The Journal of CPRI,
Vol. 10, No. 3, September 2014 pp. 465-480

# Reliability constrained unit commitment problem incorporating demand response program

Manisha Govardhan*, Fenil Master* and Ranjit Roy*

*In a restructured power market, the independent system operator (ISO) executes the reliability constrained unit commitment (RCUC) program to plan a reliable and an economical hourly generation schedule for the day-ahead market. This work presents probabilistic method for the incorporation of the unavailability of the generating units in the solution of the Unit commitment (UC) problem. In this paper, Gbest Artificial Bee Colony (GABC) algorithm is used for solving the UC problem, while the evaluation of the required spinning reserve capacity is performed by using Loss of Load Probability (LOLP) index. IEEE RTS 24 bus system is used to demonstrate RCUC problem for different reliability levels. Considerable developments in the real time telemetry of demand-side systems allow ISO to use reserves provided by demand response programs (DRPs) in a restructured power market. In this paper, the hourly demand response is incorporated into RCUC for economic and reliability purposes. The RCUC problem with Emergency Demand Response Program (EDRP) is tested on IEEE RTS 24 bus system. Minimum cost results for each case and reduction in load demands for DRPs are formulated.*

***Keywords:*** *Reliability constrained unit commitment, demand response programs, gbest artificial bee colony algorithm.*

## 1.0 INTRODUCTION

Unit commitment (UC) is an important optimization problem, solved by the system operator in pre dispatch stage. The operator seeks to minimize the system production cost during the planning horizon, while satisfying load demand, spinning reserve requirements, generation limits, minimum up/down time and ramp rate constraints of each individual unit [1].While executing UC problem, system operator allows a certain amount of generation capacity as spinning reserve (SR) to ensure that the power system network is able to withstand sudden outages of some generating units/ transmission lines or an unforeseen increase in the load. The most common approach for setting the minimum amount of SR is at least equal to the capacity of the largest unit, or to a specific percentage of the hourly system load. But the problem with this deterministic approach is that it does not reflect the stochastic nature of the system components and lead to inconsistent decision and variable operating risk levels. By incorporating various system uncertainties, such as the availability of the generating units, the outages of the transmission system, and the load forecast uncertainty, the probabilistic methods can provide a more realistic evaluation of the reserve requirements [2]. These methods combine deterministic criteria with probabilistic indexes, in order to find a UC solution that provides an acceptable level of reliability.

*Department of Electrical Engineering, S. V. National Institute of Technology, Surat- 395007, Gujarat, India. Email : rroy.svnit@gmail.com

In the last decades, several deterministic, heuristic, and hybrid methods have been proposed to solve the UC as a large scale, non-convex and mixed-integer combinatorial optimization problem [1]. Several approaches have been proposed to accommodate reliability constraints in the generation scheduling problem [2-13]. [2] & [3] are pioneers in instituting reliability criteria for the operating reserve evaluation. In [4],first time it was explained, how the spinning reserve could be optimized within the UC problem. In [5], a continuous approximation method was proposed to estimate the Capacity Outage Probability Table (COPT) explicitly within the reserve constrained UC as a function of the commitment variables. Method to find LOLP based on COPT table is explained in [6-7]. RCUC problem based on the priority list (PL) method was solved in [8]. Authors of [9] have considered the uncertainty of the load forecast in addition to the unit unavailability in the RCUC model and used simulated annealing (SA) algorithm for solving the RCUC problem. In [10-12], several models have been proposed in which both the reliability and performance records of the generators and interruptible loads were taken into consideration. Authors of [13] have considered unavailability of unit in the RCUC problem and solved it by genetic algorithm (GA), particle swarm optimization (PSO) and binary real coded firefly algorithm (BRCFF).

In recent years, Demand-side Management (DSM) has been introduced as an impressive option in all energy policy decisions because of its potential benefits at operation and economic levels. DSM is the global term that covers activities such as: Load Management (LM), Energy Efficiency & Energy Savings [14]. As electricity markets are liberalized, consumers become exposed to more volatile electricity prices and may decide to modify the profile of their demand to reduce their electricity costs. Hence, the new term is created in DSM, called "Demand Response" (DR). Customer participating in DRPs can expect savings in electricity bills if they reduce their electricity usage during peak periods. As per the US Department of Energy (DOE), DR refers to: "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"[15].

DRPs have been investigated in many recent papers. One of the first pioneer papers about DR and price elasticity of demand is [16]. In [16], price elasticity of demand in a pool-based electricity market has been taken into account, when generation scheduling is done with responsive loads and different amount of incentives are paid for curtailable loads. Based on this responsive load economic model, different DRPs have been modelled in the last decade. Authors of [17] have modelled interruptible/curtailable and capacity market programs and shown that demand and load shape could be changed due to the ISO policy of DRPs. In [18], an innovative method is proposed in which customers can participate in different DRPs to attain the maximum benefit.

This paper presents a new UC problem formulation for achieving desired reliability level under demand response programs. The Gbest artificial bee colony (GABC) algorithm is used to solve the problem. Without implementing DRPs, normal RCUC problem is also solved by GABC algorithm. The results obtained for the same is compared with existing literatures. In this paper, EDRP is considered to incorporate in RCUC problem. In subsequent sections, a primer on DRPs is given. In section 3, RCUC problem incorporating DRP is formulated. Section 4 gives an overview about evaluation of reliability indexes. Modelling of customer response to DRP is presented in section 5. Solution methodology of problem with GABC algorithm is explained in section 6. The results obtained are discussed in section 7 followed by conclusion in section 8.

## 2.0 A PRIMER ON DRPS

According to [19], DRPs have been classified into two major categories, namely, incentive-based programs (IBPs) and time-based rate (TBR) programs. In [20], IBPs are classified into three subgroups, namely, voluntary, mandatory and market clearing programs. Direct Load Control (DLC) and Emergency Demand Response Programs (EDRP) are voluntary programs, where incentive payments are made to customers for reducing their load during reliability triggered events and if customers do not curtail consumption, they are not penalized. Interruptible/curtailable (I/C) and Capacity Market Programs (CAP) are mandatory programs and the enrolled customers are subject to penalties if they do not curtail when directed. Demand Bidding/Buyback Program (DB) and Ancillary Service Programs (A/S) are market clearing programs, where large customers are encouraged to provide load reductions at a price at which they are willing to be curtailed. Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP) are types of TBR programs [21].

In TBR programs, the electricity price changes for different periods according to the electricity supply cost, for example, high price for peak period, medium price for off-peak and low-price for low load period. In these programs, there is no incentive or penalty for customer response. More detailed explanations of DR programs can be found in [19-21]. In this paper the authors have focused on emergency demand response program (EDRP).

