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Enhanced Honey Badger Algorithm With Lévy Flights for Solving Economic Load Dispatch Problems

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Abstract: The practical economic load dispatch problem is a nonconvex and non-smooth optimization problem. It is challenging for the available optimization solvers to find the global optimal solution to this problem. Therefore, new and superior optimization solvers are still desired. To introduce a novel and efficient optimization solver to the problem, a recently developed generic optimization solver, known as the Honey Badger Algorithm (HBA), is utilized in this paper. The performance of the HBA is enhanced by augmenting it with a random walk-based search mechanism, known as Levy flights, to improve the diversity of the population as the search progresses. The resultant proposed algorithm is denoted as Honey Badger Algorithm with Levy Flights (HBA-LF). Based on two benchmark problems, the proposed algorithm is compared with several state-of-the-art algorithms. The results demonstrate the superiority of the proposed algorithm compared to the previously proposed algorithms. In particular, considering a real benchmark system, the proposed algorithm could achieve a monetary saving that ranges from 243.73 $/hr to 98,253 $/hr if the proposed algorithm has been adopted for solving the problem instead of previously proposed algorithms

KEYWORDS: Economic Dispatch, Honey Badger Algorithm, Levy flights, Valve Point Effects.

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1. INTRODUCTION

The economic dispatch problem (EDP) is an optimization problem with the main objective of minimizing the total generation cost. Achieving a balance between the total generation and demand as well as respecting the upper and lower generation limits of the generating units are essential constraints of the problem. The simplest formulation of the problem constitutes a convex optimization problem; however, this convex formulation neglects several practical aspects that affect the operation of the thermal generating units. When practical features of the generating units such as valve point effects, prohibited operating zones, and multiple fuel options are considered, nonconvexity and non-smoothness are introduced to the problem formulation. Therefore, the consideration of these features renders finding the optimal solution to the problem a challenging process. If no powerful optimization solver is used for solving the problem for each dispatching interval, then a repetitive failure of finding the global optimal solution could lead to the accumulation of significant monetary losses, in particular for large systems with many thermal units having non-convex cost functions [1], [2].

Due to the challenging nature of the nonconvex EDP, several optimization solvers have been proposed for finding the global optimal solution. These optimization solvers can be classified into deterministic and stochastic solvers. Deterministic solvers include a branch-and-bound based technique [3] and a steepest decline-based method [4]. The deterministic solvers are characterized by low computational time. However, they suffer from being dependent on the problem instance [1]. A deterministic solver could successfully solve a specific variant of the problem, and it may fail to solve another. Even changing the parameters of the problem may lead to a failure of the deterministic solver.

On the other hand, stochastic solvers or metaheuristic techniques are more commonly proposed. Examples of these techniques are the improved random drift particle swarm optimization [5], social spider algorithm [6], Chaos firefly algorithm [7], improved social network search [8], enhanced heap-based Optimization techniques [9], [10], improved marine predators algorithm [11], and teaching–learning studying-based algorithm [12]. Metaheuristic techniques are flexible to the problem formulation and instance. These techniques do not impose any constraints on the specifications of the considered problem, and hence they can be applied for solving the nonconvex EDP with all the practical features considered. These techniques have achieved significant progress in solving the nonconvex EDP within the previous literature. However, there is no guarantee that the best-obtained solution of a metaheuristic technique is the global optimal solution. The performance of a metaheuristic technique is typically assessed using statistical analysis. In this analysis, the metaheuristic technique is executed a certain number of times to solve a specific instance of the problem, then the performance of the algorithm is assessed using statistical measures such as the minimum and average values of the objective function and the average computational time. The number of runs used to perform the statistical analysis is typically 50 as in [13] or 100 as in [14]. Although several metaheuristic techniques have been previously proposed for solving the nonconvex EDP, these techniques may fail in finding the global optimal solution for some instances of the problem. This demands the development of superior solvers. Recently, a generic optimization solver known as Honey Badger Algorithm (HBA) has been proposed in [15]. This algorithm has been compared with many earlier metaheuristic techniques in [15] and the results show that the HBA is capable of providing superior performance compared to many other metaheuristic techniques. On the other hand, it has been observed that a random walk-based search mechanism known as the Levy flights is capable of enhancing the performance of many metaheuristic techniques when added to them [16]. This enhancement is due to the increased diversity in the population introduced by the Levy flights. Consequently, it is proposed in this paper to combine the Levy flights with the HBA to produce the HBA-LF algorithm to be applied for solving the nonconvex EDP. To conclude, the main contributions of this paper can be stated as follows

- A recent powerful metaheuristic technique, known as the honey badger algorithm, is applied to solving the non-convex economic dispatch problem.
- The proposed algorithm has been enhanced by augmenting it with Levy flights mechanism to produce the proposed honey badger algorithm with Levy flights.
- Both the aforementioned algorithms have been compared with several previously proposed metaheuristic techniques considering the same benchmark problems.

