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Optimal Scheduled Unit Commitment Considering Wind Uncertainty Using Cuckoo Search Algorithm

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Abstract

In this paper, a new method to review the role of wind units as an energy-producer in the scheduling problem of unit commitment is presented. Today, renewable energy sources due to lack of environmental pollution, and consequently a very low marginal cost, have been receiving considerable attention in power system. But these sources are associated with uncertainty, solving unit commitment problem as a traditional power program system optimization that attempts to determine optimal entry and exit units and optimal production per unit minimizes the total cost of production. Then, in this study using an iterative algorithm randomly with allocation of density functions fits the wind speed, Uncertainty of production wind units has been modiled in the unit commitment program. Analysis of UC with wind power is performed in order to minimize total system cost. In this paper to achieve the optimum solution, a meta-heuristic Cuckoo search (CS) algorithm with high convergence speed is used to solve the unit commitment problem considering IEEE standard 10 unit test system. The simulations results show the effeciveness of the proposed method for reducing production costs and improving load profiles.

Keywords:
Renewatle energy
Wind power
Cuskoo search algorithm
Monte Carlo simoulation

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INTRODUCTION

Numerous problems resulting from the use of fossil fuels such as green-house gas (GHG) emissions and other air pollutants such as CO_2 emissions have compelled human beings to search for a suitable replacement. Renewable energy sources are a key solution to reduce dependency on fossil fuels. Because of the many benefits including significant reduction in operating costs, low depreciation, long life time and ability to provide power for a wide range of applications, it is more preferable to use them in energy sections. Among the renewable sources which can be categorized as solar energy wind and geothermal,wind power due to uninterrupted nature, fast progress and availability of technology has made a major impact on power systems. This source of energy can be utilized as a wind turbine or in large scale as a wind farm (Yousefi et al., 2013). Today, in most parts of the world including Portugal, Spain, Denmark, Germany and Ireland, the widespread use of wind energy has become a common occurrence (Beurskens et al., 2010). Various studies have been conducted on effect of wind energy on power system.In (Solymani et al., 2015), a method for modeling wind power plant in power systems reliability evaluation is proposed. In another work a review of the current methods and advances in wind power forecasting and prediction is accomplished. First, numerical wind prediction methods from global to local scales, ensemble forecasting, up scaling and downscaling processes are discussed (Foley et al., 2012). On the other hand, economic distribution of daily load requires efficient management. The use of wind turbines prevents unit commitment (UC) with high costs and therefore leads to system efficiency, reliability and cost reduction. The unit commitment has an important role in economic operation of power systems. Determining the proper time for log in or exiting the plants of circuit between the possible modes will lead to huge savings. Traditionally, unit commitment deals with generation units schedule in a power system. The purpose of such schedule is to minimize operating costs while constraints including, load balance, spinning reserve of system and minimum up/down time limits, in a set of time periods are met. Solving UC problem has been done with classic and intelligent algorithms. Classic algorithms such as priority list Algorithm (Kerr et al., 1966), Lagrange planning (li et al., 2005), dynamic planning (Wood et al., 1996) and planning based on linear mixed integer pointed (Camon et al., 2006), Smart algorithms including fuzzy logic, Neural networks, genetic algorithms (Swarup et al., 2002), Leap Frog algorithm (Ebrahimi et al., 2011) and the particle swarm algorithm (Jeong et al., 2010) had been used in studies.In (Pozo et al., 2013) a new approach for the joint energy and reserves scheduling and unit commitment with n-k reliability constraints for the day-ahead market is presented. In (Chandrasekaram et al., 2012) a binary/real coded artificial bee colony (BRABC) algorithm to solve the thermal unit commitment problem (UCP) is implemented. A novel binary coded ABC with repair strategies is used to obtain a feasible commitment schedule for each generating unit, satisfying spinning reserve and minimum up/down time constraints. In (Moghimi et al., 2012) a new approach via a new evolutionary algorithm known as imperialistic competition algorithm (ICA) to solve the unit commitment problem is employed. In (Mohammadi et al., 201) a unit commitment formulation for micro-grid is presented that includes a significant number of grid parallel proton Exchange Membrane-Fuel Cell Power Plants (PEM-FCPPs) with ramping rate and minimum up/down time constraints. In order to minimize the operation and fuel cost, renewable sources are implemented in the combined Unit Commitment and Emission (CUCE) model considering wind energy and carbon tax which are addressed in (Zhang et al., 2015). The combined wind and thermal generation scheduling problem for operating an isolated hybrid power system reliably and efficiently is discussed in (Chen, 2088). In (Jose et al., 2011) a new unit commitment (UC) formulation for a power system with significant levels of wind generation are proposed. All of these researches show that uncertainty of wind power output has a substantial impact on unit commitment.

