VOL. 7, NO. 2, FEBRUARY 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

RISK INVOKED SELF-SCHEDULING OF A GENCO IN THE DAY-AHEAD ENERGY MARKET

M. Ramesh Babu and P. Somasundaram
Department of Electrical and Electronics Engineering, CEG, Anna University, Chennai, India
E-Mail: manu_ram1@rediffmail.com

ABSTRACT

This paper proposes a novel Cauchy mutated Memetic Particle Swarm Optimization (CMPSO) algorithm to solve the risk invoked self-scheduling problem of price taking Generator Company (Genco) in a day-ahead energy market. In self-scheduling problem, certain risk is invoked due to uncertainty in forecasted electricity prices and fuel prices. The risk in the self-scheduling problem is modeled based on the portfolio selection. The risks in the forecasted energy prices are taken into account by using the covariance information of the available data. The Risk Invoked Self-Scheduling (RISS) is formulated as a mixed integer non-linear optimization problem and solved by using the proposed CMPSO. The effectiveness of the proposed CMPSO algorithm is demonstrated with two test systems.

Keywords: self-scheduling, energy market, risk analysis, Cauchy mutation, locational marginal pricing, memetic PSO.

1. INTRODUCTION

The bidding strategies of the generating companies usually entertain ample consideration in discussions related to market power exercise in electricity markets. Power producers aim to maximize the profit in day-ahead energy market. For Gencos, self-scheduling of generating units is one of the potential problems in day-ahead energy market, which is a mixed integer non-linear optimization problem. The production offers in the energy markets are based on the forecasted Locational Marginal Price (LMP), operating constraints of the generators and the risk factor due to the uncertainty of various parameters.

Recently, there are many changes tailored in the modelling and solution methodology of the Genco's self-scheduling problem [1-6]. The self-scheduling problem for the various types of participants and various types of markets without considering the uncertainties are presented in [1-5]. In [6], exhaustive description of constructing hourly bidding curves for price-taking thermal generation company to maximize their profit is presented. In literature, numerous research works have incorporated risk issues to the Genco's self-scheduling problem [1-6]. In [7], lagrangian relaxation method is proposed to solve the risk invoked Genco's self-scheduling problem. A different risk modeling based on scenario trees and condition value are presented in [8-9]. The security constrained generation scheduling for the Genco's is discussed in [10]. In [11], a different fuzzy based approach is proposed to solve the self-scheduling problem of Genco. The above indicated conventional deterministic mathematical optimization techniques for solving self-scheduling problem of Genco's, are complex and involves high computational burden for large-scale systems.

In the present scenario, simple and reliable stochastic methods are developed to solve the mixed integer problems [12-14]. Particle Swarm Optimization (PSO) is a popular stochastic search algorithm proposed by Kennedy and Eberhart [13]. Unlike other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. The primary shortcoming of classical PSO algorithm is a very large computation time due to the large number of iterations required to obtain a global optimum. It also suffers from premature convergence like most stochastic search techniques, particularly in the case of multimodal optimization problems. Hence there is a need to accelerate the convergence and to avoid entrapment in local optimum, thereby reducing the computation time of PSO technique for obtaining the global optimum. In PSO the rate of convergence is very fast at the beginning. Thereafter, it is very slow towards the end of iterations. 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 search and subsequent local search method for getting the final solution will be an effective and fast method.

Memetic PSO (MPSO) is a hybrid algorithm that combines PSO with local search techniques. MPSO consists of two main components, a global one that is responsible for the global search of the search space, and a local one, which performs more refined search around potential solutions of the problem. As Sequential Quadratic Programming (SQP) is an effective deterministic optimization technique [15], in this paper SQP is used as local search in the MPSO algorithm. Coelho [16-17] generated random numbers by using Gaussian and Cauchy probability distributions to update the velocity equation of the PSO. This method is very effective in solving economic dispatch and mixed integer problems [16-17]. Thus in the MPSO algorithm, Cauchy Mutation (CM) is incorporated with a view to enhance diversified search and to increase the rate of convergence. Hence the proposed algorithm is appropriately termed as Cauchy mutated Memetic Particle Swarm Optimization (CMPSO) algorithm.

ARPN Journal of Engineering and Applied Sciences

The proposed CMPSO algorithm is used to solve Risk Invoked Self-Scheduling (RISS) problem for the power producers with multiple generating units participating in energy market under a risk based framework. The effectiveness of the proposed CMPSO algorithm is tested with the real time data obtained from the PJM market and with the standard IEEE 30 bus system.

The rest of this paper is organized as follows: In section 2, a general problem formulation of RISS is provided. Section 3 addresses the framework of the proposed Cauchy mutated Memetic Particle Swarm Optimization (CMPSO) algorithm. The application of the proposed CMPSO algorithm for solving the RISS problem is explained in Section 4. Section 5 illustrates the numerical results of the test cases and Section 6 presents the conclusions arrived after analysis.

2. PROBLEM FORMULATION

The main aspiration of this paper is to formulate the self-scheduling problem of generator companies in a day-ahead energy market.

Forecasting the locational marginal prices (LMP) with less error is very critical. The Autoregressive Integrated Moving Average (ARIMA) [18], [20] and the Generalized Autoregressive Conditional Hetero skedasticity (GARCH) [20] modelling are the most popular methodologies for forecasting time series and future volatility, respectively. Neural Networks [21] based forecasting methods are complementary with the conventional time series forecasting methods. In paper [22] an adaptive wavelet based neural network is proposed to forecast the LMP and MCP. In [23], hybrid forecasting model based on support vector machine and particle swarm optimization with Cauchy mutation is used to improve the slow convergence of the particle swarm optimization. In this paper a training algorithm based on CMPSO is used to train the feed forward networks to forecast the energy prices.

