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Hybrid of Lambda Iteration and Meta-Heuristic Methods for Solving Economic Dispatch Problem

***Abstract**. New optimization algorithms for solving the economic dispatch problem are presented. The constraints of economic dispatch consist of power balance, generator rating, load demand, and transmission loss. In the proposed algorithms, a lambda iteration method is used to find the initial values for the meta-heuristic methods: BCO, PSO, and GA. This process results in the solution boundary being reduced. To verify the effectiveness of the proposed algorithm, two case studies with three and six generators were tested. The simulation results showed that the proposed algorithms can provide better solutions than the others in terms of convergence rate and generation outputs.*

Streszczenie.** . Przedstawiono nową technikę optymalizacji umożliwiająca zwiększenie skuteczności ekonomicznego rozsyłu energii. Uwzględnia on równowagę mocy, ocenę generatora, wymagane obciążenia oraz straty przesyłania. Proponowana metoda jest hybrydową iteracją lambda oraz metodą meta-heurystyczną wykorzystującą algorytmy genetyczne. Przetestowano dwa przypadki układu z trzema i sześcioma generatorami. **Hybrydowy algorytm optymalizacji ekonomicznego rozsyłu energii wykorzystujący iterację lambda i metodę meta-heurystyczną .

Keywords: economic dispatch, lambda iteration, meta-heuristic, optimization.
Słowa kluczowe: ekonomiczny rozsył energii, optymalizacja, iteracja lambda.

Introduction

The economic dispatch (ED) problem is the determination of generation levels, in order to minimize the total generation cost for a defined level of load. It is a kind of management for electrical energy in a power system that operates generators as economically as possible. From the view of time scale, the ED problem can be divided into two kinds: static economic dispatch (SED) and dynamic economic dispatch (DED). The SED economically allocates the load demand which is constant for a given interval of time, among the online generators while satisfying various constraints including static behaviour of the generators. The DED is an extension of the SED problem. Although, it is the most accurate formulation of the ED problem, it is the most difficult to solve because of its large dimensionality.

Many methods have been widely used to solve ED problem such as classic algorithms. Lambda iteration and gradient methods were commonly used for solving linear cost function [1]-[2]. Lagrangian relaxation [3] and dynamic program [4] are approaches to solving non-linear cost function and discrete ED problems. However, these methods are not suitable for solving ED problem with complicated and large electrical systems. In order to effectively address the issues of the nonlinear characteristics of practical power systems, a variety of random search population selection and other computational intelligence methods have been employed to solve the ED problem; specifically, meta-heuristic methods that are inspired by nature such as Simulated Annealing (SA) [5]-[6], Genetic Algorithm (GA) [7]-[10], Evolutionary Program (EP) [11]-[12], Tabu Search (TS) [13], Particle Swarm Optimization (PSO) [14]-[16], Ant Colony Optimization (ACO) [17]-[18], Cuckoo Search Algorithm (CSA) [19]-[20], Shuffled Frog Leaping Algorithm (SFLA) [21]-[22] and Bee Colony Optimization (BCO) [23]-[25]. These methods can solve non-linear problems with complex non-linear constraints. However, they will give correct solutions with short searching times if the initial populations that are randomly generated are close to the solutions.

To improve the effectiveness of the meta-heuristic methods, this paper proposes a hybrid technique. In the proposed algorithm, Lambda iteration is used to define the initial values for the meta-heuristic techniques: BCO, GA and PSO. These processes result in the best generation outputs with reduction of time period for searching when compared to the traditional of BCO, GA and PSO.

Economic Dispatch Problem Formulation

The main motive of ED is to minimize a number of electricity generation facilities, to meet the system load, at the lowest possible cost, subject to transmission and operational constraints.

Objective functions

The objective function corresponding to the cost of production can be estimated as the quadratic equation of the active power from the generating unit. The equation is shown as (1).

$$Minimize : \mathrm{F}_T = \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

$F_i(P_i)$ is the fuel cost function of the i^{th} plant and N is the total number of generators. The variation of power generation with fuel cost is shown in equation (2).

