Evolving Systems (2017) 8:233–242
DOI 10.1007/s12530-017-9189-5

ORIGINAL PAPER

Environmental economic dispatch using improved artificial bee colony algorithm

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Received: 18 August 2016 / Accepted: 29 May 2017 / Published online: 10 June 2017

Abstract Due to emissions from fossil fuel consumption in power plants, not only operational costs, but the minimization of the resulting pollution should be also considered in environmental economic dispatch problem. In this research, environmental economic dispatch problem is solved by minimization of operational cost and environmental pollution considering nonlinear constraints of generating units, forbidden regions, and ramp-rate of generating units using an improved artificial bee colony technique. With the proposed approach, data transactions among bees have been conducted using Newton's and gravitational laws, leading to a full employment of honey bees mating optimization's capability in finding the optimum solution. In order to show the effectiveness of the proposed algorithm, it is tested on IEEE 6-bus and IEEE 11-bus power systems in different load levels. Then, the obtained results are compared with those of other previously validated techniques. It is revealed that the proposed technique is superior in terms of accuracy and speed in solving power system complex problems over the other methods. In addition, it is unlikely for this approach to be trapped in local minima. Results compared to many recent competitive methods confirm the efficiency of the proposed method in term of solution quality and convergence characteristics.

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Keywords Environmental effect of power generating units · Optimization · Operational constraints of generating units · Environmental economic dispatch · Improved artificial bee colony algorithm

1 Introduction

Economic dispatch problem considering air pollution was taken into account by the enactment of the Clean Air Act of 1990. Accordingly, all utilities are required to take the rate of SO_2, NO_x, and CO_2 emissions of their generating units into consideration when dispatching them (Talaq and EI-Hawary 1994). Since then, much research has been conducted in this field and many approaches have been proposed to reduce the emissions. These methods can be divided mainly into three groups:

- Installation of equipment for cleaning emissions in site of generating units;
- Replacement of old equipment with new ones;
- Operation of generating units considering environmental pollutants.

Various approaches are available to take into account the pollution of generating units through environmental economic dispatch (EED) problem. In recent years, several swarm intelligent algorithms have been proposed and improved such as Genetic algorithms (GA) (Holland 1975), Particle swarm optimization (PSO) (Shi and Eberhart 1998), Differential evolution (DE) (Storn and Price 1997) and Artificial bee colony (ABC) (Karaboga 2005a, b), etc., and have been introduced for optimization problem. ABC is one of swarm intelligent algorithms inspired by the foraging behaviors of honeybee colony. ABC was first introduced by Karaboga (Karaboga and Basturk 2007; Gao et al. 2012) and simulates the intelligent foraging behavior of honey bee swarms. Since the ABC is simple in concept, easy to implement and it has fewer control parameters. It has attracted the attention of many researchers and has been widely used in solving numerical optimization (Liao et al. 2013). However, the convergence speed of ABC algorithm will decrease as the dimension of the problem increases. To address these issues, several methods have been proposed to improve the algorithm to overcome these drawbacks (Zhu and Kwong 2010; Yan et al. 2012). For clustering, several methods based on Evolution algorithm (EA) have been proposed such as combining K-means with ABC for clustering (Zou et al. 2010; Ebrahimian et al. 2005). The experimental study of the colony algorithm using an improved artificial bee colony (ABC) algorithm in this paper has been used to solve the ED problem, considering the objective function which consists of fuel cost of units, the constraints of the valve-point effect, the transmission losses, the balance of supply and demand in the system, the production limits the up-ramp and down-ramp rates, and the pollution issues. The resulting algorithm is implemented on the case study systems and the obtained results were compared with those of other algorithms. This algorithm has fast convergence and is less likely to be trapped in local minima compared to other algorithms (Balamurugan and Subramanian 2008).

In this paper, EED problem is solved using a hybrid approach carried out in an objective function consisting of cost and pollution considering transmission system power loss. Improved Artificial Bee Colony (ABC) algorithm, as a most novel approach employed on non-linear models, is used to solve mathematical model. The rest of the paper is presented as follows. In Sect. 2, problem formulation is provided. Section 3 presents the proposed algorithm for solving the EED problem. In Sect. 4, case studies are presented. Finally, the paper is ended with conclusions and feature works in Sect. 5.