Recently, to ensure high utilization of wind power, a chance constrained optimization model (Wang et al., 2012) and a robust optimization model (Jiang et al., 2012) have been developed to solve the problem. In (Zhao et al., 2013), a robust optimization approach for unit commitment is developed to maximize social welfare under worst-case wind power output. In another paper new requirements that integrate large amounts of variable and partly uncertain wind power production that could be brought to UC and power system operations are reviewed (Kiviluoma et al., 2011). A complex cost model for static TNEP problem with the integration of wind power uncertainty and PEVs along with an incentive based DR program is demonstrated in (Rathore et al., 2016).

This paper presents impact of wind power generator as an energy production unit on unit commitment. For UC problem a new method based on cuckoo optimization algorithm is suggested. In (Enayati et al., 2015), a novel procedure to find the firing angles of the multilevel inverters of supply voltage and, consequently, to decline the total harmonic distortion (THD), by cuckoo optimization algorithm has been presented .As mentioned above, the power output of wind units depends on the wind speed and is variable based on weather conditions. As a result, the simulation for uncertainty has been done by using randomized Monte Carlo algorithm.The remainder of this paper is organized as follows. In Section 2, mathematical problem formulation of UC-WP problem is defined. Monte Carlo method is described in section 3. The proposed COA algorithm is discussed in Section 4. Section 5 shows the simulation and results and finally conclusions are stated in Section 6.

Mathematical problem formulation of unit commitment and wind power (UC-WP)

Objective function

The objective function consists of minimizing the sum of fuel cost, the startup and shut down cost of all individual units, while the term wind energy cost has also been taken into account in this manuscript for the given period of time subjected to various constraints.

$$F=\sum_{ied=1}^{N}\sum_{t=1}^{th}\left[FC_iU_{i,t}+SUC_i\{U_{i,t}(1-U_{i,t-1})\}+SDC_i\{U_{i,t}(1-U_{i,t-1})\}\right]+\sum_{j=1}^{N_w}C_{wind,j} \tag{1}$$

Where

$$FC_i=\alpha_iP_{i,t}^2+\beta_iP_{i,t}+\gamma_i \tag{2}$$

FC_i is the fuel cost of the *ith* unit; a_i, β_i, γ_i, are the fuel cost coefficients of the *ith* unit; N is the number of generating units; *th* is the total number of hours; $P_{i,t}$ is the output power of ith unit at hour th, $U_{i,t}$ is the on/off status of unit ith at hour th; SUC_i and SDC_i are respectively the startup and shutdown cost of the *ith* generating unit.

The shut-down costs have not been taken into consideration in accordance with the other approaches in the literature (Talezadeh et al., 2014). The start-up cost is related to either hot or cold conditions, where it can be written as Eq (3).

$$SUC_i=\begin{cases}HSC_i & if \quad T_{off_i}^t\le T_{down_i}+T_{cold_i}\\ CSC_i & if \quad T_{off_i}^t> T_{down_i}+T_{cold_i}\end{cases} \tag{3}$$

HSC_i, CSC_i are the hot startup cost and cold start -up cost of the *ith* unit; $T_{off_i}^t$ is the continuous off time duration of the ith unit; T_{downi} is the minimum down time of the *ith* unit; T_{coldi} is the cold start hours of the ith unit.

