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EP BASED PSO METHOD FOR SOLVING PROFIT BASED MULTI AREA UNIT COMMITMENT PROBLEM

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Abstract

This paper presents a new approach to solve the profit based multi area unit commitment problem (PBMAUCP) using an evolutionary programming based particle swarm optimization (EPPSO) method. The objective of this paper is to maximize the profit of generation companies (GENCOs) with considering system social benefit. The proposed method helps GENCOs to make a decision, how much power and reserve should be sold in markets, and how to schedule generators in order to receive the maximum profit. Joint operation of generation resources can result in significant operational cost savings. Power transfer between the areas through the tie lines depends upon the operating cost of generation at each hour and tie line transfer limits. The tie line transfer limits were considered as a set of constraints during optimization process to ensure the system security and reliability. The overall algorithm can be implemented on an IBM PC, which can process a fairly large system in a reasonable period of time. Case study of four areas with different load pattern each containing 7 units (NTPS) and 26 units connected via tie lines have been taken for analysis. Numerical results showed comparing the profit of evolutionary programming-based particle swarm optimization method (EPPSO) with conventional dynamic programming (DP), evolutionary programming (EP), and particle swarm optimization (PSO) method. Experimental results shows that the application of this evolutionary programming based particle swarm optimization method have the potential to solve profit based multi area unit commitment problem with lesser computation time.

Keywords: Dynamic programming (DP), Evolutionary programming (EP), Evolutionary programming-based particle swarm optimization (EPPSO), Profit Based Multi Area Unit Commitment Problem (PBMAUCP), Particle Swarm Optimization (PSO).

Nomenclatures

a_i^k, b_i^k, c_i^k	Cost function parameters of unit i in area K
D_j^k	Total system demand of area K at j^{th} hour
$F(P_{g_i}^k)$	Production cost of unit i in area K
$I_{i,j}^k$	Commitment state (1 for ON, 0 for OFF)
$Lj_{\max}^k$	Maximum total import power in area K at j^{th} hour
$P_{g_i}^k$	Power generation of unit i in area K
$P_{i,j}^k$	Power generation of unit i in area K at j^{th} hour
$Pg_{i,j}^k$	Theoretical normal force slope parameter, 1/rad
$Pg_{i\max}^k$	Maximum power generation at area K at i^{th} hour
$Pg_{i\min}^k$	Minimum power generation at area k at i^{th} hour
$Pj_{\max}^k$	Maximum power generation in area K at j^{th}hour
$Pj_{\min}^k$	Minimum power generation in area K at j^{th} hour
R_j^k	Spinning reserve of area K at j^{th} hour
T_i^{off}	Minimum down time of unit i
T_i^{on}	Minimum up time of unit i
W_j	Net power exchange with outside system
$X_{i,j}^{off}$	Time duration for which unit i have been off at j^{th} hour
λ_{sys}	Marginal cost of supplying the last incremental energy to meet entire system demand

1. Introduction

The US electric marketplace is in the midst of major changes designed to promote competition. No longer vertically integrated with guaranteed customers and suppliers, electric generators and distributors will have to compete to sell and buy electricity. The stable electric utilities of the past will find themselves in a highly competitive environment [1]. Although some states (e.g., California) are already operating in a restructured environment, a standardized final market structure for the rest of the US has not yet been fully defined. The authors believe that regional commodity exchanges, in which electricity contracts are traded, will play a key role.

Power industry is undergoing restructuring throughout the world. The past decade has seen a dramatic change in the manner in which the power industry is organized [2]. It has moved from a formally vertically integrated and high regulated industry to one that has been horizontally integrated in which generation, transmission and distribution are unbundled. The basic aim of Generation companies (GENCOs) in restructuring of power system is to create competition among generating companies and provide choice of different generation options at a competitive price to consumers. The main objective of GENCOs is to maximize their own profit by satisfy the demand. Utilities had to produce power to satisfy their customers with the minimum production cost. This means utilities run multi area unit commitment (MAUC) with the condition that demand and reserve must be met.

In multi area, several generation areas are interconnected by tie lines, the objective is to achieve the most economic generation to meet out the local demand without violating tie-line capacity limits constraints [3]. In an interconnected multi area system, joint operation of generation resources can result in significant operational cost savings [4]. It is possible by transmitting power from a utility, which had cheaper sources of generation to another utility having costlier generation sources. The total reduction in system cost is shared by the participating utilities [5]. The exchange of energy between two utilities is having significant difference in their marginal operating costs. The utility with the higher operating cost receives power from the utility with low operating cost. This arrangement usually on an hour to hour basis and is conducted by the two system operators.

