Step (4): Updating the Velocity

The velocity is updated by considering the current velocity of the particles, the best fitness function value among the particles in the swarm using following Equation (45).

$$V_i^{P+1} = \omega * V_i^P + C_1 * rand() * (P_{bi}^{KP} - P_i^{KP}) + C_2 * rand() * (P_{gi}^{KP} - P_i^{KP}) \quad (45)$$

where ω is weight factor, The weight ω is computed using Equation (40)

Step (5): Updating the particle position

The position of each particle is updated by adding the updated velocity with current position of the individual in the swarm.

$$P_i^{KP} = P_i^{KP} + V_i^{P+1} \tag{46}$$

The steps described in sub Sections 3 to 5 are repeated until a criterion is met, usually a sufficiently good fitness the maximum generation count is reached. Step (6): Optimum generation schedule is obtained for four area using gbest particle. Check area generation with local demand.

Step (7): Areas with lower fuel cost may export the excessive generation to areas with higher fuel cost (deficiency areas) with tie line limit

5. Test System and Simulation Results

The proposed MAUC algorithm has been implemented in C++ environment and tested extensively. Test results of a multi-area system are presented in this section. All simulations are performed in a PC with Intel processor (1.953 GHz) and 1012 MB of RAM.

As shown in Figure 2, a sample multi-area system with four areas, IEEE reliability test system, 1996 data in [9], are used to test the speed of solving the multi-area UC and ED for a large-scale system with import/export capability and tie line capacity constraints. In the sample multi-area system, each area consists of 26 units. The total number of units tested is 104, and their characteristics are presented in [9]. There are some identical thermal units also located in each area. The system contains five tie lines four area interconnections as shown in Figure 4, and area one is the reference area. Figure 3 shows the modified same load demand profile forecast used in all four areas. The assumptions described in tie line capacity constraint are applied to the simulations.

The four areas have the same load demand profiles. As the 1oad demand is same in these four areas, the economical area will generate more power than expensive areas. Figure 3 gives the changes in area 1 power generation, committed unit capacities, unit commitment pattern of hour 7am and spinning reserve requirement of area 1 is 400MW, because the available unit capacities are not more than the power generation plus the spinning reserve. This phenomenon proves that the available capacity should comply with the area power generation instead of the local load demand.

The systems 1oad demand is 6800 MW, so area 1 generation increases steadily while that of area 2, 3 decreases. The incremental cost of area 2, 3 is higher than

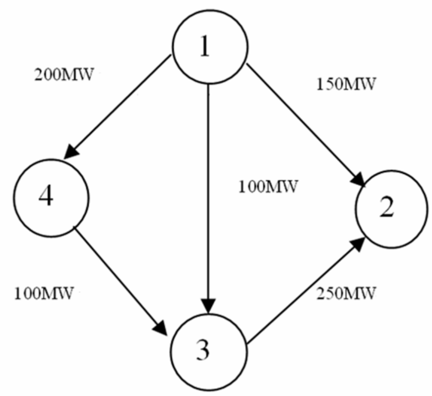

Figure 2. Topological connections of four areas.

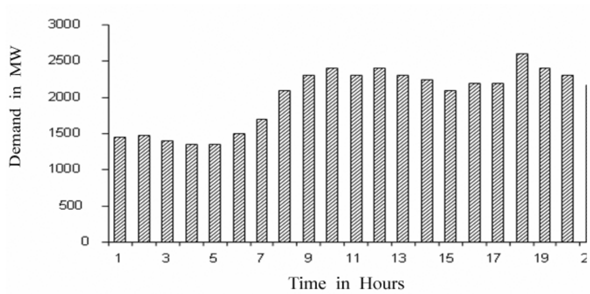

Figure 3. Load pattern for all four –area.

