International Journal of Engineering & Technology, 7 (1.1) (2018) 94-100

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Unit commitment and dispatch with coordination of wind and pumped storage hydro units by using cuckoo search algorithm

R. Jayashree [1*], R. Soundarapandian [2]

[1]*Professor, Department of EEE, B.S. Abdur Rahman University, Chennai, India*
[2] *Research Scholar, Department of EEE, B.S. Abdur Rahman University, Chennai, India*
**Corresponding author E-mail:jaysubhashree@gmail.com*

Abstract

This paper proposes a multi objective model for Advanced Unit Commitment (AUC) with wind power and Pumped Storage (PS) units using Cuckoo Search (CS) algorithm. The novelty of the proposed method is improved levy flight searching ability, random reduction and ability to adapt complex optimization problems. Here, the CS algorithm to accommodate wind output uncertainty, with the multi-objective of providing an optimal AUC schedule for the thermal generators in the day-ahead market that minimizes the total cost under the different wind power output scenario. The proposed method is more reliable for AUC because it considering the wind power uncertainty using the Artificial Neural Network (ANN) and PS units, which are significantly reduces the total cost. Then the proposed method is implemented in the MATLAB/simulink platform and tested under IEEE standard bench mark system. The proposed method performance has been verified through the comparison analysis with the existing techniques. The comparison results were proved the superiority of the proposed method.

Keywords: *AUC, PS, CS, ANN, wind power*.

1. Introduction

Regarding to worldwide environmental change with discharges and consumption of fossil fuels, renewable energy sources are utilized in the power framework systems to overcome monetary, ecological, mechanical, and group level needs [1-2]. Between that, the wind energy era possesses acquired significant expense along with transform into probably the most develop green energy program to the conventional assets [3]. As the wind power entrances have expanded in the due course of the recent decade, more inventive and advanced methodologies are usually received in the present providing restriction planning, working conventions and methods because of its irregularity and unconventionality [4-5].Several procedures may be used to cater to wind electric power variability including innovative model dedication, along with controlling wind electric power variations together with pumped-storage hydro and superior supplementary program procurement. To satisfy the need in cheaper cost, we've to make the optimization problem which determines which electric power plant life must be stimulated and/or banned on the regarded as period of time. It is termed because Unit Commitment optimization problem [6-7]. By employing, the lowest generation expense is achieved when each of the generation units together with wind electric power are usually devoted [8]. Regarding committing wind electric power from the electric power program operation, it an accurate predicting product which can figure out your behaviour connected with wind in advance generally some day to consider booking selections [9-10]. As outlined by [11], the wind velocities variations are usually simulated through the distribution operate that is utilised by electric power program employees regarding identifying generation activities. For adhering the wind force throughout most exceedingly terrible situations, pumped-capacity hydro generation units are utilized to store the overabundance vitality and give the store and adaptability when required which expands the wind power dispatchability [12-13]. Anyhow, it had regional and land constraints which makes it valuable just for a specific force framework region [14].

This paper focuses on a multi objective model for Advanced Unit Commitment (AUC) with wind power and Pumped Storage (PS) units using Cuckoo Search (CS) algorithm. The novelty of the proposed method is improved levy flight searching ability, random reduction and ability to adapt complex optimization problems. Here, the CS algorithm to accommodate wind output uncertainty, with the multi-objective of providing an optimal AUC schedule for the thermal generators in the day-ahead market that minimizes the total cost under the different wind power output scenario. The proposed method more reliable for AUC because it considering the wind power uncertainty using the Artificial Neural Network (ANN) and PS units, which are significantly reduces the total cost. The rest of the paper organized as follows: the problem formulation is explained in the section 2; the proposed algorithm brief explanation is explained in section 3; the suggested technique achievement results and the related discussions are given in section 4; and section 5 ends the paper.

2. Problem formulation of AUC

The AUC problem consists of different kinds of costs such as thermal generating units optimal combinations fuel cost and start up costs of the thermal generating units. Here, the thermal generation is limited by using the probability of the wind power generation. The operational costs of PS units are assumed to be zero [15], so there is no need to consider the objective function. Therefore the selection of objective function should minimize the above mentioned cost functions, which is described in the following equation (1).

$$F_{TC} = \sum_{t=1}^{H}\sum_{i=1}^{N}\left[f_c(P_{TG}(i,t))U(i,t) + SC(i,t)\right]\times prob_{WT}(j,t) \quad (1)$$

Where, $f_c[P_{TG}(i,t)] = a_i + b_i P_{TG}(i,t) + c_i P_{TG}^2(i,t)$ (fuel cost in $) (2)

$$SC(i,t) = k_{o,i}\left[1 - \exp\left(\frac{T_{off}(i,t)}{k_{1,i}}\right)\right] + k_{2,i} \quad \text{(Startup cost)} \tag{3}$$

F_{TC} is the total cost; $f_c[P_{TG}(i,t)]$ is the fuel cost of the thermal generating units ($); H is the total number of hours; $U(i,t)$ is the status of the unit i at t^{th} hour, i.e., 1 for ON and 0 for OFF; a_i, b_i and c_i are the fuel cost coefficients of the thermal generating unit i at t^{th} hour; $prob_{WT}(j,t)$ is the probability of the wind generator unit j at t^{th} hour, which is calculated based on wind power uncertainty; $P_{TG}(i,t)$ is the output power of the generator unit i at t^{th} hour; $SC(i,t)$ is the startup cost of unit i at t^{th} hour; N is the number of generating units; $k_{o,i}$, $k_{1,i}$ and $k_{2,i}$ are the startup cost coefficients of the thermal generating unit i and $T_{off}(i,t)$ is duration at which thermal generating unit i has been off at t^{th} hour. The generating unit's ON and OFF status was identified by using the proposed CS algorithm. The above mentioned fitness function is subjected to the following constraints.