The results demonstrated the superior performance of the honey badger algorithm with Levy flights compared to that of the honey badger algorithm and several previously proposed metaheuristic techniques.

The paper is organized as follows. Section 2 presents the formulation of the non-convex EDP. Section 3 elaborates on the proposed algorithm. The simulation results are displayed in section 4 followed by the conclusion in section 5.

2.PROBLEM FORMULATION

The nonconvex EDP is an optimization problem which can be formulated as follows:

$$Minimize \qquad C_T = \sum_{i=1}^{n} C_i(P_i) \tag{1}$$

Subject to

$$\sum_{i=1}^{n} P_i = P_{Loss} + P_L \tag{2}$$

$$max(P_i^0 - DR_i, P_i^{min}) \le P_i \le min(P_i^0 + UR_i, P_i^{max}) \tag{3}$$

$$\left.\begin{array}{ll} P_i^{min} \le P_i \le P_{i,1}^l & (i = 1,2,\cdots,n) \\ P_{i,j-1}^u \le P_i \le P_{i,j}^l & (i = 1,2,\cdots,n),(j = 2,3,\cdots,n_{pi}) \\ P_{i,n_{pi}}^u \le P_i \le P_i^{max} & (i = 1,2,\cdots,n) \end{array}\right\} \tag{4}$$

where C_T is the total generation cost, n is the total number of generating units, and $C_i(P_i)$ represents the generation cost of unit i. The generation cost of unit i is a function of the output power from unit i, which is denoted as P_i. Considering the valve point effects, the cost function $C_i(P_i)$ can be modelled as follows:

$$C_i(P_i) = a_i + b_i\, P_i + c_i\, P_i^2 + \left| e_i \, sin(f_i \times (P_i^{min} - P_i))\right| \tag{5}$$

where $a_i, b_i, c_i, e_i,$ and f_i are fuel cost coefficients of unit i. Moreover, if there are generating units having multiple fuel options in addition to the valve point effects, the generation cost function is expressed as [17]:

$$C_i(P_i) = a_{i,k} + b_{i,k}\, P_i + c_{i,k}\, P_i^2 + \left| e_{i,k} \, sin(f_{i,k} \times (P_{i,k}^{min} - P_i))\right|$$
$$if \qquad P_{i,k}^{min} \le P_i \le P_{i,k}^{max}. \tag{6}$$

In (6), $a_{i,k}, b_{i,k}, c_{i,k}, e_{i,k},$ and $f_{i,k}$ are fuel cost coefficients of unit i while using fuel type k. $P_{i,k}^{min}$ and $P_{i,k}^{max}$ are the minimum and maximum output power from unit i while using fuel type k, respectively.

Constraint (2) is the power balance constraint which states that the total output power from all the units equal to the total system load P_L plus the transmission losses P_{Loss}. P_{Loss} can be approximated using Kron's formula which is expressed as follows:

$$P_{Loss} = \sum_{i=1}^{n}\sum_{m=1}^{n} P_m B_{m,i} P_i + \sum_{i=1}^{n} B_{0i} P_i + B_{00}. \tag{7}$$

$B_{m,j}$, B_{0j}, and B_{00} represent loss coefficients determined using power flow before solving the EDP. Constraint (3) specifies the upper and lower limits for the output power of unit i while considering the ramp rate limits, where P_i^0 is the output power from unit i during the previous dispatching interval, P_i^{min} and P_i^{max} are the minimum and maximum generation limits, and UR_i and DR_i denote the upper-ramp and down-ramp rate limits of unit i, respectively. The set of constraints expressed in (4) model the prohibited operating zones, where $P_{i,j}^l$ stands for the lower bound of the jth prohibited zone, and $P_{i,j}^u$ denotes the upper bound of the jth prohibited zone. Finally, n_{pi} is the total number of prohibited zones for unit i. Figs. 1 (a) – (c) presents schematic diagrams for different nonconvex cost functions due to different considered practical features.