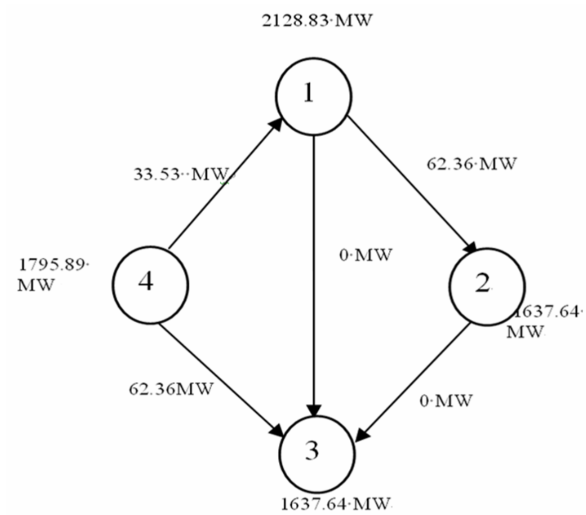

Figure 4.Tie-line flow pattern for 7am.

that of the other two areas since the tie flows to area 2, 3 are at their maximum capacities. This manifests that the proposed method considers tie-line limits effectively.

Table I shows that parameter used in EP and PSO method. Table 2, 3, 4 and Table V shows comparison result of DP and EP, PSO. Figure 4 and 5 shows the convergence characteristics for multi-area obtained using proposed methodology.

Table 2 shows that the total production cost is obta-

Table 1. Parameter used in EP & PSO.

Parameter	EP	PSO
Population size(p)	10	10
Mutation scaling factor(β)	0.03	-
Penalty factor(k1)	10000	10000
Maximum Generation	500	500
Learning factor(c1,c2)	-	2

ined by using conventional method. Table 3 and 4 shows that the total production cost is obtained for ten iterations by using EP and PSO method. Figure 4 gives the plot of EP average performance from 500 runs. Figure 5 gives the plot of number of iteration versus the time taken to complete those iterations and the maximum production cost obtained under each iteration using PSO method.

As we indicated in the paper, the PSO algorithm has also proved to be an efficient tool for solving the multi –area unit commitment with economic dispatch problem. There is no obvious limitation on the size of the problem that must be addressed, for its data structure is such that the search space is reduced to a minimum; no "relaxation of constraints" is required; instead, populations of feasible solutions are produced at each generation and throughout the evolution process. The main advantages of the proposed algorithm are speed.

The proposed PSO approach was compared to the related methods in the references indented to serve this purpose, such as the DP with a zoom feature, and the EP approaches. In addition, with the use of PSO method, the status is improved by avoiding the entrapment in local minima. By means of stochastically searching multiple points at one time and considering trial solutions of successive generations, the PSO approach gives global minima instead of entrapping in local optimum solutions. The PSO method obviously displays a satisfactory performance with respect to the quality of its evolved solutions and to its computational requirements.

The final result of PSO would save 0.12% $2865.4 is compared with the solution obtained by the conventional method but it would require 33 seconds to complete the computation .So, the EP method is reduced the operating cost by 0.08 % than the conventional method but it requires 36 seconds to complete this computation .From these results, the PSO method had less total cost and consumed also less CPU time compared to other method.

Table 2. Operating cost of DP method.

Hours (24)	Area-1 (26 Unit)	Area-2 (26 Unit)	Area-3 (26 Unit)	Area-4 (26 Unit)
1	37115.33008	24115.52148	28331.22656	22042.12500
2	24747.96094	23137.63965	22994.89974	19289.81836
3	27995.10742	23137.63965	23701.25684	19175.97998
4	29576.86719	18274.32617	26151.83789	18397.77637
5	29347.66016	18329.32617	25595.42969	18698.77344
6	36118.03711	18329.32617	23799.50977	19705.58106
7	40483.16211	28104.14453	21999.59863	24891.27832
8	39248.85547	32917.46875	19852.85547	21117.69727
9	38728.73438	34865.23828	18245.37305	21253.34180
10	37215.33984	32205.37500	22093.59570	24255.43945
11	37193.46875	32205.37500	20244.08203	23298.57031
12	38310.47266	32205.37500	20992.89258	21298.69336
13	33225.35352	34149.02930	18152.82227	26442.17773
14	31623.27930	37085.82813	17146.93945	25955.68945
15	30595.62695	33172.86133	17991.47266	23682.43359
16	36312.25000	32989.65234	22492.57813	25305.94336
17	36925.17578	32989.65234	23769.58008	25383.72656
18	35682.32031	39459.62500	27589.75977	19501.75391
19	35682.32031	39903.05859	23860.84180	22304.66016
20	35682.32031	32114.94141	21973.39063	15999.40332
21	38042.47852	29387.71680	19907.53906	20248.24805
22	30190.89648	15095.17188	21115.43164	21807.76953
23	30923.70898	18398.08203	19966.21289	22309.07813
24	30202.21094	15198.78125	19815.61328	18294.49805
Total cost	821168.9375	677771.1563	527784.7312	520660.4566

