

Solving the Green Economic Load Dispatch by Applying the Novel Meta-heuristic Algorithm

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Abstract: This study focuses on solving the green economic load dispatch problem by considering the presence of green energy sources, including wind energy and solar power plants. The main objective function of the whole study is to minimize the total fuel cost (TFC) of all the thermal generating sources (TGSs) in the system. Moreover, the multiple selection of all TGSs is also evaluated. Fire hawk optimization (FHO) and the Zebra optimization algorithm (ZOA) are applied to solve the problem of achieving the best TFC value and satisfying all the constraints involved. The results indicated that ZOA can achieve a better optimal solution compared to FHO. Particularly, the results obtained by ZOA are completely superior to FHO in all comparison criteria at two load demand levels, such as Best TFC value (Best.Cost), Average TFC value (Aver.Cost), and Maximum TFC value (Max.Cost). On top of that, ZOA is the only algorithm of two applied ones providing the fast convergence capability to the optimal value of the main objective functions in two cases of load demand levels. Therefore, ZOA is an efficient search method to deal with such GELD problems.

Keywords: Green economic load dispatch; Solar power plant; Wind power plant; Multiple fuel selection; Fire hawk optimization algorithm; Zebra optimization algorithm.

1. Introduction

Finding the optimal solution to the economic load dispatch problem (ELD) plays an important role in power system operation [1]. The main purpose of solving the ELD is to determine the optimized generation for each thermal generating source (TGS) in order to not only fulfill load demand but also minimize fuel consumption costs and satisfy all related constraints [2]. In the old-fashioned ELD problem (OELD), TGs are the only generation source in charge of powering the whole power system. However, the operation of these TGSs unleashes different emissions that negatively affect human life and the environment. In this circumstance, the integration of green energy sources (GESs), including wind power plants (WPPs) and solar power plants (SLPs), has become a rising trend and is also recognized as a perfect fit to partly reduce the negativities caused by the huge number of TGSs on the earth. By following the trend, OELD is modified with the evaluation of different types of GESs and becomes a green economic load dispatch problem (GELD).

Similar to OELD, GELD is also a complex optimization problem; while its scale becomes larger accompanied by a wide range of complicated constraints, the use of classical computing methods such as the Gradient [3], the Jacobian matrix [4] or the Gauss-Siedel method [5] are impossible to reach the optimal solution. However, meta-heuristic algorithms have been consistently proposed and developed to deal with such large-scale and highly complex optimization problems. In fact, meta-heuristic algorithms have proven to be the most capable searching method to find the optimal solution for economic and engineering problems, and GELD is not an exception. Many studies applied different meta-heuristic algorithms to solve OELD and GELD, such as the Harmony search algorithm (HSA) [6], Modified cuckoo search algorithm (MCSA) [7], Adaptive cuckoo search algorithm (ACSA) [8], Dragonfly algorithm (DA) [9], Firework algorithm (FWA) [10], adaptive simulated annealing and genetic operators (GO-ASA) [11], Whale optimization algorithm (WOA) [12], moth-

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flame optimization algorithm based on position disturbance updating (MFA-PDU) [13], Grasshopper optimization algorithm (GOA) [14], Nondominated-Sorting Grey Wolf Optimizer Algorithm (NS-GWOA) [15], Marine predator optimization algorithm (MPA) [16], the improved version of Mayfly optimization algorithm (IMOA) [17], astute black widow optimization (ABWO) [18], the equilibrium optimizer (EO) [19], the multi-objective multi-verse optimization (MOMVO) [20]

By fully understanding and acknowledging the cutting-edge characteristics of these algorithms compared to the classical ones, this study also applied two novel meta-heuristic algorithms, including the fire hawk optimization (FHO) [21] and the zebra optimization algorithm (ZOA) [22] to determine the optimal solution to the GELD with the main objective function of minimizing the total fuel cost of thermal generating sources. The selection of FHO and ZOA for solving the considered problem in the study is based on the following terms: 1) ZOA and FHO are the novel meta-heuristic algorithms proposed in 2022 and 2023, respectively. 2) In the developing phase, these algorithms are evaluated with various benchmark functions for their performance. 3) FHO and ZOA are rapidly applied to solve different optimization problems, both engineering and non-engineering problems, and reach better results when compared to previous methods. Particularly, the application of FHO can be found in [23], [24], and [25], while the implementation of ZOA is assessed in [26], [27], and [28]. FHO and ZOA are inspired by the living practices of animals in wildlife. Specifically, FHO is formed by simulating the hunting behavior of the fire hawk, while ZOA is proposed based on imitating the movement of zebra in foraging and defending from its enemies. According to the authors, both FHO and ZOA have proven their capability compared to predecessors while dealing with various optimization problems, including economic and engineering optimization problems.