$C_{wind,j}$ Shows operation cost of wind units (Hetzar et al., 2008) and is defined in the form of equation (4):

$$C_{wind,j}=d_j\times P_{wind,j} \tag{4}$$

Where *dj* is the operation cost per MW power generation and $P_{wind,j}$ the *jth* output power of wind units at hour *th*.

Constraints of UC-WP

A. System power balance: The total power generation from thermal units, wind power at hour *th* must be equal to the load demand for that hour.

$$\sum_{i=1}^{ng}(P_i^tU_i^t)+\sum_{j=1}^{N_w}P_{wind,j}=P_{D_t} \tag{5}$$

B. System spinning reserve requirements: Appropriate spinning reserve is required for stable and reliable operation.

$$\sum_{i=1}^{ng}P_i^{max}U_{i,t}+\sum_{j=1}^{N_w}P_{wind,j}\ge P_{D_t}+SR_t \tag{6}$$

Where SR_t is the maximum reserve at the *th* hour and P_{Dt} power demand at the th hour.

C. Minimum up and down time: When the unit i is started up or started down, it should not be shut down/shut up before a minimum up-time/down time *(MUT_i / MDT_i)* duration is met.

$$T_{on_i}^{t} \geq MUT_i \\ T_{off_i}^{t} \geq MDT_i \tag{7}$$

D. Unit generation limits: For stable operation, Power generation of each generating unit must be within its maximum and minimum power range.

$$P_i^{\min} \leq P_{i,t} \leq P_i^{\max} \tag{8}$$

E. Constraints related to minimum and maximum power produced by wind units (Talezadeh et al., 2014):

$$P_{wind,j}^{min} \leq P_{wind} \leq P_{wind,j}^{max} \tag{9}$$

Model of Wind energy

Wind power is a form of energy produced by wind turbines. The existence of output power is directly proportional to the availability of wind. Thus, wind speed forecasting is necessary in the process of wind power prediction. Several studies have been done to find methods for forecasting purposes (Emst et al., 2007; Sideratos et al., 2007; Taylor et al., 2009). The wind power generation output can be considered as a function of wind velocity. The formulation in (10) is used in this paper which demonstrates the relationship between the output power and wind speed (v).

$$P_W = \begin{cases} 0 & v \leq v_c \ or \ v \geq v_f \\ P_r * \frac{v - v_c}{v_r - v_c} & v_c < v < v_r \\ P_r & v_r < v < v_f \end{cases} \tag{10}$$

Where P_r is the rated power; v_c is the cut-in wind speed; v_r is the rated wind speed; and v_f is the cut-off wind speed.

Mont carlo simulation stochastic model

The main core of stochastic simulation by using Monte Carlo method is based on continuous use of random numbers. Tendency to use the Monte Carlo method results in more time to calculate the exact answer with the help of definitive algorithms that are impossible or time- consuming (Liu et al., 2011). Generally Monte Carlo method is implemented in two steps:

1. A deterministic optimization by using expected amounts of the uncertain variables will be achieved to obtain base state system performance.
2. Distribution uncertainly parameters will be modeled repeatedly and the impact of uncertainty will be seen.

Random vector ξ which has been q-dimensional represents the uncertainty in wind power generated and as a function of the normal distribution is given by the following equation (Zhang et al., 2010):

$$\rho(\xi) = \frac{1}{\sqrt{(2\pi)^q |\Sigma|}} \exp(-\frac{1}{2}(\xi - \mu)^T \Sigma^{-1} (\xi - \mu)) \tag{11}$$

Where μ and Σ are the mean vector and covariance matrix of the random variables defined by Equation (12-13):

$$\mu = [\mu_1, \mu_2, \ldots, \mu_q]^T \tag{12}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2 r_{12} & \cdots & \sigma_1\sigma_q r_{1q} \\ \sigma_2\sigma_1 r_{21} & \sigma_2^2 & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_q\sigma_1 r_{q1} & \sigma_q\sigma_2 r_{q2} & \cdots & \sigma_q^2 \end{bmatrix} \tag{13}$$

σ_i is the standard deviation of each individual random variable and $r_{ij} \in (-1,1)$ the correlation coefficient between ξ_i and ξ_j.

$$\xi = L \times \hat{\xi} + \mu \tag{14}$$

Where $LL^T = \Sigma$ and can be gained by Cholesky factorization.

