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# Environmental/Economic Power Dispatch of Thermal Units using Improved ABC Algorithm

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**ABSTRACT**

*In this paper, a new approach is proposed to solve environmental economic dispatch (EED) problem in power systems using improved artificial bee colony (IABC) algorithm. The EED problem is to minimize both the operating fuel cost and emission level simultaneously while satisfying the load demand and operational constraints. A novel best mechanism algorithm based on ABC algorithm, in which a new mutation strategy inspired from the differential evolution (DE) is introduced in order to improve the exploitation process. The effectiveness of the proposed algorithm has been tested on IEEE 30-bus test system and the results were compared with other methods reported in recent literature. The simulation results show that the proposed algorithm outperforms previous optimization methods.*

***Keywords*** *- Economic dispatch, emission dispatch, combined economic emission dispatch, improved artificial bee colony algorithm, differential evolution.*

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## I. INTRODUCTION

Optimization of the modern power system plays a major role in thermal power plants energy production. The challenges of the engineers are to optimize the real power of the generating units and to minimize the fuel cost of the power plant. Economic dispatch (ED) is one of the most fundamental issues in operation and control of power systems to allocate generations among the committed units. The main goal of the ED problem is to determine the amount of real power contributed by online thermal generators satisfying load demand at any time subject to unit and system constraints so as the total generation cost is minimized. Therefore, it is very important to solve the problem as quickly and precisely as possible [1, 2]. Therefore, recently most of the researchers made studies for finding the most suitable power values produced by the generators depending on fuel costs. In these studies, they produced successful results by using various optimization algorithms [3-5]. Despite the fact that the traditional ED can optimize generator fuel costs, it still cannot produce a solution for environmental pollution due to the excessive emission of fossil fuels.

Currently, a large part of energy production is done with thermal sources. Thermal power plant is one of the most important sources of carbon dioxide ($CO_2$), sulfur dioxide ($SO_2$) and nitrogen oxides ($NO_x$) which create atmospheric pollution [6]. Emission control has received increasing attention owing to increased concern over environmental pollution caused by fossil based generating units and the enforcement of environmental regulations in recent years [7]. Numerous studies have emphasized the importance of controlling pollution in electrical power systems [8].

The EED has been proposed in the field of power generation dispatch, which simultaneously minimizes both fuel cost and pollutant emissions. When the emission is minimized the fuel cost may be unacceptably high or when the fuel cost is minimized the emission may be high. A number of methods have been presented to solve EED problems such as multi-objective differential evolution algorithm [9], genetic algorithm [10-12], simulated annealing [13], biogeography-based optimization [14], modified bacterial foraging algorithm [15], particle swarm optimization [16-18], artificial bee colony algorithm [19-21], gravitational search algorithm [22], moth swarm algorithm [23], and adaptive wind driven optimization [24].

Swarm intelligence has become a research interest to different domain of researchers in recent years. These algorithms simulate the food foraging behavior of a flock of birds or swarm of bees. Motivated by the foraging behavior of honeybees, researchers have initially proposed artificial bee colony (ABC) algorithm for solving various optimization problems [25, 26]. Artificial bee colony (ABC) algorithm is a relatively new member of swarm intelligence. ABC tries to model natural behavior of real honey bees in food foraging. Honey bees use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms. Despite the simplicity and the superiority of ABC algorithm, recent studies reported that it suffers from a poor exploitation process and a slow convergence rate. To overcome these pitfalls, some research papers have introduced modifications to the classical ABC algorithm in order to improve its performance and tackle more complex real-world problems [27, 28].

In this paper, IABC algorithm has been used to solve the EED problem considering the practical constraints. The EED solution which was performed using IABC algorithm was tested on the standard IEEE 30-bus 6-generator test system. The results were compared to those reported in the literature.