A. Risk modeling

The self-scheduling of the power producer depends on the forecasted energy price in which all these parameters encounter certain uncertainties. Due to the uncertainty of the forecasted price during peak demand and unusual conditions, there is an associated risk in the arbitrage activities. The variance of the estimated energy market along with the covariance matrices are used to measure the risk [6] due to uncertainties. To explicitly express the Genco's risk tolerance in the optimization model, the concept of downside risk is used in [25]. If the profit is higher than its target profit, the downside risk is zero. Otherwise, the risk is quantified by the amount of profit that cannot be satisfied. The exponentially weighted moving average model to calculate the variances and covariance of the multivariate normal distribution is discussed in [26]. The volatility in the electricity prices can be studied by using its variance and covariance information. The variance between two random variables P_i and P_j can be expressed as:

$$Variance\left\{\sum_{t=1}^{T}\lambda_e.P_t^e\right\}=\sum_{i=1}^{T}\sum_{j=1}^{T}V_e^{\;est}P_i^eP_j^e \tag{1}$$

$$=\sum_{i=1}^{T}\sum_{j=1}^{T}V_e(i,j)P_i^eP_j^e+2\sum_{i=1}^{T}\sum_{j=1}^{T}COV_e(i,j)P_i^eP_j^e \tag{2}$$

Where, V_e is the variance matrix of energy price and COV_e is the covariance matrix between the prices. The variance and covariance for the day 'N' are obtained by using the following equations.

$$V_e=Exp\left\{\left(\lambda_{\mathrm{e,N}}^{\mathrm{actual\ i}}-\lambda_{\mathrm{e,N}}^{\mathrm{est\ i}}\right)\left(\lambda_{\mathrm{e,N}}^{\mathrm{actual\ i}}-\lambda_{\mathrm{e,N}}^{\mathrm{est\ i}}\right)^{\mathrm{T}}\right\} \tag{3}$$

$$COV_e=Exp\left\{\left(\lambda_{\mathrm{e,N}}^{\mathrm{actual\ i}}-\lambda_{\mathrm{e,N}}^{\mathrm{est\ j}}\right)\left(\lambda_{\mathrm{e,N}}^{\mathrm{actual\ i}}-\lambda_{\mathrm{e,N}}^{\mathrm{est\ j}}\right)^{\mathrm{T}}\right\} \tag{4}$$

If the actual prices as well as their estimated values are available up to the day $N-1$, then a better estimation for the variance and covariance matrices can be obtained by using the following exponentially weighted moving-average equation:

$$\mathrm{V_e}=(1-\alpha)\sum_{\mathrm{i=1}}^{\mathrm{N-1}}\alpha^{\mathrm{i}}(\lambda_{\mathrm{e,N-i}}^{\mathrm{act}}-\lambda_{\mathrm{e,N-i}}^{\mathrm{for}})(\lambda_{\mathrm{e,N-i}}^{\mathrm{act}}-\lambda_{\mathrm{e,N-i}}^{\mathrm{for}})^{\mathrm{T}} \tag{5}$$

$$\mathrm{COV_e}=(1-\alpha)\sum_{\mathrm{k=1}}^{\mathrm{N-1}}\alpha^{\mathrm{i}}(\lambda_{\mathrm{e,N-k}}^{\mathrm{act\ i}}-\lambda_{\mathrm{e,N-k}}^{\mathrm{for\ j}})(\lambda_{\mathrm{e,N-k}}^{\mathrm{act\ i}}-\lambda_{\mathrm{e,N-k}}^{\mathrm{for\ j}})^{\mathrm{T}} \tag{6}$$

The past prices are weighted by the smoothing constant (α) and it is varying between 0 and 1. The higher weights are assigned to the days closer to N, and decays exponentially with the distance between the considered day and the day N. The parameter 'N' is greater than or equal to one to ensure the covariance matrix positive definite [26].

B. Risk invoked self scheduling problem

The Risk Invoked Self-Scheduling (RISS) problem is formulated as an optimization problem that maximizes the Genco's profit and minimizes the risk. The objective function of the RISS problem is presented by:

$$\text{Maximize}\ :\left(\sum\text{RETURNS}\right)-\left(\sum COSTS\right)-\left(\beta*RISK\right) \tag{7}$$

Subject to,

Power balance

Generators operating constraints

The risk objective must be added with revenue to determine the actual profit involving risk. To combine these conflicting objectives, the risk term is subtracted from revenue term using risk penalty factor (β). The value of this parameter varying between (0, 1) and its actual value materialize the tradeoff between the expected profit and risk. The risky producers choose this value closer to zero to increase the profit with high risk; others can choose larger value to minimize the risk.

ARPN Journal of Engineering and Applied Sciences

The first term in (7) represents the returns of the Genco's from the market as shown by (8). Here a time frame of 24 hours is considered.

$$\sum RETURNS = \sum_{t=1}^{T}\sum_{k=1}^{N_g} \lambda^e(t)P_k^e(t)U_k(t) \tag{8}$$

Where,

P_k^e = Scheduled power output of the kth generator in the energy market

U_k = Schedule state of the kth generator (1: unit is on and 0: unit is off)

N_g = Number of generating units participates in the self scheduling

The second term in (7) represents the costs of the power producer which is explained by:

$$\sum COSTS = \sum_{t=1}^{T}\sum_{k=1}^{N_g} C_k(P_k^e(t)U_k(t) + SUC_k(t)(1-U_k(t)) \\ U_k(t) + SDC_k(t)(1-U_k(t))U_k(t-1) \tag{9}$$

Where, SUC_k is the start-up cost SDC_k is the shut-down cost and C_k is the quadratic cost function of the kth generator.