In the competitive environment, customer request for high service reliability and lower electricity prices. Thus, it is an important to maximize own profit with high reliability and maximize overall profit [6]. Profit based multi area unit commitment was studied by dynamic programming and was optimised with local demands with a simple priority list scheme on a personal computer with a reasonable execution time [7]. Even though the simplicity and execution speed are well suited for the iterative process, the commitment schedule may be far from the optimal, especially when massive unit on/off transitions are encountered. The tie-line constraint checking also ignores the network topology, resulting in failure to provide a feasible generation schedule solution [7]. The transportation model could not be used effectively in tie line constraints, as the quadratic fuel cost function and exponential form of start-up cost were used in this study.

An Evolutionary algorithm is used for obtaining the initial solution which is fast and reliable [8]. Evolutionary Programming (EP) is capable of determining the global or near global solution [9]. The EP has the advantages of good convergent property and a significant speed up over traditional Gas and can obtain high-quality solutions. The 'curse of dimensionality' is surmounted, and the computational burden is almost linear with problem scale. It is based on the basic genetic operation of human chromosomes. It operates with the stochastic mechanics, which combine offspring creation based on the performance of current trial solutions and competition and selection based on the successive generations, from a considerably robust scheme for large-scale real-valued combinational optimization. In this proposed work, the parents are obtained from a predefined set of solution's (i.e., each and every solution is adjusted to meet the requirements). In addition, the selection process is done using evolutionary strategy [10-12]. The application on this 26 unit shows that we can find the optimal solution effectively and these results are compared with the conventional methods.

PSO [13] is an exciting new methodology in evolutionary computation that is similar to GA and EP in that the system is initialized with a population of random solutions. In addition, it searches for the optimum by updating generations and population evolution is based on previous generations. In PSO, the potential solutions, called particles, are "flown" through the problem space by following the currently optimal particles. Each particle adjusts its flying according to its own flying experience and the flying experience of other particles in the swarm.PSO was traditionally considered for homogeneous swarms of potential solution vectors. The homogeneity of the swarm is not practically feasible because the loads vary continuously between the maximum and the minimum. Hence in this paper, we propose that PSO be solved as a non-homogeneous recurrence relation [14, 15]. The fitness of the particular particle to the swarm as a whole in checked through statistical fitness tests on each one of them. This increases the convergence rate and the accuracy of the solution.

From the literature review, it has been observed that there exists a need for evolving simple and effective methods, for obtaining an optimal solution for the PBMAUCP. Hence, in this paper, an attempt has been made to couple EP [16] with PSO for meeting these requirements of the PBMAUCP, which eliminates the above mentioned drawbacks. In case of PSO [17], the demand is taken as control parameter. Hence, the quality of solution is improved. Classical optimization methods are a direct means for solving this problem. EP [18] seems to be promising and is still evolving. EP has the great advantage of good convergent property, and, hence, the computation time is considerably reduced. The EP combines good solution quality for PSO with rapid convergence for EP. The EP-based PSO (EPPSO) is used to find the multi area unit commitment.

In this paper, Section 2 describes the problem formulation of multi area unit commitment and tie line constraints taken into account for power transfer between the areas. Section 3 describes the overview of particle swarm optimization method, general algorithm of evolutionary programming method and EP based PSO method for profit based multi area unit commitment problem. Section 4 describes about the numerical results and its discussions. Finally, Section5 describes about the conclusion of this proposed work.

2. Problem Formulation

The cost curve of each thermal unit is in quadratic form [1]

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

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 each thermal unit is an exponential function of the time that the unit has been off

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

The objective function for the profit based multi-area unit commitment is to minimize the entire power pool generation cost as follows [3].

M a x P.F =T.C (or) Min T.C=RV

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

To decompose the problem in above Eq. (5), it is rewritten as

$$\min \sum_{j=1}^{t} \left[F(P_{g_{i,j}}) \right] \tag{6}$$

$$F\left(P_{g_{i,j}}\right) = \sum_{k=1}^{N_A} F^k \left(P_{g_{i,j}}^k\right) \tag{7}$$

subject to the constraints of Eqs. (10) to (19). Each $F^k\left(P_{g_{i,j}}^k\right)$ for $k = 1 \ldots\ldots NA$ is represented in the form of schedule table, which is the solution of mixed variable optimization problem

$$\min_{I,P} \sum_i \left[I_{i,j}^k F_i^k \left(P_{i,j}^k\right) + I_{i,j}\left(1 - I_{i,j-1}\right)\left(S_i\left(X_{i,j}^{off}\right)\right)\right] \tag{8}$$

subject to following constraints are met for optimization

$$\sum_{i=i}^{N} P_{it} X_{it} \le D_t, t = 1 \ldots\ldots.T \quad \text{and} \quad \sum_{i=i}^{N} R_{it} X_{it} \le SR_t, t = 1 \ldots\ldots.T \tag{9}$$

Redefining the UC problem for the competitive environment involves changing the demand and reserve constrains from an equality to less than or equal to the forecasted level if it creates more profit. Here forecasted demand reserve and prices are important inputs to profit based UC Algorithm; they are used to determine the expected revenue, which affects the expected profit.

