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Solving the economic load dispatch integrating clean energies in power system using Black Kite Algorithm

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Abstract

This research applies a novel meta-heuristic algorithm called the Black Kite Algorithm (BKA) to solve the economic load dispatch integrating the clean energies (CE-ELD) with the main objective of minimizing the overall fuel cost (OFC) of all thermal power generating sources (TPGSs). A 20-TPGS power system is used to conduct the whole research and assess the actual performance of the BKA. While solving the considered problem, wind and solar generating sources are both integrated into the power system. Besides, power loss caused by the transmission process and different levels of load demand ranging from 2500, 2600, to 2700 MW are employed. The results achieved by BKA in three cases of load demand are compared with another meta-heuristic algorithm, the Coati optimization algorithm. The comparison between the results of the two methods indicates that BKA is completely superior to COZ in all criteria, especially in reaching the best values of OFC and stability throughout the test runs, regardless of the noticeable increase in load demand. Mainly, BKA always requires fewer iterations to reach the best OFC value, resulting in a lower fluctuation of OFC values among the test runs. Based on these results and evaluations, BKA is acknowledged to be the robust and stable search method, and we highly recommend using BKA to solve optimizations such as the CE-ELD problem.

Keywords: Economic load dispatch; Clean energies; Overall fuel cost; Thermal power generating sources; Black Kite Algorithm (BKA)

1. Introduction

An optimal solution to the economic load dispatch (ELD) is critical in power system operation [1]. The main purpose of resolving the ELD is optimizing the power supply from all the thermal power generating sources (TPGSs) existing in the considered power system to not only fulfill load demand but also achieve the minimum value of the overall fuel cost (OFC) and satisfy all the constraints [2]. At the time the ELD problem was first proposed, TPGSs were mostly in charge of the primary generating source in the power system, but nowadays, the trend of integrating clean energies such as wind and solar energy is widely employed. Those clean energies in the power system reduce OFC spent to run all TPGS and mitigate the environmental damage caused by TPGS operation. The integration of clean energies while solving the ELD problem is designated by the CE-ELD problem.

It is essential to note that ELD is a complex and non-linear optimization problem, which is significant when solving ELD in large-scale power systems. Inherited from the ELD problem, the CE-ELD problem is another step forward in complexity and scale. Meta-heuristic algorithms have proven to be the most effective and reliable computing methods for dealing with such problems, as compared to old-fashioned ones, such as the gradient-based method [3] and the Gauss-Siedel distribution [4]. A vast number of meta-heuristic algorithms have been applied to solve both ELD and CE-ELD problems in the last two decades ago, such as Genetic algorithm (GA) [5], Differential evolution (DE) [6], particle

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swarm optimization (PSO) [7], Grasshopper optimization algorithm (GOA) [8], Whale optimization algorithm (WOA) [9], JAYA algorithm (YA) [10], Real-Coded Elitism Genetic Algorithm (RCEGA) [11], firefly algorithm (FA) [12], harmony search algorithm (HSA) [13], Salp Swarm Algorithm (SSA) [14], crow search algorithm (CSA) [15], Squirrel Search Algorithm (SSA) [16], jellyfish search optimizer (JSO) [17], Dragonfly algorithm (DA) [18], Flower pollination algorithm (FPA) [19], Dandelion optimizer (DO) [20]. Moreover, due to their robust and reliable performance, meta-heuristic algorithms are also applied to solve other critical problems in power systems such as optimal reactive power planning [21], optimal scheduling of the wind-hydro-thermal power system [22], optimal power flow problem (OPF) [23], optimal placement of FACTS devices in power grid [24]. On top of that, the use of meta-heuristic algorithms can also be found in solving other problems, including the optimal drive system of three-phase VSI-Fed PMSM [25], structure design optimization [26], optimal path planning problem [27], feature selection [28].

In this research, a novel meta-heuristic algorithm called Black Kite Algorithm (BKA) [29] is applied to solve the CE-ELD problem to achieve the minimum value of the main objective function, which is overall fuel cost (OFC). Wind and solar generating sources are both considered in finding the optimal solution to the problem. Besides, different levels of power demand are employed to test the actual performance of the applied algorithm. Regarding BKA, this algorithm is developed based on the predatory and migratory behavior of the black-winged kites. The algorithm is tested with different benchmarks conducted by the authors, and the result performs better than many previous studies.