The novelties and the striking contributions of the study are summarized as follows:

1. Successfully apply two novel meta-heuristic algorithms to solve one of the most critical problems in power system operation, GELD.
2. Indicated the best algorithm to solve the considered problems between the two by evaluating different criteria, and that is ZOA.
3. The presence of both solar and wind energy is considered simultaneously. Besides, the constraint of multiple fuel selection for all TGSs is successfully satisfied in the process of solving the GELD.
4. Provide the typical reference for using green energy in power systems to alleviate environmental damage.

In addition to the introduction, other sections of the paper are structured as follows: Section 2 will present the main objective function and the constraints; Section 3 will briefly introduce the applied algorithms; Section 4 shows the results achieved by the two applied methods and the related discussion; and finally, the essential conclusions are revealed in Section 5.

2. Problem formula

2.1. The main objective function

This paper aims to reach the minimum value of the total fuel cost (TFC) of all TGSs existing in the power system. The determination of TFC is formulated as the main objective function in Equation (1).

$$\text{Minimize } TFC = \sum_{n=1}^{N_{TGS}} \gamma_n + \delta_n P_{TGS,n} + \varepsilon_n P_{TGS,n}^2 \quad (1)$$

with $n = 1, \dots, N_{TGS}$

Where TFC_n is the total fuel cost of the TGSs in the considered power system; γ_n , δ_n , and ε_n are the fuel coefficients specialized for the TGS n ; $P_{TGS,n}$ is the amount of power supplied by the TGS n ; and N_{TGS} is the amount of TGSs in the considered power system.

In this research, the multiple fuel option constraints of all TGS in the power system are also taken into account. Therefore, the mathematical expression presented in Equation (1) is rewritten as Equation (2).

$$TFC = \begin{cases} \gamma_{n,1} + \delta_{n,1}P_{TGS,n} + \varepsilon_{n,1}P_{TGS,n}^2; & \text{if } P_{TGS,n}^{lst} \leq P_{TGS,n} \leq P_{TGS,n}^{1,max} \\ \gamma_{n,2} + \delta_{n,2}P_{TGS,n} + \varepsilon_{n,2}P_{TGS,n}^2; & \text{if } P_{TGS,n}^{2,min} \leq P_{TGS,n} \leq P_{TGS,n}^{2,max} \\ \dots \\ \gamma_{n,k} + \delta_{n,k}P_{TGS,n} + \varepsilon_{n,k}P_{TGS,n}^2; & \text{if } P_{TGS,n}^{k,min} \leq P_{TGS,n} \leq P_{TGS,n}^{k,hst} \end{cases} \quad (2)$$

Where $\gamma_{n,1}$, $\delta_{n,1}$ and $\varepsilon_{n,1}$ are fuel coefficients using the fuel type 1 of TGS n , $P_{TGS,n}^{lst}$ and $P_{TGS,n}^{1,max}$ are the limit power generation of TGS n using the fuel type 1. Likewise, $\gamma_{n,2}$, $\delta_{n,2}$ and $\varepsilon_{n,2}$ are fuel coefficients using fuel type 2 of TGS n . $P_{TGS,n}^{2,min}$ and $P_{TGS,n}^{2,max}$ are limit power generation of TGS n using fuel type 2. Lastly, $\gamma_{n,k}$, $\delta_{n,k}$ and $\varepsilon_{n,k}$ are fuel coefficients using fuel type k of TGS n and $P_{TGS,n}^{k,min}$ and $P_{TGS,n}^{k,hst}$ are the limit of power generation of TGS t using the fuel k , with k being the number of fuel types.

2.2 The involved constraints

The power balance constraints:

This constraint infers that the total power produced by all types of generating sources at the supplying side must equal the total power required by load demand plus the loss in transmission lines as Equation (3).

$$\sum_{n=1}^{NTGS} P_{TGS,n} + P_{WPP} + P_{SLP} = P_{DM} + P_{Loss} \quad (3)$$

Where, $\sum_{n=1}^{NTGS} P_{TGS,n}$ do all TGSs in the system produce the total power; P_{WPP} and P_{SLP} are the power supplied by the WPP and SLP integrated into the system; P_{DM} and P_{Loss} are the power demand and the power loss in the transmission line, respectively.

