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Multi-objective Operation Management of a Hybrid Electric Generation System Containing Wind/Photovoltaic Power Plants

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Abstract

In this paper, a new Modified Honey Bee Mating Optimization (MHBMO) algorithm is proposed and implemented to dispatch the generations in a hybrid electric generation system. The system comprises Wind Turbine /Photovoltaic/Fuel Cell, a storage battery bank and a variable monophonic load. The desired optimal solution considering all the objectives of energy costs minimization, pollutant emissions reduction and better utilization in a unified problem is provided. The problem is formulated as a nonlinear constraint multi-objective optimization problem to minimize the total operating cost and the net emission simultaneously. The actual implementation results prove that the proposed algorithm is economical, fast and practical. They are quite valuable for further research.

Keywords: Multi-operation Planning; Energy Management; Wind Turbine (WT); Photovoltaic (PV); Modified Honey Bee Mating Optimization (MHBMO) Algorithm

1 Introduction

Typical hybrid systems often combine renewable energy sources of complementary profiles, such as wind and photovoltaic energy, with appropriate storage devices such as batteries [1]. Since the storage cost still represents a major economic restraint, usually wind/PV/battery systems are appropriately' sized, to minimize capital cost.

Recently, combined economic and environmental dispatch (CEED) is one of the most important problems in power system operation. It involves meeting the load demand at minimum total fuel cost while satisfying various unit and system constraints. The CEED model is a nonlinear optimization problem that considers its nonlinear characteristics including cost functions, Discontinuous Prohibited Zones, Power Balance constraints, Generation Limit constraints etc. Nowadays, various optimization techniques are implemented to handle the optimal operation scheduling problem, such as dynamic programming [2], where the cost function can be discontinuous or

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non-monotonically increasing. However, while the number of units' increases, its computational memory requirement and computational time increases exponentially with multiple local minimum very often the only suboptimal solutions that can be found. Random optimization methods have been developed in the Artificial Intelligence field, such as the Particle Swarm Optimization (PSO) [3], Genetic Algorithm (GA) [4], Ant Colony System (ACS)[5] and so on. These methods are effective optimization techniques with the capability to find the global optimal solution. However, the disadvantage of GA method is long computational time and the lack of guarantee that a global optimal solution can always be found. Similarly, the PSO and ACS methods have major limitations in the numerical technique problem dimensions, large computational time and complexity in programming.

Different multi-objective evolutionary approaches for electric power dispatching were also reported in Ref. [5,6]. The original HBMO often converges to local optima. In order to avoid this shortcoming, a new method is proposed to improve the mating processing. Therefore in this paper a new method based on MHBMO algorithm is proposed to investigate the operation management problem while the effects of the RESs are considered simultaneously. In order to improve the algorithm, the mating process is corrected .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.

2 Modeling for Operation Planning

The multi-operation management problem in a typical hybrid electric generation system is defined as a problem to allocate optimal power generation set points as well as suitable ON or OFF states to DG units in a sense that the operating cost and the net pollutants emission inside the grid are minimized simultaneously while satisfying several equality and inequality constraints. The mathematical model of such problem can be expressed as follows.

2.1 Objective functions

-Objective 1: Operating Cost Minimization

The cost objective function aims at finding OPFs (Optimal Power Flows) from energy sources to load centers for a definite period of time in an economical manner. Such objective function can be formulated as below:

$$\begin{aligned} Minf_1(X) = \sum_{t=1}^{T} Cost^t = \sum_{t=1}^{T} \Bigg\{ & \sum_{i=1}^{N_g} [u_i(t)P_{Gi}(t)B_{Gi}(t) + S_{Gi}\left|u_i(t) - u_i(t-1)\right| \\ & + \sum_{j=1}^{N_s} [u_j(t)P_{Sj}(t)B_{Sj}(t) + S_{Sj}\left|u_j(t) - u_j(t-1)\right|] + P_{Gd}(t)B_{Gd}(t) \Bigg\} \end{aligned} \quad (1)$$

where B_{Gi}(t) and B_{Sj}(t) are the bids of the DGs and storage devices at hour t, S_{Gi} and Ssj represent the start-up or shut-down costs for ith DG and jth storage respectively, P_{Gd}(t) is the active power which is bought (sold) from (to) the utility at time t and B_{Gd}(t) is the bid of utility at time t. X is the state variables vector which includes active power of units and their related states. Ng and Ns are the total number of generation and storage units respectively. P_{Gi}(t) and P_{sj}(t) are the real power outputs of ith generator and jth storage at time t respectively.

