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Biogeography Based Optimization for Unit Commitment with Wind Farms

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Abstract

The impact of human activities on the environment as a consequence of the industrialization process, the rising trend of the price of fossil fuels, and the incentives offered by governments in many countries have driven the development and evolution of renewable energy sources such as wind energy. The optimal selection of on-line units and optimal output levels of committed units for conventional generation need to be revised taking into account the impact of wind farms. This paper presents a new methodology for unit commitment (UC) with wind farms using biogeography based optimization (BBO). The proposed method divides the UC problem into several sub-problems, each representing an UC problem of an interval, and solves the each sub-problem using BBO. It suggests a repair mechanism for handling minimum-up/down and spinning reserve constraints. The simulation results on a 10 unit test problem with a wind farm clearly indicate that the developed method is robust and computationally efficient.

Nomenclature

$a_i\ b_i\ c_i$	fuel cost coefficients of the i^{th} generator
BBO	biogeography based optimization
CST_i	cold start up cost of unit i (\$)
ELD	economic load dispatch
$F_i(P_{Gi})$	fuel cost function of the i^{th} generator in $\$/h$

HSI habitat suitability index
HST_i hot start up cost of unit-i (\$)
h_i i^{th} habitat
$Iter^{\max}$ maximum number of iterations for convergence check
K_1 & K_2 penalty factors respectively
nt number of intervals
ng number of generators
nh number of habitats
neh number of elite habitats
PM proposed method
P_{Git} real power generation of i^{th} generator at interval-t
$P_{Gi}^{\min}$ & $P_{Gi}^{\max}$ minimum and maximum generation limits of i^{th} generator respectively
P_{Dt} total power demand at interval-t
P_{Lt} net transmission loss at interval-t
P^{mod} habitat modification probability
P_m mutation probability
P_W output of the wind turbine
P_W^{rate} rating of the wind turbine
P_{Wt} output of the wind turbine at interval-t
R_t spinning reserve at interval-t (MW)
$S^{\max}$ maximum species count
SIV suitability index variable
ST_i^t startup cost of unit-i at interval-t (\$)
T_i^{cold} cold start hour of unit-i (hours)
T_i^{down} minimum down time of unit-i
T_i^{off} continuous off time of unit-i
T_i^{on} continuous on time of unit-i
T_i^{up} minimum up time of unit-i
UC unit commitment
V wind speed (m/s)
V_{ci} cut-in speed (m/s)
V_{co} cut-out speed (m/s)
V_{ci} rated speed (m/s)
$\Phi(P_G, U)$ objective function to be minimized over the scheduling period
$U_{i,t}$ status of unit-i at interval-t $(on = 1, off = 0)$

Ω a set of uncommitted units of $t-th$ sub-problem, whose status is unknown
Ψ augmented objective function to be minimized
Λ immigration rate
μ emigration rate
α, β, γ wind generator coefficients

Introduction

Climate changes, global warming in particular, have required environmental issues to be seriously considered in power systems operation. As an alternative to traditional fossil fuels, renewable wind generation is rapidly deployed, which is plentiful, widely distributed, and environmentally friendly. The penetration of wind energy has increased substantially in recent years and is expected to continue growing in the future. Wind power is generally regarded as problematic for power system operation due to its limited predictability and variability. In particular, optimal selection of on-line units and optimal output levels of committed units for conventional generations need to be revised. As wind energy cannot be predicted accurately due to its intermittent nature, additional reserves for wind power must be allocated and conventional units must be operated in a more flexible, adaptable manner-leading to reduced efficiency through partial loading and an increase in the number of start-ups required for conventional power plants. Mathematically, the unit commitment (UC) problem can be described as a nonlinear, large-scale, mixed-integer optimization problem with a nonlinear solution space. The dimension of the problem increases rapidly with the system size and the scheduling horizon [1].