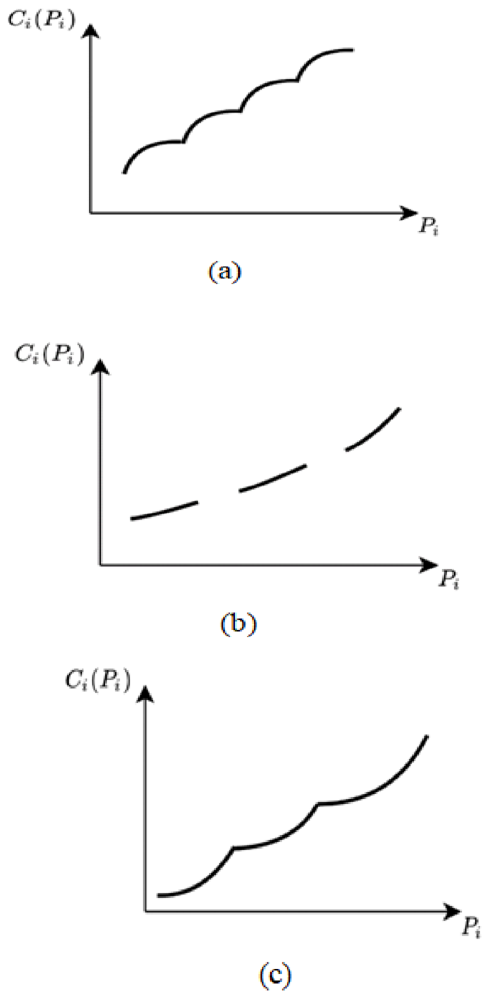

Fig 1. Nonconvex cost functions due to, (a) valve point effects, (b) prohibited operating zones, and (c) multiple fuel options.

3. PROPOSED ALGORITHM

This section elaborates on the proposed algorithm for solving the nonconvex EDP.

3.1 Honey Badger Algorithm

Honey Badger Algorithm (HBA) is inspired from the foraging behavior of a mammal with white and black fur, as indicated in Fig. 2, known as the honey badger (HB) [15].

Fig 2. Honey badger

The HB has good smelling skills. It uses theses skills to approximate its prey through walking slowly and digging. HB is also able to climb trees. It likes eating honey. However, it is unable to solely locate beehives effectively. To locate beehives, HB collaborate with a bird known as honeyguide. This bird locates the beehives while being followed by HB. Once the HB reaches to the beehive, it helps the bird to extract the honey with its strong claws and both enjoy the honey. To summarize, there are two main means used by the HB for finding food sources: the first by smelling and digging and the second by following the honeyguide bird. Inspired by this foraging behavior, the HBA is developed with two main equations for updating the search process. One equation expresses the digging phase and the second represents the honey phase. The equation expressing the digging phase is composed of three added terms as given next

$$x_{new} = x_{prey} + x_{c1} + x_{c2} \tag{8}$$

where x_{prey} is the best position found so far, i.e., the global best position. x_{c1} is given by (9) while x_{c2} is presented in (12).

$$x_{c1} = F \times \beta \times I_i \times x_{prey} \tag{9}$$

where F is a flag that takes a value of either 1 or -1 according to (10), in which r_1 is a random number between 0 and 1, β is an algorithm parameter with a value typically larger than 1 and a default value of 6, and I_i is known as the intensity which expresses the concentration strength of the prey and the closeness of the prey from the ith HB. I_i is computed using (11)

$$F = \begin{cases} 1 & if\ r_1 \leq 0.5 \\ -1 & else, \end{cases} \tag{10}$$

$$I_i = \frac{r_2}{4\pi} \times \frac{(x_i - x_{i+1})^2}{\left(x_{prey} - x_i\right)^2} \tag{11}$$

where x_{i+1} is the next individual in the population after x_i, and r_2 is a random number between zero and 1. In (8), x_{c2} is given by

$$x_{c2} = F \times r_3 \times \left(x_{prey} - x_i\right) \times \alpha \times |cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \tag{12}$$

where F has the same value as in (9), r_3, r_4, and r_5 are three random numbers each takes a value between 0 and 1. α is an update density factor used to achieve smooth transition from exploration to exploitation. α is expressed as

$$\alpha = C \times e^{\left(\frac{-t}{t_{max}}\right)} \tag{13}$$

where C is a constant with a value larger than 1 and a default value of 2. t is an iteration index and t_{max} is the maximum number of iterations. Equation (8) represents the digging phase and models the ability of HB to find foods by smelling and digging. On the other hand, the honey phase, in which the HB follows the honey guide bird to find honey, is expressed using (14).