## 3.0 PROBLEM FORMULATION OF RCUC WITH DRP

### 3.1 Objective Function

The objective of RCUC problem is to minimize the total cost of the system while satisfying the load demand, spinning reserve requirements, and other operational constraints. The operating cost is the sum of fuel cost ($F_i$ ($P_i(t)$)) and start-up cost ($STC_i(t)$) of each thermal unit over a scheduled period. For each scheduling hour, the cost of implementation of DRPs ($DR_{cost}(t)$) should be included in the total cost of the system. So, the expression for objective function is given in (1).

$$min\sum_{i=1}^{N}\sum_{t=1}^{T}\left[F_i\big(P_i(t)\big) + STC_i\big(1-I_i(t-1)\big)\right]I_i(t) + DR_{cost}(t) \quad ....(1)$$

where N is the number of thermal units, T is the total scheduled duration. $P_i(t)$ is generated power and $I_i(t)$ is ON/OFF status (1/0) of generating units.

The fuel cost of generating unit in quadratic polynomial form is given as:

$$F_i\big(P_i(t)\big) = a_i + b_i\big(P_i(t)\big) + c_i\big(P_i(t)\big)^2 \quad ....(2)$$

where $a_i$ , $b_i$ and $c_i$ are cost coefficients of the fuel cost of the unit i.

The start-up cost of the unit i is defined as:

$$SC(i) = \sigma(i) + \delta(i)(1 - e^{(X_{ioff}/\tau(i))}) \quad ....(3)$$

where σ and δ are hot and cold start-up cost respectively and τ is cooling time constant of a unit.

- Spinning reserve (SR) constraint:

($DR_{cost}(t)$) can be calculated as the difference between incentive paid by the utility and the penalty imposed to the customer over a scheduled period.

$$DR_{cost}(t) = P\big(\Delta d(t)\big) - PEN\big(\Delta d(t)\big) \quad ....(4)$$

### 3.2 Constraints

- Power balance constraint:

The total generation of each unit at hour t must be equal to load demand for that particular hour t.

$$\sum_{i=1}^{N} P_i(t) \cdot I_i(t) = d_0(t) \quad ....(5)$$

where $d_0(t)$ is the initial load demand at hour t.

For system reliability some reserve capacity has to maintain.

$$\sum_{i=1}^{N} P_{i\,max}(t) \cdot I_i(t) \geq d_0(t) + SR(t) \qquad ....(6)$$

- Generation limit constraint:

The power generation of each thermal unit must be within the specified limit.

$$P_{imin} \leq P \leq P_{imax} \qquad ....(7)$$

where $P_{imin}$ and $P_{imax}$ are the minimum and maximum power generation limits of the unit i respectively.

- Minimum up/down time constraint:

The unit has to remain ON/OFF for predefined time before any transition.

$$X_{ion} \geq MUT_i \qquad ....(8)$$

$$X_{ioff} \geq MDT_i \qquad ....(9)$$

where $X_{ion}$ and $X_{ioff}$ are continuously on and off duration of the unit i respectively. $MUT_i$ and $MDT_i$ are minimum up and down time of unit i respectively.

- Ramp Rate Constraint on Thermal Units

This constraint limits the inter-hour generation change of a unit.

$$P_i(t+1) - P_i(t) \leq RUP_i \cdot \qquad ....(10)$$

$$P_i(t) - P_i(t+1) \leq RDN_i \cdot \qquad ....(11)$$

$RUP_i$ and $RDN_i$ are ramp up and ramp down limits of generator i respectively.

- Reliability Constraint

To maintain system reliability, the LOLP reliability constraint is considered while solving the UC problem. The LOLP reliability constraint is given by

$$LOLP(t) \leq Lmax, \qquad t \in [1, T] \qquad ....(12)$$

where LOLP(t) is defined as loss of load probability at hour t, and Lmax, set by ISO, represents the maximum allowed limit of the LOLP index.

## 4.0 EVALUATION OF RELIABILITY INDEX

The objective of the reliability constrained method is the evaluation of the required spinning reserve capacity at each hour of the dispatch period. In this paper, unavailability of the generating units is considered to determine SR capacity of each hour. This method is based on the Loss of Load Probability (LOLP) index. The LOLP index expresses the probability that the generation system will not cover the forecasted demand.

### 4.1 Unavailability of Generating Units

For the purposes of the reliability analysis, each generating unit is represented by the two-state model [2], either available or unavailable for generation. In view of this model, the unavailability $U_i$ *(LT)* of the generating unit during a short time interval LT (known as the system lead time) is given by [9]

$$U_i(LT) = \frac{\lambda_i}{\lambda_i + \mu_i}\left(1 - e^{-(\lambda_i + \mu_i)LT}\right) \qquad ....(13)$$

where $\lambda_i$ and $\mu_i$ are the failure and repair rate of the unit i respectively.

Assuming that the lead time is much shorter than the repair times of the generating units, the repair process can be neglected. This assumption results in a more simplified expression:

$$U_i(LT) = 1 - e^{-\lambda_i LT} \qquad ....(14)$$

The probability $U_i(LT)$ given by (14) is known as the outage replacement rate (ORR) of the unit.

### 4.2 Calculation of LOLP Index

The LOLP index for a given solution of the UC problem is calculated using the conventional "loss of load" method. This method is based on the convolution of the capacity outage probability table (COPT) with the given load curve [7]. For each hour t, a COPT is formed using the ORR of the committed units. Each row j=1…n of the COPT represents a generation level that may be outaged, the total capacity CR(j) that remains in service, and the probability PR(j) that corresponds to this state [9]. Assuming that the load of the system is constant within each hour, the LOLP for each hour can be calculated by

$$LOLP(t) = \sum_{j=1}^{n} PR(j) * LOSS(j), \qquad \text{....(15)}$$

where LOSS(j) is given by

$$LOSS(j) = \begin{cases} 1, & if\ CR(j) < d_0(t) \\ 0, & otherwise. \end{cases} \qquad \text{....(16)}$$

The computational time required for the formation of each COPT can be considerably reduced by rounding the outage levels to a fixed increment, e.g., 5 MW [9]. The increment must be carefully chosen in order to retain the precision of the final results. A further reduction in the time requirements of the proposed method can be achieved by omitting the outage levels for which the cumulative probabilities are less than a predefined limit, e.g., $10^{-7}$.

## 5.0 MODELING CUSTOMER RESPONSE TO DRP

In order to formulate the participation of customers in DRPs on load profile characteristics, development of responsive load economic model is necessary.

### 5.1 Responsive Load Economic Model

The economic load model which represents the change of the customer's demand with respect to the changes in electricity price, incentives as well as penalties imposed to the customers is used here [18].

