Apinan AURASOPON, Wanchai KHAMSEN

Faculty of Engineering, Mahasarakham University, Mahasarakham 44150, Thailand.
Faculty of Engineering, Rajamangala University of Technology Lanna, Lampang, Thailand

doi:10.15199/48.2019.01.49

An improved local search involving bee colony optimization using lambda iteration combined with a golden section search method to solve an economic dispatch problem

***Abstract**. This paper presents an improved local search method using bee colony optimization (ILS-BCO) to solve an economic dispatch (ED) problem with smooth cost function characteristic. The proposed ILS-BCO algorithm is an integration of lambda iteration and bee colony optimization (CLI-BCO) combined with golden section search and bee colony optimization (CGS-BCO). To show its effectiveness, the ILS-BCO was applied to test two systems consisting of either 6 or 15 power generating units. Results confirm that the proposed ILS-BCO approach is capable of obtaining rapid convergence and a high quality solution efficiently.*

Streszczenie.** W artykule zaproponowano metodę rozwoiązywania problemu ekonomicznego rozsyłu energii z uwzględnieniem kosztów. Wykorzystano metodę optymalizacji opartą na algorytmach rojowych. Metodę przetestowano na dwóch systemach złożonych z 6 lub 15 jednostek generatorów. **Ulepszona metoda rozwiązywania problemu ekonomicznego rozsyłu energii wykorzystująca algorytmy rojowe i Iterację lambda

Keywords: Bee Colony Optimization, Lambda Iteration, Golden Section Search, Economic Dispatch.
Słowa kluczowe: algorytmy rojowe, ekonomiczny rozsył energii, iteracja lambda.

Introduction

The operating cost of a power plant mainly depends on the fuel cost of generators which is minimized via economic dispatch. The Economic Dispatch (ED) problem is one of the fundamental issues in power system operation. The main objective is to reduce the cost of energy production taking into account transmission losses while satisfying equality and inequality constraints. The rational distribution of economic load between running units can lead to significant cost savings making it important to research the economic dispatch problem.

Several classical methods, such as the lambda iteration method [1], quadratic programming [2], the gradient method [3], dynamic programming [4], linear programming [5], and nonlinear programming [6] have been applied to solve ED problems. However, these methods are not feasible in practical power systems owing to the non-linear characteristics of the generators. Solutions can be limited to achieving a local optimum which leads to less desirable performance. In addition, these methods often use approximations to limit complexity. Recently, a number of researchers have used meta-heuristic optimization techniques, which are unlike conventional mathematical techniques, to solve ED problems in power systems. Different meta-heuristic approaches have proved to be effective with promising performance, such as a Genetic Algorithm (GA) [7]-[9]. Such methods have been inspired by the Darwinian law of optimal survival of a species, Particle Swarm Optimization (PSO) [10]-[12] inspired by the social behavior of bird raising or fish production, Ant Colony Optimization (ACO) [13]-[14] inspired by food habits in an ant colony, and by Tabu Search (TS) [15] as a way to build a better foundation from prior knowledge. This latter method records previous answers and forbids the new solution to converge at the same point for different input data. Other methods to be used include the Cuckoo Search Algorithm (CSA) [16]-[17] which is based on the parasitic behavior of some cuckoo species and the flight behavior of some birds and insects. The Shuffled Frog Leaping Algorithm (SFLA) [18]-[19], which simulates and mimics the behavior of frogs that find food placed on random rocks, has also been used. Simulation Annealing (SA) [20]-[21], which finds a solution from a new perspective and which moves to a new location when the solution value is better than the original, has also been employed. Finally, Bee Colony Optimization (BCO) [22]-[24], where the BCO algorithm mimics the food foraging behaviors of swarms of honey bees has been shown to be effective. These methods often provide fast and reasonable solutions, including global optimization with short time searching. Among them, the BCO method is a probabilistic technique for approximating the global optimum of a given function. It has a simple structure, is efficient and employs an advanced search technique. However, like other evolutionary algorithms, BCO also has some drawbacks which limit its performance. The conventional BCO algorithm can be limited in reaching a global optimum solution in a reasonable computational time when the initial solution is far away from the region where an optimum solution is required. As a result, with a new population, it can take more time to search for a solution and a long computational time because the algorithm possesses poor convergence behavior. Therefore, accelerating convergence speed and avoiding the local optima have become two important and appealing goals in BCO research. A number of BCO variants have been proposed to achieve these two objectives [25]-[28].

The approach used was divided into three issues. The first one was to solve the optimization problem by using the principle of equal cost (λ), an estimate of the initial populations to narrow the search scope, and the use of the BCO algorithm to find the most appropriate solution around the estimates used. This method was termed “a Combination of Lambda Iteration and Bee Colony Optimization (CLI-BCO)”. Secondly, an improvement in the movement of bees was investigated using a local search method, called the golden section search method, in order to balance exploration and to identify food locations more efficiently. This was termed “a Combination of Golden Section Search and Bee Colony Optimization (CGS-BCO)”. Finally, an integration of the methods of the CLI-BCO and CGS-BCO approaches was examined. This concept was used to improve the efficiency of the traditional BCO algorithm. This paper proposes a new algorithm which is a modification of the “Improved local search in bee colony optimization (ILS-BCO)” method to solve the problems of the conventional BCO method. ILS-BCO introduces additional mechanisms for improving the search process. A feasibility study incorporating the ILS-BCO algorithm was assessed for solving the static ED problem with a smooth cost function. The best results from the ILS-BCO method are compared with conventional methods such as PSO, a Hybrid of Lambda Iteration and BCO (HLBCO), the Water Cycle Algorithm (WCA), the Krill Herd Algorithm (KHA) and a hybrid Differential Evolution Algorithm based on Particle Swarm Optimization (DEPSO) in terms of both the most appropriate answers and of solution convergence.

