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Fuzzified artificial bee colony algorithm for nonsmooth and nonconvex multiobjective economic dispatch problem

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Abstract: The economic dispatch (ED) problem is one of the important optimization problems in power system operation. Recently the power system has stressed the need for reliable, nonpolluting, and economic operation. Hence, 3 conflicting functions of reliability, emission, and fuel cost are considered in the objective function of the proposed ED problem. The problem is formulated as a nonsmooth and nonconvex problem when the valve-point effects of thermal units are considered in the proposed reliable emission and economic dispatch (REED) problem. This paper presents a multiobjective optimization methodology for solving the newly developed REED problem using a fuzzified artificial bee colony algorithm. The artificial bee colony algorithm is used to schedule the optimal dispatch and fuzzy membership approach is used to find the best compromise solution from the Pareto optimal set. The methodology is validated on an IEEE 30-bus system and 3-, 6-, 10-, 26-, and 40-unit systems and the results are compared with the existing literature. The results clearly show that the proposed method is able to produce well-distributed Pareto optimal solutions when compared with other methods reported in the literature.

Key words: Artificial bee colony algorithm, reliable emission and economic dispatch problem, fuzzy set theory

1. Introduction

The economic dispatch (ED) is a constrained optimization problem and the nature of the problem is to find the most economical schedule of the generating units while satisfying load demand and unit operational constraints [1]. The increased emphasis on environmental pollution reduction in the electricity industry has spurred serious research activity [2,3]. A major step in this direction is the Kyoto Protocol, an international treaty and an agreement under which industrialized countries were to reduce their collective emissions of greenhouse gases by 5% over the 5-year period of 2008–2012 as compared to the year 1990. For the European Union, the Kyoto Protocol target is an 8% reduction. Hence, the power industries are obliged to consider emission as another objective function in the ED problem.

On the other hand, the Energy Policy Act of 2005 (EPAct) addressed reliability issues of power systems in a number of ways. EPAct mandated the creation of a self-regulatory Electric Reliability Organization (ERO) that spans North America, with oversight by the Federal Energy Regulatory Commission (FERC). In 2006, the FERC certified the North American Electric Reliability Corporation (NERC) as the ERO for the United States [4]. As with the ERO, the NERC is responsible for establishing and enforcing FERC-approved electric reliability standards. Power industries are thereby forced to consider the reliability function as another

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objective in addition with the emission and fuel cost functions. Hence, the reliable emission and economic dispatch (REED) problem is a conflicting multiobjective optimization problem (MOOP) that is concerned with the attempt to improve each objective simultaneously while satisfying the system load and unit constraints.

A number of optimization techniques have been attempted to solve the MOOP, such as multiobjective evolutionary algorithms [5,6], evolutionary programming techniques including differential evolution [7–10], particle swarm optimization-based approaches [11–13], the harmony search algorithm [14], the biography-based algorithm [15], fuzzy adapted heuristic approaches [16,17], and soft computing techniques [18,19]. These solution techniques are found to be good for searching the near global optimal solution and can be considered successful to a certain extent. Since new swarm-based optimization techniques are seen emerging, finding the best commitment solution with the least computational time is a challenging task within the research community. In recent years, a new optimization method known as the artificial bee colony (ABC) algorithm developed by Karaboga was successfully applied to various applications such as the clustering approach [20], wireless sensor network routing [21], symbolic regression [22], neural network training by pattern classification [23], parameter optimization problems [24,25], and constrained optimization problems [26–28]. Performance and literature reviews of the ABC algorithm and applications are given in the literature [29–31]. In our previous work, the ABC algorithm was tested and validated on power system optimization problems such as the dynamic economic dispatch problem [32], unit commitment problem [33], and price-based unit commitment problem [34]. In this context, an attempt is made to solve the multiobjective REED problem using an fuzzified ABC (FABC) algorithm.

2. Proposed work

The aim of this paper is to show the efficiency of the FABC algorithm for solving a multiobjective ED problem. Similar to other evolutionary methods, the ABC algorithm starts with an initial fixed number of bees that fly around in a multidimensional search space, find the food sources, and fly back to nest. At the end of every generation of the ABC algorithm, the fuzzy fitness is used to pick up the best compromise. The fuzzy membership for the reliability function is proposed and is incorporated in the ED problem to demonstrate the importance of the reliability in the ED problem.

In this article, the ABC algorithm is used to schedule the optimal dispatch and the fuzzy membership approach is used to obtain the best compromise solution. The rest of the sections are organized as follows: in Section 3, the problem formulation of the REED problem is presented. Sections 4 and 5 describe the process of multiobjective optimization and the formulation of the fuzzy membership function for different objectives respectively. Sections 6 and 7 explain the basic behavior of the ABC and implementation of the FABC for REED. In Section 8, we explain the different case studies that are considered in the paper. In Section 9, the effectiveness of the proposed approach is validated on different test systems and the results are discussed. Finally, the conclusion is given in Section 10.

3. REED problem formulation

The objective of the REED problem is to minimize the 3 competing objectives (i.e. reliability, emission, and fuel cost) simultaneously, while satisfying the system and unit constraints. Modeling of fuel cost function, emission function, and reliability of the system for the REED problem is presented below.

3.1. Fuel cost function

The fuel cost minimization problem is formulated as:

Minimize

$$F_c = \sum_{i=1}^{N} \left(\begin{array}{l} (a_i + b_i.P_i + c_i.P_i^2) \\ + |e_i.\sin(f_i.(P_{i,\min} - P_i))| \end{array} \right), \tag{1}$$

where:

F_c	Fuel cost function ($),
a_i, b_i, c_i	Cost coefficient of ith generator unit,
e_i, f_i	Valve point coefficient of ith generator unit,
P_i	Generation power output of unit i,
$P_{i,\min}$	Minimum power output of unit i.

3.2. Emission function

Though classical dispatch is beneficial in terms of operating cost, fossil fuel-based power plants tend to produce high emissions. The emission from each unit depends on the power generated by that unit and can be modeled as a sum of a quadratic and an exponential function, which is given in Eq. (2):

$$E = \sum_{i=1}^{N} \left(\begin{array}{l} (\alpha_i + \beta_i.P_i + \gamma_i.P_i^2) \\ +\delta_i.\exp(d_i.P_i) \end{array} \right), \tag{2}$$

where:

E	Emission function (t),
$\alpha_i, \beta_i, \gamma_i$	Emission coefficient of ith generator unit,
d_i, δ_i	Exponential emission coefficient of ith generator unit.

