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Minimizing the overall electricity production cost to the large-scale power system incorporating solar and wind energy sources using Elk Herd Optimizer

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Abstract. *This study presents a strategy for addressing the green economic load dispatch problem (GELD), which is a modern iteration of the economic load dispatch problem (ELD) that includes the integration of solar and wind generation sources. The primary objective of this study is to minimize the overall electricity production cost (OEPC) of a large-scale power system comprising 20 thermal power plants. To optimize the power output of each thermal power plant (TPP) in the system, along with the contributions from solar and wind sources, two optimization algorithms are employed: the Greylag Goose Optimization (GGO) and the Elk Herd Optimizer (EHO). The results demonstrate that EHO is superior to GGO across all comparison criteria. Specifically, EHO exhibits greater stability in 50 trial tests, with smaller fluctuations and a higher success rate in achieving optimal OEPC values. Additionally, EHO features faster convergence to the optimal value when compared to GGO. Furthermore, EHO achieves savings of \$20.50 per hour on the minimum OEPC, \$65.51 per hour on the mean OEPC, and \$125.48 per hour on the maximum OEPC. These findings indicate that EHO is a robust and reliable search algorithm, and it is strongly recommended for addressing GELD problems. Lastly, the study quantitatively indicates the contribution of solar and wind generation sources to the reduction of the electricity production cost (EPC) for each thermal power plant.*

Keywords: *Green economic load dispatch, thermal power plants, solar and wind generating sources, overall electricity production cost, Elk Herd Optimizer.*

1. Introduction

Nowadays, solving the economic load dispatch problem (ELD) still remains one of the highest priorities in power system operation [1]. In the past, solving the ELD primarily involved allocating the power output of thermal power plants (TPPs), which are mostly fueled by fossil fuels, to meet load demand. Besides, the primary objective in solving the ELD problem is to minimize the overall electricity production cost for all TPPs in the considered power system, while still meeting the electricity demand and satisfying all operational constraints [2]. However, due to the harmful emissions produced by TPPs, public health and the environment have been on high alert recently [3]. In this circumstance, incorporating green energy sources (GESs) such as wind and solar into the current power system is highly considered. The integration of RESs not only reduces environmental impact but also offers economic advantages. Due to the presence of RESs in the power system, the conventional ELD is now modified and has become the green economic load dispatch (GELD).

As soon as the GELD is classified as one of the high-complex optimization problems due to its nonlinear characteristics, the classical optimization method based on gradient and iterative methods, as mentioned in [4,5], is incapable and unreliable of determining an optimal solution, especially when applied to a large-scale power system that consists of a huge number of TPPs, each with different operational boundaries. Therefore, the need for a robust and reliable search method is more necessary than ever. The presence of a meta-heuristic algorithm with cutting-edge search performance and the ability to reach optimal solutions to various optimization problems is a perfect fit for dealing with such a GELD problem. By understanding the competitive characteristics of meta-heuristic algorithms, many studies have applied different meta-heuristic algorithms to solve the ELD and GELD problems. For instance, the Growth Optimizer Algorithm (GOA) has been applied in [6] to solve the ELD problem in three different power systems, including the six-, ten-, and twenty-TPP systems, with load demand ranging from 1000 to 3000 MW. The results clearly indicated that GOA completely outperformed the previous methods in achieving the lowest power losses across all three considered power systems. Next, the authors in [7] implemented the Artificial Bee Colony (ABC) algorithm to solve a modified version of the conventional ELD, the dynamic ELD (DELD), with the main objective of meeting the load demand over a 24-period schedule while satisfying all constraints. The effectiveness of the ABC is verified through different cases based on the cost savings and the satisfaction of all the constraints. Besides, the contribution of renewable energy sources to solving the DELD problem. In [8], the turbulent flow of water algorithm (TFW) is applied to solve another modified version of the conventional ELD, called the Combined Economic and Emission Dispatch (CEED), with consideration of valve-point effects from the TPPs. The results achieved by TFW while solving the problem in the 6-TPP system have proven its effectiveness compared to many well-known meta-heuristic algorithms, such as Cuckoo Search Algorithm (CSA), Sine Cosine Algorithm (SCA), Tunicate Swarm Algorithm (TSA), etc. In [9], an improved version of the original Krill Herd Algorithm (MKHA) has been introduced to solve the ELD problem, incorporating the linear characteristics of the TPPs and transmission losses in the three test systems with load demand ranging from 1263 MW, 2630 MW, and 10500 MW. In [10], a modified version of the sine cosine algorithm (SCA), called the memetic sine cosine algorithm (MSCA), is presented to solve the ELD problem while considering ramp rate limits and the prohibited operating zones of TPPs' various power systems, ranging from 3 to 40 TPPs. The results clearly indicate that MSCA has demonstrated itself to be an effective search method in tuning the optimal parameters compared to the other previous methods. In particular, MSCA consistently ranks first and second across the test systems. Besides, the application of many other meta-heuristic algorithms in other studies such as Stochastic Shaking Algorithm (SSA) [11], osprey optimization algorithm (OOA) [12], Clustering cuckoo search (CCS) [13], Jaya Algorithm (JA) [14], multiswarm statistical particle swarm optimization (MS-PSO) [15], grasshopper optimization algorithm (GrOA) [16], Dandelion optimizer (DO) [17], improved mayfly optimization algorithm (IMOA) [18], Enhanced emperor penguin optimization (EEPO) [19], Five phases algorithm (FPA) [20], Cuckoo search algorithm (CSA) [21].