Cuckoo optimization algorithm

Cuckoo Search Algorithm is an optimization algorithm based on behavior of the Cuckoo bird.

The algorithm was introduced by Rajabioun at 2011. Cuckoo bird parasitic behavior on reproductive strategy is employed as a basic idea of the use of this algorithm. These birds lay their eggs in the nests of other birds that have been layed recently. During the time that the host bird takes care of the eggs it believes that the eggs are its own. If the host bird recognizes the eggs as not being its own, the alien eggs may be thrown out or the nest abandoned. Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. So, to start the optimization algorithm, this algorithm begins with an initial population of cuckoos in the form of arrays. Each one of the arrays is called a habitat (Rajabioun, 2011). This array is defined as follows:

$$habitate=[y_1, y_2, \ldots, y_N] \quad (15)$$

The profit of a habitat is obtained by evaluation of profit function F as:

$$profit = F\,(habitat) \quad (16)$$

Cuckoo birds abandon their eggs at maximum distance from their habitat, which is called egg laying radius (ELR). In an optimization problem for variables with upper limit *(var_{hi})* and lower limit *(var_{low})*, ELR is calculated by the following equation:

$$ELR=\alpha\times var_{hi}-var_{low})\times(Number\ of\ current\ cuckoo's\ eggs)/(Total\ number\ of\ eggs) \quad (17)$$

α = an integer number which handles maximum value of ERL.

When the cuckoo broods grow and mature, they will live for a while in a community. But when the egg laying season comes they immigrate in order to find a suitable habitat that will provide a higher chance of survival. After the cuckoo groups are formed in various regions, the population of the best value and efficiency will be chosen as goal point for immigration. Cuckoo during migration, does not move all the way to the goal point. They go through only λ percent of the entire way and in this way possess deviation with φ value.where "λ" is a random number between [0, 1] and also φ generally has between -π/6 and π/6. These two parameters will help cuckoos search more areas to find a more suitable location. When all of the cuckoos moved to the target point, some eggs will be assigned to each of them. The transition egg process will be carried out again. Cuckoo migration algorithm formula is as follows:

$$X_{NextHabitate}=X_{CurrentHabitate}+F(X_{Goalpoint}-X_{CurrentHabitate}) \quad (18)$$

