INTEGRATING GRADIENT SEARCH, LOGISTIC REGRESSION AND ARTIFICIAL NEURAL NETWORK FOR PROFIT BASED UNIT COMMITMENT

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Abstract

As the electrical industry restructures many of the traditional algorithms for controlling generating units, they need either modification or replacement. In the past, utilities had to produce power to satisfy their customers with the objective to minimize costs and actual demand/reserve were met. But it is not necessary in a restructured system. The main objective of restructured system is to maximize its own profit without the responsibility of satisfying the forecasted demand. The Profit Based Unit Commitment (PBUC) is a highly dimensional mixed-integer optimization problem, which might be very difficult to solve. Hence integrating Optimization Technique Gradient Search (GS), Logistic Regression (LR) and Artificial Neural Network (ANN) approach is introduced in this paper considering power and reserve generating in order to receive the maximum profit in three and ten unit system by considering the softer demand. Also this method gives an idea regarding how much power and reserve should be sold in markets. The proposed approach has been tested on a power system with 3 and 10 generating units. Simulation results of the proposed approach have been compared with the existing methods. It is observed that the proposed algorithm provides maximum profit compared to existing methods.

Keywords: Artificial neural network, Competitive environment, Deregulation, Gradient search, Logistic Regression, Profit Based Unit Commitment, Restructured system

1. Introduction

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. It has moved from a formally vertically integrated and highly regulated industry to one that has been horizontally integrated in which generation, transmission and distribution are unbundled.

The basic aim of GENCOs (Generating Company) 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 considering the softer demand. In the past, utilities had to produce power to satisfy their customers with the minimum production cost. This means utilities run Unit Commitment (UC) with the condition that demand and reserve must be met.

In this paper, the authors intend to explain the importance of open market environment to GENCO that gives an idea for power producers to maximize their own profit as well as to maintain the power quality to consumers. Because of the fast economic development, the electricity demand is growing rapidly and the power system expansion becomes a severe economic burden of the government and a bottleneck of overall economy sustainable development.

It is urgent to launch power system restructuring and deregulation and to establish power markets with fair competition so as to attract more investments from various sources to power industry. In [2] it is impossible to predict the future UC scheduling, but with the Genetic Based Unit Commitment Algorithm (GBUCA) ability, good UC schedules and reasonable computer execution time using the true costing approach can be obtained The authors have reported research illustrating how power producers make decisions when having the option of selling to both the spot power market and reserve market [3]. GBUCA was updated for the PBUC-GA and to provide the user with additional information that identifies which schedules ,allow the user more market flexibility for given level of profit [4]. But disadvantages of the GA solution for PBUC problem are that the final solution being heuristic in nature may not be satisfactory. In [7] the author gives an overview of concept of UC problem with a bibliographical survey of relevant back ground, and provides a representative sample of current engineering thinking pertaining to the next generation UC problem. Hybrid method LR-EP has been used for solving the PBUC problem due to their ability to solve PBUC problems more efficiently [6], [15].

PBUC problems were solved by using conventional methods such as Dynamic Programming (DP) and Lagrange Relaxation (LR) methods [10] previously. Due to the curse of dimensionality with increase in number of generating units, LR method suffers from numerical convergence and DP method takes huge computational time to obtain an optimal solution. The Muller method was introduced to solve economic dispatch problem and Improved Pre- prepared Power Demand Table was introduced to solve combinatorial sub problem for deregulated environment without the effect of r where r is the probability that the reserve is called and generated [11].

The formulation in [12] maximizes the firm's profit based on the forecasted Locational Marginal Prices (LMPs). In paper [13], price uncertainty is modeled in a procedure using fuzzy members for maximizing a GENCO's profit. In paper [14], the formulation and solution of security constrained unit commitment solves simultaneous optimization of energy and ancillary services markets. In paper [16], a methodology is proposed for managing risks faced by power producers trading in energy market a day ahead. In paper [17] ,Quantum-Inspired Evolutionary Algorithm (QEA) is applied to solve the UC problem and proposes novel QEA-based UC method (QEA-UC) in which the unit-scheduling problem is handled by QEA and the economic dispatch problem is solved by the commonly-used method, Lambda-Iteration Technique. The author in paper [18] investigates modeling approaches for the computational cost reduction of Stochastic UC formulations. Long term UCP was considered without ramp rate limit constraints of individual units [19]. In paper [20] ,Quantum Inspired Binary Particle Swarm Optimization (QBPSO) is based on the concept and principles of quantum computing and developed to enhance the conventional Binary Particle Swarm Optimization(BPSO)in solving the combinatorial optimization problems. In paper [21], Transmission switching (TS) was integrated with UC for solving the multi interval optimal generation unit scheduling with security constraints .Hybrid Particle Swarm Optimization (HPSO) which is a blend of BPSO and Real Coded particle Swarm Optimization (RCPSO)is proposed in [22]. The UC problem is handled by BPSO, while RCPSO solves the economic load dispatch problem. Both algorithms run simultaneously, adjusting their solutions in search of a better solution.