The power loss in Equation (4) is determined using the following expression:

$$P_{Loss} = \sum_{n=1}^{NTGS} \sum_{m=1, n \neq m}^{NTGS} P_{TGS,n} B_{nm} P_{TGS,m} + \sum_{n=1}^{NTGS} B_{0n} P_{TGS,n} + B_{00} \quad (4)$$

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

The operation constraint of TGSs:

Each TGS in the power system is designed to supply power in the allowed range between the lowest and the highest range. The violation of these ranges will cause damages and negatively affect the stability of the whole system:

$$P_{TGS,n}^{lst} \leq P_{TGS,n} \leq P_{TGS,n}^{hst} \quad (5)$$

Where, $P_{TGS,n}^{lst}$ and $P_{TGS,n}^{hst}$ are the lowest and highest amount of power produced by the TGS n ; $P_{TGS,n}$ is the amount of power produced by the TGS n .

The operation constraint of WPP and SLP:

Similar to TGSs, both WPPs and SLPs can only supply power to load with the values within the lowest and the highest range as in Equations (6) and (7).

$$P_{WPP}^{lst} \leq P_{WPP} \leq P_{WPP}^{hst} \quad (6)$$

$$P_{SLP}^{lst} \leq P_{SLP} \leq P_{SLP}^{hst} \quad (7)$$

Where, P_{WTP}^{lst} and P_{WTP}^{hst} are the lowest and the highest value of power supplied by WPP; P_{SLP}^{lst} and P_{SLP}^{hst} are the lowest and the highest value of power supplied by SLP; P_{WTP} and P_{SLP} are the power supplied by the WPP and the SLP, respectively.

Supposedly, the SLP is accompanied by the battery energy storage system (BESS), which is large enough to keep the SLP online regardless of day or night.

3. The applied algorithms

In this section, the Fire Hawk optimizer (FHO) [21] and the Zebra optimization algorithm (ZOA) [22] will be implemented to solve the given problem. ZOA and FHO are novel meta-heuristic algorithms, and they are all developed based on the imitation of living behaviors of species in nature. The key difference between the two algorithms is their update methods for new solutions, which is briefly presented in the following subsections:

3.1. Zebra optimization algorithm

The update process of ZOA is built chiefly based on the two phases, including the zebra group's food-searching behavior and defense behavior. These behaviors are formulated using the mathematical model as follows:

Phase 1: the food-searching behavior

The specific formula of the update process in Phase 1 of ZOA is performed as Equation (8).

$$Z_i^{new,P1} = Z_i + AF \times (LZ - CT_1 \times Z_i) \text{ with } i = 1 \dots PS \quad (8)$$

Where $Z_i^{new,P1}$ is the new position of the zebra i in Phase 1; Z_i is the current position of the considered zebra i ; AF is the amplifying factor having a value between zero and one; LZ is the best zebra with the best position of the population; CT_1 is the constant value, and according to the author CT is set by 2 for the best searching efficiency, and PS is the initial population size.

After completing Phase 1 of the update process, the refining procedure is performed to find the high-quality solution and remove the lower ones using the model in Equation (9).

$$Z_i = \begin{cases} Z_i^{new,P1}, & \text{if } F_{Z_i^{new,P1}} < F_{Z_i} \\ Z_i, & \text{else} \end{cases} \quad (9)$$

Where $F_{Z_i^{new,P1}}$ is the fitness value of the zebra with the new position; F_{Z_i} the fitness values of the zebra with the current position.

Phase 2: the defense behavior

Phase 2 of the update process for new solutions of the ZOA is executed using the following Equation (10).

$$Z_i^{new,P2} = \begin{cases} Z_i + CT_2 \times (2CT_2 - 1) \times \left(1 - \frac{CI}{HI}\right) \times Z_i, & \text{if } PB \leq 0.5 \\ Z_i + AF \times (AZ - CT_1 \times Z_i), & \text{else} \end{cases} \quad (10)$$

Where $Z_i^{new,P2}$ is the new position of the zebra i in Phase 2; CT_2 is the constant value set by 0.01; CI and HI are the current iteration index and the highest iteration index; AZ is the zebra being attacked; PB is the probability index for selecting the update method in Phase 2.