1) System power balance constraint

$$\sum_k P_{g_j}^k = \sum_k D_j^k \tag{10}$$

Sum of real power generated by each thermal unit must be sufficient enough to meet the sum of total demand of each area while neglecting transmission losses.

2) Spinning reserve constraint in each area

$$\sum_i P_{g_{i,j_{\max}}}^k \ge D_j^k + R_j^k + E_j^k - L_j^k \tag{11}$$

3) Generation limits of each unit

$$P_{j_{\max}}^k \le P_{i,j}^k \le P_{j_{\min}}^k \tag{12}$$

$i = 1 \ldots.. N_k$, $j = 1 \ldots. t$, $k = 1 \ldots N_A$

4) Thermal units generally have minimum up time and down time constraints, therefore

$$\left(X_{i,j-1}^{on} - T_i^{on}\right) * \left(I_{i,j-1} - I_{i,j}\right) \ge 0 \tag{13}$$

$$\left(X_{i,j-1}^{off} - T_i^{off}\right) * \left(I_{i,j} - I_{i,j-1}\right) \ge 0 \ge 0 \tag{14}$$

5) In each area, power generation limits caused by tie-line constraints are as follows

- Upperlimits

$$\sum_i P^k_{g_{i,j}} \le D^k_j + E^k_{j_{\max}} \tag{15}$$

- Lower limits

$$\sum_i P^k_{g_{i,j}} \ge D^k_j - L^k_{j_{\max}} \tag{16}$$

- Import/Export balance

$$\sum_i E^k_j - \sum_k L^k_j + W_j = 0$$
(17)

6) Area generation limits

$$\sum_i P^k_{g_{i,j}} \le \sum_i P^k_{g_{i\max}} - R^k_j \qquad k=1\ldots.\ N_{A,,} j=1\ldots\ldots.t \tag{18}$$

$$\sum_i P^k_{g_{i,j}} \ge \sum_i P^k_{g_{i\ \min}} \qquad k=1\ldots.\ N_{A,} j=1\ldots\ldots.t \tag{19}$$

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

$$P^k_{g_j} = D^k_j + E^k_j - L^k_j \tag{20}$$

where $P^k_{g_j} = \sum_{i=1}^{N_k} P^k_{g_{i,j}}$ (21)

Since the local demand D^k_j is determined in accordance with the economic dispatch within the pool, changes of $P^k_{g_j}$ will cause the spinning reserve constraints of Eq. (11) to change accordingly and redefine Eq. (8). Units may operate in one of the following modes when commitment schedule and unit generation limits are encountered.

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

$$\lambda_{\min,i} \le \lambda_{sys} \le \lambda_{\max,i} \tag{22}$$

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

$$\lambda_{\min,i} > \lambda_{sys} \tag{23}$$

c) Maximum mode: unit i generation is at its maximum level

$$\lambda_{\max,i} < \lambda_{sys} \tag{24}$$

Shut down mode: unit i is not in operation, $P_i = 0$

Besides limitations on individual unit generations, in a multi- area system, the tie-line constraints of Eqs. (13), (14) and (16) are to be preserved. The operation of each area could be generalized into one of the modes as follows.

i. Area coordinate mode

$$\lambda^k = \lambda_{sys} \tag{25}$$

$$D^k_j - L^k_{\max} \le \sum_i P^k_{g_{i,j}} \le D^k_j + E^k_{\max} \tag{26}$$

or

$$-L_{\max}^{k} \le \sum_{i} P_{g_{i,j}}^{k} - D_{j}^{k} \le E_{\max}^{k} \tag{27}$$

ii. Limited export mode

When the generating cost in one area is lower than the cost in the remain-ing areas of the system, that area may generate its upper limits according to Eq. (15), therefore

$$\lambda^{k} \langle \lambda_{sys} \tag{28}$$

For area k, area λ^k is the optimal equal incremental cost which satisfies the generation requirement.

iii. Limited import mode

An area may reach its lower generation limit according to Eq. (16) in this case because of higher generation cost

$$\lambda_{\min}^{k} \rangle \lambda_{sys} \tag{29}$$

2.1. Tie line constraints

To illustrate the tie-line flow in a multi-area system, the four area system given in Fig. 1 is studied. An economically efficient area may generate more power than the local demand, and the excessive power will be exported to other areas through the tie-lines [3]. For example assume area 1 has the excessive power the tie line flows would have directions from area1 to other areas, and the maximum power generation for area1 would be the local demand in area1 plus the sum of all the tie-line capacities connected to area1.If we fix the area 1 generation to its maximum level than the maximum power generation in area 2 could be calculated in a similar way to area 1. Since tie line C_{12} imports power at its maximum capacity, this amount should be subtracted from the generation limit of area 2. According to power balance Eq. (10) some areas must have a power generation deficiency and requires generation imports. The minimum generation limits in 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 power flow directions should be reserved.