Over the years, numerous methods with various degrees of near-optimality, efficiency, ability to handle difficult constraints and heuristics are suggested in the literature for solving the UC problems. These problems are traditionally solved using mathematical programming techniques such as priority list methods [2], integer programming [3], mixed-integer programming [4], dynamic programming [5], branch-and bound [6], Lagrangian Relaxation method (LRM) [7] and so on. Many of these methods suffer from natural complexity and converge slowly. Apart from the above methods, there is another class of numerical techniques called evolutionary search algorithms such as simulated annealing (SA) [8], genetic algorithms (GA) [9], evolutionary programming (EP) [10] and particle swarm optimization (PSO) [11] have been applied in solving UC problems. In the recent years, the effects of the penetration of wind farms on UC problems have been studied in [12-14].

A population based stochastic optimization technique of sharing information between candidate solutions based on their fitness values, represented as Biogeography-Based Optimization (BBO) [15], has been applied to a variety of power system optimization problems [16-19] and found to yield satisfactory results. This paper presents a BBO based solution methodology for UC problems with wind-farms by splitting the problem into several sub-problems with a view of enhancing the computational efficiency and robustness.

Problem Formulation

UC Problem:

The mathematical formulation of the UC problem with wind farms is same as that of standard UC problem except the modification in the power balance and spinning reserve constraints to include the wind generated power. The main objective of UC problem is to minimize the overall system generation cost over the scheduled time horizon under the spinning reserve and operational constraints of generator units. This constrained optimization problem is formulated as

Minimize $$\Phi(P_G, U) = \sum_{t=1}^{nt}\sum_{i=1}^{ng}\left\{F_i(P_{Git}) + ST_i^{\,t}\left(1 - U_{i,t-1}\right)\right\}U_{i,t} \quad (1)$$

Subject to Power balance constraint

$$P_{Dt} - P_{Wt} - \sum_{i=1}^{ng} P_{Git}\, U_{i,t} = 0 \quad (2)$$

Spinning reserve constraint:

$$P_{Dt} + R_t - P_{Wt} - \sum_{i=1}^{ng} P_{Gi}^{\max}\, U_{i,t} \le 0 \quad (3)$$

Generation limit constraints:

$$P_{Gi}^{\min} U_{i,k} \le P_{Git} \le P_{Gi}^{\max} U_{i,t} \quad i = 1,2,\cdots,ng \quad (4)$$

Minimum up and down time constraints:

$$U_{i,t} = \begin{cases} 1 & if\ \ T_i^{on} < T_i^{up} \\ 0 & if\ \ T_i^{off} < T_i^{down} \\ 0\ or\ 1 & otherwise \end{cases} \quad (5)$$

Start-up Cost:

$$ST_i = \begin{cases} HST_i & if\ \ T_i^{down} \le T_i^{off} \le T_i^{cold} + T_i^{down} \\ CST_i & if\ \ T_i^{off} > T_i^{cold} + T_i^{down} \end{cases} \quad (6)$$

Where

$$F_i(P_{Git}) = a_i P_{Git}^{\ 2} + b_i P_{Git} + c_i \quad (7)$$

Wind Farm Model:

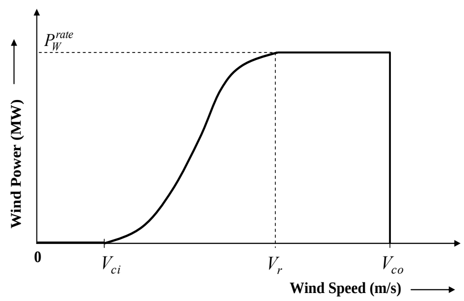

Figure 1: Typical Characteristic of a Wind Turbine

The generated power that varies with the wind speed, of a wind turbine can be determined from its power curve, which is a plot of output power against wind speed. The typical characteristic of wind turbine relating wind speed and generator power output indicating the cut-in speed, the rated wind speed and cut-out speed is shown in Fig. 1. The wind turbine starts generating power, when the wind speed is at cut-in wind speed (V_{ci}) and shut down for safety reasons at cut-out wind speed (V_{co}). It generates the rated power, P_W^{rate}, when the wind speed is in-between the rated wind speed (V_r), and the cut-out wind speed. The power output of a wind turbine for a given wind speed can be calculated from the following mathematical model.

$$P_W = \begin{cases} 0 & 0 \le V < V_{ci} \\ P_W^{rate} \times \left(\alpha V^2 + \beta V + \gamma\right) & V_{ci} \le V < V_r \\ P_W^{rate} & V_r \le V < V_{co} \\ 0 & V \ge V_{co} \end{cases} \quad (8)$$

In the proposed formulation, it is assumed that the wind speed is uniform at the entire wind farm and all the wind turbines in the wind farm possess the same characteristics. The wind farm is therefore treated as a wind turbine, possessing the rating of the entire wind farm.