2.1. System constraints

The cost function of the AUC problem given by equation (1) is subjected to the following constraints.

(i). System Power balance constraint

The total power generated from the different types of sources like thermal generating unit, wind power generating unit and PS unit at each hour must be equal to the load of the corresponding hour. This constraint is explained in the following equation (4).

$$P_{TD}(t) = \sum_{i=1}^{n} P_{TG}(i,t)U(i,t) + P_{WT}^{NN}(j,t) + \sum_{l=1}^{n} P_{PS}(l,t)S(l,t) \tag{4}$$

Where, $P_{TD}(t)$ is the total demand at period t; $P_{TGi}(i,t)$ is the power generated from thermal unit i at hour t; $P_{WT}^{NN}(j,t)$ is the power generated from wind unit j at hour t, which is attained from the ANN; $P_{PS}(l,t)$ is the output power of the PS unit l at hour t. The power system spinning reserve constraint is explained in the following section.

(ii). Spinning reserve constraint

The system spinning reserve requirement is described in the following equation (5).

$$\sum_{i=1}^{n} P_{TG}^{\max}(i,t)U(i,t) + \sum_{l=1}^{n} P_{PS-g}^{\max}(l,t) + \sum_{l=1}^{n} P_{PS}(l,t)S(l,t) - P_{TD}(t) \geq R(t) \tag{5}$$

Where, $S(l,t) = -1,0,1$ represented the pumping, idle and generating mode of PS units respectively; is the maximum output power limit of the thermal unit $P_{PS-g}^{\max}(l,t)$ is the maximum generating power of PS l at hour t; $R(t)$ is the power system spinning reserve requirement at hour t. The subjected thermal units and PS units constraints are briefly described in the following.

2.2. Thermal unit's constraints

The thermal generating system consists of different types of constraints such as generation capacity, uptime and down time of the generators and ramp generation, which are described as follow.

(i). Generating capacity constraints [16]

$$P_{TG}^{\min}(i,t) \leq P_{TG}(i,t) \leq P_{TG}^{\max}(i,t) \tag{6}$$

(ii). Minimum up time limit [16]

$$T_{on}(i,t) > Minup(t) \tag{7}$$

(iii). Minimum down time [16]

$$T_{off}(i,t) > Mindown(t) \tag{8}$$

(iv). Ramp generation [16]

$P_{TG}(i,t) - P_{TG}(i,t-1) \leq RU(i)$ as generation increases (9)

$P_{TG}(i,t) - P_{TG}(i,t-1) \leq RD(i)$ as generation increases (10)

Where, $P_{TG}^{\min}(i,t)$ and $P_{TG}^{\max}(i,t)$ are the minimum and maximum power of thermal generating unit i at t^{th} hour; $Minup(t)$ is the minimum up time of thermal generating unit at t^{th} hour; $Mindown(t)$ is the minimum down time of thermal generating unit at t^{th} hour; $T_{on}(i,t)$ is duration at which thermal generating unit i has been on at t^{th} hour; $RU(i)$ and $RD(i)$ are the ramp up and down limit of the unit i. The PS unit constraints are described in the following section 2.3.

2.3. PS unit's constraints

The PS unit contains the generating capacity constraints, water flow constraints and reservoir constraints, which are described as follow.

(i).Generating capacity constraints [16]

$$P_{PS-g}^{\min}(l) \leq P_{PS-g}(l,t) \leq P_{PS-g}^{\max}(l) \tag{11}$$

$$P_{PS-p}^{\min}(l) \leq P_{PS-p}(l,t) \leq P_{PS-p}^{\max}(l) \tag{12}$$

(ii).Water flow constraints [22]

$$Q_g^{\min}(l) \leq Q_g(l,t) \leq Q_g^{\max}(l) \tag{13}$$

$$Q_p^{\min}(l) \leq Q_p(l,t) \leq Q_p^{\max}(l) \tag{14}$$

(iii).Upper and lower limits of the reservoir [16]

$$V_{up}^{\min}(l) \leq V_{up}(l,t) \leq V_{up}^{\max}(l) \tag{15}$$

$$V_{low}^{\min}(l) \leq V_{low}(l,t) \leq V_{low}^{\max}(l) \tag{16}$$

(iv).Water balance between upper and lower reservoir [16]

$$V_{up}(l,t+1) = V_{up}(l,t) \mp \left|Q_{g(p)}(l,t)\right| S(l,t) \tag{17}$$

$$V_{low}(l,t+1) = V_{up}(l,t) \pm \left|Q_{g(p)}(l,t)\right| S(l,t) \tag{18}$$

Where the initial conditions of the upper and lower reservoirs are

$$V_{up}(l,0)=V_{up}^{0}(l) \tag{19}$$

$$V_{low}(l,0)=V_{low}^{0}(l) \tag{20}$$

Where, $P_{PS-g}^{\min}(l)$ and $P_{PS-g}^{\max}(l)$ are the minimum, maximum generating power of PS unit l; $P_{PS-p}^{\min}(l)$ and $P_{PS-p}^{\max}(l)$ are the minimum, maximum pumping power of PS unit; $Q_{g}^{\min}(l)$ and $Q_{g}^{\max}(l)$ are the minimum, maximum water discharge of PS unit l at generating mode; $Q_{p}^{\min}(l)$ and $Q_{p}^{\max}(l)$ are the minimum, maximum water discharge of PS unit l at pumping mode; $V_{up}^{\min}(l)$ and $V_{up}^{\max}(l)$ are the minimum, maximum volume of upper reservoir of PS unit l; $V_{low}^{\min}(l)$ and $V_{low}^{\max}(l)$ are the minimum, maximum volume of lower reservoir of PS unit l; $V_{up}^{0}(l)$ and $V_{low}^{0}(l)$ is upper and lower reservoir initial volume of PS unit l. The output power of the PS unit has been modeled by the following equation (21).

