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Comparative Performance of Artificial Bee Colony Based Algorithms for Wind-Thermal Unit Commitment

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***Abstract*—**This paper presents the three optimization models, namely New Binary Artificial Bee Colony (NBABC) algorithm, NBABC with Local Search (NBABC-LS), and NBABC with Genetic Crossover (NBABC-GC) for solving the Wind-Thermal Unit Commitment (WTUC) problem. The uncertain nature of the wind power is incorporated using the Weibull probability density function, which is used to calculate the overestimation and underestimation costs associated with the wind power fluctuation. The NBABC algorithm utilizes a mechanism based on the dissimilarity measure between binary strings for generating the binary solutions in WTUC problem. In NBABC algorithm, an intelligent scout bee phase is proposed that replaces the abandoned solution with the global best solution. The local search operator exploits the neighboring region of the current solutions, whereas the integration of genetic crossover with the NBABC algorithm increases the diversity in the search space and thus avoids the problem of local trappings encountered with the NBABC algorithm. These models are then used to decide the units on/off status, whereas the lambda iteration method is used to dispatch the hourly load demand among the committed units. The effectiveness of the proposed models is validated on an IEEE 10-unit thermal system combined with a wind farm over the planning period of 24 hours.

***Keywords*—**Artificial bee colony algorithm, economic dispatch, unit commitment, wind power.

I. Introduction

THE rise of environmental protection and the progressive exhaustion of traditional fossil energy sources have increased the interest in integrating renewable energy sources into the existing power systems. The wind power is one of the most important renewable energy resource that has gained widespread attention. One of the major benefits of wind energy is that, after the initial land and capital costs, there is essentially no cost involved in the power production of wind energy conversion system. In addition, the impacts of wind energy resources are environmentally friendlier than the impacts of thermal energy resources. However, the uncertainty and unpredictability of wind power would affect the stable and secure power system operation [1]. Due to this reason, an efficient algorithm is essential to determine the optimal proportion of wind generating capacity that can be integrated with the thermal system for operating an isolated hybrid power system reliably and efficiently.

A wide variety of methods has been proposed by the researchers in the literature to solve the conventional unit commitment problem. However, the less contribution has been done in developing the algorithms to solve the unit commitment problem for wind-thermal coordination. The solution methods are broadly classified into two categories, namely classical and heuristic methods. The frequently used classical methods for solving WTUC problem are mixed-integer linear programming [2], dynamic programming [3] and priority list [4], [5]. But, these methods are associated with the problems of large computational time requirement, inability to handle time dependent constraints for nonlinear and non-convex large scale unit commitment problems. These problems have motivated the researchers to develop the heuristic methods for solving the complex unit commitment problems even for the large size systems in a reasonable execution time. The mostly used meta-heuristic methods are simulated annealing [6], particle swarm optimization [7], fuzzy logic [8], chance constrained programming [9], differential evolution [10], improved gravitational search algorithm [11], quantum-inspired binary gravitational search algorithm [12], adaptive modified gravitational search algorithm [13]. Apart from these single approaches, some hybrid methods are proposed, namely hybrid of branch and bound with dynamic programming [14], fuzzy logic based mixed-integer linear programming [15], fuzzy logic based particle swarm optimization [16], hybrid of Lagrange relaxation and priority list method [17], hybrid of sequential quadratic programming and particle swarm optimization [18].

The objective of this work is to integrate the wind generators with the conventional thermal units and to investigate the problem via numerical solutions. The proposed WTUC model is formulated as a nonlinear, mixed-integer, combinatorial optimization problem considering various constraints. In WTUC model, the wind power is modeled using the two-parameter Weibull distribution. Based on the Weibull distribution, the cost related to overestimation and underestimation of wind power is considered in the proposed WTUC model. In terms of the problem solver, the proposed models, namely NBABC algorithm, NBABC-LS and NBABC-GC are developed to decide the on/off status of the wind and thermal units during the planning period. Once the on/off status is decided, the lambda iteration method is used to dispatch the load demand among the committed thermal units.

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The quality of the solutions is further enhanced by using the heuristic constraints repairing and unit decommitment strategies that keep the search space feasible throughout the iterative process. Finally, the performance of the proposed models is analyzed and tested on a modified 10-unit IEEE thermal test system integrated with the large-scale wind farm having 50 identical wind turbines over the scheduled time horizon of 24 hours. In order to validate the results obtained by using NBABC, NBABC-LS and NBABC-GC methods, the same WTUC problem is also solved by using GA.

II. Probabilistic Modeling of Wind Power

The power output characteristics of Wind Turbine Generator (WTG) are quite different from those of conventional thermal generating units. The generated wind power varies with the wind speed of the wind farm site and it is essential to accurately evaluate the electric power generated by a wind unit located at a particular geographic site during the generation scheduling. Previous research [19] has shown that the wind speed profile at a given location most closely follow the Weibull distribution over time. The Probability Density Function (PDF) and Cumulative Density Function (CDF) for the two-parameter Weibull distribution are given as:

$$f_V(v^t) = \frac{k^t}{c^t}\left(\frac{v^t}{c^t}\right)^{k^t-1} \times \exp\left[-\left(\frac{v^t}{c^t}\right)^{k^t}\right] \; ; \; 0 \le v^t < \infty \qquad (1)$$

$$F_V(v^t) = 1 - \exp\left[-\left(\frac{v^t}{c^t}\right)^{k^t}\right] \; ; \; 0 \le v^t < \infty \qquad (2)$$

where $f_V(v^t)$ and $F_V(v^t)$ are the PDF and CDF of the wind speed (v^t) at time t, respectively, V is the wind speed random variable, $k^t > 0$ is the shape parameter at time t (dimensionless) and $c^t > 0$ is the scale parameter at time t in m/s.

After the characterization of wind speed as a random variable, the output power of the WTG may also be characterized as a random variable through a transformation from wind speed to output power. The power output of a wind turbine could be determined from its power curve shown in Fig. 1, which is a plot of output power against wind speed. A WTG is designed to start generating power at the cut-in wind speed (v_i) and is shut down for safety reasons at the cut-out wind speed (v_o). When the wind speed is in between the rated speed (v_r) and the cut-out speed, the WTG generates its rated power (w_r). The output power varies linearly with speed in the region between cut-in and rated speeds [18]. It is calculated as:

$$w^t = \begin{cases} 0 & ; for \;\; v^t < v_i \;\; or \;\; v^t \ge v_o \\ w_r \dfrac{(v^t - v_i)}{(v_r - v_i)} & ; for \;\; v_i \le v^t < v_r \\ w_r & ; for \;\; v_r \le v^t < v_o \end{cases} \qquad (3)$$

where w^t is the WTG power output (a realization of the wind power random variable) and v^t is the wind speed at time instant t (a realization of the wind speed random variable).