$$x_{new} = x_{prey} + F \times r_7 \times \left(x_{prey} - x_i\right) \times \alpha \tag{14}$$

where F is computed using (10) and r_7 is a random number between 0 and 1. Before applying the digging and honey phases, the HBA algorithm starts by initializing a population of N individuals. These individuals are generated randomly between the upper and lower limits of the decision variables using

$$x_{ij} = LB_{ij} + r_{ij} \times (UB_{ij} - LB_{ij}) \tag{15}$$

where x_{ij} is the jth component of individual i, r_{ij} is a random number between zero and 1. LB_{ij} and UB_{ij} are the lower and upper bounds of component *j* of individual *i*. The pseudo code of the HBA algorithm is presented next

Algorithm 1 HBA algorithm

1: *Initialize the parameters N, t_{max}, C and β.*
2: *Develop an initial population randomly using (15).*
3: *Evaluate the objective function value for each individual x_i to get f_i*
4: *Find the minimum value of f_i to obtain x_{prey} and f_{prey}*
5: ***While** stopping criterion is not met*
6:   *Calculate α using (13)*
7:    ***For** $i = 1{:}N$*
8:      *Calculate I_i using (11)*
9:      *Generate a random value r between 0 and 1*
10:      ***If** $r \le 0.5$*
11:        *Calculate x_{new} by (8)*
12:      ***else***
13:        *Calculate x_{new} by (14)*
14:      ***end if***
15:      *Evaluate the objective function for x_{new} to obtain f_{new}*
16:      ***If** $f_{new} < f_i$*
17:        *Let $x_i = x_{new}$ and $f_i = f_{new}$*
18:      ***End if***
19:      ***If** $f_{new} < f_{prey}$*
20:        *Let $x_{prey} = x_{new}$ and $f_{prey} = f_{new}$*
21:      ***End if***
22:    ***End for***
23: ***End while***

3.2 Levy Flights

Levy Flights (LF) represents a flight behavior of many insects and birds. It is a random walk with varying step-lengths which follow the Levy probability distribution [18]. To generate steps from a Levy distribution, the Mantegna algorithm is typically used. With this algorithm, the step length h is determined by:

$$h = \frac{rn_x}{|r_{ny}|^{1/\delta}} \tag{16}$$

where δ is a constant, rn_x and rn_y are two normally distributed random numbers with zero mean and standard deviation values of σ_x and σ_y, respectively, i.e.,

$$rn_x \sim N(0, \sigma_x^2) \qquad rn_y \sim N(0, \sigma_y^2). \tag{17}$$

σ_x and σ_y are given by:

$$\sigma_x = \left[\frac{\gamma(1+\delta) \times \sin\left(\frac{\pi\delta}{2}\right)}{\gamma\left(\frac{1+\delta}{2}\right) \times \delta \times 2^{\left(\frac{\delta-1}{2}\right)}}\right]^{1/\delta} \qquad \sigma_y = 1 \tag{18}$$

where $\gamma(*)$ denotes the gamma distribution function. After determining the step length h, the component *j* of a newly proposed solution *i* by the LF is determined by:

$$x_{i,j}^{new} = x_{i,j} + \phi \times rn_{i,j} \times h \times \frac{\sigma_x}{\sigma_y} \times (x_{i,j} - x_{prey,j}). \tag{19}$$

In (19), $x_{i,j}$ and $x_{i,j}^{new}$ express the $j-th$ components of the old and new solutions corresponding to individual i in the population, respectively, ϕ is a scaling parameter, $rn_{i,j}$ is a random variable that follows the normal distribution with a zero mean and a standard deviation of 1 evaluated in correspondence to element j of solution $i. x_{prey,j}$ is the $j-th$ component of the best solution obtained so far.