- Price elasticity of electrical demand

Elasticity is defined as the demand sensitivity with respect to the price [16].

$$E = \frac{p_0}{d_0} \cdot \frac{\partial d}{\partial p} \qquad \text{....(17)}$$

where $p_0$ is the initial spot electricity price.

According to Eq (17), the price elasticity of the $t^{th}$ period with respect to the $k^{th}$ period can be defined as:

$$E(t,k) = \frac{p_0(k)}{d_0(t)} \cdot \frac{\partial d(t)}{\partial p(k)} \qquad \text{....(18)}$$

If the electricity prices vary for different periods, then the demand reacts one of the followings [16]:

Some loads are not able to move from one period to another (e.g. Illuminating loads) and they could be only on or off. So, such loads have sensitivity just in a single period and it is called "self elasticity" and it always has a negative value [16].

Some consumption could be transferred from the peak period to the off-peak or low periods (e.g. Process loads). Such behaviour is called multi period sensitivity and it is evaluated by "cross elasticity", always a positive value [16].

$$\begin{cases} E(t,k) \le 0, if t = k, \text{self elasticity} \\ E(t,k) \ge 0, if t \ne k, \text{cross elasticity} \end{cases} \qquad \text{....(19)}$$

- Modeling of single period elastic loads

Suppose that the customer changes his demand from $d_0(t)$ (initial) to $d(t)$, and then the change in load demand can be given as:

$$\Delta d(t) = d(t) - d_0(t) \quad ....(20)$$

If A(t)$ is paid as an incentive to the customer in $t^{th}$ hour for each MWh load reduction, the total incentive for participating in the DLC, I/C and CAP programs will be as follows:

$$P\big(\Delta d(t)\big) = A(t) \cdot [d_0(t) - d(t)] \quad ....(21)$$

If the customer who has been enrolled in the mentioned DRPs does not commit to his obligations according to the contract, he/she will be penalized. If the contract level for the tth hour and the penalty for the same period be denoted by IC(t) and pen(t) respectively, then the total penalty, PEN(Δd(t) ),will be accounted as:

$$PEN\big(\Delta d(t)\big) = pen(t) \cdot \{IC(t) - [d_0(t) - d(t)]\} \quad ....(22)$$

Therefore, the customer's benefit, S, for the tth hour will be as follows:

$$S = B\big(d(t)\big) - d(t) \cdot p(t) + P\big(\Delta d(t)\big) - PEN\big(\Delta d(t)\big) \quad ....(23)$$

where p(t) is the spot electricity price of hour t, after implementation of the DRP.

To maximize the customer's benefit, ∂S/(∂d(t)) should be equal to zero, therefore

$$\frac{\partial S}{\partial d(t)} = \frac{\partial B(d(t))}{\partial d(t)} - p(t) + \frac{\partial P}{\partial d(t)} - \frac{\partial PEN}{\partial d(t)} = 0 \quad ....(24)$$

$$\frac{\partial B(d(t))}{\partial d(t)} = p(t) + A(t) + pen(t) \quad ....(25)$$

The benefit function, most often used, is the quadratic benefit function [22]:

$$B\big(d(t)\big) = B_0(t) + p_0(t)[d(t) - d_0(t)]\left\{1 + \frac{d(t) - d_0(t)}{2E(t) \cdot d_0(t)}\right\} \quad ....(26)$$

By differentiating the above equation and solving for ∂B/(∂d(t)) and substituting the result in (25) we will have:

$$p(t) + A(t) + pen(t) = p_0(t)\left\{1 + \frac{d(t) - d_0(t)}{E(t) \cdot d_0(t)}\right\} \quad ....(27)$$

Therefore, customer's consumption will be as follows [18]:

$$d(t) = d_0(t) \cdot \left\{1 + E(t,t) \cdot \frac{[p(t) - p_0(t) + A(t) + pen(t)]}{p_0(t)}\right\} \quad ....(28)$$

In the above equation, if the electricity price does not change and the incentive and the penalty are zero, then d(t) will be the same as the initial value, $d_0(t)$

- Modeling of multi period loads

According to the definition of cross elasticity in (18) with the linearity assumption,

$$\frac{\partial d(t)}{\partial p(k)} \quad : \text{Constant for t, k =1, 2...24.} t \neq k \quad ....(29)$$

Apply the following linear relationship between price and demand:

$$d(t) = d_0(t) + \sum_{\substack{t=1 \\ t \neq k}}^{24} E(t,k) \cdot \frac{d_0(t)}{p_0(k)} \cdot [p(k) - p_0(k)] \quad ....(30)$$

In (30), we have considered the 24 h intervals. Now, if the incentive and penalty be included in the price, then the multi period model can be expressed as [18]:

$$d(t) = d_0(t) \cdot \left\{ 1 + \sum_{\substack{k=1 \\ k \neq i}}^{24} E(t,k) \right.$$

$$\left. \cdot \frac{[p(k) - p_0(k) + A(k) + pen(k)]}{p_0(k)} \right\} \quad \text{....(31)}$$

- Load Economic Model

By combining (28) and (31), the responsive load economic model derived as [18]:

$$d(t) = d_0(t) \cdot \left\{ 1 + E(t,t) \cdot \frac{[p(t) - p_0(t) + A(t) + pen(t)]}{p_0(t)} \right.$$

$$\left. + \sum_{\substack{k=1 \\ k \neq t}}^{24} E(t,k) \cdot \frac{[p(k) - p_0(k) + A(k) + pen(k)]}{p_0(k)} \right\} \quad \text{....(32)}$$

The equation (32) shows how much should be the customer's consumption to achieve maximum benefit in a 24 h interval while participating in DRPs.

## 6.0 SOLUTION METHODOLOGY

In this paper, Gbest Artificial Bee Colony (GABC) algorithm [23] is employed to deal with the RCUC problem. The basic ABC algorithm is a swarm based meta-heuristic algorithm developed by simulating the intelligent behaviour of honeybees. The bees are mainly classified into three groups, namely, employed bees, onlookers and scouts [24]. In ABC, bees fly to hunt food in multidimensional search space. Some bees search food source depending on their earlier experience and some find randomly without using any experience. Employed bees pass their food information to the onlooker bees. The onlookers tend to select good food sources from those founded by employed bees and they further search food source near the elected food source. If there is no improvement in the food source, then scout bees fly and explore the new food source randomly without using experience.