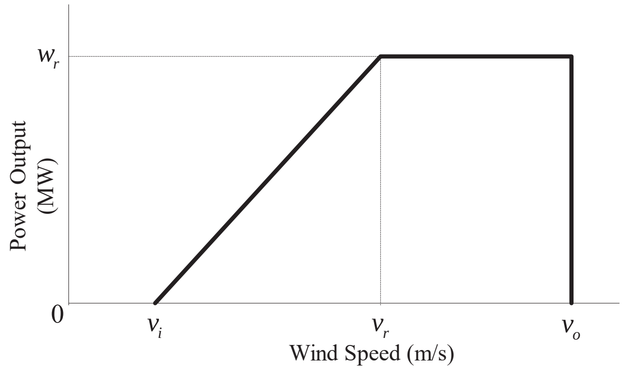


Fig. 1 Power curve of a wind turbine

Here, the WTG power output is a mixed random variable, which is discrete at values of zero and rated power output, and is continuous between values of zero and rated power. Now, it is essential to transform wind speed distribution to wind power distribution with V as the wind speed random variable and W as the wind power random variable. It is done as follows [18]: For discrete portions of the WTG power output random variable, the probabilities of getting no power output and rated power output are as:

$$\Pr(W=0) = 1 - \exp\left[-\left(\frac{v_i}{c^t}\right)^{k^t}\right] + \exp\left[-\left(\frac{v_o}{c^t}\right)^{k^t}\right] \qquad (4)$$

$$\Pr(W=w_r) = \exp\left[-\left(\frac{v_r}{c^t}\right)^{k^t}\right] - \exp\left[-\left(\frac{v_o}{c^t}\right)^{k^t}\right] \qquad (5)$$

The Weibull PDF ($f_W(w^t)$) of the WTG power output random variable in the continuous range is obtained as:

$$f_W(w^t) = \frac{k^t \cdot (v_r - v_i)}{c^t \cdot w_r} \cdot \left\{ \frac{\dfrac{(v_r - v_i)\cdot w^t}{w_r} + v_i}{c^t} \right\}^{k^t-1} \times \exp\left[-\left\{ \frac{\dfrac{(v_r - v_i)\cdot w^t}{w_r} + v_i}{c^t} \right\}^{k^t} \right] \qquad (6)$$

III. WTUC Problem Formulation

This section describes the formulation of conventional thermal unit commitment problem including wind power.

A. Objective Function

The main objective of WTUC problem is to determine the optimum on/off status of the thermal and wind units so that the total operating cost is minimized while satisfying various constraints over the scheduling time horizon of 24 hours with one-hour time interval. Mathematically, the problem [18] to be minimized is represented as:

$$TOC = \sum_{t=1}^{T}\sum_{i=1}^{N}\left[F_i(P_i^t)U_i^t + U_i^t(1-U_i^{t-1})SUC_{i,t} + U_i^{t-1}(1-U_i^t)SDC_{i,t}\right] + \sum_{t=1}^{T}\sum_{j=1}^{N_w}\left[F_j(w_j^t) + C_{o,j}\left(w_j^t - W_{j,av}^t\right) + C_{u,j}\left(W_{j,av}^t - w_j^t\right)\right]\cdot Q_j^t \quad (7)$$

where

$$F_i(P_i^t) = a_i + b_i \times P_i^t + c_i \times (P_i^t)^2 \quad (8)$$

$$SU_{i,t} = \begin{Bmatrix} HS_i,\ if\ \ T_{i,down} \le T_{i,off}^t \le T_{i,down} + T_{i,cold} \\ CS_i,\ if\ \ T_{i,off}^t > T_{i,down} + T_{i,cold} \end{Bmatrix} \quad (9)$$

$$F_j(w_j^t) = d_j \cdot w_j^t \quad (10)$$

$$C_{o,j}\left(w_j^t - W_{j,av}^t\right) = \mu_{o,j}\int_0^{w_j^t}\left(w_j^t - w^t\right)\cdot f_W(w^t)dw \quad (11)$$

$$C_{u,j}\left(W_{j,av}^t - w_j^t\right) = \mu_{u,j}\int_{w_j^t}^{w_{r,j}}\left(w^t - w_j^t\right)\cdot f_W(w^t)dw \quad (12)$$

where TOC is the total operating cost in \$, $F_i(P_i^t)$ is the thermal production cost of i^{th} unit at time t in \$/h, a_i, b_i and c_i are the fuel cost coefficients of i^{th} thermal unit, P_i^t is the real power generation of i^{th} thermal unit at time t in MW, $SU_{i,t}$ is the start-up cost of i^{th} thermal unit, $F_j(w_j^t)$ is the cost function of j^{th} wind unit at time t, which represents the payment to the wind farm operator for utilizing the wind unit, $C_{o,j}$ & $C_{u,j}$ represent the cost function associated with over- and underestimation of wind power for j^{th} wind unit respectively, w_j^t is the scheduled wind power for the j^{th} wind unit at time t, $W_{j,av}^t$ represents the available wind power for the j^{th} wind unit at time t, U_i^t & Q_j^t are the on/off status of i^{th} thermal and j^{th} wind units at time t respectively, N_T & N_w are the total number of thermal and wind units respectively is the scheduling time intervals, $T_{i,down}$ and $T_{i,cold}$ are the minimum down time and cold start-up time of i^{th} thermal unit in hours respectively, $T_{i,off}^t$ is the continuously-off time of i^{th} thermal unit till time t in hours, d_j is the direct cost coefficient for the j^{th} wind unit, $\mu_{o,j}$ is the penalty cost coefficient of buying power from reserve owing to overestimation of wind power in \$/MWh for the j^{th} wind unit, $\mu_{u,j}$ is the penalty cost coefficient for the wastage of excess wind power in \$/MWh for the j^{th} wind unit, $w_{r,j}$ is the rated generating capacity of j^{th} wind unit and $f_W(w^t)$ is the WTG wind power PDF represented in (4)-(6).

B. Constraints

The various constraints imposed on WTUC problem are as follows:

1) *System Power Balance Constraint:* The power generated from all the committed thermal and wind units must satisfy the hourly load demand over the planning period:

$$\sum_{i=1}^{N_T} P_i^t \cdot U_i^t + \sum_{w=1}^{N_w} w_j^t \cdot Q_j^t = P_D^t \quad ; \quad t = 1,2,...,T \quad (13)$$

where P_D^t is the load demand at hour t in MW.