Biogeography Based Optimization

BBO, based on the concept of biogeography, is a stochastic optimization technique for solving multimodal optimization problems [15]. In BBO, a solution is represented by a habitat-i consisting of solution features named Suitability Index Variables (SIV), which are represented by real numbers. It is represented for a problem with nd decision variables as

$$h_i = [SIV_{i,1}, SIV_{i,2}, SIV_{i,3}, \cdots, SIV_{i,nd}] \quad (9)$$

The suitability of sustaining larger number of species of a habitat-i can be modeled as a fitness measure referred to Habitat Suitability Index (HSI) as

$$HSI_i = f(h_i) = f(SIV_{i,1}, SIV_{i,2}, SIV_{i,3}, \cdots, SIV_{i,nd}) \quad (10)$$

High HSI represents a better quality solution and low HSI denotes an inferior solution. The aim is to find optimal solution in terms of SIV that maximizes the HSI.

Each habitat is characterized by its own immigration rate λ and emigration rate μ. A good solution enjoys a higher μ and lower λ and vice-versa. The immigration and emigration rates are the functions of the number of species in the habitat and defined for a habitat containing k-species as

$$\mu_k = E^{\max}\left(\frac{k}{n}\right) \quad (11)$$

$$\lambda_k = I^{\max}\left(1 - \frac{k}{n}\right) \quad (12)$$

When $E^{\max} = I^{\max}$, the immigration and emigration rates can be related as

$$\lambda_k + \mu_k = E^{\max} \quad (13)$$

A population of candidate solutions is represented as a vector of habitats similar to any other evolutionary algorithm. The features between the habitats are shared through migration operation, which is probabilistically controlled through habitat modification probability, P^{mod}. If a habitat h_i in the population is selected for modification, then its λ will be used to probabilistically decide whether or not to modify each SIV in that habitat. The μ of other solutions are thereafter used to select which of the habitats in the population shall migrate randomly chosen $SIVs$ to the selected solution h_i.

The cataclysmic events that drastically change the HSI of a habitat is represented by mutation of $SIVs$. The mutation operation modifies a habitat's SIV randomly based on mutation rate P_m and tends to increase diversity among the population, avoids the dominance of highly probable solutions and provides a chance of improving the low HSI solutions. Mutation rate of each solution set can be calculated in terms of species count probability using the following equation:

$$P_m = m^{\max}\left(\frac{1-P^k}{P^{\max}}\right) \tag{14}$$

Proposed Method

In all the evolutionary based solution methods, each member in the population consists of UC schedule of the entire scheduling horizon. These methods involve a large number of decision variables, which is the product of the number of generating units and the number of intervals over the scheduling period. For example, a problem with 10 generating units over a scheduling horizon of 24 intervals involves 240 decision variables, representing a search space with a dimension of 240, thereby making the search process very complex and time consuming [8-11]. The complexity of the UC problems grows exponentially to the number of generating units.

In the proposed method (PM), the UC problem is solved in a novel way with a view of obtaining the solution with lower computational burden. The UC problem is divided into a number of sub-problems, each representing an UC schedule of interval-t. The UC sub-problems are solved through a systematic procedure that involves determination of UC schedule of the chosen interval, comprising a maximum of ng binary decision variables, using BBO. Besides, the determination of UC schedule of an interval may eliminate one or more decision variables, thereby reducing the size of the problem to be solved for the remaining time intervals. The solution procedure is outlined below:

1. Evaluate the wind generated power, P_{Wt}, at all the intervals of the scheduling horizon using Eq. (8)
2. The UC sub-problem associated with the lowest "net power demand" that equals $\left(P_{Dt} - P_{Wt}\right)$ is chosen and solved for optimal schedule using BBO. This solution process involves a maximum of ng binary decision variables, as

the chosen sub-problem is concerned with only one time interval.

