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PROFIT BASED SELF SCHEDULING OF THE GENCO'S BY USING PARTICLE SWARM OPTIMIZATION

Ramesh Babu MUTHU[1], Somasundaram PERIASAMY[2]

This paper presents an approach for maximizing Genco's profit in a constrained power market. The main objective of this work is to develop simple, reliable and efficient stochastic algorithm for solving the optimal self scheduling of the Genco's in a deregulated environment. The solution of this problem is a two level optimization problem. In the first level the generator operators has to predict the Market Clearing Price (MCP) for the scheduling day, in the second level Genco's are self scheduling their resources to maximize their profit. A neural network based forecasting method is proposed in this paper to forecast the MCP. The solution of the self scheduling problem became complex due to the generator operating and the system constraints. In this paper a novel hybrid optimization technique based on Memetic Particle Swarm Optimization (MPSO) with Cauchy Mutation (CM) is proposed to solve the self scheduling problem. In this algorithm, PSO is used as a global optimizer and Daviden Fletcher Powel (DFP) method is used as the local optimizer. CM is used to reduce the diversity in the searching process of the PSO. The combination of the PSO with local search is referred as MPSO. Simulations have been carried out on a 5-bus practical system and a modified IEEE 30-bus system, to show the robustness and the effectiveness of the proposed algorithm.

Keywords: profit based self scheduling, Memetic particle swarm optimization, Cauchy mutation, local search, optimal bidding strategy, contingency, network constraints

1. Introduction

NOMENCLATURE

α_i , β_i	- Bidding Coefficients of the ith generator.
P_D	- Forecasted load of any hour
C_i	- Operating cost function of the ith generator unit
P_i	- Scheduled power output of the ith generator
u_i	- Schedule state of the ith generator (1: unit is on and 0: unit is off)

[1] Eng., ANNA UNIVERSITY, India, e-mail: manu_ram1@rediffmail.com
[2] Eng., ANNA UNIVERSITY, India, e-mail: mpsomasundaram@yahoomail.com

SUC_i - Start-up cost of the i[th] generator

UR_i / DR_i - Up/Down ramp limits of the i[th] unit.

MUT_i / MDT_i - Minimum Up/Minimum down time limits of the i[th] generator.

S_t - Surplus spinning reserve capacity.

$SP_{i,t} / SP_{i,t\max}$ - Reserve contribution / Maximum reserve contribution of the i[th] unit at the t[th] interval.

$LF_{i,k} / LF_{i,k}^{\max}$ - Apparent / Maximum apparent power flow limit in line k.

NE - Total number of transmission lines.

$\omega_{\max} / \omega_{\min}$ - Maximum/Minimum inertia weight.

$iter_{\max}$ - Maximum iteration count.

C_1 / C_2 - Cognitive/Social parameter.

The bidding strategies of the generating companies usually receive most of the attention in discussions related to market power exercise in electricity markets. The market operation in a deregulated power market is explained in [25]. Regardless of market design, the generator's self-scheduling problem is complicated by several factors [1], in particular, the presence of multiple markets, market design rules, and non-convexity of cost curves, inter-temporal constraints, and price uncertainty. For bidders with relatively low generation cost units, it is not difficult to build bids to make sure that the units can be dispatched at each hour, since they are competitive. However, for a bidder with a marginal or near marginal unit, if the unit cannot be dispatched in one or more hours in the day-ahead market, three alternatives have to be considered. The first is to shut off and cool down the unit. The second is to shut off the unit but keep it in banking, and the third is to build the bid for each of these hours to make sure that the unit can be dispatched to supply its minimum stable output and hence remain in continuous operation. The final decision can be determined by using a unit commitment program to account for the unit's operating constraints and start-up costs for the three alternatives and choosing a solution which maximizes total benefits.

In recent years some research has been done on building optimal bidding strategies for competitive generators. This problem was addressed for the first time by David [2]. He discussed a conceptual optimal bidding model and a dynamic programming based approach for England-Wales electricity markets, in which each supplier is required to bid a constant price for each block of generation. System demand variations and unit commitment costs were considered in the model. In [3], a brief literature survey about strategic bidding in competitive electricity market was presented. In general there are two methods for developing bidding strategies in competitive electricity market: game and non game based methods. In [4] & [5], the competition among participants is modeled as a non-cooperative game with incomplete information. The imperfect information of the suppliers is solved by using game theory to find the Nash equilibrium.

