Economic Power Dispatch with Valve Point Effects Using Bee Optimization Algorithm

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Abstract – This paper presents a newly developed optimization algorithm, the Bee Optimization Algorithm (BeeOA), to solve the economic power dispatch (EPD) problem. The authors have developed a derivative free and global optimization technique based on the working of the honey bee. The economic power dispatch problem is a nonlinear constrained optimization problem. Classical optimization techniques fail to provide a global solution and evolutionary algorithms provide only a good enough solution. The proposed approach has been examined and tested on two test systems with different objectives. A simple power dispatch problem is tested first on 6 generators and then the algorithm is demonstrated on 13 thermal unit systems whose incremental fuel cost function takes into account the value point loading effect. The results are promising and show the effectiveness and robustness of the proposed approach over recently reported methods.

Keywords: Bee optimization algorithm, Economic power dispatch, Genetic algorithm, Particle swarm optimization

1. Introduction

The objective of the economic power dispatch (EPD) problem is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating costs while satisfying all units and system equality and inequality constraints. The main aim in the economic dispatch problem is to minimize the total cost of generating real power (production cost) at various stations while satisfying the loads and the losses in the transmission links [20].

Classical optimization techniques, such as the direct search method and the gradient search method, require the judicious choice of an initial starting point so as to obtain global optima or a result close to global optima as otherwise they get stuck at a local optima [19].

Recently, as an alternative to classical optimization techniques, some heuristic optimization techniques have been developed such as evolutionary algorithms, neural networks, and ant colony optimization etc. [10-16]. The most prominent evolutionary algorithm is the Genetic Algorithm (GA)[15] based on natural genetics. The genetic algorithm (GA) uses the principles of evolution and natural selection from natural biological systems to simulate evolution. The GA begins its search with a random set of populations. After the random population of solutions is created, fitness is assigned to each population. A termination condition is then checked and if it is not satisfied then the population is modified and a new population is created. This way the function converges to global optima. The GA is most effective when the task does not require global optima to be found, finding a good enough solution quickly is sufficient and the search space is not too large. However, conventional GA often fails to find a globally optimum solution in limited evolution generations. A different approach based on genetic algorithms, known as queen-bee evolution [4], overcomes some of the problems of conventional GA and has been used to solve the EPD problem.

Particle Swarm Optimization (PSO) is based on the analogy of bird flocking and fish schooling. PSO searches in parallel using a group of individuals where each individual corresponds to a candidate solution to the problem. Individuals in a swarm approach the optimum through their present velocity, previous experience, and the experience of the neighbors. Some hybrid PSO algorithms such as Chaotic PSO and Chaotic PSO with Implicit Filtering (IF) have also been used in the past to solve the economic dispatch problem with valve point effects [23].

In this paper a new method known as Bee optimization Algorithm (BeeOA), inspired by the group decision making process used by honey bee swarms to choose a new nest site, is employed to solve the EPD problem. Two case studies demonstrate the robustness of bee optimization algorithm when compared with the results obtained from earlier optimization methods [4][23]. The remainder of the paper is organized as follows. In section 2 we discuss the nest site selection process of honey bee swarms. We present the Bee Optimization Algorithm in section 3. The problem of economic power

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dispatch is formulated in section 4. Two case studies and their results are shown in section 5, and the conclusion drawn is given in section 6.

2. Bee Decision Making Process

The problem of social choice has challenged social philosophers and political scientists for centuries. The fundamental decision making dilemma for groups is how to turn individual preferences for different outcomes into a single choice for the whole. The study of group decision making sometimes uses a "collective intelligence" perspective where the group is viewed as a single decision maker. Moreover, it has been recognized for some time that massively parallel animal-to-animal interactions underlie the cognitive abilities of individuals. Nest site selection by honey bee swarms is a highly distributed decision making process that usually occurs in the spring when a colony outgrows its hive and divides itself by swarming. The queen and approximately half the worker bees leave the parental hive, but within about 20 minutes they coalesce into a cluster at an interim site, usually a nearby tree branch. From here they choose their future nest site. Several hundred scout bees fly from the swarm cluster and search out tree cavities and other potential dwelling places. Discovered nest sites of sufficient quality are reported to the cluster via the scouts' waggle dances, which recruit other bees to evaluate the sites. Higher quality sites evoke stronger dancing and hence more recruits. A process of recruitment and selection ensues in which one site comes to dominate in visitation and dancing, and the swarm takes flight again and moves to the selected cavity [5][6].