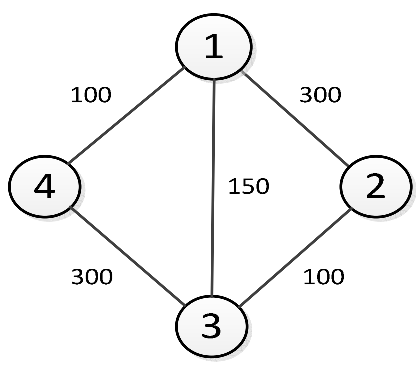

Fig. 1. Multi-area connection and tie-line limitations.

2.2. Power producer strategies for selling power and reserve

If a power producer is able to sell power in to a reserve market, then the producer strategies for profit maximization in both the spot and reserve markets are intertwined [19]. The producer decides to $Pi(S)$ in the spot market and $Pi(R)$ in the reserve market. The exact determination of Pi(S) and Pi(S) depends on the way reserve payments are made, although results are very similar.

2.2.1. Payment of power delivered

In this method reserve is paid when only reserve is actually used [20]. Therefore, the reserve price is higher than the power (spot) price revenue and cost can be calculated from

$$RV = \sum_{i=1}^{N}\sum_{i=1}^{T}(P_{g_i}^{k} SP_t)X_{it} + \sum_{i=1}^{N}\sum_{i=1}^{T} rRP_t R_{g_i}^{k} X_{it} \tag{30}$$

$$TC = (1-r)\sum_{i=1}^{N}\sum_{i=1}^{T} F(P_{g_i}^{k})X_{it} + r\sum_{i=1}^{N}\sum_{i=1}^{T} F(P_{g_i}^{k}) + R_{g_i}^{k} \tag{31}$$

2.2.2. Payment for reserve allocated

In this method, Gencos [21] receives the reserve price per unit of reserve for every time period that the reserve is allocated and not used. When the reserve is used, GENCO receives the spot price for the reserve that generated. In this method, reserve price is much lower than the spot price. Revenue and cost can be calculated from

$$TC = (1-r)\sum_{i=1}^{N}\sum_{i=1}^{T} F(P_{it})X_{it} + r\sum_{i=1}^{N}\sum_{i=1}^{T} F(P_{it} + R_{it})X_{it} + SPX_{it} \tag{32}$$

$$RV = \sum_{i=1}^{N}\sum_{i=1}^{T} P_{it}(SP_t)X_{it} + \sum_{i=1}^{N}\sum_{i=1}^{T}\left((1-r)RP_t\right) + R_{it} + r(sp_{it})R_{it}X_{it} \tag{33}$$

where $F(P_{it})$ is the generator's fuel cost function and it can be expressed as $a_i+b_iP_{it}+c_iP_{it}^2$ in which $a_{i,}$, b_i and c_i are generator's constant.

3. Proposed Method

3.1. Particle swarm optimization

3.1.1. Overview

Particle swarm optimization (PSO) is inspired from the collective behaviour exhibited in swarms of social insects [13]. It has turned out to be an effective optimizer in dealing with a broad variety of engineering design problems [14, 15]. 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

$$V_i^{P+1} = \omega V_i^{P} + C_1 \times rand() \times (P_{bi}^{KP} - P_i^{KP}) + C_2 \times rand() \times (P_{gi}^{KP} - P_i^{KP}) \tag{34}$$

$$P_i^{KP} = P_i^{KP} + V_i^{P+1} \tag{35}$$

where V_{t+1} is the updated particle velocity in the next iteration, V_t is the particle velocity in the current iteration, $\omega$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, C_1], 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,C_2], 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 global best position, and is the up-dated 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.

Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best Pbest [22]. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighbourhood of that particle. This value is called gbest. The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations, with a random weighted acceleration at each time step.

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 ($N_p \times n$), 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.

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.

3.1.2. PSO General Algorithm

The general PSO general algorithm is shown in Fig. 2.

Step 1: Initialize particles with random position and velocity vectors.
Step 2: For each particle positions (p) evaluate fitness.
Step 3: If fitness (p) better than fitness (pbest) then pbest = p.
Step 4: Check is all particles are exhausted. If yes goto step 5, otherwise goto step 2.
Step 5 Set best of pbests as gbest.
Step 6: Update particles velocity and position.
Step 7: Check is maximum iteration reached. If yes goto step 8, otherwise goto step 2
Step 8: Generate gbest optimal solution.

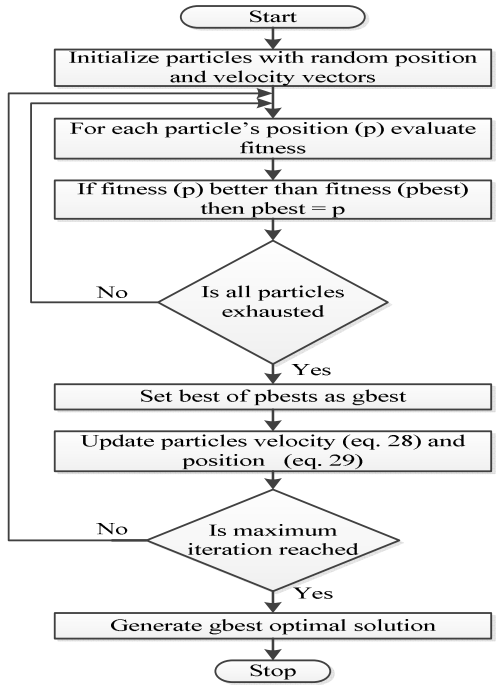

Fig. 2. Flowchart for PSO general algrithm.