Similar to Phase 1, the new update solutions in Phase 2 are also checked to retain the high-quality solutions and remove the lower ones, see Equation (11).

$$Z_i = \begin{cases} Z_i^{new,P2}, & \text{if } F_{Z_i^{new,P2}} < F_{Z_i} \\ Z_i, & \text{else} \end{cases} \quad (11)$$

3.2. Fire Hawk Optimizer

The update process for new solutions of the FHO is mostly based on the simulation of the movement of the fire hawk and their prey in a hunting time.

The movement of the fire hawk:

The movement of the fire hawk is simulated using the mathematical expression in Equation (12).

$$F_i^{new} = F_i + (rd_1 \times BF - rd_2 \times F_N) \text{ with } i = 1, \dots, N_F \tag{12}$$

Where F_i^{new} is the new position of the fire hawk i ; F_i is the current position of the considered fire hawk i ; rd_1 and rd_2 are, respectively, the random value between zero and one; BF is the best fire hawk with the best position in the whole population; F_N is the nearest fire hawk to the considered fire hawk and N_F is the number of the fire hawk in the initial population.

The movement of the prey:

Two types describe the movement of the prey: 1) the movement within the possible hunting area of a fire hawk or 2) the movement toward another hunting area of the neighborhood fire hawk. These movements will be briefly described by equations (13) and (14), respectively:

$$P_k^{new} = P_k + (rd_3 \times F_i - rd_4 \times SP_{in}) \text{ with } k = 1, \dots, N_k \tag{13}$$

$$P_k^{new} = P_k + (rd_5 \times F_N - rd_6 \times SP_{out}) \text{ with } k = 1, \dots, N_k \tag{14}$$

Where P_k^{new} is the new position of the prey k ; P_k is the current position of the prey k ; rd_3 , rd_4 , rd_5 , and rd_6 are the random value between zero and one; F_i is the position of the fire hawk i ; and F_N is the neighborhood fire hawk; SP_{in} and SP_{out} are, respectively, safe positions outside and inside the hunting area where the preys can hide from their enemies; N_k is the number of prey. Note that the total number of fire hawks (N_F) and the number of prey (N_k) are equal to the initial population size (PS).

After both fire hawks and the preys are updated for their new positions, they will be gathered together as Equation (15).

$$S^{new} = [F_i^{new}; P_k^{new}] \text{ with } i = 1, \dots, N_F \text{ and } k = 1, \dots, N_k \tag{15}$$

Then, the refining procedure for the high-quality solutions is performed as Equation (16).

$$S_n = \begin{cases} S_n^{new}, & \text{if } F_{S_n^{new}} < F_{S_n} \\ S_n, & \text{else} \end{cases} \text{ with } n = 1, \dots, PS \tag{16}$$

Where S_n is the position of the individual n created in the initialization process; S_n^{new} is the position of the individual n in the initial population size; $F_{S_n^{new}}$ and F_{S_n} are the new and old fitness value of the individual n .

4. The results and discussions

In this section, FHO and ZOA are implemented to solve the GELD to reduce the TFC of all the TGSs in the considered power system. On top of that, considering the multiple fuel selections and the presence of green generating sources, including WPP and SLP, are all given special attention. The considered power system consists of ten TGSs with two load demand levels of 2500 and 2700 MW. All the related data of the applied power system is cited from [4]. Besides, a WPP and an SLP with rated power 100 and 50 MW are connected to the system to reduce the generation of all TGSs partly. For a fair comparison of the real performance of the two applied algorithms, all initial settings of population size and the highest number of iterations are set by the same numbers, which are 30 and 100, respectively. On the other hand, both FHO and ZOA are executed with 50 test runs for the best solution.

The study is implemented in a personal computer with the main specifications: the central processing unit (CPU) with 2.2 GHz of clock speed and 8GB of Random accessing memory (RAM). All the coding and simulation are performed using MATLAB software version R2018a.

Figures 1a and 1b present the fuel cost value achieved by FHO and ZOA after 50 test runs with both load demand levels 2500 and 2700, respectively. In these figures, the pink line illustrates the TFC values achieved by FHO, while the green line displays the similar results obtained by ZOA. By observing these figures, it is very clear that ZOA provides outstanding efficiency while reaching many optimal TFC values of both load demand levels, especially in Figure 1b compared to FHO; this method cannot achieve any optimal one throughout all the test runs.