$$P_{PS}(l,t)=C_{l,1}Q^{2}(l,t)+C_{l,2}V^{2}(l,t)+C_{l,3}Q(l,t)V(l,t)+C_{l,4}Q(l,t)+C_{l,5}V(l,t)+C_{l,6} \tag{21}$$

Where, $P_{PS}(l,t)$ is the output power of the PS unit l at t^{th} hour; $C_{l,1}\ldots C_{l,6}$ is the power coefficients of the PS units; $Q(l,t)$ is the water discharging of PS unit l at t^{th} hour; $V(l,t)$ is the voltage of reservoir of PS unit l at t^{th} hour. The wind power generation, which depends on the wind power uncertainty, is attained from the ANN, which is briefly described in the following section 2.4.

2.4. Wind power generation prediction using ANN

The neural network is one of the artificial intelligence (AI) techniques [17] which workings are based on the training and testing process. It is a machine learning approach that models a human brain and consists of a number of artificial neurons. The presented neurons have the interior connections and each neuron in ANN receives a number of inputs, depending on the activation functions of the ANN results in the output level of the neuron. Here the wind power generation $P_{WT}^{NN}(j,t)$ can be identified by the ANN technique. By using the target with corresponding inputs, the ANN becomes trained using the back propagation algorithm. During the testing time the resultant wind power generation can be obtained. The back propagation algorithm training steps are explained below.

Back propagation learning algorithm steps

Step 1: Initialization of the input layer, hidden layer and output layer weights of the neural network, i.e., day (D), hour (H), wind speed $S_{WT}(j,t)$ and wind power generation $P_{WT}(j,t)$.

Step 2: Learning the network according to the input and the corresponding target.

Step 3: Calculate the back propagation error of the target $P_{WT}(j,t)_1, P_{WT}(j,t)_2\ and\ P_{WT}(j,t)_k$.

$$\left.\begin{aligned}
BP_{error}^{1}&=P_{WT}(j,t)_{1}^{NN(tar)}-P_{WT}(j,t)_{1}^{NN(out)}\\
BP_{error}^{2}&=P_{WT}(j,t)_{2}^{NN(tar)}-P_{WT}(j,t)_{2}^{NN(out)}\\
BP_{error}^{k}&=P_{WT}(j,t)_{k}^{NN(tar)}-P_{WT}(j,t)_{k}^{NN(out)}
\end{aligned}\right\} \tag{22}$$

Where, $P_{WT}(j,t)_{k}^{NN(tar)}$ is the network target of the k^{th} node and $P_{WT}(j,t)_{k}^{NN(out)}$ is the current output of the network.

Step 4: The current output of the network is determined by following them,

$$\left.\begin{aligned}
P_{WT}(j,t)_{1}^{NN(out)}&=\alpha_1+\sum_{n=1}^{N}w_{1n}\,P_{WT}(j,t)_{1}^{NN}(n)\\
P_{WT}(j,t)_{2}^{NN(out)}&=\alpha_2+\sum_{n=1}^{N}w_{2n}\,P_{WT}(j,t)_{2}^{NN}(n)\\
P_{WT}(j,t)_{k}^{NN(out)}&=\alpha_k+\sum_{n=1}^{N}w_{kn}\,P_{WT}(j,t)_{k}^{NN}(n)
\end{aligned}\right\} \tag{23}$$

Where, α_1, α_2 and α_k are the bias function of the node $1,2\,and\,k$ respectively.

$$\left.\begin{aligned}
P_{WT}(j,t)_{1}^{NN}(n)&=\frac{1}{1+\exp(-w_{1n}P_{WT}(j,t)_1-w_{2n}P_{WT}(j,t)_2)}\\
P_{WT}(j,t)_{2}^{NN}(n)&=\frac{1}{1+\exp(-w_{2n}P_{WT}(j,t)_2-w_{kn}P_{WT}(j,t)_k)}\\
P_{WT}(j,t)_{k}^{NN}(n)&=\frac{1}{1+\exp(-w_{kn}P_{WT}(j,t)_k-w_{1n}P_{WT}(j,t)_1)}
\end{aligned}\right\} \tag{24}$$

Step 5: The new weights of the each neurons of the network are updated by $w_{new}=w_{old}+\Delta w$. Here, w_{new} is the new weight, w_{old} is the previous weight and Δw is the change of weight of each output. The change of weight is determined as follows:

$$\left.\begin{aligned}
\Delta w_1&=\delta.P_{WT}(j,t)_1.BP_{error}^{1}\\
\Delta w_2&=\delta.P_{WT}(j,t)_2.BP_{error}^{2}\\
\Delta w_k&=\delta.P_{WT}(j,t)_k.BP_{error}^{k}
\end{aligned}\right\} \tag{25}$$

Where, δ is the learning rate (0.2 to 0.5).

Step 6: Repeat the above steps till the BP_{error} gets minimized $BP_{error}<0.1$. Once the neural network training process is completed, the network is trained well for the identifying $P_{WT}^{NN}(j,t)$. Based on the output of the network, the CS algorithm has been performing the AUC. The CS algorithm based optimum combination of generator units selection is depending on the load demand, which is explained in the following section 4.