The main novelties and contributions of the research are briefly summarised as follows:

- Successfully apply a new meta-heuristic algorithm called the Black Kite Algorithm (BKA) to solve the ELD problem integrating clean energies (CE-ELD).
- The research demonstrates its practicality by successfully employing wind and solar generating sources with a specific rated power supply to achieve the best values for the main objective function.
- The research introduces a new algorithm and demonstrates its superior performance over the existing one, reaching the best OFC values and maintaining stability in various scenarios.
- Present a realistic application of a modern meta-heuristic algorithm to solve the optimization problem in a power system.

2. Problem formulation

2.1. The main objective function

This research mainly focuses on minimizing the overall fuel cost (OFC) spent to run the thermal power generating sources (TPGSs) in a given power system. Normally, the OFC is approximately modeled by the following expression::

$$Minimizing\ OFC = \sum_{n=1}^{N_{TPGS}} \varepsilon_n + \delta_n P_{TPGS,n} + \rho_n P_{TPGS,n}^2 \ldots\ldots(1)$$

Where OFC is the overall fuel cost spent to run all the TPGSs; ε_n, δ_n, and ρ_n are, respectively the fuel coefficients of the TPGS n; $P_{TPGS,n}$ is the amount of active power supplied by the TPGS n; and N_{TPGS} is the number of existing TPGS in the given system.

2.2. The involved constraints

- **The power balance constraints:** This constraint represents the relationship between the generating end and the consuming end:

$$\sum_{n=1}^{N_{TPGS}} P_{TPGS,n} + P_{WGS} + P_{SGS} = P_{DM} + P_L \ldots\ldots\ldots\ldots\ldots(2)$$

Where $\sum_{n=1}^{N_{TPGS}} P_{TPGS,n}$ is the total amount of power supplied by all TPGSs in the system; P_{WGS} and P_{SGS} are the power supplied from the WGS and SGS respectively,; P_{DM} and P_L are amount required by demand and the amount of power loss in the transmission process.

The amount power loss in Equation (2) is calculated by the following expression:

$$P_{LS} = \sum_{n=1}^{N_{TPGS}} \sum_{m=1,m\neq n}^{N_{TPGS}} P_{TPGS,n} B_{nm} P_{TPGS,m} + \sum_{n=1}^{P_{TPGS}} B_{0n} P_{TPGS,n} + B_{00} \ldots\ldots\ldots(3)$$

Where, B_{nm}, B_{0n}, and B_{00} are the loss factors.

- **The operational constriants of TPGSs**: These constraints are imposed to ensure that all TPGSs operate within their designed capabilities. The mathematical expressions of these constraints are given below:

$$P_{TPGS,n}^{min} \leq P_{TPGS,n} \leq P_{TPGS,n}^{max} \ldots\ldots\ldots\ldots(4)$$

Where $P_{TPGS,n}^{min}$ and $P_{TPGS,n}^{max}$ are the minimum and maximum amount of power supplied byTPGS n.

- **The operational constraint of WGS and SGS**: These constraints are used to ensure that both WGSs and SGSs are operated within their installed capabilities, similar to the TPGSs:

$$P_{WGS}^{min} \leq P_{WGS} \leq P_{WGS}^{max} \ldots\ldots(5)$$
$$P_{SGS}^{min} \leq P_{SGS} \leq P_{SGS}^{max} \ldots\ldots (6)$$

Where $\mathrm{P}_{\mathrm{WGS}}^{\mathrm{min}}$ and P_{WGS}^{max} are the minimum and maximum amount of power supplied by WGS, P_{SGS}^{min} and P_{SGS}^{max} are the minimum and maximum amount of power supplied by SGS.

3. The applied algorithm

This research applied a novel meta-heuristic algorithm called The Black Kite Algorithm (BKA) [29]. The Black Kite Algorithm (BKA) 's main inspiration comes from black-winged kites' behavior, mainly migratory and predatory behavior. These behaviors are also the main foundations of the update mechanism for BKA's new solutions. The mathematical expression of the two behaviors is given as follows:

3.1. The predatory behavior

This behavior simulates the maneuvering of the black-winged kites while they attack their prey. The mathematical expression of this behavior is presented as follows:

$$X_k^{new} = \begin{cases} X_k + \varepsilon \times (1 + sin(rnd)) \times X_k \text{ if } rnd > rf \\ X_k + \varepsilon \times (2rnd - 1) \times X_k \text{ else} \end{cases} \ldots\ldots(7)$$

$$\varepsilon = 0.05 \times e^{-2\times\left(\frac{It}{MI}\right)} \ldots\ldots\ldots\ldots(8)$$

In Equations (7) and (8) X_k^{new} is the new position of the individual k of the population with k = 1, 2, …, NP with NP is the population number; ε is the navigating factor determined by Equation (8); X_k is the current position of the individual k; rnd is the random value between 0 and 1; rf is the reference factor which is set by 0.9.

