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SOLVING OPTIMAL UNIT COMMITMENT BY IMPROVED HONEY BEE MATING OPTIMIZATION

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Abstract- Improved version of Honey Bee Mating Optimization (IHBMO) algorithm is developed and applied for Unit Commitment Problem (UCP) in this paper. Actually, the optimal solution of the nonlinear scheduling problem is important and it has complex computational optimization process. This problem is a challenging undertaking to accommodate variations in the power system, especially when several thermal units are employed. IHBMO technique is a hybrid evolutionary algorithm which combines the power of genetic algorithms and simulated annealing with a fast problem specific local search heuristic to obtain the best possible solution. To demonstrate the effectiveness and robustness of the proposed algorithm a system with ten thermal units in various conditions is considered. The simulation results are compared with those obtained from traditional unit commitment and heuristic algorithms.

Keywords: IHBMO, Unit Commitment Problem, Optimization.

I. INTRODUCTION

In a vertically integrated system, the primary objective of power system operation referred to on the sequel as power planning, is to ensure that users' demand is met at the lowest cost [1]. This objective explicitly specifies an optimization problem with a cost function to be minimized and a variety of constraints describing the physical system and limits on acceptable performance.

The objective function is to minimize total operating costs, and the constraints involve both generator and system constraints. Generator constraints involve their ramping time and minimum on and off time, while system constraints include demand satisfaction and transmission constraints [2, 3]. The UCP is fairly complex as a large scale nonlinear mixed integer program, but there are several methods and algorithms to find a near-optimal solution [3].

One of the difficulties associated with power planning is the physical size of the system. The network may have several thousands nodes (buses), lines and the generation mix may include a large number of hydro-plants and/or thermal plants [4]. Another major difficulty in dealing with electrical power systems is the vast range of time intervals over which various processes need to be controlled. For this reason, the whole planning problem is usually divided into a hierarchy of problems according to the length of the considered planning period [5, 6].

In recent years, several UCP studies analyzing the impact of increasing adoption levels of wind power have been performed. Where, dynamic programming [6], branch-and-bound [7], Lagrangian Relaxation (LR) approach [9], Genetic Algorithm (GA) [10], and Evolutionary Programming (EP) [11], could be used to solve the extended unit commitment problem. In [11], a security-constrained stochastic UCP formulation that accounts for wind power volatility is presented together with an efficient benders decomposition solution technique. But, the issue of constructing probability distributions for the wind power is not addressed. In [9], a detailed closed-loop stochastic UCP formulation is reported. The authors analyze the impact of the frequency of recommitment on the production, startup, and shutdown costs. They find that increasing the recommitment frequency can reduce costs and increase the reliability of the system. However, the authors do not present details on the wind power forecast model and uncertainty information used to support their conclusions. In [7, 9], Artificial Neural Network (ANN) models are used to compute forecasts and confidence intervals for the total aggregated power for a set of distributed wind generators. Such approaches can thus result in inaccurate medium and long-term forecasts and over- or under-estimated uncertainty levels [6, 8], which in turn affect the expected cost and robustness of the UCP solution.

This paper presents, the IHBMO algorithm incorporated with a simplified dispatch method is developed to solve the UCP of combining unit commitment of the generating units for minimizing the cost.

The Improved HBMO (IHBMO) with time-varying queen's speed reduction factor represented in [10] is one the best technique for effectively improvements of the original HBMO performance in terms of robustness to control computational effort. The vital parameter of the algorithm i.e. queen's speed reduction factor is varied with time (iterations) to efficiently control the local search and convergence to the global optimum solution. This mechanism is caused to improve the global search and cheering the bees to converge toward the global optima at the search space process. Furthermore, it was revealed that IHBMO has a higher success convergence rate since it does exploration and exploitation processes together efficiently [11].