During the decision making process, only a few hundred of the thousands of bees in a swarm are active. Most bees remain quiescent, to conserve the swarms' energy supply, until a decision had been made and it is time to fly to the chosen site.

One of the behavioral mechanisms at the level of individual scout bees that underlie the nest site selection process is the scout bees' careful tuning of dance strength, in terms of the number of waggle dance circuits they perform for a site,

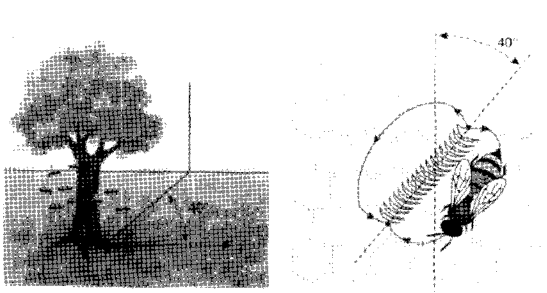

Fig. 1. Waggle dance used by bee to inform other bees about nest site & food sources

as a function of site quality. Waggle dance refers to the communication behavior that allows successful foragers to inform hive mates of the locations of rich food sources through a specific series of movements. A dancing bee runs forward and performs the waggle run, vibrating her abdomen laterally, then circles back to her starting point, producing one dance circuit. A single bout of dancing contains many of these circuits. Von Frisch found that the length of a bee's waggle run translates into the distance to the food source, and the angle of dance represents direction. This waggle dance is also done by the scout bees reporting potential nest sites. When waggle dancing refers to nest sites, it occurs on the surface of a swarm rather than on the combs inside a hive in the case of food source locations.

For the first time a scout returns to the swarm from a first rate site, she is apt to perform a waggle dance containing 100 or more dance circuits. Scouts also report mediocre but acceptable nest sites, presumably in case nothing better is located. But the first time a scout returns from a mediocre site, she is likely to perform a waggle dance containing only a dozen or so dance circuits. The greater the strength of dancing for a particular site, the larger the stream of newcomers to it, hence the buildup of scouts will be most rapid at the best site. Also, if a scout bee commits herself to a site, she will makes multiple visits to it. She will, however, decrease the strength of her dance by about 15 circuits each time she returns to the swarm and performs a dance. The result is that the overall difference in the recruitment signal strength between two sites is a nearly exponential function of the difference in quality between them. Moreover, there is a strong positive feedback in this recruitment process, such that a greater number of recruiters will in turn give rise to a still greater number of bees committed to the site. Consequently, small differences in nest site quality and waggle dance strength between two sites can snowball into large differences in the number of scouts affiliated with them. Thus the best site gains the scouts fastest.

Usually, a bee ceases making visits to a site shortly after she has ceased performing dances for it; hence bees abandon poor sites more rapidly than they do excellent ones. Once a scout abandons a site, she "resets" and can be recruited to another site, or even re-recruited to the same site. However, when a bee finishes dancing for a site, about 80 percent of the time she ceases dance completely. Scout bees therefore depend on the recruitment of other scouts who were unable to find any candidate sites on their searches and so remain uncommitted. An uncommitted scout may visit several sites before finding one she feels is worthwhile. As long as the rate of recruitment to a site exceeds the rate of abandonment, the number of scouts affiliated with this site will grow large and will automatically exclude from the competition those groups affiliated with inferior sites.