3.3. Reliability function

The reliability of the system plays a vital role in daily power system operation. Hence, in the ED problem it is necessary to consider the reliability level while dispatching the generating units. The system reliability level is dependent on the forced outage rate (FOR) or unavailability and failure rate of the committed generating units. Each generating unit is represented by a 2-state model [35], shown in Figure 1, according to which unit is either available or unavailable for generation.

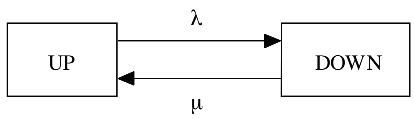

Figure 1. Generating unit 2-state model.

Here the unavailability *Ui(LT)* of the generating unit i during a short time interval LT (known as the system lead time) is given in Eq. (3):

$$U_i(LT) = \frac{\lambda_i}{\lambda_i + \mu_i}(1 - e^{-(\lambda_i + \mu_i)LT}) \tag{3}$$

where λ_i and μ_i are the failure and repair rate of unit i, respectively. Assuming that the lead time is much shorter than the repair times of the generating units, the repair process can be neglected. This assumption results in a more simplified expression of the unavailability of each unit, which is given by Eq. (4).

$$U_i(LT) = 1 - e^{-\lambda_i LT} \tag{4}$$

This is the time period (LT) for which no additional units can be brought into service. The lead time may be few minutes to several hours. Hence, the probability $U_i(LT)$ is known as the outage replacement rate (ORR) of the unit. The reliability index of the power system is calculated using the conventional loss of load method, which is based on the convolution of the capacity outage probability table (COPT). A COPT is formed using the ORR of the generating units [35]. Each row j = 1...n of the COPT represents a generation level that may be outaged, the probability of availability that corresponds to jth state of the COPT (PR_j), and load curtailment due to generator contingency j (L_j). The reliability index for the particular hour can be calculated by Eq. (5):

$$MinEENS = \sum_{j=LC} PR_j L_j \ (kWh), \tag{5}$$

where the expected energy not supplied (EENS) is the reliability function and LC is the total number of contingencies leading to load curtailment. Here, a high value of EENS indicates a low reliability level and vice versa. A reduction in time can be achieved by omitting the outage level for which the cumulative probabilities of the generation availability are less than a predefined limit (e.g., 10^{-7}) [35].

3.4. Constraints

3.4.1. Power balance constraints

The total power generated must meet the total system load (P_D) and transmission line losses (P_L). It can be defined as:

$$\sum_{i=1}^{N} (P_i) + P_D - P_L = 0, \tag{6}$$

where P_D is the total system demand and P_L, the transmission line losses, is a function of generator power outputs and can be represented using B-coefficients:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00}, \tag{7}$$

where B_0, B_{00} are the loss coefficients.

3.4.2. Generation capacity limit

The real power output of each generator is constrained by a minimum and maximum limit, i.e.:

$$P_{i,\min} \le P_i \le P_{i,\max}, \tag{8}$$

where $P_{i,\max}$ and $P_{i,\min}$ are the maximum and minimum power output of unit i.

3.4.3. Formulation of the multiobjective function

The real time optimization problems involve simultaneous optimization of several conflicting objectives. The general MOOP is posed as follows:

$$\text{Minimize}\, F(x) = [F_1(x), F_2(x), ..., F_T(x)], \tag{9}$$

$$\text{Subject to } g_i(x) \leq 0,\ j = 1, 2, ..., I_n, \tag{10}$$

$$h_k(x) = 0,\ \ k = 1, 2, ..., E_n, \tag{11}$$

where $F(x)$ is the objective function, T is the total number of objective functions, I_n is the number of inequality constraints, and E_n is the number of equality constraints. If all objective functions are for minimization, a feasible solution x_1 is said to dominate another feasible solution x_2 $(x_1 > x_2)$ if and only if $F_i(x_1) \leq F_j(x_2)$ for $(i, j \in 1, \ldots, T)$ and $F_i(x_1) < F_j(x_2)$ for at least one objective function j. A solution is said to be Pareto optimal if it is not dominated by any other solution in the solution space. The solutions that are nondominated within the entire search space X are referred to as the Pareto optimal set. For many problems, the number of Pareto optimal solutions is enormous (perhaps infinite).

In this paper, 3 conflicting objective functions are considered and formulated as a constrained multiobjective function, given as follows:

$$\text{Minimize } [F_{c,}E, EENS], \tag{12}$$

subjective to the constraints of Eqs. (6-8).

4. Fuzzy membership function formulation

The Pareto optimal concept using fuzzy membership is used to evaluate the fitness of each bee. Based on the nature of the objective function, a fuzzy membership function for each objective in the fuzzy domain is formulated, i.e. the corresponding membership function value should indicate the importance of satisfaction for that objective.

4.1. Fuzzy membership function for F$_c$ and E

In the proposed REED problem, the objective functions of fuel cost and emissions are the minimization function. Therefore, the fuzzy membership function for the F_c and E is same and it aids the ABC algorithm in maximizing the fitness function. The membership function chosen for objective functions F_c and E is the same and is shown in Figure 2.

The design of the membership function implies that for any solution, if the objective function (F_c and E) in the fuzzy domain is greater than $F_{j\max}$, then the associated fuzzy membership function value is zero. On the other hand, if the objective function is less than $F_{j\min}$, then the associated fuzzy membership function value is assigned to be one. If the objective function in the fuzzy domain is between $F_{j\min}$ and $F_{j\max}$, then the associated fuzzy membership function value is computed using Eq. (13), and such solutions will participate in the optimization process depending on the membership value.

$$\mu_j^p = \begin{cases} 1, & \text{for} \quad F_i \leq F_{i\min}; \\ \frac{(F_{j\max} - F_j)}{(F_{j\max} - F_{j\min})}, & \text{for} \quad F_{j\min} < F_j < F_{j\max}; \\ 0, & \text{for} \quad F_j\, x_j \geq F_{j\max} \end{cases} \tag{13}$$

Here, $j \in \{F_c, E\}$, F_j is the degree of the objective function in the fuzzy domain and μ_j^p is the membership function value for the objective function of pth bee position.