2 Problem formulation

The aim of solving EED problem considering pollution is to simultaneously manage fuel cost and pollution from fossil fuel consumption of generating units. This issue is considered as an optimization problem in which the objective function consists of fuel cost and pollution from generating units. In addition, various constraints are taken into account to solve this problem.

2.1 Objective function

With EED problem, operational cost of generating units is expressed as the output power. Considering that fuel cost is the main cost factor of generating units, operational cost function of generating units is expressed as the input fuel cost. It is typically written as quadratic function in terms of output active power of generating unit. Thus, production cost function of generating units is given by:

$$FC = \sum_{i=1}^{M} a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{1}$$

where M is the number of generating units, a_i, b_i, and c_i are cost coefficients of ith generating unit, P_{Gi} denotes ith generating unit's active power, and FC is cost function of production in \$.

Considering that SO_2 and NO_x are the main components for emissions from generating units, it is necessary to minimize the amount of these gases in order to reduce the pollution. Investigations revealed that output power is the most influencing factor in producing emissions by generating units. There is a nonlinear relationship between pollution of a generating unit and its output power. This can be modeled as a quadratic function in terms of output power. Thus, emission function of generating units is given by:

$$FE = \sum_{i=1}^{M} \alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i \tag{2}$$

where α_i, β_i, and γ_i are emission coefficients of ith generating unit, FE denotes total emission in kg. The EED problem's objective function, comprising of fuel cost and emission of generating units, should be minimized as:

$$\begin{aligned} FT = {} & w \times \sum_{i=1}^{M} \left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i \right) \\ & + (1 - w) \times \sum_{i=1}^{M} h_i \left(a_i P_{Gi}^2 + b_i P_{Gi} + \gamma_i \right) \end{aligned} \tag{3}$$

where w is weighting factor of fuel cost, h_i is emission penalty factor from the viewpoint of utility. The value of emission of interest may be different. In reported research, various techniques have been proposed to define this factor (Muralidharan 2006). Typically, penalty factor for emission of each generating unit is defined as fuel cost divided by emission amount and then multiplied by maximum output power of that generating unit (AlRashidi and El-Hawary 2006):

$$h_i = \frac{a_i P_{Gi}^{\max^2} + b_i P_{Gi}^{\max} + c_i}{\alpha_i P_{Gi}^{\max^2} + \beta_i P_{Gi}^{\max} + \gamma_i} \tag{4}$$

where h_i is emission penalty factor and P^{max}_{Gi} is the maximum output power of ith generating unit.

2.2 Constraints

Constraints of EED problem are given as bellow:

2.2.1 Power supply and demand balance in system

Total produced power by all generating units should be equal to total system demand.

$$\sum_{i=1}^{N_i} P_{mi} + \sum_{h=1}^{N_h} P_{mh} - P_{md} - P_{lm} = 0 \tag{5}$$

where P_{mh} is the produced power of hth hydro system in mth sub-branch, P_{md} is total load demand in mth sub-branch, P_{Lm} is total active power loss in transmission lines in mth sub-branch. They should be calculated as in Karaboga (2005):

$$P_{lm} = \sum_{i=1}^{N_i+N_h} \sum^{N_i+N_h} P_{mi} B_{ij} P_{mj} \tag{6}$$

2.2.2 Production constraint

For each generating unit, the maximum and minimum produced power, reactive power, and voltage are defined by:

$$p_i^{\min} \le p_i \le p_i^{\max} \tag{7}$$

3 Improved Artificial Bee Colony (ABC) algorithm

3.1 Standard ABC algorithm

Artificial Bee Colony is a new swarm intelligence algorithm proposed by Karaboga (Karaboga and Bahriye 2008; Palanichamy and Babu 2008) which is motivated from the intelligent food foraging behavior of Honey Bee. Since the development of ABC it has been applied to solve different kinds of problems. The ABC algorithm is developed based on inspection the behaviors of real bees on finding nectar and sharing the information of food sources to the bees in their hive. The main advantages of the ABC algorithm over other optimization methods for solving optimization are simplicity, high flexibility, strong robustness, few control parameter, ease of combination with other methods, ability to handle the objective with stochastic nature, fast convergence.