## II. PROBLEM FORMULATION

The EED problem targets to find the optimal combination of load dispatch of generating units and minimizes both fuel cost and emission while satisfying the total power demand. Therefore, the EED consists of two objective functions, which are economic and emission dispatches. Then these two functions are combined to solve the problem. The EED problem can be formulated as follows [11]:

$$F_T = Min\ f\left(FC, EC\right) \tag{1}$$

where $F_T$ is the total generation cost of the system, $FC$ is the total fuel cost of generators and $EC$ is the total emission of generators.

### 2.1 Minimization of Fuel Cost

The ED problem can be formulated in a quadratic form as follows [11]:

$$FC = \sum_{i=1}^{N} \left(a_i P_i^2 + b_i P_i + c_i\right) \tag{2}$$

where $P_i$ is the power generation of the $i$th unit; $a_i$, $b_i$, and $c_i$ are fuel cost coefficients of the $i$ th generating unit and $N$ is the number of generating units.

### 2.2 Minimization of Emission

The classical ED problem can be obtained by the amount of active power to be generated by the generating units at minimum fuel cost, but it is not considered as the amount of emissions released from the burning of fossil fuels. Total amount of emissions such as $SO_2$ or $NO_X$ depends on the amount of power generated by until and it can be defined as the sum of quadratic and exponential functions and can be stated as [11]:

$$EC = \sum_{i=1}^{N} \left(\alpha_i P_i^2 + \beta_i P_i + \gamma_i + \eta_i \exp(\delta_i P_i)\right) \tag{3}$$

where $\alpha_i$, $\beta_i$, $\gamma_i$, $\eta_i$ and $\delta_i$ are emission coefficients of the $i$th generating unit.

### 2.3 Combined Environmental Economic Dispatch (CEED)

CEED is a multi-objective problem, which is a combination of both economic and environmental dispatches that individually make up different single problems. At this point, this multi-objective problem needs to be converted into single-objective form in order to fulfill optimization. The conversion process can be done by using the price penalty factor [11]. However, the single-objective CEED can be formulated as shown in equation (4):

$$F_T = (w * FC + (1-w) * h * EC) \tag{4}$$

under the following condition,

$$0 \le w \le 1 \tag{5}$$

where $w$ is weighting factor: $w$=1 (fuel cost minimization), $w$=0 (NOx emission minimization), and $w$=0.5 (CEED minimization) and $h$ is the price penalty factor.

### 2.4 Problem Constraints

There are two constraints in the EED problem which are power balance constraint and maximum and minimum limits of power generation output constraint.

**2.4.1 Active Power Balance Equation**

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

$$P_D = \sum_{i=1}^{N} P_i - P_{Loss} \tag{6}$$

where $P_D$ is the total load demand and $P_{Loss}$ is total transmission losses. The transmission losses $P_{Loss}$ can be calculated by using $B$ matrix technique and is defined by (7) as,

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

where $B_{ij}$ is coefficient of transmission losses and the $B_{0i}$ and $B_{00}$ is matrix for loss in transmission which are constant under certain assumed conditions.

**2.4.2 Minimum and Maximum Power Limits**

Generation output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is

$$P_i^{\min} \le P_i \le P_i^{\max} \quad \text{for } i = 1, 2, \cdots, N \tag{8}$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum outputs of the $i$th generator, respectively.

## III. ARTIFICIAL BEE COLONY (ABC) ALGORITHM

Artificial bee colony is one of the most recently defined algorithms by Karaboga in 2005, motivated by the intelligent behavior of honey bees [25, 26]. In the ABC system, artificial bees fly around in the search space, and some (employed and onlooker bees) choose food sources depending on the experience of themselves and their nest mates, and adjust their positions. Some (scouts) fly and choose the food sources randomly without using experience. If the nectar amount of a new source is higher than that of the previous one in their memory, they memorize the new position and forget the previous one. Thus, the ABC system combines local search methods, carried out by employed and onlooker bees, with global search methods, managed by onlookers and scouts, attempting to balance exploration and exploitation process.