3.2. Evolutionary programming

3.2.1. Introduction

EP is a mutation-based evolutionary algorithm applied to discrete search spaces [8, 10]. Real-parameter EP is similar in principle 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.

3.2.2. Evolutionary strategies

For the case of evolutionary strategies, evolution the chromosome, the individual, the species, and the ecosystem [10-12] can be categorized by several levels of hierarchy: the gene, the chromosome, the individual, the species, and the ecosystem. Thus, while genetic algorithms stress models of genetic operators, ES emphasize mutational transformation that maintains behavioural linkage between each parent and its offspring at the level of the individual.

3.2.3. EP general algorithm

Evolutionary programming [23] is conducted as a sequence of operations and is given below. The flowchart for EP general algorithm is shown in Fig. 3.

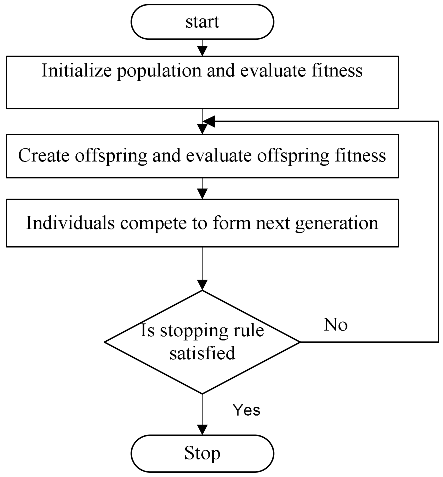

Fig. 3. Flowchart for EP general algrithm.

1) The initial population is determined by setting s_i=S_i~ $U(a_k,b_k)^k i$ =1,…,m, where S_i is a random vector, s_i is the outcome of the random vector, $U(a_k,b_k)^k$ denotes a uniform distribution ranging over $[a_k,b_k]$ in each of k dimensions, and m is the number of parents.
2) Each s_i, i=1,…, m, is assigned a fitness score $\vartheta(s_i)=G(F(s_i),v_i)$, where F maps $s_i \rightarrow R$and denotes the true fitness of s_i, v_i, represents random alteration in the instantiation of s_i, random variation imposed on the evaluation of $F(s_i)$, or satisfies another relation s_i, and $G(F(s_i), v_i)$ describes the fitness score to be assigned. In general, the functions F and G can be as complex as required. For example, F may be a function not only of a particular s_i, but also of other members of the population, conditioned on a particular s_i.
3) Each s_i, i=1,…,m, is altered and assigned to s_{i+m} such that

$$s_{i+m}=s_{i,j}+N(0,\beta j\vartheta(s_i)+z_j),\ j=1,\ldots,k \tag{36}$$

4) $N(0,\beta_j\vartheta(s_i)+z_j)$ represents a Gaussian random variable with mean μ and variance σ^2, β_j is a constant of proportionality to scale $\vartheta(s_i)$, and zj represents an offset to guarantee a minimum amount of variance,
5) Each s_{i+m}, i=1,…,m is assigned a fitness score

$$\vartheta(s_{i+m}) = G(F(s_{i+m}),v_{i+m}) \tag{37}$$

6) For each s_i,i=1,…, 2m, a value wi is assigned according to

$$w_i = \sum_{t=1}^{c} w_t^* \tag{38}$$

$$w_t^* = \begin{cases} 1, & \text{if } \vartheta(s_i) \le \vartheta(s_\rho), \\ 0, & \text{otherwise} \end{cases} \tag{39}$$

$$w_t^* = 0,\ \text{otherwise;}$$

where $\rho=[2mu_1+1]$,$\rho \neq i$,$[x]$ denotes the greatest integer less than or equal to x, c is the number of competitions, and $u_1 \sim U(0,1)$.

7) The solutions $s_i, i = 1 \ldots 2m$, are ranked in descending order of their corresponding value W_i
   [With preference to their actual scores $\vartheta(s_i)$ if there are more than m solutions attaining a value of c]. The first m solutions are transcribed along with their corresponding values $\vartheta(s_i)$ to be the basis of the next generation.
8) The process proceeds to step 3, unless the available execution time is exhausted or an acceptable solution has been discovered.

3.3. Evolutionary programming- based particle swarm optimization for MAUCP

3.3.1. EP- based PSO

In the PSO technique for solving MAUCP, initial operating schedule status in terms of maximum real power generation of each unit is given as input. As we that PSO is used to improve any given status by avoiding entrapment in local minima, the offspring obtained from the EP algorithm is given as input to PSO, and the refined status is obtained. In addition, evolutionary strategy selects the final status. EP based PSO method for solving multi area unit commitment problem is given in Fig. 4.