In this study, two novel meta-heuristic algorithms, namely the Greylag Goose Optimization (GGO) [22] and the Elk Herd Optimizer (EHO) [23], are applied to solve the GELD problem. GGO is proposed based on flying behaviors during migration at a particular time of year. In particular, the greylag goose species has excellent flying skills, enabling them to cover thousands of kilometers on a voyage. EHO, on the other hand, is proposed based on simulating the breeding practice of the elk herd species in nature. The special breeding practice helps the elk herd species grow and maintain itself by executing an effective swarm strategy. The reasons for selecting GGO and EHO for the considered problem are based on the following aspects: 1) both GGO and EHO are recently proposed meta-heuristic algorithms, 2) GGO and EHO are tested with various optimization problems in both theoretical and engineering, and demonstrate their promising capability while dealing with such problems over many others, 3) There was no previous study in the literature executing a head-to-head comparison between these two algorithms.

The two algorithms are executed to determine the optimal power output for each TPP in a 20-TPP power system, with the main objective of minimizing the overall electricity production cost (OEPC). Besides, a 200 MW solar generating source (SGS) and 350 MW of wind generating sources (WGS) are also integrated into the given system in the solving process. Both GGO and EHO are recently proposed meta-heuristic algorithms, and their capability are proven while solving different optimization problems. While GGO is developed based on the flying method of the greylag goose in a swarm to optimize the energy loss for each individual and reduce air resistance, EHO is formed by simulating the breeding process of the elk herd through seasons to improve the later generations.

The main novelties and contributions of the whole study are listed as follows:

- Apply two novel meta-heuristic algorithms, including the Greylag Goose Optimization (GGO) and Elk Herd Optimizer (EHO), to determine the optimal power output to all the TPPs in a large-scale power system for OEPC minimization.
- Integrate both solar and wind generating sources besides the given TPPs in the whole process of solving the GELD problem. Besides, the contribution of solar and wind generating sources to the electricity production cost is also clarified compared to the cases where those sources are absent.
- Present a detailed analysis and discussion about the performance of the two applied algorithms and indicate the most effective algorithm among the two using different comparison criteria.
- Provide a valuable reference on an applied novel meta-heuristic algorithm in solving the high-complex optimization in power systems, and a clear example about integrating the renewable generating sources to the given power system.

2. Problem description

2.1. Objective function

The main objective of the whole study is to minimize the overall electricity production cost (OEPC) of all the TPPs in the given power system. The OEPC for all TPPs is determined as follows [22, 23]:

$$\underset{OEPC}{\text{Minimizing}} = \sum_{i=1}^{N_{TPPs}} \left(\theta_i + \gamma_i PG_{TG,i} + \mu_i PG_{TG,i}^2\right) \tag{1}$$

where, $OEPC$ is the overall electricity production cost of all the TPPs in the given system; θ_i, γ_i, and μ_i are the fuel coefficients corresponding to the TPP i; $P_{TG,i}$ is the amount of power generated by the TPP i; N_{TPPs} is the number of thermal generators in the system.

2.2. Fitness function

As mentioned earlier, the considered problem presented in this study will be unfolded by an optimization tool, which requires a fitness function throughout the entire solving process. In fact, the fitness function is structured by the main objective function, which is shown in Equation (1), and the penalty terms as follows:

$$FN_k = OEPC_k + \varepsilon \times PT_k \tag{2}$$

where FN_k is the fitness value of the solution k, with $k = 1, 2, \ldots, N_k$ and N_k is the number of solutions; $OEPC_k$ is the overall fuel expenditure of the $(N_{TPPs} - 1)$ TPPs belonging to the solution k; ε is the penalty factor, which is set to 10^6 specifically while solving the problem;

PT_k is the penalty term which is determined by the violation of the generating boundaries of the first TPP in the given power system.