In the ABC algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlooker bees, and scout bees. The main steps of the ABC algorithm are described as follows:

• INITIALIZE
• REPEAT
  (a) Place the employed bees on the food sources in the memory;
  (b) Place the onlooker bees on the food sources in the memory;
  (c) Send the scouts to the search area for discovering new food sources;
  (d) Memorize the best food source found so far.

• UNTIL (requirements are met)

In the ABC algorithm, each cycle of the search consists of three steps: moving the employed and onlooker bees onto the food sources, calculating their nectar amounts respectively, and then determining the scout bees and moving them randomly onto the possible food source. Here, a food source stands for a potential solution of the problem to be optimized. The ABC algorithm is an iterative algorithm, starting by associating all employed bees with randomly generated food solutions. The initial population of solutions is filled with $SN$ number of randomly generated $D$ dimensions. Let $X_i = \{x_{i1}, x_{i2}, \ldots, x_{iD}\}$ represent the $i$th food source in the population, $SN$ is the number of food source equal to the number of the employed bees and onlooker bees. $D$ is the number of optimization parameters. Each employed bee $x_{ij}$ generates a new food source $v_{ij}$ in the neighborhood of its currently associated food source by (9), and computes the nectar amount of this new food source as follows:

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right) \tag{9}$$

where $\varphi_{ij} = (\text{rand} - 0.5) \times 2$ is a uniformly distributed real random number within the range [-1, 1], $i \in \{1, 2, \ldots, SN\}$, $k = \text{int}(\text{rand} * SN) + 1$ and $k \ne i$, and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes. The new solution $v_i$ will be accepted as a new basic solution, if the objective fitness of $v_i$ is smaller than the fitness of $x_i$, otherwise $x_i$ would be obtained.

When all employed bees finish this process, an onlooker bee can obtain the information of the food sources from all employed bees and choose a food source according to the probability value associated with the food source, using the following expression:

$$p_i = \alpha \times \frac{fit_i}{\max(fit_i)} + \beta; \quad \alpha + \beta = 1 \tag{10}$$

where $fit_i$ is the fitness value of the solution *i* evaluated by its employed bee. Obviously, when the maximum value of the food source decreases, the probability with the preferred source of an onlooker bee decreases proportionally. Then the onlooker bee produces a new source according to (9). The new source will be evaluated and compared with the primary food solution, and it will be accepted if it has a better nectar amount than the primary food solution.

After all onlookers have finished this process, sources are checked to determine whether they are to be abandoned. If the food source does not improve after a determined number of the trail "limit", the food source is abandoned. Its employed bee will become a scout and then will search for a food source randomly as follows:

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

where $x_{j\,min}$ and $x_{j\,max}$ are lower and upper bounds for the dimension *j* respectively.

After the new source is produced, another iteration of the ABC algorithm will begin. The whole process repeats again till the termination condition is met.

## IV. IMPROVED ARTIFICIAL BEE COLONY (IABC) ALGORITHM

Following this spirit, an improved ABC algorithm inspired from differential evolution (DE) to optimize the objective function of the ED problems. Differential evolution is an evolutionary algorithm first introduced by Storn and Price [29, 30]. Similar to other evolutionary algorithms, particularly genetic algorithm, DE uses some evolutionary operators like selection recombination and mutation operators. Different from genetic algorithm, DE uses distance and direction information from the current population to guide the search process. The crucial idea behind DE is a scheme for producing trial vectors according to the manipulation of target vector and difference vector. If the trail vector yields a lower fitness than a predetermined population member, the newly trail vector will be accepted and be compared in the following generation. Currently, there are several variants of DE. The particular variant used throughout this investigation is the DE/rand/1 scheme. The differential mutation strategy is described by the following equation:

$$v_i = x_a + F\left(x_b - x_c\right) \tag{12}$$

where $a, b, c \in SN$ are randomly chosen and mutually different and also different from the current index *i*. $F \in (0,1)$ is constant called scaling factor which controls amplification of the differential variation of $x_{bj} - x_{cj}$.