The last term in equation (7) represents the risk of forecasted market price as:

$$RISK = \sum_{i=1}^{T}\sum_{j=1}^{T} V_e^{est}(i,j)P_i^e P_j^e \tag{10}$$

The constraints of RISS problem can be clustered in two categories namely power balance and generators operating constraints follows:

i) Power balance constraint

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's will supply a portion of the demand that maximizes its profit.

$$\sum_{t=1}^{T}\sum_{k=1}^{N_g} P_k^e(t) \le P_D^e(t) \tag{11}$$

ii) Generators operating constraints

a) Generator boundary limits

$$P_k^{e,\min} \le P_k^e \le P_k^{e,\max} \quad k = 1,...N_g \tag{12}$$

$$\left.\begin{array}{l}[(P_k^e(t-1) - DR_k(1+U_k(t)))U_k(t-1)] \le (P_k^e(t)) \\ [(P_k^e(t-1) - UR_k(1+U_k(t-1)))U_k(t+1)] \ge (P_k^e(t))\end{array}\right\} \tag{13}$$

Where, UR_k / DR_k is the up/down ramp rate limits of kth unit.

b) Minimum up / down - time limit

$$\left.\begin{array}{l}(U_k(t) - U_k(t-1)(T_{on}(t-1) - MUT)) \le 0 \\ (U_k(t) - U_k(t-1)(T_{off}(t-1) - MDT)) \ge 0\end{array}\right\} \tag{14}$$

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

$$\left.\begin{array}{l}T_{on}(t) = (1 + T_{on}(t-1))U_k(t) \\ T_{off}(t) = (1 + T_{off}(t-1))(1 - U_k(t))\end{array}\right\} \tag{15}$$

Where, MUT_k / MDT_k is the minimum Up/down time limits of the generator, 'k' and DR_k / UR_k is the ramp up/down limits of the kth generator.

Where, $P_k^{\max} / P_k^{\min}$ are the minimum and maximum boundary limits of the kth generator.

c) Spinning reserve requirements

$$\sum_{k=1}^{N_g} SP_k(t) \ge S(t) \tag{16}$$

$$SP_k(t) = Min([P_k^{\max}(t) - P_k(t)], SP_k^{\max}(t)) \tag{17}$$

Where, $S(t)$ is the surplus spinning reserve capacity left after the load demand of $P_D(t)$ is met. $SP_k(t)$, $SP_k^{\max}(t)$ are the reserve contribution and the maximum reserve contribution of the unit 'k' unit at the time period time interval, t. In self scheduling problem, the Genco's are not going to meet the complete forecasted load, so that the value of surplus spinning reserve capacity depends upon the strategy of the generator company and it is volatile.

3. CMPSO

PSO is one of the modern heuristic algorithms developed by Kennedy and Eberhart [13]. In PSO, particle X_i^{iter} is a feasible solution represented by an *m*-dimensional real-valued vector, where *m* is the number of control parameters. At iteration *iter,* the i^{th} particle X_i^{iter} can be described as $X_i^{iter} = [x_{i,1}^{iter}, x_{i,2}^{iter}, ..., x_{i,K}^{iter}, ..., x_{i,m}^{iter}]$, where $x_{i,k}^{iter}$ is the position of the i^{th} particle in k^{th} dimension, i.e., the value of the k^{th} control parameter in the i^{th} particle. At iteration *iter*, the i^{th} particle velocity V_i^{iter} can be described as $V_i^{iter} = [v_{i,1}^{iter}, v_{i,2}^{iter}, ..., v_{i,k}^{iter}, ..., v_{i,m}^{iter}]$ where $v_{i,k}^{iter}$ is the velocity component of the i^{th} particle in k^{th} dimension. The particle's position with maximum fitness value in the entire run is termed as global best g_{best} and the particle's position with maximum fitness value at the end of iteration *iter* is termed as local or particle best p_{best}. Each particle is initialized with a random position and

VOL. 7, NO. 2, FEBRUARY 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

velocity. The k^{th} element's (control parameters) velocity of the i^{th} particle for next iteration is:

$$V_k^{i\ \text{iter}+1} = \chi[\omega \times V_k^{i\ \text{iter}} + C_1 \times rand_1 (p_{best}{}^{i} - x_k^{i\ \text{iter}}) +$$
$$C_2 \times rand_2 (g_{best} - x_k^{i\ \text{iter}})] \quad (18)$$

$$x_k^{i\ \text{iter}+1} = x_k^{i\ \text{iter}} + v_k^{i\ \text{iter}+1} \quad (19)$$

Where, C_1 and C_2 are the acceleration constants. The constriction factor χ is introduced by Clerc and Kennedy [18] to effectively restrain the change in velocity.

$$\chi = \frac{2}{2 - c - \sqrt{c^2 - 4c}} \quad (20)$$

Where, $c = C_1 + C_2$ and $c > 4$

PSO also has a well-balanced mechanism with flexibility by adapting to both global and local explorations. This is realized by using an inertia weight 'ω'. The dynamic change of inertia weight is represented by using the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} * iter \quad (21)$$

Where, ω_{max} and ω_{min} is the lower and upper bound for inertia weight and $iter_{max}$ is the maximum iteration count. Kennedy and Eberhart [14] extended the real-valued PSO to discrete space by calculating the probability from the velocity using the following sigmoid function,

$$sig(v_k^{i\ \text{iter}+1}) = \frac{1}{1 + e^{-(v_k^{i\ \text{iter}+1})}} \quad (22)$$

This probability determines whether $x_k^{i\ \text{iter}+1}$ is 0 or 1.

$$x_k^{i\ \text{iter}+1} = \begin{cases} 1 & if \quad \mathrm{r_j} < sig(v_k^{i\ \text{iter}+1}) \\ 0 & otherwise \end{cases} \quad (23)$$

Where, r_j is a random number in the range of [0, 1].

