



A Computational Framework for Wind Power Integration in Stochastic Optimal Power Flow Analysis

Ambarish Panda

Department of Electrical and Electronics Engineering
Sambalpur University Institute of Information Technology
Jyoti Vihar, Burla
India

Abstract: The intermittent nature of wind introduces enormous challenges in the traditional generation scheduling methodologies and operation of wind integrated power system. Considering this aspect, for solving the optimal operation of wind integrated power system in a multi objective optimal power flow (MOOPF) framework, the paper presents a hybrid approach combining modified bacteria foraging algorithm (MBFA) and genetic algorithm (GA) for evaluation of optimized generation schedule. Apart from cost minimization issues, the work focuses on voltage security aspect of the system both during normal and stressed operating conditions including aerodynamic non-linearities along with reduction in system transmission loss. To test the effectiveness of the proposed method, it is compared with efficient bio-inspired algorithms like flower pollination algorithm (FPA) and differential evolution algorithm (DE). The analysis is carried out on IEEE30 bus power system. The comparative analysis shows that HA might be a promising alternative among the intelligent techniques for solving OPF problems in practical power system.

Keywords: Wind integration; voltage security; power system operation; OPF; optimization.

I. Introduction

Economy and security are the two aspects which are given paramount importance during operation and analysis of modern power system. If wind power is integrated with conventional power generation system, the uncertainty of the wind output introduces colossal difficulties in the scheduling of the generating units which may lead to vulnerable system operation. By properly formulating and adding suitable cost components with the system operating cost, the variability of wind during under estimation (UE) and over estimation (OE) scenario can be mitigated. This fact has been demonstrated in [1,2]. OPF is a non-convex, non-linear and large-scale constrained optimization problem which aims at finding the optimal settings of a power system for economic operation subject to various system operating constraints. Various traditional optimization techniques [3-5] have been developed to solve the OPF problem. Some of these techniques which make use of derivatives and gradients have brilliant convergence characteristics and are widely used; however, they are formulated with some theoretical assumptions and fail to deal with systems having non-smooth, non-convex and non-differentiable objective functions and constraints. Application of particle swarm optimization (PSO) algorithm [6] and Tabu search (TS) based approach [7] for determination of optimal settings of control variables of OPF problem has been demonstrated on IEEE 30 bus test system. Solution of OPF problem with multiple and competing objectives with differential evolution (DE) approach is presented in [8, 10]. The objective in these works aims at handling non-smooth and non-convex generator fuel cost characteristics while considering constrain-domination approach [8], piecewise quadratic cost function [9] and optimal reactive power dispatch [10]. Generally, evolutionary methods like DE, PSO need several trials to achieve optimal or near optimal solution and require special care in tuning of parameters associated with it. To overcome these limitations advanced intelligent techniques are proposed. In this context, an effective and reliable biogeography based optimization algorithm (BBO), for solving the optimal power flow problem with non-smooth and non-convex generator fuel cost characteristics is presented in [11]. Optimization algorithms like multi-agent based differential evolution (MADE) [12] and artificial bee colony algorithm [13] have been applied for evaluation of OPF problem. The fact which is common in all the above mentioned work is that, the various intelligent techniques has been used to optimize the operational cost and other issues of conventional thermal generator based power system only. Recently, a number of researchers have focused on finding an optimal operational schedule for intermittent generation incorporated with conventional fossil fuel based power system. Authors in [14] have formulated an OPF model for minimizing the emission reduction issue of wind-thermal generation system. In [15], a modified bacteria foraging algorithm (MBFA) has been applied to solve OPF solution of wind integrated system with consideration of necessary reactive power support. The consequence of volatility

of wind power generation has been properly demonstrated by authors in [16] in a risk limiting OPF (RLOPF) formulation. Authors in [17], have formulated a multi-objective optimization of power system in the presence of FACTS devices in security constrained OPF (SCOPF) framework. Application of artificial bee colony algorithm (QCABC) with quantum theory and the chaotic local search strategy has been applied to solve the OPF problem [18] with valve point loading effects.

In this work, an improved technique known as hybrid algorithm (HA) which combines specific attributes of genetic algorithm (GA) with MBFA is applied to find the optimal operational paradigm of wind thermal generation system. In order to validate the efficiency of the proposed method, HA, DE and flower pollination algorithm (FPA) have been applied to IEEE 30 bus system. The optimized generation schedule obtained with the three techniques are compared which distinctly portrays the superiority of HA over DE and FPA in a cost effective and voltage secure manner system operation under different scenarios.