Based on their experience and position, onlookers choose appropriate food sources. Scouts select food sources randomly and without their experience. Each selected food source indicates a possible solution for the problem. The amount of nectar in food sources indicates the fitness of the problem solution. The number of employed bees is equal to the number of onlookers and equal to the random initial population size. It is initialized with the size of *Ne*, where *Ne* is the number of food sources and equal to employed bees' number. Each solution Xi = (Xi1, …, Xin) is n-dimension vector. Then, this population enters into search process for employed bee, onlookers, and scouts (Dhillon et al. 1993). The main steps of coding for the algorithm are given below:

- Initializing for initial solutions;
- Calculating initial solutions in objective function;
- Initial iteration;
- Finding new solutions based on new food sources V_{ij} in neighborhood of X_{ij} to produce new solutions by Eq. (8); use SI not CGS as primary units. Avoid combining SI and CGS units. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity in an equation:

  $$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \tag{8}$$

  where K is the obtained solution in neighborhood of i, and Φ is a random number in (−1 to 1).

- Selecting the best food source or best solution between *Vij* and *Xij*;
- Calculating the value of possibility for solutions *Xij* based on the following relationship

$$P_i = \frac{fit_i}{\sum_{i=1}^{N_e} fit_i} \tag{9}$$

In fact, in order to obtain fitness of solutions, the following relationship is used:

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & f_i \ge 0 \\ 1 + abs(f_i) & f_i \le 0 \end{cases} \tag{10}$$

Solutions are in the range (−1 to 1).

- Generating new solutions (new sources) *Vi* based on watching bees from the solutions *Xi* and determining their possibilities *Pi*;

- Selecting the best solution (the most gluttonous bee) between *Xij* and *Vij*;
- Determining wasted sources and replacing them with stochastic sources or stochastic sources produced by leader bee *Xi* using the following relationship:

$$X_{ij} = X_{j\min} + rand(0,1) * (X_{j\max} - X_{j\min}) \tag{11}$$

3.2 Improved ABC algorithm

Improved ABC (or IABC) algorithm is based upon gravitational force between objects. The steps toward implementation of this algorithm are as follows:

3.2.1 Initial framing

Ne value is chosen as initial solutions in search space of the algorithm. And, their fitness value is studied based on the objective function. Indeed, random selection of these solutions is done in search space and indicates the employed bees.

3.2.2 Movement of onlookers

The investigation of selected foods' possibility based on Eq. (13) and selection of one food source are completed in order to use roulette wheel for each onlooker and to determine nectar value for each of them on the basis of developed gravitational counterforce among onlookers. They are obtained Eqs. (10)–(15) (Karaboga and Bahriye 2008).

$$P_i = fit_i \Bigg/ \left(\sum_{n=1}^{N_e} fit_i \right) \tag{12}$$

Counterforce between two objects (masses) m_1 and m_2 is given by the following relationship and depicted in Fig. 1:

$$F_{12} = G\frac{m_1 m_2}{r_{21}^2}\hat{r}_{21} \tag{13}$$

$$\hat{r}_{21} = \frac{r_2 - r_1}{\left|r_2 - r_1\right|} \tag{14}$$

where F_{12}, r_{12}, and G are counterforce, unit vector, and gravitational constant, respectively.

