International Journal of Applied Power Engineering (IJAPE)
Vol. 15, No. 1, March 2026, pp. 430~439
ISSN: 2252-8792, DOI: 10.11591/ijape.v15.i1.pp430-439

Elk herd optimizer for cost-efficient hybrid energy systems under renewable uncertainty

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Article Info

Article history:

Received Jul 11, 2025
Revised Dec 2, 2025
Accepted Jan 9, 2026

Keywords:

Elk herd optimizer
Hydropower plant
Solar power plant
Thermal power plant
Wind power plant

ABSTRACT

This paper suggests a new method, called elk herd optimizer (EHO), for effectively addressing the optimal generation cooperation problem involving thermal, hydro, solar, and wind power plants (WPPs), in which the uncertainty of wind speed and solar radiation from renewable power plants is considered. The primary goal of this study is to minimize the costs from thermal, wind, and solar power plants (SPPs) while adhering to all operational constraints associated with these power plants and the overall power system. Two systems were tested to evaluate the performance of EHO method alongside two other techniques: the coot optimization algorithm (COOT) and the tunicate swarm algorithm (TSA). Both systems were optimally scheduled over a 24-hour period; however, the second system accounted for uncertainties in generation and cost from solar and WPPs. From the result analysis, EHO method was able to achieve a lower cost compared to COOT, TSA, and other previously employed methods for optimizing generation across all plants. Therefore, EHO is recommended as an effective optimization tool for addressing the uncertainties associated with solar radiation and wind speed.

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NOMENCLATURE

a_d, a_p, and a_r	: Price coefficients for three costs of *WPP*
A_s and A_{std}	: Solar radiation and standard solar radiation of *SPP*
a_t, b_t, c_t, e_t, and d_t,	: The fuel cost coefficients for *TPP*
b_d, b_p, and b_r	: Price coefficients for three costs of *SPP*
c_w and k_w	: The scale and shape factors of WPP
m_h, n_h, and l_h	: Discharge coefficients of *HPP*
$P_{h,min}$ and $P_{h,max}$	: Lower and upper power outputs of *HPP*
$P_{s,min}$ and $P_{s,max}$	: Lower and upper power outputs of *SPP*
$P_{t,min}$ and $P_{t,max}$	: Lower and upper power outputs of *TPP*
$P_{w,min}$ and $P_{w,max}$	: Lower and upper power outputs of *WPP*

1. INTRODUCTION

In contemporary power systems, effectively dispatching available power resources to meet the increasing demand is crucial for improving economic efficiency. Hydro energy sources offer a great opportunity for integration with thermal power plants (TPPs). By utilizing hydro energy, we can achieve cleaner and more environmentally friendly energy operations while also addressing important needs like flood control and irrigation. Therefore, effective generation scheduling in a hydro-thermal system plays a vital role in enhancing the efficiency of electric power utility systems. Given the non-operational costs associated with hydro power plants (HPPs), the focus shifts to optimizing the fuel costs for TPPs [1]. The hydro-thermal scheduling (HTS) problem has been a focus of research for many decades, leading to the development of various effective techniques. HTS problems are considered as long-term and short-term HTS problems, which is based on the scheduling of the optimization period [2]. For solving the short-term HTS scheduling (SHTS) problem, a variety of classical techniques can effectively address this problem, including mixed integer programming, gradient search techniques, decomposition and coordination methods, and Newton's method. However, these methods face challenges due to the complex problem and multiple constraints, they also open the door to new possibilities and innovative solutions. The emergence of meta-heuristic methods highlights the potential of technology-driven approaches to tackle the challenges present in real-world problems. These methods were efficient method (EM) [3], genetic algorithm (GA) and modified GA (MGA) [4], cuckoo search algorithm (CSA) [5], self-adaptive GA [6], backtracking search (BA) [7], slime mould algorithm (SMA) [8], clustered adaptive teaching-learning-based optimization (CATLBO) algorithm [9], hybrid bat algorithm with an artificial bee colony (BA-ABC) [10], non-dominated sorting particle swarm optimization (NSPSO) [11], improved teaching-learning-based optimization (ITBLO) [12] and a non-dominated sorting disruption-based oppositional gravitational search algorithm (NSDOGSA) [13]. Among methods, NSDOGSA was suggested by Nadakuditi *et al.* [13] in 2023. This method represents a significant advancement in optimization algorithms, particularly for complex multi-objective problems in energy scheduling. Its combination of nondominated sorting, oppositional learning, and disruption strategies makes it a powerful tool for researchers and practitioners in the field. In general, the mentioned studies focus on dealing with the fuel cost and not considering the heat and emission generation of TPPs [14], [15].