The trajectory of a particle $x_k^{i\ \text{iter}+1}$ converges to a weighted mean of p_{best} and g_{best}. Whenever the particle converges, it will fly to the personal best position and the global best position. This information sharing mechanism tends PSO to a very fast convergence. However due to this mechanism, PSO can't guarantee the global value as the particles usually converge to local optimum. Once the particles trap into a local optimum, in which p_{best} can be assumed to be same as g_{best}. At this condition, the velocity update equation is a function of the inertia weight alone. Since the inertia constant varies slowly the change in velocity of the particle is close to zero. After that, the position of the particle $x_k^{i\ \text{iter}+1}$ will not change. Due to this problem, PSO often fails to obtain the global maximum.

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 CM into the traditional evolutionary programming as presented in [12] and [28]. Applying Cauchy mutation improves the PSO searching ability by mutating some selected particles around the global best point. It has the ability of large jump from local minimum point to a global minimum point than the Gaussian mutation. Each particle is mutated with Cauchy distributed function and is given below:

$$f(x_k^{i\ iter}) = \frac{1}{2} + \frac{1}{\pi}\arctan(x_k^{i\ \text{iter}} / t) \quad (24)$$

Where, t >0, is a scale parameter.

The steps involved to integrate CM in the PSO algorithm is explained below:

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

$$P_m = \frac{R_m}{m} \quad (25)$$

Where, R_m and 'm' are mutation rate and the number of particles respectively. As reported in [28], R_m is set to 1 at the first iteration and linearly decreases to 0 at the final iteration.

Step 2: 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,

$$x_k^{i\ \text{iter}+1} = x_k^{i\ \text{iter}} + f(x_k^{i\ iter}) V_k^{i\ \text{iter}} \delta_k \quad (26)$$

where δ_j, is a Cauchy random number.

Petalas and Parsopoulos [29] proposed MPSO, which combines PSO with local search techniques. Memetic particle swarm optimization 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 [29]. The contribution of this paper is to combine Cauchy mutated particle swarm optimization with local search for exploring the solution space effectively to find the global optimum.

4. CMPSO BASED RISS PROBLEM

The control variables of the RISS problem are the real power output of the Generator and the commitment status of the generator. The process of implementing the CMPSO is as follows:

ARPN Journal of Engineering and Applied Sciences

a) Initialization of particles: Generate randomly the real power output of generators in the energy market within the feasible range for all the *n* particles.

$$X^i = \begin{bmatrix} U^i_{1,1}, U^i_{2,1}, \ldots U^i_{N_g,1}; & P^{e\ i}_{1,1}, P^{e\ i}_{2,1}, \ldots P^{e\ i}_{N_g,1} \\ . & . \\ . & . \\ U^i_{1,t}, U^i_{2,t}, \ldots U^i_{N_g,t}; & P^{e\ i}_{1,t}, P^{e\ i}_{2,t}, \ldots P^{e\ i}_{N_g,t} \end{bmatrix} \tag{27}$$

Where, N_g is the total number of generator and t is the number of scheduling hour. The elements of each particle $X^i; i = 1,2,\ldots..n$ are the commitment status of the generators and the real power of generators in energy market.

b) The fitness evaluation of each particle: Each particle 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. These values are chosen such that if there is any constraint violations the fitness value corresponding to that particle will be ineffective.

$$f_i = RETURNS_i + \sum_{t=1}^{T}\sum_{k=1}^{N_g} \mu_1 \left| [P^{e\ i}_k(t) - P^{e,limit}_{\mathrm{k}}(t)] U^i_k(t) \right| + \sum_{t=2}^{T}\sum_{k=1}^{N_g} \mu_2 \left| [P^{e\ i}_k(t) - P^{\mathrm{e\ \ ulimit,i}}_{\mathrm{k}}(t)] U^i_k(t) \right| + \sum_{t=1}^{T} \mu_3 \left| S(t) + P^e_D(t) - \sum_{k=1}^{N_g} P^{e\ \max}_k(t) \right| \tag{28}$$

Where, μ_1, μ_2 and μ_3 are the penalty parameter and $P^{\mathrm{e\ \ ulimit,i}}_{\mathrm{k,}}(t)$ is given below,

$$\begin{cases} P^{e\ i}_k(t-1) - DR_k, if\, P^{e\ i}_k(t) - P^{e\ i}_k(t-1 > DR_k \\ P^{e\ i}_k(t-1) + UR_k, if\, P^{e\ i}_k(t) - P^{e\ i}_k(t-1) > UR_k \\ P^{e\ i}_k(t), otherwise \quad ; \end{cases} \tag{29}$$

$$P^{\mathrm{e,limit}}_{\mathrm{k}}(t) = \begin{cases} P^{e\ \min}_k, if\, P^{e\ i}_k(t) < P^{e\ \min}_k(t) \\ P^{e\ \max}_k, if\, P^{e\ i}_k(t) > P^{e\ \max}_k(t) \\ P^{e\ i}_k(t), otherwise \end{cases} \tag{30}$$

The maximum fitness function value among the particles is stored as $f_{\max}$.

c) Determination of pbest and gbest particles: Compare the evaluated fitness value of each particle with its pbest. If current value is better than pbest, then set the current location as the pbest location. If the best pbest is better than gbest, the value is set to gbest.

e) Modification of member velocity: change the member velocity of the each individual particle v_j, according to the equation (18) and (22).

f) Modification of member position: The member position in each particle is modified according to equation (19) and (23). The mutation probability is calculated by using (25) and the mutation of the some of the selected points around the best point is calculated by using (26). Apply local search algorithm whenever there is a change in gbest value.