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{2}$$

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.

Constraints

It is intended to minimize the total costs which satisfy constraints. Assuming that the total system requirements are provided by all generators connected to the same bus. The following constraints are included.

Power balance constraint

The total power output should meet the total power demand and transmission loss which is given as equation (3).

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

where P_D is the load demand, and P_{loss} is the loss of the total transmission network, which is the function of the output of the unit, which can be expressed as equation (4).

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

where B_{ij}, B_{0i} and B_{00} are the loss coefficients in the transmission line.

Generation limits constraint

The electric power is generated by a generator that is limited by its capacity. This is represented by a pair of inequality constraints as follows:

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

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

Optimization Techniques

In the proposed algorithm, the initial value of the meta-heuristic techniques is defined by Lambda iteration, which is described as follows:

Lambda Iteration

The fuel cost of each generator is shown in equation (2) used to calculate the incremental cost, λ, by using the differential equation as follows:

(6) $$\frac{d(F_i(P_i))}{d(P_i)} = \lambda$$

From equation (6), If the λ of each generator has the same value the resulting total fuel cost is closely to the lowest value. Therefore, the λ of the system can be found by

(7) $$\lambda = \frac{P_D + \sum_{i=1}^{N} \frac{b_i}{2a_i}}{\sum_{i=1}^{N} \frac{1}{2a_i}}$$

From equation (7), the λ is used to calculate the electric power of each generator as follows:

(8) $$P_i = \frac{\lambda - b_i}{2a_i}$$

Hybrid of Lambda Iteration and Bee Colony Optimization (HLIBCO)

The BCO algorithm was proposed by Karaboga for numerical optimization. This algorithm mimics the behaviour of honeybees. The colony of artificial bees consists of two groups: employed bees and scout bees. The number of employed bees is equal to the number of food sources around the honeycomb. In the BCO algorithm, the position of the food source determines the solution and the amount of nectar indicates the performance of the solution.

In the proposed HLIBCO, the Lambda iteration is used to define the initial values for BCO. This algorithm results in a narrow boundary of searching for solutions in BCO. The steps of the proposed HLIBCO are as follows:

Step 1: Identify the parameters for HLIBCO as shown in Table 1.

Step 2: Calculate the initial value, λ, of the system for the scout bees from equation (7).

Step 3: Find the lower and upper limits of the i^{th} generating unit by defining the scope of the value of λ using equations (9)-(10).

(9) $$P_i^{\max} = \frac{\lambda - b_i}{2a_i} + \left(\frac{\lambda - b_i}{2a_i} \times rank\right)$$

(10) $$P_i^{\min} = \frac{\lambda - b_i}{2a_i} - \left(\frac{\lambda - b_i}{2a_i} \times rank\right)$$

Where $rank$ is a multiplier with interval [0 – 1].

Step 4: Randomize the initial population (*N*) of the power output of the i^{th} generation.

Step 5: Evaluate the fitness value of the initial population and arrange the fitness in ascending order.

Step 6: Select *S* best solutions for the neighborhood search and separate the *S* best solutions into two groups (*E*, *S-E*).

Step 7: Determine the size of the neighborhood for each best solution. Note that neighborhood sizes are equal to *NE* for solution group *E* and *NO* for solution group (*S-E*).

Step 8: Generate solutions around the selected solutions within the neighborhood sizes (*NE*, *NO*) and evaluate the fitness value from each patch. Then, select the best solution from each patch.

Step 9: Check the stopping criterion. If no, increase the iteration.

Step 10: Assign the new population (*N-S*) to generate new power output of the i^{th} generator. Then, return to step 4.