3. CS algorithm based optimum generation unit combination selection

The proposed method AUC problem has been solved by optimizing the generator combination using CS algorithm according to the load demand. Here, the wind power is selected according to the uncertainty of the wind characteristics, i.e., from the neural network, which should minimize the generating capacity of the generators. The attained optimal combinations of generating units are used to minimize the fuel cost and the startup cost of the generating units. The step by step process for optimizing the combination of generator unit is explained in the following subsection.

Algorithm

Step1: Initialize the input host nest and cuckoo parameters such as thermal generators generation limits, wind power generation limit from the ANN and the PS unit generation limits.

Step 2: Generate the random population of *n* host nests using the following equation (26).

$$X_i = [X_1, X_2 \ldots X_n] \tag{26}$$

Step 3: Set the iteration count k=1.

Step 4: Determine the fitness of the nests by means of the fitness equation (1).

Step 5: Determine the maximum and minimum fitness of the initial population. From the population minimum values are stored for the best solutions.

Step 6: Generate the new solution X_i^{t+1} for cuckoo i using levy flight, which can be represented as follows

$$X_i^{t+1} = X_i^t + \alpha \oplus Levy(\lambda) \tag{27}$$

Where, $\alpha > 0$ is the step size, which should be related to the scale of the problem of interest and the product $\oplus$ means entry-wise multiplications. In this work, we consider Levy flight in which the step-lengths are distributed according to the following probability distribution

$$Levy(\lambda) = t^{-\lambda}, 1 < \lambda \le 3 \tag{28}$$

Step 7: Discover the worst nests based on the probability (p_a) and substitute the worst nests by new set of solutions.

Step 8: Test the termination criteria. Go to step 9 if it is met, if not go to step 3.

Step 9: Terminate the process.

Once the process is completed the network is ready to give the better generator units combination for different types of load demand. The structure of the proposed method for optimizing the optimal generating unit is described in figure 2. The proposed technique is tested in the MATLAB/simulink platform and the results are analyzed in Section 5.

4. Computational results and discussion

In this section, we presented the numerical experiments of the proposed algorithm in MATLAB/Simulink 7.10.0 (R2012a) platform, 4GB RAM and Intel(R) core(TM) i5 with IEEE 118 standard bench mark system. There are 54 generating units in the system. In [18], the detailed system data and load profile for IEEE 118-bus system are found. The same as in [18], the spinning reserve of the system is fixed based on the proceeding events of the system. The effectiveness of the proposed method is verified by comparing with the conventional GA technique. The implementation parameters for wind power plant and PS unit are described in the table 1.

Table 1: Implementation Parameters

Sources	Parameters	Values
Wind turbine	Minimum and maximum wind speed	3 m/s to 12.25m/s
	Minimum and maximum wind power	500MW to 2000MW
PS unit	Total number of units	4
	Minimum and maximum generating power	10MW to 100MW
	Minimum and maximum absorbing power	20MW to 110MW
	Minimum and maximum water level at generation	3.5MCFT to 4 MCFT
	Minimum and maximum water level at absorption	2.8MCFT to 3 MCFT

Based on the wind power variation and the load demand value, the AUC has been performed by using the proposed CS method. The historical wind speed (m/s) and corresponding wind power generation (MW) data for 24 hours are utilized for training the ANN. From the ANN output, the wind uncertainty probability has been calculated. The ANN based wind power prediction for 24 hours are tabulated in the following table 2.

Table 2: Wind Power Probability for 24 Hours

Hour	Wind speed(m/s)	Wind power (MW)	Wind probability
1	9.0243	254.2986	0.9395
2	8.8272	119.4453	0.9951
3	3.0430	744.3672	0.7861
4	5.8141	779.3689	0.7708
5	6.7903	758.7873	0.7471
6	9.3087	544.7543	0.8487
7	4.6805	989.7023	0.7644
8	9.7762	1019.7211	0.7821
9	6.2928	1102.6122	0.7759
10	7.8732	886.8410	0.8320
11	6.8745	1126.4799	0.7890
12	7.6323	1181.4233	0.7656
13	5.6538	1380.7568	0.7123
14	7.9745	1102.0611	0.7583
15	3.5215	1467.2009	0.3433
16	9.0727	1338.6339	0.7521
17	4.8001	2345.0331	0.5402
18	8.6525	1487.6287	0.7214
19	7.0076	1746.9356	0.6903
20	4.5351	1261.3335	0.4454
21	8.8945	1913.6694	0.6811
22	4.0735	1972.9859	0.6346
23	8.8924	1805.9401	0.6540
24	8.0980	1959.8248	0.6017

The wind power variation has been attained from the ANN technique. Here, the hourly based wind speed is given as the input and found the wind power probability. The ANN technique efficient training and testing process helps to identify the optimal wind probability. From the table.2, we can understand that the wind speed variation at the different time intervals. By using the wind power probability, the generator unit's configurations have been selected. Any peak load conditions may occur in the bus system, the load curtailment has been reduced using the allocation of the PS units. The PS units power production and the unit commitment has been described in the table 3. Here, the ON/OFF status of the PS units during the AUC condition is explained. In the table 3, the PS unit power generation is varied from 96 MW to 235 MW during the required load demand. The wind power generation and PS unit's power generations are mostly exploited to decrease the usage of thermal generator units.