II. UCP FORMULATION

This problem is related to the so called "Thermal Unit Commitment" problem, that analyzes in a detailed manner operational constraints of thermal units or generators [12]. The objective of optimal thermal generating UCP minimize simultaneously the generation cost rate and meet the load demand of a power system over some appropriate period while achieving various constraints depending on assumptions and practical implications [12, 13]. The constrained UCP optimization problem can be expressed as follows:

$$\min F(U_{it}, P_{it}) = \sum_{t=1}^{24}\sum_{i=1}^{G}[U_{it}.F_{it}(P_{it}) + U_{it}.(1-U_{it-1}).S_i] \quad (1)$$

Generally speaking, the running cost, per thermal unit in any given time interval is a function of the generator power output. The total fuel cost $F_i(P_{it})$ expressed as:

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

The generator start up cost depends on the time the unit has been off prior to start up. This paper presents time-dependent start up cost is represented as follows:

$$S_i = S_{0i} + S_{1i}(1 - e^{\frac{-T}{\tau_i}}) \quad (3)$$

In the other word, the Equation (3) define the shut down cost is usually given a constant value for each unit. In this paper, the shut down cost has been taken equal to 0 for each unit.

The problem constraints are:

a) Power Balance

This constraint is based on the principle of equilibrium between total system generation and total system loads (P_D) and P_t calculated by the running units at time-step t

$$\sum_{i=1}^{G} U_{it}.P_{it} = P_{Dt} \qquad t = 1, 2, ..., 24 \quad (4)$$

according to equal loss incremental rate principle and met

$$\frac{dF_{1t}}{dP_{1t}} = \frac{dF_{2t}}{dP_{2t}} = ... = \frac{dF_{it}}{dP_{it}} = \lambda \quad t = 1, 2, ..., 24 \ ; \ i = 1, 2, ..., G \quad (5)$$

b) Spinning Reserve

If spinning reserve needs to be more than 7% of the total load at each time interval, system up/down spinning reserve requirements:

$$\sum_{i=1}^{G} U_{it}.P_{i\max} \geq 1.07 P_{Dt} \qquad t = 1, 2, ..., 24 \quad (6)$$

c) Unit Generation Output Limitation

$$P_{i\min} \leq P_{it} \leq P_{i\max} \qquad t = 1, 2, ..., 24 \ ; \ i = 1, 2, ..., G \quad (7)$$

d) Start Up/Down Times Limitation

$$\sum_{i=1}^{24} | U_{it} - U_{it-1} | \leq M_i \qquad i = 1, 2, ..., G \quad (8)$$

e) Minimum Up/Down - Time Constraints

$$TO_i \geq \underline{TO}_i \quad , \quad TS_i \geq \underline{TS}_i \quad (9)$$

III. IMPROVED HBMO PROCEDURE

A. Standard HBMO Algorithm

A honey-bee colony typically consists of a single egg laying long-lived queen, several thousand drones (depending on the season), and workers and is a large family of bees living in one bee-hive and usually contains 10000 to 60000 workers [14, 15]. Each bee undertakes sequences of actions which unfold according to genetic, ecological and social condition of the colony. Workers utilize some heuristic mechanisms such as crossover. Also any colony maybe contain one or much queen in it life′s. In the marriage process, the queens mate during their mating flights far from the nest. A mating flight starts with a dance performed by the queen who then starts a mating flight during which the drones follow the queen and mate with her in the air. After the mating process, the drones die. In each mating, sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony. Each time a queen lays fertilized eggs, she randomly retrieves a mixture of the sperm accumulated in the spermatheca to fertilize the egg and this task can only be done by the queen [16, 17].