3.3 HBA-LF

It has been demonstrated in [16] that adding the LF mechanism to several metaheuristics algorithms could significantly enhance the performance of these algorithms. The improvement in the performance is due to the increased diversity in the population and the increased ability to escape from local minimums. Consequently, it is proposed in this paper to combine the LF with HBA to produce the proposed HBA-LF algorithm. For each iteration in the HBA algorithm, N_c cycles of the Levy flights are used. The pseudocode of the HBA-LF algorithm is introduced next

Algorithm 2 HBA-LF algorithm

```
Initialize the HBA parameters and the population randomly, steps 1 and 2 in algorithm 1.
Initialize the parameters of the Levy flights φ, β, and N_c.
Apply steps 3 and 4 in algorithm 1.
While stopping criterion is not met
    Apply steps 6 - 22 in algorithm 1
    For cycle=1: N_c (Levy cycles)
        Apply (16), (17), (18), and (19) to generate new N candidate solutions
        Apply steps 15 - 21 in algorithm 1 for each new candidate solution.
    End for
End while
```

To apply the HBA-LF for solving the nonconvex EDP, the constraint handling mechanism adopted in [1] is considered in this paper.

4.RESULTS

This section presents the results of simulating the HBA-LF for solving the nonconvex EDP.

4.1 Parameters setting

The parameters of the proposed algorithm have been assumed fixed for all the case studies. The selected values for the parameters are displayed in Table 1. These values have been selected based on extensive sensitivity analysis using several benchmark problems of the nonconvex EDP. A MATLAB platform on a computer with core i7 (3.4 GHz) processor and 8 GB RAM is adopted to perform the simulation.

TABLE 1. Parameters setting of the HBA-LF

Parameters of HBA		
$C = 5$	$\beta = 5$	
Parameters of Levy flights		
$N_c = 5$	$\delta = 1.5$	$\phi = 0.1$

The population size and the maximum number of iterations vary based on the considered problem. Therefore, the values of the population size and maximum number of iterations are mentioned in each case study.

4.2 Case study 1

Ramp rate limits, prohibited operating zones, and transmission losses are included in this case study. The considered benchmark system has six thermal units, and the total system demand is 1263 MW. The system data are available in [19]. t_{max} and N are fixed to 500 and 15, respectively. A comparison between the results of the HBA-LF and the results of other algorithms from previous literature for solving the six-generator benchmark problem is shown in Table 2. The average computational time for a single run of the HBA-LF is 0.24 sec. The convergence of the HBA-LF is displayed in Fig. 3

TABLE 2. Comparison between the HBA-LF and previous literature (six-generator system)

Method	Minimum cost ($/hr)	Average cost ($/hr)	Average time (sec.)	Standard deviation
PSO [20]	15450.14	15465.83	6.82	10.1502
GA [19]	15459	15469	41.58	0.057
CTLBO [21]	15,441.697*	15441.763	NA*	0.0194
CBA [22]	15,450.238	15,454.76	0.704	2.965
HBA	15449.893	15449.913	0.172	0.0346
HBA-LF	15449.893	15449.893	0.24	0.00021

*The results in [21] do not satisfy (7), and NA denotes Data are Not Available.

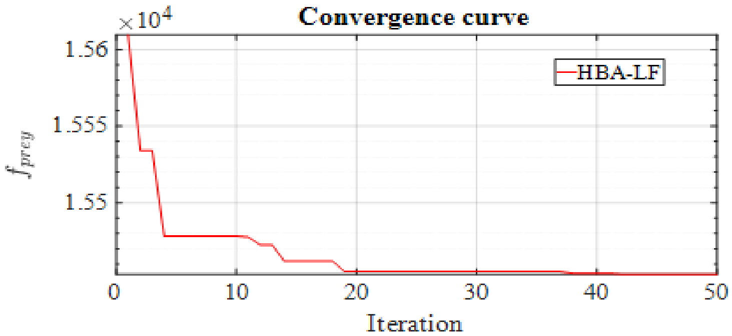

Fig 3. Convergence curve of the HBA-LF (6-units system).

From Fig. 3, it can be observed that the HBA-LF converged in less than 50 iterations. From the comparison in Table 2 and excluding the results of CTLBO [21], it can be observed that the HBA-LF has provided the lowest minimum cost, average cost, and standard deviation values. Since the reported optimal solution in [21] does not satisfy (7) as highlighted in [17], the HBA-LF algorithm is considered to present the best performance followed by the HBA algorithm.