Table 3: PS Unit Status with Generated Power

Hour	Unit 1 to 4	Generated power (MW)
1	1011	200.4766
2	1010	144.7205
3	1010	145.1663
4	1010	126.6755
5	1010	135.5367
6	1010	96.5397
7	1011	163.6424
8	1011	157.1692
9	1011	195.1307
10	1111	187.3391
11	1111	189.5104
12	1111	167.6598
13	1011	210.6700
14	1011	155.6098
15	1111	224.6370
16	1111	189.4836
17	1111	192.3884
18	1111	174.6286
19	1111	194.7727
20	1111	230.5265
21	1111	227.3319
22	1111	234.9681
23	1111	194.4548
24	1011	181.543

The IEEE 118 bus system 54 generators unit status with operating cost during the 24 hours load demand is illustrated in the table 4.From the mentioned operating cost, the initial hour occupies the maximum operating cost such as 31134.6692$. It has been reduced at the 15^{th} hour 6162.1347$. Finally the total operating cost of the total period has been calculated, which is clearly shown that the proposed AUC satisfies the reported load demand at 521778.4$ total operating cost. In the table 4, at each and every hour the operating cost of the thermal generators units are noticed. Then the thermal generator units dispatch the amount for every hour has been noticed in the table 5, which also have the startup cost of the units.

Table 4: Thermal Generator Unit Status

Hour	Unit no 1 to 54	Operating cost ($)
1	111001111001111111111111110011111111111111111111111111	31134.6692
2	111001111001111111111111110011111111111111111111111111	33113.4428
3	111001111001111111100110110011111111111111111111111111	18522.7450
4	111001111001111111100110110011111111111111111111111111	18078.6663
5	111001111001111111100110010001111110111111111111111111	15002.7260
6	111001111001111111100110010011111111111111111111111111	23294.5064
7	111001111001111111100111110011111111111111111111111111	21317.5990
8	111001111001111111101111110011111111111111111111111111	24451.7646
9	111001111001111111111111110011111111111111111111111111	24910.5582
10	111001111001111111111111110011111111111111111111111111	31224.9031
11	111001111001111111111111110011111111111111111111111111	28217.0907
12	111001111001111111101111110011111111111111111111111111	25684.6395
13	111001111001111111100110110011111111111111111111111111	20950.6756
14	111001111001111111100110110011111111111111111111111111	23009.1602
15	111001011001101111100110010001111110110011000111111111	6162.1347
16	111001111001111111101111110011111111111111111111111111	26397.6333
17	111001111001111111100110010001111110110111111111111111	13757.5323
18	111001111001111111100111110011111111111111111111111111	24130.9769
19	111001111001111111100111110011111111111111111111111111	23379.6671
20	111001111001111111100110010001111110110011111111111111	10831.4185
21	111001111001111111101111110011111111111111111111111111	23786.5527
22	111001111001111111100110010011111111111111111111111111	19104.3230
23	111001111001111111100110010011111111111111111111111111	19500.1300
24	111001111001111111100110010001111111111111111111111111	15814.8832
Total operating cost		521778.4

The effectiveness of the proposed method is compared with the different techniques such as SDP [18], ABC-LR [19], BRCFF [20] and GA in the table 8. Here, the SDP, ABC-LR and BRCFF are normal unit commitment techniques, i.e., not considers the wind power generation and PS unit power generation. The SDP has 1645445.00$ total operating cost of the thermal generator units. The ABC-LR and BRCFF consists of 1644269.70$ and 1644141.00$ total operating cost respectively. The GA technique involves in the AUC, which has the total operating cost of the generator units is 742256.81$. The proposed method has minimum total operating cost 521778.4$ compared to the other techniques. Because it effectively utilizes the renewable energy sources of power generation during the peak load conditions. According to the availability of the renewable energy power generation the thermal generator units are allowed for generation. So the startup costs and fuel costs are effectively reduced. Table 5 shows the thermal generator units dispatch for every hour and also the startup cost of the units which satisfies the load demand every hour