Economic Dispatch Problem Formulation

The purpose of addressing the ED problem is to find an optimal combination of electricity generation across different generators depending on demand. This involves the allocation of load demand commitment within the system to activate a set of generators over a specified period of time. This must be done in order to achieve minimal production costs while addressing physical constraints and operational requirements. The applicable conditions of the system include the following factors.

Objective functions

The objective of an ED problem is to minimize the total fuel costs subject to the constraints of a power generation system. Symbolically, this is represented as:

(1) $$Minimize : F_T = \sum_{i=1}^{N} F_i(P_i)$$

where F_T is the total generation cost, N is the number of generators committed to the operating system and F_i is the generation cost function of i^{th} generator is usually expressed as a quadratic polynomial as follows:

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

where a_i, b_i and c_i are the cost coefficients of the i^{th} generator; P_i is the power output of the i^{th} generator. It is an equation that represents the smooth cost function (see Figure 1).

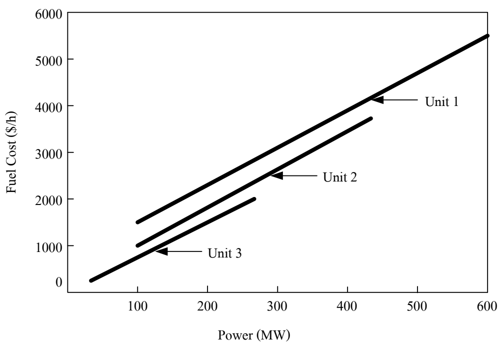

Fig.1. Characteristic of the smooth cost function

Constrain

The objective functions are subject to the following constraints.

Power balance constraint

All the load capacity that is equal to the sum of the total amount of electricity demand with a total power loss in the transmission system as:

(3) $$\sum_{i=1}^{N} (P_i) = P_D + P_{loss}$$

where P_D is the load demand and P_{loss} is the total transmission network losses, which is a function of the unit power outputs that can be represented using B coefficients as follows:

(4) $$P_{loss} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{j=1}^{N} B_{0i} P_i + B_{00}$$

Generation limits constraint

The output power of each generating unit has to lie in between a lower and an upper bound. This is represented by a pair of inequality constraints as:

(5) $$P_i^{\min} \le P_i \le P_i^{\max}$$

where, $P_i^{\min}$ and $P_i^{\max}$ are the lower and upper bounds for power outputs of the i^{th} generating unit respectively.

Improved Local Search in Bee Colony Optimization (ILS-BCO) to solve the Economic Dispatch Problem

ILS-BCO integrated the methods of the CLI-BCO and CGSS-BCO approaches. It provides an initial estimate based on the same principle of equal cost (incremental cost:λ), defines the boundaries around λ values and improves the movement of bees using a local search method called the golden section search method. The objective is to balance exploration and to get more efficient food locations. Each procedure is preformed according to the BCO method. The BCO, Lambda Iteration, Golden Section Search, CLI-BCO, CGS-BCO and ILS-BCO methods for solving the ED problem are described below.

Bee colony optimization for economic dispatch problem

The BCO algorithm was proposed by Karaboga for numerical optimization [29]. The algorithm provides a way to find the most appropriate value for Economic Dispatch that mimics the food foraging behaviors of honey bees. This method divides the bees into two categories: the first group being the scout bees, and the second group is the employee bees who attempt to find the answer. Suppose the answer is to find the honeybee source. The function of scout bees is to find random honey bee sources within the scope of possible answers (search space). After the scout bees find the sources, they fly back to the hive to communicate with other bees. Bee communication uses a variety of dances to indicate the amount and direction of the honey. The employee bees will then move the honey from the honey source. The numbers of bees will vary in relation to the number of honeybees available and the distance to the source.

The following of parameters are used for the description of the BCO algorithm used for solving a general optimization problem:

n is the number of scout bee.

m is the number of random honeybee sources from scout bees.

e is the number of nectar honeybee sources with the highest amount of honeybee selected from m

n_{ep} is the number of employee bees assigned to *e* honeybee sources.

n_{sp} is the number of employee bees assigned to *m-e* honeybee sources.

The procedure of BCO algorithm is described as follows.

Step 1: Specify the parameters of the BCO algorithm.

Step 2: The bee algorithm starts with the scout bees (*n*) being placed randomly in the search space. They are subject to the regulatory requirements of the system which can be expressed as follows:

(6) $$P_i = P_{i,\min} + ((P_{i,\max} - P_{i,\min}) \times rand(0,1))$$

Step 3: The fitness of the sites visited by the scout bees are evaluated and the solution is sorted from the most productive to the least.