-Objective 2: Pollutants emission minimization

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 second objective can be described as:

$$\begin{aligned} Minf_2(X) = \sum_{t=1}^{T} Emission^t = \sum_{t=1}^{T} \Bigg\{ \sum_{i=1}^{N_g} [u_i(t) P_{Gi}(t) E_{Gi}(t) \\ + \sum_{j=1}^{N_s} [u_j(t) P_{Sj}(t) E_{Sj}(t) + S_{Sj} \left| u_j(t) - u_j(t-1) \right|] + P_{Gd}(t) E_{Gd}(t) \Bigg\} \end{aligned} \tag{2}$$

2.2 Constraints

-Power balance

The total power generation from DGs must cover the total demand inside the grid.

$$\sum_{i=1}^{Ng} P_{Gi}(t) + \sum_{i=1}^{Ns} P_{sj}(t) + P_{Gd}(t) = \sum_{k=1}^{Nk} P_{LK}(t) \tag{3}$$

-Active power constraints

For a stable operation, the active power output of each DG is limited by lower and upper bounds as:

$$P_{Gi.\min}(t) \le P_{Gi}(t) \le P_{Gi.\max}(t), P_{sj.\min}(t) \le P_{sj}(t) \le P_{sj.\max}(t), P_{Gd.\min}(t) \le P_{Gd}(t) \le P_{Gd.\max}(t) \tag{4}$$

-Battery limits

Since there are some limitations on charge and discharge rate of storage devices during each time interval, a typical battery can be expressed:

$$\begin{aligned} & W_{ess}(t) = W_{ess}(t-1) + \eta_{ch\arg e} P_{ch\arg e} \Delta t - {P_{disch\arg e} \Delta t}/{\eta_{disch\arg e}} \\ & W_{ess}(t)_{\min} \le W_{ess}(t) \le W_{ess}(t)_{\max} \end{aligned} \tag{5}$$

Where η is the efficiency of the battery during charge(discharge) process.

3 Multi-objective Optimization and MHBMO Algorithm

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 [7]:

$$\begin{aligned} & Min \quad F = [f_1(X),\ f_2(X), ...f_n(X)]^T \\ & s.t: \begin{cases} g_i(X) < 0 & \text{i = 1,2...Nueq.} \\ h_i(X) = 0 & \text{i = 1,2...Neq} \end{cases} \end{aligned} \tag{6}$$

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:

$$\begin{aligned} \forall j \in \{1, 2...n\}. \quad f_j(X) \leq f_j(Y) \\ \exists k \in \{1, 2...n\}. \quad f_k(X) \leq f_k(Y) \end{aligned} \tag{7}$$

3.1 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[7]. 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:

$$prop(D) = \exp(-\frac{\Delta f}{S(t)}) \tag{8}$$

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:

$$S(t+1) = \alpha \times S(t) \tag{9}$$

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.

3.2 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:

$$\mu f_i(X) = \begin{cases} 1 & f_i(X) \leq f_i^{\min} \\ \frac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \leq f_i(X) \leq f_i^{\max} \\ 0 & f_i(X) \geq f_i^{\max} \end{cases} \tag{10}$$

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:

$$N_\mu(j) = \frac{\sum_{i=1}^{n} \omega_i \times \mu_{fl}(X_j)}{\sum_{j=1}^{m} \sum_{i=1}^{n} \omega_i \times \mu_{fl}(X_j)} \tag{11}$$

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. (11), 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:

$$Object(X) = \min[\mu_{f1}(X), \mu_{f2}(X), \mu_{f3}(X), \mu_{f4}(X)] \tag{12}$$

3.3 The modified HBMO (MHBMO) 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:

$$X_{brood\ j} = X_{queen} + \gamma \times (X_{queen} - S_{P_i}) \tag{13}$$

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:

$$X_{mut} = S_{Pk1} + \beta \times (S_{Pk2} - S_{Pk3}) \tag{14}$$

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:

$$X_{brood1.\ \mathrm{j}} = \begin{cases} x_{mut\ \mathrm{j}}\ ; \text{ if } \varphi_1 \le \varphi_2 \\ x_{queen\ \mathrm{j}};\ \text{otherwise} \end{cases} \quad ; \quad X_{brood2.\ \mathrm{j}} = \begin{cases} x_{mut\ \mathrm{j}}\ ; \text{ if } \varphi_3 \le \varphi_2 \\ x_{\ \mathrm{j}};\ \text{otherwise} \end{cases}$$
$$X_{brood\ 3} = \eta X_{queen} + \alpha \times (X_{queen} - SP(I_{rand,SP})) \tag{15}$$

Now by the use of Eq.(7), 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 MHBMO 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. (15).

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.

3.4 Applying MHBMO to operation management

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.

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

$$IP = [X_1, X_2, ...X_{Ni}]^T_{N_i \times (N_{Tie}+N_{sw}+N_g)} \tag{16}$$

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.(10), 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. 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. (8), 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.