The HBMO algorithm starts with random generation of a set of initial solutions according to Figure 1. Based on their fitness, randomly generated solutions are then ranked. The fittest solution is named queen, whereas the remaining solutions are categorized as drones (i.e., trial solutions). In order to form the hive and start mating process, the queen, drones and workers (predefined heuristic functions) should be defined. Each queen is characterized with a genotype, speed, energy and a spermatheca with defined capacity. In the next step, drones must be nominated to mate with the queen probabilistically during the mating flight. At the start of the flight, the queen is initialized with some energy content and returns to her nest when the energy is within some threshold of either near zero or when the spermatheca is full. The mating flight may be considered as a set of transitions in a state-space (the environment). An annealing function is used to describe the probability of a drone (D) that successfully mates with the queen (Q) as follows [8]:

$$\text{prob}(Q, D) = \mathrm{e}^{\frac{-\Delta(f)}{S(t)}} \quad (10)$$

where, $\Delta(f)$ is the absolute difference of the fitness of D and the fitness of Q and the $S(t)$ is the speed of queen at time t. The fitness of the resulting chromosomes of drone, queen or brood is determined by evaluating the value of the objective function. After each transition in space, the queen's speed and energy decays is given by:

$$S(t+1) = \alpha.S(t) \quad (11)$$

$$E(t+1) = E(t) - \gamma \quad (12)$$

where $\alpha(t)$ is speed reduction factor and γ is the amount of energy reduction after each transition ($\alpha, \gamma \in [0,1]$).

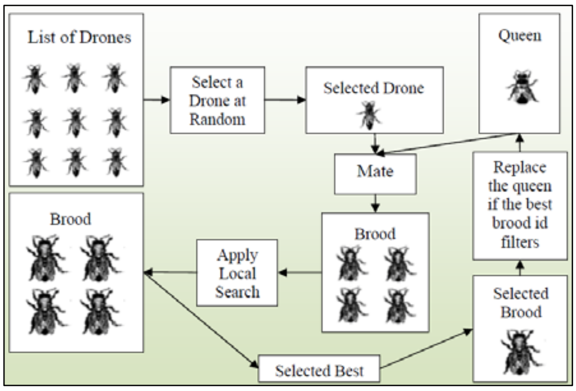


Figure. 1. The proposed HBMO technique

In order to develop the algorithm, the capability of workers is restrained in brood care and thus each worker may be regarded as a heuristic that acts to improve and/or take care of a set of broods. The rate of improvement in the brood's genotype, defines the heuristic fitness value. The fitness of the resulting genotype is determined by evaluating the value of the objective function of the brood genotype and/or its normalized value. It is important to note that a brood has only one genotype.

In general, the whole process of HBMO algorithm as shown in Figure 1 can be summarized at the five main steps as follows:

i) Generate the initial drone sets and queen: The algorithm starts with the mating flight, where a queen (best solution) selects drones probabilistically to form the spermatheca (list of drones). A drone then selected from the list randomly for the creation of broods.

ii) Flight matting: This step do the flight matting of queen Q. The best drone D_k with the largest prob(Q, D) among the drone set D is selected the object of matting for the queen Q. After the flight matting the queen's speed and energy decay is reduced by Equation (4). The flight matting is continues until the speed $S(t)$ is less than a threshold d or the number of sperms of the queen's spermatheca is less than the one threshold.

iii) Breeding process: In this step, a population of broods is generated based on matting between the queen and the drones stored in the queen's spermatheca. The breeding process can transfer the genes of drones and the queen to the jth individual based on the Equation (13).

$$child = parent_1 + \beta(parent_2 - parent_1) \quad (13)$$

where β is the decreasing factor ($\beta \in [0,1]$).

iv) Adaptation of worker's fitness: The population of broods is improved by applying the mutation operators as follows:

$$Brood_i^k = Brood_i^k \pm (\delta + \varepsilon) Brood_i^k$$
$$\delta \in [0,1] \quad , \quad 0 < \varepsilon < 1 \quad (14)$$

The δ is randomly generated and ε is predefined.

The best brood ($Brood_{best}$) with maximum objective function value is selected as the candidate queen. If the objective function of $Brood_{best}$ is superior to the queen, the queen replace with $Brood_{best}$.

v) Check the termination criteria: If the termination criteria satisfied finish the algorithm, else generate new drones set and go to step 2.