Step 4: Choose the solution that can be used for a number of *m* responses from *n* to find a solution in the neighborhood by requiring the bee colony to choose a solution that is within the number of *m.*

Step 5: Choose the best solution for the amount of *e* from within the *m* solution. Separated the *m* best solution to two groups, the first group has *e* best solutions and other group has *m-e* best solutions.

Step 6: The employee bees to find a solution in the area for the two groups that were divided in step 5. The n_{ep} employee bees go to find a solution surrounding *e* and the number of n_{sp} employee bees go out to find a solution in the area *m-e*. The duty of the employed bees is to determine the new food source say, v_i with the help of the food source x_i assigned to it during the initialization phase. The equation used is:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{7}$$

where v_i is the new food source generated by using both the current food source x_i and a randomly chosen food source x_k from the population and ϕ_{ij} is a uniform random number from [-1, 1] (generated at random every time it is used).

Step 7: Evaluate the value of the answer and compare each component and choose the best approach or solution that matches the given conditions.

Step 8: Check the threshold for downtime. If conditions are set to be met, then show the most appropriate solution; otherwise, go back to step 2.

Lambda iteration (λ)

When a solution is reached, multiple generators have the same marginal (or incremental) cost which is equal to λ. If the costs between generators are different, by reducing capacity at higher cost margins and by increasing capacity at lower cost, overall costs can be reduced. If demand changes, changes in total costs can be estimated from λ and the solved value of λ can be used to evaluate P_i. Equation (2) is the fuel cost of power generation for each generator. This equation is used to calculate the incremental cost; (λ) using the differential equation shown in Equation (8).

$$\frac{d(F_i(p_i))}{d(p_i)} = \lambda \tag{8}$$

Total fuel cost is lowest when λ are equal. The value of λ for the initial configuration of the system can be calculated from equation (9) and the electric power from each generator can be calculated from equation (10).

$$\lambda = \frac{P_D + \sum_{i=1}^{N} \frac{b_i}{2a_i}}{\sum_{i=1}^{N} \frac{1}{2a_i}} \tag{9}$$

$$p_i = \frac{\lambda - b_i}{2a_i} \tag{10}$$

Golden section search

The golden section search is a technique for finding the extremes (minimum or maximum) of a strictly unimodal function by successively narrowing the range of values inside which the extreme is known to exist. The technique derives its name from the fact that the algorithm maintains function values for triples of points whose distances form a golden ratio. The golden-section search was discovered by Kiefer (1953). It is a classical local search algorithm for non-differentiable fitness functions that was introduced in [30]. A local search procedure is applied to *F* in order to detect the scale factor value. This can be gained by minimizing the function *f(F)* in the decision space [−1, 1]. The scale factor applies the Golden Section Search to the scale factor in order to generate a high quality food sources. This scheme processes in the interval [*a* = -1, *b* = 1] and generates two intermediate points as follows:

$$F_1 = b - \frac{b-a}{\delta} \tag{11}$$

$$F_2 = a + \frac{b-a}{\delta} \tag{12}$$

where δ is the golden section ratio as follow:

$$\delta = \frac{1+\sqrt{5}}{2} \tag{13}$$

The evaluated values of $f(F_1)$ and $f(F_2)$ are then compared and if $f(F_1) < f(F_2)$ then F_2 replaces *F* and this procedure is repeated in a new smaller interval [*a*, *b*]. The upper and lower bounds of scaling factor are calculated as follows:

Repeat
Compute $F_1 = b - \frac{b-a}{\delta}$, $F_2 = a + \frac{b-a}{\delta}$
Evaluate *f(F1)* **and** *f(F2)*
If f*(F1) < f(F2)* **then**
F=(F1)
Else
F=(F2)
End If

Combining Lamda Iteration and Bee Colony Optimization (CLI-BCO) to solve the Economic Dispatch Problem

BCO has the advantage of providing global optimal solutions and has the capability for solving combinatorial optimization problems. However, in this algorithm, the initial populations are generated randomly causing long computation times and a long time to convergence when the generated initial populations are too far from the optimum solution. To avoid these problems, λ is used for determining the initial value for BCO algorithm. The CLI-BCO algorithm used to solve economic dispatch is described as follows:

Step 1: Identify parameters for CLI-BCO algorithm.

Step 2: Calculate the value of λ for the system's initial configuration for the scout bees from Equation (9).

Step 3: Find the lower and upper limits of the i^{th} generating unit by defining the scope of the value of λ as follows (14)-(15).

$$P_i^{max} = \frac{\lambda - b_i}{c_i} + \left(\frac{\lambda - b_i}{c_i} \times rank\right) \tag{14}$$

$$P_i^{max} = \frac{\lambda - b_i}{c_i} - \left(\frac{\lambda - b_i}{c_i} \times rank\right) \tag{15}$$

rank, which is a multiplier in scoping the answer, is more than 0 and less than 1. The value of *rank* in this article is defined as 0.15. Then, follow Steps 2 to 8 from the BCO algorithm.

