Election Campaign Optimization in Unit Commitment Problem with Wind Power Effect

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Abstract— The Election Campaign Optimization (ECO) is proposed to solve the Unit Commitment (UC) problem between thermal generating units with wind impact an electricity market to minimize total cost in this paper. This issue is used in this paper to achieve a real system considered with various generator and wind constraints in power systems. The effectiveness of the proposed technique is compared with PSO, GA and λ-iteration to understand the wind generator capacity in production cost analysis and to provide valuable information for both operational and planning problems. The achieved results represent the superiority of the ECO technique.

Keywords; *Unit Commitment, ECO, Wind Power.*

I. Introduction

Wind power is becoming worldwide a significant component of the power generation portfolio. In Europe, different countries already present adoption levels in the range of 5-20% of the total annual demand. In the U.S. an adoption level of 20% is expected by the year 2030 [1]. Such as wide scale adoption resents many challenges to the operation of the electrical power grid because wind power is highly intermittent and difficult to predict. Specially, unit commitment (UC) and energy dispatch (ED) operations are of great importance because of their strong economic impact (on the order of billions of dollars per year) and increasing emissions concerns.

Because of the stochastic nature of the wind speed, we need to consider the probable considerations in its modeling equations. Without contemplation the probable issues scheduled, the system will be determined with definitive security, and because of additional reserve allocation this method will impose additional cost to the system [1-2].

Recently, several UC studies analyzing the impact of increasing adoption levels of wind power have been performed. Where, dynamic programming [7], branch-and-bound [8], Lagrangian Relaxation (LR) approach [9], Genetic Algorithm (GA) [10], and Evolutionary Programming (EP) [11], could be used to solve the extended unit commitment problem. In [11], a security-constrained stochastic UC formulation that accounts for wind power volatility is presented together with an efficient Benders decomposition solution technique. But, the issue of constructing probability distributions for the wind power is not addressed. In [9], a detailed closed-loop stochastic UC formulation is reported. The authors consider the impact of the frequency of recommitment on the production, startup, and shutdown costs. They discover that increasing the recommitment frequency can reduce costs and increase the reliability of the system. However, the authors do not present details on the wind power forecast model and uncertainty information used to support their conclusions. In [8-9], Artificial Neural Network (ANN) models are used to compute forecasts and confidence intervals for the total aggregated power for a set of distributed wind generators. Such approaches can thus result in inaccurate medium and long-term forecasts and over- or under-estimated uncertainty levels [7-8], which in turn affect the expected cost and robustness of the UC solution.

Election Campaign Optimization (ECO) is a new heuristic optimization algorithm which acts by simulating the behavior that the election candidates pursue the highest support from voters in election campaigns. In ECO the whole space of searching is assumed to be assembly of voters, and the current solutions are supposed to be the candidates of election. The candidates can influence the voters round them, the effect from candidates to voters will decrease gradually with the increase of distances between the candidates and the voters. The better prestige a candidate comports, the larger investigated range he has. In order to obtain an exact and global investigated, local investigated voters are generated in the probability determined by a normal distribution function that the mean is the location coordinates of candidates, and universal investigated voters is generated in the probability determined by a uniform distribution function [12]. This feature is caused that it has been had a flexible and well-balanced mechanism to enhance the global and local exploration abilities and found to be robust in optimization problems featuring non-linearity, non-differentiability and high dimensionality.

The proposed technique is applied over several test systems as case study which achieved good robustness and performance than the other compared techniques.

II. Problem Formulation

The formulation for the stochastic unit commitment is described in detail in this section. Wind energy conversion is the fastest-growing source of new electric generation in the world and it is expected to remain so for some time. Its long lifespan, emission-free operation and low cost have made it more attractive compared to the other sources [13]. One of the most important functions of modern energy management system is solving the wind–thermal scheduling problem, which determines the optimal real power settings of generating units for a specific period of operation and in return satisfying the system load demand with minimizing the total fuel cost subjected to the operating constraints of a power system [14]. In this paper considered wind power energy by the public utility. The objective of optimal wind-thermal generating unit commitment problem is to simultaneously minimize the generation cost rate and meet the load demand of a power system over some appropriate period while achieving various constraints depending on assumptions and practical implications [15]. The constrained UC optimization problem can be expressed as follows:

$$F_T = \sum_{t=1}^{T} \sum_{i=1}^{NT} F_i(P_i(t)) \tag{1}$$

The problem constraints are:

(1) Power balance: This constraint is based on the principle of equilibrium between total system generation and total system loads (PD) and losses (PL),

$$\sum_{i=1}^{NT} U_i(t) \times P_i(t) + P_{wt}(t) = P_L(t) \tag{2}$$

b) System up/down spinning reserve requirements:

$$\sum_{i=1}^{NT} U_i(t) \times US_i(t) \geq USR_B + ASR_1(P_{WT}(t)) \quad (3)$$

$$\sum_{i=1}^{NT} U_i(t) \times DS_i(t) \geq ASR_2(P_{WT}(t)) \quad (4)$$

c) Minimum/maximum thermal plant output constraints:

$$\mathrm{P_L(t) - P_{WT}(t) = ASR_2\ (P_{WT}(t))} + \sum_{i=1}^{NT} U_i(t) \times P_i^{\min}(t) \quad (5)$$

$$\sum_{i=1}^{NT} U_i(t) \times P_i^{\max}(t) + P_L(t) + USR_B + ASR_1(P_{WT}(t)) \quad (6)$$

2) Thermal Generator Constraints:

a) Unit's maximum up/down reserve contribution constraints:

$$US_i^{\max} = d\% \times P_{i,r}^{\max} \quad (7)$$

$$DS_i = d\% \times P_{i,r}^{\max} \quad (8)$$

b) Unit's up/down spinning reserve contribution constraints:

$$US_i(t) = \min\left\{US_i^{\max}, P_{i,r}^{\max} - P_{i,r}(t)\right\} \quad (9)$$

$$DS_i(t) = \min\left\{DS_i^{\max}, P_i(t) - P_{i,r}^{\min}\right\} \quad (10)$$

c) Unit's ramping up/down capacity constraints:

$$UR_i(t) = \min\left\{UR_i^{\max}, P_{i,r}^{\max} - P_i(t)\right\} \quad (11)$$

$$DR_i(t) = \min\left\{DR_i^{\max}, P_i^{\max} - P_{i,r}^{\min}\right\} \quad (12)$$

d) Unit generation limits:

$$P_i^{\min}(t) \times U_i(t) \leq P_i(t) \leq P_i^{\max}(t) \times U_i(t) \quad (13)$$

$$P_i^{\max}(t) = \begin{cases} \min\left\{P_{i,r}^{\max}, P_i(t-1) + UR_i^{\max}\right\} & if\ U_i(t)=U_i(t-1)=1 \\ \min\left\{P_{i,r}^{\max}, P_i(t-1) + SR_i\right\} & if\ U_i(t)=1, U_i(t-1)=0 \end{cases} \quad (14)$$

$$P_i^{\min}(t) = \begin{cases} \min\left\{UR_i^{\max}, P_i(t-1) - DR_i^{\max}\right\} \\ P_{i,r}^{\min}\ if \quad U_i(t)=1, U_i(t-1)=0 \end{cases}$$

$$if \quad U_i(t) = U_i(t-1) = 1$$

e) Minimum up/down time constraints:

$$[t_{ON,i}(t-1) - T_{ON,i}] \times [U_i(t-1) U_i(t)] \geq 0 \quad (15)$$

$$[t_{OFF,i}(t-1)-T_{OFF,i}]\times[U_i(t-1)U_i(t)]\geq 0 \quad (16)$$

3) Wind Generator Constraints:

a) Wind generation fluctuation constraints:

$$P_{WT}(t)-P_{WT}(t-1)\leq TDR(t), if P_{WT}(t-1)\leq P_{WT}(t) \quad (17)$$

$$P_{WT}(t-1)-P_{WT}(t)\leq TDR(t), if P_{WT}(t-1)\leq P_{WT}(t) \quad (18)$$

b) Wind power curve constraints:

$$P^*_{wi}(t)=\begin{cases} 0 & V(t)\leq V_{Ij} \; or \; V(t)>V_{Oj} \\ \varphi_j(v(t)) & V_{Ij}\leq V(t)\leq V_{Rj} \\ P^{max}_{wj} & V_{Rj}\leq V(t)\leq V_{Oj} \end{cases} \quad (18)$$

c) Total available wind generation:

$$P^*_{wi}(t)=\sum_{j=1}^{NW} P^*_{wi}(t) \quad (19)$$

d) Total actual wind generation limit:

$$0\leq P_{WT}(t)\leq P_{WT}{}^* \quad (20)$$

III. Election Campaign Optimization Technique

An election is a formal decision-making process by which a population chooses an individual to hold public office. When elections are named, politicians and their supporters attempt to influence policy by competing directly for the votes of constituents in what are called campaigns. Sponsors for a campaign can be either formally organized or loosely affiliated, and mostly utilize campaign advertising. It can be considered that there is an optimization process in the election process that can be proposed to establish as a new optimization algorithm. ECO is a new heuristic optimization algorithm which acts by simulating the behavior that the election candidates pursue the highest support in campaign all along [16]. In ECO, the whole searching space is supposed to be assembly of voters, and the current solutions are supposed to be the election candidates. The candidates can impress the voters round them; the impressions from candidates to voters will decrease gradually with the increase of distances between the candidates and the voters. The better prestige a candidate comports, the larger considered range he has [17]. The patronage from the different voters are discrepant clearly, voters have to allot their support proportionally according to the effects imposed by the candidates. Sampling check to voters is done to investigate the support of candidates. In order to choose an exact and global investigated, local considered voters are generated in the probability determined by a normal-distribution function that the mean is the location coordinates of candidates, and global considered voters is generated in the probability determined by a uniform distribution function. The ratio of the support to a candidate from a voter to the sum of the support of the candidate from all voters is the contribution of a voter to the candidate. The aggregate of position coordinates of every voters powered by its contribution is a new position coordinates, which is named support focus, it is the next position of the candidate. Such computational circle is done continually until a candidate finds the position of the highest support, which is the global solution of the proposed optimization problems [18]. In ECO algorithm, solution space is imagined as an assembly of all voters, current feasible solutions are imagined as candidates. The function value of a candidate is defined as the prestige of the candidate that of a voter in is defined as the prestige of the voter. Assume that a few candidates are generated between the higher and lower bounds which are denoted as *Ci* and their location coordinate are *xCi*. The search mechanism of ECO algorithm is described within a computing cycle as follows [19]:

1) Compute the prestige of candidates: *The function value of a current solution, namely a candidate, is the prestige of the current candidate. Thus, the prestige of candidates can be obtained as follows:*

$$P_{Ci} = f(xc_i) \tag{21}$$

Where, *PCi* represents the prestige of candidate *Ci* and $f(xc_i)$ is the objective function.

2) Compute the effect ranges of candidates: *The higher prestige a candidate is, the larger cover range the candidate has. Thus, it can be given by:*

$$R_{Ci} = \frac{P_{Ci} - P_{\min}}{P_{\max} - P_{\min}}(R_{\max} - R_{\min}) + R_{\max} \tag{22}$$

Where, *RCi* represents the cover ranges of candidate *Ci*; *R*max and *R*min are the maximum and minimum cover ranges of candidates, they are the parameters of ECO algorithm, which need to set before computing; *P*max and *P*min are the maximum and minimum prestige of current candidates.

3) *Compute the mean square deviation of local sample survey:*

The higher prestige a candidate is, the smaller the mean square deviation the candidate has, so that the ECO is able to converge to local best solution rapidly and steadily. The local sample-survey mean square deviation of candidate *Ci* (σCi) is computed as follows:

$$\sigma_{Ci} = \sigma_{\max} - \frac{P_{Ci} - P_{\min}}{P_{\max} - P_{\min}}(\sigma_{\max} - \sigma_{\min}) \tag{23}$$

Where, σ_{max} and σ_{min} are the maximum and minimum of σ_{Ci} and they are the parameters of ECO algorithm.

4) *Generate the global and local sample-survey voters*: The uniform distribution is employed to generate global:

$$V_j^{\,g} = x_{\min} + rand \times (x_{\max} - x_{\min}) \tag{24}$$

Where, x_{max} and x_{min} are lower and upper limit of solutions field. The local voters (*Vi,j*) are generated around each candidate using the normal distribution as [9]:

$$x_{V_{i,j}^{l}} = norm(x_{Ci}, \sigma_{Ci}^{2}) \tag{25}$$

5) *Voter's effect*: A voter may be affected by several candidates. So his total effect (*FVi*) is the sum of effect from all candidates:

$$F_{V_i} = \sum F_{C_i V_j} \tag{26}$$

$$F_{C_i V_j} = \begin{cases} \dfrac{R_{C_i} - D_{C_i V_j}}{R_{C_i}} P_{C_i}, R_{C_i} \geq D_{C_i V_j} \\ 0, others \end{cases} \tag{27}$$

$$D_{C_i V_j} = \sqrt{x_{C_i}^2 - x_{V_j}^2} \tag{28}$$

Where, $D_{C_i V_j}$ is the distance between candidates and voters and $F_{C_i V_j}$ is effect on sample-survey vector V_j from candidate C_i.