2.3. The involved constraints

- The power balance constraints: This constraint is imposed to ensure the balance between the total amount of power supplied by all the available generating sources and the amount consumed by the load, plus the amount of loss [24]:

$$\sum_{i=1}^{N_{TPP}} PG_{TPP,i} + \sum_{w=1}^{N_{WGS}} PG_{WGS,w} + \sum_{s=1}^{N_{SGS}} PG_{SGS,s} = PG_{CS} + PG_{PL} \quad (3)$$

where $\sum_{i=1}^{N_{TPP}} PG_{TPP,i}$ is the total amount of power output generated by all the TPPs in the given power system; PG_{WGS} and PG_{SGS} are the power generated by the wind and solar generating sources; PG_{CS} and PG_{PL} are the power consumption and the power loss; N_{WGS} and N_{SGS} are, respectively the number of wind generating sources and solar generating sources.

The power loss in Equation (2) is determined using the following expression [25]:

$$P_{\text{Loss}} = \sum_{i=1}^{N_{TPP}} \sum_{\substack{l=1 \\ l\neq i}}^{N_{TPP}} PG_{TPP,i} R_{il} PG_{TPP,l} + \sum_{i=1}^{N_{TPP}} R_{0i} PG_{TPP,i} + R_{00} \quad (4)$$

where R_{il}, R_{0i}, and R_{00} are the loss coefficients.

- The operational constraints of TPPs: This constraint is applied to ensure that the power supplied by all the TGs in the given system can only change within their physical limits as designed [26, 27]:

$$PG_{TPP,i}^{\min} \leq PG_{TPP,i} \leq PG_{TPP,i}^{\max} \quad (5)$$

where $PG_{TPP,i}^{min}$ and $PG_{TPP,i}^{max}$ are the lower bound and upper bound of power output supplied by the TPP i in its physical design; $PG_{TPP,i}$ is the power generated by TPP i.

- The operational constraint of WGS and SGS: This constraint means that the amount of power supplied by these generating sources must be varied within their design capability as follows [28–30]:

$$PG_{WGS,w}^{\min} \leq PG_{WGS,w} \leq PG_{WGS,w}^{\max} \quad (6)$$

$$PG_{SGS,s}^{\min} \leq PG_{SGS,s} \leq PG_{SGS,s}^{\max} \quad (7)$$

where $PG_{WGS,w}^{\min}$ and $PG_{WGS,w}^{\max}$ are the minimum and maximum power supplied by the WGS w; $PG_{SGS,s}^{\min}$ and $PG_{SGS,s}^{\max}$ are the minimum and maximum power supplied by the SGS s; $PG_{WGS,w}$ and $PG_{SGS,s}$ are the power supplied by the WGS w and the SGS s.

3. The applied algorithms

3.1. The Greylag Goose Optimization

In this section, the Greylag Goose Optimization (GGO) [31] will be briefly introduced, focusing on the updated mechanism for generating new solutions throughout the optimization process. As stated previously, the GGO is proposed based on the flying behavior of the greylag goose. The detailed mathematical models for each behavior will be presented in the next section, which align with the exploration and exploitation principles in the search process of most meta-heuristic algorithms.

- **Stage 1: The exploration phase**

In this first stage, the update method for new solutions is executed by simulating two behaviors: moving toward the individual with the best solution and moving toward random solutions.

In some cases, if these two behaviors do not result in a clear improvement in solution quality, a secondary behavior called the "surrounding reference" will be applied. The mathematics of the two behaviors and the secondary one are presented as follows in Equation (8).

In Equation (8), $S_i^{new\_st1}$ is the newly solution i updated in Stage 1 with $i = 1, 2, \ldots, N_{pz}$ and N_{pz} is the population size; AF is the amplifying factor; δ is the gaining term; S_{GB} is the best solution of the population; S_i is the current solution i; Rf is the reference factor; γ_1, γ_2, γ_3, and γ_4 are the multiplying operators and their values are varied within $[0, 2]$ according to the authors; sp is the spiral coefficient; cf is the random value within $[-1, 1]$; rn_1 and rn_2 are the random values between zero and one.