Combining Golden Section Search and Bee Colony Optimization (CGS-BCO) to solve the Economic Dispatch Problem

Follow Steps 1 to 5 from the BCO algorithm.

Step 6: Use the employed bees to replace abandoned food sources as follows:

$$v_{ij} = x_{ij} + F(x_{ij} - x_{kj}) \tag{16}$$

where *F* is the scaling factor, calculated using **Golden section search.** Evaluate and store the best solution found to date and again follow Steps 7 to 8 from the BCO algorithm.

The generation of new food sources is seen as an opaque procedure depending on the scale factor *F* and depends on the values of *a* and *b*. The scaling factor becomes an important aspect that is to be controlled in order to guarantee a high quality food source (solution) that can have an important role in the succeeding generations.

Improved local search in bee colony optimization (ILS-BCO) to solve the Economic Dispatch Problem

In order to maximize the exploitation capacity of the BCO algorithm, the integration of the CLI-BCO and CGS-BCO approaches is purposed. This algorithm, uses the principle of equal costs (lamda iteration), an estimate of the initial populations to narrow the search scope, and improving the movement of bees using the golden section search method, in order to balance exploration and to get more efficient identification of food locations. The procedure of the ILS-BCO algorithm to solve the ED problem is described as follows:

Step 1: Specify the parameters of the ILS-BCO algorithm as shown in Table 1. These parameters were found by trial and error. The values of n, m, e, nep and nsp were adjusted between 10 to 100, 5 to 90, 3 to 80, 10 to 100 and 10 to 100, respectively. This processing gives the optimal parameters as shown in Table 1 that result the best answer and the minimum number of iterations.

Table 1. The parameters used within BCO, CLI-BCO, CGS-BCO and ILS-BCO

Parameters	Number
Population size (*n*)	20
Number of selected sites (*m*)	10
Number of best sites (*e*)	5
Number of bees around best sites (n_{ep})	50
Number of bees around other sites (n_{sp})	50

Step 2: Calculate the value of λ for the system initial configuration for the scout bees from Equation (9).

Step 3: Find the lower and upper limits of the i^{th} generating unit by defining the scope of the value of λ as in equations (14) and (15).

Step 4: The bee algorithm starts with the scout bees (*n*) being placed randomly in the search space and they are subject to the regulatory requirements of the system which can be expressed as (6).

Step 5: The fitness of the sites visited by the scout bees are evaluated and a solution is determined from the most to the least fitness.

Step 6: Choose a solution that can be used for a number of *m* responses from *n*.

Step 7: Choose the best solution for the amount of *e* from within the *m* solution. Separated the *m* best solution to two groups, the first group has *e* best solutions and other group has *m-e* best solutions.

Step 8: The n_{ep} employee bees go to find a solution surrounding *e* and the number of n_{sp} employee bees go out to find a solution in the area *m-e*. The employed bees are used to replace the abandoned food sources, as in (16).

Step 9: Evaluate the value of the answer and compare each component and choose the best approach or solution that matches the given conditions.

Step 10: Check the threshold for downtime. If conditions are set to be met, then show the most appropriate solution; otherwise, back to step 4.

Case Studies

The proposed ILS-BCO algorithm was applied to economic dispatch problems in two different test cases for verifying its feasibility. These were a six units system and a fifteen unit system. Each optimization method was implemented in a MATLAB program which runs on a TOSHIBA Satellite P745, Intel (R) Core (TM) i5, 2.30 GHz with 8 GB of RAM.

The first case study

The test system for this case consisted of six thermal units, including defined generation limits, power balance constraints, generators rating constraints, 26 buses and 46 transmission lines. It needed to generate electric power of 1263 MW. The generator feature of each is shown in Table 2 and the B-coefficient matrix was as follows [31].

$$B_{ij} = \begin{bmatrix} 1.7 & 1.2 & 0.7 & 0.1 & 0.5 & 0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & 0.6 & 0.1 \\ -0.1 & 0.1 & 0.0 & 0.2 & 0.6 & 0.8 \\ -0.5 & 0.6 & 0.1 & 0.6 & 12.9 & 0.2 \\ 0.2 & 0.1 & 0.6 & 0.8 & 0.2 & 15 \end{bmatrix}$$

$$B_{0i} = 10^{-3} \times [\text{-}0.3908 \;\; \text{-}0.1297 \;\; 0.7047 \;\; 0.0591 \;\; 0.2161 \;\; \text{-}0.6635]$$

$$B_{00} = 0.056$$

Table 2. Generator characteristics in case 1

Unit	a_i	b_i	c_i	$P_i^{\min}$	$P_i^{\min}$
1	0.0070	7.00	240	100	500
2	0.0095	10.0	200	50	200
3	0.0090	8.50	220	80	300
4	0.0090	11.0	200	50	150
5	0.0080	10.5	220	50	200
6	0.0075	12.0	190	50	120

The second case study

This system contained of 15 thermal generating units and their characteristics are given in Table 3. These generation units must support a total of 2630 MW, including transmission losses. The B-coefficient matrix is as shown in the references [31].