The algorithm continues with three user-defined parameters and one predefined parameter. The predefined parameter is the number of workers (W), representing the number of heuristics encoded in the program [8, 15]. The user-defined parameters are number of queens, the queen's spermatheca size representing the maximum number of mating per queen in a single mating flight and the number of broods that will be born by all queens. The speed of each queen at the start of each mating flight initialized at randomly. As this algorithm is combination of simulated annealing, genetic operator and swarm intelligence it is very interesting optimization algorithm that used in optimization problems of reservoir operation.

B. Improved HBMO

In the HBMO, appropriate chosen of the queen's speed reduction factor provides a balance between global and local exploration and exploitation, and results in less iteration on average to find a properly optimal solution. On the other word, suitable choose of queen's speed reduction factor expresses the collaborative effect of the bees, to obtain the global optimal solution is more accurately and successfully. Hence, a new parameter adjustment mechanism for the HBMO concept called Improved HBMO with time varying vital parameter i.e. queen's speed reduction factor is developed, in this study. The motivation for using this method is improvement the global search in the early stage of the optimization stages and cheering the particles to converge toward the global optima at the end of it. The main concept of IHBMO is similar to classic HBMO in which the Equations (10)-(12) are used. However, for IHBMO the speed reduction factor (α) is updated for calculation queen's speed in Equation (11) at each iteration as follows [16, 17]:

$$\alpha(t) = \left(M - m(t)\right) / M \quad (15)$$

where, M is the spermatheca size; $m(t)$ is the total number of drones selected for mating during the first t transitions.

IV. THE IHBMO BASED UC PROBLEM

When any optimization process is applied to the UC problem some constraints are considered [18, 19]. In this paper some different constraints are considered. Among them the equality constraint is summation of all the generating power must be equal to the load demand and the inequality constraint is the powers generated must be within the limit of maximum and minimum active power of each unit. The procedure of IHBMO algorithm for the UC problem solution can be described as follows:

Step1: Initialization - The individuals of the drone's population are randomly initialized according to the limit of each unit including individual dimensions. The velocities of the different particles are also randomly generated keeping the velocity within the maximum and minimum value of the velocities [18]. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints. The *i*th drone for n generating units is represented as:

$$P_i = [P_{i1}, P_{i2}, ..., P_{in}] \tag{16}$$

Step 2: Satisfy the Constrains - Each set of solution in the space should satisfy the equality constraints. So equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

$$\sum_{i=1}^{NT} U_i(t).P_i(t) = P_L(t) \tag{17}$$

Step 3: Evaluation of Fitness - The evaluation function of each individual P_{gi}, is calculated in the population using the evaluation function F_T. Where F_T is

$$F_T = \sum_{t=1}^{T} \sum_{i=1}^{NT} F_i(P_i(t)) \tag{18}$$

Step 4: Greedy Selection Mechanism - Each bee values are compared with other bee values in population. The best evaluation value among drones is denoted as queen.

Step 5: Check Criteria - If number of iterations reaches the maximum, then go to step 6. Otherwise, go to step 2.

Step 6: Display - The individual that generates the latest gbest is the optimal generation power of each unit with the minimum total generation cost.

V. RESULTS AND DISCUSSIONS

In order to illustrate the efficiency of the proposed IHBMO algorithm for the solution of the proposed problems, three power systems, including several test systems. All the computations are performed on a Not Book (NB) Intel core 2 Dual processor P8700 (2.53 GHz), RAM 4 GB and several computer programs were developed in Matlab 2009a. In order to acquire better performance, the control parameters of the proposed algorithm are given in Table 1.

Table 1. IHBMO control parameters for optimization

Number of Drone	100
Number of Worker	20
Number of Child	10
Specthrea	15
α	1.9
β	0.98
Factor for reduce speeds queen	0.98

A. Case I: 10 Thermal Unit System

In this test case contains 10 generating units for [20] to verify the correctness, and the results are compared with other algorithms. The Tables 2 and 3, and Figure 2 show the results. It can be apparent from this Table that the proposed IHBMO technique provided superior solutions compared with other reported evolutionary algorithm methods. Figure 3 shows the minimum fitness functions evaluating process.