Table 5: Thermal Generators Dispatch

unit	Hour																							
no	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	25.19	24.00	9.48	20.98	17.42	24.33	20.21	16.07	22.96	17.43	13.69	13.62	15.79	24.34	13.86	26.17	25.82	26.99	15.01	14.43	21.55	23.96	14.38	22.85
2	23.19	19.00	4.48	4.98	5.42	17.33	21.21	18.07	27.96	14.43	23.69	9.62	15.79	19.34	16.86	25.17	13.82	14.99	23.01	24.43	26.55	25.96	26.38	25.85
3	28.19	27.00	5.48	13.98	19.42	15.33	13.21	26.07	9.96	26.43	18.69	28.62	23.79	28.34	27.86	28.17	22.82	20.99	25.01	24.43	26.55	26.96	14.38	16.85
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	24.19	24.00	24.48	16.98	11.42	28.33	27.21	17.07	20.96	26.43	27.69	27.62	23.79	19.34	26.86	23.17	26.82	9.99	24.01	23.43	23.55	25.96	17.38	17.85
7	93.19	63.00	23.48	75.98	87.42	78.33	71.21	88.07	63.96	60.43	86.69	88.62	61.79	88.34	0.00	85.17	73.82	77.99	67.01	58.43	88.55	84.96	97.38	56.85
8	21.19	19.00	19.48	3.98	26.42	13.33	22.21	7.07	15.96	21.43	21.69	14.62	10.79	21.34	19.86	25.17	26.82	17.99	27.01	22.43	24.55	21.96	19.38	23.85
9	24.19	19.00	19.48	8.98	22.42	19.33	3.21	13.07	23.96	27.43	21.69	20.62	17.79	26.34	22.86	13.17	24.82	11.99	24.01	25.43	22.55	24.96	24.38	20.85
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	16.19	18.00	20.48	6.98	12.42	25.33	25.21	28.07	27.96	24.43	19.69	17.62	22.79	26.34	21.86	22.17	23.82	18.99	24.01	11.43	28.55	21.96	19.38	24.85
13	8.192	24.00	25.48	20.98	20.42	16.33	21.21	28.07	21.96	22.43	28.69	26.62	26.79	15.34	22.86	27.17	23.82	23.99	22.01	23.43	23.55	23.96	27.38	16.85
14	60.19	64.00	51.48	45.98	58.42	68.33	77.21	98.07	93.96	77.43	62.69	76.62	80.79	69.34	0.00	96.17	79.82	94.99	74.01	56.43	90.55	60.96	84.38	45.85
15	25.19	19.00	21.48	18.98	7.42	20.33	21.21	28.07	23.96	22.43	26.69	17.62	16.79	26.34	23.86	14.17	19.82	16.99	28.01	15.43	22.55	19.96	20.38	22.85
16	62.19	77.00	59.48	65.98	30.42	67.33	89.21	62.07	81.96	97.43	52.69	81.62	64.79	74.34	83.86	84.17	79.82	54.99	76.01	73.43	60.55	87.96	60.38	77.85
17	26.19	15.00	14.48	26.98	19.42	27.33	26.21	24.07	20.96	20.43	20.69	28.62	26.79	26.34	23.86	27.17	15.82	17.99	26.01	18.43	17.55	27.96	24.38	24.85
18	18.19	20.00	7.48	20.98	23.42	8.33	14.21	20.07	23.96	28.43	26.69	26.62	13.79	10.34	26.86	16.17	11.82	19.99	17.01	28.43	26.55	26.96	26.38	26.85
19	53.19	78.00	43.48	69.98	56.42	79.33	68.21	57.07	56.96	95.43	66.69	95.62	62.79	90.34	91.86	89.17	94.82	70.99	98.01	76.43	90.55	58.96	72.38	44.85
20	195.1	246.0	0	0	0	0	0	0	150.9	209.4	184.6	0	0	0	0	0	0	0	0	0	0.00	0	0	0
21	201.1	201.0	0	0	0	0	0	139.0	145.9	173.4	248.6	115.6	0	0	0	181.1	0	0	0	0	222.5	0	0	0
22	55.19	83.00	32.48	72.98	69.42	78.33	85.21	69.07	96.96	64.43	78.69	84.62	79.79	91.34	52.86	98.17	41.82	89.99	94.01	76.43	70.55	94.96	74.38	82.85
23	80.19	67.00	50.48	26.98	84.42	51.33	72.21	94.07	68.96	91.43	55.69	33.62	74.79	26.34	91.86	93.17	55.82	76.99	81.01	85.43	77.55	90.96	70.38	75.85
24	162.1	51.00	0	0	0	0	102.2	74.07	189.9	187.4	158.6	154.6	0	0	0	154.1	0	83.99	152.01	0	142.5	0	0	0
25	190.1	173.0	124.4	95.98	0	0	141.2	173.0	183.9	166.4	101.6	147.6	157.7	147.3	0	199.1	0	193.9	181.01	0	192.5	0	0	0
26	54.19	62.00	88.48	80.98	77.42	75.33	81.21	66.07	38.96	86.43	85.69	86.62	64.79	37.34	73.86	77.17	81.82	55.99	94.01	51.43	59.55	89.96	83.38	86.85
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0.	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	265.1	259.0	85.48	84.98	0	203.3	172.2	215.0	221.9	220.4	209.6	238.6	208.7	295.3	0	174.1	0	275.9	174.0	0	244.5	246.9	238.3	0
30	70.19	60.00	75.48	58.98	34.42	60.33	67.21	73.07	38.96	77.43	55.69	73.62	72.79	76.34	65.86	34.17	76.82	53.99	63.01	54.43	76.55	64.96	72.38	54.85