3. Similar to previous step, the optimal schedule for the sub-problem linked with the "largest net power demand" that equals $\left(P_{Dt} - P_{Wt}\right)$ is obtained.
4. The units that are simultaneously committed by the binary schedules obtained in the previous two steps, are set to be committed for the all the sub-problems, whose power demand lies in between the chosen smallest and largest power demands in steps 2 and 3.
5. The sub-problems associated with the smallest and largest power demands are eliminated in the subsequent scheduling process. Besides, the common units, that are committed in the previous step, are also discarded in the subsequent scheduling process. This elimination reduces both the number of intervals and number of binary variables.
6. Repeat steps 1-4, till all the sub-problems over the scheduling period are eliminated.
7. The schedule obtained at the end of step-6 may not reduce the start-up cost. If the start-up cost (ST_i) of any of the unit equals the respective CST_i, then a check is made whether the commitment of the unit at the previous interval reduces the ST_i to HST_i. If so, the sub-problem associated with that interval is solved again using BBO and another check is made whether the net-generation cost decreases due to this alteration. If not, the alteration could be undone.
8. The above schedule, obtained through steps 1-7, may not satisfy the minimum up and down time constraints. A check is made for the violation of minimum up/down time and spinning reserve constraints. If there is violation, the interval that may require repairing is chosen and the status of the units of the chosen interval may be forcefully altered to eliminate violation; and the remaining variables of that interval are again optimized using BBO. This may be repeated till there are no constraint violations.

The encoding of decision variables, the HSI function and the ELD technique, required in the above solution process, are explained below:

Encoding of Decision Variables:

The UC variables of each sub-problem at interval-t, involving a maximum of ng decision variables, are considered to denote the habitat as

$$h_i = \left[U_{1,t}, U_{2,t}, \cdots, U_{n,gt}\right] \tag{14}$$

The above representation, involving ng decision variables, is used only while solving the first two sub-problems. In the subsequent sub-problems, there may be reduced number of decision variables. The representation of the habitat can be generalized as

$$h_i = \left[U_{j,t};\ j \in \Omega\right] \tag{15}$$

Where Ω is a set of uncommitted units of $t-th$ sub-problem, whose status is yet to be determined.

It is to be noted that the wind farm is not included as a variable in the above representation, as its commitment is based on the wind speed as governed by Eq. (8).

HSI Function:

The HSI function can be tailored through penalizing the fuel cost by the power balance constraint for the $t-th$ sub-problem as

Maximize $HSI = \dfrac{1}{1+\Psi}$ (16)

Where

$$\Psi = \sum_{i=1}^{ng} F_i(P_{Git})\, U_{i,t} + K_1\left(P_{Dt} - P_{Wt} - \sum_{i=1}^{ng} P_{Git}\, U_{i,t}\right)^2 \quad (17)$$

Economic Load Dispatch

The ELD is an intensive computational part in UC problem. It is solved using λ iteration method [1] based on the principle of equal incremental cost through the following equation.

$$P_i^t = \frac{\lambda}{2a_i + b_i} \quad (18)$$

Repair Mechanism

Spinning reserve and minimum-up/down time constraints are important in UC problems. The solution obtained at the end of step-6 of the solution procedure narrated at the beginning of this section may violate any of those constraints. The following repair mechanism is applied to eliminate the constraint violations.