Wind and solar power are clean energy sources that offer a promising solution to meet energy demands in a cost-effective manner while generating no harmful emissions. Given these significant benefits, many researchers are actively exploring the challenges of integrating renewable energy sources like wind and solar with traditional power plants [16]. Damodaran and Kumar [17] described four methods, including GA, PSO, harmony search (HS), and JAYA algorithms are applied for searching solution to hydro-thermal-wind generation scheduling (HTWGS) considering economic and emission factors. Similar to study in [17], Pham *et al.* [18] have integrated wind energy into traditional hydrothermal power system to minimize the cost of TPPs by the use of improved CSA (ICSA). The authors of [19]-[22] have considered wind and solar energies as alternative sources to reduce fuel costs from TPPs. In these studies, the uncertainty and certainty of wind speed and solar irradiation are investigated. For the certainty case, the power output of renewable energy sources can be calculated as [22]. For another, wind speed and solar irradiation are modeled by using probability density functions (PDF) such as Weibull, Beta, and Lognormal ones. In the above studies, data on renewable energy resources were cited by previous research and not chosen from specific locations for installing plants. In addition, according to the No Free Lunch theorem, no single optimization approach is optimal for every potential issue. Clearly, these are the opportunities for researchers to continue the deep exploration.

In the paper, the HTS problem with the existence of wind and solar energies, called WSHTS problem, will be solved, taking uncertain costs like direct, penalty, and reserve costs into account by the application of elk herd optimizer (EHO) [23]. In addition to EHO, the coot optimization algorithm (COOT) proposed by Qin *et al.* [24] in 2022 and tunicate swarm algorithm (TSA) proposed by Kaur *et al.* [25] in 2020 are applied to get results for comparison. Here are some contributions:

i) It formulates a robust optimal scheduling problem specifically designed for a new complex integration structure that incorporates four distinct types of power plants.
ii) It identifies and selects suitable decision variables tailored for the methodologies employed in the analysis.
iii) It conducts a thorough evaluation of the performance of EHO, COOT, and TSA, providing valuable insights into their effectiveness.
iv) It thoughtfully considers the uncertainties associated with solar radiation, thereby improving the reliability of the scheduling solutions.

The rest of the paper is constructed as follows: Section 2 shows problem formulation. Section 3 presents the structure of the applied method. Section 4 discusses and analyzes the results obtained by the methods. Finally, section 5 gives a conclusion and future research.

2. PROBLEM FORMULATION

2.1. The objective function

To supply electricity to urban consumers, commercial centers, and industrial zones, a wind-solar-hydrothermal power system is designed. This system includes TPPs, hydroelectric power plants (HPPs), wind power plants (WPPs), and solar power plants (SPPs), all scheduled for optimization during specific periods. Since hydro power plants have zero fuel costs, the main goal is to minimize the costs (FC) of TPPs, WPPs, and SPPs. The objective is indicated in (1).

$$FC = \sum_{p=1}^{24}\{f(P_t) + f(P_w) + f(P_s)\} \quad (1)$$

Where, $f(P_t)$, $f(P_w)$, and $f(P_s)$ are the costs of N_t thermal power plants, N_w wind power plants, and N_s solar power plants.