6) The support barycenter of the candidates: The contribution from a sample-survey voter to a candidate is a power which will lead the candidate to the orientation of that sample-survey voter. A new position coordinate will achieve by mean of summing the products of the contribution from the sample-survey voters to the candidate (Q_{VjCi}) and the position coordinate of the sample-survey voters. It is called the support barycenter of the candidate which is given by:

$$x_{C_i}^{m} = \sum Q_{V_jC_i} x_{V_j} \tag{29}$$

$$Q_{C_iV_j} = \frac{S_{C_iV_j}}{S_{C_i}} \tag{30}$$

$$S_{C_i} = \sum S_{C_iV_j} \tag{31}$$

$$S_{C_jV_i} = \frac{F_{C_jV_i}}{F_{V_i}} P_{V_i} \tag{32}$$

Where, $S_{C_jV_i}$ represents the support from the sample-survey voter V_i to candidate C_j and S_{ci} is the total supports of candidates. The support barycenter of a candidate is compared by means of sample-surveying, which depends on the position of those sample-surveying voters whose distance to the candidate are nearer and prestige are higher relatively. The next election location of the candidate should be his support barycenter, where the candidate will have the higher support. Do that circularly unit the highest support is found? In order to jump out of local optimization solution and increase search efficiency, the prestige of candidates and compared to voters if the prestige of a voter is better than a candidate, that voter will be replaced by the previous one [20].

IV. Simulation Results

In order to illustrate the efficiency of the proposed algorithm for the solution of the UC problems, three power systems are considered.

A. Case I: 10- Thermal Unit System without wind power

This case study concludes 10 generating units without wind power effect. The require system unit data and the generation requirements for each stage given in [13]. The optimal results using the proposed methods in comparison than the other heuristic methods are shown in Table 1 that satisfies the generator constraints. It can be seen that the proposed technique achieved minimum cost in this power system than the other algorithms. Also, Figure 1 shows the minimum fitness functions evaluating process.

TABLE I. THE COMPUTING TIME AND THE TOTAL COST FOR TEST I

Method	Time (sec)	Min Cost ($)
λ - iteration	10.93	78907
FDP	NA	78895.5
GA	13.92	78896.14
PSO	8.827	78804.65
ECO	8.313	78759.51

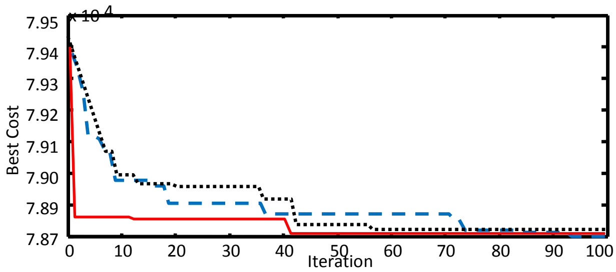

Figure 1. Figure 4. Fitness convergence, Dashed (ECO)

TABLE II. THE DETERMINED COMMITMENT SCHEDULE

<table>
<tr><td rowspan="2">Units</td><td>Hour (1→24)</td></tr>
<tr><td>ECO</td></tr>
<tr><td>1
2
3
4
5
6</td><td>0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0
1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0
1 1 1 1</td></tr>
</table>

7 8 9 10	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
PSO	
1 2 3 4 5 6 7 8 9 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 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
GA	
1 2 3 4 5 6 7 8 9 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 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

B. Case II: Test for a Ten-Unit Thermal System With an Equivalent Wind Generator

In this test, the performance of the proposed ECO based UC under practical conditions is verified by applying an equivalent wind generator. For achieved better discussion and analyze of the numerical results considered system with small capacitor. The accessible wind power generation considered 400 MW for all hours. Actually, the adjustments of the power output are instantaneous that it is considered in the studied cases. Accordingly, generators are constrained because of ramp rate limits where, generation may increase or decrease with corresponding upper and downward ramp rate limits. The generator ramp rate and startup ramp rate constraints are set at 60% of its rated capacity. Also, the system up spinning reserve requirement is assumed to be 300 MW for all time periods. The thermal power units is more than 20% of its rated capacity (*d*% = 20%). The best cost solution for different methods with constraint satisfaction is shown in Tables 5.