Once the quorum threshold is reached at one of the sites, the bees start a behavior that is well understood. The scouts at this site will return to the swarm cluster and begin to produce a special, high pitched acoustic signal that stimulates the non scouts in the swarm cluster to begin warming their flight muscles, by shivering, to the 33 to 35 degrees Celsius needed for flight. This signal, known as the "piping signal", lasts about 0.8 seconds and has a fundamental frequency of about 200 hertz. Because the stimulus for worker piping is a quorum of scouts at the chosen site, not a consensus among the scouts for this site, the process of swarm warming generally begins before the scouts have reached a consensus. But because the warm-up usually takes an hour or so, there is usually time for scouts to achieve a consensus for the chosen site before the entire swarm launches into flight.

Thus during the decision making process, bees take into consideration two key factors. First, only a few hundred of the thousands of bees in the swarm were active, the others remaining quiescent in order to conserve the swarm's energy. Secondly, bee dances represent the various sites found, but with time the waggle dance for the dominant site increases and after reaching the quorum, the entire cluster of bees would suddenly take off and fly towards the selected site. Seeley, Visscher & Kevin [5] found in their research that the quality of the chosen site depends upon quorum threshold size, dance decrease rate and the tendency to explore [7] [8]. The former process is how a swarm finds all possible nest sites, and the latter process is how the swarm chooses among possible nest sites.

3. Bee Optimization Algorithm (BeeOA)

The proposed Bee Optimization Algorithm (BeeOA) is based on this nest site selection process by honey bee swarms. In the proposed algorithm, firstly all possible local optimum points are found through exploration, which corresponds to the good enough quality sites in the landscape. For this purpose the total range of the independent parameters are divided into smaller volumes each of which determines the starting point for the exploration of each bee. The bee finds an optimum point by using a suitable optimization technique starting from this starting point. After all optimum point information is obtained, the optimum point with the best fitness value is chosen as the global optimum. We will assume that the quality of nest site is constant during the nest site selection process. To be constant with empirical studies, we assume that during the nest site selection process, at most 10 percent of the scouts that act as committed scouts or nest site explorers die, but that bees in the cluster do not.

3.1 The Landscape of Nest Site Quality

In general, the optimization problems involve the minimization of a given function. The function to be minimized is known as the objective function and its value corresponding to a point is known as the fitness value of the function at that point.

Let F be the given objective function to be minimized and its value depends on p number of independent parameters. Each parameter can be denoted as h_j where $j = 1, 2\ldots.., p$.

Therefore the fitness value at a point can be found by putting the value of all parameters at that point in the objective function.

$$\text{Fitness value} = F(h_1, h_2, \ldots\ldots\ldots, h_{p-1}, h_p) \tag{1}$$

This objective function denotes the landscape of nest site quality and the fitness value denotes the quality of the nest site.

3.2 Exploration

The value of the objective function depends on p number of independent parameters. Let the range of each parameter be given as

$$\text{Range of } j_{th} \text{ parameter} \in [W_{ij}, W_{fj}] \tag{2}$$

Where W_{ij} and W_{fj} represent the initial and final value of the parameter.

Thus the complete domain of the objective function can be represented by a set of p number of axis. Each axis will be in a different dimension and will contain the total range of one parameter.

The next step is to divide each axis into smaller parts. Each of these parts is known as a step. Let the j_{th} axis be divided in n_j number of steps each of length s_j ($j = 1$ to p). This length s_j is known as step size for the j_{th} parameter.

The relationship between n_j and s_j can be given by the formula

$$n_j = \frac{W_{fj} - W_{ij}}{S_j} \tag{3}$$

And hence each axis is divided into their corresponding branches. If we take one branch from each axis then these p number of branches will constitute a p dimensional volume.

Total number of such volumes can be calculated by the formula

$$\text{Number of volumes, } N_v = \prod_{j=1}^{p} n_j \tag{4}$$

Number of volumes indicates the number of scouts that went for exploration. One point inside each volume is chosen as the starting point for the search for a particular bee. The cluster is assumed to be at the midpoint of the total landscape which is given by

$$[\frac{W_{i1}+W_{f1}}{2},\frac{W_{i2}+W_{f2}}{2},\ldots\ldots,\frac{W_{ip}+W_{fp}}{2}] \quad (5)$$

It is assumed that bees fly from the cluster at one time and first reach the mid points of the volumes such that each volume has one bee corresponding to it. The bee starts the search from the midpoint of the volume and can search the complete domain until a good quality site is found.

