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A New Multi-objective Approach for Voltage Optimization Control of Distributed Generation

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Abstract: The voltage optimization control is one of the most important problems in distribution networks. In this paper a multi-objective voltage optimizes control modeling is presented, which including objectives that are the total active power losses; the voltage deviations of the bus and the total emission. Moreover, a new optimization algorithm based on a fuzzy improved Honey Bee Mating Optimization (HBMO) algorithm is proposed to determine the best operating point for reactive power generation and the active power generated by Wind turbine and Photovoltaic. In the proposed algorithm, the mating process is corrected; also a fuzzy clustering technique is used to control the size of the repository within the limits, where a set of non-dominated (Pareto) optimal solutions are stored. Finally, the proposed algorithm is tested on a typical IEEE 33-bus distribution test systems. The results of the simulation show the effectiveness of the proposed algorithm.

Key words: Multi-objective optimization, improved Honey Bee Mating Optimization (HBMO), Distributed Generation (DG), voltage optimization control

INTRODUCTION

In recent years, commercial and environmental concerns have led to worldwide large-scale Distributed Generation (DG) integration. DG units can bring a number of advantages, such as reduced losses, improved grid reliability and security (M. Dicorato *et al*., 2008; Liu *et al*.,2011). However, high penetration of DG sources into the grid will bring new challenges for the efficient and safe power system operation, especially on the distribution networks. Using DG sources impose a different set of operating factors in distribution network such as voltage rise, reverse power flow, reduction of power losses and decreasing fault level, harmonic distortion and stability problems (Viawan and Karlsson, 2008).

The voltage control is one of the most important control schemes in distribution networks, which can be affected by DGs, because the X/R ratio of distribution lines is small and the configuration of distribution network is radial. The voltage control is defined as regulation of voltage over the feeders and reactive power (or power factor) at the substation bus (Borges and Falcao, 2006; Chen *et al*., 2006).

The control is achieved by adjusting the Load Tap Changer transformers (LTCs), Voltage Regulators (VRs) and capacitor banks as control variables to minimize an objective function considering the constraints (Bridenbaugh *et al*., 1992). In this regard, various optimization techniques are applied to the voltage control problem in distribution networks. De Souza *et al*. (2004) has proposed a voltage optimization control model, which objective function is voltage profile and using Genetic Algorithm (GA) to cope with the optimization problem. Hong and Luo (2009) study using probabilistic load-flow and gray-based genetic algorithms to optimized VAR control but the objective function are single objective. Nowadays, Different multi-objective evolutionary approaches are also implemented to the voltage control problem. Niknam *et al*. (2008) studied dynamic ant colony search algorithms used to the voltage control in radial distribution networks considering Distributed Generations. Niknam *et al*. (2010) used a Particle Swarm Optimization (PSO) approach to improve the voltage profile. But they have not considered the impact of active power of DGs on the Voltage control problem.

In this study, a new multi-objective approach for daily voltage control in distribution networks considering DGs, such as Wind and solar Photovoltaic energy, also considering the active power as a control variable was presented. The objectives are the total electrical energy losses; the total emission and the grid and the voltage deviations of the bus. Moreover, a new optimization algorithm based on Improved HBMO algorithm has been put into use to solve the daily voltage control, which not only has a better response but also converges more quickly than ordinary evolutionary methods like genetic algorithm and original HBMO.

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The original HBMO often converges to local optima (Fathian *et al*., 2007). In order to avoid this shortcoming, a new method is proposed to improve the mating processing. Therefore, the mating process is corrected so that to overcome the two main shortcomings which exist in the traditional HBMO. During the optimization process, the set of Pareto optimal solutions which are found by the algorithm would be stored in an external memory called repository. In addition, to find the 'best compromised' solution among the Pareto optimal solutions, a fuzzy-based mechanism is introduced and applied to the set Pareto solutions set. Finally, a typical IEEE 33-bus distribution test system is used to investigate the feasibility and effectiveness of the proposed method.

The study is organized as follows: the model for the multi-objective voltage control is presented in Section 2. In Section 3, the basic mechanism of HBMO, improved HBMO is described. In Section 4. The feasibility of proposed approach is demonstrated and its performance is compared with other methods for IEEE 33-bus distribution test feeder. In Section 5 are the conclusions.