1) Get the unit data, tie-line data, and load demand profile for n areas and number of iterations to be carried out.
2) Generate population of parents (N) by adjusting the existing solution to the given demand to the form of state variables.
3) Find initial feasible solution.
4) Check is commitment for new schedule. If yes go to step 5 otherwise repairs the schedule.
5) Initialize particles with random position and velocity vectors.
6) Calculate fuel cost and start-up cost of each particle of population.
7) Calculate the fitness function of each particle of population and total production cost.
8) Check is all particles exhausted. If yes go to step 9 otherwise go to step 3.
9) Update particles velocity and position.
10) Check is iteration count reached. If yes g to step 11 otherwise increment iteration counts by one then go to step 2.
11) Generate optimal generation schedule.
12) Export power from lower operating cost areas to higher operating cost areas by following tie-line constraints.
13) Print the commitment schedule of n areas and tie-line flows.

3.3.2. Repair mechanism

A repair mechanism to restore the feasibility of the constraints is applied and described as follows [23]

- Pick at random one of the OFF units at one of the violated hours.
- Apply the rules in section 6.1 to switch the selected units from OFF to ON keeping the feasibility of the down time constraints.
- Check for the reserve constraints at this hour. Otherwise repeat the process at the same hour for another unit.

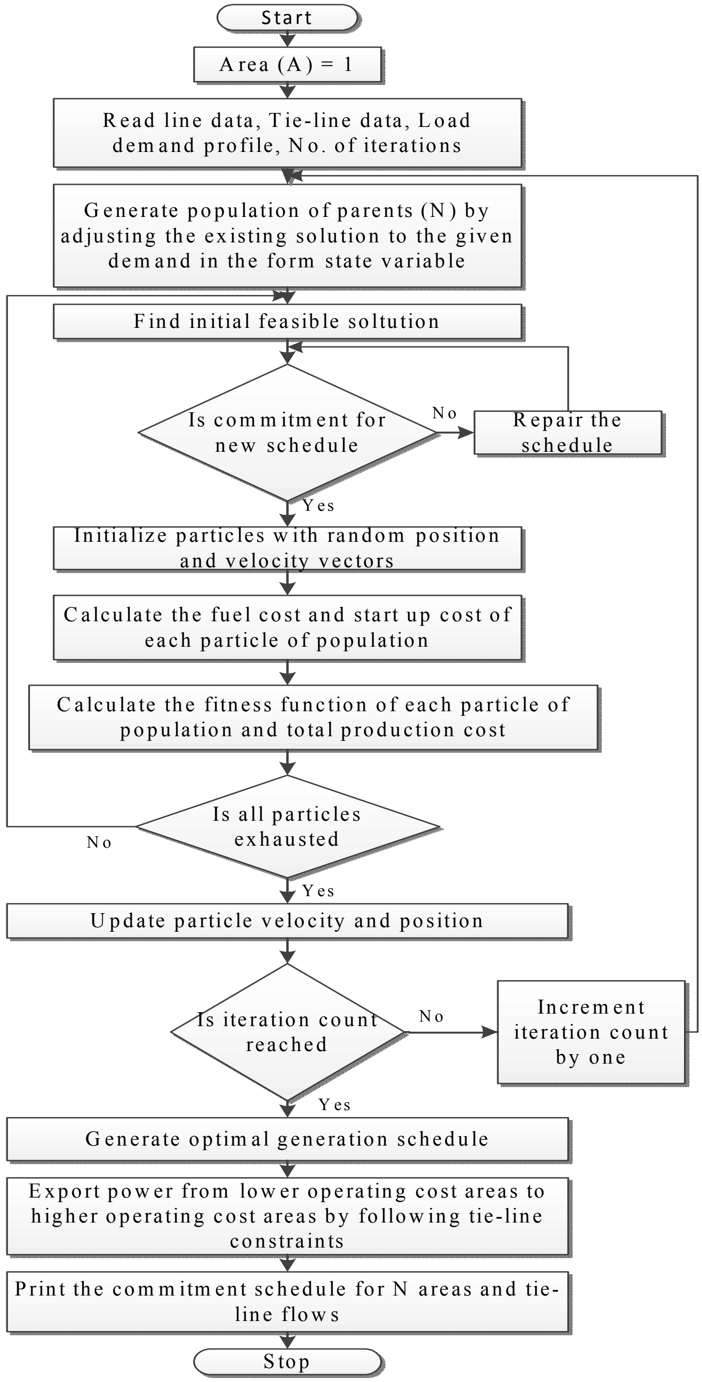

Fig. 4. Flowchart for EPPSO algorithm for PBMAUCP.