Table 2. Optimal unit commitment result

Units	On/Off Statue of Per Time-Step
1	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
2	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
3	0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0
4	0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0
5	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
6	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
7	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
8	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0
9	0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
10	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0

Table 3. The computing the total cost for Case I

Algorithms	Total Cost
LR [20]	80766.0
Hopfield-SA [21]	79114.6
Evolutionary Method [22]	79043
AC-PSO[23]	79010.1
HPSO [24]	81118.3
GA[25]	78988.8
GA [26]	79807.0
Advanced GA [13]	78965.8
IHBMO	78304.34

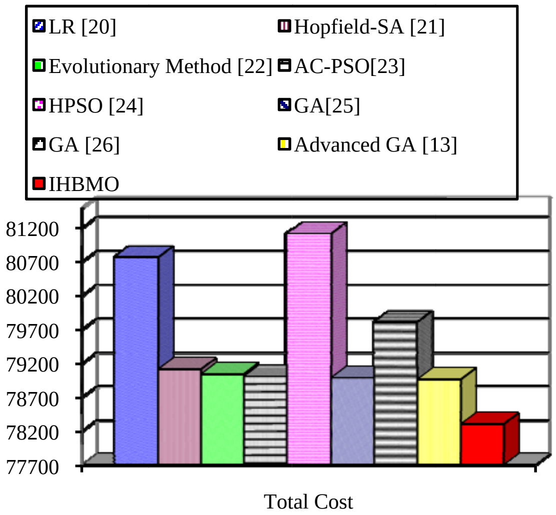


Figure 2. Comparison results of various algorithms

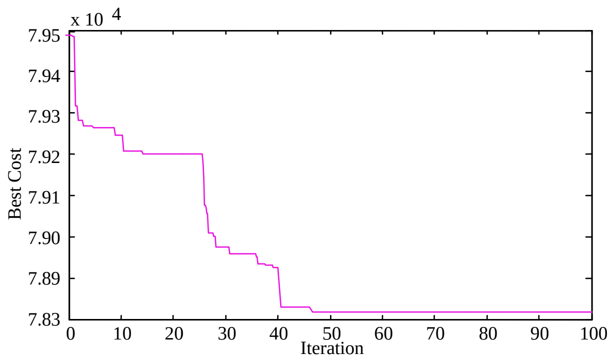


Figure 3. Fitness convergence, Dashed (PSO-TVIW)

Since, the proposed IHBMO is a stochastic search method, another aspect of investigating the effectiveness and robustness of the proposed algorithm is the sensitivity analysis to the IHBMO operators used in this study. A robust algorithm will exhibit low sensitivity to the operator variations as evidenced by the Standard Deviation (SD) of the best solution found during the search. Thus, to demonstrate the effectiveness and robustness of the proposed IHBMO technique ten different optimization runs have been carried out for 10-unit system and to compare the standard deviation of the problems.

The computational results are shown in Table 4. Figure 4 depicts the standard deviation of the best solution to each problem. There are no significant differences amongst the standard deviations of the found solutions. Thus, the proposed IHBMO technique is a robust optimization algorithm.

Table 4. Different methods results for 10 trials

Run	IHBMO				
	Min	Max	Mean	Time	Iter
1	78304.34	79532.12	78955.67	35.092	48
2	78304.36	79532.78	78955.44	35.091	46
3	78304.34	79531.86	78955.98	35.092	48
4	78304.38	79532.99	78955.42	35.092	49
5	78304.57	79533.57	78954.09	35.091	46
6	78304.54	79532.71	78953.63	35.092	46
7	78304.78	79532.01	78955.30	35.091	40
8	78304.39	79532.41	78955.67	35.092	43
9	78304.37	79532.09	78954.48	35.092	57
10	78304.57	79532.87	78955.69	35.093	58
SD	0.1382	0.5097	0.7471	0.0006	5.31