AN OPTIMIZATION MODEL FOR VOLTAGE CONTROL

The effect of WFs and PVs on voltage profile of distribution networks: With installation of WFs and PVs in the distribution networks, any change in the power flow may change the voltage profile. Since the X/R ratio of the distribution lines is small, the WF or PV has much impact on the voltage profile. The voltage drop along the line is calculated as follows:

$$\Delta V = V_1\angle\delta_1 - V_2\angle\delta_2 = (R+jX)\,I \tag{1}$$

$$I = \frac{P - jQ}{V_2^*} \tag{2}$$

$$P = P_g + P_{Load},\; Q = Q_g + Q_{Load} \tag{3}$$

$$|\Delta V|^2 = \frac{(RP+XQ)^2 + (XP-RQ)^2}{V_2^2} \approx \frac{(RP+XQ)^2}{V_2^2} \tag{4}$$

It is obvious from the above equation that neither RP nor XQ is negligible. Also, since the X/R ratio is small and Q is less than P, the impact of the active power of WFs or PVs on the system voltage is much more than their reactive power.

Objective functions: As mentioned before, power systems are inherently stochastic due to uncertainties in both intermittent energy sources and load demands. Consequently, the multi-objective daily Voltage control in distribution networks considering DGs is a nonlinear optimization problem with both continuous and discrete parameters and variables. The objective functions and constraints can be formulated as follows:

Voltage deviations of the buses: Voltage deviation determines the difference between the voltages in nodes with respect to the nominal voltage. It is assumed that tap position of transformers and the values of capacitors change stepwise:

$$\operatorname{Min} f_1(X) = \frac{1}{N_d}\sum_{t=1}^{N_d}\sum_{i=1}^{N_{bus}}\left|\frac{V_i^t - V_i^*}{V_i^*}\right| \tag{5}$$

where, V_i^* is desired voltage of network at the ith bus, V_i^t is actual voltage of network at node i during time t. N_{bus} is number of buses. N_d is number of load variation steps.

Total power losses: The second objective is to minimize the total active power losses for the next day, which can be modeled as:

$$\operatorname{Min} f_2(X) = \sum_{t=1}^{T}\sum_{i=1}^{N_{br}}(R_i\,|I_i^t|^2 . h^t) \tag{6}$$

where, N_{br} is the number of branches.

Pollutants emission: Three of the most important pollutants are involved in the objective function: CO_2 (carbon dioxide), SO_2 (sulfur dioxide) and NOx (nitrogen oxides). The mathematical formulation of the objective can be described as(Niknam *et al*., 2010):

$$\begin{aligned}\operatorname{Min} f_4(X) &= \sum_{t=1}^{T}E^t = \sum_{t=1}^{T}(E_{Sub}^t + E_{WF}^t + E_{PV}^t)\\ &= \sum_{t=1}^{T}E_{Sub}^t = \sum_{t=1}^{T}(CO_2 + NOx + SO_2)\\ &= (2031 + 5.06 + 7.9)^{lb/MWh}.P_{sub}^t\end{aligned} \tag{7}$$

Constraints: In order to have an optimal plan while maintaining the security and operational conditions, the following constraints should be met:

- Power balance:

$$P_i = \sum_{i=1}^{N_{bus}} V_i V_j \cos(\theta_{ij} - \delta_i + \delta_j)$$

$$Q_i = \sum_{i=1}^{N_{bus}} V_i V_j \sin(\theta_{ij} - \delta_i + \delta_j) \tag{8}$$

- Active power constraints of Dgs:

$$P_{PV.min} \le P_{PV}^{t} \le P_{PV.max}$$

$$P_{WF.min} \le P_{WF}^{t} \le P_{WF.max} \quad (9)$$

- Line flow limits:

$$\left|P_{ij}^{Line}\right|^{t} < P_{ij.max}^{Line} \quad (10)$$

- Limits on the transformers' tap:

$$Tap_i^{min} < Tap_i < Tap_i^{max} \quad (11)$$

- Hourly limits on Substation power factor:

$$Pf_{min} < Pf^{t} < Pf_{max} \quad (12)$$

- limits on bus voltage magnitude:

$$V_{min} < V_i^{t} < V_{max} \quad (13)$$

MULTI-OBJECTIVE OPTIMIZATION

Multi-objective optimization the process of optimization of different conflicting objective functions when all the constraints and limitations are observed simultaneously is called Multi-Objective Optimization Problem (MOP). The MOP can be described as (Coello 1999):