3.3.3. Making offspring feasible

While solving the constrained optimization problem, there are various techniques is to repair an infeasible solution [23].In this paper, we have chosen the technique, which evolves only the feasible solutions. That is, the schedule which satisfies the set of constraints as mentioned earlier. Here, in this paper, the selection routine is involved as "curling force" to estimate the feasible schedules. Before the best solution is selected by evolutionary strategy, the trial is made to correct the unwanted mutations.

3.3.4. Implementation

Software program were developed using MATLAB software package, and the test problem was simulated for ten independent trials using EPPSO. The training and identification part as implemented in the EPPSO technique is employed here and considered as a process involving random recommitment, constraint verification, and offspring creation.

4. Numerical Results and Discussions

The test system consists of four areas, and each area has 26 thermal generating units [3] is taken for analysis. Units have quadratic cost functions, and exponential start-up cost functions. Generating unit characteristics like the minimum up/down times, initial conditions and generation limits of units in every area, the cost functions of units given in the four areas [3] are taken for analysis. Load demand profile for each area is different and is given in Fig. 5.

The tie line flow pattern at 11 am and 4 pm are shown in Figs. 6 and 7 respectively. The hourly operating cost of four areas by Evolutionary Programming-based Particle Swarm Optimization (EPPSO) method is given in Table 1. Table 2 shows the generation levels of all areas at 11 am and 4 pm respectively.

Figure 8 shows the effect of probability of reserve for power payment and reserve payment on profit. From Fig. 8, GENCO receives revenue from reserve power market even reserve power is not exactly used. Therefore, when the reserve price is high enough, GENCO might select to sell an allocated reserve rather than sell power in order to maximize its own profit. Comparison of profit of EPPSO method with DP, EP and PSO and EPPSO by power payment method is shown in Fig. 9.

Table 3 shows comparison of operating cost of 7 units (NTPS) and 26 units system. The proposed algorithm reaches maximum profit compared to DP, EP and PSO method, which indicates that the proposed algorithm could determine the appropriate schedule within a reasonable computation time. It is noted that cost in each iteration may be lower than that of the previous iteration, indicating that our optimization rules always comply with the equal incremental cost criterion for dispatching power generation among thermal units.

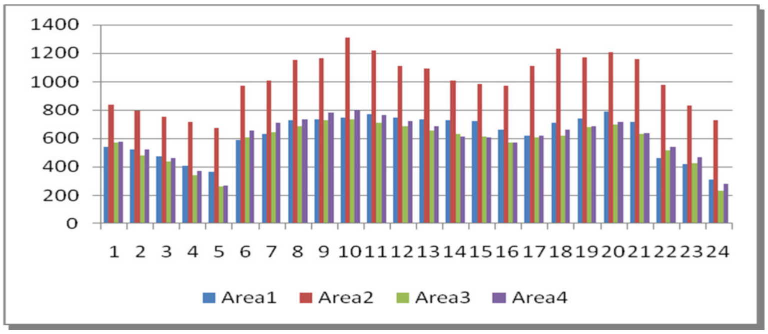

Fig. 5. Load demand profile in each area.

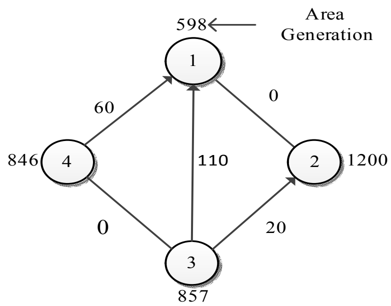

Fig. 6. Tie line flow pattern at 11 am.

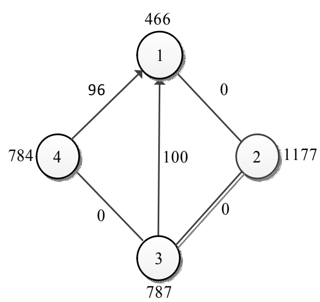

Fig. 7. Tie line flow pattern at 4 pm.

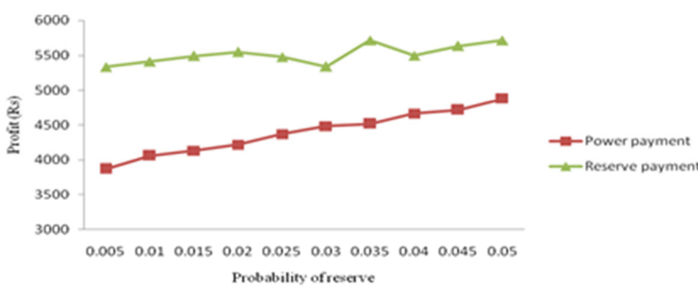

Fig. 8. Effect of probability of reserve for power payment and reserve payment on profit.

Table 1. Hourly operating cost of each area of EPPSO method for 26 unit system.