In [6], a dynamic model of strategic bidding for the situation with three power suppliers was proposed by utilizing the historical and current market clearing prices. This model is heuristic in principle, and is not directly applicable to the general case with more than three suppliers. In [7], the bidding behavior model of the suppliers is developed, and how a supplier would construct his bid as a function of his private cost and cost distributions of other bidders are also discussed. In [8], an optimization-based bidding and self-scheduling are discussed with respect to New England market. In [9], an optimal bidding strategy for the power suppliers are framed as a stochastic optimization problem and it is solved by Monte Carlo based optimization methods. An interior - point optimal power flow model was proposed in [10] for the sensitivity based optimal bidding strategy for the suppliers. The impact of congestion on the profit of the suppliers and clear problem formulation with the solution by using Nash equilibrium is discussed by Peng [11]. In [12], the bidding strategy problem is modeled as a two level optimization problem. In the first level the suppliers are maximizing their own profit and in the second level ISO dispatching the power subject to minimization of total system cost. The bidding strategy model for risk averse and risk seeker suppliers are discussed in [13].

In [14] a probability based method is discussed to forecast market clearing price and the dispatch of the Genco's under price uncertainty. The optimal scheduling of the Genco's with security constraints are discussed in [15]. The optimal bidding strategy of generating companies including the emission constraint is discussed in [16]. In this paper the optimization problem is solved by using simulated annealing and it is compared with other heuristics methods.

PSO is a stochastic search algorithm [17], [18] and it searches randomly from point to point to reach the optimum point. The rate of solution convergence is very fast at the beginning with PSO. Thereafter, it is very slow up to the end of convergence. This results in large computation time. In contrast the deterministic local search method is accurate and fast when the variations in the control variables are small and is very effective in correcting the moderate constraint violations. The above fact suggests that a hybrid method with PSO algorithm for initial solution and local search method for getting the final solution be an effective and fast method [19].

The effectiveness and the convergence of the Evolutionary Programming (EP) are improved by using CM and are discussed in [21] and [22]. In this paper

Cauchy mutation operator is used in some randomly selected point around the global best point to reduce the diversity of the PSO with non linear constraints.

This paper proposes a profit based self scheduling of Genco's based on memetic particle swarm optimization with Cauchy mutation. The effectiveness of this algorithm is discussed with the practical 5-bus system and the modified IEEE 30-bus system.

2. Problem formulation

2.1 Forecasting of Market Clearing Price

The market clearing price for the particular hour is mathematically formulated as a maximization problem. The objective is to maximize the social welfare function or to minimize the total system operating cost. The uncertainty in MCP is depending upon the bidding strategy followed by the Genco's and distribution companies (Disco's). The MCP value is also a function of the load variations. Many papers discussed about the estimation of the market clearing price by using probability theory and neural networks. This paper presents a price forecasting methodology based on neural networks. For simplicity, a single auction model is used, i.e. bidding function is available only for generators and load side bidding is constant. It is assumed that all the generators are submitting a linear bidding curve to the ISO. A multi layer feed forward network is used for this problem. The linear bid function of the i^{th} generator is given in equation 1.

$$\lambda_i = \alpha_i P_i + \beta_i \tag{1}$$

The market price forecasting by using GRNN is discussed in [24]. The proposed feed forward network has (2i+1) logsig neurons in the input layer and (2i+1)*4 tansig neurons in the hidden layer. The output layer is consisting of one purelin neuron. Where, 'i' is the number of inputs. The number of inputs is varying depends on the number of generators participated in the bidding process. The data to train the network is obtained by running the market clearing program with various sets of bidding coefficients and loads. Lavenberg-Marquardt algorithm is used to train the feed forward network to forecast the value of the MCP. The self scheduling problem of the Genco's is based on the results obtained from MCP forecasting. The problem formulations of the self scheduling problem with various constraints are briefed in next sub section.

2.2 Profit Based Self-Scheduling Problem

The profit based self scheduling problem (PB-SS) is formulated as an optimization problem that maximizes the Genco's profit. The profit of the Genco's depends on the forecasted market clearing price of the particular hour. The MCP value is known for the hour only after the bidding process was over. This value is used for solving the PB-SS problem. The profit of the price taker generators depends on this uncertain price. This paper considers a time frame of 24 hours to calculate the profit of the Genco's and the objective function is given in (2)

$$\max \sum_{t=1}^{T} \sum_{i=1}^{N_g} \left[MCP(t)P_i(t)u_i(t) - C_i(P_i(t)u_i(t) - SUC_i(t)(1 - u_i(t-1))u_i(t) \right] \tag{2}$$

The linear and nonlinear constraints of the self scheduling problem are listed below,

i) Power balance equation

In the price takers self scheduling problem it is not necessary to satisfy the total forecasted demand. It may be equal or less than the forecasted system demand. A Genco will supply a portion of the demand that maximizes its profit.