Table 3. Generator characteristics in case 2

Unit	a_i	b_i	c_i	$P_i^{\min}$	$P_i^{\min}$
1	0.000299	10.1	671	150	455
2	0.000183	10.2	574	150	455
3	0.001126	8.80	374	20	130
4	0.001126	8.80	374	20	130
5	0.000205	10.4	461	150	470
6	0.000301	10.1	630	135	460
7	0.000364	9.80	548	135	465
8	0.000338	11.2	227	60	300
9	0.000807	11.2	173	25	162
10	0.001203	10.7	175	25	160
11	0.003586	10.2	186	20	80
12	0.005513	9.90	230	20	80
13	0.000371	13.1	225	25	85
14	0.001929	12.1	309	15	55
15	0.004447	12.4	323	15	55

Simulation Results

To evaluate the feasibility of using the BCO, CLI-BCO, CGS-BCO and ILS-BCO methods to solve the ED problem, two examples of power generation, with the 6 and 15 units, were applied. All optimization methods that were used were compared with differential random initial solutions. To evaluate the effectiveness of each technique, all search algorithms were executed over the same time interval. Consequently, the fastest convergence would indicate the most effective method. The simulations take time so speed speed is useful for comparisons. In this test, the parameters of BCO, CLI-BCO, CGS-BCO and ILS-BCO are shown in Table 1.

Simulation results in case 1

Four methods (BCO, CLI-BCO, CGS-BCO, and ILS-BCO), were employed to test the two study systems. In this case, each individual P_g contained 6 generator power outputs. For the 1,263 MW electricity demand, the results from all methods are compared in terms of minimum generation cost and computation efficiency. The methods that offer the best solution are shown in Table 4. The convergence characteristics of all methods for the 6 unit system are shown in Figure 2. The results of the ILS-BCO method are compared with the PSO [32], HLBCO [33] and WCA [34] methods (Table 5).

Table 4. Results of six units system in case 1

Unit	BCO	CLI-BCO	CGS-BCO	ILS-BCO
P_1 (MW)	445.19	446.70	452.04	455.27
P_2 (MW)	177.26	178.21	170.37	168.78
P_3 (MW)	262.49	258.24	255.72	259.18
P_4 (MW)	140.15	138.58	141.54	132.55
P_5 (MW)	161.58	159.85	167.74	169.65
P_6 (MW)	88.47	93.23	87.42	89.56
P_T (MW)	1275.12	1274.81	1274.83	1274.78
F_T ($/h)	**15440.73**	**15436.70**	**15436.19**	**15433.72**
P_{loss} (MW)	12.12	11.80	11.83	11.78

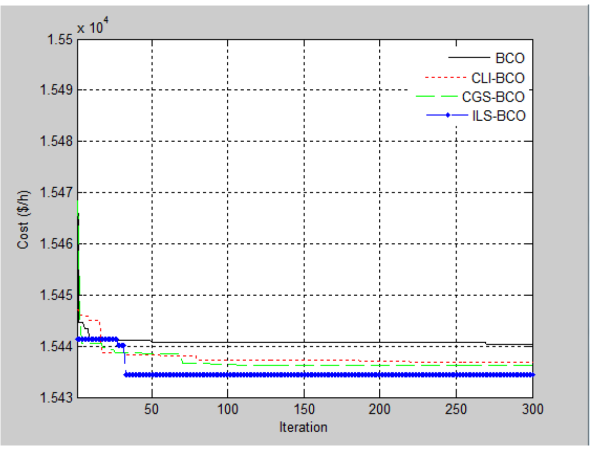

Fig.2. Convergence curve of the 6 unit system

Table 5. Results and comparison to other optimization methods evaluated in case 1

Unit	PSO	HLBCO	WCA	ILS-BCO
P_1 (MW)	440.58	449.028	447.83	455.27
P_2 (MW)	167.44	172.48	172.21	168.78
P_3 (MW)	278.24	258.05	261.15	259.18
P_4 (MW)	150	137.72	138.40	132.55
P_5 (MW)	157.60	166.52	166.35	169.65
P_6 (MW)	81.22	91.3657	89.08	89.56
P_T (MW)	1275.07	1275.16	1275.02	1274.78
F_T ($/h)	**15445.48**	**15439.63**	**15437.41**	**15433.72**
Ploss(MW)	12.08	12.16	12.02	11.78

Table 4 shows that the ILS-BCO algorithm had more ability to find the optimal points in a search space compared to BCO, CLI-BCO and also the proposed CGS-BCO method. The optimal cost obtained by the ILS-BCO was 15433.72, which compares favorably with the other results in the table. The BCO method converged to an optimum cost from 270 iterations onwards, CLI-BCO from 180 iterations onwards, CGS-BCO from 70 iterations onwards, whereas ILS-BCO converged in less than 30 iterations. It can be seen that the level of the cost function didn't change too much, while ILS-BCO had the fastest convergence speed. Similarly, the cost function achieved by the ILS-BCO method was significantly better than those obtained by the PSO, HLBCO, and WCA methods (Table 5).