The distinctive contributions of the work may be enumerated as below

- Implementation of HA, FPA and DE Algorithm on optimal operation of wind integrated power system in MOOPF framework.
- Effect of aerodynamic non-linearity in the form of turbulence on system voltage.
- Validation of the proposed results in IEEE 30 bus power system .
- Demonstrations of superiority of HA compared to FPA and DE in terms of getting a faster, better and secure solution.

The paper is organized in the following manner. The main problem is formulated in Section II. Section III presents a brief overview of optimization techniques implemented in this work. In Section IV, procedural details of simulations and results are depicted with discussion. In the same section few pertinent observations are made concerning the results acquired which has led to conclusions in Section V.

II. Problem Formulation

The intermittency of wind is reflected in the operation of system in terms of lower controllability, lower predictability and higher vulnerability. Therefore, to take this intermittency into consideration, properly configured cost component are added with the cost of overall system operation [1]. These extra components are intended to mitigate the cost of operation during any imbalance between available and scheduled wind power.

The problem is formulated as follows,

Minimize

$$F = F_T + F_W + F_L + pf \quad (1)$$

In the above equation F_T and F_W corresponds to operational cost of thermal and wind power generation respectively, F_L denotes the cost associated with of real power transmission loss and pf is the component in the form of penalty function to restrict the constraints from being violated.

The mathematical interpretation of the above components are described as

$$F_T = \sum_u^{N_g} C_u(P_{gu}) \quad (2)$$

In this expression, subscript 'u' denotes the thermal units and subscript m and w denote the wind units. The term F_T in (2) is the cost of thermal power generation where

$$C_u(P_{gu}) = a_u P_{gu}^2 + b_u P_{gu} + c_u \quad (3)$$

Where a_u, b_u, c_u are the cost coefficients of u^{th} thermal unit and P_{gu} is the power output of u^{th} generator. Thus, (3) represents the cost correlated to thermal power generation. Similarly the mathematical formulation of different cost components associated with wind power is mentioned in (4) and the detailed expression is given in (5-7).

$$F_W = \sum_m^{N_w} [C_{wm}(P_{wm}) + C_{p,wm}(P_{wm,av} - P_{wm}) + C_{r,wm}(P_{wm} - P_{wm,av})] \quad (4)$$

The first term in F_2 is the purchase cost of wind power from the wind power producer, second and third terms reflect the cost of wind power intermittency during under and over estimation of actual available wind power respectively. Mathematical interpretation of these terms may be expressed as below

$$C_{wm}(P_{wm}) = d_m P_{wm} \quad (5)$$

Here d_m is the direct cost coefficient of the m^{th} wind generator and the scheduled power output of m^{th} wind unit is denoted by P_{wm} . The cost due to UE of available wind power may be expressed by (6)

$$\begin{aligned} C_{p,wm}(P_{wm,av} - P_{wm}) &= K_{pm}(P_{w,av} - P_{wm}) \\ &= K_{pm} \int_{P_{wm}}^{P_{mo}} (w - P_{wm}) f_w(w) dw \end{aligned} \quad (6)$$

When the actual available wind power (WP) becomes more than the estimated/ forecasted value, it is realized as under estimation scenario (UE). As maximum utilization of WP has to be ensured in a wind integrated system, the system operator (SO) attempts to achieve this objective in one of the following possible ways.

- The amount equal to surplus WP (i.e. the difference between actual available value and estimated value) may be lowered from the thermal power generated.
- The surplus WP (SWP) may be sold to adjacent utility.
- In case the above options fail then the SO has to pay a cost corresponding to SWP to the wind power producer (WPP) for not using the available wind resource. This cost component is called penalty cost which is formulated in (6).

In (6), K_{pm} is the penalty cost coefficient for the m^{th} windgenerator and $f_w(w)$ is the wind power probability density function(PDF) [15], known as Weibull distribution function. P_{wm} , P_{mo} , P_{mav} are respectively the scheduled, rated power and available wind power from m^{th} wind power generator. Cost associated with OE scenario may be expressed as

$$\begin{aligned} C_{Rwm}(P_{wm} - P_{mav}) &= K_{Rm}(P_{wm} - P_{mav}) \\ &= K_{Rm} \int_0^{P_{wm}} (P_{wm} - w)f_w(w)dw \end{aligned} \quad (7)$$

OE is a scenario which is taken into consideration when the actual available WP becomes less than the estimated/ forecasted value. To ensure the fact that the deficit wind power (DWP) which is the difference between estimated WP and available WP should not alter the load balance equation (11), some reserve units need to be called for compensating the DWP. Hence, certain amount of cost needs to be paid for calling the reserve units. This cost is termed as reserve cost and is denoted by the expression (7).