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

5. NUMERICAL RESULTS AND DISCUSSIONS

Two test cases are taken to demonstrate the feasibility of the proposed method. In the first test case a producer having single generating unit in PECO control zone of PJM market is selected and an IEEE 30 bus system is used as second test case. The MATLAB based simulations are carried out on a Pentium IV, 2.2-GHz, 1-GB RAM processor. The real time data are taken from PECO control zone [30]. The two year data from December 2008 to December 2010 is used as input data. The LMP values of the 10th of January 2010 are forecasted using ANN [31] to find the variance of the locational marginal price. The number of neurons in the proposed network is fifty. Two layers are used; both the first and second layer considers a hyperbolic tangent transfer function. The forecasted LMP value by using the proposed method is tabulated in Table-1.

Table-1. Forecasted LMP values of the single generator test system.

Hours	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
LMP	33.31	26.53	22.16	23.1	22.6	23.15	24.65	24.75
Hours	9	10	11	12	13	14	15	16
LMP	25.5	27.58	31.6	35.6	41.05	41.61	38.98	39.74
Hours	17	18	19	20	21	22	23	24
LMP	42.02	40.74	38.80	39.63	46.14	39.04	33.68	42.09

VOL. 7, NO. 2, FEBRUARY 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

The technical data and cost data for the test case 1 is taken from [6] with some modification in upper and lower boundary limits of the real power.

The risk penalty parameter ‘β’ is depending on the value of the confidence level. The results are simulated by using the proposed CMPSO based method. The comparison of the results obtained for various values of confidence level and for comparison two extreme cases are tabulated in Table-2. The generation scheduling values of the energy market for the two extreme risk values are shown in the Figure-1.

Table-2. Profit comparison of the single generating machine for 24 hours.

Method	GAMS	PSO	MPSO	CMPSO
B = 0.0	29,209.56	28,981	29,108	29,209.79
B = 0.05	3,836.3	3,817.4	3,822.7	3,836.3

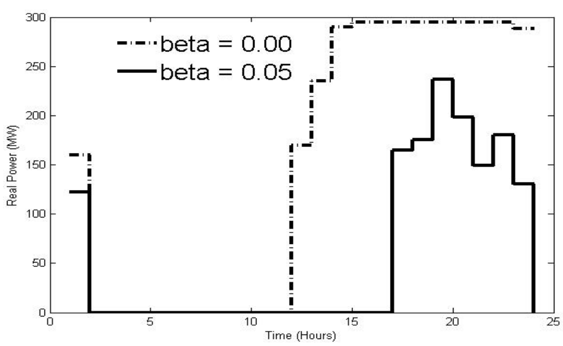

Figure-1. Geneation scheduling for the single generating unit for 24 hours.

The variation of the expected profit with respect to the standard deviation for the different risk levels is plotted in Figure-2. This frontier curve shows the trade-off between the expected profit and the risk for the different levels of risk penalty factor. The expected profit above this curve is not possible and below this curve is not efficient.

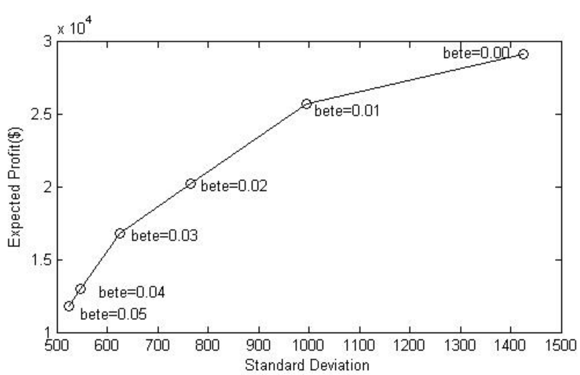

Figure-2. Frontier curve of the single generator system.

The convergence characteristic of the test case 1 is shown in Figure-3. The proposed method converged in to a better solution compare to the general PSO. The application of Cauchy mutation and local search with respect to the change in the global best position extends the execution time. The comparison of the execution time is given in Table-3. The execution time is linearly increasing which depends upon the number of variables and number of constraints added to the problem.

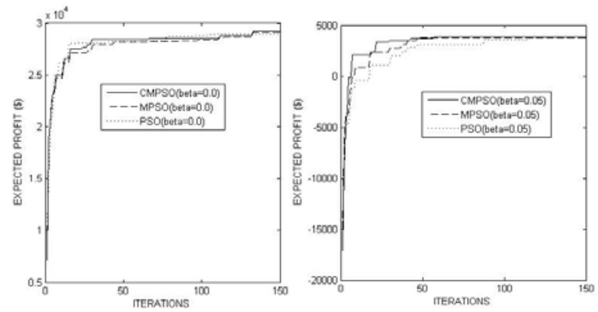

Figure-3. Convergence characteristics of the single generator system.

Table-3. Comparison of execution time of the single generator system.

Method	**Average execution time** (Sec)		
	PSO	**MPSO**	**CMPSO**
β = 0.0	842.3747	1,011	1,049
β = 0.05	872.1423	947	1,037

A standard IEEE 30 bus system is chosen as a second test case. The actual values of LMP for various set of data are calculated based on a DC load flow model. The technical data of the IEEE 30 bus system is taken from [15]. The must up time and down time of all the units are fixed to 3 hours. The forecasted LMP values are tabulated in Table-4.

The covariance matrix is calculated for each generator with the value of α equal to 0.98. The covariance matrix of all the generators for the energy market is calculated. The comparisons of results by various methods for the different confidence levels are tabulated in Table-5. The frontier curve for the various risk values are plotted in Figure-4.

VOL. 7, NO. 2, FEBRUARY 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

Table-4. Forecasted LMP values of the IEEE 30 bus system.