### 6.1 Solution procedure to implement GABC for UC problem

The unknown variables in optimization process are active power outputs of thermal units in MW. The optimum value of these unknown variables produces desired power at minimum cost. The step by step procedure to formulate the basic UC problem using GABC algorithm is as follows:

**Step 1 (Input parameters)**

- Specify the cost coefficients, ramp rate limits and active power limits for each thermal unit.
- Specify parameters of the GABC algorithm such as the number of employed bees NP, onlookers NO, trial limit (TL) value and tuning constant C

**Step 2 (Initialization of population with random solutions)**

Initial population is generated arbitrarily from the multi-dimensional search space, X= $[X_1, X_2 \ldots\ldots X_m]^T$, $X_1, X_2 \ldots\ldots X_m]$T where m is the size of the population and X1, X2 ….Xm are candidate solutions. Each solution vector $X_i = [P_{i1}, P_{i2} \ldots P_{iN}]$ is subjected to iterative search processes of the employed bees, the onlooker bees and the scout bees. The index N represents the number of thermal units, $i \in [1,m]$. All decision variables given by vector $X_i$ are distributed uniformly between their upper and lower generation limits. For thermal unit dispatch study, the random values of solution vector $X_i$ are produced using (33).

$$P_{ij} = P_{minj} + rand(P_{maxj} - P_{minj}) \quad \text{....(33)}$$

where rand is a random number between 0 to 1, j € {1,2…D}.For a given scheduling horizon, an initial population is generated according to (34),

$$X = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1N} \\ P_{21} & P_{22} & \cdots & P_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mN} \end{bmatrix} \quad \text{....(34)}$$

**Step 3 (Fitness evaluation)**

The fitness value of each food source position is checked by evaluating objective function value. Set the cycle count at 1 and repeat the steps given below until the maximum number of cycles are reached (termination criteria).

**Step 4 (Employed bee phase)**

In this step, each employed bee produces a new candidate food source in the vicinity of its current position using (35) as [24]:

$$v_{ij} = P_{ij} + \emptyset_{ij}(P_{ij} - P_{kj}) + C(y_j - P_{ij}) \quad ....(35)$$

where $v_{ij}$ is the new food source and $P_{ij}$ is the previous food source found by the employed bees. The term $P_{kj}$ specifies the alternative food source selected by onlooker bees in neighbourhoods and $\varnothing_{ij}$ is the random number between -1 to 1. The last term on the right-hand side of (35) is Gbest term, P is the $j^{th}$ element of the global best solution and C is a random nonnegative constant. If a value of decision parameter produced by (33) or (35) exceeds its limit, the parameter is set to its limit value. The modified food source position is checked for constraints in (5)–(12). Other constraints such as ramp rate limits are also checked depending upon test system. The equality constraints are handled by the procedure given in [25]. Then the fitness value (objective function value) of each candidate food source is evaluated. If the new fitness value is better than the old one, the new food source position is remembered; otherwise, the old one is retained in the memory.

**Step 5 (Calculating probabilities)**

An onlooker chooses a food source position of employed bee depending upon possibility (probability $PR_i$) of getting even better food source using (36).

$$PR_i = \frac{fit_i}{\sum_j^{N_P} fit_j} \quad ....(36)$$

where $fit_i$ is the fitness value of the $i^{th}$ candidate solution (food source). Equation (36) suggests that the good food sources attract more on looker bees compared to the bad ones.

**Step 6 (Onlookers phase)**

Once the onlooker bee selects the food source position of employed bee, it is further modified to obtain a better food source position by using (35).Again greedy selection is applied to retain better solution and discard inferior solution.

**Step 7 (Scout bee phase)**

If a particular solution is not improved for certain trial limits, it is discarded and the scout bee produces a new random solution according to (33).

**Step 8 (Best food source position)**

Remember the best solution (food source position) obtained so far. Increment the iteration count.

**Step 9 (Stopping criterion)**

If the stopping criterion is not fulfilled, go to step 4. The stopping criterion in this case is the maximum number of cycles (MNC).

### 6.2 Implementation of the LOLP Reliability Constraint

The LOLP reliability constraint is implemented in order to incorporate this index in the formulation of the UC problem. Step by step procedure for the reliability constrained method can be described as follows:

**Step 1**

A new candidate solution $X_{new}$ is generated by the GABC algorithm with a small perturbation of the current one $X_{curr}$ by changing the state of a random number of units during a randomly selected period of consecutive hours t, where $t \in [H1,H2]$.

**Step 2**

Set time counter t=H1.

**Step 3**

Calculate the LOLP(t):

- If LOLP(t)≤Lmax, go to Step 6.
- If LOLP(t)>Lmax, the solution is rejected.

**Step 4**

Update commitment status of units, by changing the state of the next priority unit (i.e., to make it on) for time period t=H1.

**Step 5**

Generate a new trial solution, and go to Step 8.

**Step 6**

If t<H2, increase time counter t=t+1, and go to Step 3; else, go to Step 7.

**Step 7**

The solution $X_{new}$ is accepted.

**Step 8**

Return to the GABC algorithm.

The above procedure is based on the presumption that the current solution $X_{curr}$ is feasible with regard to the LOLP reliability constraint. Therefore, during the analysis of the initial solution of the GABC algorithm, above procedure is applied for the entire dispatch period, i.e. $t \in [1,T]$ .

## 7.0 RESULTS & DISCUSSIONS

All the programs are developed using MATLAB 7.8.0 and the system configuration is "Core i5" processor with 3.2 GHz speed and 4 GB of RAM. Two case studies are considered to demonstrate the methodology. In case 1, GABC algorithm is used to solve RCUC problem for three different reliability levels. In case 2, reliability constrained UC problem incorporating EDRP is solved using GABC algorithm.

The results and discussions of each case are in the following sections.

### 7.1 Case 1-RCUC

The IEEE RTS 24-bus system is used to demonstrate the performance of the RCUC problem. The IEEE RTS 24-bus system consists of 26 generating units. The generation cost coefficients and reliability data are given in Table 1 [13]. 24 hour load profile is given in Table 2 [9]. In this case, reliability constraints are included along with all constraints of the conventional UC problem. The desired level of reliability depends on the predefined values of the maximum allowed limit Lmax.

#### *7.1.1 Parameter Selection for GABC Algorithm*

The proper parameter tuning for GABC algorithm is a challenging task. Fast converge behaviour can be obtained if all the four control parameters, namely, employed bees (NP), onlooker bees, trial limit (TL) value and constant C, are optimally tuned. Optimal settings of these parameters yield better solution. By default setting of parameters taken initially, one of the parameter is varied and the other parameters are kept constant. It has been tested for each parameter taking several values within a boundary limit.All experiments were run for 500 iterations while estimating optimal settings of GABC parameters. For illustrative purposes, however, the IEEE 24 bus system with reliability level 0.5% is considered.