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From the literature survey, it is observed that most of the existing algorithms have some limitations to provide the qualitative solution. The proposed method considers both power and reserve generation at the same time. This paper is organized as follows: Part II briefly describes the UC problem formulation and highlights modification needed for the competitive environment. Part III explains the market structure of selling power and energy. Part IV discusses the fundamentals of Gradient Search (GS), Logistic Regression (LR) and Artificial Neural Network (ANN) and its implication on PBUC. Finally, part V provides conclusion and future scope of the work.

2. Problem Formulation

The objective of UC is not to minimize costs as before but to provide the maximum profit for a company. It is an optimization problem and can be formulated mathematically by the following equations.
The Objective function is

$$MaxP.F = TC \tag{1}$$

(or)

$$MinTC = RV \tag{2}$$

Subject to

$$\sum_{i-1}^{N} P_{it} X_{it} \leq D_t^{'}, \qquad t = 1..........T \tag{3}$$

$$\sum_{i-1}^{N} R_{it} X_{it} \leq SR'_t, \quad t = 1..........T \tag{4}$$

Redefining the UC problem for the competitive environment involves changing the demand and reserve constraints from an equality to less than or equal to the forecasted level if it creates more profit.

$$P_{i\min} \leq P_i \leq P_{i\max} \tag{5}$$

$$0 \leq R_i \leq P_{i\max} - P_{i\min} \tag{6}$$

$$R_i + P_i \leq P_{i\max} \tag{7}$$

Minimum Up and Downtime constraints: where variables are defined as follows:

PF profit of Genco ;
RV revenue of Genco ;
TC total cost of Genco ;
P_{it} power generation of generator at hour t;
R_{it} reserve generation of generator at time t;
X_{it} on/off status of generator at hour t;

D'_t forecasted demand at hour t;
SR'_t forecasted reserve at hour t;
$P_{i\,min}$ minimum generation limit of generator i ;
$P_{i\,max}$ maximum generation limit of generator I;
N number of generator units;
T number of hours;

Here forecasted demand, reserve and prices are important inputs to the PBUC algorithm; they are used to determine the expected revenue (1), which affects the expected profit.

3. 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's strategies for profit maximization in both the spot and reserve markets are intertwined. The producer decides to pi (S) in the spot market and Pi(R) in the reserve market. The exact determination of Pi (S) & Pi(R) depends on the way reserve payments are made, although results are very similar. (3)

3.1 Payment for Power Delivered

In this method, the reserve is paid when only it is actually used. Therefore, the reserve price is higher than the power (spot) price. Revenue and cost in (1) can be calculated from

$$RV = \sum_{i=1}^{N}\sum_{t=1}^{T}\left(P_{it}.SP_t\right).X_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T} r.RP_t.R_{it}X_{it} \tag{8}$$

$$TC = (1-r)\sum_{i=1}^{N}\sum_{t=1}^{T} F\left(P_{it}\right).X_{it} + r\sum_{i=1}^{N}\sum_{t=1}^{T} F\left(P_{it}+R_{it}\right).X_{it} + ST.X_{it} \tag{9}$$

Where
SP_t -forecasted Spot price at hour t
RP_t - forecasted reserve price at hour t
F_i -fuel cost function of generator i
ST - start up cost.
r- probability that the reserve is called and generated

3.2 Payment for reserve allocated

In this method, GENCO 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 is generated. In this method, reserve price is much lower than the spot price. Revenue and costs in (1) can be calculated from.

$$RV = \sum_{i=1}^{N}\sum_{t=1}^{T}(P_{it}.SP_t).X_{it} + \sum_{i=1}^{N}\sum_{t=1}^{T}((1-r).RP_t + r.SP_t)R_{it}X_{it} \qquad (10)$$

$$TC = (1-r)\sum_{i=1}^{N}\sum_{t=1}^{T}F(P_{it}).X_{it} + r\sum_{i=1}^{N}\sum_{t=1}^{T}F(P_{it}+R_{it}).X_{it} + ST.X_{it} \qquad (11)$$

Where

$F\ (P_{it})$ is the Generator's fuel cost function and it can be expressed as $a_i + b_i\ p_{it} + c_i\ p_{it}^2$ in which a_i, b_i and c_i are generator's constants.

4. Proposed Methodology

The proposed methodology deals with solving the UC problem in a fitting way than all the previous methods defined for the same cause. Gradient Descent (GD) proves to be the best possible machine learning optimization available to determine the global minima of a particular function. Similarly Logistic regression is the recent and most efficient technique in predicting the Best Fit among binary status options, generator on/off status in this case, using a predefined criterion or a training data set. The hybrid obtained between these techniques applies state of the act machine learning techniques to the unit commitment problem.

Gradient Descent (GD) is a met heuristic optimization algorithm used to obtain the global or near global minimum of most functions. Gradient descent is based on the observation that if the multivariable function is defined F(x) and differentiable in a neighborhood of a point a, then $F(x)$ decreases very fast if one goes from a in the direction of the negative gradient of *F* at **a**.

