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Artificial Bee Colony Algorithm for Economic Load Dispatch Problem

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ABSTRACT

In practical cases, the fuel cost of generators can be represented as a quadratic function of real power generation and satisfied constraints for minimizing of fuel cost. Artificial bee colony (ABC) algorithm is used for the optimization of active power dispatch of generating units. The proposed method is able to determine, the output power generation for all of the power generation units, so that the total cost is minimized. Simulation and analysis of economic load dispatch using artificial bee colony (ABC) algorithm is proposed. The obtained results are compared with the conventional method, genetic algorithm (GA) and shows that the ABC algorithm approach is more feasible and efficient for finding minimum cost.

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1. INTRODUCTION

The operating cost of a power plant mainly depends on the fuel cost of generators and is minimized via economic load dispatch (ELD). Economic load dispatch problem can be defined as determining the least cost power generation schedule from a set of on line generating units to meet the total power demand at a given point of time [1]. The main objective of ELD problem is to decrease fuel cost of generators, while satisfying equality and inequality constraints. In this problem, fuel cost of generation is represented as cost curves and overall calculation minimizes the operating cost by finding a point where total output of generators equals total power that must be delivered plus losses.

In conventional economic load dispatch, cost function for each generator has been approximately represented by a single quadratic function and is solved using lambda iteration method, gradient-based method, etc. [2]. These methods require incremental fuel cost curves which are piecewise linear and monotonically increasing to find the global optimal solution. For generating units, which actually having non-monotonically incremental cost curves, conventional methods ignores or flattens out portions of incremental cost curve that are not continuous or monotonically increasing. Unfortunately, input-output characteristics of modern units are inherently highly non-linear because of valve point loadings, ramp rate limits, prohibiting operating zones etc., resulting in multiple local minimum points in the cost function. So, their characteristics have to be approximated to meet requirements of classical dispatch algorithms. However, such approximations may lead to huge loss of revenue over the time. Consideration of highly nonlinear characteristics of units demand for solution techniques having no restrictions on shape of fuel cost curves [3]-[4].

Classical methods like Newton-based and gradient methods cannot perform very well for problems having highly nonlinear characteristics with large number of constraints and many local optimum solutions.

Dynamic programming is one of the approached to solve non-linear and discontinuous ELD problem, but it suffers from problem of curse of dimensionality or local optimality [5]. Methods based on artificial intelligence techniques, such as artificial neural networks, are presented [6]-[9]. However, neural network-based approaches may suffer from excessive numerical iterations, resulting in huge calculations. Heuristic search techniques, such as particle swarm optimization [10], genetic algorithms [11]-[13], differential evolution [14], tabu search [15], and biogeography-based optimization [16] have also been successfully applied to ELD problems.

Artificial bee colony (ABC) algorithm is a relatively new member of swarm intelligence. ABC tries to model natural behaviour 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.

In this paper, Artificial bee colony (ABC) algorithm is discussed to solve the ELD problem by considering the linear equality and inequality constraints for a three units, six units, and fifteen units system and the results were compared with conventional method (quadratic programming) and genetic algorithm (GA). The algorithm described in this paper is capable of obtaining optimal solutions efficiently.

The rest of this paper is organized as follow. Section 2 presents the research method consist of ELD formulation, quadratic programming and ABC algorithm. Results and analysis are given in section 3, and section 4 gives some conclusions.

2. RESEARCH METHOD

2.1. Economic Load Dispatch Formulation

The objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

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

where F_T is total fuel cost of generation in the system ($/hr), a_i, b_i, and c_i are the cost coefficient of the i th generator, P_i is the power generated by the i th unit and n is the number of generators.

The cost is minimized subjected to the following generator capacities and active power balance constraints.

$$P_{i,\min} \le P_i \le P_{i,\max} \quad \text{for } i = 1,2,\cdots,n \tag{2}$$

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

$$P_D = \sum_{i=1}^{n} P_i - P_{Loss} \tag{3}$$

where P_D is the total power demand and P_{Loss} is total transmission loss.

The transmission loss P_{Loss} can be calculated by using **B** matrix technique and is defined by (4) as,

$$P_{Loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j \tag{4}$$

where B_{ij} 's are the elements of loss coefficient matrix **B**.