Table 1. The parameters used within HLIBCO

Parameters	Number
Population size (*N*)	20
Number of selected sites (*S*)	10
Number of best sites (*E*)	5
Number of bees around best sites (*NE*)	50
Number of bees around other sites (*NO*)	50

Hybrid of Lambda Iteration and Particle Swarm Optimization (HLIPSO)

Kennedy and Eberhart developed the PSO algorithm that is inspired by the social behaviour of organisms such as the food-finding behaviour of fish and the bird foraging behaviour. PSO has a search procedure based on the population of individuals called "particles". In the PSO system, particles will fly around in the multi-dimensional search area. During the fight, each particle will adjust its position based on its own experience and the experience of neighboring particles using the best positions that they themselves and their neighbors encounter. The orbital direction of the particle is determined by the set of particles near the particle and its historical experience. The main parameters of this algorithm are the number of particles, particle dimension, particle velocity interval ($V_{\max}, V_{\min}$), $W_{\max}$ and $W_{\min}$, c_1 and c_2, particle position interval ($X_{\max}$, $X_{\min}$). The detail of PSO is described in [14-17].

For the HLIPSO algorithm, Lambda iteration is used to define the initial values and the boundary of searching the population or particle around the lambda, λ. This process results in the best solutions and reduces the time period required for searching. The steps of implementation are as follows:

Step 1: Determine the system parameters of HLIPSO as shown in Table 2.

Step 2: Calculate the inertial weight by equation (11).

(11) $$W = W_{\max} - \frac{W_{\max} - W_{\min}}{iter_{\max}} \times iter$$

Step 3: Calculate the value of λ for the initial configuration for the particles and population from equation (7).

Step 4: Define dimension of initial boundary (P_i^{max}, P_i^{min}) for the particle, population, and other individual particle variables, which are generated randomly in the permissible range of equations (9)-(10).

Step 5: Find answers and compare each individual's evaluation value with its *pbest*. The best evaluation value among the *pbest* is denoted as *gbest.*

Step 6: Adjust each individual V_i speed by using equation (12).

$$(12)\quad V_i^{t+1}=WV_i^t+c_1 * rand_1 *(pbast_i\text{-}x_i^t)+c_2\ rand_2 *(gbast_i\text{-}x_i^t)$$

The term $rand_1 *(pbast_i\text{-}x_i^t)$ is called particle memory influence and the term $rand_2 *(gbast_i\text{-}x_i^t)$ is called swarm influence.

Step 7: Edit x_i position using equation (13).

$$(13)\quad x_i^{t+1}=x_i^t+V_i^{t+1}$$

Step 8: Evaluate the fitness function for the population using the objective function for the system. The best fitness value is denoted as *gbest.*

Step 9: Increase the number of iterations and check for exit conditions. If conditions are not met, return to step 5 if conditions are met, stop operations.

Table 2. The parameters used within HLIPSO

Parameters	Number
Population size (*N*)	300
Inertia weight factor (W_{max})	0.9
Inertia weight factor (W_{min})	0.4
Acceleration constant (c_1, c_2)	1.9
Limit of change in velocity (V_{max})	0.5 P^{max}
Limit of change in velocity (V_{min})	-0.5 P^{min}

Hybrid of Lambda Iteration and Genetic Algorithm (HLIGA)

Genetic algorithm is a metaheuristic search algorithm for solving both constrained and unconstrained optimization problems based on a natural selection process that imitates biological evolution. The GA algorithm repeatedly modifies a population of individual solutions. In each step, the GA randomly selects individuals from the current population and uses them as parents to produce the children for the next generation.

For the proposed algorithm, the Lambda iteration is used to determine an initial values, λ, for substituting the random population generation in GA. Then, GA randomly selects the population within the defined limits around the initial value and selected chromosomes are encoded and decoded using the objective function, fitness evaluation by genetic operation. The steps of the proposed HLIGA are as follows:

Step 1: Determine the system parameters of HLIGA as shown in Table 3.