For $\alpha \geq 0$ a small enough number, then $F(a) \geq F(b)$. With this observation in mind, one starts with a guess $\mathbf{x_0}$ for a local minimum of *F*, and considers the sequence x_0, x_1, x_2**…**such that

$x_{n+1} = x_n -$

$n \geq 0$ where α is the learning rate

We have

$$F(X_0) \geq F(X_1) \geq F(X_2)$$

so hopefully the sequence (x_n) converges to the desired local minimum. Note that the value of the step size ***γ*** is allowed to change in each iteration Here *F* is assumed to be defined on the plane, and that its graph has a bowl shape. The blue curves are the contour lines, that is, the regions on which the value of *F* is constant. A red arrow originating at a point shows the direction of the negative gradient at that point. Note that the (negative) gradient at a point is orthogonal to the contour line going through that point. We see that gradient descent leads us to the bottom of the bowl, that is, to the point where the value of the function *F* is minimal.

Logistic regression (LR) is used for prediction of the probability of occurrence of an event by fitting data to a logistic function. It is a generalized linear model used for binomial regression. Like other forms of regression analysis, it makes use of one or more predictor variables that may be either numerical or categorical.

The logistic function used in solving logistic regression is, Where $f(Z) = \dfrac{1}{1+e^{-z}}$ (12)

z is the input to the sigmoid function, $z = \theta^T X$

x is the input to the logistic regression classifier.

f (z) is the event probability.

The function is sometimes called sigmoid function and it takes the values between 0 and1. Therefore it predicts only the probability of the event happening. Thus it is a suitable tool for solving the on\off criterion based on the constraints.

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

4.1 Network function

The word *network* in the term 'artificial neural network' refers to the inter–connections between the neurons in the different layers of each system. An example system has three layers. The first layer has input neurons, which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons. More complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The synapses store parameters called "weights" that manipulate the data in the calculations.

An ANN is typically defined by three types of parameters:

1. The interconnection pattern between different layers of neurons
2. The learning process for updating the weights of the interconnections
3. The activation function that converts a neuron's weighted input to its output activation.

Mathematically, a neuron's network function $f(x)$ is defined as a composition of other functions $g_i(x)$, which can further be defined as a composition of other functions. This can be conveniently represented as a network structure, with arrows depicting the dependencies between variables. A widely used type of composition is the nonlinear weighted sum, where $f(x)=k\left(\sum_i w_i g_i(x)\right)$, where k is commonly referred to as the activation function is some predefined function, such as the hyperbolic tangent. It will be convenient for the following to refer to a collection of functions g_i as simply a vector g $(g_1,g_2,\ldots,g_n)$.

The first view is the functional view: the input x is transformed into a 3-dimensional vector h, which is then transformed into a 2-dimensional vector g, which is finally transformed into f. This view is most commonly encountered in the context of optimization.

The second view is the probabilistic view: the random variable F = f(G) depends upon the random variable, G = g(H) which depends upon H =h(X), which depends upon the random variable X. This view is most commonly encountered in the context of graphical models.

The two views are largely equivalent. In either case, for this particular network architecture, the components of individual layers are independent of each other (e.g., the components of g are independent of each other given their input h). This naturally enables a degree of parallelism in the implementation.

Networks such as the previous one are commonly called feed forward, because their graph is a directed acyclic graph. Networks with cycles are commonly called recurrent. Such networks are commonly depicted in the manner shown at the top of the figure, where f is shown as being dependent upon itself. However, an implied temporal dependence is not shown.

4.2 Learning

What has attracted the most interest in neural networks is the possibility of *learning*. Given a specific *task* to solve, and a *class* of functions F, learning means using a set of observations to find $f^* \in F$ which solves the task in some optimal sense.

This entails defining a cost function $C: F \rightarrow R$ such that, for the optimal solution $f^* c(f^*) \leq c(f) \forall f \in F$ (i.e., no solution has a cost less than the cost of the optimal solution).

The cost function C is an important concept in learning, as it is a measure of how far away a particular solution is from an optimal solution to the problem to be solved. Learning algorithms search through the solution space to find a function that has the smallest possible cost.

For applications where the solution is dependent on some data, the cost must necessarily be a function of the observations; otherwise we would not be modeling anything related to the data. It is frequently defined as a statistic to which only approximations can be made. As a simple example, consider the problem of finding the model f, which minimizes $C = E[(f(x) - y)^2]$, for data pairs(x, y) drawn from some distribution D. In practical situations we would only have N samples from D and thus, for the above example, we would only minimize

$$\hat{C}=\frac{1}{N}\sum_{i=1}^{N}(f(x_i)-y_i)^2.$$

Thus, the cost is minimized over a sample of the data rather than the entire data set.

When $N \rightarrow \infty$ some form of online machine learning must be used, where the cost is partially minimized as each new example is seen. While online machine learning is often used when $\mathcal{D}$ is fixed, it is most useful in the case where the distribution changes slowly over time. In neural network methods, some form of online machine learning is frequently used for finite datasets.

4.3 Hybrid between GD-LR using ANN

This method first involves the determination of minimum fuel cost of each generator from the function defined **(1)** using gradient descent. Next the power corresponding to the minimum fuel cost is determined.

If $P_{mincost}<P_{min}$ $\quad P_{mincost}=P_{min}$

If $P_{mincost}>P_{max}$ $\quad P_{mincost}=P_{max}$

Then the dataset consisting of all the power values at an increment of one unit from $P_{mincost}$ to D_t' is formed.