TABLE III. THE COMPUTING TIME AND THE TOTAL COST FOR TEST I

Method	Time (sec)	Min Cost ($)
FDP[13]	84.81	58233
HDP[13]	30.87	58233
HDP*[13]	10.71	58233
GA	47.82	58232.87
PSO	9.716	58232.19
ECO	9.277	58229.87

To illustrate the accuracies of these methods, a maximum number of iteration cycles are considered as a stopping condition. Each algorithm is run for ten trials and the best fitness value, Standard Deviation (SD), the least iteration and elapsed time achieved by each algorithm are considered as criteria of the strength and computational effort of the method. The results using the PSO, GA and ECO algorithms based on the objective function as given in Eq. (1) for optimal setting of the UC problem are listed in Table 6. It can be seen that the best SD and the best fitness value in 6 times are achieved by the ECO than the other methods. Also, it has fewer iterations and less computational time to reach a predefined threshold in comparison to other algorithms. The best fitness achieved by the ECO is 58229.87 which is the lowest among the three algorithms.

TABLE IV. DIFFERENT METHODS RESULTS FOR 10 TRIALS

Run	GA

	Min	Max	Mean	Time	Iter
1	58232.87	58235.43	58233.86	47.82	97
2	58233.54	58237.67	58233.64	47.85	95
3	58232.99	58235.49	58234.82	47.84	98
4	58233.23	58236.74	58233.89	47.83	89
5	58232.83	58235.92	58234.77	47.85	76
6	58233.07	58238.45	58233.87	47.82	96
7	58232.56	58235.44	58233.10	47.83	90
8	58232.76	58238.23	58235.34	47.82	93
9	58233.25	58236.78	58234.55	47.84	87
10	58232.80	58235.48	58233.76	47.84	88
SD	0.2735	1.1369	0.6445	0.0111	6.2
Run	PSO				
	Min	Max	Mean	Time	Iter
1	58232.19	58235.32	58233.45	9.716	57
2	58232.34	58235.39	58233.56	9.717	64
3	58232.24	58235.38	58233.78	9.716	54
4	58232.31	58234.67	58233.89	9.718	60
5	58232.27	58235.39	58233.90	9.715	53
6	58232.33	58234.38	58233.12	9.716	49
7	58232.30	58235.56	58233.03	9.716	65
8	58232.42	58235.78	58233.65	9.717	63
9	58232.26	58235.29	58233.33	9.716	58
10	58232.37	58235.56	58233.75	9.717	84
SD	0.0633	0.4030	0.2923	0.0008	9.1
Run	ECO				
	Min	Max	Mean	Time	Iter
1	58231.94	58234.78	58231.35	9.146	36
2	58231.93	58233.76	58231.43	9.146	36
3	58231.92	58234.56	58232.13	9.145	38
4	58230.93	58233.97	58232.43	9.146	42
5	58231.94	58234.39	58231.12	9.145	38
6	58231.94	58234.94	58232.52	9.145	37

7	58231.94	58234.84	58232.23	9.147	40
8	58230.93	58233.88	58231.34	9.146	37
9	58231.94	58235.76	58232.54	9.145	41
10	58231.88	58234.43	58232.12	9.145	38
SD	0.0124	0.2275	0.0359	0.0009	3.3

Furthermore, to evaluate the efficacy and robustness of the proposed optimization technique numerous operating conditions and the system configurations, simultaneously is are considered. The multiple operation conditions are given in Table 7. The scenario I and III give a comparison of results considering the wind generation curtailment or not.

TABLE V. COMPARISON OF RESULTS FOR FIVE DIFFERENT CASES IN CASE 2

Scenario	I	II	III	IV	V
$P^*_{WT}(t)$ MW	0	400	400	400	400
USR_B MW	300	300	300	300	300
ASR_1	---	LM	LM	LM	SM
ASR_2	---	---	---	LM	LM
WGC	---	without	with	with	with
HDP*	78911	58134	57955	58233	58790
GA	78913	58133	57955	58233	58791
PSO	78910	58133	57954	58233	58790
ECO	78908	58130	57952	58232	58789

WGC: Wind Generation Curtailment.

LM (Linear Model): γ%=0.2.

SM (Secound-order Model): α%=0.2, β%=10^{-4}.

