A NOVEL APPROACH FOR ECONOMIC POWER DISPATCH USING BEE OPTIMIZATION ALGORITHM

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Abstract: The economic power dispatch problem is a non linear constrained optimization problem. Classical optimization techniques like direct search and gradient methods fails to give the global optimum solution. Evolutionary algorithms like genetic algorithm and queen-bee evolution algorithm provides only a good enough solution. In this paper a new optimization algorithm developed by authors, known as bee optimization algorithm (BeeOA), is employed to solve the economic power dispatch problem. Two test systems comprising of 6 generators and 13 generators are used to test the performance of the bee optimization algorithm The results shows that this algorithm is more accurate and robust in finding the global optimum than previous optimization techniques.

Key words: Bee Optimization Algorithm, genetic algorithm, queen-bee evolution, optimization, economic power dispatch

1. Introduction

Though Economic power dispatch (EPD) is the scheduling of 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 [1]. Different optimization techniques (Classical & Evolutionary algorithms) are used to achieve the same.

There are two kinds of classical optimization techniques: direct search method and gradient search method. In direct search method only the objective function and constraints are used for search procedure whereas in gradient search method the first order or second order derivatives are used for search procedure. Direct search methods are very slow because of requirement of many function iterations whereas the gradient search methods are faster but they are inefficient on discontinuous and non differentiable functions. Furthermore both the methods seek local optima. Thus starting the search in the vicinity of local optima will cause one to miss the global optima [2].

Evolutionary algorithms eradicate some of the above mentioned difficulties and are quickly replacing the classical methods in solving practical problems. Mimicking the behavior of intelligence available in various swarms a new intelligence comes into existence which is known as Swarm Intelligence (SI). A natural example of SI includes ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling. Various algorithms derive from SI are Genetic Algorithm (GA) [3], Ant Colony Optimization (ACO) [4][5], Particle Swarm Optimization (PSO) [6].

The most prominent evolutionary algorithm is the Genetic Algorithm (GA) [3] which is based on natural genetics. The genetic algorithm (GA) uses the principles of evolution and natural selection from natural biological systems to simulate evolution. GA is a search procedure that uses random choice as a tool to guide a highly exploitative search through a coding of parameter choice. 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. However conventional GA often fails to find a globally optimum solution in a limited evolution generations. A different approach based on genetic algorithm, known as queen-bee evolution [7] overcomes some of the problems of conventional GA. The queen-bee evolution algorithm reinforces the exploitation of genetic algorithms. That is, offspring mainly depend on the crossover operation and the fittest individual. As a result, it also increases the probability of premature convergence. Also the exploration of genetic algorithms is increased through strong mutation. These two features enable genetic algorithms to evolve quickly as well as to maintain good solutions.

In the past some algorithms based on bee behaviour have been developed which governs its principle from Particle Swarms. Bee Colony Optimization (BCO), Bee System (BS) [8][9][10] and few other algorithms have been successfully employed to solve various optimization problems. Here, the Bee optimization Algorithm (BeeOA) which is inspired from the group decision making process of honey bee swarms to choose a new nest site is employed to solve the economic dispatch problems. Two case studies demonstrate the robustness of bee

optimization algorithm when compared with the results obtained from conventional genetic algorithm and queen-bee algorithm.

The remainder of the paper is organized as follows. In section 2 authors discuss the nest site selection process of honey bee swarms. Authors present their Bee Optimization Algorithm in section 3. The problem of economic power 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 to how to turn individual preferences for different outcomes into a single choice as a whole. The study of group decision making sometimes uses a "collective intelligence" perspective where the group is viewed as a single decision maker. Nest site selection by honeybee 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 [11]. The mother 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 on 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 [11][12].

During the decision making process, only a few hundred of the thousand 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.
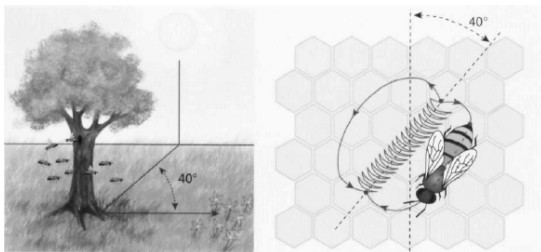

Fig.1. Overview of waggle dance used by bee to inform other bees about nest site & food sources [8].