This dataset is fed to the logistic regression classifier. The logistic regression is already trained with a classifier dataset obtained by applying the required constraints to the available dataset. Thus the classifier is trained to a parameter set **θ** which is obtained by minimizing the cost function,

$$J(\theta)=\frac{1}{m}\sum_{i=1}^{m}[-Y^{(i)}\log(h_e(X^{(i)})-(1-y^{(i)})\log(1-h_e(x^{(i)})] \tag{13}$$

Where

$y^{(i)}$ status of generator i corresponding to the $P_{mincost}$

$h_\theta(x^{(i)})$ Predicted status of generator i for supplying the entire forecasted demand.(subject to sigmoid function in equation 3)

m product of total number of generators and number of hours

$J(\theta)$ cost function

This parameter set theta is multiplied to the input forecasted power and the status of the generator corresponding to the hour of demand is found by feeding it to the sigmoid function as described by (12)**.** This output of the sigmoid function is deciphered as,

$X_{it} = 1$ if $f(z_{it}) \geq 0.5$

$X_{it} = 0$ if $f(z_{it}) < 0.5$

Where

X_{it} is the on/off status of generator described in Equations (8) and (9).

$f(z_{it})$ is the predicted probability of the generator being turned ON which is the output of logistic regression classifier.

The value of 0.5 is decided assuming zero bias conditions of generators. But they can be redefined to various values depending on the precision and recall values.

This on/off status uses an artificial neural network to decide the power limit between switching on a new generator. This dynamic power varies as a function of the forecasted demand. This demand if exceeds the particular limit as set by the ANN, the next generator status is turned to ON. It uses a single direction logic, multi- input forward backward prediction algorithm. The network has 6 inputs and a hidden layer of 6 units and one output unit which gives a dynamic value of the power difference for each stage. The ANN is implemented just once to make sure that computational overhead is avoided. The stage uses forecasted demand to predict the power difference for each stage which is fed to the logistic regression classifier for the prediction process. This constraint is a main factor in deciding the On/Off status for the machine as this value is given a very high weightage is given to this parameter during mean normalization. The cost function and network parameters are as defined earlier.

The various **inputs** are

- forecasted demand (i)
- spot price
- start up cost
- fuel cost
- forecasted demand of previous hour (i-1)
- initial status

The **output** is the power difference for the current hour (i) which opens up the next generator. This neural function aids the improvement of the reliability of the system and thus improving the efficiency to a considerably higher level than using a static prediction of data from forecasted demand. This On/off status along with the power dataset is fed to the total cost function where the profit of each of the possible combination of power is calculated. The entire value is negated and the global minimum of the function is determined using the gradient descent operation (which is called gradient ascent). Thus the maximum value of the profit obtained and the corresponding power are calculated by the algorithm.

The dataset used to train logistic regression is regenerated by the principle of symmetry subject to the constraints. The main constraint that is maintained to improve the profit is

$T_{on} \geq$ minimum up time

$T_{off} \geq$ minimum down time

This regeneration creates a huge dataset thus enabling the better performance of the classifier. The generator has to be scheduled to generate its rated power at the hour it is marked on. Thus the up time is considered for the process also. After the process is complete the generated power and the on/off status is supplied to the same logistic regression classifier to check the reserve generation of limit of each generator and the iteration process is repeated for reserve to find the reserve generation ranging from 0 to SR_t'. The final profit of the GENCO is calculated. The learning rate of the classifier for the reserve power is maintained at a relatively less value to enable proper convergence of metaheuristic minimization technique.

ALGORITHM

1 Start the process
2 Obtain the input data (number of generators, demand hours, forecasted demand and forecasted price)
3 Check if the current time period exceeds the required demand period
4 Find power corresponding to minimum cost of each generator, by feeding the cost curve and a suitable learning rate to the gradient descent algorithm
5 By iterating from the value obtained in step 4 to the maximum limit, find all the possible values of profit in steps of one (assuming each generator is on)
6 Find the maximum profit and the power corresponding to it, by feeding the data input and the learning rate to the gradient descent algorithm
7 The minimum difference in power between the demands for the generators to turn on is fixed dynamically for each generator by the ANN classifier which takes demand, fuel cost, profit and the demand sustenance (how much time the demand stays) given by Ton >> Tstart, as input parameters
8 Feed the input data such as number of generators, demand, maximum and minimum limit, constraints, power difference from step 7 and others to the logistic regression classifier
9 Multiply the output schedule of generators (binary value (0, 1)) with the power obtained in step 6 and sum them up to obtain the total power supplied
10 Find the corresponding cost, revenue and profit
11 Separate the reserve power if it gives better profit by iterating over the profit values for various combinations
12 Stop when the process is complete for all the demand hours

5. Numerical Results

The proposed method has been implemented in Matlab and tested using two different systems to solve PBUC problem. Before running PBUC-GS, LR and ANN, the Gencos need to get an accurate hourly demand and price forecast for the scheduling period. Fuel cost function of each generator is estimated into quadratic form. Based on the forecasted information, power is dispatched economically by the proposed method. Simulations are carried out to find optimal solution, and profit and they are also compared with existing methods. The proposed method considers the effect of probability that reserve is called and generated for 3 and 10 unit system. The forecasted demand, forecasted prices and fuel cost data of 3 unit system are listed in TableA1 and TableA2. In PBUC, Gencos no longer have the obligation to meet the demand. Gencos may choose to generate less than the demand.