The third term of **F**, i.e. **F_L** represents the cost associated with minimization of real power transmission loss in the system. It may be expressed as

$$\begin{aligned} F_L &= C_L(P_{loss}) \\ &= C_L \sum_{k=1}^{NL} g_k [V_i^2 - V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \end{aligned} \quad (8)$$

In (8), g_k is the conductance of a transmission line k connected between buses i and j ; V_i , V_j , δ_i and δ_j are the voltage magnitude and phase angle of bus i and j respectively; NL - number of transmission lines.

The fourth term i.e. **pf** reflects the cost associated with violation of constraints in the form of penalty to be added to the objective function **F**. Mathematically, it may be formulated as below

$$pf = pf_1 + pf_2 \quad (9)$$

Where

$$Pf_1 = \text{abs}[\text{sign}(P_{max} - P_k) - 1] * pf + \text{abs}[\text{sign}(P_{min} - P_k) + 1] * pf \quad (10)$$

$$Pf_2 = \text{abs}[1 + \text{sign}(V_k - V_{max})] * pf + \text{abs}[1 - \text{sign}(V_k - V_{min})] * pf \quad (11)$$

In (10) and (11), P_k is the real power flow in K^{th} line under consideration. V_k is the voltage magnitude of K^{th} bus with limiting values V_{max} and V_{min} . Pf_1 , Pf_2 is the high penalty to be added in the objective function once the constraints begin to violate their limits. The inclusion of (10-11) ensures that, as long as the constraints are within the limit, the penalty term **pf** becomes zero. But, once the constraints begin to violate their min or max limit, a high value of penalty will be added. Thus, in a problem of minimization, these penalty factors increase the value of the objective function by adding a larger value in the case of limit violation.

The above mentioned objective function represented by (1) is subjected to the following equality and in-equality constraints.

$$\sum_{u=1}^{N_g} P_{gu} + \sum_{m=1}^{N_w} P_{wm} = P_{loss} + P_{load} \quad (12)$$

$$\sum_{u=1}^{N_g} Q_{gu} + \sum_{m=1}^{N_w} Q_{wm} = Q_{loss} + Q_{load} \quad (13)$$

$$P_{gu}^{min} \leq P_{gu} \leq P_{gu}^{max} \quad (14)$$

$$Q_{gu}^{min} \leq Q_{gu} \leq Q_{gu}^{max} \quad (15)$$

$$P_{wm} \leq P_{wm}^{max} \quad (16)$$

$$Q_{wm}^{min} \leq Q_{wm} \leq Q_{wm}^{max} \quad (17)$$

$$V_t^{min} \leq V_t \leq V_t^{max} \quad (18)$$

$$S_{lj} \leq S_{lj}^{max} \quad (19)$$

In the above expressions (12)-(19), the real and reactive power output of thermal generators are represented as P_{gu} , Q_{gu} respectively where as P_{wm} , Q_{wm} are the corresponding powers of wind powered units. S_{lj} defines apparent power flow of j^{th} branch. As line flow through each transmission line ought to be restricted by its capacity

limits, it is expressed in terms of constraint (19). Detailed modeling aspect of wind power variability may be referred from section-3 of [19] which is done by the author of this paper.

III. Implementation of Optimization Techniques

A. Flower Pollination Algorithm (FPA)

FPA proposed by X. S. Yang [22] is based on survival of the fittest member and the optimal reproduction of plants in terms of numbers as well as the fittest one. There are two key steps in this algorithm; namely global pollination and local pollination. The different stages of FPA may be summarized as follows

- 1 Global pollination may be represented by biotic cross-pollination, and movement of pollen-carrying pollinators is done according to Lévy flight.
- 2 Local pollination is realised by abiotic and self-pollination.
- 3 Pollinators can extend flower constancy, which is comparable to the probability of reproduction that is proportional to the resemblance of two flowers concerned.
- 4 A switch probability $p \in [0, 1]$ may control the interaction of local pollination and global pollination.
- 5 FPA has been applied by researchers in determination of optimal sizing and placement of capacitors in distribution system [20], combined economic and emission dispatch [21] and multi objective optimization [23].