3.2. The migratory behavior

Black-winged kites and other birds conduct migratory behavior, while the current place does not provide enough living conditions to maintain and develop all individuals' growth. So they need to move, and the following mathematical model simulates this movement:

$$X_k^{new} = \begin{cases} X_k + CM \times \left(X_k - X_{LD,k}\right) \text{ } if \text{ } F_k < F_r \\ X_k + CM \times \left(X_{LD,k} - t \times X_k\right) \text{ } else \end{cases} \ldots\ldots\ldots\ldots\ldots(9)$$

$$t = 2 \times sin(r - \tfrac{\pi}{2}) \ldots\ldots\ldots\ldots\ldots\ldots(10)$$

Where CM is the value of the Cauchy mutation; $X_{LD,k}$ is the best solar position of the individual k; F_k and F_r are, respectively, the fitness value of the individual k and random selected individual r from the population; t is the amplifying coefficient; r is the index of the individual r in the population.

4. Results and evaluations

In this section, BKA will be applied to solve the CE-ELD with the main objective of minimizing OFC of all TPGSs in a 20-TPGS power system for different cases of power demand ranging from 2500, 2600, and 2700 MW. Besides, a 100-MW WGS and a 50-MW SGS are also integrated into the considered system. The results obtained by BKA in each case will be presented and compared to another meta-heuristic algorithm called the Coati optimizer algorithm (COZ) [30] using a detailed evaluation of different criteria. For a fair comparison between the two algorithms, their initial control parameters regarding population number (NP) and the maximum number of iterations (MI) are set to the same values of 50 and 100, respectively. Besides, each algorithm is executed for 50 test runs to find the best solutions.

This work is carried out on a personal computer, demonstrating the efficiency and effectiveness of the methods. The computer has a basic configuration, including a CPU Intell Core i7 12700H with 2.35 GHz clock speed and 8 GB of Random accessing memory (RAM). Additionally, we perform codings and simulations using the MATLAB programming language, version 2018a, further showcasing the efficiency of our work.

4.1. The results obtained Case 1

In this case, the load demand of 2500 MW is employed for the first investigation of the actual performance of the COZ and BKA. During the 50 test runs shown in Figure 1, BKA is the only method among the two to reach the optimal value of the main objective function multiple times, while COZ cannot provide the same capability. Moreover, the observation on the minimum, average, and maximum convergence curves in Figures 2a, 2b, and 2c also indicates that BKA can reach the optimal value in each type of convergence much faster than COZ.