4.2. Fuzzy membership function for EENS

The membership function chosen for the EENS function is shown in Figure 3. The design of the membership function implies that, for an objective function of EENS in the fuzzy domain that is less than $F_{j\,\min}$, the system cost is increased proportionally. Hence, the fuzzy membership function value is assigned to be zero. Such solutions (corresponding bee positions) do not participate in the optimal solution set.

$$\mu_r^p = \begin{cases} 0, & \text{for} \quad F_j \leq F_{j\,\min}; \\ \frac{(F_{javg} - F_j)}{(F_{javg} - F_{j\,\min})}, & \text{for} \quad F_{j\,\min} < F_j < F_{javg}; \\ 1 & \text{for} \quad F_j = F_{javg} \\ \frac{(F_{j\,\max} - F_j)}{(F_{j\,\max} - F_{javg})}, & \text{for} \quad F_{javg} < F_j < F_{j\,\max}; \\ 0, & \text{for} \quad F_j > F_{j\,\max} \end{cases} \tag{14}$$

On the other hand, when the objective function of *EENS* in the fuzzy domain is greater than $F_{j\,\max}$, it will affect the system reliability and hence will not take part in the optimal solution set. If the value of the objective function in the fuzzy domain is between $F_{j\,\min}$ and $F_{j\,\max}$, then the associated fuzzy membership function value is computed using Eq. (14) and such solutions will participate in the optimization process depending on the fitness value.

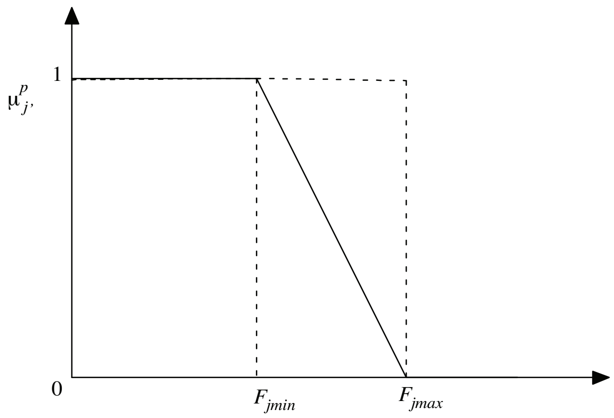

Figure 2. Fuzzy membership function for F_c and E.

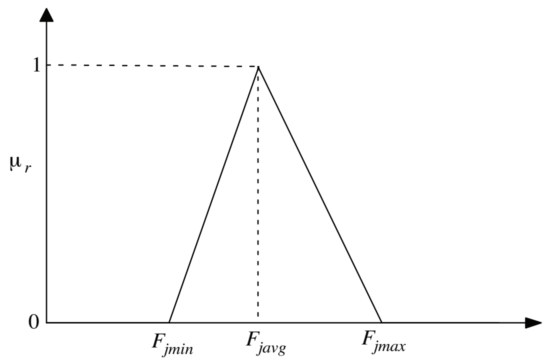

Figure 3. Fuzzy membership function for EENS.

5. Overview of the ABC algorithm

The ABC algorithm is a swarm based metaheuristic algorithm, introduced by Karaboga in [26–28] for optimizing numerical problems. It has been developed by simulating the intelligent behavior of honeybees. It is a population-based search procedure and the foraging behavior of real bees in finding food sources is shown in Figure 4. The model consists of 3 essential components: employed bees, unemployed bees, and food sources.

Figure 4a clearly shows the essential parts of the model: employed bees, unemployed bees, food sources, and a dancing area. Employed bees fly around in a multidimensional search space and choose their food sources depending on their own experience, which is shown in Figure 4b. Once the employed bees complete their search process, they share their food source information with unemployed bees or onlooker bees waiting in the hive by dancing in the dancing area, which is shown in Figure 4c.

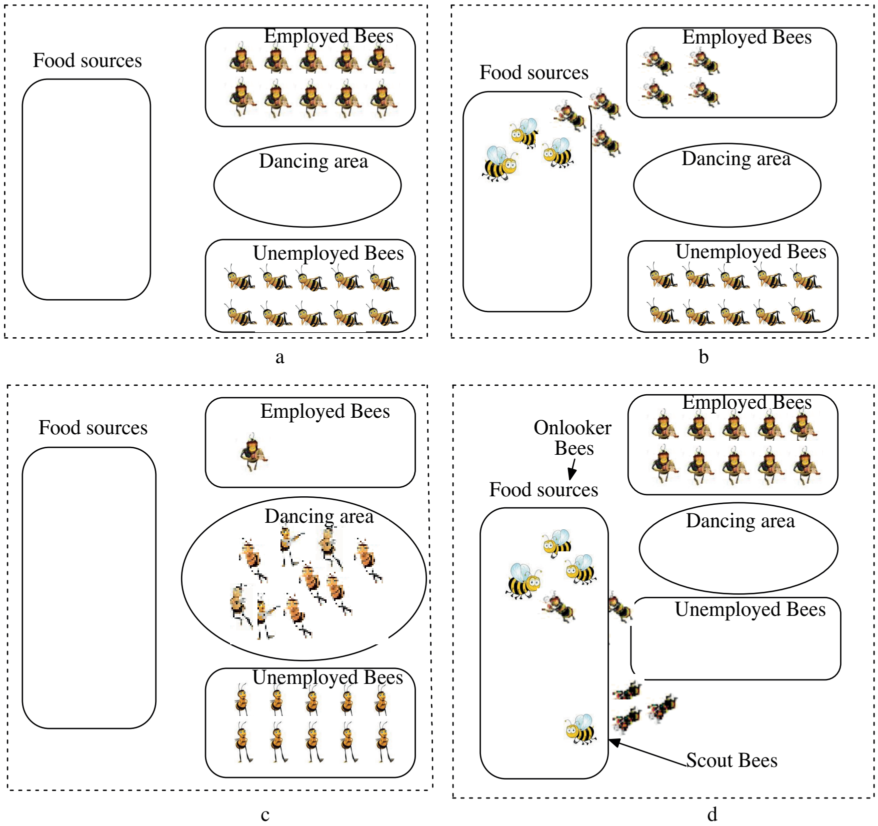

Figure 4. Behaviors of artificial bee colonies.