2) *Thermal Unit Ramp Rate Limits:* Practically, the operating range of all thermal generators is limited by their ramp rate limits that are considered as:

$$\begin{cases} P_i^t - P_i^{t-1} \le UR_i & \text{when unit } i \text{ ramps up} \\ P_i^{t-1} - P_i^t \le DR_i & \text{when unit } i \text{ ramps down} \end{cases} \quad (14)$$

where UR_i and DR_i are the ramp-up and ramp down limits of i^{th} thermal unit in MW.

3) *Thermal Generation Limit Constraints:* Each committed thermal unit must be within its specified generation limits as:

$$P_i^{\min}U_i^t \le P_i^t \le P_i^{\max}U_i^t \quad (15)$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum power generation capacities of i^{th} thermal unit in MW.

4) *Wind Generation Limit Constraints:* The power generated from each wind unit must be within its specified limits as:

$$0 \le w_j^t \le w_{r,j} \quad ; \ j = 1,2,...,N_w \ ; \ t = 1,2,...,T \quad (16)$$

5) *Spinning Reserve Constraint:* Spinning reserve should be available during the operation of a power system and considered as a pre-specified value or a given percentage of the forecasted demand and wind capacity at a particular time instant t as mentioned below:

$$\sum_{i=1}^{N} P_i^{\max} \cdot U_i^t \ge \left[\left(1 + SR_D\right) \times P_D^t + SR_W \times \sum_{j=1}^{N_w} w_{r,j} \cdot Q_j^t\right] \quad (17)$$

where SR_D is the fraction of total system load at time t in MW and SR_W is the fraction of total wind power employed to compensate wind power prediction errors (%)?

6) *Thermal Unit Minimum Up/Down Time Constraint:* A unit must be kept online or offline for a minimum number of hours before committing ($0 \rightarrow 1$) and decommitting ($1 \rightarrow 0$) as:

$$U_i^t = \begin{cases} 0 \rightarrow 1, \; if \;\; T_{i,off}^{t-1} \geq T_{i,down} \\ 1 \rightarrow 0, \; if \;\; T_{i,on}^{t-1} \geq T_{i,up} \\ 0 \; or \; 1, \; otherwise \end{cases} \tag{18}$$

where $T_{i,up}$ is the minimum-up time of i^{th} thermal unit in hours, $T_{i,on}^{t-1}$ is the continuously-on time of i^{th} thermal unit till hour (t-1) in hours.

IV. Artificial Bee Colony (ABC) Algorithm

ABC is a population based meta-heuristic algorithm developed by Karaboga and Basturk [20], which is inspired by the intelligent foraging behavior of honeybee swarm. In this algorithm, the bees are classified into three categories namely employed, onlooker and scout. When an initial colony is generated randomly, the employed and onlooker bees exert a probabilistic modification on the position of current food sources for finding the new food sources using the difference equation as:

$$v_{j,d}^g = u_{j,d}^g + \psi_{j,d}^g (u_{j,d}^g - u_{k,d}^g) \tag{19}$$

where $j \in \{1,2,...,N_e\}$, $d \in \{1,2,...,D\}$, D is the dimension of the food source and k is randomly selected food source in a colony such that $k \neq j$, $u_{j,d}^g$, $u_{k,d}^g$ and $v_{j,d}^g$ are the old, randomly and newly generated food source positions in a colony at the g^{th} cycle respectively, $\psi_{j,d}^g$ is a random variate scaling factor between from 0 to 1 and N_e is the colony size. On the other hand, the onlooker bees tend to choose a food source based on the probability (p_{rj}) proportional to the quality of that food source given as:

$$p_{rj} = fit_j \Big/ \sum_{m=1}^{Ne} fit_m \tag{20}$$

where fit_m is the fitness value of the j^{th} food source representing the nectar amount consist by that food source.

If the position of a food source in a colony is not updated after a predefined number of cycles called 'limit' ($\in$), then the scout bee replaces that source with the new randomly generated food source as:

$$x_{j,d} = x_d^{\min} + (x_d^{\max} - x_d^{\min}) \times rand(0,1) \tag{21}$$

where $x_d^{\min}$ and $x_d^{\max}$ are the lower and upper limits of the d^{th} parameter respectively and can be either 0 or 1 for WTUC problem.

V. Proposed Optimization Models For WTUC Problem

In this section, the three optimization models namely NBABC, NBABC-LS and NBABC-GC are presented to solve the WTUC problem over the scheduling time horizon of 24 hours.

A. A New Binary Artificial Bee Colony Algorithm

The decision of WTUC problem incorporates the binary variables, and thus the difference equation (19) used in the original ABC algorithm could not be applied directly for the solution of WTUC problem. Therefore, in this work, an algorithm is presented, which is based on the new strategy that measures the dissimilarity between two binary strings and shows how far the two binary strings are apart from each other. The concept of similarity between two binary strings indicates that they share a common pattern among their bits [21]. The difference equation (19) can be adjusted to get $V_j^g - U_j^g = \psi \times (U_j^g - U_k^g)$ and replacing arithmetic operator "-" with "dissimilarity" measure that quantifies the distance between two binary strings. Thus, the new difference equation is obtained as:

$$Dissimilarity(V_j^g, U_j^g) \approx \psi \times Dissimilarity(U_j^g, U_k^g) \tag{22}$$

where V_j^g, U_j^g and U_k^g are the new, old and randomly selected food sources respectively at the g^{th} cycle in a colony and representing the possible solutions of WTUC problem and ψ is a positive random variate scaling factor from 0 to 1.