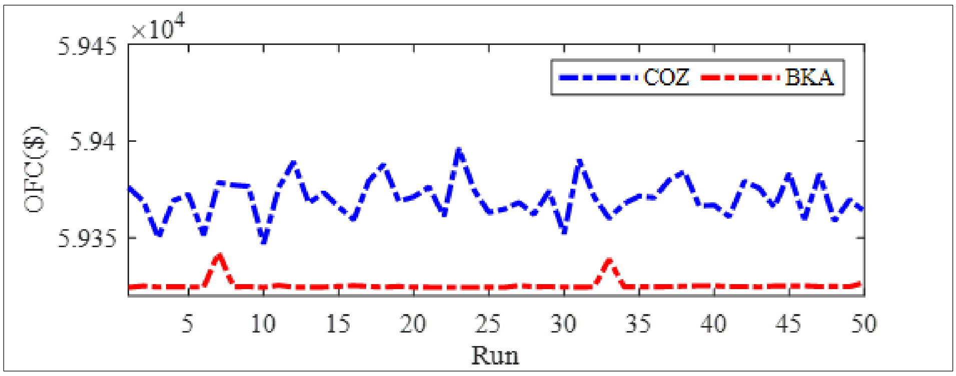

Figure 1 The results achieved by the COZ and BKA after 50 test runs in Case 1

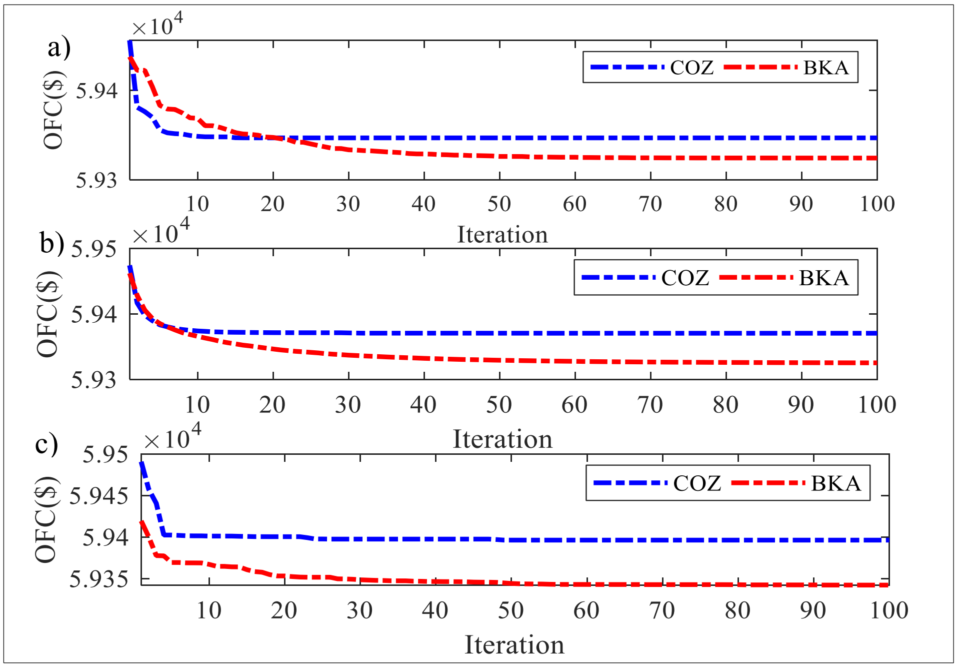

Figure 2 The minimum, average, and maximum convergences achieved by COZ and BKA in Case 1

Figure 3 shows a quantitative comparison between COZ and BKA in different criteria, including the minimum OFC (Min. OFC), average OFC (Aver. OFC), maximum OFC (Max. OFC), and the standard deviation (Std). The comparison shows that BKA is more effective than COZ, resulting in higher stability while solving the considered problem. On top of that, the standard deviation (Std) reported by BKA is only 3.176, which is surprisingly good compared to COZ, which is up to 10,545.

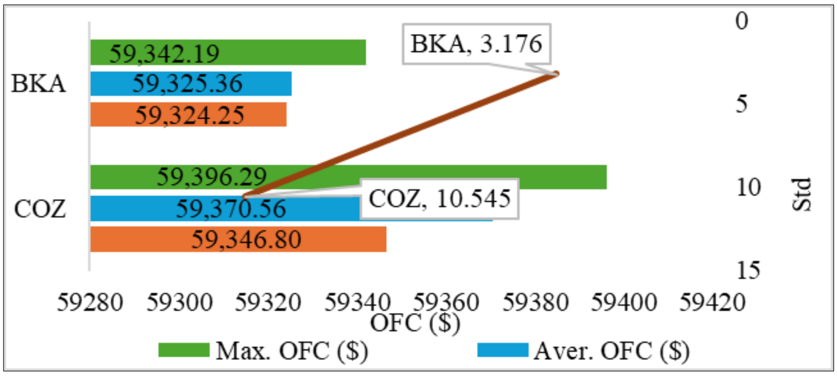

Figure 3 The result summary of the two applied methods in Case 1

4.2. The results obtained Case 2

In this section, the 2600 MW load demand is employed to test the actual performance of COZ and BKA. Similar to the previous section, the results, in this case, are also presented with the objective function values obtained after 50 test runs and three types of convergence curves, which are displayed in Figure 4 and Figure 5, respectively.