Onlooker bees probabilistically choose their food sources depending on this information gained from the employed bees using Eq. (15), which is shown in Figure 4d. If there is no improvement in the food source (fitness), then the scout bees fly and choose the food sources randomly without using experience, which is also shown in Figure 4d.

$$Pro_p = \frac{FIT_p}{\sum\limits_{z=1}^{m} FIT_z} \tag{15}$$

Here, FIT_p is the fitness value of the solution p, which is proportional to the nectar amount of the food source in the bee position p, and $m$is the total number of bees' positions. Now the onlookers produce a modification in the position selected by using Eq. (16) and evaluate the nectar amount of the new source.

$$V_{pq} = x_{pq} + \varphi_{pq}(x_{pq} - x_{fq}) \tag{16}$$

Here, $f \in \{1, 2 \ldots m\}$ and $q \in \{1, 2 \ldots D\}$ are randomly chosen indexes. Although f is determined randomly, it has to be different from p, and D is the number of parameters to be optimized. ϕ_{pq} is a random number in [0, 1]. It controls the production of neighborhood food sources. If the nectar amount of the new source is higher than that of the previous one, the onlookers remember the new position; otherwise, it retains the old position. In other words, a greedy selection method is employed as the selection operation between old and new food sources.

If a solution representing a food source is not improved by a predetermined number of trials, then that food source is abandoned and the employed bee associated with that food source becomes a scout. The number of trials for releasing a food source is equal to the value of the 'limit', which is an important control parameter of the ABC algorithm. The limit value usually varies from 0 to 15. If the abandoned source is x_{pq}, $q \in \{1, 2 \ldots D\}$, then the scout discovers a new food source x_{pq} using Eq. (17).

$$x_{pq} = x_{q\,\min} + rand(0,1) * (x_{q\,\max} - x_{q\,\min}) \tag{17}$$

Here, $x_{q\,\min}$ and $x_{q\,\max}$ are the minimum and maximum limits of the parameter to be optimized.

6. Implementation of FABC for the REED problem

In solving the REED problem using FABC, the fuzzy fitness mechanism is employed to pick up the best compromise solution form the Pareto optimal set. For each nondominated solution, the normalized membership fuzzy fitness function (FIT) is calculated using Eq. (18).

$$FIT_p = \frac{(\mu_c^p + \mu_e^p + \mu_r^p)}{\sum_{p=1\,to\,m} (\mu_c^p + \mu_e^p + \mu_r^p)} \tag{18}$$

Here, m is the total number of nondominated solutions or population of the bees, and $p$is the pth position of bees or food sources. The best compromise solution is the one that has the maximum value in the population of bees, i.e. the food sources having the highest quality of nectar information compared with other food sources.

6.1. Initialization of population

A randomly generated population of R initial solutions is represented by real values (generator output) with a S-dimensional vector. Hence, we randomly initialize an initial population $R = [Y_1;\ Y_2;\ Y_3; ...; Y_m]$ of m solutions or bees in the multidimensional solution space is shown in Figure 5, where m represents the size of the population and each solution of Y is represented by the S-dimensional vector. Here S is equal to N. N is the number of generating units.

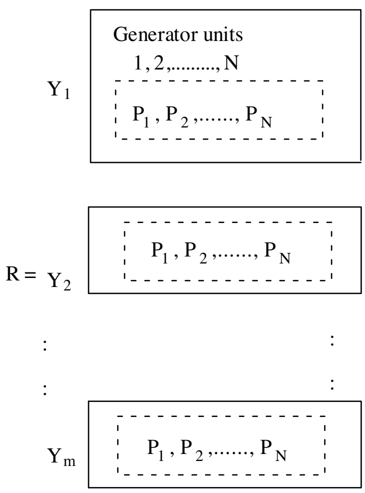

Figure 5. Random initialization.

6.2. Repair strategy for constraint management

Whenever there is modification of a bee position in the ABC algorithm, it is necessary to check for the constraints of Eq. (6) and Eq. (8). If there is any violation in constraint, the repair scheme given in Figure 6 is performed to overcome the violation.

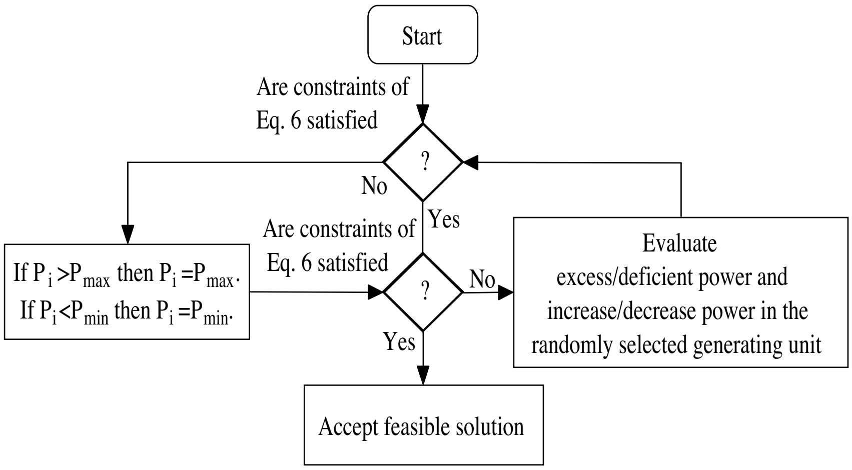

Figure 6. Repair strategies for constraint management.

6.3. Pseudocode of the FABC algorithm for the REED problem

1. Initialize the control parameters and read system data.
2. Generate the initial population as in Section 7.1.
3. Evaluate the cost, emission, and reliability for each food source using Eqs. (1)–(5)
4. Evaluate the fitness of the population using Eq. (18).
5. Set iteration count (Iter) to 1.
6. Repeat.
7. For each employed bee:

   - modify the bee position using Eq. (16);
   - if there is any violation in constraints of Eq. (6) and Eq. (8), the repair scheme given in Section 7.2 is performed to overcome the violation;
   - evaluate the cost, emission, and reliability for new food sources and calculate the fitness using Eq. (18);
   - apply greedy selection process.

8. Calculate the probability values Pro_p for the solutions using Eq. (15).
9. For each unemployed or onlooker bee:

   - select a solution depending on Pro_p;
   - modify the bee position using Eq. (16) and check for constraints;
   - calculate the fitness value using Eq. (18);
   - apply greedy selection process.