The fuel cost function for the tth TPP is represented over 24 intervals as (2).

$$f(P_t)=\sum_{t=1}^{N_t}\left(a_t+b_tP_t+c_t(P_t)^2+\left|d_t\times sin\left(e_t\times\left(P_{t,min}-P_t\right)\right)\right|\right) \quad (2)$$

The total operating cost of a *WPP* includes three components: direct cost (C_{dwpp}), penalty cost (C_{pwpp}) for underestimating power production (when planned power is less than actual output), and reserve cost (C_{rwpp}) for overestimating production (when planned power exceeds actual output) as given by (3) [26].

$$f(P_w) = \sum_{w=1}^{N_w}\left(C_{dwpp} + C_{pwpp} + C_{rwpp}\right) \quad (3)$$

$$C_{dwpp}=a_d.P_w;\ \ C_{pwpp}= a_p.\int_{P_w}^{P_{wr}}(p-P_w).f_w(p).dp;\ \ C_{rwpp}= a_r.\ \int_0^{P_w}(P_w-p).f_w(p).dp \quad (4)$$

In (4), P_{wr} is the rated power output of the *wth WPP*; $f_w(p)$ indicates the probability density function. Similar to *WPP*, the total operating cost of SPP is presented under direct cost (C_{dspp}), penalty cost (C_{pwpp}), and reserve cost (C_{rwpp}) as shown in (5).

$$f(P_s) = \sum_{s=1}^{N_s}\left(C_{dspp} + C_{pspp} + C_{rspp}\right) \quad (5)$$

$$C_{dspp}=b_d.P_s;\ C_{pspp}= b_p.\int_{P_s}^{P_{sr}}(p-P_s).f_s(p).dp;\ C_{rspp}= b_r.\ \int_0^{P_s}(P_s-p).f_s(p).dp \quad (6)$$

In (6), P_{sr} is the rated power output of the *sth SPP*; $f_s(p)$ indicates the probability density function.

2.2. The constraints

Power system balance constraint: Power generated by plants must match load demand (P_d) plus transmission line losses (P_l), as stated in (7) [21].

$$\sum_{t=1}^{N_t}P_{t,p} + \sum_{h=1}^{N_h}P_{h,p} + \sum_{w=1}^{N_w}P_{w,p} + \sum_{s=1}^{N_s}P_{s,p} - P_{l,p} - P_{d,p} = 0;\ \ p = 1, \ldots, 24 \quad (7)$$

Where, P_t, P_h, P_w, and P_s are power outputs of the *tth* thermal power plant, the *hth* hydroelectric power plants, the *wth* wind power plant, and the *sth* solar power plant, respectively.

Discharge constraint: The water discharge of the *hth HPP* (wQ_h) through turbines used for electricity generation is limited to specific parameters (i.e., lower water discharge ($wQ_{h,\ min}$) and upper water discharge ($wQ_{h,\ max}$)) as (8).

$$wQ_{h,min} \le wQ_h \le wQ_{h,max} \quad (8)$$

Where, wQ_h indicates a quadratic function as defined by (9).

$$wQ_h=m_h+n_hP_h+l_hP_h^2 \quad (9)$$

Water availability constraint: The total water discharge across the 24 intervals must be precisely matched to the available amount ($WV_{h,av}$) as specified by (10).

$$\sum_{p=1}^{24}wQ_{h,p}=WV_{h,avai}\ ;p=1,\ \ldots,\ 24 \quad (10)$$

Power generation limits: Power generation from *TPPs*, *HPPs*, *WPPs,* and *SPPs* must adhere strictly to their established capacity limits.

$$P_{t,min} \leq P_t \leq P_{t,max};\ P_{h,min} \leq P_h \leq P_{h,max} \tag{11}$$

$$P_{w,min} \leq P_w \leq P_{w,max};\ P_{s,min} \leq P_s \leq P_{s,max} \tag{12}$$