- If spinning reserve constraint of $t-th$ sub-problem is not satisfied, then solve the sub-problem with the following augmented objective function instead of Eq. (17).

$$\Psi = \sum_{i=1}^{ng} F_i(P_{Git})\, U_{i,t} + K_1\left(P_{Dt} - P_{Wt} - \sum_{i=1}^{ng} P_{Git}\, U_{i,t}\right)^2 + K_2\left(P_{Dt} + R_t - P_{Wt} - \sum_{i=1}^{ng} P_{Gi}^{\max}\, U_{i,t}\right)^2 \quad (19)$$

- If minimum up/down time constraint is violated, identify the stream of bits that causes violation and alter them in order to overcome this violation. For example, a string of 1111001111 may be modified either as 1111111111 or 1110001111 or 1111000111. However, the one that requires least bit (unit) changes is chosen for repair. Once a status of a generating unit (bit) in a sub-problem is altered, then the sub-problem is once again solved for the remaining units (bits).
- The above two steps should be repeated till all the constraints are satisfied.

BBO Routine

The BBO routine is used to solve each sub-problem involving migration and mutation operations. The flow of this routine for an UC sub-problem is explained through a flow chart of Fig. 2. However, it requires selection of BBO parameters such as nh, neh, P^{mod}, P_m and $Iter^{\max}$.

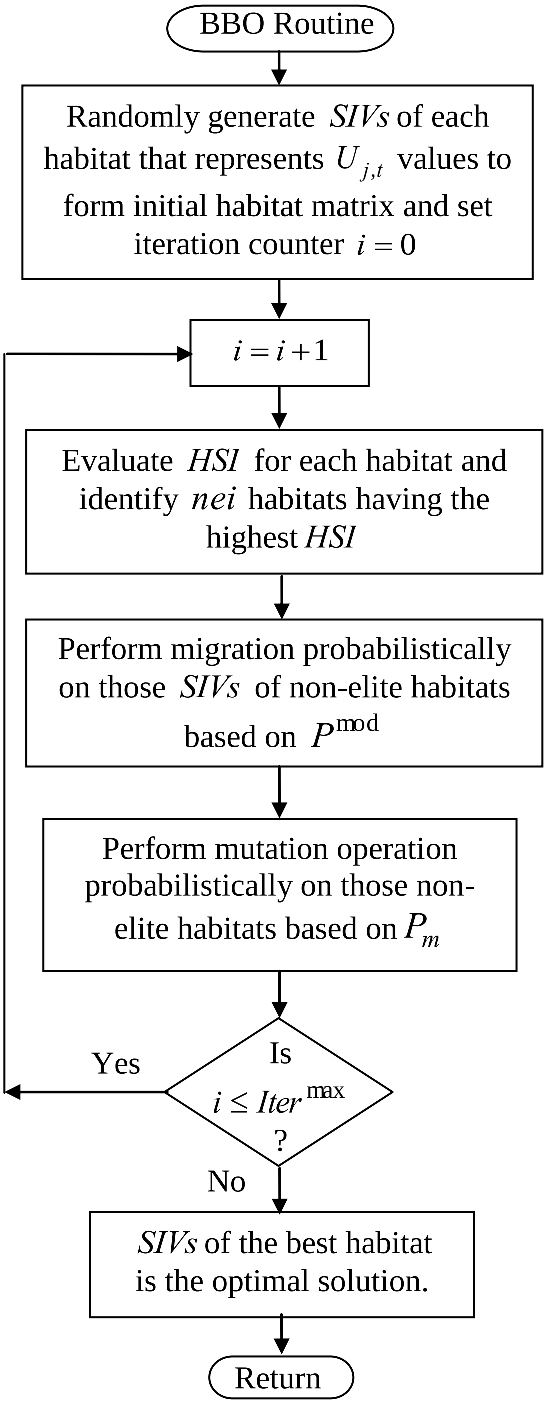

Figure 2: Flow Chart of the BBO routine

Numerical Results

The PM is tested on a test system possessing 10 generating units. The unit data and load demand data for 24 hours for the system with 10 units are taken from [9]. The spinning reserve requirements are assumed to be 10% of the load demand. The wind farm data and wind speed data is given in Table 1 and 2 respectively.