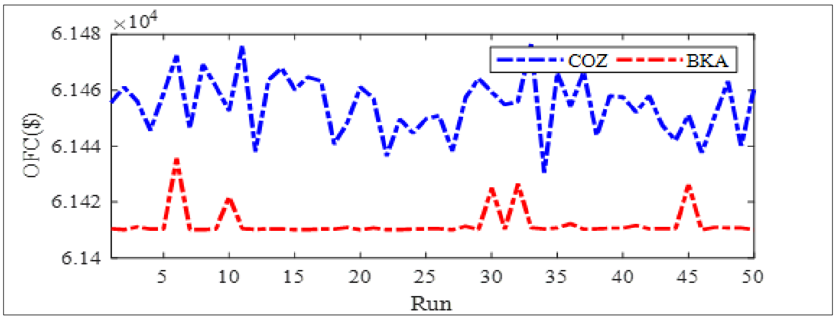

Figure 4 The results achieved by the COZ and BKA after 50 test runs in Case 2

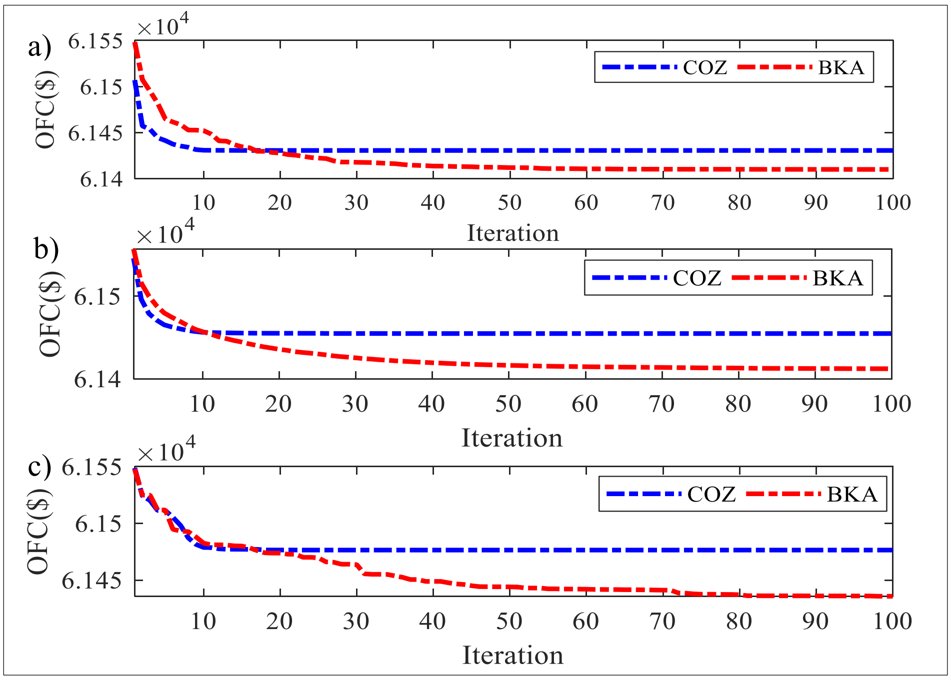

Figure 5 The minimum, average, and maximum convergences achieved by COZ and BKA in Case 2

Regardless of the increase in load demand compared to the first case, BKA consistently reaches the optimal value of the main objective function, as shown in Figure 4. In contrast, COZ fails to reach this value in the 50 test runs. Moreover, the fluctuation of the OFC values in BKA's test runs is significantly lower than in COZ, indicating a higher level of stability in BKA's optimization process. Note that stability is a crucial factor in assessing the actual performance of a meta-heuristic algorithm, providing valuable insights for our research.

Next, Figures 5a, 5b, and 5c reveal more details of the two applied algorithms regarding the minimum, average, and maximum convergence curves on their best runs. It is easy to recognize that BKA is entirely superior to COZ in all three considerations because it reached the optimal values significantly faster than COZ.

Figure 6 presents the specific measurement on different criteria of the comparison between COZ and BKA. BKA demonstrates its high effectiveness one again over COZ in all criteria, specially in the Min. OFC and the Std. The particular results achieved by BKA in these criteria are, $ 61410.06 and 5.251 while those of COZ are $61430.62 for Min.OFC and upto 10.569 for Std. Clearly, the difference between the BKA and COZ is huge.