Three Unit Systems

The effect of probability that reserve is called and generated (r) is tested using 3 generator 12 hour test data. Here, reserve price is fixed at the triple and 0.01 times of spot price for reserve payment method A and B, respectively, while is r varied from 0.005 to 0.05. Simulation results are shown in Tables I and II, and it is clear that profit obtained by method A is higher than method B when r is varied. In method A, reserve is paid only when the reserve power is actually delivered and used. Profit is more sensitive when r is varied.

The effect of reserve price is investigated in reserve payment method A and method B. In this case r is fixed at 0.005 while the reserve price is varied. From table III and table IV, it is observed that profit obtained by

Table I

Effect of ‘r’ in reserve payment Method A (reserve price = 3* spot price)

r	Profit($) (LR-EP)	Profit($) (proposed)
0.005	9074.35	10228
0.010	9094.23	10234
0.015	9116.18	10241
0.020	9140.40	10247
0.025	9166.98	10254
0.030	9195.88	10260
0.035	9228.00	10267
0.040	9262.87	10273
0.045	9300.76	10280
0.050	9340.77	10287

Table II

Effect Of ‘r’ in Reserve Payment Method B (reserve price = .01* spot price)

r	Profit($) (LR-EP)	Profit($) (proposed)
0.005	9074.26	10227
0.010	9075.40	10228.2
0.015	9076.53	10228.6
0.020	9077.67	10229.1
0.025	9078.80	10229.7
0.030	9079.93	10230.3
0.035	9081.07	10230.8
0.040	9082.20	10231.2
0.045	9083.34	10231.7
0.050	9084.47	10232

method B is higher than method A. For method B, reserve is paid all the time even reserve is not delivered. Here profit is more sensitive when reserve price is varied. Here profit is more sensitive when reserve price is varied.

Table III

Effect of Reserve Price in Payment Method A (r=0.005)

Reserve price (times of spot price)	Profit($) LR-EP Method	Profit ($) Proposed Method
1	9057.72	10221
2	9065.78	10224
3	9074.35	10228
4	9083.42	10231
5	9093.00	10234
6	9103.07	10237
7	9113.65	10240
8	9124.75	10243
9	9136.48	10246
10	9148.75	10249

Table IV

Effect Of Reserve Price In Reserve Payment Method B (r=.005)

Reserve price (times of spot price)	Profit($) (LR-EP)	Profit($) (proposed)
0.01	9074.26	10227
0.02	9092.80	10223
0.03	9113.33	10239
0.04	9136.00	10245
0.05	9160.90	10251
0.06	9187.94	10257
0.07	9217.76	10263
0.08	9250.13	10269
0.09	9285.20	10275
0.10	9322.59	10281

Table V and VI show examples of power and reserve scheduling plans for reserve payment methods A and B respectively. The results are compared with those obtained via the traditional UC algorithm and via the hybrid LR –EP profit-based unit commitment algorithm developed in [6],Muller method [11], LR-ACSA method[24] and profit is found to be higher as it is shown in Table VI1 for method A. In Table VIII, for method B, results will be compared with those obtained via the traditional UC algorithm and hybrid BUC algorithm developed in [6] and profit is found to be higher.

Effect of probability of reserve is applied to both methods and it is observed that profit of method A is comparatively higher as shown in Fig 2. In Fig. 3 and Fig. 4 profit obtained by the proposed method is compared with LR- EP method for the method A and B respectively. From this it is observed that profit is high in 6th and 7th hour of time period.

Ten unit systems

In addition to three unit system, proposed algorithm worked well for larger system also. The forecasted demand and forecasted prices are listed in Table 6.The fuel cost data of 10 unit system are listed in Table 5. Based on the forecasted information, power is dispatched economically with the effect of probability of reserve that is called and generated by the proposed method and it is shown in Table IX and Table X for reserve payment method A and B respectively. From

Table V
Power and reserve generation of reserve payment method A(r=.005, reserve price = 3* spot price)