Step 2: Calculate the value of λ for the initial configuration for the particles and population by equation (7).

Step 3: Define the scope for random selection of population to select the species using the equation (9)-(10).

Step 4: The Random population is started using equation (14) within the boundary of step 3.

$$(14)\quad P_i=P_{min}(i)+((P_{max}(i)-P_{min}(i)*rand(1))$$

Step 5: Select the prototype with the objective function.

Step 6: This step reproduces the new child generation and adds the child chromosomes in the same parent matrix.

Step 7: Create new chromosome mothers by crossover and mutation. This procedure will bring new variants to the best selection of the objective function again.

Step 8: Replace the original chromosome with the new chromosome, which is the optimum production capacity and the lowest cost in the processing cycle.

Step 9: Update the iteration count.

Step 10: Increase the number of iterations and check for exit conditions. If conditions are not met, return to step 4 if conditions are met, stop operations.

Table 3. The parameters used within HLIGA

Parameters	Number
Population size (*N*)	300
Crossover probability	0.8
Mutation probability	0.01
Binary bits	8
fraction of population	0.5

Case Studies

The objective of this paper is to solve the SED problem by minimum iteration. Therefore, Lamda iteration is used to define the initial value for the meta-heuristic algorithms. Two cases were tested to verify the proposed algorithms by using MATLAB program with TOSHIBA Satellite P745, Intel (R) Core (TM) i5, 2.30 GHz with 8 GB of RAM.

First case study

For this case study, the system consists of three thermal units, 26 buses and 46 transmission lines including the generation limits, power balance constraints and generator rating constraints. The system needs the electric power of 300 MW. The data of each generator are shown in Table 4 and the *B*-coefficient or the loss coefficient matrix was as follows [26].

$$B_{ij}=\begin{bmatrix} 0.000136 & 0.0000175 & 0.000184 \\ 0.0000175 & 0.000154 & 0.000283 \\ 0.000184 & 0.000283 & 0.00161 \end{bmatrix}$$

$$B_{0i}=\begin{bmatrix} \text{-}0.0766 & \text{-}0.00342 & 0.0189 \end{bmatrix}$$

$$B_{00}=0.040357$$

Table 4. Generator characteristics in case 1

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

Second case study

The test system of this case consists of six thermal units, 26 buses and 46 transmission lines including the generation limits, power balance constraints and generator rating constraints. It needs the electric power of 1263 MW. The generator feature is shown in Table 5 and the *B*-coefficient matrix is as shown in reference [27].

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

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

$$B_{00} = 0.056$$

Table 5. Generator characteristics in case 2

Unit	a_i	b_i	c_i	P_i^{min}	P_i^{max}
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

Simulation and Comparison Results of Case 1

To investigate the performance in case of accuracy and convergence of solutions, the results of the proposed algorithms: HLIBCO, HLIPSO and HLIGA are compared with those of different optimization methods: BCO, PSO and GA.

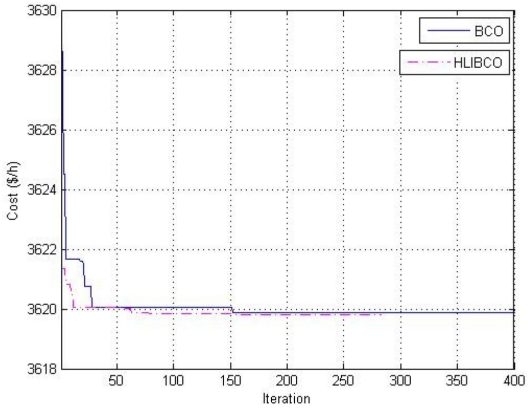

Fig. 1. Convergence curve of BCO and HLIBCO in case 1

Table 6. Results of BCO and HLIBCO in case 1

Unit output	BCO	HLIBCO
P_1 (MW)	208.91	207.53
P_2 (MW)	85.90	87.37
P_3 (MW)	15.16	15.02
PT (MW)	309.97	309.92
FT ($/h)	3619.84	3619.76
Power Loss (MW)	9.97	9.92
Iteration	**575**	**286**