For an objective function having one independent parameter, the complete domain will be given by one axis only, represented as h_1. Here each step will give us one volume. Let us take the following values:

$p=1, W_{i1}=1, W_{f1}=6, S_1=1$

Therefore $n_1=5$ and $N_v=5$

Thus 5 bees are sent for exploration. The starting point for each bee is the midpoint of each step as shown in Fig 2.

For an objective function having two independent parameters, the complete domain will be given by set of two axis represented as h_1 and h_2. Let us take the following values:

$p=2, W_{i1}=1, W_{f1}=5, S_1=1$ *and*

$W_{i2}=1, W_{f2}=5, S_2=1$

Therefore $n_1=4, n_2=4$ and $N_v=16$

Thus 16 bees are sent for exploration which was shown in Fig 3. The starting point of each bee is the midpoint of each volume which in this case is two dimensional rectangles.

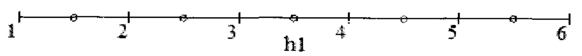

Fig. 2. Domain of the objective function with one independent parameter

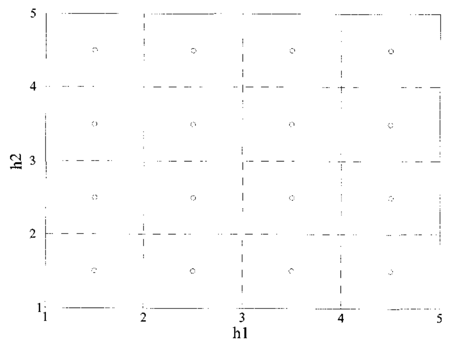

Fig. 3. Domain of the objective function with two independent parameters

For an objective function with three independent parameters, the complete domain will be given by a set of three axis represented as h_1, h_2 and h_3. Let us take the following values:

$p=3, W_{i1}=1, W_{f1}=5, S_1=1$

$W_{i2}=1, W_{f2}=4, S_2=1$ *and*

$W_{i3}=1, W_{f3}=4, S_3=1$

Therefore $n_1=4$, $n_2=3, n_3=3$ *and* $N_v=36$

Thus 36 bees are sent for exploration. The starting point for each bee is the midpoint of the corresponding volume which is a 3 dimensional cuboid in this case as shown in Fig. 4.

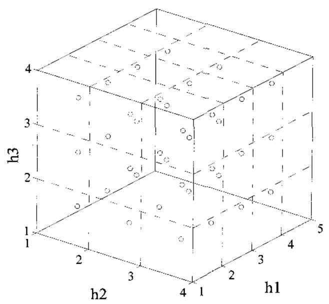

Fig. 4. Domain of the objective function with three independent parameters

Objective functions with more than three independent parameters can be solved in a similar manner.

The larger the number of scout bees and smaller the step size, greater is the total time taken and the accuracy of the search.

3.3 Search Methodology

For optimization of the given objective function we have modified a very popular optimization technique usually known as the NM method. The methodology used is similar to the working of bees. Let $f(x,y)$ be the function that is to be minimized. For bees this is a food function. To start, we assume that bees take three positions of a triangle for two variables problems. $V_1=(x_1,y_1)$ represents the initial position of the bee $V_2=(x_2,y_2)$ and $V_3=(x_3,y_3)$ are the positions of probable food points. The movement of the bee from its initial position towards the food position, i.e. the optimization point, is as follows. The function $z_i=f(x_i,y_i)$ for *i=1, 2, 3* is evaluated at each of these three points. The obtained values of z_i are recorded in a way that $z_1 \le z_2 \le z_3$ and hence $V_1 \le V_2 \le V_3$ correspond to the bee positions and food points. The construction process uses the midpoint of the line segment joining the two best food positions V_1 and V_2 as shown in figure 5(a).

$$V_{12}=\frac{V_1+V_2}{2}=\left(\frac{x_1+x_2}{2},\frac{y_1+y_2}{2}\right) \quad (6)$$