$$\sum_{t=1}^{T} \sum_{i=1}^{N_g} P_i(t) \le P_D(t) \tag{3}$$

ii) Generators operating constraints

a) Generator boundary limits

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{4}$$

Where, $i = 1 \ldots N_g$

b) Generating Unit ramp rate limits

$$\left. \begin{array}{l} \max(P_i^{\min}, (P_{i,t-1} - DR_i)) \le P_{i,t} \\ \min(P_i^{\max}, (P_{i,t-1} + UR_i)) \ge P_{i,t} \end{array} \right\} \tag{5}$$

c) Minimum up / down – time limit

$$\left. \begin{array}{l} (u_i(t) - u_i(t-1)(T_{on,t-1} - MUT)) \le 0 \\ (u_i(t) - u_i(t-1)(T_{off,t-1} - MDT)) \ge 0 \end{array} \right\} \tag{6}$$

Where, the time counter for which a unit has been on/off at hour t, T_{on}/T_{off} can be expressed as:

$$\left. \begin{array}{l} T_{on,t} = (1 + T_{on,t-1})u_i(t) \\ T_{off,t} = (1 + T_{off,t-1})(1 - u_i(t)) \end{array} \right\} \tag{7}$$

d) Spinning reserve requirements

$$\sum_{i=1}^{N_g} SP_{i,t} \geq S_t \tag{8}$$

$$SP_{i,t} = Min([P_{i,t\,\max} - P_{i,t}], SP_{i,\max}) \tag{9}$$

iii) Security constraints

$$LF_{i,k} \leq LF_{i,k}^{\max}, \tag{10}$$

3. Memetic particle swarm optimization

3.1 Overview of PSO

PSO is one of the modern heuristic algorithms developed by Kennedy and Eberhart [17]. It has been developed through simulation of simplified social models. Compared to other evolutionary methods, the advantages of PSO are ease of implementation and only few parameters to adjust.

The position with maximum fitness value in the entire run is called the global best (G_{best}), each agent also keeps track of its maximum fitness value, called its local best (P_{best}), and each agent is initialized with a random position and random velocity. The velocity v_j of the j[th] agent, each of n dimensions, is accelerated toward the global best and its own personal best.

Agent's velocities on each dimension are clamped to maximum allowable velocity v_{max} if the sum of accelerations exceeds this limit. The value of v_{max} is an important parameter that determines the resolution with which regions between the present position and the target positions searched. If v_{max} is too high, agents may fly past good regions. If it is low, agents may not explore sufficiently beyond locally good regions. To enhance the performance of the PSO v_{max} is set to the value of the dynamic range of each control variable in the problem. After performing sufficient experiments on various types of test cases, it has been concluded that a better approach is to use a "rule of thumb" to limit v_{max} to the maximum limit of the control variable of the problem.

PSO also has a well-balanced mechanism with flexibility to enhance and adapt to both global and local exploration abilities. This is realized by using an inertia weight ω and is usually calculated using the following expression:

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \frac{iter}{iter_{max}} \tag{11}$$

For largest values of inertia weight, PSO has global exploration feature and vice versa. Even then, there is a need for a trade-off between the quality of solution and fine-tuning of the PSO while selecting its simulation parameters.

Experimental results indicate that it is preferable to initialize the inertia weight to a large value, in order to promote global exploration of the search space, and gradually decrease it to get more refined solutions. Thus an initial value around '1' and a gradual decline towards '0'.If $\omega_{\max}$ is the maximum value of the inertia weight. The two real valued parameters ω_{scale} and $\omega_{iterscale}$ are determined. The value of ω is linearly decreased from $\omega_{\max}$ to $\omega_{\max}\omega_{scale}$ over $iter_{scale}\omega_{iterscale}$ iterations. Then for the last $iter_{\max}(1-\omega_{iterscale})$ iterations it has a constant value equal to $\omega_{\max}\omega_{scale}$. Proper fine-tuning of the parameter may results in faster convergence and alleviation of local minima.

The voltage updating equation with constriction factor [18] is given below,

$$v_j = \chi[\omega * v_{j-1} + C_1 * rand_1(P_{best} - X_{j-1}) + C_2 * rand_2(G_{best}, X_{j-1})] \tag{12}$$

X is the control variables of the objective function f(X).