Likewise, based on the fitness values of bees, the following relationships are provided.

$$F_{ik_j} = G\frac{F(\theta_i) \times F(\theta_k)}{(\theta_{kj} - \theta_{ij})^2} \cdot \frac{\theta_{kj} - \theta_{ij}}{\left|\theta_{kj} - \theta ij\right|} \tag{15}$$

$$X_{ij}(t+1) = \theta_{ij}(t) + F_{ik_j}\left[\theta_{ij}(t) - \theta_{kj}(t)\right] \tag{16}$$

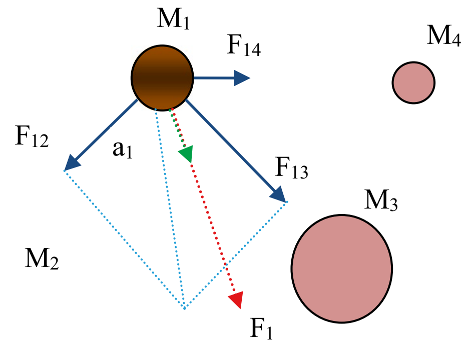

Fig. 1 Counterforce between two objects

where *F(θi)* and *F(θj)* are the fitness expressed for employed bees. Equation (16) expresses the resulting effect for new supply source. Considering counter effect of all bees on the selected bee, Eq. (16) is extended to Eq. (17) (Zou et al. 2010):

$$x_{ij}(t+1) = \theta_{ij}(t) + \sum_{k=1}^{n} F_{ik_j}\left[\theta_{ij}(t) - \theta_{kj}(t)\right] \tag{17}$$

3.2.3 Movement of scouts

If function fitness is not corrected in following iterations of the algorithm, it will be named Limit and the corresponding sources are called obsolete. With the aid of scouts' movement, obsolete sources are recovered and replaced with the new sources. The movement process will be as follows:

$$\theta_{ij} = \theta_{ij\min} + r.(\theta_{ij\max} - \theta_{ij\min}) \tag{18}$$

3.2.4 Replacement

If food sources found become better in the next steps compared to the earlier steps, this value will be stored in bee memory.

3.2.5 Program termination

The program is iterated until all iterations are terminated. If a satisfactory value is obtained, the program will terminate. Otherwise, the second step is restarted. Figure 2 illustrates the proposed algorithm's flowchart.

4 Case study

In this section, the results obtained from implementation of proposed algorithm are studied and analyzed. EED problem was solved in order to fulfill numerical studies and show the effectiveness of the proposed algorithm in two

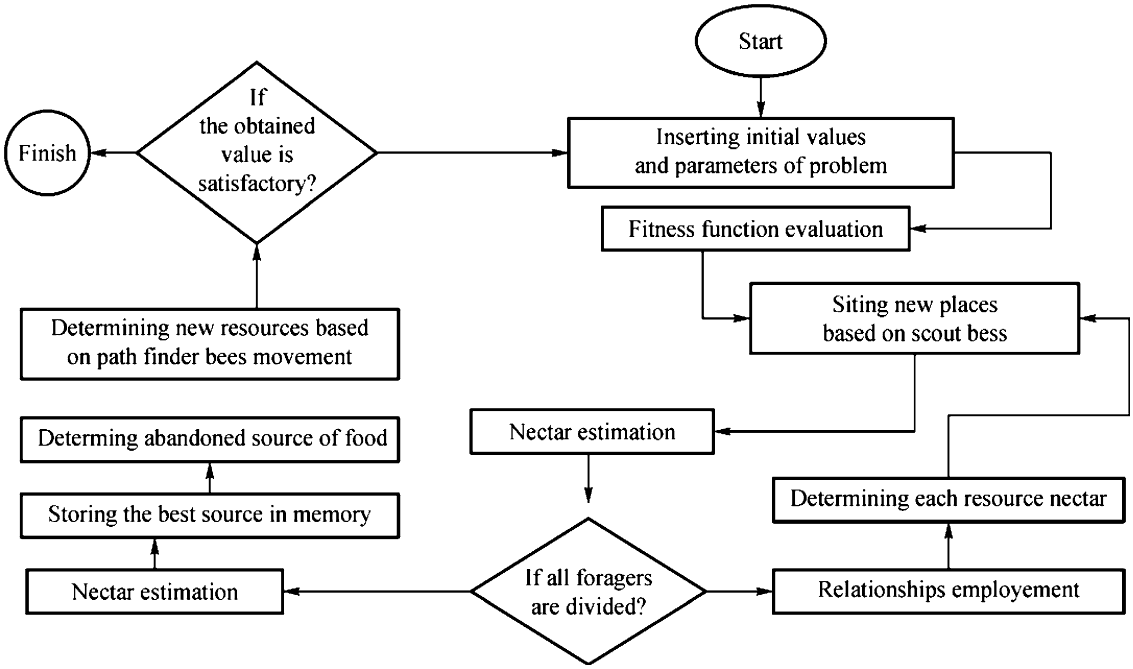

Fig. 2 IABC algorithm's flowchart

Table 1 Required parameters for the algorithm implementation

Parameter	Value
Population size	30
Bee swarm groups	10
Local iteration number	3
Maximum algorithm iteration	30
Overshoot coefficient	2
Initial inertia	0.9
Final inertia	0.4