- Selection of Number of Employed Bees (NP) & Onlooker Bees (NO)

After trying different combinations of parameters the best value of employed bees for the IEEE 24 bus system to reliability level 0.5% is found to be 150, which is plotted in Figure 1.

TABLE 1

GENERATING CHARACTERISTICS OF IEEE RTS 24 BUS SYSTEM

| Unit | $P_{max}$ (MW) | $P_{min}$ (MW) | a ($) | b ($/ MWh) | c ($/ MWh$^2$) | RU (MW/h) | RD (MW\h) | σ($) | δ($) | τ | MUT(h) | MDT(h) | IS(h) | MTTF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 12 | 2.4 | 24.389 | 25.547 | 0.02533 | 48 | 60 | 0 | 0 | 1 | 0 | 0 | -1 | 2940 |
| 2 | 12 | 2.4 | 24.411 | 25.675 | 0.02649 | 48 | 60 | 0 | 0 | 1 | 0 | 0 | -1 | 2940 |
| 3 | 12 | 2.4 | 24.638 | 25.803 | 0.02801 | 48 | 60 | 0 | 0 | 1 | 0 | 0 | -1 | 2940 |
| 4 | 12 | 2.4 | 24.76 | 25.932 | 0.02842 | 48 | 60 | 0 | 0 | 1 | 0 | 0 | -1 | 2940 |
| 5 | 12 | 2.4 | 24.888 | 26.061 | 0.02855 | 48 | 60 | 0 | 0 | 1 | 0 | 0 | -1 | 2940 |
| 6 | 20 | 4 | 117.755 | 37.551 | 0.01199 | 30.5 | 70 | 20 | 20 | 2 | 0 | 0 | -1 | 450 |
| 7 | 20 | 4 | 118.108 | 37.664 | 0.01261 | 30.5 | 70 | 20 | 20 | 2 | 0 | 0 | -1 | 450 |
| 8 | 20 | 4 | 118.458 | 37.777 | 0.01359 | 30.5 | 70 | 20 | 20 | 2 | 0 | 0 | -1 | 450 |
| 9 | 20 | 4 | 118.821 | 37.89 | 0.01433 | 30.5 | 70 | 20 | 20 | 2 | 0 | 0 | -1 | 450 |
| 10 | 76 | 15.2 | 81.136 | 13.327 | 0.00876 | 38.5 | 80 | 50 | 50 | 3 | 2 | 3 | 3 | 1960 |
| 11 | 76 | 15.2 | 81.298 | 13.354 | 0.00895 | 38.5 | 80 | 50 | 50 | 3 | 2 | 3 | 3 | 1960 |
| 12 | 76 | 15.2 | 81.464 | 13.8 | 0.0091 | 38.5 | 80 | 50 | 50 | 3 | 2 | 3 | 3 | 1960 |
| 13 | 76 | 15.2 | 81.626 | 13.407 | 0.00932 | 38.5 | 80 | 50 | 50 | 3 | 2 | 3 | 3 | 1960 |
| 14 | 100 | 25 | 217.895 | 18 | 0.00623 | 51 | 74 | 70 | 70 | 4 | 2 | 4 | -3 | 1200 |
| 15 | 100 | 25 | 218.335 | 18.1 | 0.00612 | 51 | 74 | 70 | 70 | 4 | 2 | 4 | -3 | 1200 |
| 16 | 100 | 25 | 218.775 | 18.2 | 0.00598 | 51 | 74 | 70 | 70 | 4 | 2 | 4 | -3 | 1200 |
| 17 | 155 | 54.25 | 142.735 | 10.694 | 0.00463 | 55 | 78 | 150 | 150 | 6 | 3 | 5 | 5 | 960 |
| 18 | 155 | 54.25 | 143.029 | 10.715 | 0.00473 | 55 | 78 | 150 | 150 | 6 | 3 | 5 | 5 | 960 |
| 19 | 155 | 54.25 | 143.318 | 10.737 | 0.00481 | 55 | 78 | 150 | 150 | 6 | 3 | 5 | 5 | 960 |
| 20 | 155 | 54.25 | 143.597 | 10.758 | 0.00487 | 55 | 78 | 150 | 150 | 6 | 3 | 5 | 5 | 960 |
| 21 | 197 | 68.95 | 259.131 | 23 | 0.00259 | 55 | 99 | 200 | 200 | 8 | 4 | 5 | -4 | 950 |
| 22 | 197 | 68.95 | 259.649 | 23.1 | 0.0026 | 55 | 99 | 200 | 200 | 8 | 4 | 5 | -4 | 950 |
| 23 | 197 | 68.95 | 260.176 | 23.2 | 0.00263 | 55 | 99 | 200 | 200 | 8 | 4 | 5 | -4 | 950 |
| 24 | 350 | 140 | 177.057 | 10.862 | 0.00153 | 70 | 120 | 300 | 200 | 8 | 5 | 8 | 10 | 1150 |
| 25 | 400 | 100 | 310.002 | 7.492 | 0.00194 | 50.5 | 100 | 500 | 500 | 10 | 5 | 8 | 10 | 1100 |
| 26 | 400 | 100 | 311.91 | 7.503 | 0.00195 | 50.5 | 100 | 500 | 500 | 10 | 5 | 8 | 10 | 1100 |

*MTTF (Mean time to failure) = (1/ Failure rate)

TABLE 2

HOURLY LOAD DEMAND OF IEEE RTS 24 BUS SYSTEM

| **Hour** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Demand (MW)** | 1700 | 1730 | 1690 | 1700 | 1750 | 1850 | 2000 | 2430 | 2540 | 2600 | 2670 | 2590 |
| **SP($)** | 19 | 19 | 19 | 19 | 19 | 19 | 24 | 24.5 | 42 | 39 | 42.5 | 42 |
| **Hour** | **13** | **14** | **15** | **16** | **17** | **18** | **19** | **20** | **21** | **22** | **23** | **24** |
| **Demand (MW)** | 2590 | 2550 | 2620 | 2650 | 2550 | 2530 | 2500 | 2550 | 2600 | 2480 | 2200 | 1840 |
| **SP($)** | 42 | 42 | 39 | 39 | 42 | 29 | 29 | 29 | 39 | 29 | 24.5 | 19 |

*SP represents the spot electricity price

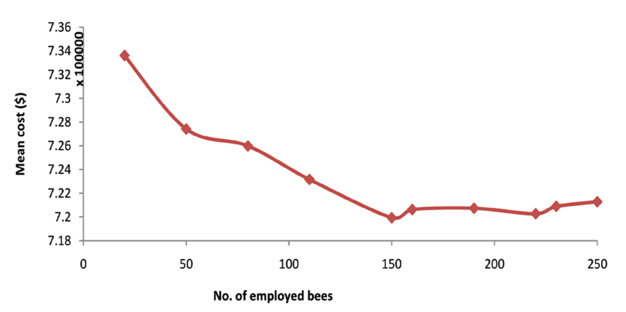


FIG. 1 VARIATION OF MEAN COST FOR DIFFERENT VALUES OF EMPLOYED BEES

The value of trail limit parameter is set to 2. The number of onlookers is varied from 150 to 900. For every step the program was run for 20 trails and mean cost value was recorded. Figure 2 shows the variation of mean cost for different values of onlooker bees. It is observed that the algorithm gives least mean cost value when the number of onlooker bees is twice the employed bees.