2.2. Quadratic Programming Method

A linearly constrained optimization problem with a quadratic objective function is called a quadratic programming (QP) [17]. Due to its numerous applications; quadratic programming is often viewed as a discipline in and of itself. Quadratic programming is an efficient optimization technique to trace the global minimum if the objective function is quadratic and the constraints are linear. Quadratic programming is used recursively from the lowest incremental cost regions to highest incremental cost region to find the optimum allocation. Once the limits are obtained and the data are rearranged in such a manner that the incremental cost limits of all the plants are in ascending order.

The general quadratic programming can be written as:

$$\text{Minimize } f(x) = cx + \frac{1}{2}x^T Qx \tag{5}$$

$$\text{Subject to } Ax \le b \text{ and } x \ge 0 \tag{6}$$

where **c** is an *n*-dimensional row vector describing the coefficients of the linear terms in the objective function, and **Q** is an ($n \times n$) symmetric matrix describing the coefficients of the quadratic terms. If a constant term exists it is dropped from the model. As in linear programming, the decision variables are denoted by the *n*-dimensional column vector **x**, and the constraints are defined by an ($m\times n$) **A** matrix and an *m*-dimensional column vector **b** of right-hand-side coefficients. We assume that a feasible solution exists and that the constraint region is bounded. When the objective function *f*(**x**) is strictly convex for all feasible points the problem has a unique local minimum which is also the global minimum. A sufficient condition to guarantee strictly convexity is for **Q** to be positive definite.

If there are only equality constraints, then the QP can be solved by a linear system. Otherwise, a variety of methods for solving the QP are commonly used, namely; interior point, active set, conjugate gradient, extensions of the simplex algorithm etc. The direction search algorithm is minor variation of quadratic programming for discontinuous search space. For every demand the following search mechanism is followed between lower and upper limits of those particular plants. For meeting any demand the algorithm is explained in the following steps:

1) Assume all the plants are operating at lowest incremental cost limits.
2) Substitute $P_i = L_i + (U_i - L_i)X_i$,

   where $0 < X_i < 1$ and make the objective function quadratic and make the constraints linear by omitting the higher order terms.
3) Solve the ELD using quadratic programming recursively to find the allocation and incremental cost for each plant within limits of that plant.
4) If there is no limit violation for any plant for that particular piece, then it is a local solution.
5) If for any allocation for a plant, it is violating the limit, it should be fixed to that limit and the remaining plants only should be considered for next iteration.
6) Repeat steps 2, 3, and 4 till a solution is achieved within a specified tolerance.

2.3. Artificial Bee Colony (ABC) Algorithm

Artificial bee colony (ABC) is one of the most recently defined algorithms by Dervis Karaboga [18], [19] in 2005. It has been developed by simulating the intelligent behavior of honeybees. In ABC system, artificial bees fly around in a multidimensional search space and the employed bees choose food sources depending on the experience of themselves. The onlooker bees choose food sources based on their nest mates experience and adjust their positions. Scout bees fly and choose the food sources randomly without using experience. Each food source chosen represents a possible solution to the problem under consideration. The nectar amount of the food source represents the quality or fitness of the solution. The number of employed bees or the onlooker bees is equal to the number of food sources or possible solutions in the population. A randomly distributed initial population is generated and then the population of solutions is subjected to repeated cycles of the search process of the employed bees, onlookers and scouts. An employed bee or onlooker probabilistically produces a modification on the position in her memory to find a new food source (solution) and evaluates the nectar amount (fitness) of the new food source. If the nectar amount of the new food source is higher than that of the previous one then the bee remembers the new position and forgets the old one. Once the employed bees complete their search process, they share the nectar information of the food sources and their position information with the onlooker bees on the dance area. The onlooker bees evaluate the nectar information and choose a food source depending on the probability value associated with that food source using (7).

$$P_i = \frac{fit_i}{\sum_{j=1}^{N_e} fit_j} \tag{7}$$

where fit_i is the fitness value of the solution i which is proportional to the nectar amount of the food source in the position i and N_e (i.e. Npop/2) is the number of food sources which is equal to the number of employed bees, N_e. Now the onlookers produce a modification in the position selected by it using (8) and evaluate the nectar amount of the new source.

$$v_{ij} = x_{ij} + \phi_{ij}\left(x_{ij} - x_{kj}\right) \tag{8}$$

where $k \in \{1, 2,\ldots., N_e\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes. Although k is determined randomly, it has to be different from i. ϕ_{ij} is a random number between [-1, 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 one. In other words, greedy selection method is employed as the selection operation between old and new food sources.