6. Conclusions

Application of PSO is a novel approach in solving the MAUC problem. Results demonstrate that PSO is a very competent method to solve the MAUC problem. PSO generates better solutions than the other methods, mainly because of its intrinsic nature of updates of positions and velocities. The reason is due to the hourly basis solution. This is somehow similar to the "divide and conquer" strategy of solving a problem. Owning to this

Table 3. Opearting cost of EP method.

Hour-s (24)	Area-1 (26 Unit)	Area-2 (26 Unit)	Area-3 (26 Unit)	Area-4 (26 Unit)
1	37112.33008	24093.52148	28311.22656	22002.12500
2	24741.96094	23127.63965	22964.89974	19259.81836
3	27988.10742	23127.63965	23681.25684	19151.97998
4	29566.86719	18254.32617	26121.83789	18367.77637
5	29337.66016	18309.32617	25572.42969	18678.77344
6	36108.03711	18309.32617	23789.50977	19683.58106
7	40473.16211	28084.14453	21975.59863	24861.27832
8	39238.85547	32897.46875	19822.85547	21087.69727
9	38718.73438	34841.23828	18215.37305	21223.34180
10	37202.33984	32185.37500	22063.59570	24205.43945
11	37183.46875	32185.37500	20224.08203	23278.57031
12	38296.47266	32185.37500	20972.89258	21268.69336
13	33212.35352	34129.02930	18132.82227	26412.17773
14	31607.27930	37063.82813	17126.93945	25920.68945
15	30578.62695	33152.86133	17981.47266	23642.43359
16	36281.25000	32969.65234	22462.57813	25286.94336
17	36919.17578	32969.65234	23749.58008	25353.72656
18	35662.32031	39439.62500	27569.75977	19471.75391
19	35662.32031	39893.05859	23839.84180	22274.66016
20	35662.32031	32094.94141	21943.39063	15969.40332
21	38032.47852	29365.7168	19887.53906	20218.24805
22	30177.89648	15065.17188	21073.43164	21797.76953
23	30913.70898	18387.08203	19946.21289	22279.07813
24	30182.21094	15168.78125	19796.61328	18254.49805
Total cost	820859.9375	677300.1562	527225.7396	519950.4565

Table 4. Operating cost of PSO method.