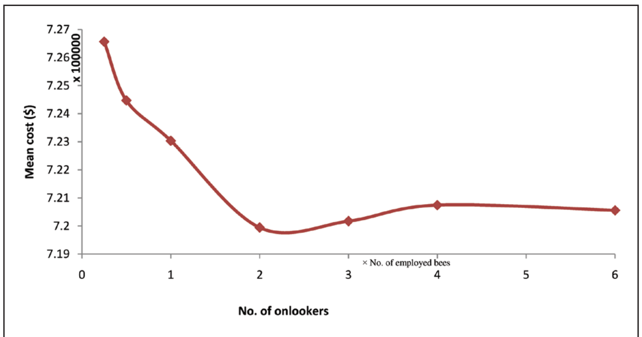


FIG. 2 VARIATION OF MEAN COST FOR DIFFERENT VALUES OF ONLOOKERS

- Selection of trial limit value

In order to see the effect of TL value on the mean cost, the number of employed bees is set to 150 and number of onlookers is set to 300 i.e. twice number of employed bees. The Figure 3 shows the variation of mean cost for different value of TL varied from 2 to 12.

When the value of TL is high i.e. near to 12 the mean cost obtained by GABC algorithm is on higher side. For this system, therefore, the optimal results for mean cost were obtained for TL value set to 2.

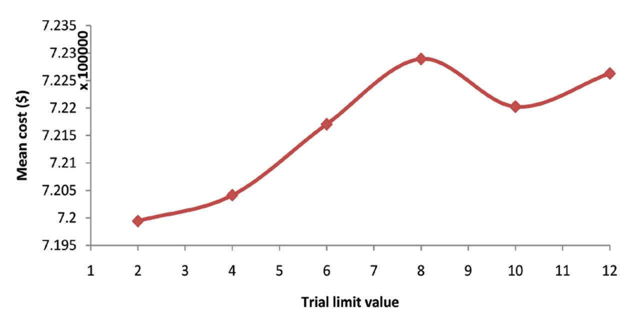


FIG. 3 VARIATION OF MEAN COST FOR DIFFERENT VALUES OF TL VALUE

- Selection of parameter C

In order to direct the search trajectory towards feasible reason, suitable value of parameter C has to be selected. The variation of parameter C with respect to mean cost for considered system is given in Figure 4. It can be seen that the mean fuel cost is minimum for C parameter value of 1.5.

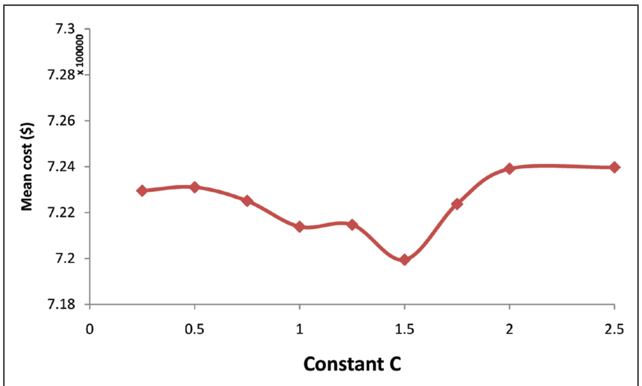


FIG. 4 VARIATION OF MEAN COST FOR DIFFERENT VALUES OF PARAMETER C

### *7.1.2 Results of RCUC*

The simulation results for various values of Lmax limits are shown in Table 3. It is noted that Lmax is given in percent (%) form. In all cases, the lead time of the system is fixed at 4 h [9]. As discussed in previous sections, the minimum cost result is achieved with parameter settings of NP=150, NO=300, TL value set to 2, Constant C= 1.5 with max no of cycles 500.

| TABLE 3 | | | |
|---|---|---|---|
| RESULTS FOR VARIOUS RELIABILITY LEVELS | | | |
| **(%)** | **Best Cost($)** | **Average Cost($)** | **Worst Cost($)** |
| **1.5** | 716056 | 718139 | 719569 |
| **1.0** | 719898 | 720808 | 721776 |
| **0.5** | 721825 | 723784 | 724009 |

The results show that the total operating cost of the system increases as the maximum allowed limits Lmax decreases. As expected, the enforcement of reliability constraints requires the commitment of additional generating units, resulting in a significant increase in the total operating cost of the system. Thus, there is a trade-off between the desired level of reliability and the total cost of the system. For the maximum allowed limit Lmax set to 1.5%, solution of reliability constrained UC problem results in a total cost of $ 716056. This optimal result is obtained out of 20 trials. As shown in Table 3, for this reliability level average cost of $ 718139 is achieved. For reliability level set to 1.0%, best cost of $ 719898 is attained. Out of 20 trials, reliability constrained UC problem results in best cost of $ 721825 for reliability level set to 0.5%. As per [13], the minimum cost result achieved for reliability level 0.5% is less than the minimum solution reported in the existing literature. Table 4 gives the comparison of the best cost value obtained by GABC algorithm with respect to other techniques for 0.5% of LOLP index.