A. Cuckoo Search Algorithm (CSA) Implementation

The algorithm for the improved unit commit-

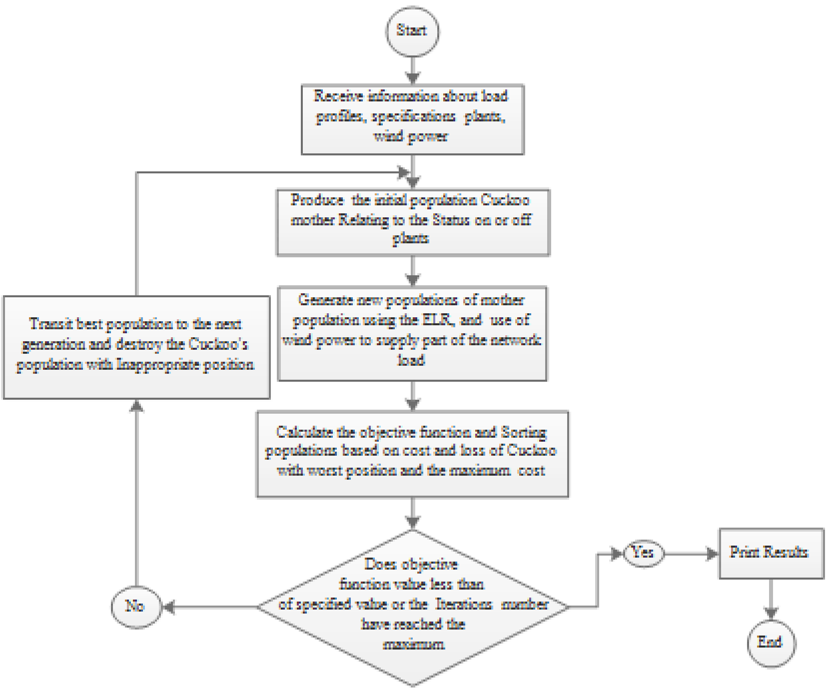

Fig.1. Flowchart of proposed method

ment problem is shown in Fig. 1. The aim is to find the best state of ON or OFF plants in order to achieve minimum cost.

Simulation results and discussion

A standard IEEE 10-unit system is considered for simulation study (Govardhan et al., 2015). Wind power plant with capacity of 30 MW is intended as a unit addition to the existing units. Profile related to power system units is compiled in Table 1. This information includes the minimum and maximum generation power, fuel cost function coefficients, minimum up and down time, hot start-up and cold start-up cost, and also information on time up and down units before start schedule. Spinning reserve is considered to be ten percent of the hourly load demand 24 hour period. Fig. 2 shows daily load curve system. In this study, three scenarios have been investigated (Table 2).

The first scenario is composed of usual unit commitment problems using the algorithm Cuckoo, while in the second step, the integration of wind power generators to unit commitment problem. The influence of uncertain wind power has been studied.

Scenario 1: The generation dispatch of UC without wind power is shown in Table 3. As can be observed, according to the network requirement, units 1 and 2 as a mother plant are present in the network for 24 hours. Affordable units U1, U3 and U4 always generate maximum power. Additionally, units U7, U9 and U10 which are more expensive, produce power with their minimum capacity to spinning reserve equipment. Then total cost in this scenario is \$56640.644

Scenario 2: Wind power generation and related costs regardless of uncertain wind power is considered in this case. This article assumes a wind plant of 30 MW according to (Jagar et al., 1996). The existence of output power is directly proportional to the availability of wind. Thus, wind speed forecasting is necessary in the process of wind power prediction. In this paper a multilayer perceptron (MLP) which is a feed forward artificial neural network is used to forecast the wind