LMP / hours	Bus 1	Bus 2	Bus 5	Bus 8	Bus 11	Bus 13
1	3.48	3.51	3.49	3.55	3.57	3.55
2	3.48	3.52	3.50	3.57	3.59	3.57
3	3.48	3.52	3.51	3.58	3.59	3.58
4	3.48	3.52	3.52	3.58	3.61	3.58
5	3.48	4.71	4.73	4.80	4.83	4.84
6	3.48	4.74	4.98	5.28	5.35	5.37
7	3.48	4.75	5.45	6.21	6.31	6.46
8	3.48	6.11	7.55	9.09	9.28	9.64
9	3.48	4.76	5.44	6.20	6.31	6.46
10	3.48	4.75	5.43	6.18	6.29	6.43
11	3.48	4.73	4.97	5.26	5.32	5.37
12	4.78	4.79	4.80	4.90	4.95	4.96
13	3.48	4.74	5.40	6.13	6.23	6.39
14	3.48	4.75	5.43	6.18	6.28	6.43
15	4.75	4.77	4.80	4.91	4.96	4.95
16	4.82	4.80	4.80	4.88	4.93	4.95
17	5.43	5.35	5.31	5.36	5.43	5.41
18	8.09	7.81	7.55	7.70	7.82	7.80
19	7.91	7.72	7.60	7.68	7.79	7.75
20	4.80	4.80	4.80	4.89	4.94	4.95
21	3.48	4.76	5.47	6.25	6.36	6.51
22	3.48	4.75	5.43	6.18	6.29	6.43
23	3.48	4.73	4.97	5.27	5.33	5.36
24	3.48	4.70	4.58	4.52	4.55	4.50

Table-5. Profit comparison of the IEEE 30 bus system for 24 hours.

Method	GAMS	PSO	MPSO	CMPSO
B = 0.0	16,535	16,049	16,399	16,535
β = 0.05	11,707	10,969	11,555	11,700

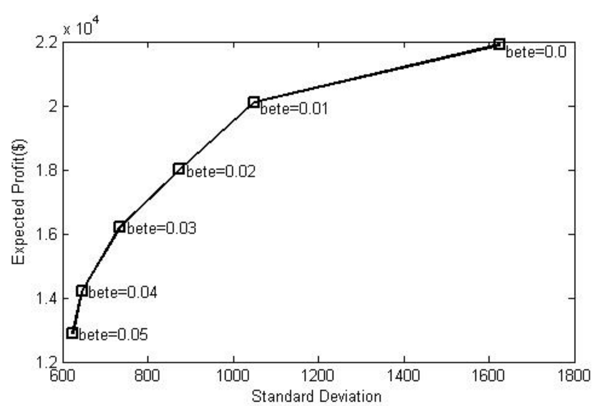

Figure-4. Frontier curve of the IEEE 30 bus system.

The generation scheduling values of all the generators for the two risk values are given in Figure-5

The convergence characteristics of the IEEE 30 bus system is plotted in Figure-6. The execution time is high when the numbers of variables are increasing. The number of variables to be obtained for the IEEE 30 bus system is 450. The comparison of execution time is tabulated in Table-6.

Computation analysis of proposed algorithm

In the first stage, the LMP values are forecasted by using the CMPSO trained feed forward neural network. The discussion of results about the LMP forecasting is not within the scope of this paper.

The proposed algorithm is robust in terms of producing quality solution. To test the robustness of the proposed method, the test case 1 was experimented on for 50 trial runs. The average, minimum and maximum profit of the proposed method is compared with other methods and it is tabulated in Table-7.

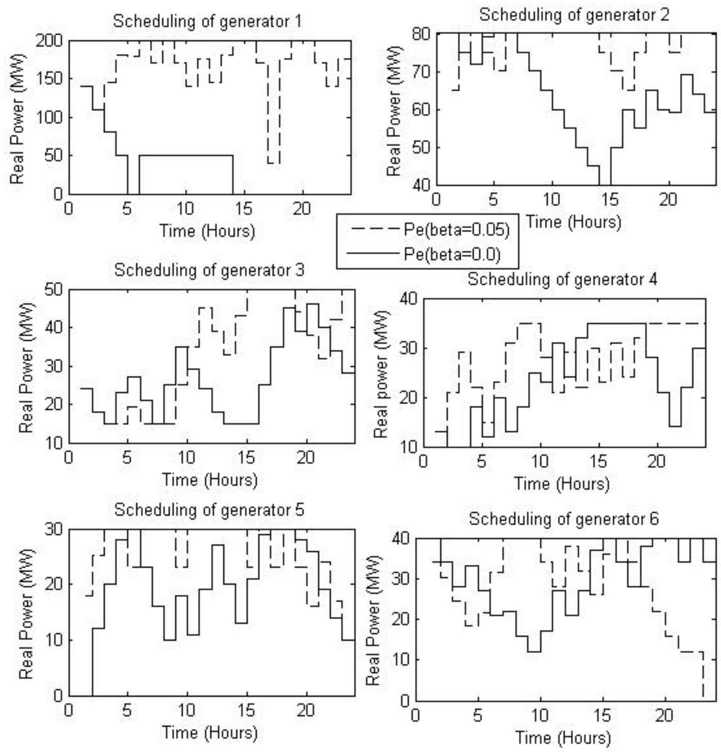

Figure-5. Generation scheduling for the IEEE 30 bus systemfor 24 hours.