- **Stage 2: The exploitation phase**

In this stage, the update method for new solutions is based on the references of the pathfinder solutions, which are denoted as follows:

$$S_i^{new\_st2} = \frac{X_1 + X_2 + X_3}{3} \tag{9}$$

With

$$X_1 = X_{ph1} - RAF_1 \times |G_1 \times X_{ph1} - S_i| \tag{10}$$

$$X_2 = X_{ph2} - RAF_2 \times |G_1 \times X_{ph2} - S_i| \tag{11}$$

$$X_3 = X_{ph3} - RAF_3 \times |G_1 \times X_{ph3} - S_i| \tag{12}$$

In Equations (9)–(11), $S_i^{new\_st2}$ is the newly updated solution i in Stage 2; X_1, X_2, and X_3 are the three unguided solutions that will be led by the three pathfinder solutions which are X_{ph1}, X_{ph2}, and X_{ph3}; RAF_1, RAF_2, and RAF_3 are the reference amplifying factors corresponding to X_{ph1}, X_{ph2}, and X_{ph3}; G_1 is the constant gain term.

3.2. The Elk Herd Optimizer

As mentioned earlier, the elk herd optimizer (EHO) [32] is proposed based on the breeding practice of the elk herd species. According to the author, the execution of the breeding practice consists of two stages, and the simulation of these two stages is also the main foundation of the update procedure for new solutions. The following contents will give the details of each stage:

- **Stage 1: The foundation of the sub-families**

In this stage, EHO focuses on creating the sub-families in the initial population. Particularly, the number of sub-families is determined by the rate of lead solutions and the initial population. For each newly created sub-family, a high-quality solution based on its value will be designated as the lead for a specific family, and the number of members is determined by how well the lead solution compares to the other leads. The high quality of the lead solution will attract more members to join in. The determination of the lead solutions or sub-families and the ranking of the lead solutions compared to other leads will be presented as follows:

$$L = R_L \times N_{pz} \tag{13}$$

$$R_{FN,k} = \frac{FN(X_k)}{\sum_k^{N_{Sfa}} X_k} \tag{14}$$

where L is the number of the lead solutions which will lead a family in the initial population; N_{Sfa} is the number of the sub-families allowed to exist in the initial population; R_L is the rate of lead solutions in the search space; $R_{FN,k}$ is the ranking of the fitness value belonging to solution k compared to the others in the group of lead solutions.

- **Stage 2: The foundation of the new generation**

In this stage, the new solutions are updated based on two methods, including: 1) the correspondence with a lead solution, which is selected from a smaller group with high-quality solutions, and 2) the correspondence to both a lead and a

$$S_i^{new\_st1} = \begin{cases} S_{GB} - AF \times (\delta \times S_{GB} - S_i), & Rf < 0.5 \text{ and } |AF| < 1, \\ \gamma_1 \times S_{R1} + \sigma \times \gamma_2 \times (S_{R2} - S_{R3}) & \\ \quad +(1-\sigma) \times \gamma_3 \times (S_i - S_{R1}), & Rf < 0.5 \text{ and } |AF| \geq 1, \\ \gamma_4 \times S_i \times e^{sp \times cf} \times \cos(2\pi l) & \\ \quad +[2 \times \gamma_4 \times (rn_1 + rn_2) \times S_{GB}], & \text{otherwise.} \end{cases} \tag{8}$$

random solution, which is randomly picked from the current population. The following equations give the mathematical expression of these two methods:

$$X_i^{new} = \begin{cases} X_i + \tau \times \left(X_i^{Rb1} - X_i\right), & \text{if } i \in L, \\ X_i + \theta \times \left(X_i^{Re} - X_i\right) & \\ \quad +\mu \times \left(X_i^{Rb2} - X_i\right), & \text{otherwise} \end{cases} \tag{15}$$

With

$$X_l^{Rb1},\ X_l^{Rb2} \in L \tag{16}$$

where X_i^{new} is the newly updated solution i; X_l^{Rb1} and X_l^{Rb2} are the two solutions belonging to the group of lead solutions and $X_l^{Rb1} \neq X_l^{Rb2}$; X_i^{Re} is the random solution selected from the initial population; τ is the amplifying term; θ and μ are the two random values within $[0, 2]$.

3.3. The implementation of GGO and EHO to the considered problem

This section will provide details of the entire process of implementing GGO and EHO, as mentioned earlier, to resolve the considered problem. Particularly, all the steps of the entire implementation process of these two algorithms will be presented as follows:

- ***Step 1***: Set up the control parameters such as the population size (N_{pz}) and the highest number of iterations (HI).
- ***Step 2***: Clarify the upper and lower boundaries of all the desired variables, and the dimensions of the considered problem.
- ***Step 3***: Generate the population based on the data provided by ***Step 1*** and ***Step 2*** above.
- ***Step 4***: Calculate the fitness value for each individual (solution) of the population.
- ***Step 5***: Perform the first evaluation on the quality of each solution based on its fitness value determined in ***Step 4***.
- ***Step 6***: Set the current iteration (CI) by 1.
- ***Step 7***: Perform solution update to all the solutions generated in ***Step 3***.
  - For GGO, this Step is executed using Equations (8) and (9).
  - For EHO, this Step is executed using Equations (13)–(15).
- ***Step 8***: Perform the boundary check on all the solutions that have been newly produced in ***Step 6*** to ensure their legality and that they still locate within the allowed ranges of the search space specified in ***Step 2***.
- ***Step 9***: Calculate the new fitness values for all the new solutions.
- ***Step 10***: Evaluate the solution quality of the new solutions based on their new fitness values determined in ***Step 8***.
- ***Step 11***: Perform the refining procedure to retain the high-quality solutions and abandon the low-quality ones based on the comparison of their new fitness values with the old ones.
- ***Step 12***: Check the terminating condition. This Step is executed as follows:

  If $CI = HI$

  Stop the whole searching process and export the optimal solution,

  Else

  Increase CI by one and go back to

Step 3
End.

4. Simulation results and discussion

In this section, EHO and GGO are applied to solve the GE-ELD on a power system consisting of 20 thermal power plants, along with a 200 MW SGS and a 350 MW WGS. The entire system is designed to meet a total load demand of 2600 MW, plus power loss. Both GGO and EHO are preset by the same operational parameters, including the initial population size (N_{ps}) and the highest number of iterations (HI). Actually, these two parameters are set to 20 and 200, respectively. Additionally, GGO and EHO are operated for 50 trial runs to determine the best solution for a comprehensive comparison.

Figure 1 displays the OEPCs achieved by GGO and EHO after 50 trial runs. In the figure, GGO exhibits a high fluctuation of OEPCs across all test runs compared to EHO, which offers greater stability throughout the entire test runs. Additionally, EHO is the only algorithm that reaches the optimal value of OEPCs, while GGO cannot.

Figure 2 presents the convergences achieved by GGO and EHO for their best runs, including (a) the minimum, (b) the mean, and (c) the maximum convergences. The observation of these three subfigures indicates that EHO completely outperforms GGO in terms of reaching the optimal OEPC for each consideration and convergence speed.

Figure 3 presents the details regarding the superiority of EHO over GGO using three different criteria: the minimum OEPC (Min_OEPC), the mean OEPC (Mean_OEPC), and the maximum OEPC (Max_OEPC). In the figures, all the OEPC values obtained by EHO are clearly superior to those of GGO. Particularly, EHO can save \$20.05/h over GGO on the first criterion, \$65.51/h and \$125.48/h for the second and last criteria, respectively. Note that the OEPC values presented for each comparison criterion are for one operational hour; hence, the savings offered by EHO will be a large number if considered in the larger operational schedule.

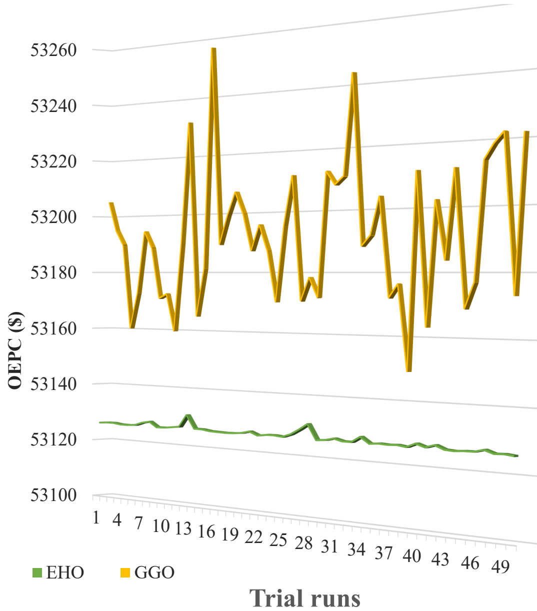

Figure 1: The results after 50 trial runs of EHO and GGO.

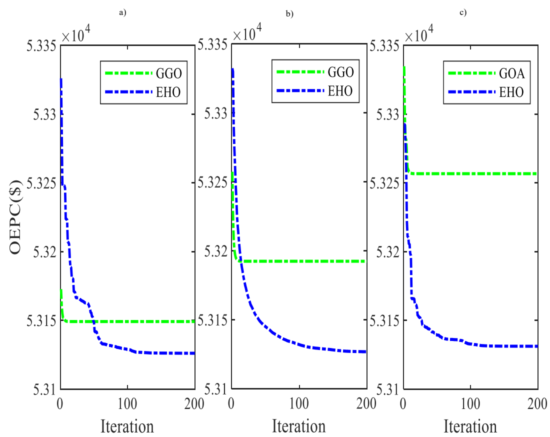

Figure 2: a) The minimum, b) mean, and c) maximum convergences obtained by the GGO and EHO for best run.