B. Differential Evolution Algorithm (DE)

DE algorithm (DE) [8-10] is an established bio-inspired based algorithm, which has been applied in numerous optimization problems in power systems. The fundamental thought of DE is to acclimatize the exploration during the evolutionary process. At the set off of the evolution, the perturbations are large since parent populations are distant from each other. As the evolutionary process builds up, the population converges to a small region and the perturbations gradually become small [9]. As a result, the algorithm achieves a global exploratory search during the early phases of the evolutionary process and local exploitation during the later stage of the search. In DE, the fittest offspring competes one-to-one with that of corresponding parent which is different from other evolutionary algorithms. This one-to-one competition brings accelerated convergence rate. A population of P_m solution vectors is initialized randomly within the parameter bounds. By applying mutation, crossover and selection operators the population is adapted. Individuals of the present population become target vectors for the subsequent generation. By adding the weighted difference between two randomly chosen vectors to a third vector, the mutation operation produces a mutant vector for each target vector. A trial vector is generated by the crossover operation. It is done by assimilation of the parameters of the mutant vector with those of the target vector. Upon obtaining a better fitness value than the target vector, the trial vector replaces the target vector in the next generation.

C. Hybrid Algorithm (HA)

In [19], HA was implemented to the analysis of hybrid power system operation, where it was formulated by combining mutation with original version of BFA [24]. But in this work in order to improve the optimization efficiencies of GA and MBFA, HA is synthesized by hybridizing the mutation strategies of GA along with a modified strategy of BFA, i.e. MBFA which is implemented in [15,17]. The steps involved in HA can be explained as follows

At first, variables like number of control parameters (p), bacteria (S), chemotactic process (N_c), reproduction events (G) and elimination & dispersal events (D) for the algorithm, are initialized. Additionally, the control parameters like maximum swimming length N_s ($\leq N_c$), the probability of elimination and dispersal P_{ed} , the swarming coefficients i.e. $d_{attract}$, $\omega_{attract}$, $h_{repellent}$ and $\omega_{repellent}$, run length unit ($C(i)$) and swim length SL are all chosen judiciously. $P(p, S, I)$, specifies the location of the initial set of S bacteria, each consisting of p random numbers. After scaling up, each of the random numbers represents a possible solution of the control variables. The iterative steps of HA proceeds as follows. The cost function for the initial bacterial population inside the inner most chemotaxis loop, is evaluated. Any i^{th} bacterium and its corresponding cost function in the j^{th} chemotactic, k^{th} reproduction and l^{th} elimination stages is identified by $\theta^i(j, k, l)$ and $F(i, j, k, l)$ respectively. j , k , and l are initialized before the first iteration. Procedural details of HA may be referred from [19].

IV. Simulation, Results and Discussion

For simulation of the work, the IEEE 30 bus test system [15] is considered. The system is modified by replacing conventional generators with wind farms located at fifth, eleventh and thirteenth bus.

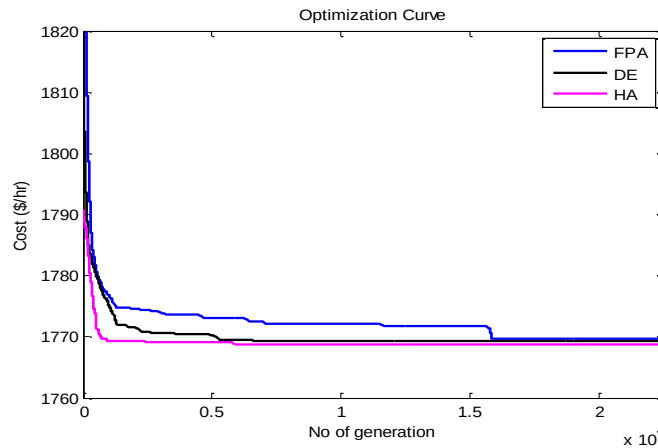


Fig.1.Comparison of convergence characteristics of FPA,DE and HA.