If a predetermined number of trials do not improve a solution representing a food source, 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 'limit', which is an important control parameter of ABC algorithm. The limit value usually varies from 0.001*NeD* to *NeD*. If the abandoned source is x_{ij}, $j \in (1, 2,..., D)$ then the scout discovers a new food source x_{ij} using (9).

$$x_{ij} = x_{j\,\min} + rand(0,1) * \left(x_{j\,\max} - x_{j\,\min}\right) \tag{9}$$

where $x_{j\min}$ and $x_{j\max}$ are the minimum and maximum limits of the parameter to be optimized. There are four control parameters used in ABC algorithm. They are the number of employed bees, number of unemployed or onlooker bees, the limit value and the colony size. Thus, ABC system combines local search carried out by employed and onlooker bees, and global search managed by onlookers and scouts, attempting to balance exploration and exploitation process.

Main steps of ABC algorithm for ELD problems are as follows:

Step-1: Initialize the population of solutions with in boundaries of the system

$$P = P_{\min} + rand * (P_{\max} - P_{\min})$$

Step-2: Calculate the objective function and fitness of each solution. Store the best fitness as *Pbest* solution.

Step-3: A mutant solution is formed using a randomly selected neighbour,

$$P_{k\,mutant} = P_k(i) + \left(P_j(i) - P_k(i)\right) * \left(2 * rand - 1\right)$$

where j is the randomly selected neighbour and i is a random parameter

Step-4: Replace $P_{k\,mutant}$ by P_k , if the mutant has higher fitness or lower fuel cost of generation.

Step-5: Repeat the above procedure for all the solutions

Step-6: Probability of each solution is calculated as
Probability (i) = a*fitness (i)/max (fitness) + b
where {a+b =1}

Step-7: The solution P is selected if its probability is greater than a random number,
If (rand < probability (i))
    Solution is accepted for mutation
Else
    Go for next solution
    Counter is incremented
While (Counter = population/2)

Step-8: Again the best P is determined. Replace P by random P if its trial counter exceeds threshold.

Step-9: Repeat the above for maximum number of iterations.

Step-10: The *Pbest* and F(*Pbest*) are the best solution and global minimum of the objective function.

3. RESULTS AND ANALYSIS

To verify the feasibility and effectiveness of the proposed ABC algorithm, three different power systems were tested consisting of three, six, and fifteen generating units [20-23]. Results of proposed artificial bee colony (ABC) algorithm are compared with quadratic programming (QP) method and genetic algorithm (GA). A reasonable B-loss coefficients matrix of power system network has been employed to calculate the transmission loss. The software has been written in the MATLAB-7 language.

3.1. Case 1: 3-Units System

In this case, a simple power system consists of three-unit thermal power plant is used to demonstrate how the work of the proposed approach. Characteristics of thermal units are given in Table 1 [20], the followed by coefficient matrix B_{ij} losses.

Table 1. Generating unit capacity and coefficients

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i (\$/MW^2)	b_i (\$/MW)	c_i (\$)
1	50	250	0.00525	8.663	328.13
2	5	150	0.00609	10.04	136.91
3	15	100	0.00592	9.76	59.16

$$B_{ij} = \begin{bmatrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.000175 & 0.0001540 & 0.000283 \\ 0.000184 & 0.0002830 & 0.000161 \end{bmatrix}$$

By using the proposed ABC technique obtained the results as shown in Table 2 and Table 3. Test results in Table 2 for 3-generator system with load change from 250 MW to 400 MW with taking into account transmission losses. Table 3 shows the optimal power output, total cost of generation, as well as active power loss for the power demands of 275 MW, 300 MW, 350 MW and 400 MW. Table 3 shows that the ABC algorithm is better than conventional method (quadratic programming) for each loading.