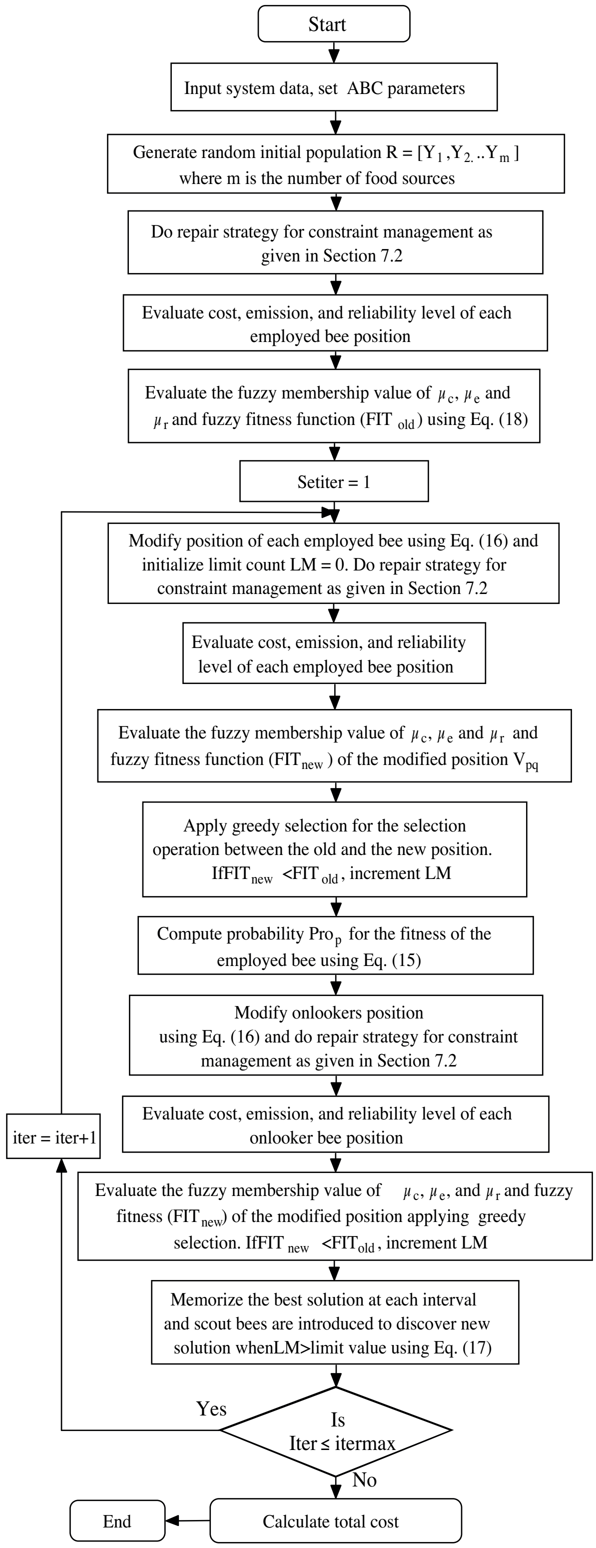

Figure 7. Flowchart for proposed FABC for solving REED problem.

10. Abandon sources exploited by the bees using Eq. (17) based on the limit value (LM).
11. Memorize the best solution achieved so far.
12. Iter = Iter + 1.
13. Until iteration = Iter. max.

The flowchart for the proposed FABC algorithm is shown in Figure 7.

7. Case studies

All the programs were developed using MATLAB 7.01. The system was configured using a Pentium IV processor with 3.2 GHz speed and 1 GB RAM. Different test cases were carried out to show the efficiency of the proposed FABC, which are given below.

7.1. Case 1

In Case 1, to validate the FABC algorithm in a multiobjective problem, an emission and economic dispatch (EED) problem is solved and the obtained results are compared with the existing literature. Four test systems with different characteristics of the objective function are considered in Case 1. In the first test system (6-unit system), the fuel cost and emission are considered as a quadratic function. In the second test system (IEEE 30-bus system), the fuel cost is given as a quadratic function and an emission function is given as the sum of quadratic and exponential term. In the third test system (10-unit system), the cost and emission function includes both sinusoidal and exponential terms with a quadratic function. Finally, in the fourth test system (40-unit system), the proposed method is tested and validated on the largest test system, where the cost and emission function includes both sinusoidal and exponential terms with a quadratic function.

7.2. Case 2

In Case 2, the proposed methodology is applied for 3 objective functions (i.e. fuel cost, emission, and reliability) for solving the REED problem. The proposed methodology is applied and tested on 2 test systems with 3 objective functions (i.e. fuel cost, emission, and reliability level) for solving the REED problem. To demonstrate the importance of the reliability function, a 3-unit test system is considered and the REED problem is solved. Finally, the REED is solved for a larger system comprising 26 generating units.

8. Results and discussion

8.1. Case 1

8.1.1. Test system 1: 6-unit system

The generating unit data and load profile of the 6-unit system are adapted from [36]. Here the system loss is calculated using a B-loss coefficient that is available in the same reference. Here the number of variables in the FABC algorithm is 6 (6 generating units). The membership functions given in Section 5 are used to identify the best compromise solution from the Pareto optimal set. Out of 20 trials, Table 1 shows the best compromise solution of FABC. The FABC algorithm takes 5.41 s of CPU time on average to converge to an optimal solution. The solutions are nondominated within the entire search space as shown in Figure 8. At the end of the FABC algorithm, feasible designs are filtered in the design space to obtain a Pareto optimal set. There are 78 solutions in this set, which is shown as Figure 9, and the best compromise solution (shown in red) is also shown in Figure 9.

Table 1. EED Problem solution: 6-unit system.