Hour	PBUC by LR –EP[6]						Profit ($)	PBUC by GS,LR &ANN						Profit ($)
	Power (MW)			Reserve (MW)				Power (MW)			Reserve (MW)			
	U1	U2	U3	U1	U2	U3		U1	U2	U3	U1	U2	U3	
1	**0**	**0**	**170**	**0**	**0**	**20**	**531.4**	**0**	0	169.6	**0**	0	**20**	**529.47**
2	0	0	200	0	0	0	**570**	0	0	199.6	0	0	0	**568.7**
3	0	0	200	0	0	0	**300**	0	0	199.6	0	0	0	**300.62**
4	0	0	200	0	0	0	**390**	0	0	199.6	0	0	0	**390**
5	0	379.9	200	0	20.1	0	**201**	0	399	200	0	0	0	**501.25**
6	0	400	200	0	0	0	**1350**	400	400	200	0	0	0	**1829.01**
7	0	400	200	0	0	0	**1380**	400	400	200	0	0	0	**1878.97**
8	0	400	200	0	0	0	**990**	0	399	200	0	0	0	**1290.39**
9	0	400	200	0	0	0	**810**	0	399	200	0	0	0	**1110.79**
10	0	130	200	0	35	0	**818.1**	0	329	0	0	35	0	**686.89**
11	0	200	200	0	40	0	**804.6**	0	399	0	0	0	0	**600.52**
12	0	350	200	0	50	0	**829.2**	0	399	0	0	0	0	**540.82**
							9074.3					**TOTAL**		**10,228**

Table VI
Power and reserve generation of reserve payment method B (r=.005, reserve price =.04 x spot price)

Hour	PBUC by LR –EP[6]						Profit ($)	PBUC by GS ,LR&ANN						Profit ($)
	Power (MW)			Reserve (MW)				Power (MW)			Reserve (MW)			
	U1	U2	U3	U1	U2	U3		U1	U2	U3	U1	U2	U3	
1	**0**	**0**	**170**	**0**	**0**	**20**	**537.7**	**0**	0	169.6	**0**	0	**20**	**535.76**
2	0	0	200	0	0	0	**570**	0	0	199.6	0	0	0	**568.77**
3	0	0	200	0	0	0	**300**	0	0	199.6	0	0	0	**300.62**
4	0	0	200	0	0	0	**390**	0	0	199.6	0	0	0	**390**
5	0	330	200	0	70	0	**215.7**	0	399	200	0	0	0	**501**
6	0	400	200	0	0	0	**1350**	400	400	200	0	0	0	**1829**
7	0	400	200	0	0	0	**1380**	400	400	200	0	0	0	**1878.97**
8	0	400	200	0	0	0	**990**	0	399	200	0	0	0	**1290.39**
9	0	387.2	200	0	12.8	0	**810.4**	0	399	200	0	0	0	**1110.79**
10	0	130	200	0	35	0	**829.8**	0	329	0	0	35	0	**698.57**
11	0	200	200	0	40	0	**817.4**	0	399	0	0	0	0	**600.52**
12	0	350	200	0	50	0	**945.0**	0	399	0	0	0	0	**540.82**
							9136					**TOTAL**		**10245**

Table VII
Comparison of the results of 3 unit system with existing methods by proposed method (Method –A)

S.no	Method	Profit ($)
1	Traditional UC[6]	4048.8
2	PBUC by LR-EP method [6]	9074.3
3	PBUC by Muller method [11]	9030.5
4	PBUC by LR-ACSA method [24]	9081.1
5	**Proposed method**	**0228**

Table VIII
Comparison of the results of 3 unit system with existing methods by proposed method (Method –B)

S.no	Method	Profit ($)
1	Traditional UC[6]	4262.7
2	PBUC by LR-EP method [6]	9136.0
5	**Proposed method**	**10245**

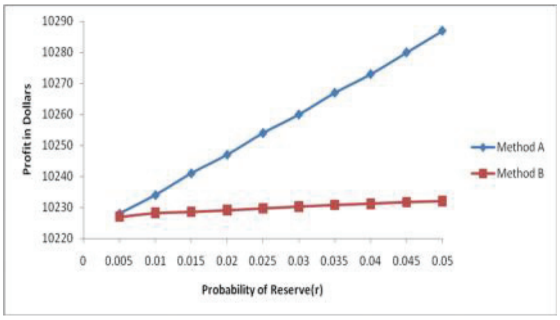

Fig 2. Effect of Probability of Reserve

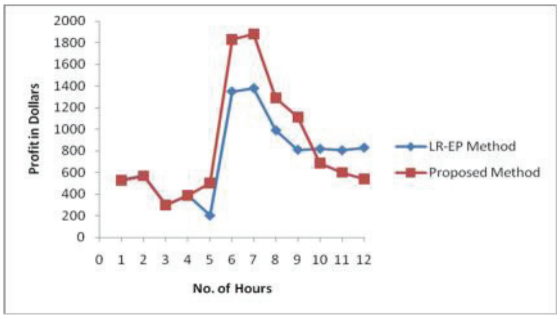

Fig 3. Comparison of Profit between LR-EP & Proposed Method A

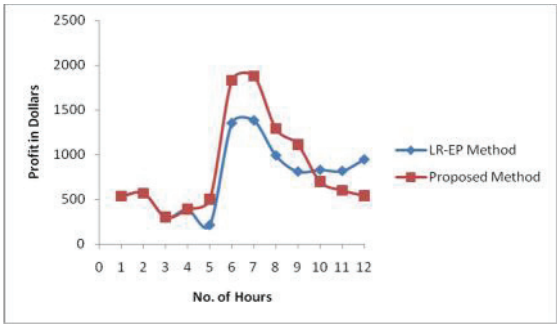

Fig 4. Comparison of Profit between LR-EP & Proposed Method B

Table XI, it is clear that the proposed method provides maximum profit for method A compared to the existing methods of PBUC by LR-EP method [6], Muller method [11], MAS [23], TS –RP [26], TS – IRP [26] and improved PSO [25] . For method B ,profit obtained by LR-EP method [6] is compared with proposed method as shown in Table XII.