In this work, wind farm (WF) at bus number 5 consists of ten WTG (each of 5 MW) having a total capacity of 50 MW. Similarly WF at bus numbers 11 and 13 each consist of ten WTG of 4 MW capacities with a total capacity of 40MW. Three different optimization techniques implemented on the objective function (1) are examined for a comparative study. Details of parameters used in the optimization techniques are mentioned in Appendix.A. The operating cost of wind-thermal system is evaluated for the objective as specified in (1) and is optimized by applying FPA, DE and HA separately. The convergence characteristics obtained by these techniques are illustrated in Fig.1. The corresponding optimum generation scheduling obtained with the above techniques is depicted in Table.1.

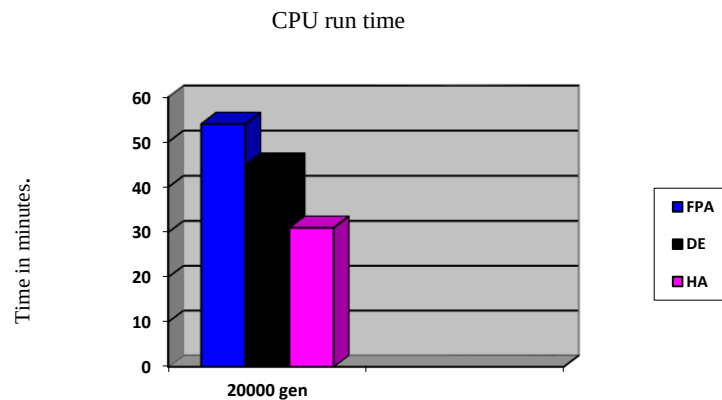


Fig.2. Time elapsed during the different optimization processes.

It is observed that solutions obtained with the HA converges at 1768.82 \$/hr, where as FPA and DE have managed to converge at 1769.60 \$/hr and 1769.33 \$/hr respectively. Thus, the effectiveness of HA is clearly portrayed in terms of obtaining most economic operating cost. The time taken by the three optimization techniques in achieving the converged solution is shown in Fig.2 which clearly depicts the superiority of HA in terms of faster convergence and thus consumption of minimum time. As shown in Table-1, the loss is converged to the minimum value in HA i.e. 0.0488 p.u. as compared to that obtained with DE (0.0492 p.u.) and FPA (0.0493 p.u.) optimized scenario.

Table-1. Optimal generation schedule obtained with HA, DE and FPA.

	HA		DE		FPA	
	P_g	Q	P_g	Q	P_g	Q
G1	1.334	0.9222	1.4392	0.9386	1.5288	0.9559
G2	0.179	-0.3266	0.1614	-0.3266	0.1612	-0.3266
G5	0.499	0.1100	0.4923	0.1100	0.4772	0.1100
G8	0.119	-0.4500	0.1083	-0.4500	0.0839	-0.4500
G11	0.400	0.3000	0.3792	0.3000	0.3282	0.2986
G13	0.379	0.3000	0.3377	0.2989	0.3465	0.3000
P_L (p.u.)	0.0488		0.0492		0.0493	
TC(\$/h)	1768.821		1769.335		1769.607	

IV.A. Analysis of system Voltage security during wind turbulence

In an attempt to examine the effectiveness of the HA optimized schedule over DE and FPA schedule, the wind-thermal system is intentionally subjected to aerodynamic non-linearity in the form of increasing wind turbulence [25]. This aspect has been properly modelled by formulating turbulence intensity (TI) (γ) and output coefficient under turbulence (Ψ_w) as mentioned below

$$\Psi_w(v_w, \gamma) \cong 1 - \exp \left[- \left\{ \frac{v_w / v_w^r}{c(\gamma)} \right\}^{k(\gamma)} \right] \quad (24)$$

Where v_w and v_w^r are the actual and rated wind speed in p.u. $c(\gamma)$ and $k(\gamma)$ are the scale and shape parameters expressed as a function of turbulence intensity (γ). Using suitable curve fitting approach $c(\gamma)$ and $k(\gamma)$ can be obtained [34] by

$$k(\gamma) \cong 3.49 - 6.01 * \gamma \quad (25)$$

$$c(\gamma) \cong 0.71 + 0.21 * \gamma - 1.26 * \gamma^2 \quad (26)$$

Thus, taking into account (24), (25) and (26), the effect of diverse level of turbulence on system operating voltage may be analyzed.

With the optimized schedule obtained with HA, DE and FPA algorithms as mentioned in Table-1, the system voltage security is investigated when the system is intentionally subjected to greater randomness of wind with increasing level of turbulence. Corresponding to each turbulence intensity i.e. (5% - 40%), a comparison between the voltage profiles obtained with the three intelligent techniques i.e. HA, DE and FPA is carried out individually. For 5% and 40% turbulence, the voltage profile is represented by Fig.3 and Fig.4, respectively. This gives a clear illustration of operational competency of HA optimised scenario over other efficient bio-inspired techniques even during highly intricate operating scenarios.