The value of function decreases as the bee moves along V_3 to V_1 or V_3 to V_2. Hence it is feasible that $f(x,y)$ takes a smaller value if the bee moves towards V_{12}. For the further movement of the bee a test point V_t is chosen in such a way that it is a reflection of the worst food point i.e. V_3 as shown in figure 5(a). The vector formula for V_t is

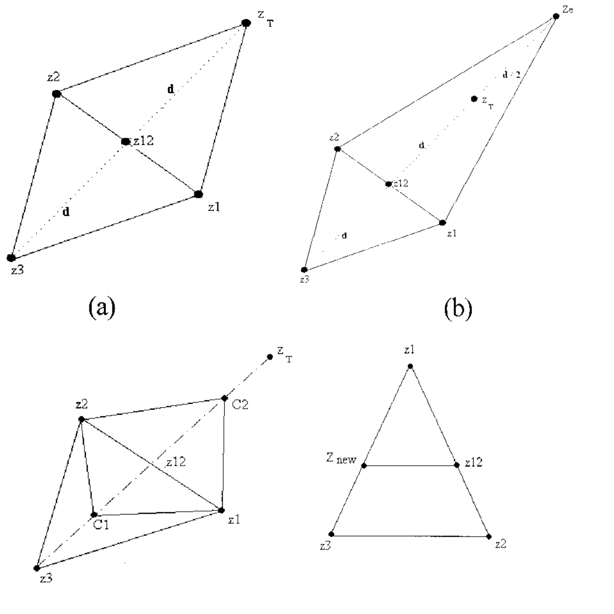

Fig. 5. Agents search Movements with the proposed optimization algorithm. (a) Starting of the motion in search of solution, (b) Extension in the direction of good optimal point, (c) Contraction of the movement in case optimal point quality is not good, (d) Shrinking of the space towards optimistic solution

$$V_t = 2 \times V_{12} - V_3 \quad (7)$$

If the function value at V_t is smaller than the function value at V_3, then the bee has moved in the correct direction towards minimum. Perhaps the minimum is just a bit further than the point V_t. So the line segment is extended further to V_e through V_t and V_{12}. The point V_e is found by moving an additional distance *d/2* along the line as shown in figure 5(b). If the function value at V_e is less than the function value at V_t, then the bee has found a better food point than V_t.

$$V_e = 2 \times V_t - V_{12} \quad (8)$$

If the function value at V_{12} and V_3 are the same, another point must be tested. Two test points are considered by the bee on the both sides of V_{12} at distance *d/2* as shown in figure 5(c).

The point of smaller value will frame a new triangle with the other two best points. If the function value at the two test points is not less than the value at V_3, the points V_2 and V_3 must be shrunk towards V_1 as shown in figure 5(d). The point V_2 is replaced with V_{12}, and V_3 is replaced with the midpoint of the line segment joining V_1 and V_3.

Figure 6 shows the path traced by the bees and the sequences of triangles $\{T_k\}$ converging to the optimal point for the objective function

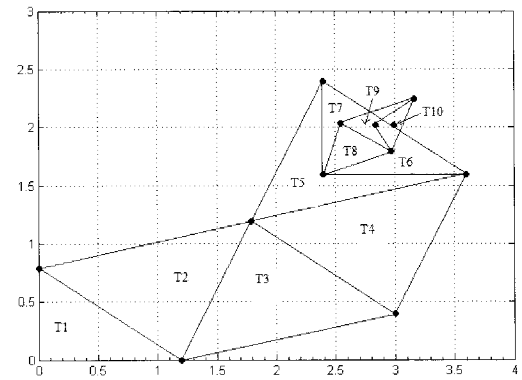

Fig. 6. Movement of the Bee in search of food and finally reaching for the best one

$$f(x,y) = x^2 - 4x + y^2 - y - xy$$

3.4 Waggle Dance

The bee, after returning from her search, performs the waggle dance to inform other bees about the quality of site

$$Wd_i = \min(F_i(X)) \quad (9)$$

Where $F_i(X)$ represents the different search values obtained by a bee. Each of these points is recorded in a table known as an optimum vector table. X is a vector containing p number of elements. These elements contain the value of parameters at that point. Also, the number of occurrences of X in the optimum vector table is also noted. Fitness value at point X is given by $F(X)$

3.5 Consensus

Bees use the consensus method to decide the best obtained or search value. We mimic this event and behavior by comparing the results obtained. After exploration and the waggle dance is finished the global optimized point is chosen by comparing the fitness values of all optimized points in the optimum vector table.