Hours (24)	Area-1 (26 Unit)	Area-2 (26 Unit)	Area-3 (26 Unit)	Area-4 (26 Unit)
1	37096.33008	24048.52148	28309.22656	21998.12500
2	24514.96094	23004.63965	22910.89974	19251.81836
3	27980.10742	23004.63965	23674.25684	19145.97998
4	29568.86719	18286.32617	26111.83789	18374.77637
5	29387.66016	18286.32617	25578.42969	18671.77344
6	35838.03711	18286.32617	23769.50977	19673.58106
7	40497.16211	28043.14453	21945.59863	24858.27832
8	39228.85547	32977.46875	19815.85547	21081.69727
9	38648.73438	34802.23828	18245.37305	21201.34180
10	37229.33984	32191.37500	22063.59570	24199.43945
11	37184.46875	32191.37500	20212.08203	23272.57031
12	38294.47266	32191.37500	20979.89258	21262.69336
13	33200.35352	34120.0293	18127.82227	26401.17773
14	31630.27930	37051.82813	17124.93945	25928.68945
15	30578.62695	33162.86133	17978.47266	23631.43359
16	36281.25000	32960.65234	22459.57813	25277.94336
17	36949.17578	32960.65234	23748.58008	25365.72656
18	35766.32031	39439.62500	27569.75977	19465.75391
19	35766.32031	39811.05859	23839.8418	22243.66016
20	35766.32031	32081.94141	21943.39063	15968.40332
21	38122.47852	29353.71680	19897.53906	20208.24805
22	30177.89648	15065.17188	21073.43164	21791.76953
23	31583.70898	18379.08203	19966.21289	22270.07813
24	29449.21094	15159.78125	19816.61328	18211.49805
Total cost	820740.9375	676860.1562	527162.7396	519756.4565

hourly solution, the complexity of the search is greatly reduced. The total objective function is the sum of objectives and constraints, which are fuel cost, start-up cost, spinning reserve, power demand, tie-line limit, and import and export constraints. For a better solution, generated powers by N unit of generators and K areas, tie –line limits are constantly checked so that feasible particles can meet the power demand .This reduces the pressure of

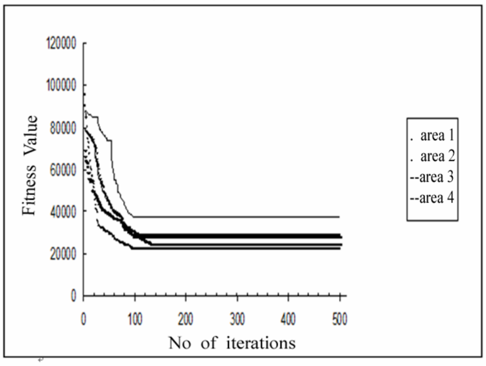

Figure 4. Convergence characteristics of EP method.

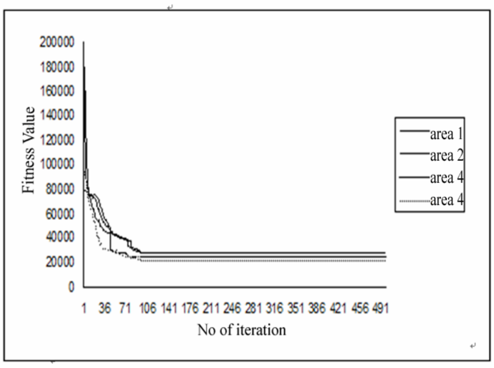

Figure 5. Convergence characteristics of PSO method.

Table 5. Comparison of DP, EP, PSO method.

Method	Area-1 (26)	Area-2 (26)	Area-3 (26)	Area-4 (26)	Total Cost ($)	Time (S)
DP	821168.9	677771.1	527784.7	520660.45	2547385.2	36.7
EP	820859.7	677300.1	527225.9	519950.19	2545336.2	35.1
PSO	820740.9	676860.1	527162.7	519756.45	2544519.3	34.2

the constraint violation of the total objective function. Finally, the result obtained from the simulation is most encouraging in comparison to the best-known solution so far. In the future work, the power flow in each area can be considered to further increase the system security. Other issues such as transmission losses, transmission costs, call and put options policies between and bilateral contract areas can also be considered to reflect more realistic situations in MAUC problems.

7. References

[1] S. Salam, "Unit commitment solution methods," Proceedings of World Academy of Science, Engineering and Technology, Vol. 26, December 2007.

[2] B. Lu and M. shahidehpour, "Short term scheduling of combined cycle units," IEEE Transaction on Power System, Vol. 19, pp. 1616–1625, August 2004.

[3] F. Gao, "Economic dispatch algorithms for thermal unit system involving combined cycle units," IEEE and Gerald Bushel IEEE Lowa State University Ames, IA, USA, IEEE Transaction on Power Systems, pp. 1066–1072, November 2003.