2.3. Solar uncertainties modeling

To effectively assess the uncertainty of solar irradiance, it is advisable to utilize a lognormal probability distribution (PDF) as shown in (13).

$$PDF\ (A_s) = \left(\frac{1}{A_s.\ \tau.\sqrt{(2.\pi)}} \right) \times exp\ . \left[- \frac{(ln(A_s)\text{-}\varphi)^2}{2.\tau^2} \right] with\ A_s > 0 \tag{13}$$

Where, τ and φ are the scale and location parameters. When solar irradiance is a known factor, we can determine the power output of *SPP* by applying the principles of energy conservation related to solar radiation as in (14).

$$P_s(A_s) = \begin{cases} P_{sr} \times \frac{A_s^2}{A_{std}+R_c} & if\ 0<A_s<R_c \\ P_{sr} \times \frac{A_s}{A_{std}} & if\ A_s>R_c \end{cases} \tag{14}$$

In (14), R_c is radiation intensity in W/m^2.

2.4. Wind uncertainties modeling

To effectively assess the uncertainty of wind speed, it is advisable to utilize a Weibull probability distribution (PDF) as shown in (16).

$$\text{PDF}\ (V_w) = \left(\frac{k_w}{c_w} \right) \times \left(\frac{V_w}{c_w} \right)^{k_w\text{-}1} \times \exp\left[- \left(\frac{V_w}{c_w} \right)^{k_w} \right], \quad V_w > 0 \tag{15}$$

When wind speed is a known factor, we can determine the power output of *WPP* by applying (16).

$$P_w = \begin{cases} 0, & \left(V_w < V_{w,ci},\ V_w > V_{w,co}\right) \\ P_{wr} \times \frac{(V_w - V_{w,ci})}{(V_{wr} - V_{w,ci})}, & \left(V_{w,ci} \leq V_w \leq V_{wr}\right) \\ P_{wi,r}, & \left(V_{wr} \leq V_w \leq V_{w,co}\right) \end{cases} \tag{16}$$

In (16), V_w, V_{wr}, $V_{w,ci}$, and $V_{w,co}$ denote wind speed, rated wind speed, cut-in wind speed, and cut-out wind speed of the wth *WPP*.

3. METHOD

The elk herd optimizer (EHO) [23] is an advanced metaheuristic algorithm that draws inspiration from the natural behaviors exhibited by elk herds, particularly during the critical periods of rutting and calving. The process of EHO begins with the initialization of the population and the establishment of problem parameters. It then progresses into the rutting season, where the population is organized into families led by the strongest bulls. In the calving season, these families generate new solutions based on the characteristics of each bull and its harems. Finally, during the selection season, all solutions are assessed, and only the fittest individuals are chosen to form the next generation. The detailed steps of the EHO are presented as follows:

- Initialization: Similar to metaheuristic methods, the population (N_{pz}) of EHO is generated randomly within established parameters, ensuring variability while maintaining control within defined limits (EH^{max} and EH^{min}) as shown in (18).

$$EH_d = EH^{min} + rand \times (EH^{max} - EH^{min}), \quad d = 1,2 \ldots N_{pz} \tag{18}$$

After the initialization, the fitness f(x_d) of solutions will be calculated and sorted to find the top best solutions.

– Rutting phase: The population is divided into different families based on the number of bulls (Nb). Each family has one bull and many harems, in which the harems are assigned by applying the roulette-wheel selection as given in (19).

$$p_k = \frac{f(x_k)}{\sum f(x_k)};\ k = 1,2 \ldots, N_b \tag{19}$$

– Calving phase: New solutions called calves are generated based on the genetics of the father bull or mother harem. If the calf has genetic traits from the father bull (i.e., the index of the calf is the index of the father), the generation is created by (20). Otherwise, (21) is applied.

$$EH_d^{new} = EH_{bull} + rand \times (EH_r - EH_{bull}),\quad d = 1,2 \ldots N_{pz} \tag{20}$$

$$EH_d^{new} = EH_{harem} + rand \times (EH_{bull} - EH_{harem}) + rand \times (EH_{r,bull} - EH_{harem}),\ d = 1,2 \ldots N_{pz} \tag{21}$$

In (20) and (21), EH_r is a solution selected from the population; $EH_{r,bull}$ is a solution selected from bulls.