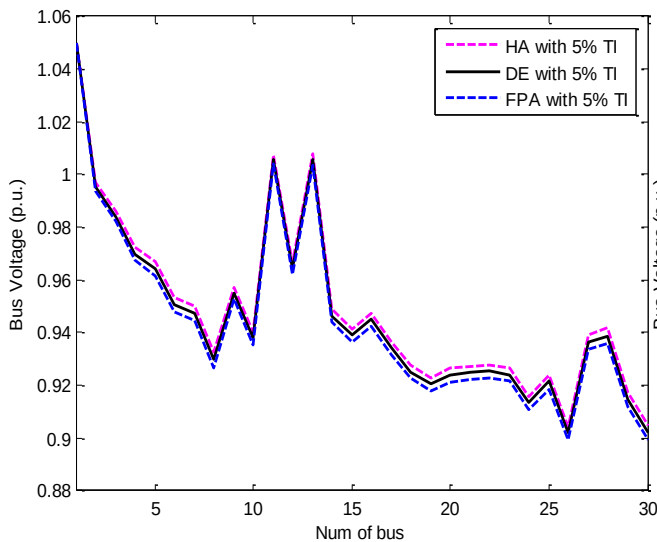


Fig.3. Effect of 5% TI on system voltage

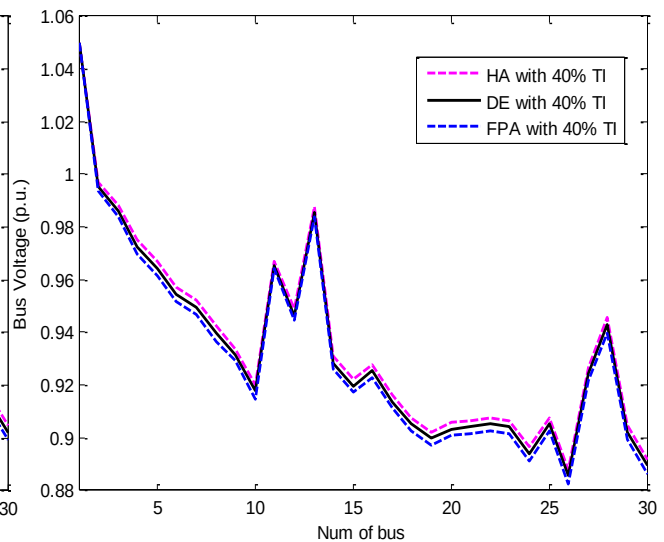


Fig.4. Effect of 40% TI on system voltage with different optimized scenario.

From the Figures (3 and 4), a statistical performance evaluation is done which may be summarized as below

- With of 5% TI, the mean and minimum system voltage as found from HA schedule is 0.9489 p.u. and 0.9043 p.u. while those with DE optimized schedule is 0.9466 p.u. and 0.9019 p.u. respectively and from FPA optimized schedule 0.9442 p.u. and 0.8991 p.u. It implies that HA schedule shows better voltage profile.
- Besides these findings, the standard deviation (SD) with 5% TI for HA, DE, FPA optimized schedule is 0.0329 p.u., 0.0333 p.u. and 0.0338 p.u. respectively.

V. Conclusion

A computational framework incorporating various operational issues associated with wind-thermal generation system, is properly formulated in a MOOPF framework. The objectives are formulated with pertinent consideration of real time operational constraints. Evaluation of the optimal generation schedule for which the wind thermal system may operate most effectively under normal, stressed and highly intricate operating conditions is done. For this purpose, the performance of HA, DE and FPA optimized schedules are evaluated and compared. All the simulations are carried out in MATLAB environment and finally, it is observed that HA retains its supremacy over the efficient bio-inspired algorithms like DE and FPA in terms of minimizing the cost and loss of system operation and enhancing the voltage security during different operating conditions. The obtained results

are validated in IEEE 30 bus power system with incorporation of wind powered generators. Further HA presented faster computation and convergence of the objective towards optimum value compared to other efficient techniques. So, in the real time planning, operation and analysis of power system with intermittent resources HA may be considered as a promising tool for power system operators.

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