Load, MW	700	
Method	TOPSIS method [36, Case 1]	FABC
Fuel cost, Fc, \$/h	37,136.3339	37,016
Emission, E, kg/h	417.7938	418.51
Emission price penalty factor, h_i, \$/kg	44.7879	44.7879
Total cost, \$/h	55,848.4791	55,760.18
P1, MW	75.1270	73.833
P2, MW	75.5840	69.43
P3, MW	110.0420	108.38
P4, MW	113.3860	116.62
P5, MW	165.3620	164.58
P6, MW	160.3970	167.16
PL, MW	15.8980	15.8012
Total savings, \$/h	TOPSIS method – FABC = 88.29	

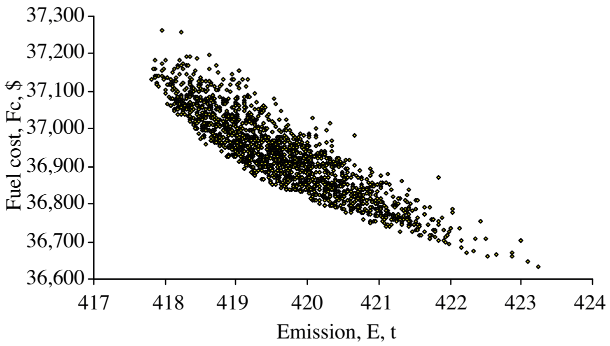

Figure 8. Nondominated solution within the entire search.

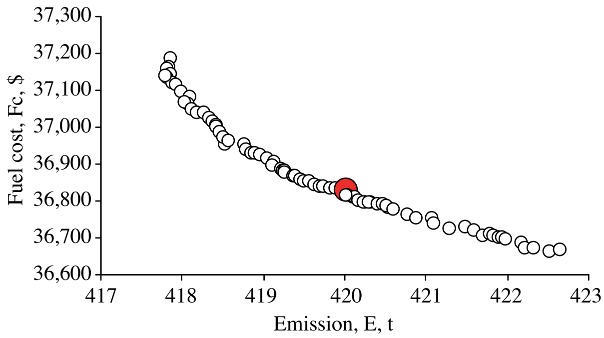

Figure 9. Pareto optimal front of the proposed approach.

To validate the proposed approach with the existing techniques, using the steps given in [37–39], the price penalty factor for the 6-unit system is calculated as 44.7879 \$/kg and it is used to obtain the total cost. It is observed from Table 1 that the proposed approach provides slightly better results than the TOPSIS method [36] for the EED problem.

8.1.1.1. Effect of variation of colony size and limit value

In order to avoid misleading results due to the foraging behavior of real bees of the FABC, several test runs are carried out to set the colony size and the limit value. Ten trials are run for each problem set, with each run starting with a different random colony size. The colony size (50 to 300) and limit value (0–15) is varied appropriately in equal intervals. The maximum iteration is set as 1000.

Figures 10 and 11 show the average value of fitness out of the 10 trials for different values of colony size and limit value for the 6-unit system. Studying the behavior of the convergence, an optimal colony size of 200 and a limit value of 5 are chosen. Once the control parameters are tuned for a particular system, they can be retained for all load conditions.

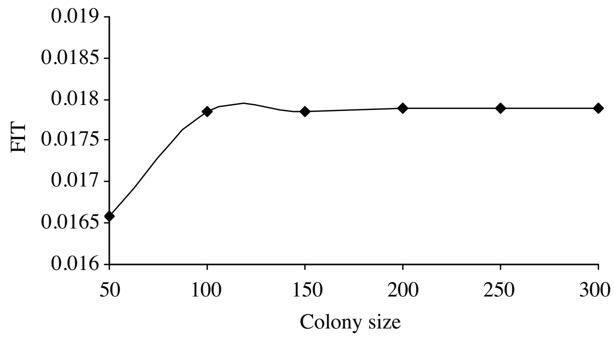

Figure 10. Production cost for different colony size.

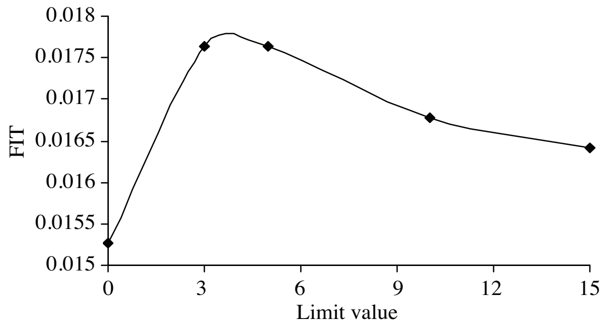

Figure 11. Total cost for different limit values.

8.1.2. Test system 2: IEEE 30-bus system

The generating unit data and B-loss coefficient for the IEEE 30-bus system are adapted from [12]. Here the EED problem is solved without considering the system losses. In the existing literature, the IEEE 30-bus system is solved for 2 different load conditions, 2.834 and 2.8339 MW, respectively. Hence, in this section, the EED problem is solved for 2 different load conditions and the results are compared. The number of variables in the FABC algorithm is 6 (6 generating units). The best combination of ABC parameters for the IEEE 30-bus system is evaluated similar to as in Section 9.1.1, and it is found to be a colony size of 200 and a limit value of 5. Out of 20 trials, Table 2 shows the best compromise solution of FABC. To validate the proposed approach with the existing techniques, using the steps given in [37–39], the price penalty factor for a 6-unit system is calculated as 1637.1 $/t and it is used to obtain the total cost. It is observed from Table 2 that, for the 2 different load conditions, the proposed approach provides slightly better results than MOPSO [12], NSGA [40], MOHS [13], and MBFA [41] for the EED problem. The algorithm takes 5.04 s of CPU time on average to converge to an optimal solution.

Table 2. EED problem solution: IEEE 30-bus system.