The reason of introducing the "$\approx$" (almost equal) operator in place of "=" (exactly equal) operator is that the newly generated solution may not be equal to the randomly selected solution in (22) due to the difference in the on/off status of the units. Now let us consider L_{11} represents the total number of bits with value 1 in both U_j^g and U_k^g (i.e. $u_{j,d}$ = $u_{k,d}$ = 1), L_{01} represents the total number of bits with value 0 in U_j^g and 1 in U_k^g (i.e. $u_{j,d}$ = 0 and $u_{k,d}$ = 1), L_{10} represents the total number of bits with value 1 in U_j^g and 0 in U_k^g (i.e. $u_{j,d}$ = 1 and $u_{k,d}$ = 0) and finally L_{00} represents the total number of bits with value 0 in both U_j^g and U_k^g (i.e. $u_{j,d}$ = $u_{k,d}$ = 0). Here $L_{11} + L_{01} + L_{10} + L_{00}$ = D. As per [21], Jaccard's coefficient of similarity is used to measure the degree of similarity between U_j^g and U_k^g as:

$$Similarity(U_j^g, U_k^g) = L_{11}/(L_{11} + L_{01} + L_{10}) \tag{23}$$

Therefore, the measure of dissimilarity between U_j^g and U_k^g is defined as:

$$Dissimilarity(U_j^g, U_k^g) = 1 - Similarity(U_j^g, U_k^g) \\ = 1 - L_{11}/(L_{11} + L_{01} + L_{10}) \tag{24}$$

The range of similarity and dissimilarity measure is 0 to 1. In (22), let $M = \psi \times Dissimilarity(U_j^g, U_k^g)$ then the value of $Dissimilarity(V_j^g, U_j^g)$ must be close to the value of M. Now, to produce the new binary solution V_j^g, the value of the following three variables must be determined:

- N_{11}: Number of bits with value 1 in both V_j^g and U_j^g
- N_{10}: Number of bits with value 1 in V_j^g and 0 in U_j^g
- N_{01}: Number of bits with value 0 in V_j^g and 1 in U_j^g

The optimum valuesof N_{11}, N_{10} and N_{01} is determined by solving the mathematical model as follows:

$$Minimize\ \left| 1 - N_{11}/(N_{11} + N_{10} + N_{01}) - M \right| \tag{25}$$

subject to:

$$N_{11} + N_{01} = n_1 \tag{26}$$

$$N_{10} \le n_0 \tag{27}$$

$$N_{11}, N_{01}, N_{10} \ge 0 : \text{ and integer} \tag{28}$$

where n_1 and n_0 be the total number of bits with value 1 and 0 in U_j^g respectively. It requires $(n_1+1)(n_0+1)$ evaluations to solve the above mathematical model (25)-(28) optimally.

1) *Procedural Steps for Generating New Binary Solutions for WTUC Problem Using NBABC Algorithm:*

Step 1: Calculate the value of M using $M = \psi \times Dissimilarity(U_j^g, U_k^g)$ and use it in the mathematical model (25)-(28) to determine the values of N_{11}, N_{01} and N_{10}.

Step 2: Initialize V_j^g by a ($1 \times D$) zero vector.

Step 3: Randomly select N_{11} number of zero bits from V_j^g which their corresponding bits in U_j^g is 1 and then flip the selected bits in V_j^g from 0 to 1.

Step 4: Randomly select N_{10} number of zero bits from V_j^g which their corresponding bits in U_j^g is 0 and then flip the selected bits in V_j^g from 0 to 1.

Step 5: The new binary solution V_j^g is generated. Repeat the procedure for other binary strings.

2) *Choice of the Value of ϕ:* In order to avoid the slow and premature convergence speed, it is more appropriate to use the dynamic value of ψ. It depends on upper value ($\psi_{\max}$) and lower value ($\psi_{\min}$) that changes linearly throughout the iterative process as:

$$\psi^g = \psi_{\max} - ((\psi_{\max} - \psi_{\min})/g_{\max}) \times g \tag{29}$$

where g and $g_{\max}$ are the current and maximum number of cycles respectively.

3) *Intelligent Scout Bee Phase:* In an original ABC algorithm, the scout bee generates the new source randomly in order to replace the abandoned food source in a colony. But this randomly generated food source may not be feasible [22]. Therefore, in this work, the abandoned food source is replaced with the so-far found global best solution as:

$$U_n^g = U_{gbest}^g \tag{30}$$

where U_n^g is a newly assigned food source at the g^{th} cycle and U_{gbest}^g is the so-far found global best solution till cycle g.

B. Hybridizing Local Search with NBABC Algorithm

In this work, a swap move-based Local Search (LS) operator is integrated with the NBABC algorithm to form NBABC-LS algorithm. This LS operator exploits the neighborhood region of the current solution determined by NBABC algorithm and if a better solution exists, then it replaces the current solution with the so-far found best neighborhood solution. The operation of LS operator is based on the swap moves that flip the bit from 0 to 1 and vice versa in such a way that the total number of online units over the complete planning period in an individual string in a colony remains same. Basically, it has two input parameters, namely α_{local} and β_{local} out of which α_{local} controls the rate of recalling the LS in NBABC algorithm, whereas β_{local} determines the number of food sources in a current population on which the LS operator is to be performed. During the iterative process, whenever the value of uniformly distributed random number is less than or equal to the value of α_{local} i.e. $rand(0,1) \le \alpha_{local}$, the LS operator is applied to the number of β_{local} food sources in a colony.

C. Hybridizing Genetic Crossover with NBABC Algorithm

In order to enhance the exploration capability of the NBABC algorithm for solving the WTUC problem, the third model is proposed in which the Genetic Crossover (GC) is integrated with the NBABC algorithm. Since, each high ranking local best solution U_{lbest}^g rather than a single global best solution U_{gbest}^g may have a useful property that could be shared to evolve a new food source. Therefore, in each cycle, the 2-point crossover operator is applied between U_{lbest}^{g} (best food source in a current cycle) and U_{gbest}^{g} (best food source till the current cycle) to generate the two new genotypes. Out of the four food sources, the best food source having higher fitness value replaces the U_{gbest}^{g} and thus maintain the diversity in the solution search space. In any cycle, if the local best solution is same as the global best solution, then the next local best solution in a colony of the current cycle is selected for crossover with the global best solution.

D.Constraint Repairing Strategies

When an initial solution is randomly generated or whenever the modification in the position of food sources is made by the employed and onlooker bees, then the constraints of the problem may violate typically the load balance and minimum up/down time constraints that makes the solution infeasible. Also, it slows down the convergence process. Therefore, in this work, the repairing strategies as suggested in [23] are adapted to satisfy these constraints in order to obtain the feasible solutions during the iterative process.

E. Wind and Thermal Dispatch

Once the on/off status of the thermal and wind units are decided over the complete scheduling time horizon, the hourly load demand is dispatched economically among the committed thermal and wind units. First, the output of wind generation unit is calculated, which is closely related to the wind speed at the height of unit hub. The available power of the wind that crosses the rotor of the j^{th} WTG [24] at time t ($P_{j,w}^{t}$) is calculated as:

$$P_{j,w}^{t} = \frac{1}{2}\cdot \rho \cdot A \cdot \left(v^{t}\right)^{3} \tag{31}$$

where ρ is the air density in Kg/m^3, *A*is the rotor swept area in m^2 and v^t is the wind speed at time *t*.