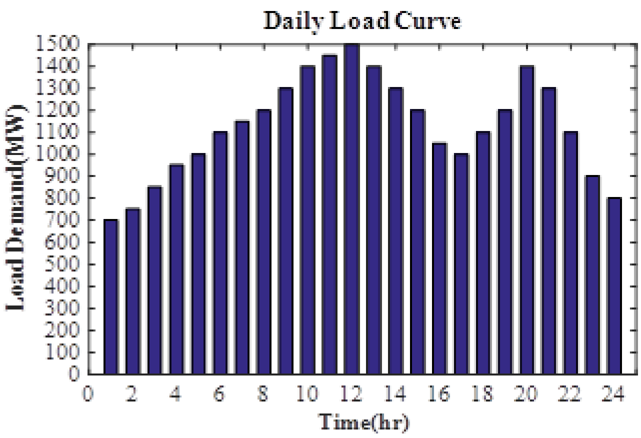

Fig.2. Load demand curve for 24 hour

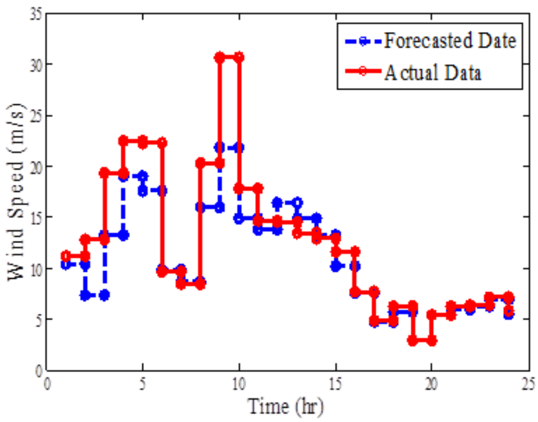

Fig. 3. Amount of forecasted and actual wind speed

Table 1: Characteristics of 10 generation units

Parameters	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit1
P_{max} *(MW)*	455	455	455	130	162	80	85	55	55	55
P_{min} *(MW)*	150	150	150	20	25	20	25	10	10	10
a ($/h)	0.00048	0.00031	0.00031	0.00211	0.00398	0.007	0.00079	0.004	0.00222	0.002
b ($/h)	16.19	17.26	17.26	16.5	19.7	22.26	27.74	25.92	27.27	27.29
c ($/h)	1000	970	970	680	450	370	480	660	665	670
MUT(h)	8	8	8	5	6	3	3	1	1	1
MDT(h)	8	8	8	5	6	3	3	1	1	1
$H_{start\ up}$ *($)*	4500	5000	5000	560	900	170	260	30	30	30
$C_{start\ up}$*($)*	9000	10000	10000	1120	1800	340	520	60	60	60
T_{cold} *(h)*	5	5	5	4	4	2	2	0	0	0
T_o *(h)*	8	8	8	-5	-6	-3	-3	-1	-1	-1

Table 2: Different scenario for simulation

Scenarios	Scenario Description
1	UC without wind power
2	UC with wind power
3	UC with uncertain wind power

speed according to wind speed and weather conditions data in last ten years (Jagar et al., 1996). Generally in neural networks, there are three types of neuronal layers: the input layer, hidden layer and output layer. Input layer include average peak wind speed, average deviation of wind speed and average turbulence intensity, the output layer consists of wind speed in the desired day and average turbulence intensity. The wind speed parameters are: $V_C=3\ {}^{m}\!/\!{}_{s}$, $V_r=12\ {}^{m}\!/\!{}_{s}$, $V_f=30\ {}^{m}\!/\!{}_{s}$ and the rated output power of wind system is 30MW.

The amount of wind speed in study day is shown in Fig.3. After finding the wind speed the output power of the wind turbines which is shown in Fig.4, is obtained from equation (10). Hence, considered values for simulation analysis are d = 1.10 for per hour scheduling (Hetzar et al., 2008).