Table 2 Fuel cost coefficients for 6-unit system (Dhillon et al. 1993)

Generating unit	a_i	b_i	c_i	P_{Gi}^{min}	P_{Gi}^{max}
G1	0.1525	38.54	756.8	10	125
G2	0.1060	46.16	451.325	10	150
G3	0.0280	40.40	1050	35	225
G4	0.3550	38.10	1243.53	35	210
G5	0.0211	36.326	1658.57	130	325
G6	0.0180	38.270	1356.66	125	315

case tests, i.e. IEEE 6 bus power system and IEEE 11 bus power system. The obtained results were compared with those of other techniques.

For numerical studies, parameters related to IABC are provided in Table 1. The precise selection of these parameters can be effective in reaching optimal solution. For instance, increasing the population size up to a definite value leads to improved quality and at the same time reduces the algorithm's speed. Thus, in order to select population size, a reasonable trade-off should be made between accuracy and speed of the algorithm. Groups of bees should be also selected in a way that the number of available bees in each group is not high in order to avoid quality reduction. It must be also not too small to prevent the movement of bees and, in turn, to trap in local minima. Due to affectability of movement of each member in the group, the maximum useful iteration of local search is equal to the number of group size. The maximum iteration of algorithm is also selected in a way to obtain problem solution with appropriate accuracy at the least possible time. Further, tests carried out on two case systems are described and the numerical results of the proposed algorithm will be presented.

4.1 6-Unit system

Coefficients of the fuel cost and generating units' power limits as well as emission function coefficients of each generating unit in this system are presented in Tables 2 and 3 (Dhillon et al. 1993). Formulation coefficients of transmission network losses in this system are expressed by Eq. (16) (Eusuff and Lansey 2003). EED problem for this system in two modes, i.e. with and without losses, in load levels varying between 500 and 1100 MW are calculated (Fig. 3).

Table 3 Emission function coefficients for 6-unit system (Dhillon et al. 1993)

Generating unit	α_i	β_i	γ_i
G1	0.00420	0.33	13.86
G2	0.00420	0.33	13.86
G3	0.00683	−0.54551	40.267
G4	0.00683	−0.54551	40.267
G5	0.00460	0.5112	0.42.900
G6	0.00460	0.5112	0.42.900

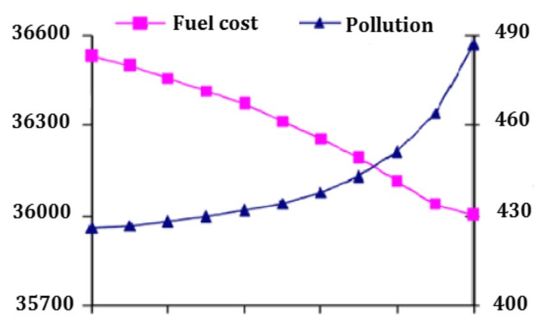

Fig. 3 Variations of fuel cost and pollution functions of 6-unit system

In modes of with/without power loss, the obtained results were compared with those of λ-iteration algorithm (Dhillon et al. 1993), recursive algorithm (Dhillon et al. 1993), simplified recursive algorithm (Palanichamy and Babu 2008), differential evolutionary (Palanichamy and Babu 2008), PSO (Palanichamy and Babu 2008), SA (Xuebin 2009), shuffled frog leaping algorithm (Muralidharan 2006), and provided in Tables 4 and 5 for the mode without power loss and Tables 6 and 7 of the mode with power loss. For the comparison purpose, importance weighting factors of each objective function is taken 5.0.