$$\text{Min } F = [f_1(X), f_2(X), \ldots f_n(X)]^T \quad (14)$$

$$\text{s.t:} \quad \begin{cases} g_i(X) < 0 & i = 1,2\ldots Nueq. \\ h_i(X) = 0 & i = 1,2\ldots Neq \end{cases}$$

where, X is the control variable of making decision. Also n is the number of objective functions. For a multi-objective optimization problem, two solutions X and Y can have one of these two possibilities: one dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution X dominates Y if the following two conditions are satisfied:

$$\begin{aligned} &\forall j \in \{1,2\ldots n\}.\, f_j(X) \le f_j(Y) \\ &\exists k \in \{1,2\ldots n\}.\, f_k(X) \le f_k(Y) \end{aligned} \quad (15)$$

Original HBMO: Honey bee as a social insect with special behaviors and instructions has been the source of inspiration for the human beings during the years(Afshar *et al*., 2007). The honey bees' society is consisted of three groups in general: the queen or female, the drones or males and the workers. Each of these groups has a special task which should be implemented in such a way that the total condition of their society improves effectively. HBMO algorithm simulates each of the phases of the natural mating process so that to give a satisfying algorithm which would be profitable in the optimization applications. The mating process between the queen and each of the drones is implemented probabilistically with an annealing function as follows(Fathian *et al*., 2007):

$$Prop(D) = \exp\left(-\frac{\Delta f}{S(t)}\right) \quad (16)$$

After each mating process, the queen speed decreases. If the mating process is successful, the corresponding drone sperm is added to the queen spermatheca, else it is discarded and the next drone is chosen for mating. The speed of the queen after each mating process is updated as follows:

$$S(t+1) = \alpha \times S(t) \quad (17)$$

The mating process continues until the time that the speed of the queen reaches to a specific value or her spermatheca become full. Now the breeding process is simulated. If the position of any of the new broods is better than that of the queen, then it will replace the queen. This process of mating and breeding continues until the time that the best satisfying queen (solution) would be achieved.

Improved HBMO algorithm: The original HBMO suffers from two main deficiencies; that is the reliance of the HBMO algorithm on its parameters and the possibility of being trapped in local optima. These two shortcomings root from the mating process. Thus in order to improve the algorithm performance, the mating process should be corrected sufficiently. In the original HBMO, after that the process of adding the drones' sperm to the queen spermatheca is completed and the queen spermatheca is constructed, then the breeding process is implemented as follows:

$$X_{brood\,j} = X_{queen} + \gamma \times (X_{queen} - S_{Pi}) \quad (18)$$

After that the queen spermatheca is constructed similar to original HBMO, then three drones k1, k2 and k3 are chosen from the queen spermatheca randomly in a way that k1, k2, ..., ki where, i is the ith individual in the drones' population. Thus by the use of the queen spermatheca, a new improved brood is generated as follows:

$$X_{mut} = S_{Pk1}+\beta\times(S_{Pk2}-S_{Pk3}) \quad (19)$$

Now by the use of Xmut, Xqueen and Xi (the ith drone), three new modified broods would be generated. The modification process is implemented as follows:

$$X_{brood1,j} = \begin{cases} X_{mut\,j}; & \text{if } \varphi_1 \le \varphi_2 \\ X_{queen\,j}; & \text{otherwise} \end{cases}$$

$$X_{brood2,j} = \begin{cases} X_{mut\,j}; & \text{if } \varphi_3 \le \varphi_2 \\ X_j; & \text{otherwise} \end{cases}$$

$$X_{brood3} = \eta X_{queen}+\alpha\times(X_{queen}-SP\,(I_{rand,\,SP})) \quad (20)$$

Now by the use of Eq. (15), the non-dominated solutions among Xbrood,1, Xbrood,2, Xbrood,3 and the ith individual in the drones population are evaluated and stored in the repository.

In order to improve the HBMO algorithm, the process of generating drones' population should be amended too. In the original HBMO, after that the breeding process for all the drones' population is finished then the old drones' population is discarded and a new generation is produced randomly. In the Improved HBMO algorithm, this process is corrected as follows: As mentioned before, for each drone in the population (Xi), three new modified broods are generated by Eq. 20. After selection of the non-dominated solutions among the three generated modified broods and the ith drone, the individual who the summation of its membership functions is the most will replace the corresponding drone (Xi) in the drones' population. Subsequently after a complete breeding process, the old drones' population is up-dated and utilized as the new generation of drones satisfactorily.