The wind generator can recover some of this wind power and represents the power produced by the wind generator ($P_{j,e}^{t}$) as:

$$P_{j,e}^{t} = C_p \times P_{j,w}^{t} \tag{32}$$

where C_p is the power coefficient of WTG, which is a nonlinear function of the tip speed ratio and pitch angle [25].

Since the wind speed profile at a particular geographic location most closely follow the Weibull distribution over time. Therefore, the expression for calculating wind power generation in (31) is modified based on the Weibull PDF and is expressed as [26]:

$$w_{j}^{t} = \frac{1}{2}\cdot \rho \cdot A \cdot \left(c^{t}\right)^{3} \cdot \Gamma\left(1+\frac{3}{k^{t}}\right) \tag{33}$$

where w_j^t is the scheduled wind power of the j^{th} wind unit at time t, $k^t > 0$ is the shape parameter at time t, $c^t > 0$ is the scale parameter at time *t* in m/s and $\Gamma(\cdot)$ is the gamma function represented as folows:

$$\Gamma(z) = \int_{0}^{\infty} s^{z-1}\cdot e^{-s} ds\ ; \qquad s > 0 \tag{34}$$

In order to calculate the wind power using (33), the Weibull shape and scale parameters (k^t and c^t) need to be estimated. For this purpose, the energy pattern factor method [27] is used for the measured wind speed data. It is defined as:

$$E_{pf} = \frac{\overline{(v^{t})^{3}}}{\left(\overline{v}^{t}\right)^{3}} \tag{35}$$

where E_{pf} is the energy pattern factor, $\overline{(v^{t})^{3}}$ is the mean of hourly wind speed cubes and $\overline{v}^{t}$ is the mean of hourly wind speed. Now, the Weibull shape and scale parameters are estimated as:

$$k^{t} = 1 + \frac{3.69}{E_{pf}^{2}} \tag{36}$$

$$c^{t} = \frac{\overline{v}^{t}}{\Gamma(1+1/k^{t})} \tag{37}$$

After obtaining the scheduled wind power over the planning period, the residual load demand is calculated by subtracting the magnitude of the scheduled wind power from the hourly system load demand (P_D^t). Hereafter, this residual load demand obtained in each hour is dispatched economically over the committed conventional thermal units with and without considering ramp rate limits. The classical lambda iteration method is used to calculate the output power of each committed thermal unit. When ramp rate constraints are considered, the minimum and maximum generation capacities of thermal units are modified based on the ramp rate limits as in (14). The procedural steps for performing dispatch are as:

Step 1: Set time counter $t = 1$.

Step 2: Calculate the scheduled power of each committed wind unit using (33).

Step 3: Use lambda iteration method to calculate the output power of each committed thermal unit without considering ramp rate limits and go to Step 6.

Step 4: Modify the generation capacities of each committed thermal units based on the ramp rate limits.

Step 5: Perform economic dispatch on committed thermal units using lambda iteration method to calculate the output power at time *t*.

Step 6: If $t < T$, set $t = t+1$ and go to Step 4; else, print the optimum dispatch schedule.

VI. Computational Framework of Proposed Optimization Models for WTUC Problem

The computational framework for solving the WTUC problem is presented as follows:

Step 1: Load historical wind speed and turbine data, thermal unit data and load pattern.

Step 2: Randomly generate the initial population of food sources in which each food source represents the units on/off status over the complete scheduling time horizon, and thus consist of $(N_T + N_w)\times T$ bits. The string is represented as:

$$X_i = [U_1^1 \ \dots \ U_1^T \ \dots \ U_i^t \ \dots \ U_N^1 \ U_N^2 \ \dots \ U_N^T \\ Q_1^1 \ \dots \ Q_1^T \ \dots \ Q_j^t \ \dots \ Q_N^1 \ Q_N^2 \ \dots \ Q_N^T] \tag{38}$$

Step 3: Apply constraint repairing strategies on infeasible strings and then perform economic dispatch on feasible strings as described in Section V E.

Step 4: Evaluate the fitness function of each food source using (7).

Step 5: Identify U_{lbest}^g and U_{gbest}^g of the population.

Step 6: Start employed bee phase and generate the new colony. Apply constraint repairing strategies on infeasible strings and then perform economic dispatch on feasible strings. Evaluate the fitness of new food sources in a colony. If a new solution is fitter than the old one, then a new solution replaces the old one.

Step 7: For NBABC-GC algorithm, update U_{lbest}^g and U_{gbest}^g of the colony and then apply genetic crossover between U_{lbest}^g and U_{gbest}^g to further update the U_{gbest}^g food source position.

Step 8: Start onlooker bee phase to update the positions of food sources based on the probability (p_{rj}) proportional to the quality of that food source calculated using (20). If a new food source position is fitter than that of old one, then it replaces the old food source position. Here, the Roulette wheel selection mechanism is used to select the food source sites based on their fitness values.

Step 9: For NBABC-GC algorithm, update U_{lbest}^g and U_{gbest}^g of the colony and then apply genetic crossover between U_{lbest}^g and U_{gbest}^g to further update the U_{gbest}^g food source position.

Step 10: Perform intelligent scout bee phase.

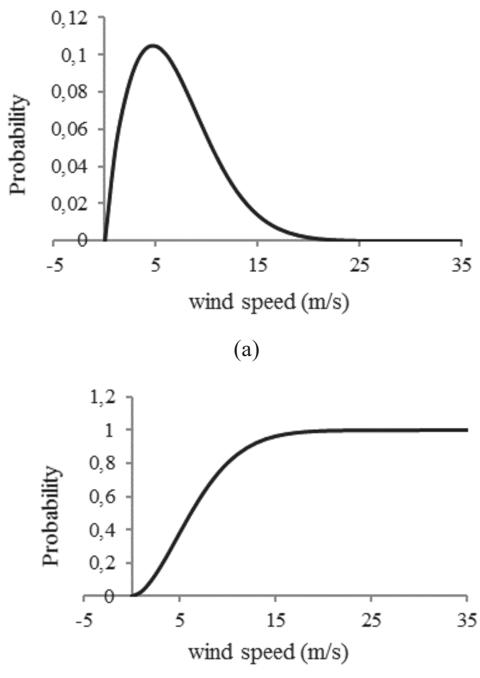
Step 11: For NBABC-LS algorithm, apply a local search operator to modify the food source positions in a colony and then perform Step 3 and Step 4 to evaluate the fitness of new food source positions. If a new food source position is fitter than that of the old one, then it replaces the old food source position.

Step 12: Memorize the best solution found so far and increment the cycle count.