Fig. 1-3 shows the results in the case of convergent solutions. The BCO, PSO and GA methods converged to an optimal cost from 575, 696 and 505 iterations whereas the proposed methods, HLIBCO, HLIPSO and HLIGA converged in less than 286, 323 and 282 iterations, respectively. The comparison of the results of generation outputs (PT, FT and power loss) of all optimization methods is shown in Table 6-8. The results indicate that HLBCO, HLIPSO and HLIGA can provide better solutions than the other methods. Furthermore, the results of generation output of the proposed algorithms are compared with quadratic programming (QP), simulated annealing (SA) and Differential Evolution Algorithm (DE) methods [26] and [28] as shown in Table 9 which shows that the proposed algorithms have the optimal solutions.

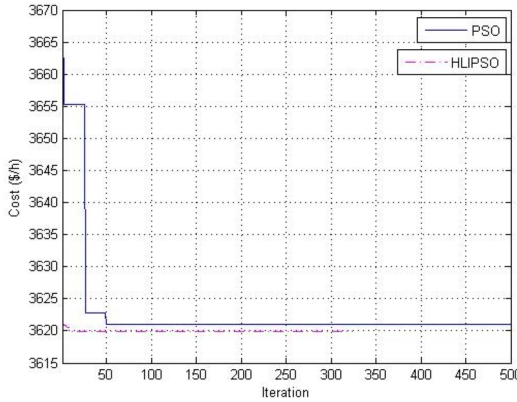

Fig. 2. Convergence curve of PSO and HLIPSO in case 1

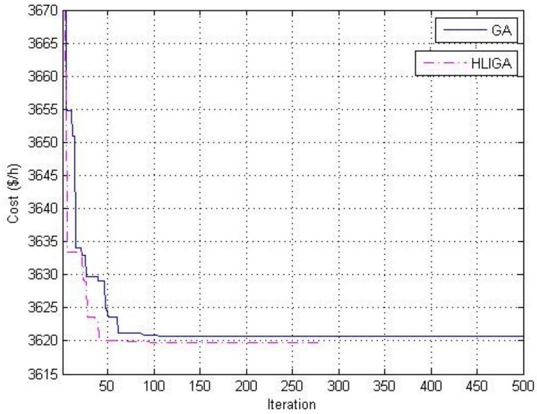

Fig. 3. Convergence curve of GA and HLIGA in case 1

Table 6. Results of BCO and HLIBCO in case 1

Unit output	BCO	HLIBCO
P_1 (MW)	208.91	207.53
P_2 (MW)	85.90	87.37
P_3 (MW)	15.16	15.02
PT (MW)	309.97	309.92
FT ($/h)	3619.84	3619.76
Power Loss (MW)	9.97	9.92
Iteration	**575**	**286**

Table 7. Results of PSO and HLIPSO in case 1

Unit output	PSO	HLIPSO
P_1 (MW)	197.20	207.52
P_2 (MW)	97.12	87.12
P_3 (MW)	15.45	15.32
PT (MW)	309.77	309.96
FT ($/h)	3621.48	3619.88
Power Loss (MW)	9.77	9.96
Iteration	**696**	**323**

Table 8. Results of GA and HLIGA in case 1

Unit output	GA	HLIGA
P_1 (MW)	215.36	208.09
P_2 (MW)	79.52	86.83
P_3 (MW)	15.27	15.00
PT (MW)	310.15	309.93
FT ($/h)	3620.72	3619.76
Power Loss (MW)	10.15	9.93
Iteration	**505**	**282**