For minimization problems the point with the lowest fitness value is selected as the global optimized point.

Let the number of optimized points obtained be given by A. Then each optimized point is represented as X_l

where $l = 1$ to A

The global optimized point X_G is found by:

$$F(X_G) = \min[F(X_1), F(X_2), \ldots\ldots\ldots, F(X_{N_v})] \quad (10)$$

A summary of all symbols and their meanings is given in table 1.

Table 1. Symbols and their meanings

F	Objective function
P	Total number of parameters
h_j	j_{th} parameter (j = 1 to p)
W_{ij}	Initial value of j_{th} parameter
W_{fj}	Final value of j_{th} parameter
n_j	Number of steps for j_{th} parameter
S_j	Step length for j_{th} parameter
N_v	Total number of volumes
X_l	Optimized point found by l_{th} bee (l = 1 to N_v)
X_G	Global optimized point

Algorithm

1) Initialize the number of parameters, p Initialize the length of steps, S_j ($j = 0$ to p)
2) Initialize the range of each parameter as $\left[W_{ij}, W_{fj}\right]$ where $j = 0, 1, \ldots, p$
3) Calculate the number of steps:

$$n_j = \frac{W_{fj} - W_{ij}}{S_j}$$

4) Calculate the total number of volumes:

$$N_v = \prod_{j=1}^{p} n_j$$

5) For each volume, take the starting point of the exploration as the midpoint of the volume

$$\left[\frac{W_{i1}+W_{f1}}{2}, \frac{W_{i2}+W_{f2}}{2}, \ldots\ldots, \frac{W_{iP}+W_{fP}}{2}\right]$$

6) Record the value of the optimized point obtained corresponding to each volume in the optimum vector table in the following way $[X_1, X_2, \ldots\ldots\ldots\ldots, X_{N_v}]$
7) After exploration has been completed, calculate the global optimized point in the following manner:

$$F(X_G) = \min[F(X_1), F(X_2), \ldots\ldots\ldots\ldots, F(X_{N_v})]$$

4. Economic Power Dispatch Problem

The economic dispatch problem is to simultaneously minimize the overall cost rate and meet the load demand of a power system. Assuming the power system includes n generating units. The aim of economic power dispatch is to determine the optimal share of load demand for each unit in the range of 3 to 5 minutes [1][2][3]. Generally, the economic power dispatch problem can be expressed as minimizing the cost of production of the real power which is given by objective function F_T

where,

$$F_T = \sum_{i=1}^{n} F_i(P_i) \quad (1)$$

which is subjected to the constraints of equality in real and reactive power balance

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (2)$$

where a_i, b_i and c_i are the cost coefficients of the i^{th} generator and n is the number of generators committed to the operating system. P_i is the power output of the i^{th} generator.

The inequality of real and reactive power limits on the generator output are:

$$P_{\min,i} \le P_i \le P_{\max,i} \quad \text{where } i = 1, 2, \ldots\ldots, n \quad (3)$$

$$\sum_{i=1}^{n} P_i - D - L = 0 \quad (4)$$

where D is the load demand and L is the transmission losses.

The generator costs are usually approximated using quadratic functions. However, it is more practical to consider the valve-point loading for fossil-fuel-based plants.

In this context, a cost function is obtained based on the ripple curve for more accurate modeling. This curve contains higher order nonlinearity and discontinuity due to the valve point effect.