Step 13: Terminate the process if the maximum number of cycles are reached and print the optimum WTUC schedule. Otherwise, increase the cycle number and go to Step 6.

VII. Results and Discussion

In order to verify the feasibility and efficiency of the proposed optimization models namely NBABC, NBABC-LS and NBABC-GC for solving WTUC problem, these are tested on a modified 10-unit IEEE thermal test system integrated with the wind farm consisting 50 wind turbines of the same type with rotor diameter of 90 m. Each turbine rated power is 3.0 MW, cut-in wind speed $v_i = 4$ m/s, cut-out wind speed $v_o = 25$ m/s and rated wind speed is $v_r = 16$ m/s that are taken from [18]. Here, the whole wind farm would be regarded as one unit to participate in the commitment and dispatch process. The underestimated unbalanced coefficient ($\mu_{u,j}$) and the overestimated unbalanced coefficient ($\mu_{o,j}$) are considered as 10 and 15 \$/MWh respectively. The wind speed historical data are adopted from the wind observation station [28]. The 10-unit thermal system data and load demand are adopted from [23]. The program is written in MATLAB and is performed on Intel (R) core (TM) 2 duo T6600 @ 2.20 GHz processor with 32-bit operating system.



(b)

Fig. 2 Weibull (a) PDF (b) CDF for k = 1.76 and c = 7.58

The wind speed probability distribution at the wind farm site is characterized by the Weibull parameters (k^t and c^t). The curves of Weibull probability and cumulative distribution functions for the obtained wind speeds are illustrated in Fig. 2.

To tune the parameters of the NBABC and NBABC-GC methods, namely bee colony size (N_e), maximum cycle number ($g_{\max}$), limit count ($\in$) and random variate scaling factor (ψ), whereas local search parameters (α_{local} and β_{local}) in combination with N_e, ψ, $\in$ and $g_{\max}$ for the NBABC-LS method. For better convergence characteristics, these controlling parameters must be tuned optimally. During the parameters sensitivity analysis for all the three methods, the colony size was set not more than 40 to show the effect of a small colony size, and the maximum cycles ($g_{\max}$) were set not more than 200 in order to reduce the computational overhead. The range of ψ is considered as [0,1]. In order to enhance the exploration during the initial process, higher value of ψ is used initially and with the lapse of iterations it decreases gradually and finally set to a minimum value i.e. exploration fades-out and exploitation fades-in using (29). The value of $\in$ is set as 10 to 40 cycles with a step size of 10 for each food source in the colony. The range of α_{local} is considered as [0.01, 0.3], which is appropriate to exploit the neighborhood of the current food source. Whenever slow or premature convergence is observed, the value of α_{local} is increased or decreased by 0.01, respectively. The local search is performed on each food source in a colony and therefore, the value of β_{local} is same as colony size. The best found parameters of NBABC algorithm are $N_e = 20$, $g_{\max} = 200$, $\psi = [0.5,0.1]$, $\in = 20$. The best found parameters of NBABC-LS method are $N_e = 20$, $g_{\max} = 200$, $\psi = [0.5\text{-}0.1]$, $\in = 20$, $\alpha_{local} = 0.02$ and β_{local} is set equal to N_e. The best found parameters of NBABC-GC algorithm are $N_e = 20$, $g_{\max} = 200$, $\psi = [0.9\text{-}0.1]$, $\in = 30$.

In order to compare the optimal characteristics of the proposed methods, the same WTUC problem is also solved by using GA. To tune the GA parameters, ten random trials were conducted on the considered test system for both case studies. The best found parameters of GA are population size = 30, maximum generation count = 200, crossover probability p_c = 0.8 and mutation probability $p_m = 0.012$.

In order to guarantee the robustness of the proposed methods, the simulation is repeated 30 times over the best found parameters. When thermal ramp rate constraints are not considered, the values of SR_D and SR_W are set as 10% of the hourly load demand and 5% of the online rated wind unit capacity, respectively. The total System Reserve Requirement (SRR) is calculated by using (17). For instance, the SRR without ramp rate constraints at hour 12 is 157.5 MW, which is obtained by summation of the two parts; the first part is 150 MW (10 % of the total load) and the second part is 7.5 MW (5 % of total rated capacity of the wind farm). This is the maximum possible reserve that can be distributed on the thermal units. When ramp rate constraints are considered, the fixed value of SR_D is not considered in each hour, whereas the value of SR_W is set as 5% of the online rated wind unit capacity. Moreover, the thermal units ramp-up (UR_i) and ramp-down (DR_i) limits are considered as 20% of the maximum capacity of units. Therefore, the MW/hour values of UR_i and DR_i for thermal units 1 to 10 in 10-unit system are set to 91, 91, 26, 26, 33, 17, 16, 11, 11, and 11, respectively.

TABLE I
OBTAINED WEIBULL PARAMETERS FOR THE HISTORICAL WIND DATA

Hour	1	2	3	4	5	6
k^t	1.53	1.49	1.53	1.49	1.41	1.43
c^t (m/s)	6.35	5.96	5.57	5.76	5.59	5.54
Hour	7	8	9	10	11	12
k^t	1.44	1.36	1.47	1.66	1.82	1.83
c^t (m/s)	5.48	5.34	5.84	6.80	7.29	7.63
Hour	13	14	15	16	17	18
k^t	1.77	1.76	1.87	1.90	2.07	1.90
c^t (m/s)	8.22	8.66	8.97	9.34	9.67	9.09
Hour	19	20	21	22	23	24
k^t	1.90	1.78	1.63	1.53	1.50	1.35
c^t (m/s)	8.61	7.77	6.90	6.71	6.66	6.56

Based on the wind speed data, the Weibull shape and scale parameters (k^t and c^t) are estimated and are provided in Table I.

The best generation schedules obtained in 30 runs using NBABC-GC method without and with thermal unit ramp rate constraints are presented in Tables II and III respectively.

In Tables II and III, T1 to T10 represent the scheduled output of thermal units, WF is the scheduled output of a wind farm comprises of 50 wind turbines and *TOC* is the total operating expected cost of wind-thermal system. From these tables, it is inferred that although the wind energy is freely available, the wind unit is kept off for some hours. It is due to higher expected costs associated with overestimation and underestimation penalties on wind power fluctuations. It is also observed from these tables that, in a 10-unit thermal system, the first unit is the most economical unit and thus, set at its maximum capacity (455 MW). Moreover, based on the economic dispatch solution, thermal units 3 and 4 mostly run at their maximum capacity (130 MW), if these units are online. However, this is not always true when thermal ramp rate limits are considered. Since, ramp rate limits modify the minimum and maximum thermal generating capacity of units, and thus making them a function of time in this process. It can be seen in these tables, the inclusion of thermal ramp rate limits not only changes the on/off status of the thermal and wind units, but the thermal generation values are also changed for the same on/off status at a particular time interval. It results in higher total operating cost of WTUC system, which is increased by $2216.09 compared to the wind-thermal schedule without thermal ramp rate limits obtained using the proposed NBABC-GC method.