4 Simulation Results

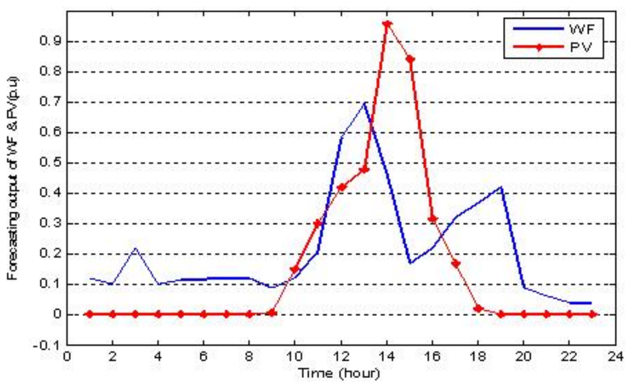
In this section, the proposed MHBMO algorithm is employed to solve the multi-operation management problem. The maximum power outputs predicted values and the daily load variation are shown in Fig. 1. There are several parameters to be determined for implementation of MHBMO algorithm. The best values for these parameters are selected as: $S_{\max} = 1$, $S_{\min} = 0.2$, $\alpha = 0.92$, $N_D = 20$, $N_W = N_S = N_B = 10$

The type of each RES, also their minimum and maximum generation limits are given in Table 1, and the bid coefficients per kWh as well as emissions in kilogram per MWh assumed by the DG sources are given in the same table[6].

Table 1: The installed DG sources and the bids & emissions

ID	Type	Capacity(kw)	Bid($/kwh)	ON/OFF ($)	Emissions (1b/MWh)		
					CO2	SO2	NOx
1	FC	350	1.281	1.65	1108	0.008	1.15
2	PV	450	1.584	0	0	0	0
3	WT	500	1.073	0	0	0	0
4	Bat	500	0.38	1.12	10	0.002	0.01
5	Grid	500	0	0	2031	7.9	5.06

All the units are dispatched regarding their real constraints. To get a better insight into the MHBMO performance, the convergence characteristics of the MHBMO algorithms for the best solution and in the case of each single objective are shown in Fig.2. It is obvious that the total electrical energy cost, the total emissions are greatly reduced by controlling DGs. It also can be seen that for MHBMO algorithm the objective function reaches its minimum after about 254 iterations, and does not vary thereafter while the HBMO algorithm converges to global optimum in about 362 iterations. So MHBMO algorithm has better outperforms the original HBMO.



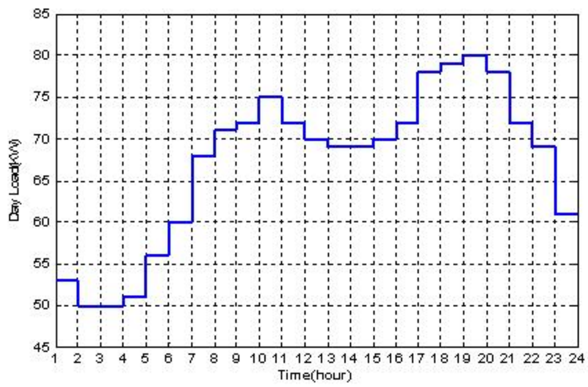


Fig. 1: Forecasting output of WT & PV and load demand in a day

5 Conclusion

In this paper, a new modified evolutionary algorithm based on HBMO is proposed to solve the multi-objective operation management problem in a typical a hybrid electric generation system

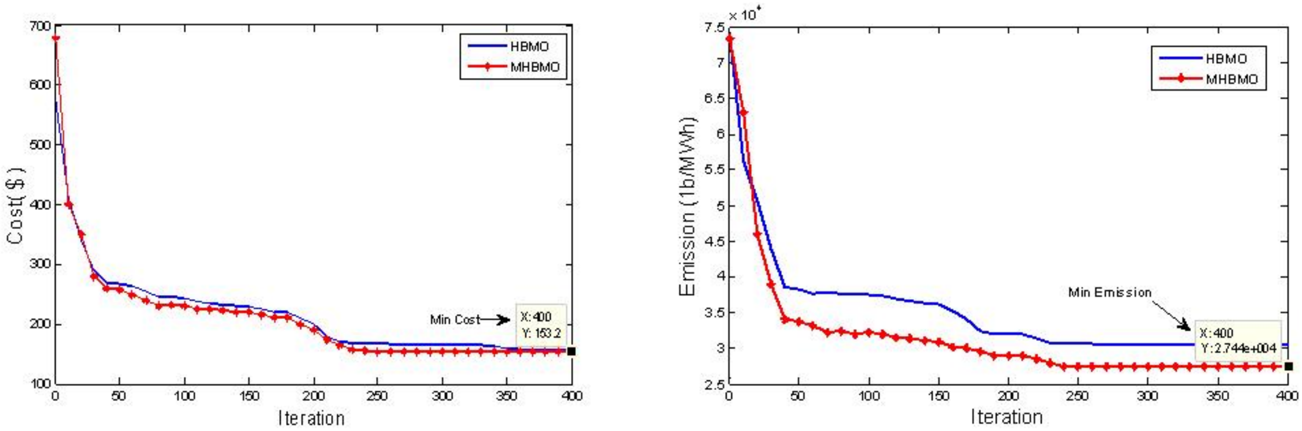


Fig. 2: Convergence characteristics of MHBMO of cost objective and emission objective

with RESs. The simulation results show dynamic stability and excellent convergence of the algorithm. The proposed method also yields a true and well distributed set of Pareto-optimal solutions giving the system operators various options to select an appropriate power dispatch plan according to environmental or economical considerations. In addition the simulation results show that the dependability of the proposed algorithm on the initial parameters is much less than the original HBMO.

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