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, 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 as shown in fig1 [11]. A single bout of dancing contains many of these circuits. 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 case of food source locations.

For the first time a scout returns to the swarm from a first rate site, bee 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, bee 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, bee makes multiple visits to the site. Bees however decrease the strength of her dance advertisement by about 15 dance circuits each time. 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 the sites. Moreover there is a strong positive feedback in this recruitment process, such that the greater the number of recruiters, which in turn gives 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 these sites. Thus the best site gains the scouts fastest [13].

Usually, a bee ceases making visits to a site shortly after bee has ceased performing dances for the site; hence bees abandon poor sites more rapidly than they do excellent ones. Once a scout abandons a site, bee "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 bee 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 to any site. An uncommitted scout may visit several sites before finding one bee feel s 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 grows large, it automatically excludes from the competition the groups affiliated with the 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 "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 [11].

Thus during the decision making process, bee take into consideration two key factors. First, only a few hundred of the thousands of bees in swarm were active other remaining quiescent to conserve the swarm's energy. Secondly, bee dances represent various sites found, but with time the waggle dance for dominated side increases and after reaching the quorum, the entire cluster of bees would suddenly take off and fly towards the selected site. Seeley, Visscher & Kevin [11] from their research found that quality of next site depends upon quorum threshold size, dance decrease rate and tendency to explore [13] [14]. The former process is how a swarm finds all the possible nest sites and the latter process is how the swarm chooses among the possible nest sites.

3. Bee Optimization Algorithm

The proposed Bee Optimization Algorithm (BeeOA) is based on this nest-site selection process by honey bee swarms. In the proposed algorithm firstly all the possible local optimum points are found by exploration which corresponds to the good enough quality sites in the landscape. For this purpose 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 a suitable optimization technique starting from this starting point. When all the information of optimum points is obtained then the optimum point having best fitness value is chosen as the global optimum. Authors will assume that the quality of nest site is constant during the nest-site selection process.

A. 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 the parameters at that point in the objective function.

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

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

B. Exploration

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

$$\text{Range of } j^{th} \text{ parameter} \in \left[W_{ij}, W_{fj}\right] \qquad (2)$$

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 jth 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 jth parameter.

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

$$n_j = \frac{W_{fj} - W_{ij}}{S_j} \qquad (3)$$

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

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

Number of volumes indicates the number of scouts 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

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

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 by it.

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 Fig2.
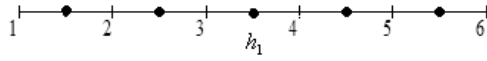

Fig. 2: Domain of the objective function with one independent parameter

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 is two dimensional rectangles in this case.
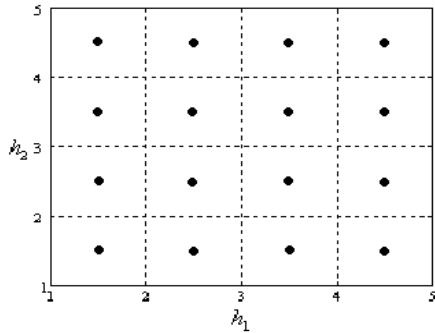

Fig. 3: Domain of the objective function with two independent parameters

For an objective function with three independent parameters, the complete domain will be given by 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 mid point of corresponding volume which is a 3 dimensional cuboids' which is shown in Fig4.
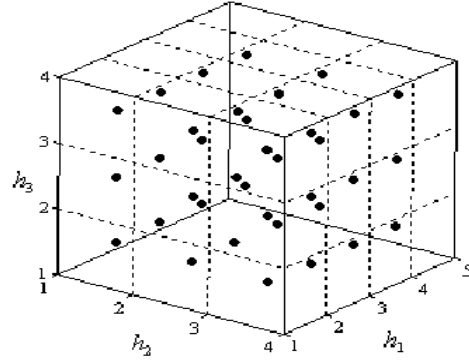

Fig. 4: Domain of the objective function with three independent parameters

Objective functions with more than three independent parameters can be solved in similar manner. The larger the number of scout bees and smaller the step size, more is the total time taken and the accuracy of the search.