Load, MW	2.834		2.8339			
Method	MOPSO [40, Case 1]	ABC	NSGA [41]	MOHS [13]	MBFA [42]	ABC
Fuel cost, Fc, \$/h	608.65	609.88	610.0670	608.7367	610.9060	611.1520
Emission, E, t/h	0.2017	0.2008	0.2006	0.2023	0.2	0.1998
Emission price penalty factor, h_i, \$/t	1637.1	1637.1	1637.1	1637.1	1637.1	1637.1
Total cost, \$/h	938.9060	938.7547	938.46926	939.92203	938.326	938.244
P1, MW	0.2516	0.2692	0.2571	0.2127	0.2661	0.2687
P2, MW	0.3770	0.3929	0.3774	0.4004	0.3792	0.3792
P3, MW	0.5283	0.5126	0.5381	0.5951	0.5387	0.5387
P4, MW	0.7124	0.7044	0.6872	0.7065	0.675	0.6710
P5, MW	0.5566	0.5366	0.5404	0.4987	0.5383	0.5383
P6, MW	0.4081	0.4180	0.4337	0.4205	0.4366	0.4380

8.1.3. Test system 3: 10-unit system

The generating unit data and B-loss coefficient for the 10-unit system are adapted from [42]. Here MOEDP is solved considering the system losses and the problem is solved for a load of 1480 MW. The number of variables in the FABC algorithm is 10 (10 generating units). The best combination of ABC parameters for the 10-unit system is evaluated and is found to be a colony size of 200 and a limit value of 5. Out of 20 trials, Table 3 shows the best compromise solution of the FABC. To validate the proposed approach with the existing techniques, using the steps given in [37–39], the price penalty factor for a 6-unit system is calculated as 4.1162 $/t and it is used to obtain the total cost. It is observed from Table 3 that the proposed approach provides slightly better results than NSGA-II [42] and WSMSL [37] for the EED problem. The algorithm takes 7.29 s of CPU time on average to converge to an optimal solution.

Table 3. EED problem solution: 10-unit system.

Load, MW	1480		
Method	NSGA-II [43]	WSMSL [37]	FABC
Fuel cost, Fc, $/h	87,750.28	87,309.85	86,757.0682
Emission, E, t/h	9299.34	7946.14	8050.3180
Emission price penalty factor, h_i, $/t	4.1162	4.1162	4.1162
Total cost, $/h	126,028.50	120,017.97	119,893.7819
P1, MW	201.34	166.31	153.0000
P2, MW	138.36	188.95	190.2069
P3, MW	291.42	186.65	198.0726
P4, MW	166.32	190.01	196.0000
P5, MW	220.38	243.00	237.0000
P6, MW	159.41	160.00	160.0000
P7, MW	129.58	130.00	130.0000
P8, MW	94.25	120.00	120.0000
P9, MW	64.15	80.00	80.0000
P10, MW	54.98	55.00	55.0000
PL, MW	40.22	39.92	39.76
Total savings, $/h	WSMSL – FABC = 124.18		

8.1.4. Test system 4: 40-unit system

In this case, to validate the applicability of the FABC for large-scale system, the EED problem is solved for a 40-unit system. Cost curves including valve-point effects and the test data are adapted from [43] and the load of the system is taken as 10,500 MW. The emission coefficient with exponential term is adapted from [41] and loss of the system is neglected. The best combination of ABC parameters is evaluated and found to be a colony size of 200 and a limit value of 3.

Out of 20 trials, the optimum dispatch of generators and the solution of the EED are given in Tables 4 and 5. The price penalty factor for a 40-unit system is calculated as 1.9857 $/t using the steps given in [37–39] and it is used to obtain the total cost. The minimum cost so far reported in the literature is 498,879.61 $/h [42], which is 1528.51 $/h higher with respect to the FABC.

8.2. Case 2

8.2.1. Test system 1: 3-unit test system

The generating unit data and B-loss coefficient for the 3-unit system are adapted from [44]. The reliability data are given in the Appendix. To demonstrate the importance of incorporation of the reliability function in the economic dispatch problem, the 3-unit system is individually solved for all 3 objective functions (Fc, E, and $EENS$) and the corresponding variations in other objectives are evaluated, as given in Table 6.

Table 4. Optimal dispatch: 40-unit system.

Unit no.	P, MW	Unit no.	P, MW	Unit no.	P, MW	Unit no.	P, MW
1	102.5411	11	289.2487	21	430.0623	31	179.6566
2	114.000	12	292.2012	22	437.8856	32	182.4798
3	111.01	13	434.6912	23	440.4616	33	190.0000
4	164.073	14	440.9812	24	459.7697	34	199.1945
5	97.000	15	435.0789	25	460.1191	35	200.0000
6	114.5707	16	442.7936	26	418.5907	36	200.0000
7	297.5997	17	457.1068	27	25.0957	37	90.1203
8	300.000	18	459.4132	28	27.4216	38	93.2479
9	278.1663	19	423.4216	29	12.4747	39	101.6382
10	140.5923	20	430.4126	30	89.7624	40	436.6199

Table 5. EED problem solution: 40-unit system.

Load, MW	10,500	
Method	MBFA [42]	ABC
Fuel cost, Fc, \$/h	123,638	129,999.09
Emission, E, t/h	188,963	184,998.74
Emission price penalty factor, h_i, \$/t	1.9857	1.9857
Total cost, \$/h	498,879.61	497,351.10
Total savings, \$/h	MBFA – ABC = 1528.51	

Table 6. REED problem solution: 3-unit system.

Objective function	Minimization of F_c	Minimization of E	Minimization of EENS	REED solution
P1, MW	435.1731	504.9140	271.4169	428.3700
P2, MW	300.0056	253.2780	399.9962	299.2100
P3, MW	130.6501	106.5920	199.9964	138.2800
PL, MW	15.8289	14.7840	21.4095	15.8600
Fuel cost F_c, \$	8344.5832	8363.1178	8450.8180	8345
Emission E, t	0.09868	0.095929	0.1284	0.09967
Reliability level, EENS, kWh	4879.8	5025.6	4532.0	4856.6

When the economic dispatch problem is solely solved for the minimization of F_c, a minimum cost of \$8344.5832 is obtained by neglecting all other objectives. When fuel cost is considered alone, emission is found to be higher, whereas a downward trend is seen in the reliability level (i.e. increase in reliability index) of the system. Since the generating units are committed solely based on the cost, the reliability of the system is very low due to the low reliability generating unit to dispatch more power.

When emission alone is minimized, neglecting other objectives, the resultant emission is 0.095929 t/h. The minimum emission is obtained with a higher fuel cost. This is due to the low emission of a sophisticated generating unit, which involves higher fuel cost. The reliability level is low for a similar reason as was mentioned earlier.

When the reliability level of the system is alone maximized, neglecting other objectives, the resultant EENS is 4532.0 KWh. The corresponding changes in the fuel cost and emission are given in Table 6. When solving the F_c, E, and reliability function individually, the changes in the system reliability level are significant and should not be neglected. This thus stresses the need for the incorporation of the reliability function in the EED problem, and thereby the novel REED problem is formulated to obtain a best compromise solution.