Table 9. Results of the proposed and other methods in case 1

Unit output	HLIBCO	HLIPSO	HLIGA	QP [26]	SA [26]	DE [28]
P_1 (MW)	207.53	207.52	208.09	207.68	207.63	207.64
P_2 (MW)	87.37	87.12	86.83	87.40	87.27	87.28
P_3 (MW)	15.02	15.32	15.00	15.00	15.00	15.00
PT (MW)	**309.92**	**309.96**	**309.93**	310.08	309.92	309.92
FT ($/h)	**3619.76**	**3619.88**	**3619.76**	3621.50	3619.76	3619.80
Power Loss (MW)	**9.92**	**9.96**	**9.93**	10.08	9.92	9.92

Simulation and Comparison Results of Case 2

This test system has a demand of 1263 MW. The data of the test system is shown in the second case study. To determine the effectiveness of the proposed algorithms, this test case was repeatedly solved 100 times. The convergence characteristics and the best solution are shown in the Fig.4-6 and Table 10-12.

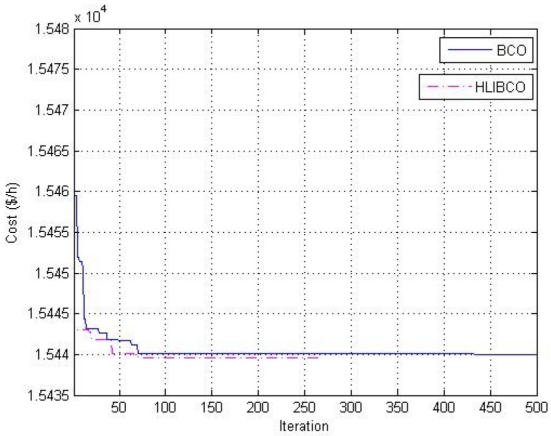

Fig. 4. Convergence curve of BCO and HLIBCO in case 2

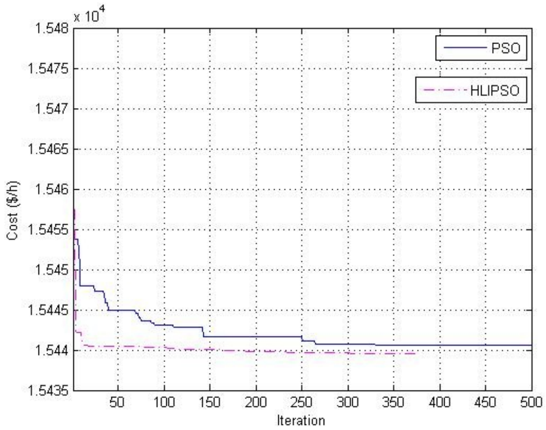

Fig. 5. Convergence curve of PSO and HLIPSO in case 2

Table 10. Results of BCO and HLIBCO in case 2

Unit output	BCO	HLIBCO
P_1 (MW)	415.01	450.28
P_2 (MW)	172.71	174.67
P_3 (MW)	261.90	259.46
P_4 (MW)	138.33	136.47
P_5 (MW)	165.21	163.25
P_6 (MW)	86.04	91.03
PT (MW)	1275.21	1275.15
FT ($/h)	15439.87	15439.55
Power Loss (MW)	12.20	12.15
Iteration	**521**	**264**