C. Search Methodology

For optimization of the given objective function we have modified a very popular optimization technique usually known as NM method [15]. 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 food function. To start, we assume that bees take three positions of a triangle for two variables problem. $V_1 = (x_1, y_1)$ represents the initial position of bee $V_2 = (x_2, y_2)$ and $V_3 = (x_3, y_3)$ are the positions of probable food points. The movement of bee from its initial position towards the food position i.e. 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 $z_1 \leq z_2 \leq z_3$ and hence $V_1 \leq V_2 \leq V_3$ the corresponding 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).

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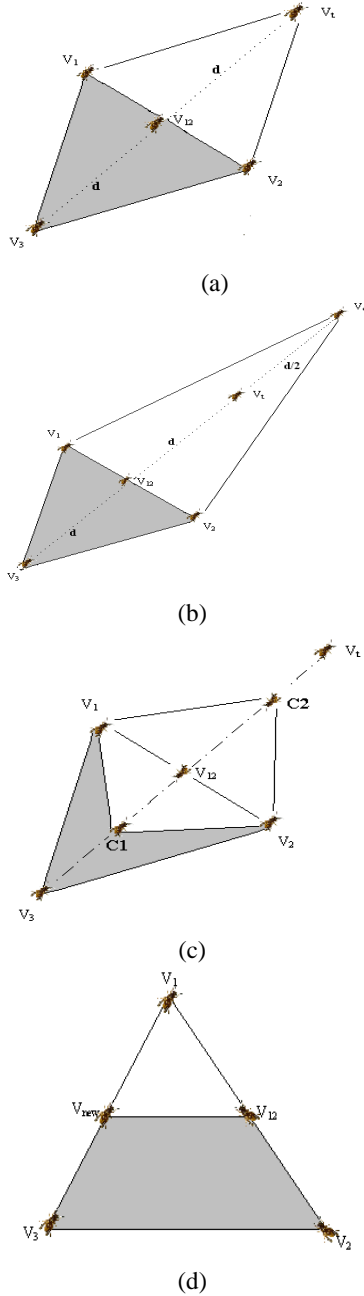
(a)

(b)

(c)

(d)

Fig 5: Bee search Movements with the proposed optimization algorithm. (a) Starting of the motion in search of food, (b) Extension in the direction of good food, (c) Contraction of the movement in case food quality is not good, (d) shrinking of the space towards good food.

The value of function decreases as bee moves along V_3 to V_1 or V_3 to V_2. Hence it is feasible that $f(x,y)$ takes smaller value if 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 reflection of the worst food point i.e. V_3 as shown in figure 5(a). The vector formula for V_t is

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

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 as 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.

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

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 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.
Fig 6 shows the path trace by the bees and the sequences of triangles $\{T_k\}$ converging to the optimal point for the
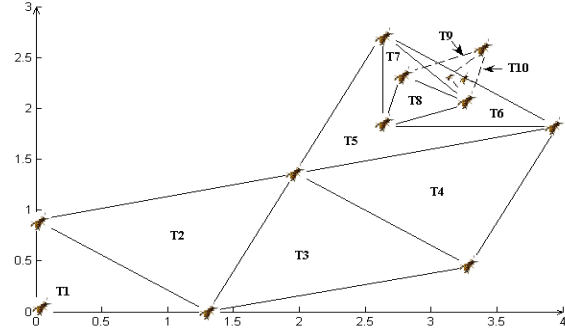
objective function $f(x,y) = x^2 - 4x + y^2 - y - xy$

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

D. Waggle Dance
Bee after returning from search perform waggle dance to inform other bees about the quality of site

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

Where $F_i(X)$ represent the different search value obtained by a bee. Each of these points is recorded in a table known as 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 occurrence of X in optimum vector table is also noted.

Fitness value at point X is given by $F(X)$

E. Consensus

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

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

Table I: 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 $[W_{ij}, W_{fj}]$ where $j = 0, 1, ... , P$
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 $[\frac{W_{i1} + W_{f1}}{2}, \frac{W_{i2} + W_{f2}}{2}, ..., \frac{W_{iP} + W_{fP}}{2}]$
6) Record the value of optimized point obtained corresponding to each volume in optimum vector table in following way $[X_1, X_2, ..., X_{N_v}]$
7) After the exploration is being completed, the global optimized point in the following manner
$$F(X_G) = \min[F(X_1), F(X_2), ..., F(X_{N_v})]$$

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 [16][17][18]. 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,

$$F_T = \sum_{i=1}^{n} F_i(P_i) \qquad (11)$$

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

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \qquad (12)$$

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

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

$$P_{min,i} \le P_i \le P_{max,i} \quad \text{where} \quad i = 1, 2, ..., n \qquad (13)$$

$$\sum_{i=1}^{n} P_i - D - L = 0 \qquad (14)$$

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

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 [16]. For experimental purposes the value of $N_v = 120$.