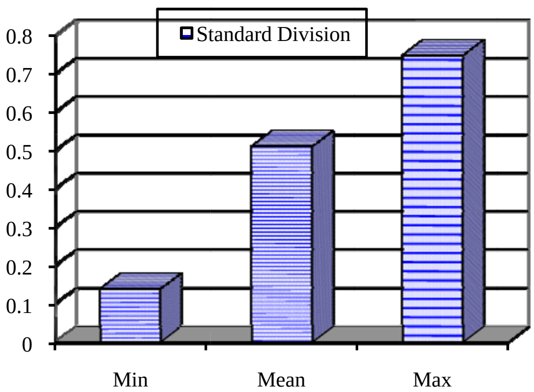


Figure 4. Standard deviation for ten trial

B. Case II: 40 Thermal Unit System

To demonstrate performance robustness of the proposed method used a practical power system, Taiwan Power system (Taipower system). In the other word, to ensure the robustness of the proposed stabilizers, the design process takes a wide range of operating conditions into account. The Taipower system consists of 40 main thermal units while the parameters of operation of units are provided in Appendix. The require system unit data and the generation requirements for each stage given in [27]. The best cost solution for different methods with constraint satisfaction is shown in Tables 5 and Figure 5. The results of these studies show that the proposed coordinated controllers have an excellent capability in UC problem.

Table 5. The computing the total cost for Case I

Algorithms	Total Cost
LR [27]	2,258,503
GA [27]	2,249,072
IHBMO	2,243,134

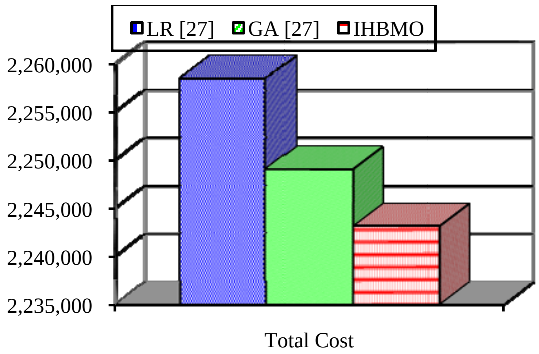


Figure 5. Comparison results of various algorithms

C. Case III: Benchmark

For more information about IHBMO algorithm the rastrigin function used in this paper, is presented as:

$$f(x) = 20 + \sum_{i=1}^{n} (x_i^2 - 10.\cos(2\pi x_i)) \tag{19}$$

$$-3 \le x_1 \le 12.1 \quad , \quad 4.1 \le x_2 \le 12.8$$

Also Figure 6 shows the output of the software for objective function's shape.

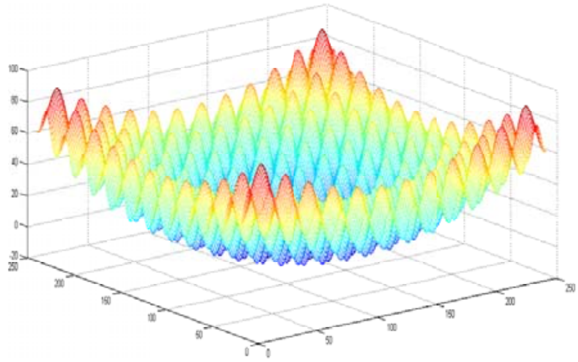


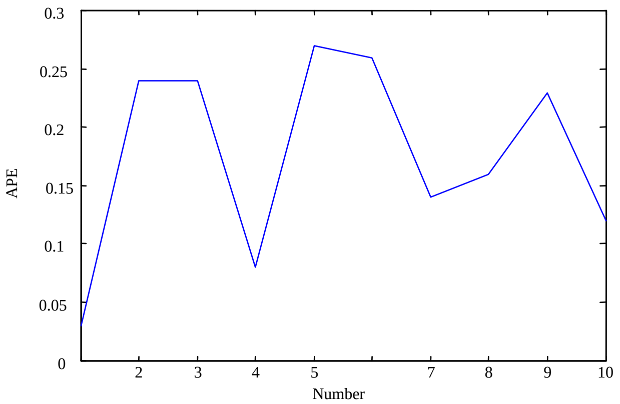
Figure 6. 3-D display of rastrigin function