Table 2. Best power output for 3-generator system

P_{demand} (MW)	P1 (MW)	P2 (MW)	P3 (MW)	PLoss (MW)	Fcost (\$/hr)
250	177.62	60.08	19.52	7.22	3046.5
275	189.95	70.44	23.40	8.80	3328.3
300	202.47	80.98	27.08	10.54	3615.1
325	215.18	91.70	30.56	12.44	3907.1
350	228.08	102.62	33.81	14.50	4204.3
375	241.17	113.72	36.83	16.72	4506.8
400	249.96	123.85	45.91	19.72	4815.1

Table 3. Best power output for 3-generator system

P_{demand} (MW)	Methods	P1 (MW)	P2 (MW)	P3 (MW)	PLoss (MW)	Fcost (\$/hr)
275	Conv.	189.34	68.40	26.93	9.66	3334.9
	ABC	189.95	70.44	23.40	**8.80**	**3328.3**
300	Conv.	201.70	78.67	31.26	11.63	3623.6
	ABC	202.47	80.99	27.08	**10.56**	**3615.1**
350	Conv.	226.96	99.71	39.51	16.18	4217.3
	ABC	228.08	102.61	33.81	**14.50**	**4204.3**
400	Conv.	250.00	122.98	48.59	21.57	4833.1
	ABC	249.89	126.87	42.59	**19.35**	**4815.0**

3.2. Case 2: 6-Units System

In this case, a standard of six-unit thermal power plant (IEEE 30 bus test system) is used to demonstrate how the work of the proposed approach, as shown in Figure 1. Characteristics of thermal units are given in Table 4 [21], the followed by coefficient matrix B_{ij} losses.

The simulation results with the proposed ABC algorithm are shown in Table 5 and Table 6 respectively with the load variation of 700 MW and 800 MW. From the simulation results show that the generation output of each unit is obtained correction reduces the total cost of generation and transmission losses when it compared with the genetic algorithm (GA) is taken from [22].

Table 4. Generating unit capacity and coefficients

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i ($/MW^2)	b_i ($/MW)	c_i ($)
1	10	125	0.0033870	0.856440	16.817750
2	10	150	0.0023500	1.025760	10.029450
3	35	225	0.0006230	0.897700	23.333280
4	35	210	0.0007880	0.851234	27.634000
5	130	325	0.0004690	0.807285	36.856880
6	125	315	0.0003998	0.850454	30.147980

$$B_{ij} = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

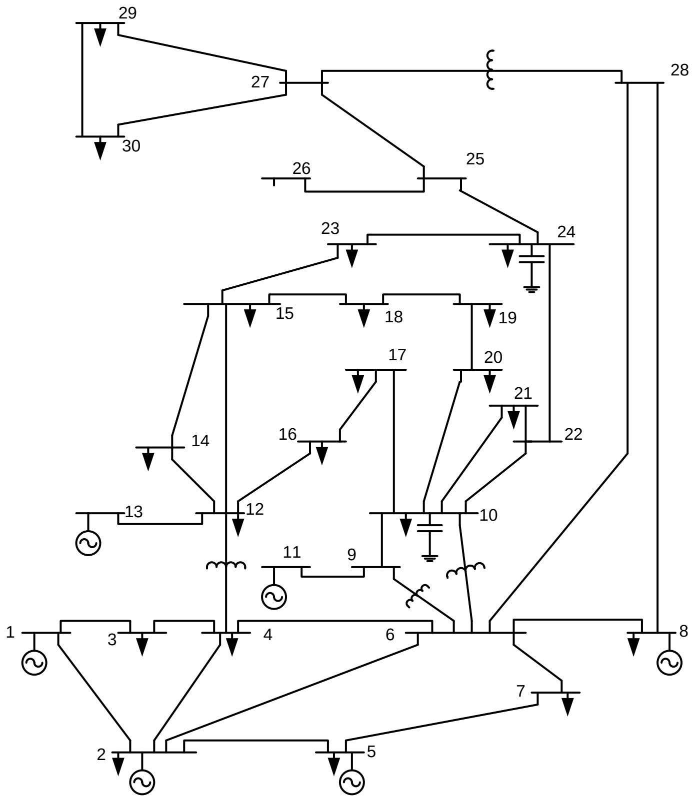

Figure 1. IEEE 30-bus 6-generator test system.