6. Conclusion

In this paper, the authors have proposed an algorithm to solve the PBUC for three and ten unit restructured power system. Based on forecasted demand, PBUC is solved with the effect of r. The effect of probability of reserve and reserve power is considered for three unit system and two types of reserve payment methods are simulated. All simulated results of three and ten unit system are compared with results of existing methods and it is observed that profit is obtained by the proposed method is higher. For further research, PBUC with transmission losses and emission constraints will be considered. With these constraints added, the end user can enjoy emission free economic power

Table XI

Comparison of the results of 10unit system (24Hr) with existing methods by proposed methodA

S.no	Method	Profit ($)
1	PBUC by LR-EP method [6]	112818.93
2	PBUC by Muller method [11]	103296
3	PBUC –MAS [23]	109485.19
4	PBUC by TS –RP [26]	101086.
5	PBUC by TS – IRP [26]	103261
6	PBUC by improved PSO [25]	113018.7
7	**Proposed method**	**130990**

Table XII

Comparison of the results of 10unit system (24Hr) with existing methods by proposed method B

S.no	Method	Profit ($)
2	PBUC by LR-EP method [6]	107838.58
5	**Proposed method**	**130349**

TableA1 Forecasted Demand and Price for 3 Generator Case

Hour	Forecasted demand (MW)	Forecasted spot price ($/MWH)	Forecasted reserve(MW)
1	170	10.55	20
2	250	10.35	25
3	400	9.00	40
4	520	9.45	55
5	700	10.00	70
6	1050	11.25	95
7	1100	11.30	100
8	800	10.65	80
9	650	10.35	65
10	330	11.,20	35
11	400	10.75	40
12	550	10.60	55

Table A2
Fuel cost data of 3 Generator Case

	Unit 1	Unit 2	Unit 3
P max (Mw)	600	400	200
P min (Mw)	100	100	50
a ($/h)	500	300	100
b($/Mwh)	10	8	6
c ($/Mw^{2}h)	0.002	0.0025	0.005
Min up time (h)	3	3	3
Min down time(h)	3	3	3
Startup cost ($)	450	400	300

Table A3
Forecasted Demand, Reserve and Spot Prices for Ten-Unit 24-Period System

Hour	Forecasted Demand (MW)	Forecasted Reserve (MW)	Forecasted Spot Price ($ / MW-Hr)
1	700	70	22.15
2	750	75	22.00
3	850	85	23.10
4	950	95	22.65
5	1000	100	23.25
6	1100	110	22.95
7	1150	115	22.50
8	1200	120	22.15
9	1300	130	22.80
10	1400	140	29.35
11	1450	145	30.15
12	1500	150	31.65
13	1400	140	24.60
14	1300	130	24.50
15	1200	120	22.50
16	1050	105	22.30
17	1000	100	22.25
18	1100	110	22.05
19	1200	120	22.20
20	1400	140	22.65
21	1300	130	23.10
22	1100	110	22.95
23	900	90	22.75
24	800	80	22.55

TABLE A4 Unit Data (Ten-unit 24-Period System)

	Unit 1	**Unit 2**	**Unit 3**	**Unit 4**	**Unit 5**	**Unit 6**	**Unit 7**	**Unit 8**	**Unit 9**	**Unit 10**
Pmax	455	455	130	130	162	80	85	55	55	55
Pmin	150	150	20	20	25	20	25	10	10	10
a	0.00048	0.00031	0.00200	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
b	16.19	17.26	16.60	16.50	19.70	22.26	27.74	25.92	27.27	27.79
c	1000	970	700	680	450	370	480	660	665	670
min up	8	8	5	5	6	3	3	1	1	1
min down	8	8	5	5	6	3	3	1	1	1
ST	4500	4500	550	560	900	170	260	30	30	30
Ini.	8	8	-5	-5	-6	-3	-3	-1	-1	-1