– Selection phase: In this phase, new solutions in the calving phase are combined to the old solutions to form a new group with 2. Npz. The fitness of each solution in the new group is calculated and sorted. From the ranked solutions in the new group, the best solution group with Npz is selected for the next iteration. For solving the WSHTS problem, the fitness function of solutions, which are initialized or updated by the method, is first established. Then, the solutions-determining mechanism of EHO is implemented by using (18)–(21). This cycle continues until the algorithm converges or reaches the predetermined iteration limit.

4. RESULTS AND DISCUSSION

The study employs EHO, COOT, and TSA methods to address the optimal generation problem for a hybrid power system. To find the ideal parameters for the problem, two test systems were used. System 1 includes hydro and thermal power plants, and System 2 consists of hydropower, thermal energy, solar power, and wind power plants. The analysis spans a 24-hour period divided into twenty-four intervals. These algorithms are programmed by MATLAB software with version 2019, and executed on a computer with 8 GB of RAM and a 2.4 GHz processor.

4.1. The simulation results for System 1

The combination operation of *TPPs* and *HPPs* to form System 1 is applied to investigate the parameters of EHO, COOT, and TSA methods based on minimum cost (*Mi.c*), average cost (*Av.c*), maximum cost (*Ma.c*), and standard deviation (ST_d). The data of System 1 is cited from [8]. Based on previous studies, three methods identify the optimal cost by examining the population size (N_{pz}), number of highest iterations (H_{iter}), and trial runs. Consequently, N_{pz} of 30 and H_{iter} of 400 are chosen for EHO, COOT, and TSA. Figure 1 shows the result of three methods across 50 independent runs, in which the curves are color-coded: black for TSA, blue for COOT, and red for EHO. From Figure 1, the curve of COOT and EHO is straightforward, while that of TSA has some high fluctuations. Out of 50 runs, we will showcase the most successful run to highlight the process of identifying the optimal solution with the lowest cost of the three methods, as illustrated in Figure 2. As seen in the figure, EHO reaches the optimal solutions faster than COOT, while TSA cannot reach the best solution. The metrics of EHO, COOT, and TSA from the best-run, such as *Mi.c*, *Av.c*, *Ma.c*, and ST_d, are collected and presented in Table 1. Observing these costs of the three applied methods, we see that the *Mi.c* of EHO is \$96024.34 and less than COOT and TSA by \$0.102 and \$64.154. Other costs of EHO are \$96024.374 and \$96024.431, compared to (\$96024.73 and \$96025.076) of COOT and (\$131366.5 and \$711421.23) of TSA. The ST_d is the smallest from EHO (0.0089), while the ST_d is the biggest from TSA (139753.87). From these analyses, EHO is more effective than COOT and TSA.

In comparison to other methods, the *Mi.c* of EHO demonstrates a notable improvement over the values declared by EM [3] (\$96024.37), GA [4] (\$96028.65), SMA [8] (\$96024.35), CSA [5] (\$96024.68), and equals MGA [4] (\$96024.34). However, MGA did not show ST_d, N_{pz}, and H_{iter}, making it difficult to conclude that the MGA method is more effective than EHO. Regarding ST_d, EHO is 0.0089, CSA [5] is 0.003, and is less than the others; however, CSA uses 1000 iterations, but others use from 200 to 400 iterations.