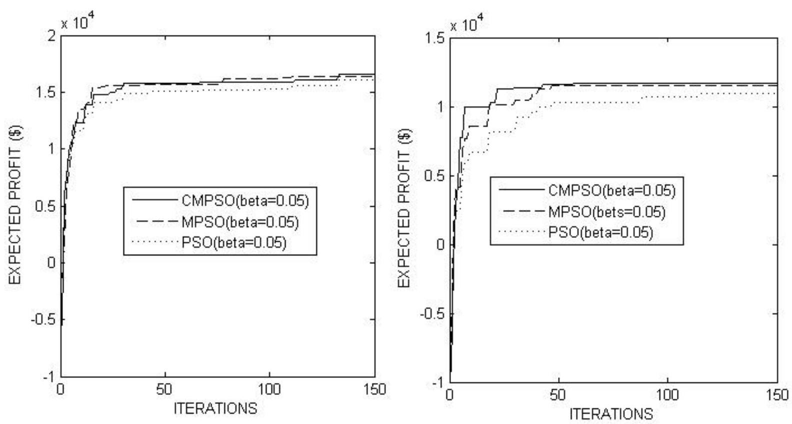

Figure-6. Convergence characteristics of the IEEE 30 bus system.

Table-6. Comparison of execution time of the IEEE 30 bus system.

Method	Average execution time (Sec)		
	PSO	MPSO	CMPSO
β = 0.0	997.323	1,108	1,218
β= 0.05	1,098	1,244	1,321

VOL. 7, NO. 2, FEBRUARY 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Table-7. Profit comparison of the single generating machine for 24 hours.

Method	Risk parameter	Minimum profit	Maximum Profit	Average profit
PSO	β = 0.0	27, 821	28,981	28, 420
	β = 0.05	3,200	3,817.4	3,520.7
MPSO	β = 0.0	28,972	29,108	28,832.1
	β = 0.05	3,521.2	3,822.7	3,623.24
CMPSO	β = 0.0	29,153.6	29,209.79	29,178.32
	β = 0.05	3,751.45	3,836.3	3,795.12

While solving the test cases, even though they have the same number of units, inclusion of additional constraints in the fitness function considerably affects the performance of the solution procedure. To demonstrate this, the test case 2 is considered, and in the following order, the constraints are added to the problem: 1) Minimum Up/Down time constraints 2) Ramp Up/Down rate limits and 3) spinning reserve. The test case 2 was experimented for 50 trial runs. The percentage variation of the average time and Profit of the CMPSO method after all constraints are added one by one is plotted in Figure-7.

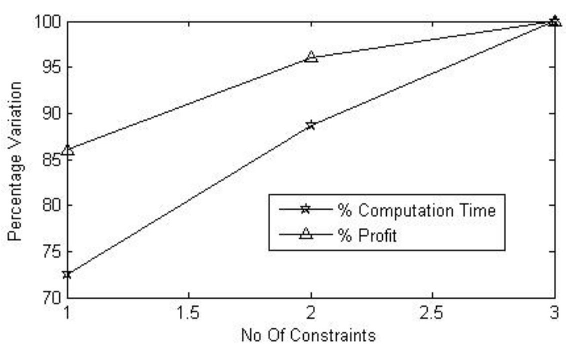

Figure-7. Performance of the CMPSO method on the addition of constraints.

As can be seen from Figure-7, the average profit and the mean computation time taken by the CMPSO method considerably increases as the constraints are added one by one. It is observed in Table-7, CMPSO method produces better results compared to the PSO and MPSO method when constraints are added. Inclusion of additional constraints increases the solution space as more bounded and reflected in the total computation time. The handling of non linear constraints is easier by using the proposed method.

There are 50 and 300 variables have to be determined by solving the self scheduling problem for the test case 1 and case 2 respectively. The population size is set as 450 for the single generator system and 1200 for the second test case. For both the system the number of iterations is set as to 150. The inertia constant is varying from 0.35 to 0.65 for the both cases. The application of the CM is very critical to explore the solution space in effective manner to avoid the local convergence. The application of the CM at various positions of the solution space is changed the result considerably. Use CM for the entire particles instead of using CM only at the gbest and around some points is improving the convergence characteristics of the solution. 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 iteration. The average execution time of the proposed method is marginally higher than the PSO algorithm.

The results are comparable with the mixed integer linear programming. Linearization of the non linear constraints is not required for the proposed method. This shows that the CMPSO method is capable of handling the Risk invoked self scheduling problem in a more effective way. The work on the parallel processing of the method to reduce time for combined self scheduling and risk management is underway and will be presented in a future paper.

In the first stage, the LMP values are forecasted by using the CMPSO trained feed forward neural network. The discussion of results about the LMP forecasting is not within the scope of this paper.

There are 50 and 300 variables have to be determined by solving the self scheduling problem for the test case 1 and case 2, respectively. The population size is set as 450 for the single generator system and 1500 for the second test system. For both the system the number of iterations is set as to 150. The inertia constant is varying from 0.35 to 0.65 for the both cases. The application of the CM is very critical to explore the solution space in effective manner to avoid the local convergence. The application of the CM at various positions of the solution space is changed the result considerably. Use CM for the entire particles instead of using CM only at the gbest and around some points is improving the convergence characteristics of the solution. 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 iteration. The average execution time of the proposed method is marginally higher than the PSO algorithm. The ramp rate constraints of the generators are affecting the solution in terms of convergence and execution time. Inclusion of additional constraints increases the solution space as more bounded and reflected in the total computation time. The handling of non linear constraints is easier by using the proposed method.

The results are comparable with the linear programming. Linearizations of the non linear constraints are not required for the proposed method. Finally, it is clear from the test results that the CMPSO outperforms the PSO method in terms of solution quality, reliability in producing it and convergence.