Step length is set as $S_1 = 100, S_2 = S_3 = S_4 = S_5 = S_6 = 200$.

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

$$F_1 = 0.001562 P_1^2 + 7.92 P_1 + 561.0 \quad 100 \le P_1 \le 600 \qquad (15)$$

$$F_2 = 0.001940 P_2^2 + 7.85 P_2 + 310.0 \quad 100 \le P_2 \le 400 \qquad (16)$$

$$F_3 = 0.004820 P_3^2 + 7.97 P_3 + 78.0 \quad 50 \le P_3 \le 200 \qquad (17)$$

$$F_4 = 0.001390 P_4^2 + 7.06 P_4 + 500.0 \quad 140 \le P_4 \le 590 \qquad (18)$$

$$F_5 = 0.001840P_5^2 + 7.46P_5 + 295.0 \quad 110 \le P_5 \le 440 \quad (19)$$

$$F_6 = 0.001840P_6^2 + 7.46P_6 + 295.0 \quad 110 \le P_6 \le 440 \quad (20)$$

The load demands are 800, 1200 and 1800 MW. Optimization results are given in Table 1. Fig7 shows the computational time taken by the three methods for different load demands.

TEST SYSTEM 2 The second test system has 13 units, the cost function of the units is expressed as follows:

$$f(P) = c + bP + aP^2 + \left| e\sin\left[\rho\left(P_{\min} - P \right) \right] \right| \quad (21)$$

and details of this test system are given in Table 2. The load demand is 2520 MW. Optimization results of the 13-unit system are given in Table 3.

Table 1: Optimization results of CGA, QEGA and BeeOA for 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)	ρ (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	200	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 CGA, QEGA and BeeOA for 13 generator system

Method	Load (MW)	Unit1 (MW)	Unit2 (MW)	Unit3 (MW)	Unit4 (MW)	Unit5 (MW)	Unit6 (MW)	Unit7 (MW)	Unit8 (MW)	Unit9 (MW)
CGA	2520	638.60	357.29	357.15	110.88	152.51	160.06	161.45	161.21	116.09
QEGA	2520	628.32	356.80	359.45	159.73	109.86	159.73	159.73	159.73	159.73
BeeOA	**2520**	**628.27**	**298.82**	**298.82**	**159.64**	**159.68**	**159.68**	**159.68**	**159.68**	**159.68**

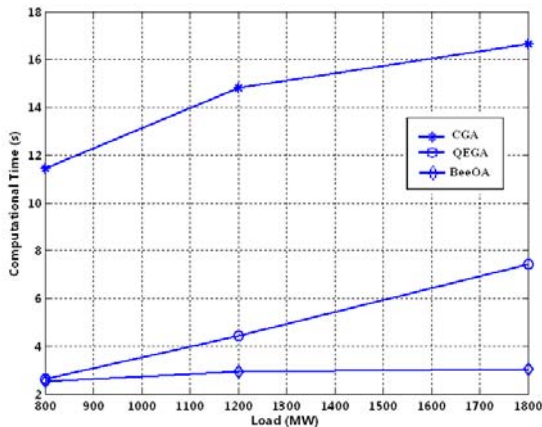| Method	Unit10 (MW)	Unit11 (MW)	Unit12 (MW)	Unit13 (MW)	Total Cost ($)
CGA	76.63	75.00	60.00	93.13	24703.32
QEGA	76,92	75.00	60.00	55.00	24398.63
BeeOA	**75.17**	**77.15**	**92.03**	**91.65**	**24172.00**

Fig 7: Computational time taken by different methods.

6. Conclusion

In this paper a new optimization algorithm known as bee optimization algorithm is employed to solve the economic power dispatch problem. The results obtained from the conventional genetic algorithm and queen-bee evolution based genetic algorithm are just good enough solutions and they seldom yield the global optimum. The results obtained from the BEEOA are more robust and yields the global optimum or results more close to the global optimum than genetic algorithms.

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