Fuzzy-based clustering: As mentioned before, the set of Pareto optimal solutions which are found during the optimization process are stored in an external memory (or repository). Since the repository size is constant, the number of the Pareto solutions should not exceed a specified number. Therefore a fuzzy-based clustering technique is utilized here to control the size of the repository. The membership function assigned to each objective function is as follows:

$$\mu f_i(X) = \begin{cases} 1 & f_i(X) \le f_i^{min} \\ \dfrac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}} & f_i^{min} \le f_i(X) \le f_i^{max} \\ 0 & f_i(X) \ge f_i^{max} \end{cases} \quad (21)$$

The values of f_i^{min} and f_i^{max} are separately evaluated by single optimization of each objective function. Finally, for each of the solutions in the repository, the normalized membership function can be evaluated as follows:

$$N_\mu(j) = \frac{\sum_{i=1}^{n} \omega_i \times \mu_{fi}(X_j)}{\sum_{j=1}^{m}\sum_{i=1}^{n} \omega_i \times \mu_{fi}(X_j)} \quad (22)$$

Where n is the number of the objective functions and m is the number of the Pareto solutions in the repository. Therefore, after the evaluation of N_μ for all the Pareto solutions by Eq. 22, the repository is sorted in descending order. The best compromised solution is that for which the value of N_μ is maximum. Note that here ω_i is supposed to be unit so that to give equal preferences to all the objective functions. For multiple objective problems, the fuzzy solution can be calculated as:

$$\text{Object}\,(X) = \min\,[\mu_{f1}(X), \mu_{f2}(X), \mu_{f3}(X), \mu_{f4}(X)]$$

The maximum value of object (X) is considered as the optimal solution.

Applying the improved HBMO for voltage deviation control: The contribution of the proposed problem and the method of applying the improved HBMO algorithm is shown in Fig. 1 (Appendix A). Solution procedure of Multi-objective Approach for Voltage Optimization Control considering RESs:

Step 1: Defining the input data

Step 2: Changing the constrained MOP to an unconstrained one: in this step, the constrained MOP is changed to an unconstrained one by constructing an augmented objective function

Step 3: Generation of the initial population. The initial population (IP) is as follows:

$$IP = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_{Ni} \end{bmatrix}_{N_i\times(N_{Tr}+N_{sw}+N_g)} \quad (23)$$