31	27.19	17.00	21.48	12.98	15.42	25.33	20.21	15.07	22.96	27.43	14.69	20.62	13.79	18.34	21.86	25.17	26.82	27.99	22.01	15.43	27.55	26.96	17.38	26.85
32	23.19	12.00	10.48	11.98	17.42	22.33	20.21	17.07	18.96	20.43	17.69	17.62	21.79	19.34	21.86	27.17	24.82	24.99	26.01	20.43	23.55	10.96	25.38	16.85
33	13.19	11.00	7.48	15.98	11.42	10.33	9.21	8.07	14.96	16.43	16.69	17.62	5.79	13.34	10.86	18.17	16.82	9.99	13.01	17.43	13.55	14.96	10.38	4.85
34	90.19	63.00	46.48	23.98	96.42	80.33	52.21	70.07	46.96	96.43	84.69	93.62	89.79	87.34	93.86	46.17	84.82	65.99	80.01	94.43	98.55	56.96	77.38	44.85
35	34.19	91.00	85.48	63.98	47.42	74.33	85.21	87.07	50.96	85.43	96.69	62.62	47.79	85.34	86.86	53.17	82.82	55.99	75.01	77.43	81.55	59.96	56.38	45.85
36	211.1	187.0	250.4	219.98	0.00	275.3	179.2	272.0	210.9	232.4	276.6	179.6	231.7	183.3	0	208.1	0	279.9	277.0	0	212.5	242.9	272.3	262.85
37	72.19	97.00	74.48	67.98	44.42	43.33	85.21	54.07	48.96	96.43	45.69	89.62	80.79	75.34	50.86	97.17	82.82	73.99	87.01	34.43	46.55	84.96	71.38	36.85
38	21.19	22.00	23.48	15.98	19.42	21.33	23.21	29.07	21.96	25.43	28.69	24.62	14.79	25.34	22.86	29.17	18.82	23.99	26.01	29.43	21.55	17.96	22.38	22.85
39	168.1	271.0	227.4	186.98	247.4	278.3	274.2	257.0	226.9	283.4	243.6	213.6	233.7	265.3	0	240.1	0	217.9	296.0	0	228.5	214.9	280.3	191.85
40	115.1	190.0	84.48	114.98	52.42	112.3	115.2	192.0	100.9	195.4	144.6	157.6	67.79	172.3	0	199.1	197.8	194.9	110.0	0	136.5	96.96	185.3	112.85
41	10.19	9.00	9.48	15.98	10.42	16.33	13.21	12.07	9.96	16.43	12.69	13.62	13.79	14.34	16.86	16.17	10.82	13.99	12.01	19.43	10.55	17.96	16.38	11.85
42	38.19	48.00	25.48	44.98	20.42	30.33	39.21	23.07	42.96	45.43	47.69	37.62	44.79	39.34	38.86	47.17	34.82	45.99	46.01	47.43	32.55	42.96	30.38	19.85
43	238.1	155.0	284.4	111.9	152.4	188.3	152.2	217.0	270.9	233.4	256.6	259.6	232.7	176.3	0	280.1	244.8	293.9	251.0	267.4	291.5	233.9	194.3	249.85
44	171.1	285.0	105.4	196.9	183.4	168.3	119.2	275.0	242.9	287.4	256.6	293.6	223.7	231.3	0	167.1	268.8	243.9	292.0	268.4	157.5	259.9	202.3	216.85
45	265.1	236.0	203.4	121.9	158.4	191.3	163.2	159.0	175.9	159.4	242.6	223.6	204.7	258.3	0	266.1	216.8	268.9	170.0	189.4	259.5	226.9	242.3	274.85
46	9.192	17.00	11.48	16.98	12.42	17.33	18.21	9.07	16.96	19.43	18.69	18.62	13.79	8.34	16.86	15.17	16.82	12.99	18.01	16.43	17.55	17.96	16.38	11.85
47	56.19	33.00	61.48	46.98	37.42	36.33	53.21	50.07	94.96	55.43	82.69	86.62	90.79	50.34	88.86	68.17	67.82	76.99	83.01	83.43	66.55	44.96	34.38	79.85
48	77.19	89.00	50.48	89.98	28.42	87.33	76.21	61.07	33.96	89.43	71.69	72.62	80.79	87.34	96.86	86.17	59.82	70.99	89.01	87.43	86.55	84.96	69.38	78.85
49	12.19	18.00	15.48	8.98	8.42	13.33	13.21	13.07	14.96	15.43	12.69	17.62	13.79	19.34	16.86	18.17	16.82	16.99	15.01	12.43	16.55	16.96	16.38	14.85
50	41.19	26.00	26.48	38.98	26.42	47.33	46.21	34.07	42.96	41.43	36.69	47.62	28.79	32.34	40.86	48.17	34.82	42.99	44.01	47.43	38.55	38.96	42.38	41.85
51	73.19	35.00	59.48	76.98	60.42	53.33	97.21	52.07	55.96	70.43	86.69	93.62	94.79	48.34	75.86	94.17	53.82	62.99	58.01	95.43	88.55	63.96	77.38	50.85
52	60.19	71.00	30.48	26.98	36.42	95.33	60.21	56.07	63.96	92.43	89.69	51.62	81.79	49.34	46.86	87.17	89.82	91.99	75.01	85.43	90.55	53.96	69.38	60.85
53	87.19	55.00	40.48	89.98	88.42	48.33	46.21	70.07	75.96	95.43	94.69	43.62	91.79	61.34	87.86	83.17	42.82	87.99	77.01	66.43	85.55	70.96	60.38	89.85
54	47.19	46.00	27.48	27.98	46.42	44.33	42.21	35.07	40.96	45.43	46.69	44.62	40.79	40.34	44.86	37.17	47.82	39.99	47.01	48.43	45.55	38.96	41.38	39.85
S.cost	40	40	40	440	110	40	50	40	40	100	100	40	40	50	40	50	40	40	59	100	100	50	50	100