Based on DE and the property of ABC algorithm, we modify the search solution described by (13) as follows:

$$v_{ij} = x_{aj} + \varphi_{ij}\left(x_{ij} - x_{bj}\right) \tag{13}$$

The new search method can generate the new candidate solutions only around the random solutions of the previous iteration.

Akay and Karaboga [27] proposed a modified artificial bee colony algorithm by controlling the frequency of perturbation. Inspired by this algorithm, we also use a control parameter, i.e., modification rate (*MR*). In order to produce a candidate food position $v_{ij}$ from the current memorized $x_{ij}$, improved ABC algorithm uses the following expression [28]:

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{ if } & R_{ij} \le MR \\ x_{ij} & \text{otherwise} \end{cases} \tag{14}$$

where $R_{ij}$ is a uniformly distributed real random number within the range [0, 1]. The pseudo-code of the improved ABC algorithm is given below:

---

Initialize the population of solutions $x_{ij}$, $i = 1...SN$; $j = 1...D$, $trial_i = 0$; $trial_i$ is the non-improvement number of the solution $x_i$, used for abandonment
Evaluate the population
cycle = 1
**repeat**

---

{--- Produce a new food source population for employed bee ---}

**for** $i$ = 1 to $SN$ **do**

Produce a new food source $v_i$ for the employed bee of the food source $x_i$ by using (14) and evaluate its quality:

Select randomly $a \neq b \neq i$

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{if} \quad R_{ij} \leq MR \\ x_{ij} \quad \text{otherwise} \end{cases}$$

Apply a greedy selection process between $v_i$ and $x_i$ and select the better one. If solution $x_i$ does not improve $trial_i = trial_i + 1$, otherwise $trial_i = 0$

**end for**

Calculate the probability values $p_i$ by (10) for the solutions using fitness values:

$$p_i = \alpha \times \frac{fit_i}{\max(fit_i)} + \beta; \quad \alpha + \beta = 1$$

{--- Produce a new food source population for onlooker bee ---}

$t$ = 0, $i$ = 1

**repeat**

**if** random < $p_i$ **then**

Produce a new $v_{ij}$ food source by (14) for the onlooker bee:

Select randomly $a \neq b \neq i$

$$v_{ij} = \begin{cases} x_{aj} + \varphi_{ij}(x_{ij} - x_{bj}), \text{if} \quad R_{ij} \leq MR \\ x_{ij} \quad \text{otherwise} \end{cases}$$

Apply a greedy selection process between $v_i$ and $x_i$ and select the better one. If solution $x_i$ does not improve $trial_i = trial_i + 1$, otherwise $trial_i = 0$

$t = t + 1$

**end if**

**until** ($t = SN$)

{--- Determine scout bee ---}

**if** max ($trial_i$) > limit **then**

Replace $x_i$ with a new randomly produced solution by (11)

$$x_{ij} = x_{j\min} + \text{rand}(0,1) * (x_{j\max} - x_{j\min})$$

**end if**

Memorize the best solution achieved so far

cycle = cycle+1

**until** (cycle = Maximum Cycle Number)

## V. SIMULATION RESULTS

The proposed IABC algorithm is tested on the standard IEEE 30-bus power system with six-generating units in order to investigate its effectiveness. The single-line diagram of the IEEE 30-bus test system is shown in Figure 1 and the detailed data are given in [21, 22]. The parameters of all thermal units (generation limits, fuel cost and $NO_x$ emission coefficients) are presented in Table 1, followed by $B$-loss coefficients are presented in Table 2. The load demand of the system is 283.4 MW. The values of IABC algorithm for solving EED problem in this paper are designated as follow:

The number of colony size, $NP$ = 20; the number of cycles for aging, maxCycle = 300; the number of variables, $NV$ = 6; and limit = 100.