The software package for PM is developed in Matlab platform and executed in a 2.3 GHz Pentium-IV personal computer. There is no guarantee that different executions of the BBO converge to the same solution due to the stochastic nature of the algorithm, and hence the PM is applied to these test system for 20 independent trials (100 iterations per trial) with the selected parameters and the best ones are presented. The effectiveness of the PM is demonstrated through comparing the performances with those of the GA, PSO and HSO based approaches. In this regard, all the variables over the scheduling horizon is taken to represent a member in the solution process of the GA, PSO and HSO based approaches and the constraints are blended with the objective function to build the cost/fitness function.

The detailed results comprising UC schedule, the net start-up cost, the net fuel cost and the net generation cost for 10-unit system, obtained by PM, are presented in Table 3. The optimal generations of the UC schedule over the scheduling period is graphically presented in Fig. 3. The corresponding fuel cost over the scheduling horizon is presented through Fig. 4. The best generation cost obtained by the PM is compared with those of the existing methods in Fig. 5. It is observed from these results that the PM offers the lowest generation cost of 512534.508 $\$/h$ compared to those of other methods, thereby ensuring that the PM is able to produce the global best solution. The computational efficiency of any optimization method is a crucial factor for its practical applicability. Therefore the normalized execution time (NET) in seconds is compared with those of the existing methods in Fig.6. It can be observed from the figure that the PM is computationally efficient in offering the optimal solution.

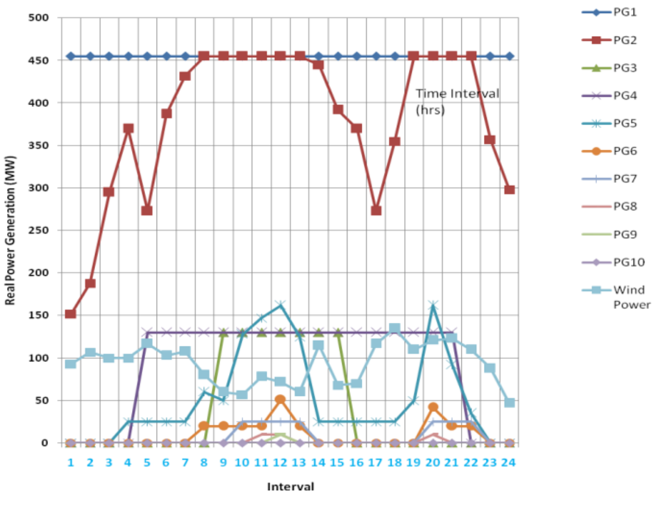

Figure 3: Optimal real power generations of the PM

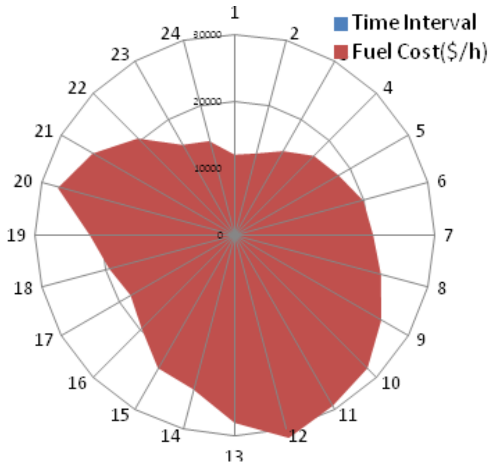

Figure 4: Fuel cost of the PM over the scheduling period ($/h)

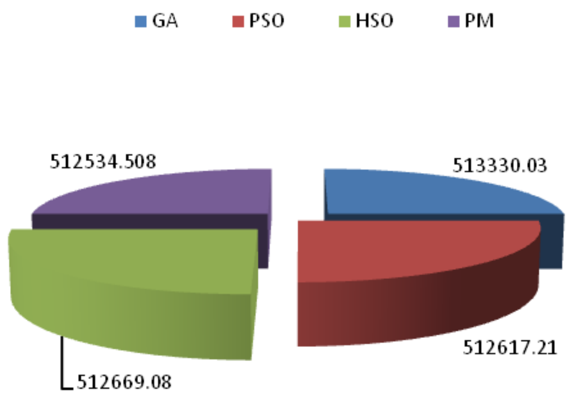

Figure 5: Comparison of Generation Costs ($/h)