TABLE II
BEST GENERATION SCHEDULE OBTAINED USING NBABC-GC METHOD IN 30 RUNS WITHOUT RAMP RATE CONSTRAINTS

T	Units output power (MW)											*TOC* ($/h)
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	WF	
1	455	245	0	0	0	0	0	0	0	0	0	13,683.07
2	455	279.18	0	0	0	0	0	0	0	0	15.82	14,581.03
3	455	357.78	0	0	25	0	0	0	0	0	12.22	17,754.93
4	455	455	0	0	40	0	0	0	0	0	0	18,597.47
5	455	375.47	0	130	25	0	0	0	0	0	14.53	20,612.99
6	455	360	130	130	25	0	0	0	0	0	0	23,487.18
7	455	410	130	130	25	0	0	0	0	0	0	23,262.03
8	455	446.32	130	130	25	0	0	0	0	0	13.68	24,175.35
9	455	455	130	130	69.78	20	25	0	0	0	15.22	28,096.74
10	455	455	130	130	155.49	20	25	10	0	0	19.51	30,024.04
11	455	455	130	130	162	51.90	25	10	10	0	21.10	31,835.31
12	455	455	130	130	162	80	25	18.85	10	10	24.15	33,690.08
13	455	455	130	130	143.55	20	25	10	0	0	31.45	29,797.74
14	455	455	130	130	48.05	20	25	0	0	0	36.95	26,954.73
15	455	421.99	130	130	25	0	0	0	0	0	38.01	23,921.88
16	455	267.69	130	130	25	0	0	0	0	0	42.31	21,254.73
17	455	217.40	130	130	25	0	0	0	0	0	42.60	20,358.07
18	455	320.94	130	130	25	0	0	0	0	0	39.06	22,158.59
19	455	427.05	130	130	25	0	0	0	0	0	32.95	23,984.02
20	455	455	130	130	148.68	20	25	10	0	0	26.32	30,362.47
21	455	455	130	130	63.99	20	25	0	0	0	21.01	27,176.40
22	455	455	0	0	123.60	20	25	0	0	0	21.40	22,646.17
23	455	420	0	0	25	0	0	0	0	0	0	17,684.64
24	455	319.22	0	0	0	0	0	0	0	0	25.78	15,371.88
Total operating cost (*TOC*) over 24-hour time horizon												**$ 561,471.54**

TABLE III
BEST GENERATION SCHEDULE OBTAINED USING NBABC-GC METHOD IN 30 RUNS WITH RAMP RATE CONSTRAINTS

T	Units output power (MW)											*TOC* ($/h)
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	WF	
1	455	226.79	0	0	0	0	0	0	0	0	18.21	13691.86
2	455	279.18	0	0	0	0	0	0	0	0	15.82	14581.24
3	455	370	0	0	25	0	0	0	0	0	0	17,709.62
4	455	455	0	0	25.75	0	0	0	0	0	14.25	18,597.45
5	455	390	0	130	25	0	0	0	0	0	0	20,580.12
6	455	346.21	130	130	25	0	0	0	0	0	13.79	23524.22
7	455	410	130	130	25	0	0	0	0	0	0	23261.81
8	455	455	130	130	30	0	0	0	0	0	0	24,150.15
9	455	455	130	130	63	42	25	0	0	0	0	28163.92
10	455	455	130	130	96	58	25	0	31.49	0	19.51	30265.45
11	455	455	130	130	129	74	25	10.41	20.49	0	21.10	31956.20
12	455	455	130	130	162	80	25	18.85	10	10	24.15	33690.12
13	455	425.55	130	130	129	64	25	10	0	0	31.45	29,984.67
14	455	379.06	130	130	96	48	25	0	0	0	36.95	27232.93
15	455	384.01	130	130	63	0	0	0	0	0	38.00	24018.46
16	455	293.01	105.75	123.93	30	0	0	0	0	0	42.31	21278.12
17	455	260	130	130	25	0	0	0	0	0	0	20,641.71
18	455	351	130	130	34	0	0	0	0	0	0	22,408.96
19	455	442	130	130	43	0	0	0	0	0	0	24182.05
20	455	455	130	130	76	80	25	22.68	0	0	26.32	30573.87
21	455	431.99	130	130	43	64	25	0	0	0	21.01	27356.02
22	455	455	0	0	76	67.60	25	0	0	0	21.40	22759.48
23	455	380.24	0	0	43	0	0	0	0	0	21.76	17707.48
24	455	319.22	0	0	0	0	0	0	0	0	25.78	15,371.72
Total operating cost (*TOC*) over 24-hour time horizon												**$ 563,687.63**