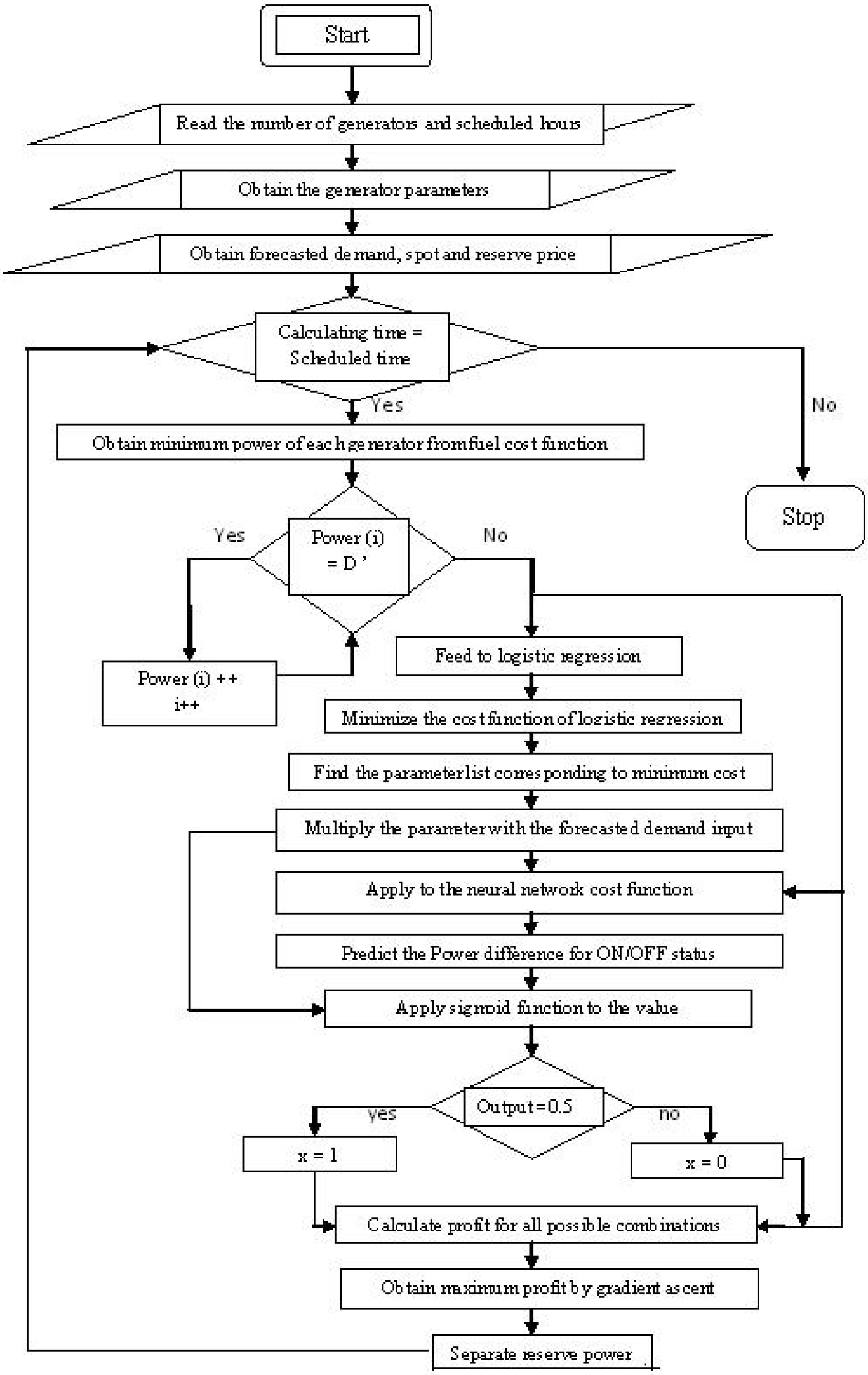

Fig 1.Flow Chart of proposed method

Table IX
Example of power and Reserve generation of reserve payment method A (10 Units system)
(r=0.05, reserve price =5 X spot price)

Hr	PBUC(method A)by proposed method																				
	Power(MW)										Reserve(MW)										Profit $
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	
1	345	354	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	3907.3
2	370	379	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	0	0	0	4076.3
3	420	429	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5153.7
4	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5127. 3
5	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5673.3
6	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5400.3
7	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4990.8
8	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4672.3
9	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5263.8
10	455	456	0	0	0	0	0	56	0	0	0	0	0	0	0	0	0	0	0	0	11401
11	455	456	0	0	0	0	0	56	56	0	0	0	0	0	0	0	0	0	0	0	12326
12	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	14068
13	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	6468
14	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	6360
15	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	4204
16	436	455	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	3823.9
17	411	420	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	3512
18	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	3719
19	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	3881
20	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	4366
21	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	4851
22	455	456	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	4689
23	0	455	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	1586
24	0	455	0	0	0	0	0	56	56	56	0	0	0	0	0	0	0	0	0	0	1462
Total Profit $																					1,30,990

Table X
Example of power and Reserve generation of reserve payment method B (10 Units system)
(r=0. 05, reserve price = 0.01 X spot price)

Hr	PBUC(method B) by proposed method																				
	Power(MW)										Reserve(MW)										Profit $
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U1	U2	U3	U4	U5	U6	U7	U8	U9	U1	
1	345	354	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	0	0	0	3598
2	370	379	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	0	0	0	3744
3	420	429	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5153
4	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5127
5	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5673
6	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5400
7	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4990.8
8	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4672.3
9	455	456	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5263.8
10	455	456	0	0	0	0	0	56	0	0	0	0	0	0	0	0	0	0	0	0	11401

11	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**12326**
12	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**14068**
13	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**6468**
14	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**6360**
15	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4204**
16	**436**	**455**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**3823.9**
17	**411**	**420**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**3512**
18	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**3719**
19	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**3881**
20	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4366**
21	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4851**
22	**455**	**456**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4689**
23	**0**	**455**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1586**
24	**0**	**455**	**0**	**0**	**0**	**0**	**0**	**56**	**56**	**56**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1462**
Total Profit $																					**1,30,349**

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