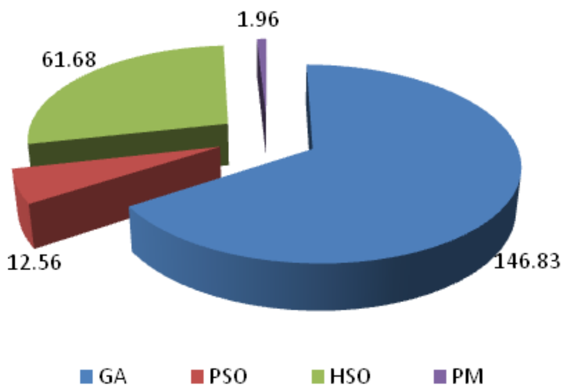

Figure 6: Comparison of NET (Seconds)

Table 1: Wind Farm data

Wind Farm rating	P_W^{rate}	135 MW
Wind Farm Coefficients	α	0.0031
	β	0.0474
	γ	-0.1401

Table 2: Wind Speed data for 24 hours

Interval	Wind Speed m/s	Interval	Wind Speed m/s	Interval	Wind Speed m/s
1	10.4065	9	8.0714	17	11.9306
2	11.3105	10	7.8417	18	13.0000
3	10.8640	11	9.3849	19	11.4987
4	10.8640	12	8.9586	20	12.1733
5	11.9306	13	8.0714	21	12.2935
6	11.0567	14	11.8082	22	11.4987
7	11.3734	15	8.6682	23	10.0725
8	9.5246	16	8.8141	24	7.0500

Table 3: Results of PM

		Unit										Wind farm	Start-up Cost	Net Fuel Cost	Net Generation Cost ($/h)
		1	2	3	4	5	6	7	8	9	10				
Interval	1	1	1	0	0	0	0	0	0	0	0	1	4460	508074.508	512534.508
	2	1	1	0	0	0	0	0	0	0	0	1			
	3	1	1	0	0	0	0	0	0	0	0	1			
	4	1	1	0	0	1	0	0	0	0	0	1			
	5	1	1	0	1	1	0	0	0	0	0	1			
	6	1	1	0	1	1	0	0	0	0	0	1			
	7	1	1	0	1	1	0	0	0	0	0	1			
	8	1	1	0	1	1	1	0	0	0	0	1			
	9	1	1	1	1	1	1	0	0	0	0	1			
	10	1	1	1	1	1	1	1	0	0	0	1			
	11	1	1	1	1	1	1	1	1	0	0	1			
	12	1	1	1	1	1	1	1	1	1	0	1			
	13	1	1	1	1	1	1	1	0	0	0	1			
	14	1	1	1	1	1	0	0	0	0	0	1			
	15	1	1	1	1	1	0	0	0	0	0	1			
	16	1	1	0	1	1	0	0	0	0	0	1			
	17	1	1	0	1	1	0	0	0	0	0	1			
	18	1	1	0	1	1	0	0	0	0	0	1			
	19	1	1	0	1	1	0	0	0	0	0	1			
	20	1	1	0	1	1	1	1	1	0	0	1			
	21	1	1	0	1	1	1	1	0	0	0	1			
	22	1	1	0	0	1	1	1	0	0	0	1			
	23	1	1	0	0	0	0	0	0	0	0	1			
	24	1	1	0	0	0	0	0	0	0	0	1			

Conclusion

The rising trend of utilization of wind energy have significant impact on the optimal selection of on-line units and optimal output levels of committed units for conventional generation. A elegant methodology using BBO has been suggested for solving UC problems with wind farms, which is a complex, non-linear and mixed-integer optimization problem involving large number of decision variables. The problem has been split into a number of sub-problems and each sub-problem has been solved using BBO. The minimum-up/down and spinning reserve constraint violations have been handled by the newly developed repair mechanism. The simulation results on 10 unit test system with a wind farm clearly exhibited that the developed method is robust and computationally efficient.

Acknowledgements

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