As seen in Tables above the proposed algorithm greatly outperforms the other techniques. In addition, ABC algorithm-based technique has outstanding results both in terms of fuel cost and emission reduction.

4.2 11-Unit system

This system's characteristics consisting of fuel cost function's coefficients, permissible production limits, and pollution function's coefficients of each generating unit are provided in Tables 7 and 8 (Palanichamy and Babu 2008). In this condition, EED is defined for this system

Table 4 Fuel cost comparison in various loads in 6-unit system without fuel cost power loss ($, h^{-1})

Load (MW)	λ-iteration (Karaboga and Bahriye 2008)	Recursive (Palanichamy and Babu 2008)	Simplified recursive (Karaboga and Bahriye 2008)	Differential evolutionary (Karaboga and Bahriye 2008)	Particle swarm optimization (PSO) (Karaboga and Bahriye 2008)	Simulated annealing (SA) (Eusuff and Lansey 2003)	Shuffled frog leaping algorithm (Balamurugan and Subramanian 2008)	The proposed algorithm
500	27092.4	27092.5	27092.5	27098.1	27097.5	27092.4	27091.4	27081.0
600	31628.7	31628.6	31628.6	31629.2	31634.9	31628.6	31627.7	31627.6
700	36314.0	36331.8	36313.9	36314.0	36314.2	36313.9	36312.4	36311.4
800	41148.4	41148.3	41148.3	41152.6	41160.3	41148.3	41147.7	41047.6
900	46131.8	46131.5	46131.8	46132.1	46160.6	46131.9	46130.1	46129.2
1000	51264.8	51264.5	51264.5	51264.5	51269.6	51264.4	51263.9	51263.9
1100	56546.8	56546.2	56546.6	56556.7	56546.1	56546.1	56545.7	56544.7

Table 5 Emission comparison in 6-unit system without power loss

Load (MW)	λ-iteration (Karaboga and Bahriye 2008)	Recursive (Palanichamy and Babu 2008)	Simplified recursive (Karaboga and Bahriye 2008)	Differential evolutionary (Karaboga and Bahriye 2008)	Particle swarm optimization (PSO) (Karaboga and Bahriye 2008)	Simulated annealing (SA) (Eusuff and Lansey 2003)	shuffled frog leaping algorithm (Balamurugan and Subramanian 2008)	The proposed algorithm
500	361.635	361.634	361.634	361.859	362.225	361.63	361.552	360.669
600	338.993	338.992	338.992	339.820	338.990	338.99	338.94	337.93
700	434.380	434.380	434.380	434.453	434.605	434.380	434.330	433.320
800	547.797	547.796	547.796	547.453	547.844	547.790	547.747	547.745
900	679.241	679.241	679.241	679.283	679.724	679.240	679.171	679.170
1000	828.720	828.715	828.715	828.715	828.863	828.710	828.698	828.698
1100	996.223	996.224	996.218	996.218	996.222	996.220	996.101	996.102

Table 6 The best results obtained in various loads in 6-unit system with power loss

Load (MW)	P1	P2	P3	P4	P5	P6	PL	Fuel cost ($ h^{-1})	Emission (kg h)
500	21.163	20.199	92.879	91.575	144.300	139.290	9.208	27528.544	266.780
600	33.583	31.446	110.549	106.670	166.393	164.434	13.074	32246.836	349.616
700	46.179	46.787	127.404	119.559	192.214	185.397	17.580	37180.946	451.634
800	58.292	61.748	144.465	134.385	217.056	206.872	22.818	42312.869	574.568
900	70.069	77.374	160.863	151.208	240.496	228.766	28.777	47654.173	718.012
1000	83.517	93.108	181.405	165.884	262.994	253.674	35.488	53223.795	882.232
1100	96.085	113.542	193.265	178.856	289.136	275.198	42.950	59060.706	1065.035

Table 7 Fuel cost coefficients in 11-unit system (Palanichamy and Babu 2008)