HOURS (24)	AREA-1 (26 unit)	AREA-2 (26 unit)	AREA-3 (26 unit)	AREA-4 (26 unit)
1	36867.398	23978.521	28416.216	21898.126
2	24332.916	22896.680	21740.900	19324.823
3	27998.167	23114.640	22667.246	18655.978
4	29612.861	18326.321	25117.837	18417.701
5	29363.621	17831.323	25472.429	18553.713
6	35721.176	18312.326	23869.510	18573.596
7	38617.164	28143.146	20845.592	24765.272
8	39328.856	36076.468	19905.851	20342.616
9	345649.734	34843.238	18245.373	21291.120
10	37219.318	32416.347	21163.591	23207.432
11	37184.469	31691.375	20612.082	23542.570
12	38316.472	30581.138	19647.893	20978.693
13	33116.354	34120.029	18027.822	24401.178
14	31630.279	36501.828	17124.939	22704.619
15	30466.627	33150.817	16878.473	23576.431
16	36281.163	32861.752	22306.578	23454.946
17	36894.174	32860.606	21648.580	24226.725
18	35696.310	37439.616	22612.752	17314.724
19	34975.326	37811.059	22379.842	22343.624
20	35766.320	32081.951	21834.391	14358.403
21	38622.479	29125.272	19798.539	18118.242
22	30614.829	14302.122	17985.432	21816.770
23	31483.724	18412.089	16796.273	20294.078
24	29540.211	13162.711	19716.613	18314.498

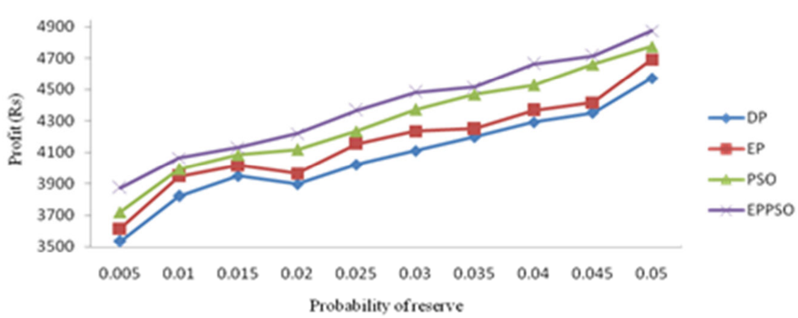

Fig. 9. Comparison of profit if EPPSO with DP, EP and PSO methods by power payment method.

Table 2. Generations and committed capacity in each iteration of EPPSO method of 26 unit system at 11 AM and 4 PM.

Iteration	Area 1	Area 2	Area 3	Area 4	Total
Time: 11 AM					
Generations: Total system load demand = 3461					
1	597.62	1199.87	848.38	815.13	3461.00
2	595.73	1195.67	851.11	818.84	3461.35
3	592.45	1197.76	849.05	821.91	3461.07
4	597.50	1199.75	848.02	815.78	3461.05
5	597.50	1199.75	848.02	815.78	3461.05
Time: 4 PM					
Generations: Total system load demand = 2776					
1	465.76	973.05	730.42	607.33	2776.56
2	463.45	974.97	727.35	611.17	2776.94
3	460.32	976.81	736.67	603.06	2776.86
4	464.94	973.50	735.48	602.23	2776.15
5	464.94	973.50	735.48	602.23	2776.15

Table 3. Comparison of cost for 7 unit (NTPS) and 26 unit systems.

System	Method	Total Operating Cost (pu)			
		Area 1	Area 2	Area 3	Area 4
7Unit (NTPS)	DP(9)	1.00000	1.00000	1.00000	1.00000
	EP(9)	0.96623	0.98033	0.96142	0.96611
	PSO(9)	0.95478	0.97987	0.95989	0.95879
	EPPSO	0.94680	0.96320	0.94025	0.94201
26 Unit	DP(9)	1.00000	1.00000	1.00000	1.00000
	EP(9)	0.98876	.0.99543	0.97675	0.98541
	PSO(9)	0.97211	0.97456	0.96467	0.97599
	EPPSO	0.96489	0.95323	0.95780	0.96154

4. Conclusions

This paper presents EPPSO method for solving profit based multi area unit commitment problem. In comparison with the results produced by the technique DP, EP and PSO method obviously proposed method displays satisfactory performance. 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. It works only with feasible solutions generated, thus avoiding the computational burden entailed by the GA methods which first generated all feasible solutions and then purge the infeasible ones. Test results have demonstrated that the proposed method of solving profit based multi area unit commitment problem increases profit of GENCOs. An effective tie line constraint checking procedure is implemented in this paper. This method provides more accurate solution for profit based multi area unit commitment problem.

The profit based multi area unit commitment scheduling depends on forecasted demand, reserve and market prices. Therefore the accuracy in forecasting all parameters is necessary. However, these forecasted values might be uncertain. By considering uncertainly, better solution will be obtained by using fuzzy theory. Fuzzy theory is an excellent tool for modelling the kind of uncertainty associated with vagueness, with imprecision and with lack of information regarding a particular element of the problem at hand. In future authors would like to include this kind of uncertainly using fuzzy theory in to a profit based multi area unit commitment problem.

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