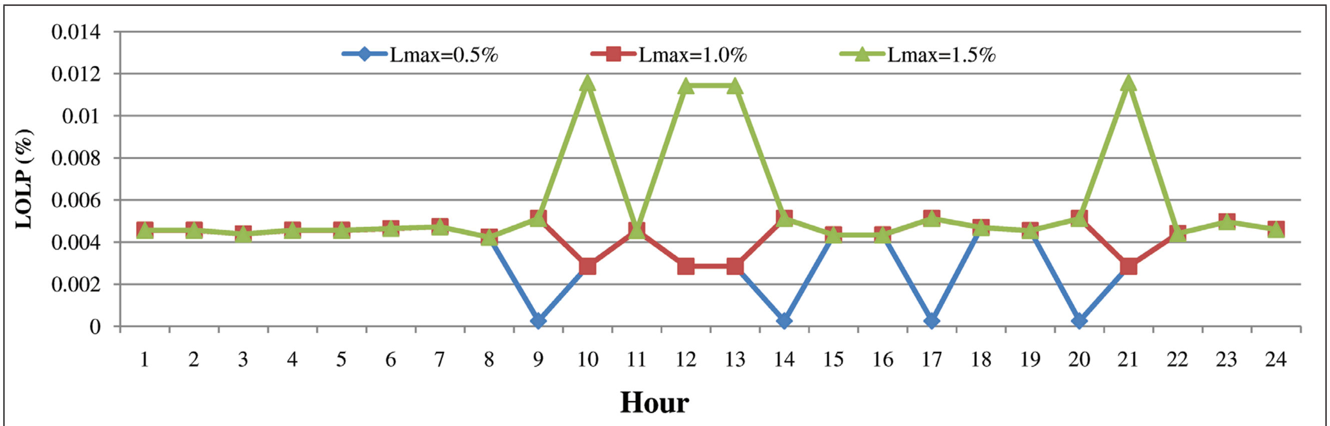


FIG. 5 LOLP AT EACH HOUR FOR BEST COST RESULTS FOR THREE RELIABILITY LEVEL

| TABLE 4 | |
|---|---|
| COMPARISON OF BEST COST RESULTS FOR LOLP 0.5% | |
| **Solution Technique** | **Best Cost ($)** |
| SA[9] | 722401 |
| GA[13] | 722466 |
| PSO[13] | 722358 |
| BRCFF[13] | 721927 |
| **GABC** | **721825** |

Figure 5 illustrates the variation of the hourly LOLP over the scheduling period for three different reliability levels for the best solution obtained through GABC algorithm. It is observed that for each hour, the LOLP is less than the corresponding maximum allowed limit Lmax, confirming that the final solution of the RCUC problem provides the desired level of reliability.

## 7.2 RCUC incorporating EDRP

In this case, reliability constraint unit commitment problem is executed with demand side management. The IEEE RTS 24 bus system is used to solve RCUC problem incorporating DRP. In this case EDRP is implemented with RCUC problem. Spot prices for IEEE RTS 24 bus system is given in Table 2 [16]. The load curve is divided into three intervals: valley period (00:00 hrs-08:00 hrs), peak period (17:00 hrs-00:00 hrs) and off-peak period (08:00 hrs-17:00 hrs). For implementation of EDRP, the price elasticity of demand is given in Table 5 [26].

| TABLE 5 | | | |
|---|---|---|---|
| ELASTICITY OF DEMAND FOR IEEE RTS 24 BUS SYSTEM | | | |
| **Hour** | **1-8 (valley)** | **9-16 (off peak)** | **17-24 (peak)** |
| **1-8 (valley)** | -0.1 | 0.014 | 0.016 |
| **9-16 (off peak)** | 0.014 | -0.1 | 0.012 |
| **17-24 (peak)** | 0.016 | 0.012 | -0.1 |

As in Table 5, considered value of own elasticity is -0.1 and cross elasticity is 0.012 related to peak and off-peak time periods, 0.014 related to low and off-peak time periods and 0.016 related to low and peak time periods.Two sub cases are considered as follows:

**Sub Case 1**

In this case potential of implementing EDRP, i.e. "η," is considered to be 10%. So under system emergency, 10 % load reduction can be achieved. In this case it is assumed that the emergency has been called for hours 9 to 21. To achieve the 10 % load reduction,the optimum value of incentive found to be $ 4.90. Figure 6 shows the load reduction due to implemented EDRP. Now this new demand is considered to solve RCUC problem with a reliability level of 0.5 %, which results in operating cost of $ 670341. The incentive of $ 13954 is paid to the customers for their load reduction under EDRP program and hence the total cost of $ 684295 is obtained.

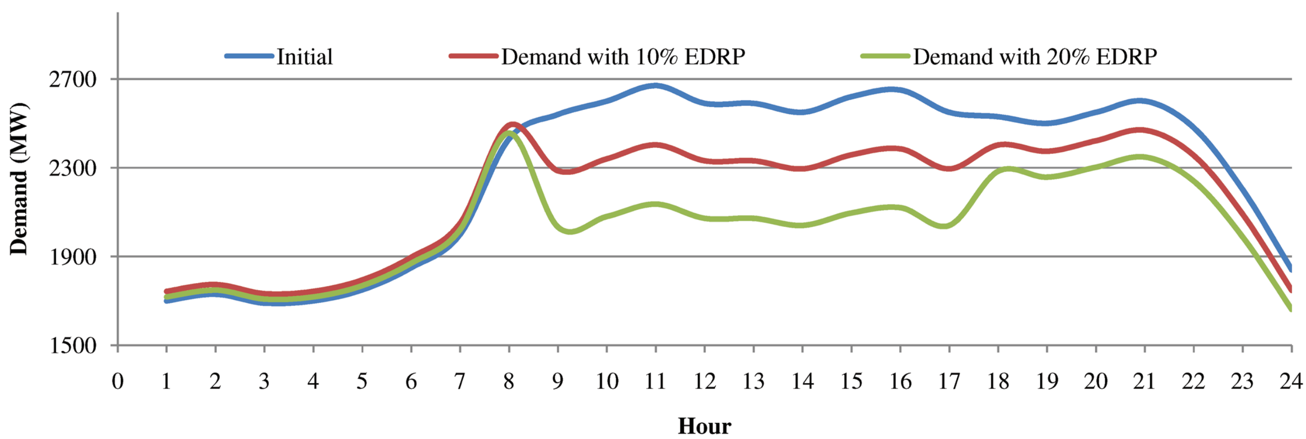


FIG. 6 CHANGE IN LOAD PROFILE DUE TO 10% EDRP & 20% EDRP

**Sub Case 2**

In this case η is considered as 20%. To achieve the 20 % load reduction, the incentive value $ 10.085 (Optimum value to achieve the 20 % load reduction) is considered. Here, it is also assumed that the emergency has been called for hours 9 to 21. Change in the load profile with 20 % EDRP is also given in Figure 6. For reliability level 0.5 %, RCUC problem with 20 % EDRP results in total cost of $ 677445.