Generating unit	a_i	b_i	c_i	P_{Gi}^{min}	P_{Gi}^{max}
G1	0.00762	1.92699	387.85	20	250
G2	0.00838	2.11969	441.62	20	210
G3	0.00523	2.19196	422.57	20	250
G4	0.00140	2.01983	552.50	60	300
G5	0.00154	2.22181	557.75	20	210
G6	0.00177	1.91528	562.18	60	300
G7	0.00195	2.10681	568.39	20	215
G8	0.00106	1.99138	682.93	100	455
G9	0.00117	1.99802	741.22	100	455
G10	0.00089	2.12352	617.83	110	460
G11	0.00098	2.10487	674.61	110	465

Table 8 Pollution function coefficients in 11-unit system (Palanichamy and Babu 2008)

Generating unit	α_i	β_i	γ_i
G1	0.00419	−0.67767	23.93
G2	0.00461	−0.69044	24.62
G3	0.00419	−0.67767	33.93
G4	0.00683	−0.54551	27.14
G5	0.00751	−0.40060	24.15
G6	0.00683	−0.54551	27.14
G7	0.00751	−0.40006	24.15
G8	0.03355	−0.51116	30.45
G9	0.00417	−0.56228	25.59
G10	0.00355	−0.41116	30.45
G11	0.00417	−0.56228	25.59

on various load levels between 1000 and 2500 MW. In order to compare the results of the proposed algorithm and other techniques, transmission network losses are neglected. As seen in Tables 9 and 10, the proposed algorithm has high accuracy. Compared to the other computational algorithms in this system, the proposed algorithm has the minimum fuel cost and minimum pollution on each load level (Table 11; Figs. 4, 5, 6).

As seen in Tables 9 and 10, the proposed algorithm has high accuracy and it reaches the least possible fuel cost and pollution on each load level compared to the other computational algorithms.

5 Conclusion

In this paper, Artificial Bee Colony (ABC) algorithm was used in order to solve economic dispatch problem considering reduction of costs related to operation and pollution in two standard systems. In fact, one approach for accurate prediction of power production cost in power systems is to model objective functions appropriately and precisely. Thus, in this paper, by taking into account these functions and employing a proper algorithm, this goal was realized. In order to show the effectiveness of the algorithm, obtained results of load flow calculations for case system using improved ABC algorithm were compared with those of various algorithms. Results of economic dispatch indicate that the proposed algorithm is highly effective in dealing with much more complicated problems. In the presented objective function, simultaneous minimization of production cost and reduction of transmission system losses were considered, leading to more successful achievements in finding optimal points near to global one. Thus, implementation of proposed algorithm in practical power systems is significantly effective in achieving more precise operating costs in these systems. For the purpose of ED problem, we will implement ABC algorithm on large standard and practical systems.

Table 9 Fuel cost comparison in various loads in 11-unit system

Load (MW)	λ-iteration (Karaboga and Bahriye 2008)	Recursive (Palanichamy and Babu 2008)	Simplified recursive (Karaboga and Bahriye 2008)	Differential evolutionary (Karaboga and Bahriye 2008)	Particle swarm optimization (PSO) (Karaboga and Bahriye 2008)	Simulated annealing (SA) (Eusuff and Lansey 2003)	Shuffled frog-leaping algorithm (Balamurugan and Subramanian 2008)	The proposed algorithm
1000	8502.30	8502.29	8502.29	8505.81	8508.24	8502.30	8502.02	8500.00
1250	9108.38	9108.38	9108.38	9117.63	9114.42	9108.38	9107.57	9107.56
1500	9733.54	9733.54	9733.54	9736.22	9733.33	9733.53	9732.83	9732.83
1750	10377.77	10377.77	10377.77	10377.86	10380.82	10377.53	10376.92	10376.00
2000	11041.08	11041.08	11047.08	11041.09	11041.09	11041.9	11041.79	11040.88
2250	11723.47	11723.47	11723.47	11723.47	11725.68	11723.47	11723.24	11723.223
2500	12424.94	12424.94	12424.94	12425.06	12428.63	NA	12423.55	12482.45