χ, is the constriction factor and it is derived analytically through the formula

$$\chi = \frac{2w}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|} \tag{13}$$

$\varphi = C_1 + C_2$ And $w = 1$

where $C_1 = C_2$

3.2 Memetic Algorithms

Memetic Algorithms (MAs), which incorporates local search components. MAs constitute a class of Meta heuristics that combines population based optimization algorithms with local search procedures. MAs consists of global component, which is responsible for a rough search of the search space and the detection of the most promising regions, and a local search component, which is used for probing the detected promising regions, in order to obtain solutions with high accuracy.

Petalas and Parsopoulos propose a modified PSO algorithm that combines PSO with local search techniques. MPSO [20] consists of two main components, a global one that is responsible for the search space, and a local one, which performs more refined search around potential solutions of the problem at hand. The application of local search method at various positions is discussed in ref [20].

3.3 Cauchy Mutation

The proposed algorithm utilizes a mutation operator, called Cauchy mutation. The idea of CM is coming from fast simulated annealing. It is aimed at coping with the loss of diversity in global search by incorporating Cauchy mutation into the traditional evolutionary programming as presented in [22]. Applying Cauchy mutation improves the PSO searching ability by mutating some selected particles around the global best point. Cauchy mutation explores more search space than the Gaussian mutation. It has the ability of large jump from local minimum point to a global minimum point than the Gaussian mutation. The comparison of probability distribution function of the Gaussian and Cauchy mutation is given in Fig [1].

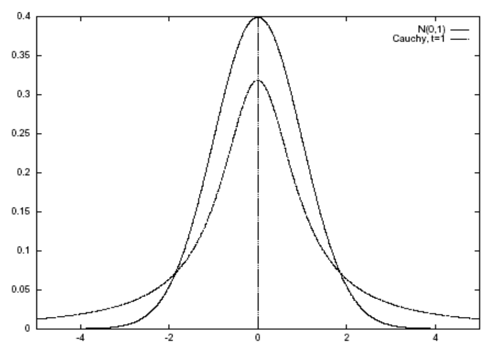

Fig. 1. comparison of probability distribution of gaussian and cauchy distribution

The probability distribution function of the CM is,

$$f_t(x) = \frac{1}{\pi} \frac{t}{t^2 + x^2}, -\infty < x < \infty \quad (14)$$

Where, t is a scale parameter and its value is greater than zero. The corresponding distribution function is,

$$F_t(x) = \frac{1}{2} + \frac{1}{\pi} \arctan(\frac{x}{t}) \quad (15)$$

The steps involved to integrate CM in the MPSO algorithm is explained below,

Step 1: Determine the mutation probability (P_m) by:

$$P_m = \frac{R_m}{m} \quad (16)$$

Where R_m and m are mutation rate and the number of particles respectively. As reported in [21], R_m is set to 1 at the first iteration and linearly decreases to 0 at the final iteration.

Step2: generate a uniformly distributed random number ($rand_i$) between 0 and 1 for each iteration.

Step 3: compare each generated random number (rand$_i$) with P_m. If P_m >rand$_i$ then mutate the particle by following equation

$$x'_i(j) = x_i(j) + \eta_i(j)\delta_j \tag{17}$$

Where δ_j is a Cauchy random number variable with the scale parameter t=1, and is generated a new for each value of j.

3.4 MPSO – CM based self scheduling of generators

1) Generation of Initial Conditions of Each Agent: The initial conditions of each agent have to be generated randomly within the limits. For self scheduling problem the random numbers has to be generated for the real power output of generating units P_i, where, i = 1, 2, 3… N_g, where, N_g is the total no of generating units. Check for any violations in the constraints. Set the iteration count t = 1.

2) Evaluation of Each Agent: Each agent is evaluated using the fitness function of the problem to maximize the profit of the Genco's. The constraints are added to the objective function as a penalty function. The formation of fitness function with inequality constraint is given below,

$$\max(\mathit{profit}_i) = \sum_{t=1}^{T}\sum_{i=1}^{N_g}\begin{bmatrix} MCP(t)P_i(t)u_i(t) - \\ SUC_i(t)(1-u_i(t-1))u_i(t)\end{bmatrix} + \sum_{t=1}^{T}\mu_1\left|[P_i(t) - P_{ir,\lim it}(t)]u_i(t)\right| + \sum_{t=2}^{T}\sum_{i=1}^{N_g}\mu_2\left|[P_i(t) - P_{iu,\lim it}(t)]u_i(t)\right| + \sum_{t=1}^{T}\sum_{k=1}^{NE}\mu_3\left|\left|LF_k(t)\right| - LF_k^{\max}\right| + \sum_{t=1}^{T}\mu_4\left|S_h + P_{Dt} - \sum_{i=1}^{N_g}P_{it,\max}\right| \tag{18}$$