Figure 4 and Figure 5 show the power output and the electricity production cost (EPC) of each TPP in the entire system in two cases: (1) the optimal power output and (2) the maximum power output obtained by GGO and EHO. In the figure, the EPC values for each TPP in the two cases that both SGS and WGS are absent are also clarified. Clearly, all the power output values obtained by GGO and EHO satisfy the

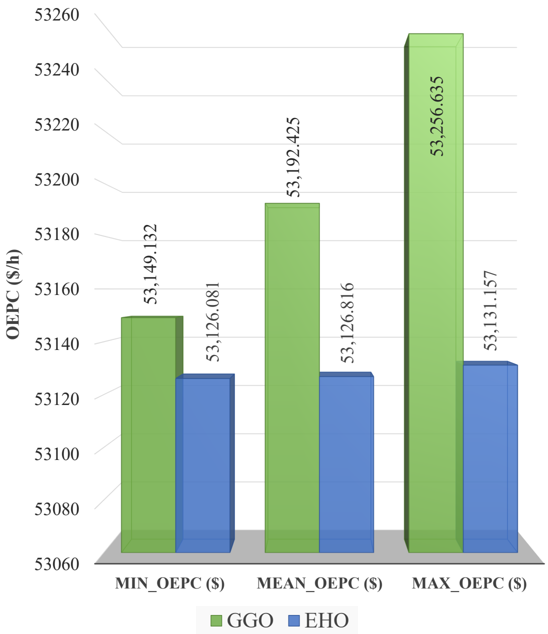

Figure 3: The qualitative comparison of the results obtained by GGO and EHO.

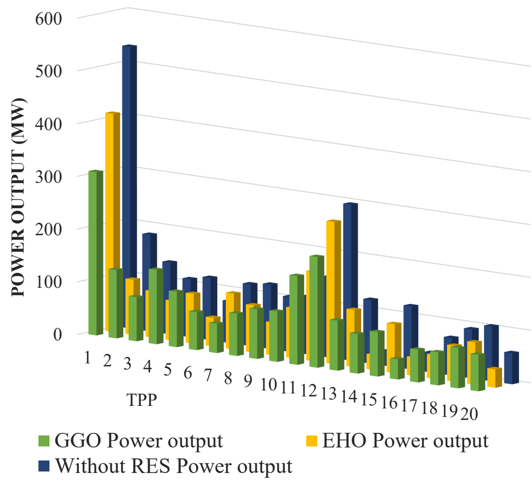

Figure 5: The maximum power output for each TPPs in the system and their corresponding EPC obtained by GGO and EHO.

operational constraints of TPPs as presented in Table 1. It is very clear to observe that the presence of SGS and WGS has noticeably reduced the power output of each TPP.

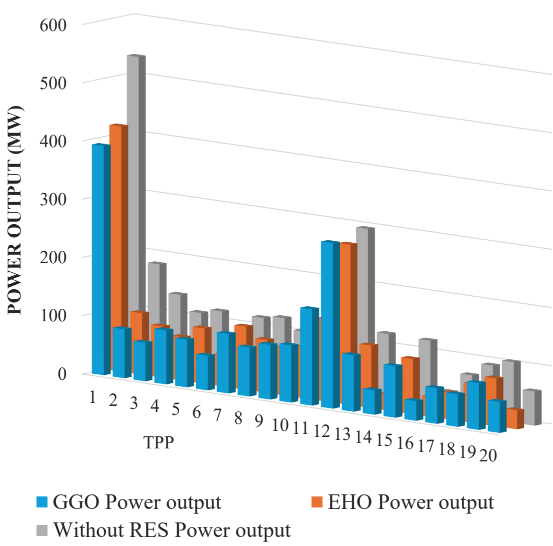

Figure 4: The optimal power output for each TPPs in the system and their corresponding EPC obtained by GGO and EHO.

Figure 6 and Figure 7 show the minimum and maximum EPC values of each TPP obtained by GGO and EHO. Besides, the EPC values for each TPP in the original case, where SGS and WGS are not integrated into the system and the optimization algorithms are not applied, are also displayed one by one for comparison. It is very clear to observe that the presence of both SGS and WGS and the implementation of GGO and EHO have brought an apparent reduction of the EPC at TPPs compared to the case that is not. Additionally, the implementation of EHO in Figure 6 has resulted in lower EPC values at TPPs with higher costs than GGO, such as TPPs 4, 6, 9, 10, 11, 12, 14, 17, and 20. Moreover, EHO also offers lower EPC values at TPPs 2, 4, 6, 9, 14, 17, and 20 for the case with maximum EPC presented in Figure 7. These lower-cost values largely contribute to the OEPC of the entire system.