$$N_g = N_{PV}+N_{WP}$$

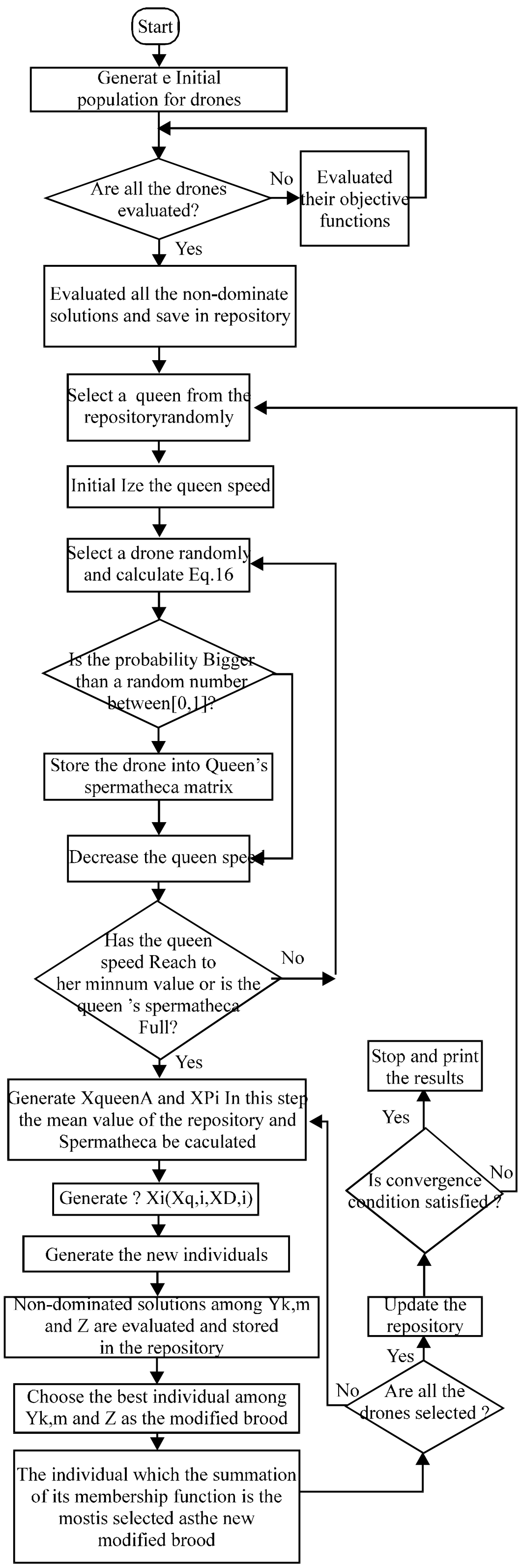

Fig. 1: Block diagram of MHBMO algorithm

Step 4: Evaluation of the objective functions. In this step the values of the objective functions and their corresponding membership functions are evaluated

Step 5: Formation of the repository. Here by the use of Eq. 21 and the membership functions evaluated in the last step, all the Pareto solutions are evaluated and stored in the repository

Step 6: Selection of the queen. The queen is selected from the repository randomly

Step 7: Formation of the queen spermatheca matrix. Firstly, the queen flies by her maximum speed far from the nest. Now a drone is selected from the drones' population randomly and mates with the queen. Therefore according to the values of the objective functions and by the use of Eq. 19, prob (D) would be evaluated. Now a value in the range of [0,1] is generated randomly and compared to prob (D). If prob (D) is bigger than the generated random value, then the sperm of the specified drone is added to the queen spermatheca, else another drone is chosen from the population randomly and the mating process is repeated. The mating process continues until the time that the queen spermatheca becomes full or her speed reduces to the specified value

Step 8: Breeding process. This process is implemented as described in Section 3.3

Step 9: Generation of the new drones' population. Among the ith drone, Xbrood,1, Xbrood,2 and Xbrood,3 the individual who the summation of its membership functions is the most (so the fittest individual) will replace the ith drone

Step 10: If all the drones are checked go to step 11, else return to step 8

Step 11: Updating the repository. In this step the repository is updated so that all solutions in the repository would be Pareto optimal solutions

Step 12: Updating the queen. A new queen is selected from the updated repository randomly

Step 13: Generation of the queen speed: The queen speed will be generated randomly as follows:

$$S_{queen} = rand(.) \times (S_{max} - S_{min}) + S_{min}$$

Step 14: Termination criterion. If the termination criterion is achieved, finish the algorithm, else return to step 6

SIMULATION RESULTS

To demonstrate the effect of uncertainty in WFs, PVs and load demands on the voltage control problem, the IEEE33-bus distribution test feeder shown in Fig. 2.

There are several parameters to be determined for implementation of the proposed algorithm. The best values for these parameters are selected as: $S_{max} = 1$, $S_{min} = 0.2$, $\alpha = 0.92$, $N_D = 20$, $N_W = N_S = N_B = 10$.

These values before applying the proposed algorithm are 0.9512 (p.u), 251.79 (kWh) and 14624.12 (kg). The best solutions obtained by optimizing the three objectives separately are 0.4898 (p.u), 91.21 (kWh) and 6840.24 (kg). It is obvious that the total electrical energy cost, total electrical energy losses and voltage deviation are greatly vreduced by controlling DGs.

Figure 3 shows the convergence rate of the Improved HBMO algorithm in 10 trials. According to Fig. 3, algorithm reached to best solution in 9 trials and only in one trial, the best solution was not obtained. Also, in Fig. 4 a comparison is done between the Improved HBMO and original HBMO algorithms for the best solution. It can be observed from the figures that the bus voltages are maintained within the permitted range of tolerance, i.e., ±5% of the nominal value. The simulation results show that the control scheme improve performance of the system.

Also it can be seen from Fig. 4 that for the proposed algorithm the objective function reaches its