In both sub cases, minimum cost solutions obtained with 150 number of employed bees, 300 number of onlookers, limit value 2, constant C 1.5 and MNC of 500 are shown in Table 6. For each sub case 10 trail solutions are obtained and the minimum cost solution is considered.

| TABLE 6 | | |
|---|---|---|
| RESULTS OBTAINED FOR BOTH SUB CASES FOR 10 TRAILS | | |
| **Trials** | **10% EDRP** | **20% EDRP** |
| 1 | $ 672029 | $ 620523 |
| 2 | $ 673228 | $ 621778 |
| 3 | **$ 670341** | $ 623130 |
| 4 | $ 672389 | $ 621628 |
| 5 | $ 673915 | $ 624623 |
| 6 | $ 674341 | $ 622207 |
| 7 | $ 671313 | $ 621399 |
| 8 | $ 673204 | $ 620628 |
| 9 | $ 674093 | **$ 620462** |
| 10 | $ 672961 | $ 622858 |

| TABLE 7 | | | | |
|---|---|---|---|---|
| TOTAL COST FOR RCUC PROBLEM INCORPORATING EDRP | | | | |
| **Minimum Cost solutions** | | | | |
| **Sub Case** | | **Operating Cost ($)** | **Incentive ($)** | **Total Cost ($)** |
| **1** | **10 % EDRP + 0.5% LOLP** | 670341 | 13954 | 684295 |
| **2** | **20 % EDRP + 0.5% LOLP** | 620462 | 56983 | 677445 |

Table 7 shows the total cost of the system, after paying incentives to the customers. From Table 7 it is clearly observed that cost is reduced for 20 % EDRP, due to more load reduction compared to 10 % EDRP. The total incentive paid to the customer is more for 20 % EDRP.

## 8.0 CONCLUSION

The RCUC problem is solved using GABC algorithm for IEEE RTS 24 bus system for different reliability levels. The results show that the total operating cost of the system increases as reliability level increases. The feasibility and performance of the RCUC incorporating EDRP are demonstrated on IEEE RTS 24-bus system. The results confirm that implementation of EDRP yield reduction in the total cost with a reduction in the load demands. Hence,the system becomes more reliable, economical with enhanced load profile.

## REFERENCES

[1] N P Padhy, "Unit Commitment-A Bibliographical survey", IEEE Trans. Power Syst., Vol. 19, No. 2, pp. 1196-1205, May 2004.

[2] R Billinton and R N Allan, Reliability Evaluation of Power Systems, 2nd ed. New York: Plenum, 1996.

[3] L T Anstine, et. al, "Application of probability methods to the determination of spinning reserve requirement for the Pennsylvania - New Jersey - Maryland interconnection," IEEE Trans. Power App. Syst., Vol. PAS-82, No. 68, pp. 720-735, Oct. 1963.

[4] H B Gooi, D P Mendes, K R W Bell, and D S Kirschen, "Optimal scheduling of spinning reserve," IEEE Trans. Power Syst., Vol. 14, No. 4, pp. 1485-1492, Nov. 1999.

[5] D Chattopadhyay and R Baldick, "Unit commitment with probabilistic reserve," in Proc. IEEE Power Eng. Soc. Winter Meeting, New York, Jan. 2002, Vol. 1, pp. 280-285.

[6] R Billinton and M Fotuhi-Firuzabad, "Generating system operating health analysis considering stand-by units, interruptible load and postponable outages," IEEE Trans. Power Syst., Vol. 9, No. 3, pp. 1618-1625, Aug. 1994.

[7] R Billinton and R Karki, "Capacity reserve assessment using system well-being analysis," IEEE Trans. Power Syst., Vol. 14, No. 2, pp. 433-438, May 1999.

[8] R Billinton and M Fotuhi-Firuzabad, "A basic framework for generating system operating health analysis," IEEE Trans. Power Syst., Vol. 9, No. 3, pp. 1610-1617, Aug. 1994.

[9] D N Simopoulos, S D Kavatza, and C D Vournas, "Reliability constrained unit commitment using simulated annealing," IEEE Trans. Power Syst., Vol. 21, No. 4, pp. 1699-1706, Nov. 2006.

[10] J Bai, H B Gooi, L M Xia, G Strbac, and B Venkatesh, "A probabilistic reserve market incorporating interruptible load," IEEE Trans. Power Syst., Vol. 21, No. 3, pp. 1079-1087, Aug. 2006.

[11] J Bai, H B Gooi, and L M Xia, "Probabilistic reserve schedule with demand-side participation," Elect. Power Comput. Syst., Vol. 36, No. 2, pp. 138-151, Feb. 2008.

[12] F Aminifar, M Fotuhi-Firuzabad, and M Shahidehpour, "Unit commitment

with probabilistic spinning reserve and interruptible load considerations," IEEE Trans. Power Syst., Vol. 24, No. 1, pp. 388-397, Feb. 2009.

[13] K Chandrasekaran, S P Simon, "Network and reliability constrained unit commitment problem using binary real coded firefly algorithm," Electrical Power and Energy Systems 43 (2012) pp. 921-932.

[14] Charles River Associates, "Primer on demand side management", Report for the World Bank, February 2005

[15] U S Department of Energy, "Energy policy Act of 2005", section 1252, February 2006.

[16] D S Kirschen, G Strbac, P Cumperayot, and D Mendes, "Factoring the elasticity of demand in electricity prices," IEEE Trans. Power Syst., Vol. 15, No. 2, pp. 612-617, May 2000.

[17] H A Aalami, M Parsa Moghaddam, G R Yousefi, "Demand response modeling considering Interruptible/Curtailable loads and capacity market programs", Applied Energy 87 (2010) pp. 243-250.

[18] H A Aalami, M Parsa Moghaddam, G R Yousefi, "Modeling and prioritizing demand response programs in power markets", Electric Power System Research 80 (2010) pp. 426-435.

[19] FERC: Staff Report, 'Assessment of demand response and advanced metering'. [Online]. Available at http://www.FERC.gov. August 2006.

[20] FERC: Staff Report, 'Assessment of demand response and advanced metering'. [Online]. Available at http://www.FERC.gov. August 2006.

[21] FERC: Staff Report, 'Assessment of demand response and advanced metering'. [Online]. Available at http://www.FERC.gov. August 2006.

[22] Schweppe F, Caramanis M, Tabors R Evaluation of spot price based electricity rates. IEEE Transaction on Power Apparatus Systems PAS 1985;104(7): pp. 1644-55.

[23] B Basturk and D Karaboga, "An Artificial Bee Colony (ABC) Algorithm for Numeric function Optimization," IEEE Swarm Intelligence Symposium May 12-14, 2006, Indianapolis, Indiana, USA.

[24] Guopu Zhu, Sam Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," Applied Mathematics and Computation, 217 (2010), pp. 3166-3173.

[25] Deb K (2000). "An efficient constraint handling method for genetic algorithms," Computer Methods in Applied Mechanics and Engineering, 186(2–4), pp. 311-338.

[26] M Nikzad, B Mozafari, M Bashirvand, S Solaymani, "Designing time-of-use program based on stochastic security constrained unit commitment considering reliability index," Energy 41 (2012) pp. 541-548.