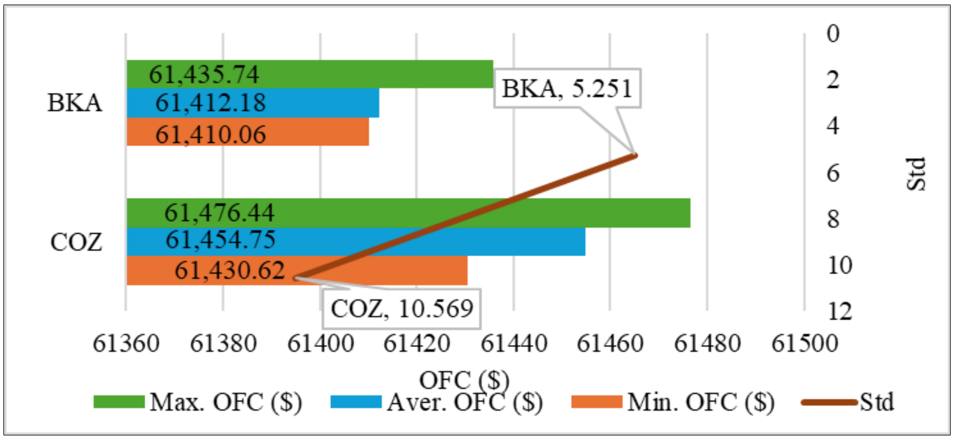

Figure 6 The result summary of the two applied methods in Case 2

4.3. The results obtained Case 3

In this last case, the 2700 MW load demand is considered to provide more references for the two applied algorithms. With the largest consideration of load demand, BKA still preserves a significant difference over COZ, which can be seen through the results of 50 test runs in Figure 7. While COZ continuously shows its poor performance in this case, BKA still maintains its promising capability of reaching optimal values with lower fluctuation among the test runs.

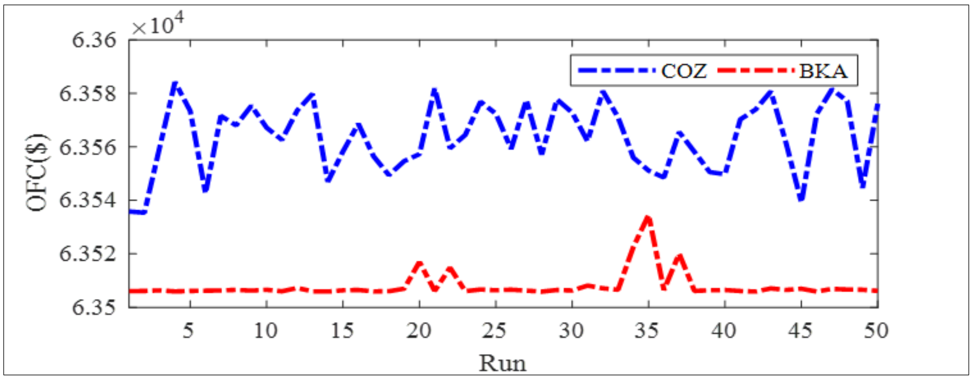

Figure 7 The results achieved by the COZ and BKA after 50 test runs in Case 3

Similar to the first two cases, the minimum, average, and maximum convergence achieved by COZ and BKA in the last case are also presented in Figures 8a, 8b, and 8c. In these figures, BKA only requires over 70 iterations to reach the best value of OFC at the minimum convergence, while COZ cannot do the same even when the last iteration is reached. Similarly, BKA requires over 80 and 90 iterations to achieve the best values of OFC in the last two convergences, while COZ cannot achieve the same performance.

Figure 9 shows the summary of the results achieved by COZ and BKA in the last case of load demand, in particular, the criteria identical to the first two cases. Besides reaching the better value in Min. OFC and Std, which are $63505.87 and 5.175 compared to those of COZ with $63535.38 for Min.OFC and 13.029, BKA also completely outperforms COZ considering the Aver.OFC and Max.OFC.