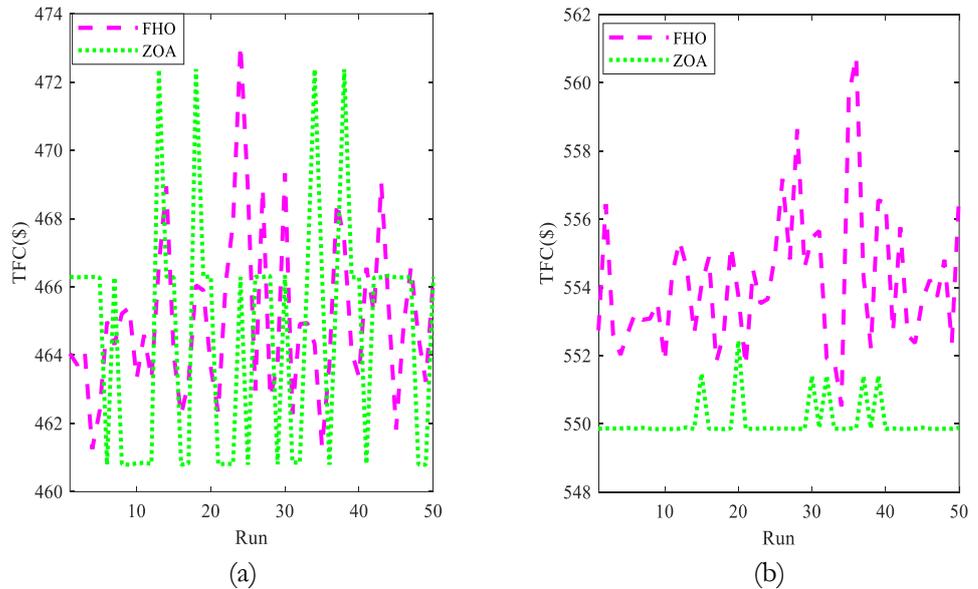


Figure 1. The results obtained the FHO and ZOA after 50 test runs

Next, the best convergences of the two applied algorithms are presented in Figures 2a and 2b, respectively. In these figures, ZOA only requires over 40 iterations to reach the best optimal TFC values with a load demand of 2500 MW and around 45 iterations to do the same with a load demand of 2700 MW, while FHO cannot provide similar capabilities in both two levels of load demand even at the last iteration.

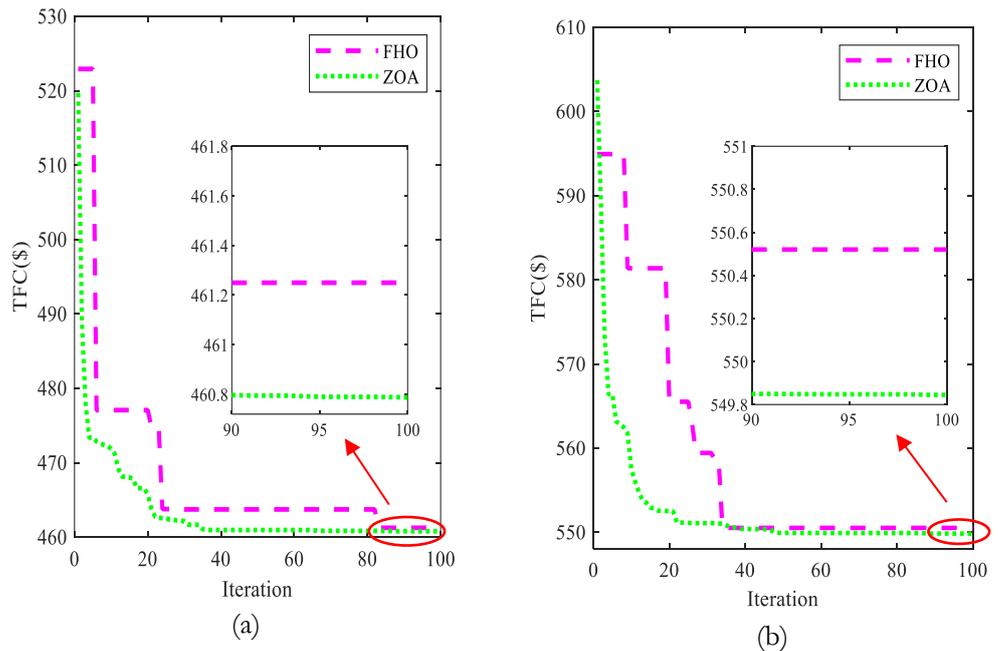


Figure 1. The best convergences achieved by FHO and ZOA for the best test run

The average convergences achieved by FHO and ZOA are displayed in Figures 3a and 3b, corresponding with the two load demand levels. ZOA continuously outperforms FHO in this comparison in both cases of load demand levels. Specifically, ZOA achieves the best average TFC values at around 60th and 80th iterations for load demand levels 2500 and 2700 MW, respectively. Meanwhile, FHO cannot reach any best average TFC values in both cases of load demand levels. Moreover, in the case of load demand 2700 MW, the difference between TFC values at the last iteration between ZOA and FHO is huge.