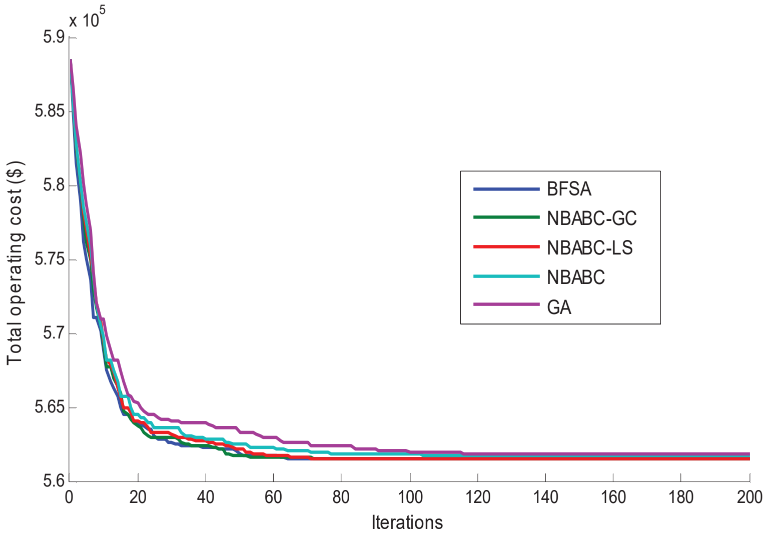


Fig. 3 Convergence characteristics without ramp rate constraints

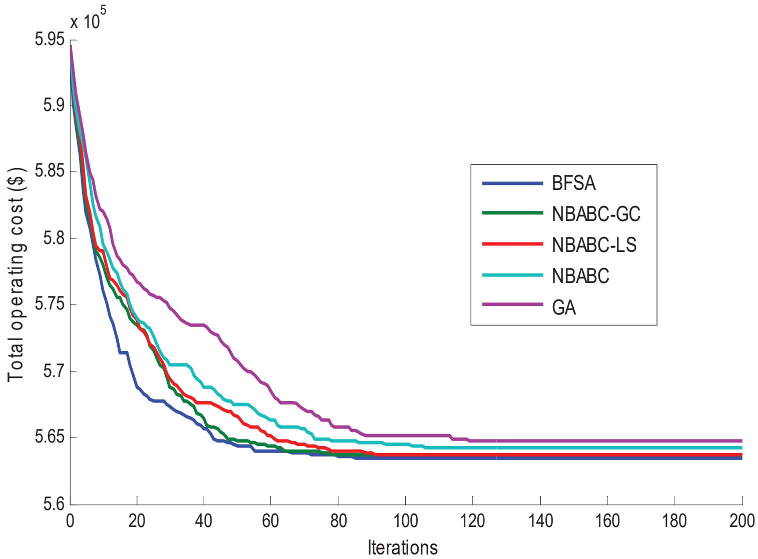


Fig. 4 Convergence characteristics with ramp rate constraints

Figs. 3 and 4 illustrate the convergence characteristics obtained by using GA, NBABC, NBABC-LS and NBABC-GC methods for the best run out of a set of 30 runs without and with thermal ramp rate constraints, respectively. From these figures, it is deduced that starting with the same initial point, NBABC-GC method is capable in reaching to the better optimal solution at the end of the convergence process compared to GA, NBABC, NBABC-LS, and NBABC-GC methods. It is because; the genetic crossover explores the search space rapidly by comparing the local best solution with the so-far found global best solution during the iterative process and thus avoids the problem of slow and premature convergence problems. Moreover, the constraints repairing and unit decommitment strategies keep the search space feasible throughout the iterative process. From Fig. 4, it is deduced that the GA method becomes more sluggish with the incorporation of ramp rate constraints compared to that without ramp rate constraints. It is due to the more local trappings encountered with the GA method during the search process.

Fig. 5 shows the solution quality of the schedule obtained using NBABC-GC method without thermal ramp rate constraints. From Fig. 5, it is inferred that the sufficient amount of maximum online capacity of thermal units is available in each hour to satisfy the load demand and spinning reserve requirements.

The statistical comparison of the obtained results in terms of total operating cost (best, average and worst), mean time and standard deviation (*STD*) using proposed methods are presented in Table IV. It is inferred from this table that when thermal ramp rate constraints are not considered, the best cost achieved by using NBABC-GC method is \$ 50.93, \$ 233.28 and \$ 393.53 less than that obtained by using NBABC-LS, NBABC and GA methods, respectively. However, when thermal ramp rate constraints are considered, the NBABC-LS method is successful in achieving the same best cost as obtained using the NBABC-GC method. It is $ 533.25and $ 1121.99 less than that obtained by using the NBABC and GA methods, respectively. From Table IV, it is inferred that the NBABC-GC method is capable to achieve the quality cost solutions in less execution time compared to all the other methods.

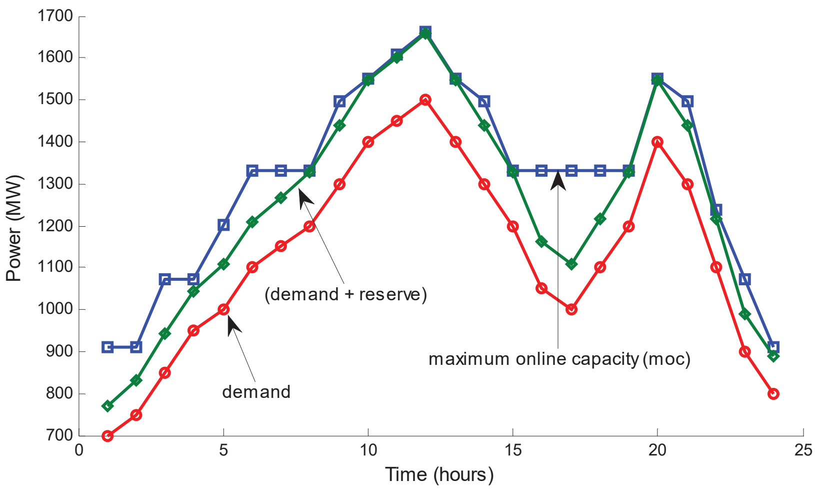


Fig. 5 Comparison between available total online generation capacity, load and demand considering spinning reserve without ramp rate constraints using NBABC-GC method

TABLE IV
STATISTICAL COMPARISON OF THE PROPOSED METHODS

Methods	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Mean Time (s)	*STD*
without thermal unit ramp rate constraints					
GA	561,865.07	561,996.77	562,181.36	46.61	103.30
NBABC	561,704.82	561,839.94	561,993.07	50.29	94.55
NBABC-LS	561,522.47	561,662.90	561,838.95	39.13	85.48
NBABC-GC	561,471.54	561,624.47	561,754.24	34.80	86.74
with thermal unit ramp rate constraints					
Methods	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Mean Time (s)	*STD*
GA	564,809.62	565,030.50	565,616.04	81.07	244.76
NBABC	564,220.88	564,591.18	564,877.61	79.52	187.84
NBABC-LS	563,687.63	564,059.06	564,362.15	67.45	183.39
NBABC-GC	563,687.63	564,017.91	564,185.36	59.86	161.82

VIII. CONCLUSION

In this paper, the proposed optimization models namely NBABC, NBABC-LS and NBABC-GC are successfully applied to solve the WTUC problem over the 24-h scheduling time horizon. The uncertain nature of the wind speed has been represented by the Weibull probability distribution function. In addition, the wind generator cost modeling in terms of penalties associated to over- and underestimation of wind power has been successfully incorporated in the WTUC model. To compare the results obtained by using the proposed methods, GA has been utilized to solve the same WTUC problem. The numerical results show that the sufficient reserve has been maintained in the system that could cater the generation deficit occur due to load forecasting and wind prediction errors. The extensive computation study reveals that the NBABC-GC method is capable to provide quality solutions in terms of minimum total operating cost and execution time, when applied repeatedly to solve the same WTUC problem. Compared to all other methods, the NBABC-GC method has enhanced the quality of the solutions and therefore could be used as an efficient optimization tool for practical applications.

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