The best solutions for power outputs, fuel cost and $NO_x$ emission obtained by using IABC algorithm for $w$=1, $w$=0, and $w$=0.5 are given in Table 3. The results obtained by IABC algorithm for the test system along with corresponding data from the literature are summarized in Table 4. As can be seen in Table 4, the IABC algorithm provided better values for the minimum fuel cost and $NO_x$ emission in regard to the values obtained by the algorithms proposed in [9, 14, 16, 22, 23, 24].

**Table 1:** Generation limits, fuel cost and $NO_x$ emission coefficients for IEEE 30-bus test system [21]

| Unit | $P_i^{min}$ | $P_i^{max}$ | $a_i$ | $b_i$ | $c_i$ | $\alpha_i$ | $\beta_i$ | $\gamma_i$ | $\eta_i$ | $\delta_i$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 5 | 150 | 10 | 200 | 100 | 4.091e-2 | -5.554e-2 | 6.940e-2 | 2.0e-4 | 2.857 |
| 2 | 5 | 150 | 10 | 150 | 120 | 2.543e-2 | -6.047e-2 | 5.638e-2 | 5.0e-4 | 3.333 |
| 3 | 5 | 150 | 20 | 180 | 40 | 4.258e-2 | -5.094e-2 | 4.586e-2 | 1.0e-6 | 8.0 |
| 4 | 5 | 150 | 10 | 100 | 60 | 5.326e-2 | -3.550e-2 | 3.380e-2 | 2.0e-3 | 2.0 |
| 5 | 5 | 150 | 20 | 180 | 40 | 4.258e-2 | -5.094e-2 | 4.586e-2 | 1.0e-6 | 8.0 |
| 6 | 5 | 150 | 10 | 150 | 100 | 6.131e-2 | -5.555e-2 | 5.151e-2 | 1.0e-5 | 6.667 |

**Table 2:** Transmission loss coefficients [21]

$$B_{ij} = \begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix}$$

$$B_{0i} = \begin{bmatrix} -0.0107 & 0.0060 & -0.0017 & 0.0009 & 0.0002 & 0.0030 \end{bmatrix}$$