[4] E. Fan, X. H. Guan, and Q. Z. Zhai, "A new method for unit commitment with ramping con straints," IEEE Transaction on Power Systems, March 2001.

[5] H. T. Yang and C. L. Huang, "Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions," IEEE Transactions on power system, Vol. 11, No. 2, pp. 112–118, 1996.

[6] Z. Ouyang and S. M. Shahidehpour, "Heuristic multi-area unit commitment with economic dispatch," IEEE Proceedings, Vol. 138, No. 3, pp. 242–252, 1991.

[7] C. L. Tseng, "Multi-area unit commitment for large scale power system," IEEE Proceedings - Generation and Distribution, Vol. 145, No. 41, pp. 415–421, 1999.

[8] C. Wang and M. Shahidehpour, "A decomposition approach to non-linear multi-area generation scheduling with tie-line constraints using expert systems," IEEE Transactions on Power System, Vol. 7, No. 4, pp. 1409 –1418, 1992.

[9] C. K. Pang, G. B. Sheble, and F. Albuyeh, "Evaluation of dynamic programming based methods and multiple area representation for thermal unit commitments," IEEE Transactions on Power Apparatus System, Vol. 100, No. 3, pp. 1212–1218, 1981.

[10] F. N. Lee, J. Huang, and R. Adapa, "Multi-area unit commitment via sequential method and a DC power flow network model," IEEE Transactions on Power System, Vol. 9, No. 1, pp. 279– 284, 1994.

[11] C. Yingvivatanapong, W. J. Lee, and E. Liu, "Multi-area power generation dispatch in competitive markets," IEEE Transactions on Power Systems, pp. 196–203, 2008.

[12] U. B. Fogel, "On the philosophical differences between evolutionary algorithms and genetic algorithms," IEEE Proceedindings in Second Annual Conference on Evolutionary Programming, pp. 23–29, 1993.

[13] T. Biick and H. P. Schwefel, "An overview of evolutionary algorithm for parameter optimization," Evolutionary Computation, Vol. 1, No. 1, pp. 1–24. 1993.

[14] C. C. Asir Rajan and M. R. Mohan, "An evolutionary programming-based tabu search method for solving the unit commitment problem," IEEE Transactions on Power System, Vol. 19, No. 1, pp. 577–585, 2004.

[15] D. Srinivasan, F. Wen, and C. S. Chang, "A survey of applications evolutionary computing to power systems," IEEE Proceedings, USA, pp. 35–41, 1996.

[16] J. Kennedy, "The particle swarm: Social adaptation of knowledge," Proceedings in International Conference on Evolutionary Computation, Indianapolis, pp. 303–308, 1997.

Appendix A

Nomenclature

D_j^k	Total load demand in area k at jth hour
L_j^k	Total import power to area k at jth hour
E_j^k	Total export power to area k at jth hour
$I_{i,j}^k$	Commitment state (1 on, 0 for off)
Irlist	List of committed units ascending priority order
i	Index for units
j	Index for time
λ_i	Lagrangian multiplier for unit
λ_{sys}	Lagrangian multiplier for entire system
N_A	Total number of areas
N_k	Total number of units in area K
O_{plist}	List of uncommitted units in descending order
Pg_j^k	Power generation of area k at jth hour
$\underline{Pg_i^k}$	Lower limit of power generation of unit i in area k
$\overline{Pg_i^k}$	Upper limit of power generation of unit i in area k
$Pg_{i,j}^k$	Power generation of unit i in area k at j th hour
R_j^k	Spinning reserve of area k at j th hour
S_j^k	Total commitment capacity for area k at j th hour
SD_j^k	Total system demand at j th hour t Total time span in hours
T_i^{on}	Minimum up time of unit i
T_i^{off}	Minimum down time of unit i
τ_i	Time constant in start up cost function for unit i
W_j	Net power exchange with outside systems
$X_{i,j}^{on/off}$	Time duration for which unit i has been on/off at j^{th} hour