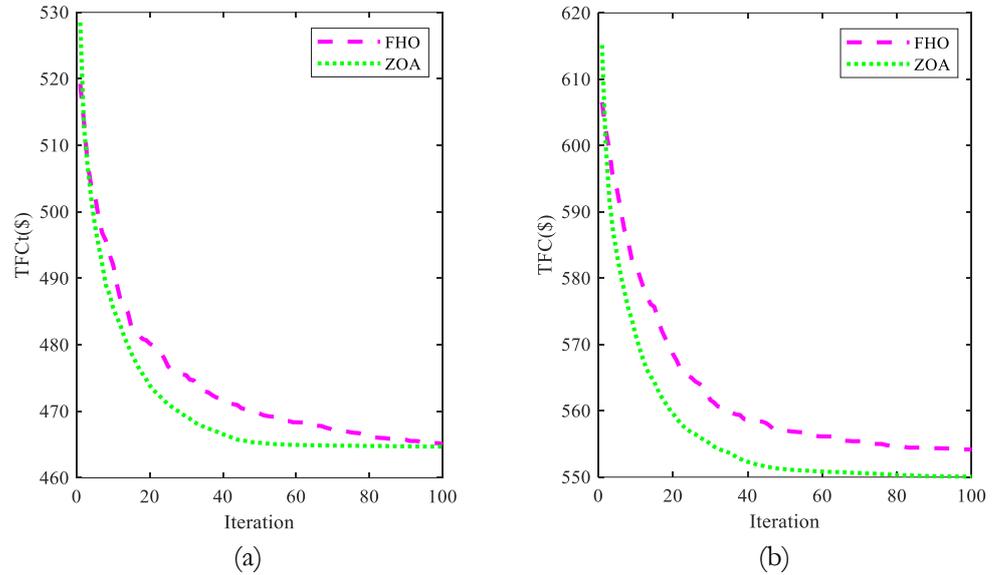


Figure 2. The average convergences achieved by FHO and ZOA among 50 test runs

Figures 4a and 4b show the maximum convergences obtained by FHO and ZOA for two load demand levels. ZOA again shows its high performance compared to FHO while reaching the best maximum TFC values much faster than FHO in both cases of load demand levels. Particularly, ZOA obtained the best maximum TFC value at around the 70th iteration for a load demand of 2500 MW and the 85th iteration for a load demand of 2700 MW. FHO shows its low efficiency, while this algorithm cannot reach any of the best maximum TFC values even in the case of load demand of 2500 MW.