One way of representing this effect is to use a rectified sinusoidal function to represent the valve-point loading in the cost function [23]. In this case the equation (2) can be written as:

$$f(P) = c + bP + aP^2 + \left|e\sin\left[\rho\left(P_{\min} - P\right)\right]\right| \quad (5)$$

5. Case Study

The proposed algorithm is applied to two test systems: a power system with 6 units and 13 units respectively. For simplicity, transmission losses are ignored in the two test systems. The results obtained from BOA are compared with that obtained from the CGA and QEGA [1].

TEST SYSTEM 1: The first test system has 6 units and details of this test system are given as follows:

$$F_1 = 0.001562P_1^2 + 7.92P_1 + 561.0 \quad 100 \le P_1 \le 600 \quad (5)$$

$$F_2 = 0.001940P_2^2 + 7.85P_2 + 310.0 \quad 100 \le P_2 \le 400 \quad (6)$$

$$F_3 = 0.004820P_3^2 + 7.97P_3 + 78.0 \quad 50 \le P_3 \le 200 \quad (7)$$

$$F_4 = 0.001390P_4^2 + 7.06P_4 + 500.0 \quad 140 \le P_4 \le 590 \quad (8)$$

$$F_5=0.001840P_5^2+7.46P_5+295.0 \quad 110\leq P_5\leq 440 \tag{9}$$

$$F_6=0.001840P_6^2+7.46P_6+295.0 \quad 110\leq P_6\leq 440 \tag{10}$$

The load demands are 800, 1200 and 1800 MW. Optimization results are given in Table 1 and a comparison of computational time taken by different methods is shown in figure 7.

Table 1. Optimization results of CGA, QEGA and BeeOA for a 6 generator system

Method	Load (MW)	Unit1 (MW)	Unit2 (MW)	Unit3 (MW)	Unit4 (MW)	Unit5 (MW)	Unit6 (MW)	Total cost ($)
CGA	800	109.17	104.08	52.04	305.05	114.83	114.83	8232.89
QEGA	800	104.89	102.87	51.74	314.18	113.16	113.16	8231.03
BeeOA	**800**	**100.00**	**100.00**	**50.00**	**305.63**	**122.19**	**122.19**	**8227.10**
CGA	1200	142.55	117.80	58.90	515.20	182.78	182.78	11493.74
QEGA	1200	131.50	129.05	52.08	494.08	200.61	200.61	11480.03
BeeOA	**1200**	**123.76**	**117.68**	**50.00**	**448.42**	**230.06**	**230.06**	**11477.08**
CGA	1800	222.42	190.73	95.36	555.63	367.92	367.92	16589.05
QEGA	1800	250.49	215.43	109.92	572.84	325.66	325.66	16585.85
BeeOA	**1800**	**247.99**	**217.719**	**75.18**	**588.04**	**335.52**	**335.53**	**16579.33**

Table 2. Cost coefficients of generators

Generator	a	b	c	e	P_{min} (MW)	P_{max} (MW)	f (rad/MW)
1	0.00028	8.10	550	300	0	680	0.035
2	0.00056	8.10	309	200	0	360	0.042
3	0.00056	8.10	307	100	0	360	0.042
4-9	0.00324	7.74	240	150	60	180	0.063
10,11	0.00284	8.60	126	100	40	120	0.084
12,13	0.00284	8.60	126	100	55	120	0.084

Table 3. Optimization results for a 13 generator system

Optimization Method	Mean Time(s)	Minimum Cost ($/h)	Mean Cost ($/h)	Maximum Cost ($/h)
IF	1.4	18812.3852	18962.0139	19111.6426
PSO	2.6	18874.7634	19159.3967	19640.4168
Chaotic PSO	3.3	18161.1013	18809.8275	19640.7556
PSO-IF	14.8	18605.1257	18854.1601	19111.6426
Chaotic PSO-IF	15.3	17963.9571	18725.2356	19057.2663
BeeOA	**1.5**	**17961.6962**	**17961.6962**	**17961.6962**