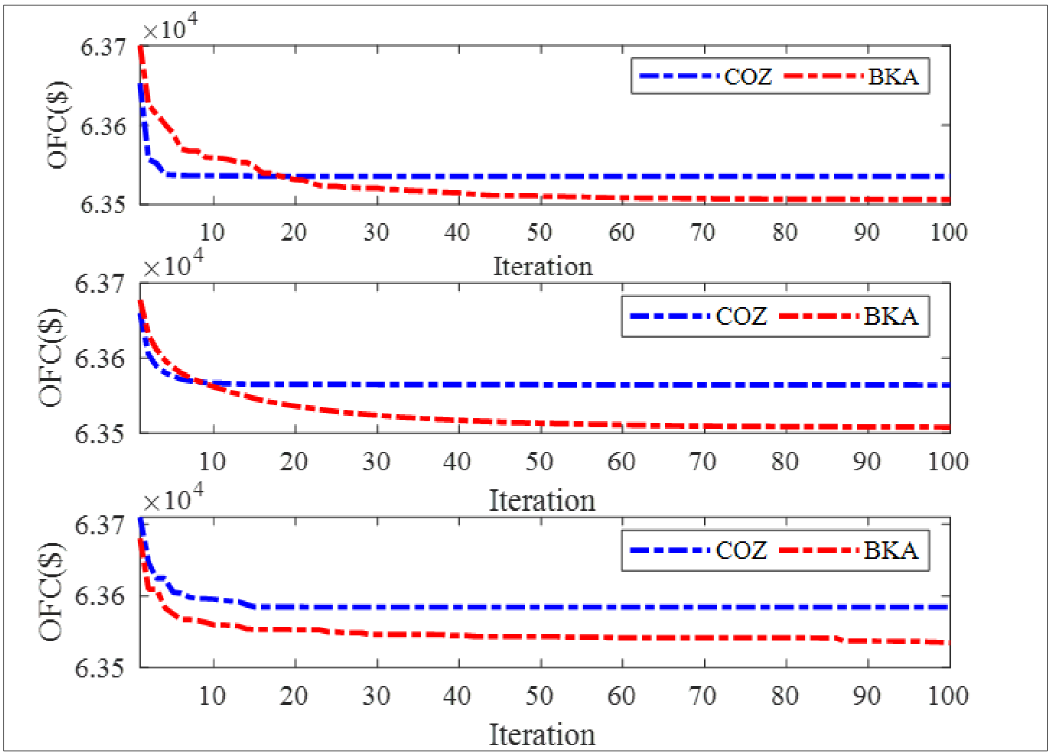

Figure 8 The minimum, average, and maximum convergences achieved by COZ and BKA in Case 3

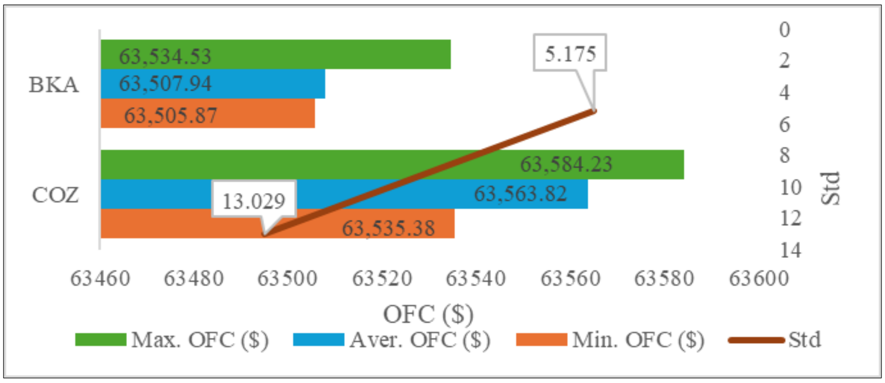

Figure 9 The result summary of the two applied methods in Case 3

5. Conclusions

In this research, a novel meta-heuristic algorithm called the Black Kite Algorithm (BKA) is successfully applied to solve the CE-ELD problem, considering the integration of both wind and solar generating sources. The main objective of the whole research is to minimize the overall fuel cost of all thermal power-generating sources in the system. Besides, different load demand levels ranging from 2500, 2600, and 2700 MW are employed to test the actual performance of the two applied algorithms. The results achieved by COZ and BKA are compared using different criteria such as Min. OFC, Aver. OFC, Max. OFC, and Std. The comparison indicates that BKA completely outperformed COZ in all criteria, especially in Min. OFC and Std, regardless of the increase in load demand. Besides, BKA also provides a faster response capability while reaching the best values in three convergences compared to COZ and maintaining this high performance throughout three cases of load demand. Through these results and analyses, BKA deserves a robust and stable searching method, and by that, we highly suggest using BKA to unfold optimization problems, such as CE-ELD.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

The authors declare that they have no conflicts of interest.

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