Here the number of the generating units in the system is 3. The dispatch of the REED problem and the best compromise solution are given in Table 6. The solutions that are nondominated within the entire search space are shown in Figure 12. At the end of the FABC algorithm, feasible designs are filtered in design space to obtain a Pareto optimal set. There are 90 solutions in this set, which is shown in Figure 13, and the best compromise solution is also shown in Figure 13.

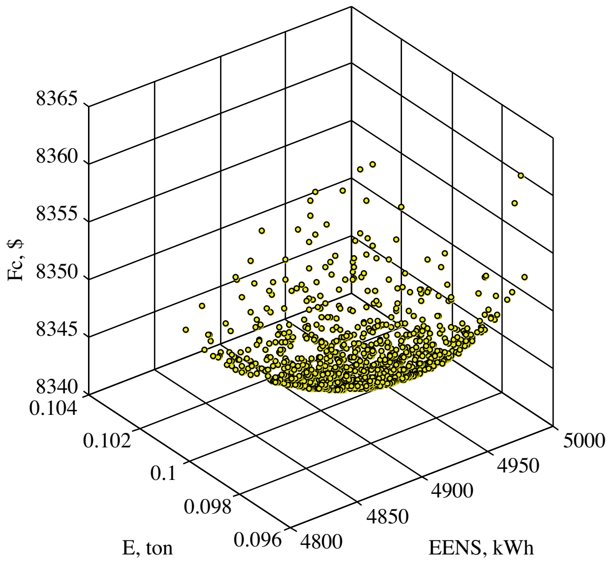

Figure 12. Nondominated solution within the entire search.

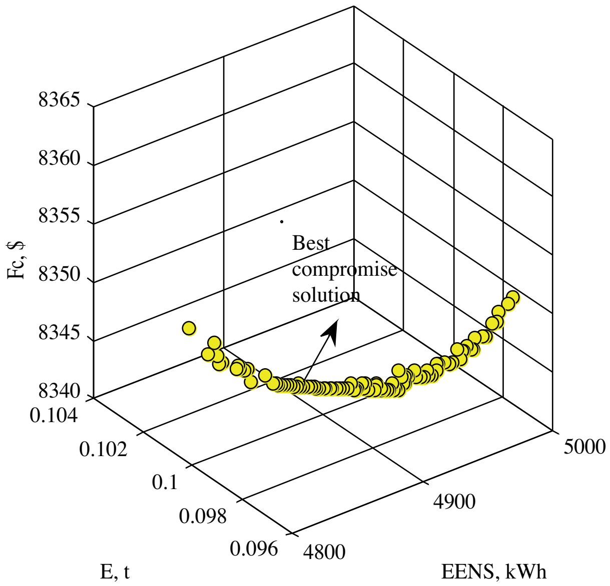

Figure 13. Pareto optimal front of the proposed approach.

8.2.2. Test system 2: 26-unit test system

The generating unit data for a 26-unit system are adapted from [45] and reliability data are adapted from [46]. The system power demand is 2430 MW. When solving the objective function individually, the corresponding variation of each generating unit can be observed in Table 7. The dispatch of the REED problem and the best compromise solution are also given in Table 7.

Table 7. REED problem solution: 26-unit system.

Objective function	Minimization of F_c	Minimization of E	Minimization of EENS	REED solution
P1, MW	400:0000	255:6786	400:0000	400:0000
P2, MW	400:0000	272:3214	400:0000	400:0000
P3, MW	350:0000	350:0000	350:0000	350:0000
P4, MW	155:0000	54:2500	85:5746	121:0000
P5, MW	155:0000	54:2500	111:8056	118:0000
P6, MW	155:0000	54:2500	57:9212	117:0000
P7, MW	155:0000	54:2500	127:5561	123:0000
P8, MW	76:0000	76:0000	76:0000	76:0000
P9, MW	76:0000	76:0000	76:0000	76:0000
P10, MW	76:0000	76:0000	76:0000	76:0000
P11, MW	76:0000	76:0000	76:0000	76:0000
P12, MW	47:8775	100:0000	100:0000	68:4906
P13, MW	40:4657	100:0000	100:0000	60:1854
P14, MW	32:8068	100:0000	100:0000	84:0740
P15, MW	68:9500	197:0000	68:9500	68:9500
P16, MW	68:9500	197:0000	68:9500	68:9500
P17, MW	68:9500	197:0000	79:2421	68:9500
P18, MW	2:4000	12:0000	12:0000	12:0000
P19, MW	2:4000	12:0000	12:0000	12:0000
P20, MW	2.4000	12.0000	12.0000	12.0000
P21, MW	2.4000	12.0000	12.0000	12.0000
P22, MW	2.4000	12.0000	12.0000	12.0000
P23, MW	4.0000	20.0000	4.0000	4.0000
P24, MW	4.0000	20.0000	4.0000	4.0000
P25, MW	4.0000	20.0000	4.0000	4.0000
P26, MW	4.0000	20.0000	4.0000	4.0000
Fuel cost F_c, $	33,632.0118	42,748.9984	35,712.22	34,924.96
Emission E, t	23,915.1108	22,144.5424	24,438.9519	23,914.4036
Reliability level, EENS, KWh	8729.70	8909.00	8446.10	8514.61

9. Conclusion

This paper has employed the intelligent behavior of honeybees for solving the multiobjective economic dispatch problem. It is a population-based search procedure that is used as an optimization tool in solving complex, nonlinear, nonconvex, and conflicting optimization problems.

- The FABC, when applied to the practical EED problem, outperforms the other techniques reported in the literature in obtaining the best compromise solution.
- The membership function for the reliability level of the system was modeled and the importance of incorporation of the reliability function in the practical EED problem was demonstrated.
- Finally, the FABC was applied to the proposed REED problem and the best compromise solution was presented.

The robustness and efficiency of the proposed methodology was demonstrated on small- and large-scale systems for the multiobjective economic dispatch problem. From the results, it is clear that the proposed method is able to give a well distributed Pareto optimal set and is capable of finding a compromise solution of more desirable quality as compared to other methods reported in the literature. The method is straightforward, easy to implement, and applicable for any large-scale power systems.

Appendix. Reliability data.

Unit. no	Maximum capacity, MW	FOR
1	600	0.14
2	400	0.11
3	200	0.08

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