$$B_{00} = 0.00098573$$

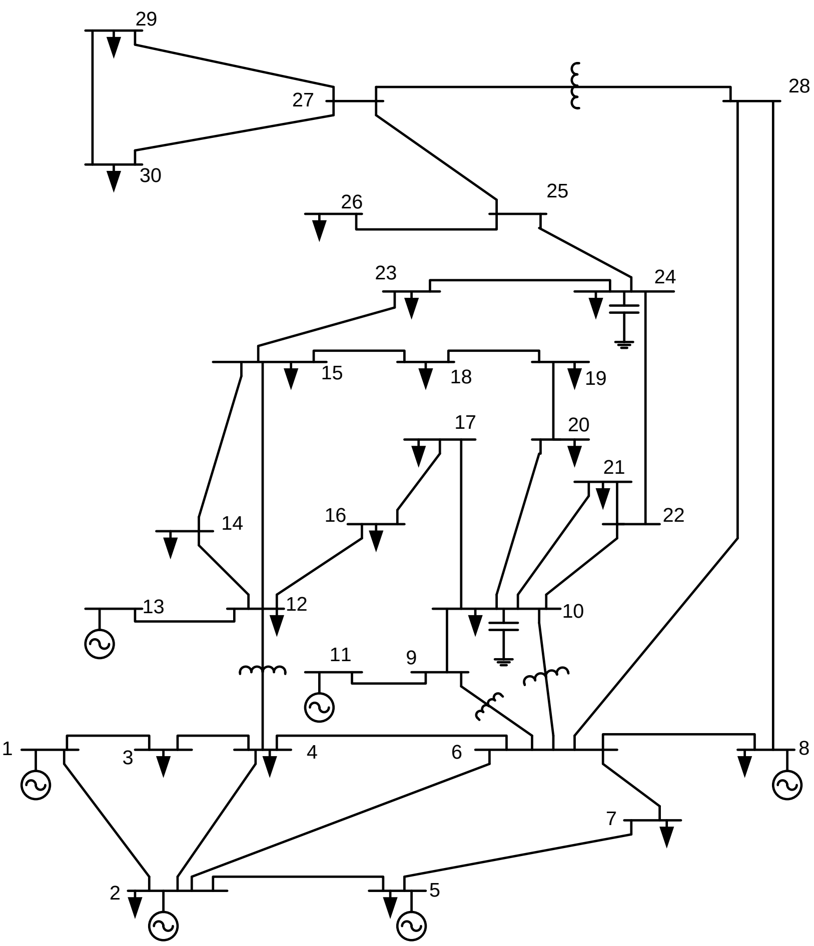


**Figure 1.** Single-line diagram of IEEE 30-bus test system [20]

**Table 3:** The best solutions obtained by using IABC algorithm

| *w* | Generation (MW) | | | | | | Fuel Cost ($/h) | $NO_x$ Emission (ton/h) | $P_{Loss}$ (MW) |
|---|---|---|---|---|---|---|---|---|---|
| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | | | |
| 1 | 12.0971 | 28.6313 | 58.3555 | 99.2850 | 52.3973 | 35.1900 | 605.99837 | 0.20453 | 2.55619 |
| 0 | 37.3419 | 50.1791 | 51.2265 | 46.6136 | 51.2816 | 50.1836 | 639.75215 | 0.18672 | 3.42623 |
| 0.5 | 23.3937 | 37.4253 | 54.3055 | 76.8477 | 52.4012 | 41.6773 | 612.22522 | 0.19249 | 2.65088 |

**Table 4:** Comparison of best solution

| Methods | Fuel cost minimization (*w*=1) | | $NO_x$ emission minimization (*w*=0) | | CEED minimization (*w*=0.5) | |
|---|---|---|---|---|---|---|
| | Fuel cost ($/h) | $NO_x$ emission (ton/h) | Fuel cost ($/h) | $NO_x$ emission (ton/h) | Fuel cost ($/h) | $NO_x$ emission (ton/h) |
| MODE [9] | 606.41060 | 0.2221 | 643.5190 | 0.1942 | 614.1700 | 0.2043 |
| MBFA [14] | 607.6700 | 0.2198 | 644.4300 | 0.1942 | 616.4960 | 0.2002 |
| MOPSO [16] | 607.7900 | 0.2193 | 644.7400 | 0.1942 | 615.0000 | 0.2021 |
| GSA [22] | 605.9984 | 0.2207 | 646.2070 | 0.1942 | 612.2530 | 0.2036 |
| MSA [23] | 605.9984 | 0.2207 | 646.2049 | 0.1942 | 612.2519 | 0.2038 |
| AWDO [24] | 605.9984 | 0.2207 | 646.2070 | 0.1942 | 612.2528 | 0.2036 |
| IABC | 605.99837 | 0.20453 | 639.75215 | 0.18672 | 612.22522 | 0.19249 |

## VI. CONCLUSION

In this paper, a new approach based on improved artificial bee colony (IABC) algorithm has been presented and successfully applied to solve the EED problem. The problem has been formulated as multiobjective optimization problem with competing fuel cost and environmental impact objectives. The effectiveness of proposed algorithm is demonstrated on the standard IEEE 30-bus test system with six generating units. The comparison of the results obtained with other methods reported in the literature shows the superiority of the proposed algorithm and its potential for solving the combined economic emission dispatch problems in large-scale power systems. The results obtained from the test systems have indicated that the proposed technique has better performance in terms of minimum fuel costs and $NO_x$ emissions than other optimization methods reported in the literature.

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