Table 4. Best Result Obtained using BeeOA Method for a 13 generator system

Power	Generation (MW)	Power	Generation (MW)
P_1	106.6667	P_8	166.6667
P_2	106.6667	P_9	166.6667
P_3	106.6667	P_{10}	120.0000
P_4	166.6667	P_{11}	120.0000
P_5	166.6667	P_{12}	120.0000
P_6	166.6667	P_{13}	120.0000
P_7	166.6667	**Total**	**1800.0000**

Table 5. Comparison of Case Study Results for Fuel Costs Presented in the Literature

Optimization Technique	Case Study with 13 Thermal Units
Evolutionary Programming	17994.07
Particle Swarm Optimization	18030.72
Hybrid evolutionary programming with SQP	17991.03
Hybrid Particle Swarm with SQP	17969.93
Chaotic PSO-IF Approach	17963.96
Best Result of this paper using BeeOA method	**17961.70**

TEST SYSTEM 2: The second test system consists of 13 units with the effect of valve point loading. The cost function of the units is expressed using equation (5).

The details of this test system are given in Table 2. The load demand is 1800 MW. Optimization results of the 13-unit system using the BeeOA method are compared with other methods [23] in Table 3 and Table 5. A comparison of time taken by different methods is given in figure 8. It is seen that the time taken by the proposed algorithm is less than its counterparts, with only the IF method being a bit faster than BeeOA.

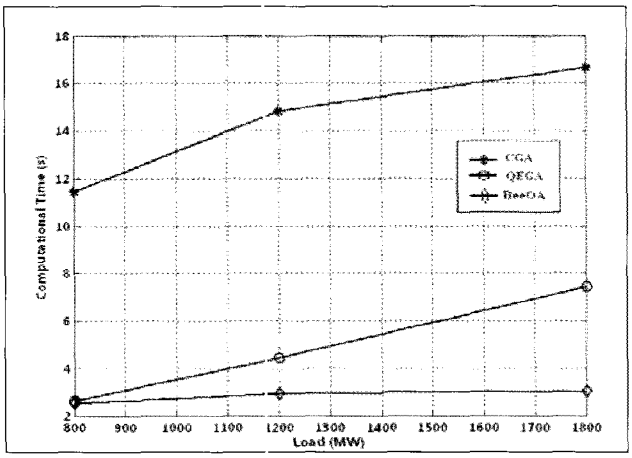

Fig. 7. The computational time taken by different methods for Test System 1

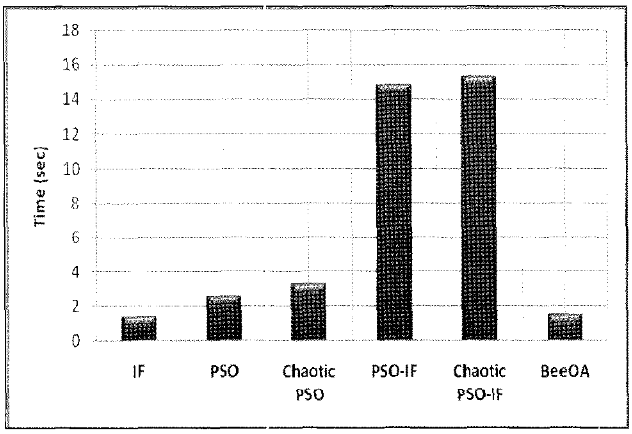

Fig. 8. Comparison of time taken by different methods for Test System 2

6. Conclusion

In this paper a new optimization algorithm known as the Bee Optimization Algorithm is employed to solve the economic power dispatch problem. The results obtained from the Genetic Algorithm and Particle Swarm Optimization and their combinations are compared with those obtained from the Bee Optimization Algorithm. The upshot of the proposed algorithm is that it generates better optimal solutions as compared to its counterparts. The solution provided by BeeOA shows consistency in the solution and hence it gives a better option to optimize real-time and on-line optimization problems.

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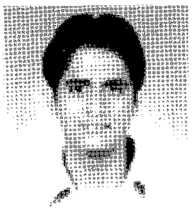

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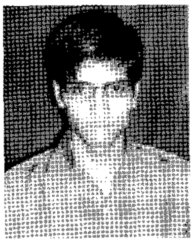

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