Where μ_1, μ_2, μ_3 and μ_4 are the penalty parameter, S_t is the spinning reserve demand and

$$P_{it,\max} = \begin{cases} P_{i,\max}, if\ \mathrm{t} = 1 \\ Min(P_{i(t-1)} + DR_i, P_i^{\max}, if\ \mathrm{t} \neq 1 \end{cases} \tag{19}$$

$$P_{iu,\lim it}(t) = \begin{cases} P_{i,t-1} - DR_i, if\ P_{i,t} < P_{i,t-1} \\ P_{i,t-1} + UR_i, if\ P_{i,t} > P_{i,t-1} + UR_i \\ P_{it}, otherwise \end{cases} \tag{20}$$

$$P_{ir,\lim it}(t)=\begin{cases}P_i^{\min},if\ P_i(t)<P_i^{\min}\\P_i^{\max},if\ P_i(t)>P_i^{\max}\\P_i(t),otherwise\end{cases} \tag{21}$$

Search for the best value of all the fitness function values $profit_{i,best}$ from $profit_i$, $i=1,2.....M$. where M is the no of agents. Set the agent associated with $profit_{i,best}$ as the global best (G_{best}) of all the agents. The best fitness value of each agent up to the current iteration is set to that if the local best of that agent (P_{best}).

3) Modification of Each Searching Point: Using the global best and the local best of each agent up to the current iteration, the searching point of each agent has to be modified according to the following expression:

$$p_i(t)=v_i+p_i(t-1) \tag{22}$$

Where,

$$v_i=\chi*[\omega*v_i(t-1)+C_1*rand_1\left(P_{best}-P_i(t-1)\right)+C_2*rand_2\left(G_{best}-P_i(t-1)\right)] \tag{23}$$

Where, $rand_1$ and $rand_2$ are random numbers between 0 and 1, C_1 and C_2 are positive constants called as the cognitive and social parameters (acceleration parameters) respectively. Similar to inertia weight, these factors also controls the exploration of the PSO. This acceleration factors are pull the solution towards P_{best} and G_{best} positions. After fixing the value of C1 and C2, find the value of constriction factor [χ], select the Proper values of $\omega_{\max}$, ω_{scale} and $\omega_{iterscale}$. The mutation probability is calculated by using (14) and the mutation of the some of the selected points around the best point is calculated by using (15).

4) Modification of the Global and the Local Bests: The value of g (index of the best particle) is updated for the current iteration. The local search subroutine is applied if any change to overall best position as well as on some randomly selected best position. P_{best} and G_{best} values are updated by evaluating the fitness function of current iteration to find the current best value and compare it with all the previous iterations respectively.

5) Termination Criteria: Repeat from 2) until the tolerance value is reached or maximum value of iteration is reached

4. Pseudo code

Step 1) Get the data for the system (MCP, $P_i^{\max}$, $P_i^{\min}$, $UR_i, DR_i, SP_{i,t}, SP_{i,t\max}, P_D$, $LF_{i,k}$)
Step 2) Randomly initialize the population size, searching points, velocities and acceleration of the agents and set the iteration count t=0.
Step 3) Evaluate the fitness function (18) and update the inertia weight and P_m.
Step 4) Determine global best value indices g_i from the current population.
Step 5) Modify the velocities and searching points by using (22) and (17)
Step6) Evaluate $profit(p_i^{(t+1)}), i = 1,....N_g$.
Step 7) If $profit(p_i^{(t+1)}) \geq profit(p_i^{(t)})$ Then $p_i^{(t)} \leftarrow p_i^{(t+1)}$
Step 8) Else $p_i^{(t)} \leftarrow p_i^{(t)}$
Step 9) Update the indices g_i.
Step 10) When (local search is applied) Do
Step 11) Apply local search on $p_q^{(t+1)}$ and obtain a new solution, y.
Step12)If $y > profit(p_i^{(t+1)})$ Then $p_i^{(t)} \leftarrow p_q^{(t+1)}$.
Step 13) Exit if termination criterion is met; set t = t+1; End While; Go to step 3

5. Numerical results and discussion

5.1 Optimal Selection of MPSO Parameters

Selecting the optimal range of inertia weigh ω and acceleration factors C_1 and C_2 considerably affects the performance of the PSO algorithm. Therefore, to fix an optimal range of inertia weight, experiments were conducted using the proposed method by varying the value of the agent size, cognitive parameter(C_1), social parameter(C_2), starting value of the inertia weight$(\omega_{\max})$, final value(ω_{scale}) of ω in percentage of $\omega_{\max}$ $\omega_{iterscale}$ percentage of iterations, for which $\omega_{\max}$ is reduced and maximum value of step size($V_{\max}$).