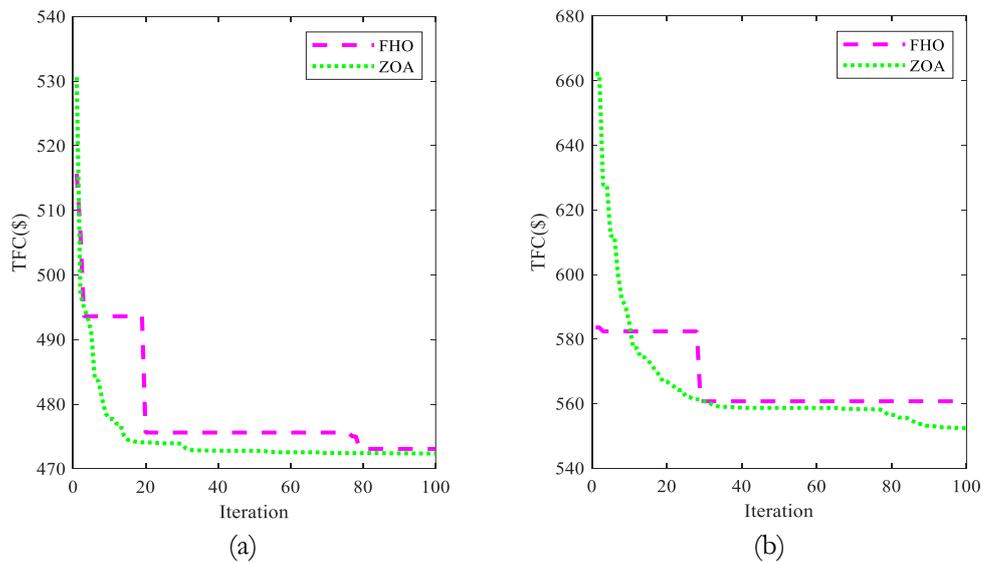


Figure 3. The maximum convergences achieved by FHO and ZOA among 50 test runs

Figures 5a and 5b show the detailed comparison of the two applied algorithms using different criteria for two cases of load demand level. Particularly, the comparison for load demand 2500 is displayed in Figure 5a, while a similar comparison for load demand 2700 MW is presented in Figure 5b. ZOA is superior to FHO in all criteria regardless of the load demand increase from 2500 to 2700. Specifically, in the case of load demand 2500 MW, ZOA achieves (\$) 460.787 of the Best TFC value (Best.Cost) while the similar value obtained by FHO is (\$) 461.25. by taking a simple calculation, ZOA is 0.1% better than FHO in the first criterion. While analyzing the Average TFC value (Aver.Cost) and the Maximum TFC value (Max.Cost), ZOA continuously maintains its better efficiency over FHO. In fact, the values achieved ZOA in these two criteria are \$464.797 and \$ 472.376, while those of FHO are \$465.028 and \$473.089. By converting to percentage, ZOA is 0.07% and 0.15% better than FHO in these criteria. While observing Figure 5b where the comparison of FHO and ZOA for the case of load demand 2700 MW are shown, the superiority of ZOA over FHO is largely expanded, especially in the last two criteria. Particularly, ZOA reaches \$550.07 and \$552.436 for Aver.Cost and Max.Cost, respectively, while those values obtained by FHO for these two criteria are \$554.173 and \$560.764, respectively. The superiority degree in percentages of ZOA over FHO in these criteria of load demand are 0.74% and 1.5%. More importantly, in this case of load demand, ZOA is the only algorithm reaching the Best.Cost value, which is \$549.845 while that of FHO is \$550.52, and the ZOA is 0.12% better than FHO in this criterion.

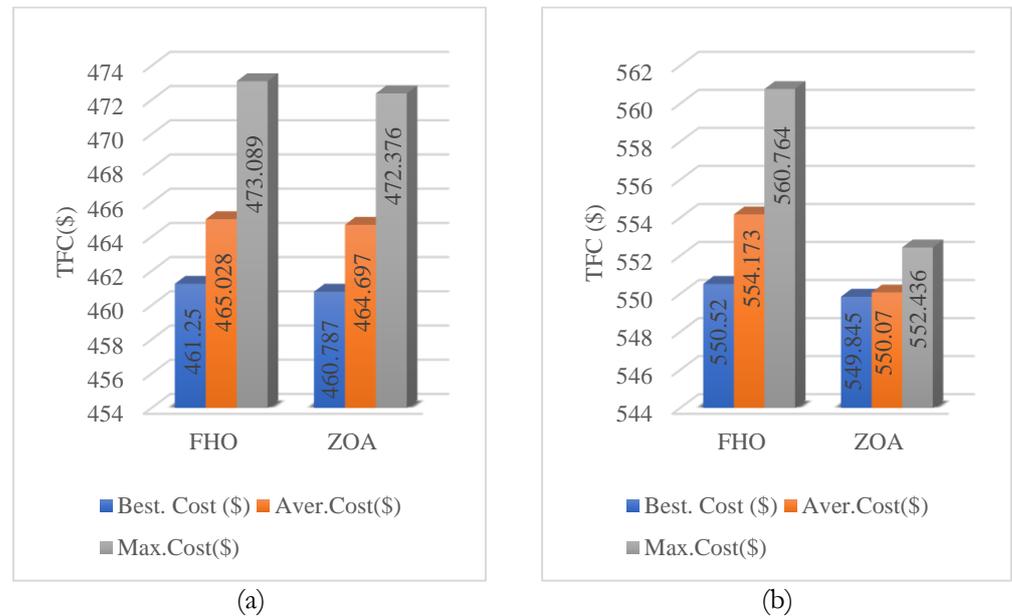


Figure 4. The brief comparison between FHO and ZOA on different criteria

In fact, the superiority of ZOA over FHO comes from the update mechanism for the new solutions after each iteration, especially in phase 2. Particularly, ZOA using the constant value (CT_2), the amplifying factor (AF), and the subtraction between one and the ratio of current and maximum iteration ($1 - \frac{CI}{HI}$) to shrink the search space as presented in Equation (10). As a result, this implementation accelerates the speed of reaching the optimal solution much easier, while the update process of FHO has highly relied on the SP_{in} and SP_{out} along with the utilization of the neighborhood solution and other random terms, such as rd_3 and rd_4 as given in the Equations (13) and (14), respectively. This implementation can somehow increase the diversity of solutions in the search space. However, this approach will lead to the low convergence phenomenon, and sometimes, the searching process may be trapped in the local optima, especially while dealing with large-scale optimization problems such as the GELD problem.