There is no doubt that IHBMO algorithm is one of the heuristic algorithms. Also this algorithm should be run several times to find the best answer for objective function. Table 6 presents the average results over many runs. To demonstrate the performance and robustness of the proposed method, a performance index: the *APE* based on the error system performance characteristics are defined as the following and is shown in Figure 7.

$$APE = \left| \frac{Sol_{Act} - Sol_{EPSO}}{Sol_{Act}} \right| \times 100 \tag{20}$$

Table 6. The average results over many runs of PSO-IIW

max	ave	min	x_1	x_2	Run
28.2810	20.454	19.8321	0.9928	4.1024	1
28.2712	20.409	19.8325	0.9924	4.1011	2
28.2811	20.411	19.8320	0.9928	4.1018	3
28.2913	20.411	19.8378	0.9920	4.1011	4
28.2816	20.415	19.8343	0.9928	4.1025	5
28.2817	20.411	19.8376	0.9927	4.1017	6
28.2812	20.404	19.8384	0.9924	4.1010	7
28.2987	20.477	19.8345	0.9928	4.1013	8
28.2709	20.434	19.8398	0.9929	4.1012	9
28.2856	20.411	19.8331	0.9928	4.1018	10
0.0079	0.0228	0.0028	0.0003	0.0005	SD



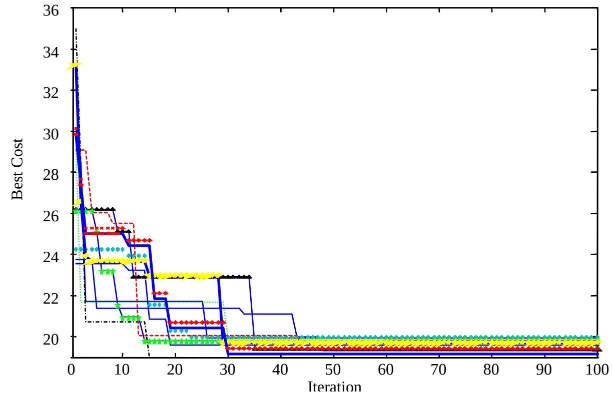


Figure 7. IHBMO convergence curve in many runs

VI. CONCLUSIONS

The development of an electricity simulation model taking into account electrical network constraints is peresnets this paper. The base of the model is optimizing a Unit Commitment (UC) problem through the use of Mixed Improved Honey Bee Mating Optimization (IHBMO).

It has a strong ability to successful control the local search and convergence to the global optimum solution. The problem of find best answer is formulated as an optimization problem according to the time domain-based objective function for a wide range of operating conditions and is solved by the IHBMO technique which is simple, robust and capable to solve difficult combinatorial optimization problems.

The results obtained for three test systems were always comparable or better that the earlier best reported results. From these comparative studies, it is evident that the IHBMO can be effectively used for the solution of UC problems in the real world power systems.