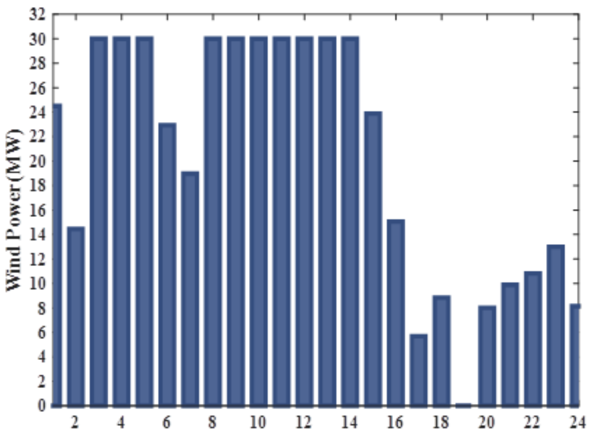

Fig.4. wind output power in 24 hour

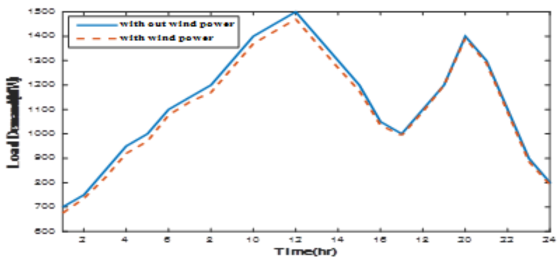

Fig.5. Load demand variation without and with WP

Table 3: Optimal scheduling and dispatch of generation for scenario1

Time	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10	SUC	Cost($)
1	455	245	0	0	0	0	0	0	0	0	0	13683.12
2	455	295	0	0	0	0	0	0	0	0	0	14554.5
3	455	370	0	0	25	0	0	0	0	0	900	17709.45
4	455	455	0	0	40	0	0	0	0	0	0	18597.68
5	455	390	0	130	25	0	0	0	0	0	560	20580.02
6	455	360	130	130	25	0	0	0	0	0	1100	23487.04
7	455	410	130	130	25	0	0	0	0	0	0	23261.99
8	455	455	130	130	30	0	0	0	0	0	0	24150.32
9	455	455	130	130	85	20	25	0	0	0	860	28111.07
10	455	455	130	130	162	33	25	10	0	0	60	30117.54
11	455	455	130	130	162	73	25	10	10	0	60	31976.07
12	455	455	130	130	162	80	25	43	10	10	60	33950.15
13	455	455	130	130	162	33	25	10	0	0	0	30057.54
14	455	455	130	130	85	20	25	0	0	0	0	27251.07
15	455	455	130	130	30	0	0	0	0	0	0	24150.32
16	455	310	130	130	25	0	0	0	0	0	0	21513.64
17	455	260	130	130	25	0	0	0	0	0	0	20641.83
18	455	360	130	130	25	0	0	0	0	0	0	22387
19	455	455	130	130	30	0	0	0	0	0	0	24147.34
20	455	455	130	130	162	33	25	10	0	0	490	30547.54
21	455	455	130	130	85	20	25	0	0	0	0	27251.07
22	455	455	130	0	35	0	25	0	0	0	0	22559.52
23	455	425	0	0	20	0	0	0	0	0	0	17645.36
24	455	345	0	0	0	0	0	0	0	0	0	15427.43
Total Cost (fuel cost + start-up cost)= 563758.61 $												

In this scenario, the total cost is $551336.44 and the associated generation scheduled is given in Table 4. As can be seen from Table 4, cost of power produced by wind plants is much lower than power generation by thermal units. So total cost dropped the amount $12422.17 compared to scenario 1. Hourly load demand variation for this scenario is shown in Fig. 5.

Scenario 3: In this section, uncertainty in the production capacity wind plant is considered in unit commitment problem using Monte Carlo method. For this purpose the system uncertainty and extracted probability density function must be identified according to their non-deterministic behavior. The next step is to produce a sufficient number of random points for each of the uncertain variables. Then in an iterative process using Monte Carlo method, simulations have been investigated in the system. In this study, Monte Carlo simulation with 1000 iterations is done for modeling uncertainty of wind power. In each iteration is produced a random vector according to multivariate normal distribution function. So using the mean value of wind power and also the correlation coefficient between different hours generates 1000 random signals with normal dis-

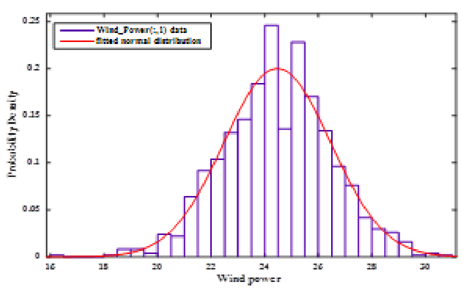

Fig. 6. Normal estimated distribution of wind power

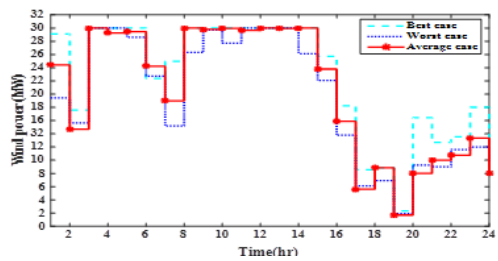

Fig7. The power output of wind plants in different case under consideration the uncertainty