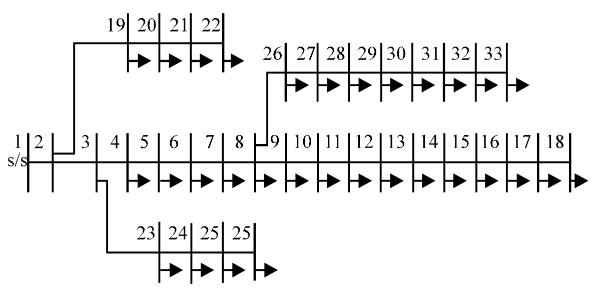

Fig. 2: IEEE 33 bus distribution test system

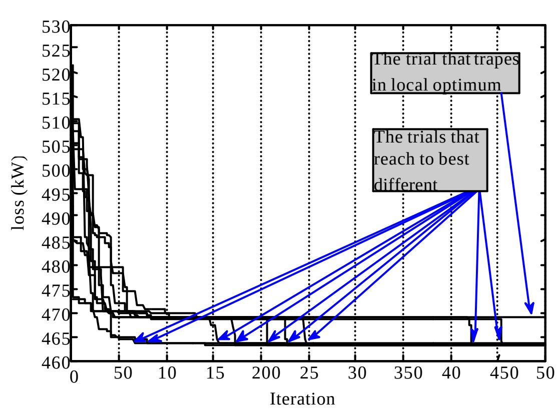

Fig. 3: Convergence process of the proposed algorithm in 10 trials

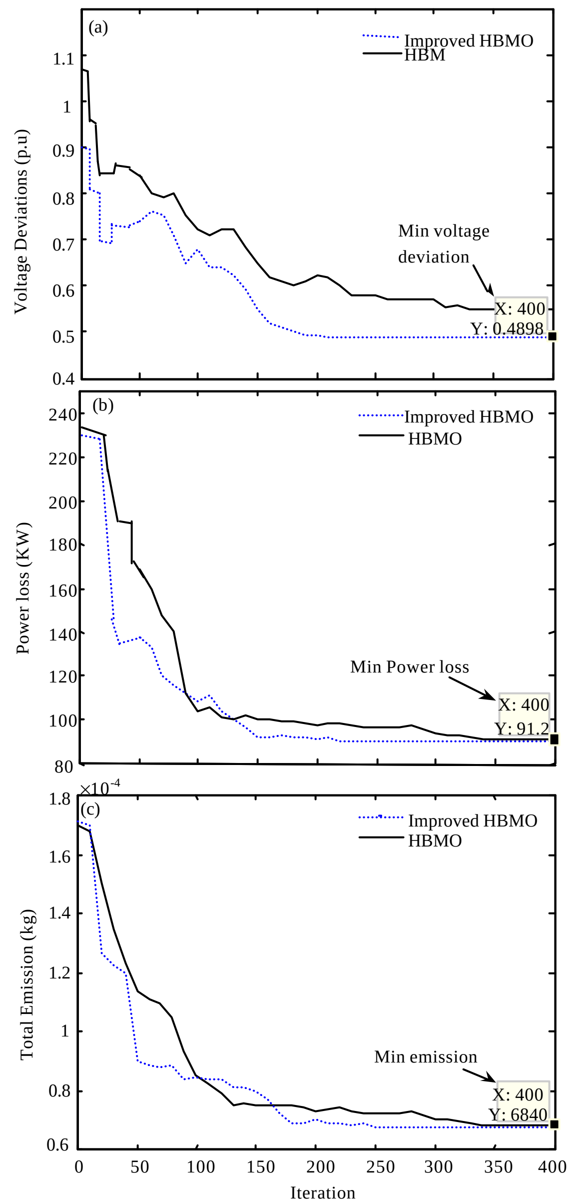

Fig. 4(a-c): Convergence characteristics of the Improved HBMO for the best solution, (a) The best solution for voltage deviation and (b) The best solution for power loss (c)The best solution for total emission minimum after about 230 iterations and does not vary thereafter while the HBMO algorithm converges to global optimum in about 350 iterations. So the proposed algorithm has better outperforms the original HBMO.

CONCLUSION

In this study, a new multi-objective approach for the voltage optimization control in distribution systems. The uncertainty in the electrical power generated by Wind Farms (WFs) and Photovoltaic (PV) pants was taken into account. The total electrical energy losses; the total emission and the voltage deviations of the bus were included in the objective function. A new optimization algorithm based on Improved Honey Bee Mating Optimization (HBMO) algorithm was proposed to determine the strategy. In the proposed algorithm, a set of non-dominated solutions called Pareto-optimal solutions are found and stored in the repository which its size is controlled by the use of fuzzy clustering method. In order to see the feasibility and ability of the proposed method, the improved HBMO algorithm is applied to the33-bus test systems and the results are compared by the original HBMO algorithms. The simulation results show that the good performance and credibility of the proposed method in the multi-objective voltage optimization control problem. Also it was shown that the voltage magnitude of buses is in the desired limits.

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