The figure.1 shows the load demand of the system for 24 hours. It was clearly shown that the peak load demand of the system is 6000 MW. Here, the load demand has been varied between the 3400 MW to 6000 MW. According to the load demand variation, the AUC has been performed.

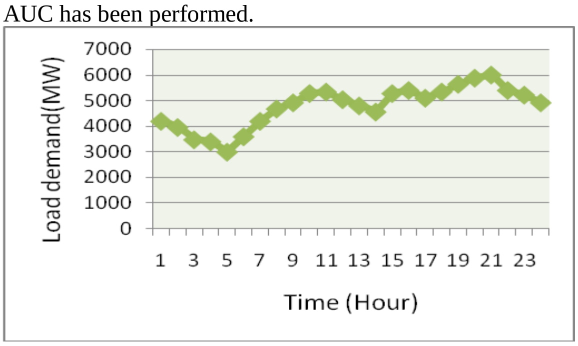

Fig. 1: Load demand curve

The listed load demand is solved by the proposed AUC technique. By using the wind power generation and PS unit's power, the fuel cost and startup cost of the thermal generators are reduced. The IEEE 118 bus systems with 54 generator units using different techniques are compared in the figure 2. It was clearly shown that the proposed method have reduced the operating cost compared to the other techniques.

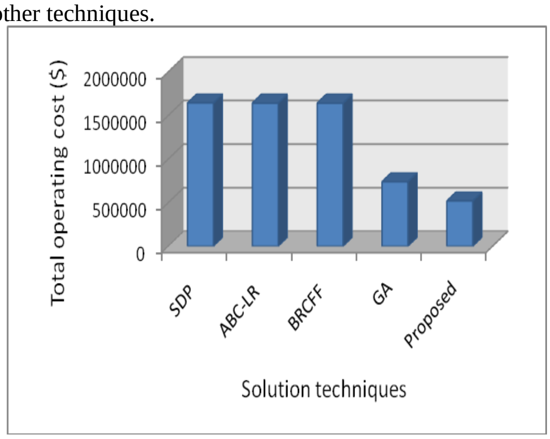

Fig. 2: Performance comparison of different techniques

5. Conclusion

This paper discussed about the proposed innovative approach for Advanced Unit Commitment (AUC) with wind power and Pumped Storage (PS) units. In the proposed method mainly schedule the AUC of the thermal generators units for a day-ahead market by considering the wind power uncertainty and PS units. The attained AUC schedule considers the wind uncertainty from the ANN technique and PS units, which significantly minimizes the total cost of the system. The advantage of the proposed method is effective, more reliable and feasible for complex problems. The proposed technique tested under IEEE 118 standard bench mark system with 54 generator units and the numerical results were compared with the Genetic Algorithm (GA). The comparison analysis shows that the proposed method effectively minimizes the total cost while comparing with the GA technique.

References

[1] Saber AY & Venayagamoorthy GK, “Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles”, *IEEE systems journal*, Vol.6, No.1, (2012), pp.103-109.

[2] Liu G & Tomsovic K, “Quantifying spinning reserve in systems with significant wind power penetration”, *IEEE Transactions on Power Systems*, Vol.27, No.4, (2012), pp.2385-2393.

[3] Xu Y, Hu Q & Li F, “Probabilistic model of payment cost minimization considering wind power and its uncertainty” *IEEE Transactions on Sustainable Energy*, Vol.4, No.3, (2013), pp.716-724

[4] Chen CL, “Optimal Wind-Thermal Generating Unit Commitment”, *IEEE Transactions on Energy Conversion*, Vol.23, No.1, (2008), pp.273-280.

[5] Billinton R, Karki B, Karki R & Ramakrishna G, “Unit commitment risk analysis of wind integrated power systems”, *IEEE Transactions on Power Systems*, Vol.24, No.2, (2009), pp.930-939.

[6] Delarue E & D’haeseleer W, “Adaptive mixed-integer programming unit commitment strategy for determining the value of forecasting”, *Applied Energy*, Vol.85, No.4, (2008), pp.171-181.

[7] Hargreaves JJ & Hobbs BF, “Commitment and dispatch with uncertain wind generation by dynamic programming”, *IEEE Transactions on sustainable energy*, Vol.3, No.4, (2012), pp.724-734.

[8] Venkatesh B, Yu P, Gooi HB & Choling D, “Fuzzy MILP unit commitment incorporating wind generators”, *IEEE transactions on power systems*, Vol.23, No.4, (2008), pp.1738-1746.

[9] Lowery C & O'Malley M, “Impact of wind forecast error statistics upon unit commitment”, *IEEE Transactions on Sustainable Energy*, Vol.3, No.4, (2012), pp.760-768.

[10] Khodayar ME, Wu L & Shahidehpour M, “Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC”, *IEEE Transactions on Smart Grid*, Vol.3, No.3, (2012), pp.1271-1279.

[11] Methaprayoon K, Yingvivatanapong C, Lee WJ & Liao JR, “An integration of ANN wind power estimation into unit commitment considering the forecasting uncertainty” *IEEE Transactions on Industry Applications*, Vol.43, No.6, (2007), pp.1441-1448.

[12] Zhang N, Kang C, Kirschen DS, Xia Q, Xi W, Huang J & Zhang, Q, “Planning pumped storage capacity for wind power integration”, *IEEE Transactions on Sustainable Energy*, Vol.4, No.2, (2013), pp.393-401.

[13] Khodayar ME, Shahidehpour M & Wu L, “Enhancing the dispatchability of variable wind generation by coordination with pumped-storage hydro units in stochastic power systems” *IEEE Transactions on Power Systems*, Vol.28, No.3, (2013), pp.2808-2818.

[14] Zhao C, Wang J, Watson JP & Guan Y, “Multi-stage robust unit commitment considering wind and demand response uncertainties”, *IEEE Transactions on Power Systems*, Vol.28, No.3, (2013), pp.2708-2717.

[15] Mohan MR, Kuppusam K & Abdullah Khan M, “Short-term hydrothermal scheduling of power systems with a pumped hydro plant using the local variation approach”, *Electric Power Systems Research*, Vol.27, (1993), pp.153-159.

[16] Nazaria ME, Ardehali MM & Jafari S, “Pumped-storage unit commitment with considerations for energy demand, economics, and environmental constraints”, *Energy*, Vol.35, (2010), pp.4092-4101.

[17] Micusik D, Stopjakova V & Benuskova L, “Application of Feed-forward Artificial Neural Networks to the Identification of Defective Analog Integrated Circuits”, *Neural Computing and Applications*, Vol.11, (2002), pp.71-79.

[18] Bai X & Wei H, “Semi-Definite Programming-Based Method For Security-Constrained Unit Commitment with Operational and Optimal Power Flow Constraints”, *IET Generation, Transmission and Distribution*, Vol.3, No.2, (2009), pp.182–197.

[19] Chandrasekaran K, Hemamalini S, Simon SP & Padhy NP, “Thermal unit commitment using binary/real coded artificial bee colony algorithm”, *Electrical Power System Research*, Vol.84, (2009), pp.109–119.

[20] Chandrasekaran K & Simon SP, “Optimal Deviation Based Firefly Algorithm Tuned Fuzzy Design for Multi-Objective UCP”, *IEEE Transactions on Power Systems*, Vol.28, No.1, (2013).