Simulation results in case 2

This system contained 15 thermal generating units. These generation units had to support a load demand of 2630 MW. The results of the ILS-LBCO method are compared with those obtained by BCO, CLI-BCO, and CGS-BCO in terms minimum generation cost and computation efficiency. This sample has a rather problematic search area when compared with the previous example. After using the proposed algorithm for the problem, the results are shown in Table 6, which satisfy the constraints of the generation units. Figure 3 shows the convergence of values for the fitness function and the cost function achieved by the ILS-BCO method when compared with the DEPSO [35], KHA [36] and WCA [34] methods (Table 7).

Table 6. Results of fifteen units system in case 2

Unit	BCO	CLI-BCO	CGS-BCO	ILS-BCO
P_1 (MW)	452.56	432.11	438.77	450.45
P_2 (MW)	443.26	437.27	438.24	442.81
P_3 (MW)	129.13	129.76	129.95	128.74
P_4 (MW)	126.77	128.39	124.60	129.45
P_5 (MW)	266.61	331.28	330.85	329.35
P_6 (MW)	458.12	446.38	436.35	435.20
P_7 (MW)	462.26	441.75	458.13	437.53
P_8 (MW)	63.57	70.90	63.98	65.27
P_9 (MW)	43.07	29.31	29.13	28.51
P_{10} (MW)	40.07	26.15	28.72	29.49
P_{11} (MW)	61.82	53.57	60.15	59.38
P_{12} (MW)	52.52	71.90	56.76	62.87
P_{13} (MW)	25.02	25.67	28.25	25.49
P_{14} (MW)	17.86	16.25	15.23	16.39
P_{15} (MW)	15.17	15.40	16.95	15.07
P_T (MW)	2658.52	2656.10	2656.02	2655.97
F_T ($/h)	**32565.32**	**32542.07**	**32543.36**	**32535.23**
P_{loss} (MW)	28.51	26.09	26.01	25.97

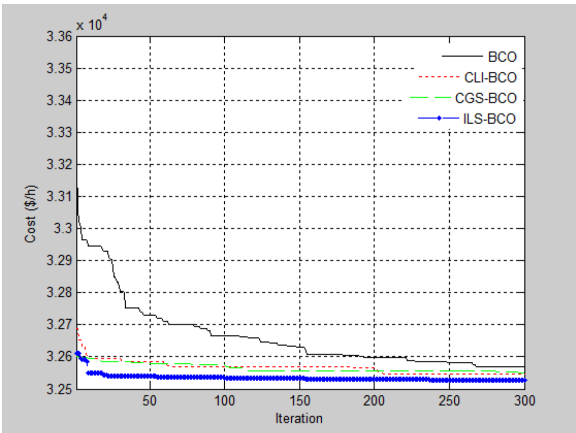

Fig.3. Convergence curve of the 15 unit system

The ILS-LBCO algorithm had a greater ability to find the optimal points in a search space compared to either BCO or CLI-BCO and also the proposed CGS-BCO method (Table 6). The optimal cost obtained by the ILS-BCO method was 32535.23, which compares favorably with the other methods. The BCO converged to the optimum cost from 270 iterations onwards, CLI-BCO from 210 iterations onwards, CGS-BCO from 120 iterations onwards, whereas the LIS-BCO method converged in less than 50 iterations. Similarly, the cost function achieved by the ILS-BCO method was significantly better than those obtained by the DEPSO, KHA, and WCA methods (Table 7).

Table 7. Results and comparison to other optimization methods evaluated in case 2

Unit	DEPSO	KHA-IV	WCA	ILS-BCO
P_1 (MW)	455.00	455.00	NA	450.45
P_2 (MW)	420.00	455.00	NA	442.81
P_3 (MW)	130.00	130.00	NA	128.74
P_4 (MW)	130.00	130.00	NA	129.45
P_5 (MW)	270.00	230.80	NA	329.35
P_6 (MW)	460.00	460.00	NA	435.20
P_7 (MW)	430.00	465.00	NA	437.53
P_8 (MW)	60.00	60.00	NA	65.27
P_9 (MW)	25.00	25.00	NA	28.51
P_{10} (MW)	62.97	31.27	NA	29.49
P_{11} (MW)	80.00	76.70	NA	59.38
P_{12} (MW)	80.00	80.00	NA	62.87
P_{13} (MW)	25.00	25.00	NA	25.49
P_{14} (MW)	15.00	15.00	NA	16.39
P_{15} (MW)	15.00	15.00	NA	15.07
P_T (MW)	2657.97	2656.77	2656.25	2655.97
F_T ($/h)	**32588.81**	**32547.37**	**32541.86**	**32535.23**
P_{loss} (MW)	27.97	26.77	26.25	25.97

Conclusion

New local search methods were implemented for different ED problems within the two case studies. Several sophisticated techniques, such as initial estimation using lambda iteration, improving the movement of bees using a local search method called the golden section search method, and bee colony optimization have been added to the ILS-BCO method in order to enhance the search potential. The ILS-BCO algorithm has been proposed to solve the ED problem by combining an initial estimation using the lambda iteration method, the use of the BCO method to find the best solution, and the use of the golden section search method as a mechanism for increasing efficiency in finding the solution. The ILS-BCO optimization mechanisms outperformed other recently reported algorithms. The strength of the algorithm was proved in the two case studies used to find solutions for the ED problem. It is obvious from the convergence quality of the ILS-BCO algorithm in two case studies, that the robustness of the algorithm is proved. Study results from the 6 and 15 generating unit cases confirmed that the ILS-BCO was much superior to the BCO, CLI-BCO and CGS-BCO methods in terms of providing a high-quality solution with stable convergence characteristics and good computation efficiency. This method provided fast and accurate results when compared with conventional methods. By using the ILS-IBCO method, execution time could also be reduced. In case studies, the proposed method produced better results in comparison with the PSO, HLBCO, WCA, KHA and DEPSO methods depending on the test conditions that were evaluated. The numerical results clearly showed that the proposed algorithm gave better results. Power system operators can use this algorithm for optimization.