Table 5. Best power output for 6-generator system (P_D = 700 MW)

Unit Output	GA [22]	ABC
P1 (MW)	27.3010	27.3761
P2 (MW)	15.6124	10.5000
P3 (MW)	120.3109	118.7326
P4 (MW)	116.7756	118.9831
P5 (MW)	226.8377	230.6243
P6 (MW)	212.4050	212.7142
Total power output (MW)	719.2426	**718.9303**
Total generation cost ($/hr)	820.4200	**820.2667**
Power losses (MW)	19.2426	**18.9303**

Table 6. Best power output for 6-generator system (P_D = 800 MW)

Unit Output	GA [22]	ABC
P1 (MW)	32.6737	32.6026
P2 (MW)	15.8161	14.6148
P3 (MW)	141.6623	141.5610
P4 (MW)	131.3117	136.2852
P5 (MW)	252.3711	258.0475
P6 (MW)	251.5507	242.2064
Total power output (MW)	825.3855	**825.3175**
Total generation cost ($/hr)	931.1060	**931.0326**
Power losses (MW)	25.3855	**25.3175**

3.3. Case 3: 15-Units System

In this case, the sample system has 15 thermal units and the characteristics of thermal units are given in Table 7 [22, 23]. The total demand is considered as 2630 MW and the transmission losses are neglected. To demonstrate the superiority of the proposed artificial bee colony algorithm, results are compared with conventional method and genetic algorithm.

The optimal solution obtained through the proposed method has been compared with the results obtained through conventional method and behavioral random search such as genetic algorithm. The generation schedule of committed thermal units is summarized in Table 8. The total fuel cost of the ABC algorithm is 32257.0510 $/h and that conventional method and GA are 32388.1165 $/h and 32282.7032 $/h, respectively.

Table 7. Generator characteristics of 15 unit systems

Unit	P_i^{min} (MW)	P_i^{max} (MW)	a_i ($/MW^2)	b_i ($/MW)	c_i ($)
1	150	455	0.000299	10.1	671
2	150	455	0.000183	10.2	574
3	20	130	0.001126	8.8	374
4	20	130	0.001126	8.8	374
5	150	470	0.000205	10.4	461
6	135	460	0.000301	10.1	630
7	135	465	0.000364	9.8	548
8	60	300	0.000338	11.2	227
9	25	162	0.000807	11.2	173
10	25	160	0.001203	10.7	175
11	20	80	0.003586	10.2	186
12	20	80	0.005513	9.9	230
13	25	85	0.000371	13.1	225
14	15	55	0.001929	12.1	309
15	15	55	0.004447	12.4	323

Table 8. Best power output for 15-generator system (P_D = 2630 MW)

Unit Output	Conventional	GA	ABC
P1 (MW)	450.0328	453.7345	454.8494
P2 (MW)	455.0000	396.5920	455.0000
P3 (MW)	130.0000	130.0000	130.0000
P4 (MW)	130.0000	130.0000	130.0000
P5 (MW)	275.7610	304.8259	271.0350
P6 (MW)	417.1226	460.0000	460.0000
P7 (MW)	461.6271	465.0000	465.0000
P8 (MW)	95.3816	69.8569	60.0000
P9 (MW)	25.0000	25.7484	25.0000
P10 (MW)	39.8072	31.4771	25.0000
P11(MW)	22.3441	36.3567	42.4991
P12 (MW)	36.2597	68.9115	56.6164
P13 (MW)	54.5553	25.9143	25.0000
P14 (MW)	22.1086	16.3911	15.0000
P15 (MW)	15.0000	15.1917	15.0000
TPO (MW)	2630.0000	2630.0000	2630.0000
TGC ($/hr)	32388.1165	32282.7032	**32257.0510**

TPO = Total Power Output; TGC = Total Generation Cost

4. CONCLUSION

In this paper, a new optimization of artificial bee colony (ABC) algorithm has been successfully introduced to obtain the optimum solution of economic load dispatch problem. Power system has large variation in load from time to time and it is not possible to have the load dispatch for every possible load demand as there is no general procedure for finding out optimum solution of economic load dispatch. Three test cases consisting of 3-unit, 6-unit and 15-unit system have been tested and the results are compared with conventional method and GA. The comparison shows that ABC algorithm performs better than above mentioned methods.

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