The inertia weight varied from 2.0 to 0.1, in steps of 0.1, the agent's size is varied from 10 to 1000 in steps of 10, and the maximum number of iteration is varied from 10 to 250 in steps of 10. Different possibilities of trial runs were conducted to optimally estimate all the parameters for the proposed method.

To ensure reliability in producing quality solutions by the proposed method, the relative frequency of convergence toward a quality solution is targeted. The proposed method has produced reliable and quality solutions for inertia weights above 0.6 for all of the cases. DFP method is used as local search. It will take lesser time to compute the Hessian matrix. The optimal values for C_1 and C_2 are selected by conducting similar experiments for all the cases considered in this paper.

5.2 Numerical Solution

Two test cases are taken to demonstrate the feasibility of the proposed method. A 5 bus system and a modified IEEE 30–bus system are taken as test systems. For simplicity in this paper it is assumed that the generators are submitting the linear bidding coefficients α_i and β_i. After the market clearing mechanism the Genco's are got their allotment of power and they have to dispatch this power by considering the generation constraints and also the system constraints. The change in power scheduling, profit and the cuts in generation are calculated by comparing the results. A DC load flow model is used to check the violations in the line limits. MATLAB based Simulations are carried out on a Pentium IV, 1-GHz, 512–MB RAM processor.

Test System1: A five bus test system with 3 suppliers and seven lines are considered. The network diagram, generator data and line data of the five bus system is given in ref [26].

The line flow limits of the lines are fixed at 62.5MW. The outage of line 2-3 is considered for the contingency case. This line is more critical line of the proposed 5 bus system and it is identified by using sensitive analysis. The spinning reserve requirements are assumed by taking in to account the maximum possible power generation of all the committed units: $SP_{i,\max} = P_{i,\min}$ for all units.

The comparison of profit gained by the Genco's considering line flow limits and the contingency case is as shown in Fig 2.

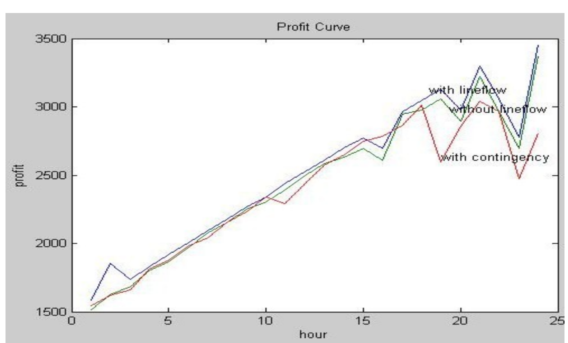

Fig. 2. profit variation of the 5-bus system

The generators have to alter their power output to get more profit from the market. The changes in power from the generators for the constrained (line flow and contingency) cases are compared with unconstrained case and are tabulated in Table 1.

Table 1

Change in power of the generators of the 5-bus systems

Hour	P1		P2		P3	
	With line flow limits	With 2-3 line outage	With line flow limits	With 2-3 line outage	With line flow limits	With 2-3 line outage
1	7.01	0.0203	3.838	23.854	-10.864	2.9028
2	2.4514	1.6318	-3.4796	16.123	-10.25	1.0277
3	4.1231	5.4389	-9.2668	3.8552	-4.518	0.7441
4	0.548	-1.942	11.689	27.338	-12.20	-4.34
5	6.9215	6.8547	1.338	20.581	-8.074	-3.203
6	9.3347	-4.231	-8.7054	-1.159	-0.728	20.598
7	-6.323	-9.268	-2.8862	13.346	9.1432	11.937
8	-13.832	6.4105	4.159	14.649	-5.057	-10.31
9	-0.688	1.4222	-0.1921	9.9244	0.9088	1.907
10	1.4367	-4.381	-1.8593	3.1512	0.3544	5.1325
11	-2.536	1.5014	2.9219	7.899	-0.341	4.4711
12	-7.8017	-6.695	6.1654	18.818	1.6014	-2.194
13	10.955	4.2564	-4.5554	6.9969	-6.393	6.2853
14	-9.2306	-1.561	4.3521	15.098	4.8126	-5.851
15	-6.606	-10.04	-5.9388	14.557	12.559	14.035
16	-10.102	0.9044	-6.5153	-3.712	5.1342	5.1322
17	14.574	13.136	-20.149	-4.936	5.601	-0.747
18	-5.6686	-16.16	2.2842	17.878	3.4199	15.285
19	13.641	7.0676	-8.0408	20.086	-5.689	-4.424
20	0.4629	9.3112	-0.4451	9.1371	14.144	8.7194
21	-22.285	0.9557	18.587	29.049	8.014	-12.87
22	-2.4701	3.6793	-3.0703	11.991	5.4178	1.025
23	-22.542	-4.244	8.9454	10.059	13.609	13.467
24	-0.9575	-8.783	12.1	0.8529	17.365	9.4725

From the Table 1 it is clear that the generators have to change the generation levels to extract the benefit from the market. From the Fig 2 it is clear that the profits gained by the generators are decreasing due to system constraints and the operating constraints of the generators.