Acknowledgments

This research project is financially supported by Mahasarakham University (Fast Track 2019) and I would like to thank Prof. Ian Warrington for encouragement and insightful comments.

***Authors**: The authors are with the Faculty of Engineering, Mahasarakham University, Thailand and Faculty of Engineering, Rajamangala University of Technology Lanna, Lampang, Thailand*
E-mail: apinan.a@msu.ac.th; Assoc. Prof. Dr. Apinan Aurasopon
E-mail: wanchai_kh@rmutl.ac.th; Asst. Prof. Dr. Wanchai Khamsen
The correspondence address is: E-mail: apinan.a@msu.ac.th

REFERENCES

[1] A. J. Wood and B. F. Wollenberg, Power Generation Operation and Control. New York: Wiley, 1984.
[2] Leandro dos Santos Coelho and Viviana Cocco Mariani, "Combining of Chaotic Differential Evolution and Quadratic Programming for Economic Dispatch Optimization With Valve-Point Effect", IEEE TRANSACTIONS ON POWER SYSTEMS, 21 (2006), No. 2, 989-996
[3] M. Ramamoorty, R. N. Dhar, and P. K. Mukherjee, "Reduced-gradient method for economic dispatch," in Electrical Engineers Proceedings of the Institution of Electrical Engineers, 120 (1973), Issue 11, 608-610
[4] R.J. Ringlee and D.D. Williams, "Economic dispatch operation considering valve throttling losses II-distribution of system loads by the method of dynamic programming," IEEE Trans. Power Appar. Syst. 81 (1963), Issue 3, 615-620
[5] Ahmed Farag, S. Al-Baiyat and T. C. Cheng, "Economic Load Dispatch Multi objective Optimization Procedures Using Linear Programming Techniques," IEEE Transactions On Power Systems, 10 (1995), No. 2, 731-738
[6] Albert M. Sasson, "Nonlinear Programming Solutions for Load-Flow, Minimum-Loss, and Economic Dispatching Problems," IEEE Transactions on Power Apparatus and Systems, 88 (1996), No. 4, 399_409
[7] V. Kumar, J. Singh, Y. Singh, and S. Sood, "Optimal Economic Load Dispatch Using Genetic Algorithms," International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering, 9 (2015), No. 4, 463-470
[8] Samuel A. Oluwadare, Gabriel B. Iwasokun, Olatubosun Olabode, O. Olusi, and Akintoba E. Akinwonmi, "Genetic Algorithm-based Cost Optimization Model for Power Economic Dispatch Problem," British Journal of Applied Science & Technology, 15 (2016), Issue 6, 1-10
[9] Ali Q. Al-Shetwi and Muwaffaq I. Alomoush, "A New Approach to the Solution of Economic Dispatch using Genetic Algorithm," Journal of Engineering and Technology, 7 (2016), No. 1, 40-48
[10] K. Srikanth and V. HariVamsi, "Partical Swarm Optimization Technique for Dynamic Economic Dispatch," International Journal of Research in Engineering and Technology, 5 (2016), Issue 5, 460-466
[11] Haifeng Zhang, "An Improved Particle Swarm Optimization Algorithm for Dynamic Economic Dispatch Problems," International Journal of Innovative Research in Engineering & Management (IJIREM), 3 (2016), Issue 4, 264-266
[12] Hossein Lotfi, Ali Dadpour, and Mahdi Samadi, "Solving Economic Dispatch in Competitive Power Market Using Improved Particle Swarm Optimization Algorithm," International Journal of Smart Electrical Engineering, 6 (2017), No.1, 35-41
[13] Dhaval K. Thesia, Pradeep Jangir, and Indrajit N. Trivedi, "Economic Emission Dispatch Problem Solution Using Ant Colony Optimization of Micro-grid in Island Mode," International Journal of Advance Engineering and Research Development, 2 (2015), Issue 5, 89-95
[14] M. N. Nwohu and Osaremwinda Osarobo Paul, "Evaluation of Economic Load Dispatch Problem in Power Generating Stations by the Use of Ant Colony Search Algorithms," International Journal of Research Studies in Electrical and Electronics Engineering (IJRSEEE), 3 (2017), Issue 1, 20-29
[15] Vijay Kumar Joshi, "Optimization of Economic Load Dispatch Problem by using Tabu Search Algorithm," International Journal of Latest Trends in Engineering and Technology, 8 (2017), Issue 4-1, 182-187
[16] K. Chandrasekaran, S. P. Simon, and N. P. Padhy, "Cuckoo Search Algorithm for Emission Reliable Economic Multi-Objective Dispatch Problem," IETE Journal of Research, 60 (2014), Issue 2, pp.128-138
[17] Thang Trung Nguyen, Dieu Ngoc Vo, and Bach Hoang Dinh, "Cuckoo search algorithm for combined heat and power economic dispatch," Electrical Power and Energy Systems, ELSEVIER, 81 (2016), 204-214
[18] Mohsen Darabian, Seyed Masoud Moheni-Bonab, and Behnam Moohammadi-Ivatloo, "Improvement of Power System Stability by Optimal SVC Controller Design Using Shuffled Frog Leaping Algorithm," IETE Journal of Research, 61 (2015), Issue 2, 160-169
[19] K. Selvakumar, K. Vijayakumar, D. Sattianadan, and C. S. Boopathi, "Shuffled Frog Leaping Algorithm (SFLA) for Short Term Optimal Scheduling of Thermal Units with Emission