Figure 8 and Figure 9 present the savings of minimum and maximum savings EPC values obtained by GGO and EHO compared to the original case without SGS and WGS. In Figure 8, the savings costs for each TPP are determined by the difference between the EPCs obtained by GGO and EHO for that TPP relative to the original case. Besides, Figure 8 shows that GGO offers higher saving EPC values than EHO at

Table 1: The minimum and maximum power output of all TPPs in the considered power system.

No.	Minimum power output (MW)	Maximum power output (MW)	No.	Minimum power output (MW)	Maximum power output (MW)
TPP1	150	600	TPP11	100	300
TPP2	50	200	TPP12	150	500
TPP3	50	200	TPP13	40	160
TPP4	50	200	TPP14	20	130
TPP5	50	160	TPP15	25	185
TPP6	20	100	TPP16	20	80
TPP7	25	125	TPP17	30	85
TPP8	50	150	TPP18	30	120
TPP9	50	200	TPP19	40	120
TPP10	30	150	TPP20	30	100

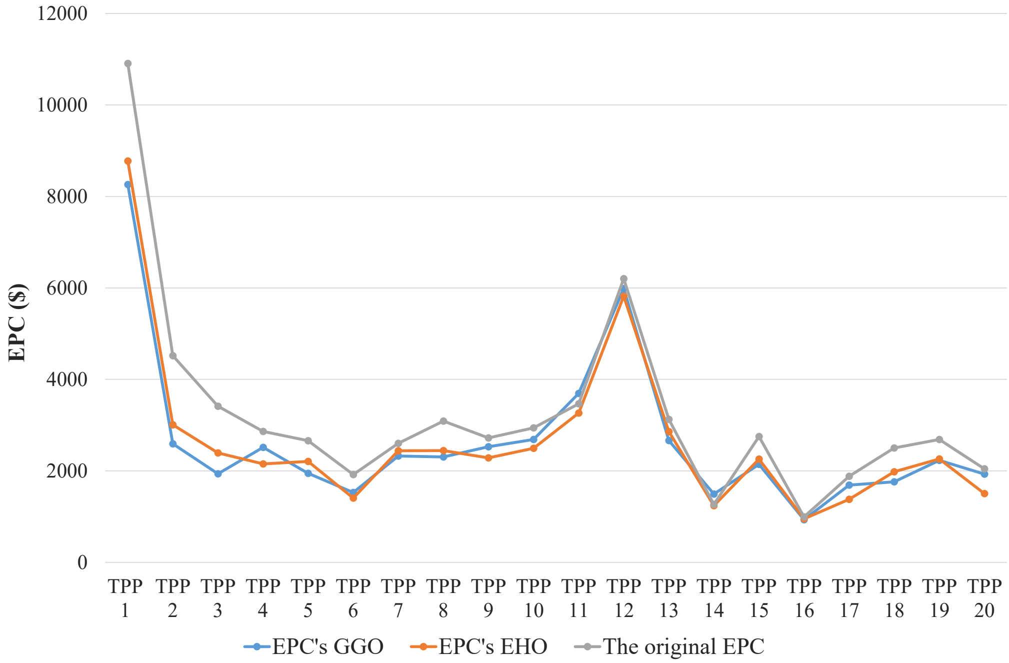

Figure 6: The minimum EPC values of the 20 TPP in the considered power system given by GGO, EHO, compared to the original case.

several TPPs; however, GGO fails to establish a positive savings EPC at TPPs 11 and 14. Furthermore, GGO has to suffer more negative EPC values at TPPs 4, 11, 14, and 20 as seen in Figure 9 for maximum saving EPC. Those negative saving EPC values at the mentioned TPPs, combined with lower saving EPC values from the remaining TPPs, have resulted in a lower overall OEPC for GGO compared to EHO, which does not suffer any negative EPC.

5. Conclusions

In this study, the two novel meta-heuristic algorithms, including Greylag Goose Optimization (GGO) and the Elk herd optimizer (EHO), have been successfully applied to solve the green economic load dispatch (GELD) with the primary objective function of reducing the overall electricity production cost (OEPC) to a 20-TPP power system incorporating renewable energy sources. The entire system is designed to supply