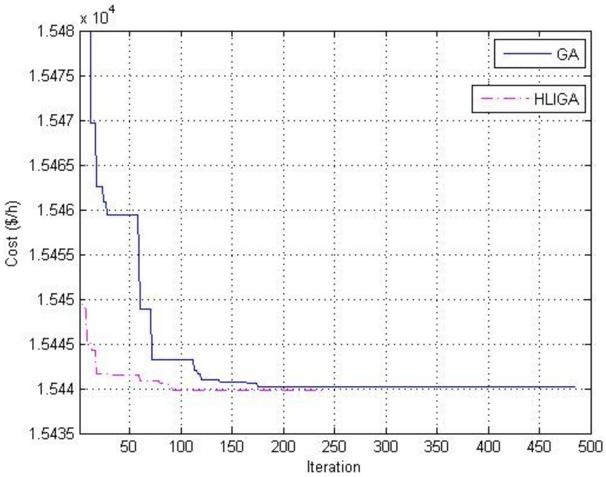

Fig. 6. Convergence curve of GA and HLIGA in case 2

Table 11. Results of PSO and HLIPSO in case 2

Unit output	PSO	HLIPSO
P_1 (MW)	452.61	449.85
P_2 (MW)	171.90	175.57
P_3 (MW)	259.21	257.20
P_4 (MW)	138.56	136.43
P_5 (MW)	166.37	164.07
P_6 (MW)	85.59	92.01
PT (MW)	1275.24	1275.13
FT ($/h)	15440.53	15439.60
Power Loss (MW)	12.24	12.13
Iteration	**618**	**378**

Table 12. Results of PSO and HLIPSO in case 2

Unit output	GA	HLIGA
P_1 (MW)	452.75	452.73
P_2 (MW)	175.83	171.03
P_3 (MW)	259.48	258.07
P_4 (MW)	131.49	137.27
P_5 (MW)	163.90	164.43
P_6 (MW)	91.79	91.61
PT (MW)	1275.24	1275.15
FT ($/h)	15440.20	15439.77
Power Loss (MW)	12.24	12.14
Iteration	**485**	**238**

Table 13. Results of proposed and other Methods in case 2

Unit output	HLIBCO	HLIPSO	HLIGA	CSA [29]	MHSA [30]	DE [31]
P_1 (MW)	450.28	449.85	452.73	447.48	446.73	448.27
P_2 (MW)	174.67	175.57	171.03	173.22	173.49	172.96
P_3 (MW)	259.46	257.20	258.07	263.38	263.76	263.44
P_4 (MW)	136.47	136.43	137.27	138.95	138.83	139.30
P_5 (MW)	163.25	164.07	164.43	165.41	165.65	165.28
P_6 (MW)	91.03	92.01	91.61	87.00	86.95	86.68
PT (MW)	1275.15	1275.13	1275.15	1275.45	1275.42	1275.93
FT ($/h)	15439.55	15439.60	15439.77	15443.08	15442.52	15449.58
Power Loss(MW)	12.15	12.13	12.14	12.45	12.42	12.95

Fig. 4 shows the convergence characteristics of the HLIBCO and the BCO. It was seen that the iterations of HLIBCO were less than in the traditional BCO. Fig. 5 and Fig. 6 also clearly demonstrate that the HLIPSO and HLIGA methods appear to converge faster than PSO and GA methods.

The comparison of the generator outputs of the proposed and traditional methods are presented in Table 10-12. The results show that the generator outputs are better than those of BCO, PSO and GA methods. While, the iteration of the proposed HLBCO, HLIPSO and HLIGA has a faster convergence rate than that of BCO, PSO and GA methods.

Furthermore, the generator outputs of the proposed algorithms are compared in Table 13 with the results in references [29]-[30] revealing that the HLBCO, HLIPSO and HLIGA can provide better solutions than the Cuckoo search algorithm (CSA), modified harmony search algorithm (MHSA) and DE algorithm in terms of PT, FT and power loss.

Conclusion

New optimization algorithms were implemented for solving the difference ED problems within two case studies. In the proposed algorithms, the Lambda iteration was used to determine the initial values for the traditional BCO, PSO and GA methods. These processes result in a fast convergence rate and optimal generation outputs.

In terms of convergence rate, because the traditional PSO algorithm uses many initial values which are determined the boundary by Lambda iteration. This results in the HLIPSO was the fastest when compared with HLIBCO and HLIGA.

While in terms of generation outputs, HLBCO algorithm gives the best generation outputs. This is because the traditional BCO algorithm using scout bees randomly search for the scope of possible solutions. However, convergence rate of HLIBCO is lower than that of HLIPSO and HLIGA.

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