APPENDIX

Taipower 40 units' data and load demands for Case II

Units	P_{max}	P_{min}	*a*	*b*	*c*	*stc*	*Up*	*Down*	*it*
1	80	40	170.44	8.336	0.03073	247.3962	2	3	3
2	120	60	309.54	7.0706	0.0202	248.1078	2	3	3
3	190	80	369.03	8.1817	0.00942	245.8377	2	3	3
4	42	24	135.48	6.9467	0.08482	246.2440	2	3	3
5	42	26	135.19	6.5595	0.09693	231.7961	2	3	3
6	140	68	222.33	8.0543	0.01142	267.5881	2	3	3
7	300	110	287.71	8.0323	0.00357	267.0076	2	3	3
8	300	135	391.98	6.999	0.00492	326.6603	2	3	3
9	300	135	455.76	6.602	0.00573	267.6292	2	3	3
10	300	130	722.82	12.908	0.00605	376.2845	2	3	3
11	375	94	635.20	12.986	0.00515	383.9118	2	3	3
12	375	94	654.69	12.796	0.00569	384.0180	2	3	3
13	500	125	913.40	12.501	0.00421	384.0245	2	3	3
14	500	125	1760.4	8.8412	0.00752	380.3792	2	3	3
15	500	125	1728.3	9.1575	0.00708	386.9936	2	3	3
16	500	125	1728.3	9.1575	0.00708	380.0032	2	3	3
17	500	125	1728.3	9.1575	0.00708	247.3962	2	3	3
18	500	220	647.85	7.9691	0.00313	248.1078	2	3	3
19	500	220	649.69	7.9550	0.00313	245.8377	2	3	3
20	550	242	647.83	7.9691	0.00313	246.2440	2	3	3
21	550	242	647.81	7.9691	0.00313	231.7961	2	3	3
22	550	254	758.96	6.6313	0.00298	267.5881	2	3	3
23	550	254	758.96	6.6313	0.00298	267.0076	2	3	3
24	550	254	794.53	6.6611	0.00284	326.6603	2	3	3
25	550	254	794.53	6.6611	0.00284	267.6292	2	3	3
26	550	254	801.32	7.1032	0.00277	376.2845	2	3	3
27	550	254	801.32	7.1032	0.00277	383.9118	2	3	3
28	150	10	1055.1	3.3353	0.52124	384.0180	2	3	3
29	150	10	1055.1	3.3353	0.52124	384.0245	2	3	3
30	150	10	1055.1	3.3353	0.52124	380.3792	2	3	3
31	70	20	1207.81	3.052	0.25098	380.2535	2	3	3
32	70	20	810.79	21.887	0.16766	380.0032	2	3	3
33	70	20	1247.7	10.244	0.26350	267.6292	2	3	3
34	70	20	1219.2	8.3707	0.30575	376.2845	2	3	3
35	60	18	641.43	26.258	0.18362	383.9118	2	3	3
36	60	18	1112.8	9.6956	0.32563	384.0180	2	3	3
37	60	20	1044.4	7.1633	0.33722	384.0245	2	3	3
38	60	25	832.24	16.339	0.23915	380.3792	2	3	3
39	60	25	834.24	16.339	0.23915	386.9936	2	3	3
40	60	25	1035.2	16.339	0.23915	380.0032	2	3	3

NOMENCLATURES

F_T: Total operation cost over the scheduling horizon
i: Index for thermal units
j: Index for wind units
N_T: Number of thermal units in the system
$P_i(t)$: Generation of thermal unit *i* at hour *t*
$P_{i,r}^{max}$: Upper generation limit of thermal unit *i*
$P_{i(t)}^{max}$: Maximum generation of thermal unit *i* at hour *t*
$P_{i,r}^{min}$: Lower generation limit of thermal unit *i*
$P_{i(t)}^{min}$: Minimum generation of thermal unit *i* at hour *t*
$P_L(t)$: System load demand at hour *t*
T_i^{OFF}: Minimum down time of thermal unit *i*
T_i^{ON}: Minimum up time of thermal unit *i*
t^{ON}, $i(t)$: Time period that thermal unit *i* had been continuously up till period *t*
$TUR(t)$: System ramping up capacity at hour *t*
$U_i(t)$: Scheduled state of thermal unit *i* for hour *t* (1: unit *i* is up, 0: unit *i* is down)
UR_i^{max}: Maximum ramp-up rate for thermal unit *i*
$US_i(t)$: Up reserve contribution of thermal unit *i* at hour *t*
US_i^{max}: Maximum up reserve contribution of thermal unit *i*
USRB: System up spinning reserve requirement not considering wind power generation
P_{max}, P_{min}: the maximum and minimum power generation
a, *b*, *c*: the coefficients of the fuel cost function
stc: start up cost
up, *down*: the minimum up and down time
it: the initial time of the unit, if it is positive (or negative), indicates the number of hours the unit has been already up (or down).

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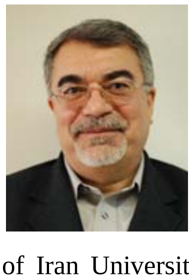
BIOGRAPHIES



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