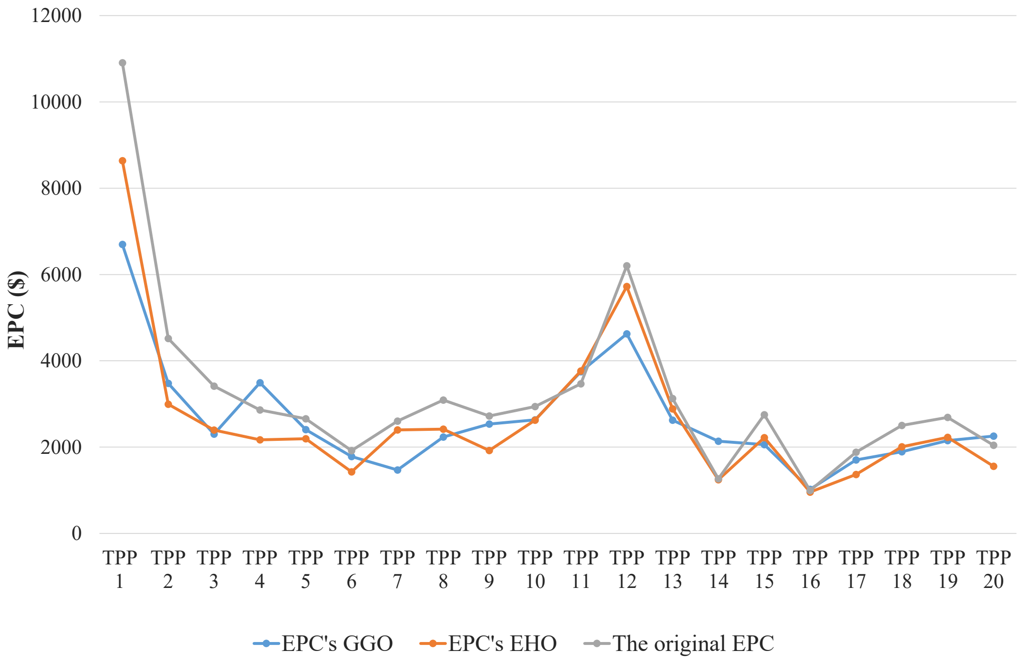

Figure 7: The maximum EPC values of the 20 TPP in the considered power system given by GGO, EHO, compared to the original case.

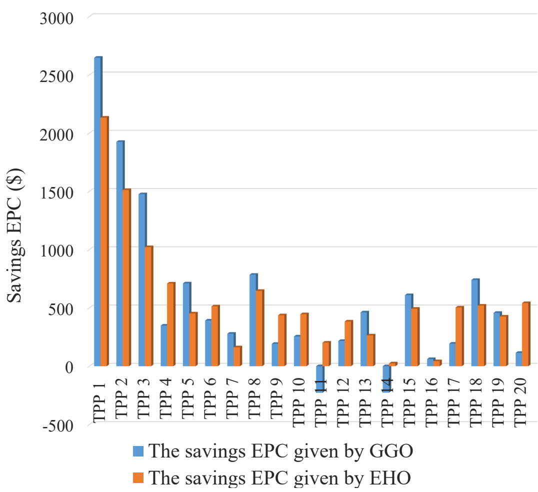

Figure 8: The minimum saving EPC values obtained by GGO and EHO over the original case.

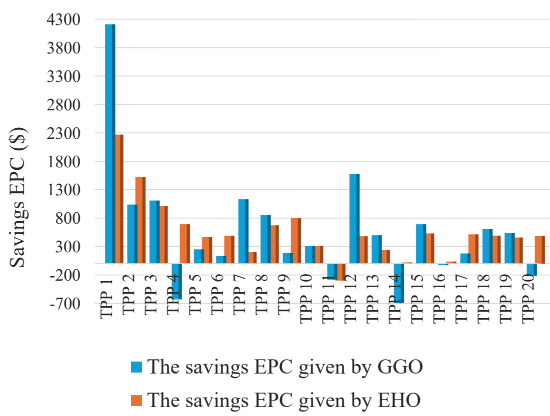

Figure 9: The maximum saving EPC values obtained by GGO and EHO over the original case.

power to meet the load demand of 2600 MW, with power loss also taken into account. The results indicate that EHO completely outperforms GGO in all comparison criteria, such as stability and standard deviation after 50 trial runs, as well as faster convergence speed to the optimal values of OEPC in three aspects: minimum, mean, and maximum criteria. As a result, EHO showed clear savings in OEPC for each mentioned aspect, with a minimum OEPC of \$20.50/h, a mean OEPC of \$65.51/h, and a maximum OEPC of \$125.48/h. Therefore, EHO is considered an effective search algorithm, and it is highly recommended for use in determining the best solution to GELD problems on large-scale power systems. Furthermore, the contribution of solar and wind generation sources to the electricity production cost of each TPP is also clarified. In the future, EHO can be modified for better search performance in dealing with a large-scale power system with hundreds of generating sources, including renewable and non-renewable ones. Additionally, more complex constraints will be introduced, requiring a robust and reliable search tool.

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