6. CONCLUSIONS

The generator output is varying to maximize the expected profit and to minimize the risk from the energy market. The proposed CMPSO based method is reliable and gives realistic results within the reasonable computation time. CM is used to avoid the local minima convergence property of the PSO algorithm. 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 cases. The risk is accounted to the self scheduling problem by using variance information of the forecasted LMP. Inclusion of the wind, hydro energy sources and the temporal constraints of the generator give more realistic approach to the self scheduling problem. The bids submitted by the generators for the day-ahead market is depend on its self scheduling values. Therefore any supplier should be aware of its self scheduling, it's bidding strategy, and ultimately, on its actual profits.

REFERENCES

[1] Conejo A.J and Arroyo J.M. 2000. Optimal response of a thermal unit to an electricity spot market. IEEE Trans. Power System. 15(3): 1098-1104.

[2] Conejo A.J Javier Contreras Arroyo J.M and Sebastián de la Torre. 2002. Optimal response of an oligopolistic generating company to a competitive pool-based markets electric power market. IEEE Trans. Power System. 17(2): 424-430.

[3] Conejo A.J and Arroyo J.M. 2002. Optimal response of a power generator to Energy, AGC, and Reserve pool-based markets. IEEE Trans. Power System. 17(2): 404-410.

[4] Conejo A.J, Arroyo J.M, Contreras J and Villamor F.A. 2002. Self-scheduling of a hydro producer in a pool based electricity market. IEEE Trans. Power System. 17(2): 1265-1272.

[5] Conejo A.J, Nogales F.J and Arroyo J.M. 2002. Price-taker bidding Strategy under price uncertainty. IEEE Trans. Power System. 17(4): 1081-1088.

[6] Conejo A.J, Nogales F.J, Arroyo J.M and García-Bertrand R. 2004. Risk constrained self scheduling of a thermal power producer. IEEE Trans. Power System. 19(3): 1569-1574.

[7] Yamin H.Y and Shahidehpour S.M. 2004. Risk and profit in self-scheduling for GenCos. IEEE Trans. Power System. 19(4): 2104-2106.

[8] Denton M, Palmer A, Masiello R and Skantze P. 2003. Managing market Risk in energy. IEEE Trans. Power System. 18(2): 494-502.

[9] Rabih A. Jabr. 2005. Robust Self-Scheduling under price uncertainty using conditional value-at-risk. IEEE Trans. Power System. 20(4): 1852-1858.

[10] Yamin H.Y, Al-Agtash S and Shahidehpour S.M. 2004. Security-constrained optimal generation scheduling for GENCOs. IEEE Trans. Power System. 19(3): 1365-1372.

[11] Yamin H.Y. 2005. Fuzzy self-scheduling for Gencos. IEEE Trans. Power System. 20(3): 503-505.

[12] Yao X, Liu Y and Lin G. 1999. Evolutionary Programming made faster. IEEE Trans. on Evolutionary Computations. 3(2): 82-102.

[13] Kennedy J and Eberhart R.C. 1995. Particle swarm optimization. IEEE international conference on neural networks proceeding 1995 in IEEE service centre, Piscataway, NJ. 4: 1942-1948.

[14] Kennedy J and Eberhart R.C. 1997. A discrete binary version of the particle swarm algorithm. IEEE international conference on systems, Man, and Cybernetics. pp. 4104-4109.

[15] Ramesh Babu, M and Somasundaram, P. 2009. PSO based Pool Strategies for deregulated market. Journal of Electrical engineering. 9(1): 46-56.

[16] Leandro dos Santos Coelho. 2009. An efficient particle swarm approach for mixed-integer programming in reliability-redundancy optimization applications. Reliability Engineering and System Safety. 94(4): 830-837.

[17] Leandro dos Santos Coelho and Chu-Sheng Lee. 2008. Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches. International Journal of Electrical Power and Energy Systems. 30(5): 297-307.

[18] Box G.E.P and Jenkins G.M. 1976. Time series analysis: forecasting and control. SAN Francisco: Holden-Day.

[19] Brooke A, Kendrick D, Meeraus A and Raman R. 1998. GAMS: A User's Guide. Washington, DC: GAMS Development Corporation.

[20] Bollerslev T. 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics. 31: 307-327.

[21] Simon Haykin. 1999. Neural Networks A Comprehensive Foundation. 2nd Edition, IEEE Press.

[22] Pindoriya N.M, Singh S.N and Singh S.K. 2008. An adaptive wavelet neural network based energy price forecasting in electricity markets. IEEE Trans. Power System. 23(3): 1423-1432.

[23] Qi Wu. 2010. Hybrid forecasting model based on support vector machine and particle swarm optimization with adaptive and Cauchy mutation. Expert systems with applications. 38(8): 9070-9075.

[24] Brockwell P.J and Davis R.A. 2002. Time Series: Theory and Methods. 2nd edition, New York: Springer-Verlag.

[25] Eppen G.D, Martin R.K and Schrage L. 1989. A scenario approach to capacity planning. Operations Research. 37: 517-527.

[26] Markowitz H.M. 1952. Portfolio selection. Journal of Finance. 8: 77-91.

[27] Clerc M and Kennedy J. 2002. The particle swarm-explosion, stability, and convergence in a multidimensional complex space. IEEE Transactions on Evolutionary Computation. 6(1): 58-73.

[28] Lee C.Y and Yao X. 2004. Evolutionary Programming using the mutations based on the Levy Probability distribution. IEEE Trans. on Evolutionary Computations. 8(1): 1-13.

[29] Petalas Y.G, Parsopoulos K.E and Vrahatis M.N. 2007. Memetic Particle Swarm Optimization. Ann Oper Rese, Springer. 156: 99-127.

[30] PJM Electricity market website. [Online]. http://www.pjm.com/.

[31] Sakamoto N, Ozawa K and Niimura T. 2006. Grid Computing Solutions for Artificial Neural Network-based Electricity Market Forecasts. International Joint Conference on Neural Networks. pp. 4382-4386.