The power generation of each TGS in the system for both cases of load demand levels is given in Figures 6a and 6b, respectively.

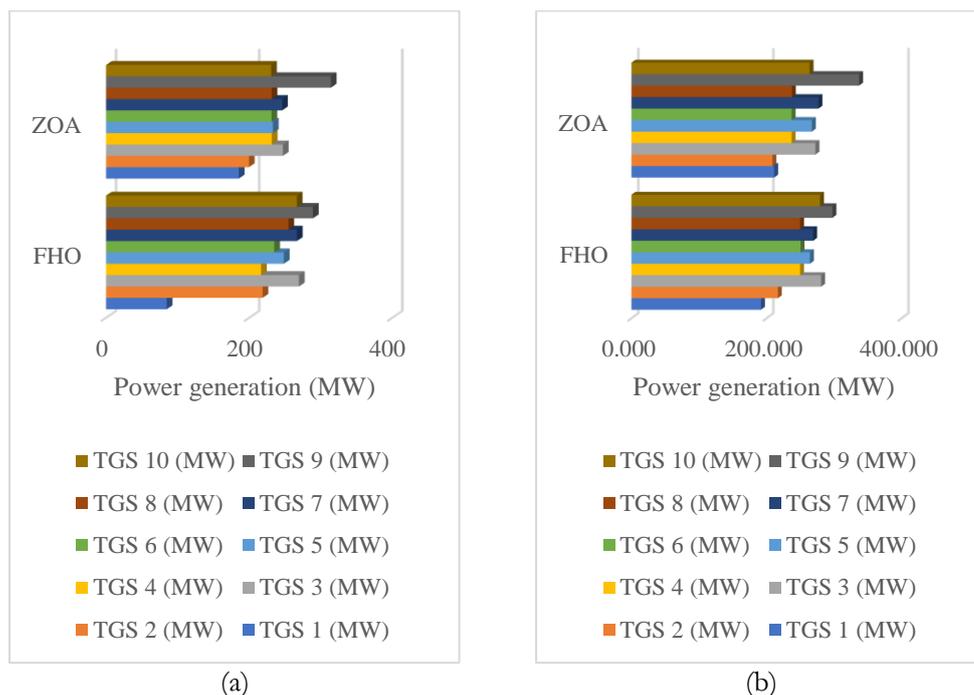


Figure 5. The power generation of all TGSs determined by FHO and ZOA

5. Conclusions

In this research, two novel meta-heuristic algorithms, including Fire Hawk Optimization (FHO) and Zebra Optimization Algorithm (ZOA), are successfully applied to solve the GELD to minimize the total fuel cost of all thermal generating sources with consideration of both wind power plants and solar power plants. The results indicate that ZOA outperforms FHO at all comparison criteria, regardless of the increase in load demand from 2500 to 2700 MW. Besides, ZOA is the only applied algorithm reaching the optimal value of the main objective function and satisfying the involved constraints in the tests. At the same time, FHO cannot provide a similar capability. For more details, ZOA is 0.1%, 0.07%, and 0.15% better than FHO in Best.Cost, Aver. Cost, and Max.Cost for the case of load demand of 2500 MW. When the load demand of 2700 MW is considered, the better percentages of ZOA over FHO are 0.12%, 0.74%, and 1.5%. The impressive performance of ZOA while dealing with the GELD problem mainly comes from the effective update mechanism, which can shrink the search space for better acceleration to the optimal solution, as mentioned earlier. The results indicate that ZOA is a highly efficient search method for solving large-scale optimization problems accompanied by highly complex constraints, and the algorithm is highly recommended for solving such GELD problems.

Author Contributions: Author 1 initiated the project, supervised the project and validated the experiment. Authors 2 performed the experiment, edited, proofread the work and wrote the manuscript

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Data Availability Statement: All the related data of the applied power system is cited from [4].

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