Limitation and Prohibited Operational Zone (POZ) Constraints," Indian Journal of Science and Technology, 9 (2016), No. 42, 1-6
[20] M. Venkatesh and R. Raghutu, "Economic Load Dispatch using Simulated Annealing Algorithm," International Research Journal of Engineering and Technology (IRJET), 2 (2015), Issue 3, 1961-1964
[21] Ziane Ismail, Benhamida Farid, and Graa Amel, "Simulated Annealing Optimization for Generation Scheduling with Cubic Fuel Cost Function," WSEAS Transactions on Information Science and Applications, 14 (2017), 64-69
[22] Ehsanolah Assareh and Mojtaba Biglari, "A Novel Approach to Capture the Maximum Power Generation from Wind Turbines Using Hybrid MLP Neural Network and Bees Algorithm (HNNBA)," IETE Journal of Research, 62 (2015), Issue 3, 368-378
[23] Navpreet Singh Tung and Sandeep Chakravorty, "Solution to Economic Power Dispatch Planning Problem considering Generator Constraints using Artificial Bee Colony Algorithm," International Journal of Hybrid Information Technology, 9 (2016), No. 5, 399-406
[24] Gitanjali Mehta, Raghvendra Pratap Singh, and Vinod Kumar Yada, "Optimization of Combined Economic Emission Dispatch Problem using Artificial Bee Colony Method," International Journal on Cybernetics & Informatics (IJCI), 6 (2017), No. 1, 107-118
[25] G. Li, P. Niu, X. Xiao, "Development and investigation of efficient artificial bee colony algorithm for numerical function optimization", Applied Soft Computing, 12 (2012), Issue 1 320–332
[26] A. Bahriye, D. Karaboga, "A modified Artificial Bee Colony algorithm for real-parameter optimization", Information Sciences, 192 (2012), Issue 1, 120-142
[27] 27. WF. Gao, S. Liu, L. Huang, "A global best artificial bee colony algorithm for global optimization", Journal of Computational and Applied Mathematics, 2362 (2012), Issue 11, 2741-2753
[28] T.K. Sharma, M. Pant, "Enhancing the food locations in an artificial bee colony algorithm," in: IEEE Swarm Intelligence Symposium (SIS), Paris, France, 17 (2013), Issue 10, 1939–1965
[29] D. Karaboga and B. Basturk. "On the performance of artificial bee colony (ABC) algorithm," Applied soft computing, Science Direct, Elsevier, 8 (2006), Issue 1, 687-697
[30] J. Kiefer, "Sequential minimax search for a maximum", in Proceedings of the American Mathematical Society, 4 (1953), 502–506
[31] R. Rahmani, M. F. Othman, R. Yusof, and M. Khalid, "Solving Economic Dispatch Problem using Particle Swarm Optimization by an Evolutionary Technique for Initializing Particles", Journal of Theoretical and Applied Information Technology, 46 (2012), No. 2, 526-536
[32] Ankur Sharma and Hemant Mahala, "Economic Load Dispatch Problem by Particle Swarm Optimization", International Journal of Engineering Science and Computing, 6 (2016), No. 3, 2237-2243
[33] Wanchai Khamsen and Chiraphon Takeang, "Hybrid of Lamda and Bee Colony Optimization for Solving Economic Dispatch", PRZEGLAD ELEKTROTECHNICZNY, 9 (2016), 220-223
[34] A. Dihem, A. Salhi, D. Naimi and A. Bensalem, "Solving smooth and non-smooth economic dispatch using water cycle algorithm," 2017 5th International Conference on Electrical Engineering - Boumerdes (ICEE-B), Boumerdes, Algeria, (2017), 1-6
[35] 35. S. Sayah, A. Hamouda, "A hybrid differential evolution algorithm based on particle swarm optimization for non-convex economic dispatch problems", Applied Soft Computing journa1 home, 13 (2013), Issue 4, 1608-1619
[36] B. Mandal, P.K. Roy, S. Mandal, "Economic load dispatch using krill herd algorithm", International Journal of Electrical Power & Energy Systems, 57 (2014), 1-10