It can be seen according to Table 8 that the wind generator is out in power system at low system load times (hours 11–17). Also, it shows the impact of introducing power system down spinning reserve requirement into the generation scheduling problem.

TABLE VI. COMPARISON OF RESULTS CONSIDERING THE WIND GENERATION CURTAILMENT OR NOT

Scenario	Hour	1→10	11→14	15→16	17	18→24
II	$P_{WT}(t)$	400	400	400	400	400
III	MW	400	395	385	395	400

The determined schedule using GA, PSO and ECO technique with contain the system down spinning reserve requirement or not are given in Table 9.

TABLE VII. THE DETERMINED COMMITMENT SCHEDULE

Units	Hour (1→24)
	ECO
1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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	1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
6	1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
	PSO

1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
4	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
5	1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1
6	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
	GA
1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
3	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
6	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
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V. Conclusions

The Election Campaign Optimization (ECO) is proposed to solve the Unit Commitment (UC) problem between thermal generating units with wind impact an electricity market to minimize total cost in this paper. The problem of find best answer is formulated as an optimization problem according to the time domain-based objective function for a wide range of operating conditions which is solved by the ECO technique. ECO is a new heuristic optimization algorithm which mimics the behavior of the election candidates pursues the highest support from voters in election campaigns. The candidates can influence the voters round them, the effect from candidates to voters will decrease gradually with the increase of distances between the candidates and the voters. The better prestige a candidate comports, the larger investigated range he has. In order to obtain an exact and global investigated, local investigated voters are generated in the probability determined by a normal distribution function that the mean is the location coordinates of candidates, and global investigated voters is generated in the probability determined by a uniform distribution function. This feature is caused that it has been had a flexible and well-balanced mechanism to enhance the global and local exploration abilities and found to be robust in optimization problems featuring non-linearity, non-differentiability and high dimensionality. From these comparative studies, it is evident that the proposed technique can be effectively used for the solution of UC problems in the real world power systems.

Nomenclatures

F_T: Total operation cost over the scheduling horizon.

i: Index for thermal units.

j: Index for wind units.

N_T: Number of thermal units in the system.

N_W: Number of wind units in the system.

$P_i(t)$: Generation of thermal unit i at hour t.

$P_{i,r}^{max}$: Upper generation limit of thermal unit i.

$P_{i(t)}^{max}$: Maximum generation of thermal unit i at hour t.

$P_{i,r}^{min}$: Lower generation limit of thermal unit i.

$P_{i(t)}^{min}$: Minimum generation of thermal unit i at hour t.

$P_L(t)$: System load demand at hour t.

ASR_1: Additional up reserve requirement considering wind power generation.

ASR_2: Additional down reserve requirement considering wind power generation.

Cn: Number of states saved at each hour in the HDP algorithm.

d%: Percentage of maximum unit capacity.

DR_i^{max}: Maximum ramp-down rate for thermal unit *i*.

DS_i^{max}: Maximum down reserve contribution of thermal unit *i*.

$DS_i(t)$: Down reserve contribution of thermal unit *i* at hour *t*.

P_{Wj}^{max}: Upper generation limit of wind unit j.

$P_{Wj}(t)$: Actual generation of wind unit j at hour t.

$P^*_{Wj}(t)$: Available generation of wind unit j at hour t.

$P_{WT}(t)$: Total actual wind generation at hour t.

$P^*_{WT}(t)$: Total available wind generation at hour t.

r%: Coefficient of additional up (or down) reserve requirement (linear model).

SR_i: Startup ramp rate limit of thermal unit i.

T: Number of time intervals (hours).

$TDR(t)$: System ramping down capacity at hour t.

$t_{i(t)}^{OFF}$: Time period that thermal unit i had been continuously down till period t.

T_i^{OFF}: Minimum down time of thermal unit i.

T_i^{ON}: Minimum up time of thermal unit i.

$t^{ON},i(t)$: Time period that thermal unit i had been continuously up till period t.

$TUR(t)$: System ramping up capacity at hour t.

$U_i(t)$: Scheduled state of thermal unit i for hour t (1: unit i is up, 0: unit i is down).

UR_i^{max}: Maximum ramp-up rate for thermal unit i.

$US_i(t)$: Up reserve contribution of thermal unit i at hour t.

US_i^{max}: Maximum up reserve contribution of thermal unit i.

USRB: System up spinning reserve requirement not considering wind power generation.

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