Table 4: Optimal scheduling and dispatch of generation for scenario2

Time	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10	SUC	PW(MW)	Cost($)
1	455	220.5	0	0	0	0	0	0	0	0	560	24.50	13843.65
2	455	280	0	0	0	0	0	0	0	0	0	14.46	14318.2
3	455	340	0	0	25	0	0	0	0	0	0	30	16317.98
4	455	440	0	0	25	0	0	0	0	0	0	30	18068.18
5	455	360	130	0	25	0	0	0	0	0	0	30	19559.38
6	455	337	130	130	25	0	0	0	0	0	0	22.93	22911.50
7	455	391.03	130	130	25	0	0	0	0	0	0	18.97	22950.74
8	455	430	130	130	25	0	0	0	0	0	290	30	23935.38
9	455	455	130	130	55	20	25	0	0	0	170	30	26846.32
10	455	455	130	130	145	20	25	10	0	0	30	30	29470.6
11	455	455	130	130	162	43	25	10	10	0	30	30	31286.32
12	455	455	130	130	162	80	25	13	10	10	0	30	33113.14
13	455	455	130	130	162	38	0	0	0	0	0	30	28110.7
14	455	455	130	130	70	20	0	10	0	0	0	30	26724.9
15	455	436.1	130	130	25	0	0	0	0	0	0	23.88	23745.94
16	455	294.9	130	130	25	0	0	0	0	0	0	15.06	21267.44
17	455	254.3	130	130	25	0	0	0	0	0	0	5.69	20548.92
18	455	351.1	130	130	25	0	0	0	0	0	0	8.85	22242.11
19	455	455	130	130	25	0	0	0	0	0	200	0	24350.41
20	455	455	130	130	162	25	25	10	0	0	0	8	29884.97
21	455	455	130	130	75	20	25	0	0	0	260	9.89	27318.57
22	455	455	130	0	29.19	20	0	0	0	0	0	10.81	22103.39
23	455	407	0	0	25	0	0	0	0	0	0	13	17471.28
24	455	336.8	0	0	0	0	0	0	0	0	0	8.14	15294.15
Total Cost (fuel cost + start-up cost + wind power generation cost) = 550784.176$													

Table 5: Results related to costs in scenario 3

Scenario	Best Case ($)	Worst case ($)	Average case($)
Scenario 3	550508.98	553688.43	552844.44

tribution. After the probability density function related to wind power is produced, initial population is determined and then each of the signals is used in programming optimizing cuckoo algorithm and the amount of costs relating to these populations and status of on or off units will be stored.

Then, based on the number of iterations the wind power normal distribution curve is generated, and the average case, worst and best cases of performance system are obtained.

The normal distribution estimated for 24 hours of wind power data is shown in Fig. 6. The wind power due to the existence of uncertainty compared to expected value is different. Then, amount of wind power that leads to the best, worst and average value Cost is shown in Fig. 7, and cost results are tabulated in Table5. As can be seen, considering the uncertainty in wind power production, Cost in the best case has a minimum amount of $550538.98, in the worst case the cost reaches a value of $553688.43, and in mean case, the amount of expected Cost is $552844.44.

In this scenario the total cost in comparison with scenario 2 at best case 0.05% decrease, at mean case 0.345% increase and in worst case 0.527 % increased.

CONCLUSION

In this paper economic analysis with wind power generator on unit commitment has been considered. Wind power is a form of energy produced by wind turbines. Since the wind speed forecasting is necessary to estimate amount of power generation, in this work the order to estimate wind speed has used a multi-layer neural network algorithms release (MLP). The proposed model has been successfully tested on an IEEE standard 10 unit test system. Therefor efficient Cuckoo search algorithm is executed to attain the optimum solution. The results show that with the use of wind plants, production requirements more than the whole schedule time horizon is significantly reduce, leading to decrease in the total cost of the system. Also, load demand curve improves by a considerable amount. Finally, by investigating uncertainty of wind energy with Monte Carlo method it is found that higher than penetration wind generation in the network will be more effective in reducing total cost of the system.

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