Test System2: A modified thirty bus test system with 6 suppliers and forty lines are considered. The network diagram, generator data and line data of the IEEE 30-bus system is given in ref [22]. Eight hundred set of test data's are used to train the proposed network. The data is simulated by solving the market clearing problem. An optimal power flow frame work is used. The variations of forecasted MCP with respect to actual values are shown in Fig.3

The forecasted error in the proposed feed forward network is less compare to time series and regression based methods. The variation of the predicted value of MCP with respect to time is given in Table 2.

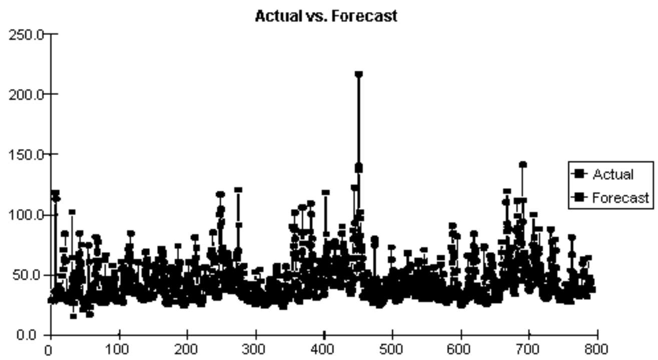

Fig. 3. Variation of actual and forecasted MCP

Table 2

Forecasted MCP

Hour	MCP (Rs/MWh)	Hour	MCP (Rs/MWh)	Hour	MCP (Rs/MWh)
1	35.25	9	26.31	17	26.87
2	35.03	10	26.28	18	23.39
3	27.23	11	27.38	19	34.12
4	28.00	12	34.89	20	34.52
5	34.32	13	35.05	21	23.86
6	32.22	14	36.21	22	28.21
7	26.45	15	36.26	23	29.38
8	27.25	16	33.89	24	25.25

The profit variations of the generators with and without considering the various constraints are given in Fig.4.

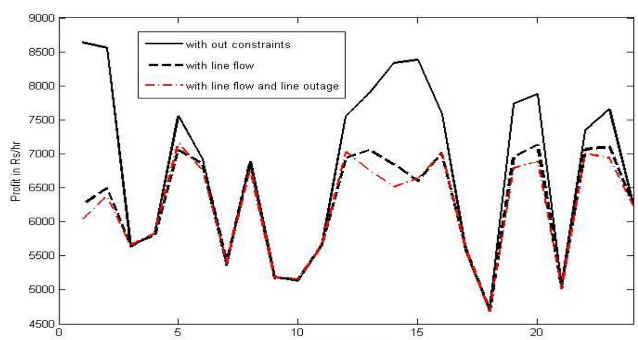

Fig. 4. Profit comparision curve of the IEEE 30 – bus system

The change in power output from the generators without any system constraint and with considering the line flow limits is given in Fig.5.

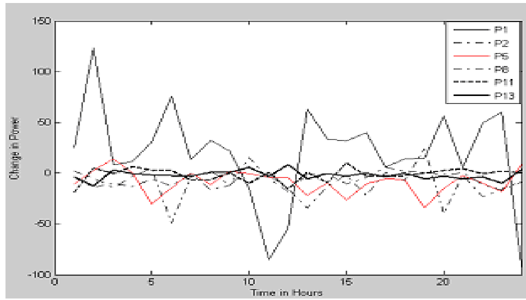

Fig. 5. change in power output for the 30-bus system considering line flow limits

The change in power output from the generators without any system constraint and with considering the line outage is given in Fig.6.