NA not mentioned in corresponding reference

Table 10 Pollution comparison in various loads in 11-unit system

Load (MW)	Iteration λ (Karaboga and Bahriye 2008)	Recursive (Palanichamy and Babu 2008)	Simplified recursive (Palanichamy and Babu 2008)	Differential evolutionary (Karaboga and Bahriye 2008)	Particle swarm optimization (PSO) (Karaboga and Bahriye 2008)	Simulated annealing (SA) (Xuebin 2009)	Shuffled frog-leaping algorithm (Balamurugan and Subramanian 2008)	The proposed algorithm
1000	205.205	205.204	205.204	208.206	205.012	208.20	205.181	205.180
1250	339.870	339.870	339.870	339.935	345.669	339.87	339.751	339.751
1500	540.545	540.545	540.545	544.298	545.307	540.540	540.010	545.000
1750	807.220	807.220	807.220	807.236	807.863	807.23	806.770	205.770
2000	1139.912	1139.911	1139.901	1139.911	1142.182	1139.91	1139.835	1139.834
2250	1538.600	1538.600	1538.600	1538.600	1538.659	1538.60	1538.436	1537.436
2500	2003.301	2003.300	2003.300	2003.350	2009. 720	2003.300	2002.903	2002.902

Table 11 11-unit system

	Load (MW)						
	1000	1250	1500	1750	2000	2250	2500
P1	86.874	95.100	102.549	113.673	120.983	131.482	138.833
P2	73.038	82.932	87.927	92.678	100.917	105.999	112.597
P3	89.432	94.632	108.146	116.220	127.119	135.618	146.121
P4	76.432	101.317	125.704	144.557	176.199	199.015	221.629
P5	50.250	61.873	80.910	93.665	109.977	123.151	136.070
P6	78.499	97.464	125.101	147.075	173.713	192.275	218.301
P7	52.087	70.226	80.243	94.942	108.942	123.486	144.685
P8	124.540	170.226	204.383	240.515	271.704	313.036	346.727
P9	123.872	156.984	186.550	227.461	261.696	292.488	324.536
P10	125.284	156.686	198.439	246.017	279.665	323.688	362.267
P11	119.800	162.458	200.048	233.196	269.084	309.762	348.234

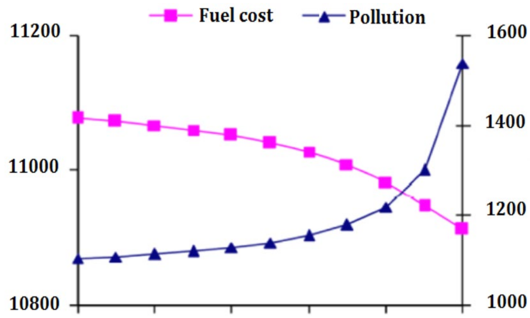

Fig. 4 Variations of fuel cost and pollution functions of 11-unit system

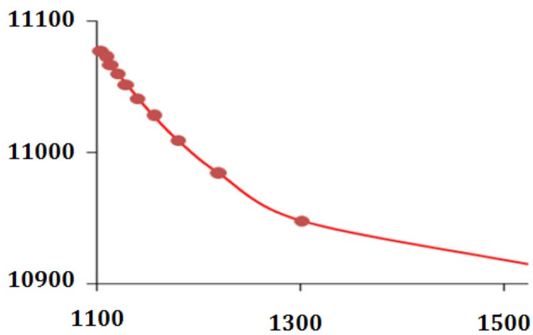

Fig. 5 Interaction curve among objectives of 6-unit system

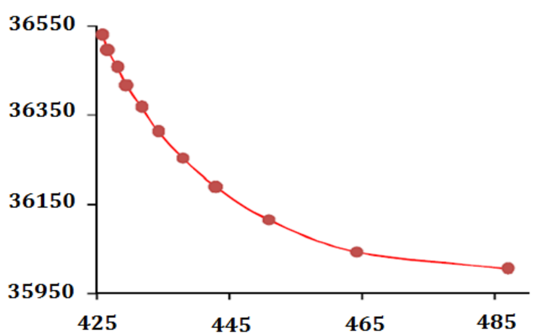

Fig. 6 Interaction curve among objectives of 11-unit system

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