4.3 Case study 2

A real large-scale system is adopted for this case study. It is the power system of Korea [23]. There are 140 units in this system and the total system load is 49342 MW. The system has 12 units having valve point effects and 4 units with prohibited operating zones. The data of the system is given in [23]. t_{max} and N are fixed to 2000 and 50 in this case study. Table 3 presents a comparison between the performance of the HBA-LF, HBA, and five other algorithms from the previous literature, and Fig. 4 presents the convergence curve of the proposed algorithm. From fig. 4, it can be noted that the HBA-LF converged in less than 1000 iterations. The best solution of the considered literature in Table 3 has a total cost of 1,559,953.18 $/hr [24], yet the optimal solution found by the HBA-LF has a cost of 1,559,709.45 $/hr. This means that a saving of 243.73 $/hr can be achieved if the HBA-LF algorithm has been used for solving the EDP instead of the GWO algorithm. On the other hand, if the proposed algorithm has been used instead of the CTPSO [23], a saving of 98,253 $/hr can be attained. Furthermore, the lowest average cost value is obtained by the HBA-LF. So, the HBA-LF offers superior performance compared to that of the other algorithms in Table 3. The lowest value for the standard deviation is given by GWO [24], however, the minimum and average cost values of the HBA-LF are lower than those of the GWO [24]. Table 3 shows that the average cost and standard deviation values of the HBA-LF are significantly lower than those of the HBA, which confirms the improvement added to the algorithm by augmenting it with the Levy flights mechanism.

TABLE 3. Comparison between the statistical results of the HBA-LF and previous literature (140-generator benchmark system)

Method	Minimum cost ($/hr)	Average cost ($/hr)	Average time (sec.)	Standard deviation
GWO [24]	1,559,953.1	1,560,132.9	8.93	1.024
CTPSO [23]	1,657,962.7	1,657,964.0	100	7.315
MPSO [25]	1,560,436	1,560,445	18.43	NA
DEL [26]	1,657,962.7	1,658,001.7	57.98	57.983
KGMO [27]	1,583,944.6	1,583,952.1	28.14	NA
HBA	**1,559,709.51**	**1,559,962.98**	**4.77**	**1200.1**
HBA-LF	**1,559,709.45**	**1,559,808.19**	**6.75**	**97.49**

NA: - Data are Not Available.

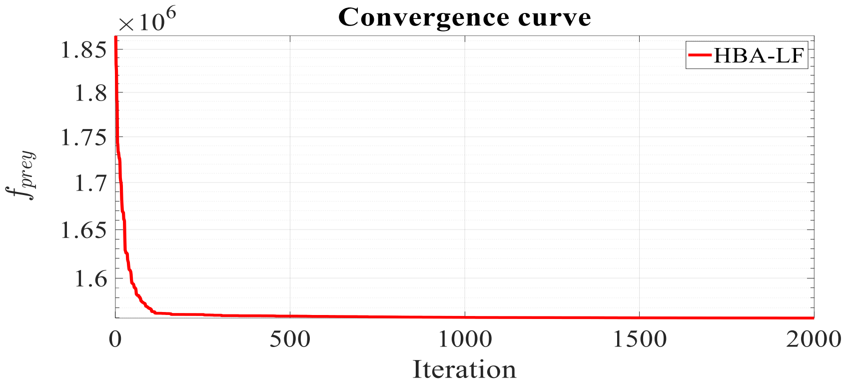

Fig 4. Convergence curve of the HBA-LF (140-units system).

5.CONCULSION

This paper proposes a novel algorithm for solving the nonconvex economic dispatch problem. The proposed algorithm, denoted as HBA-LF, is an enhanced version of the newly developed honey Badger algorithm. The enhancement is achieved by adding Levy flight cycles. The Levy flight cycles improved the diversity of the population and the ability to escape from local minimums. To assess the performance of the proposed algorithm, two benchmark test systems have been adopted. Each benchmark system is characterized by a different feature and/or size. The last benchmark system is a real large-scale system. For both the considered benchmark systems, the best minimum and average cost values have been obtained by the HBA-LF. Moreover, the results showed that a saving up to 98,253 $/hr can be attained if the HBA-LF has been adopted for solving the problem instead of other previously proposed algorithms in the literature. The results also clearly demonstrated the improvement added to the HBA algorithm due to augmenting it with Levy flight cycles.

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