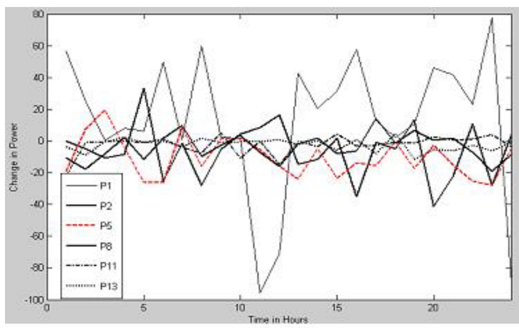

Fig. 6. change in power out put for the 30-bus system considering outage of line 4-6

5.3 Computation Analysis of Proposed Method

To compare the computation efficiency of both methods, the test system 2 was experimented on for 25 trial runs. The average computation time during the progress of the iterations is taken and plotted against the various percentage of the maximum iteration count as shown in Fig.7.

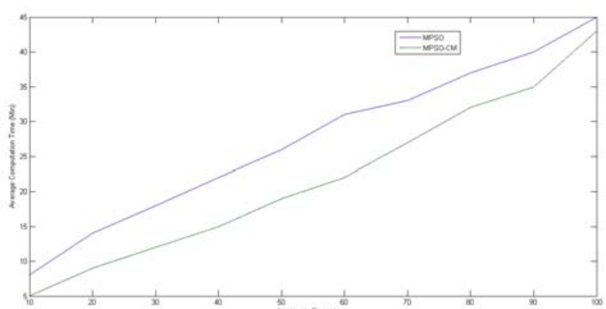

Fig. 7 Average computation time for 25 trial runs using MPSO and MPSO-CM

From that, it is clear that the MPSO-CM method has better average time. Since local search is invoked whenever there is an improvement in the PSO run, better solution regions are retained during the progress of the run; this finally leads to a better solution at the termination of the run. MPSO-CM is quick and saves considerable computation time on the whole, even though the Cauchy mutation parameters and local search routine takes considerable time, and thereby, the average computation time of the MPSO-CM method is less compared to the MPSO.

While solving the test systems, inclusion of additional constraints as penalty terms in the fitness function considerably affects the performance of the solution procedure. To demonstrate this, the test case 2 is adopted, and in the following order, the constraints are added to the problem:1) line flow limits 2) line outage (contingency).for both the cases the spinning reserve limitation and the ramp rate limits are also considered. Each case was experimented for 25 trial runs.

Time taken by the MPSO method considerably increases as the constraints are added one by one. It is observed in Table 3.

Table 3

Comparison solution for test case 2

Method		Maximum Profit (Rs/Hr)	Minimum Profit (Rs/Hr)	Average Profit (Rs/Hr)	Average Time (min)	Minimum Time (min)
C1	PSO	163278.3	159998.3	161998.3	25.72	22.98
	MPSO	163282.7	161298.3	162998.3	24.22	23.52
	MPSO with CM	163282.7	161299.2	162999.3	26.22	25.32
C2	PSO	150630.2	140597.1	142622.2	34.37	31.17
	MPSO	150636.5	143446.5	144666.8	33.92	31.98
	MPSO with CM	150638.5	143448.5	144668.8	35.71	32.67
C3	PSO	149060.9	132120.9	141592.9	39.87	35.23
	MPSO	149068.0	140220.1	143972.9	38.23	35.13
	MPSO with CM	149070.5	140222.1	143973.7	39.13	36.41

To sum up, when the load and MCP has more variations, the MPSO method takes more computation time due to the local search routine invoked more times, compared to when it is less. Inclusion of additional constraints increases complexity and the number of computations involved. This increases average computation time of both solution methods, irrespective of the load demand pattern they handle.

Finally, it is clear from the test systems that the MPSO with CM outperforms the MPSO method in terms of solution quality, reliability in producing it, convergence and computation time.

The MPSO is capable of handling the PB-SS problem in a more effective way. The solution of this problem is mainly depends on the forecasted value of the MCP, generator operating constraints and the system constraints. In this paper the self scheduling problem is framed for price taker Genco's and day – ahead market model is followed. The proposed algorithm is very effective in real time market when spot prices are changing with respect to changes in market parameters.

6. Conclusion

The proposed hybrid method is simple, reliable and gives accurate results within the reasonable computation time. The PSO with constriction factor explores the solution space to obtain near global solution. The application of scaling factor for inertia constant ensures the convergence of the solution. CM is used to reduce the diversity in the searching process of the PSO and it will reduce the number of iterations. It will effectively explore the solution space when the number of constraints added to the objective function is non linear in nature. Local search is used to fine tune the solution obtained from PSO and CM. The proposed algorithm is tested with two test systems and the results are analyzed with various factors. The self scheduling problem of the Genco's is varying with respect to the variations of the market clearing price and the forecasted demand for the hour. In this paper a simple feed forward neural network is used to predict the MCP value. Therefore any supplier should be aware of its self scheduling, it's bidding strategy, and ultimately, on its actual profits.

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