Table 1. Costs of three appied methods and previous methods

Method	EM [3]	GA [4]	MGA [4]	CSA [5]	SMA [8]	TSA	COOT	EHO
Mi.c ($)	96024.37	96028.65	96024.34	96024.68	96024.35	96088.49	96024.44	96024.340
Av.c ($)	-	96050.15	96024.37	96024.68	96024.46	131366.5	96024.73	96024.374
Ma.c ($)	-	96086.70	96024.42	96024.69	96024.57	711421.23	96025.076	96024.431
ST_d	-	-	-	0.003	0.036	139753.87	0.1533	0.0089
N_{pz}	-	-	-	20	50	30	30	30
H_{iter}	-	-	-	1000	200	400	400	400

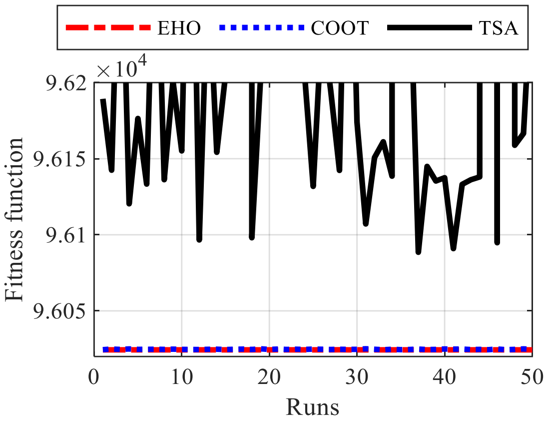

Figure 1. Results of 50 runs obtained by the methods

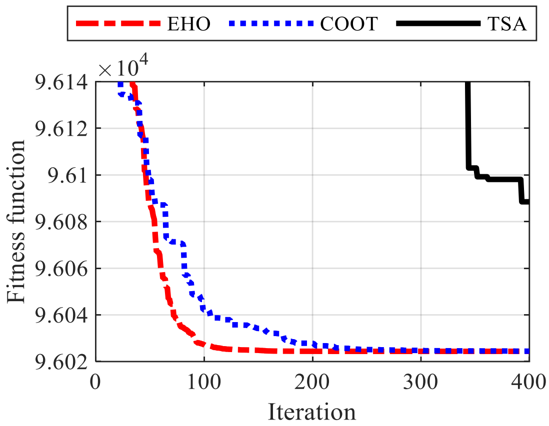

Figure 2. Convergence features obtained by the methods

4.2. The simulation results for System 2

System 2 is more complicated than System 1 because of the addition of wind and solar power plants. Where the data of *TPP* is cited from [8], and the data of *SPP* and *WPP* are cited from [27]. Furthermore, we take into account the uncertainties associated with solar radiation and wind speed. To effectively evaluate the impact of the uncertain costs of *SPP* and *WPP* on total cost of the system, direct costs, penalty costs, and reserve costs of them are added into the fuel cost of *TPP*. Therefore, three costs mentioned are vital elements of the functional objective of the problem. Like in system 1, N_{pz} and H_{iter} for executing the three methods are 30 and 400, and the results found by EHO, COOT, and TSA are shown in Table 2.

Table 2. Costs of three applied methods

Method	TSA	COOT	EHO
Mi.c ($)	71744.938	71698.131	71593.31
Av.c ($)	72350.067	72131.772	71875.253
Ma.c ($)	74144.616	73416.885	72822.814
ST_d	707.4304	365.7155	360.5618

Table 2 shows that *Mi.c*, *Av.c,* and *Ma.c* of EHO are $71593.31, $71875.253, and $72822.814, respectively, and are less than those from COOT ($71698.131, $72131.772, and $73416.885), and TSA ($71744.938, $72350.067, and $74144.616). Comparing ST_d of three methods, we see that EHO has ST_d of 360.5618 and is smaller than COOT and TSA by 5.1537 and 364.8686. Figure 3 illustrates the costs of fifty solutions achieved through EHO, COOT, and TSA methods. Cost values of the three methods also fluctuate between each run; however, EHO has the smallest fluctuation among the three. Besides, EHO has the best solutions as they are beneath those of COOT and TSA. Figure 4 shows convergence features obtained by methods, in which EHO tends to reach solutions better than COOT and TSA from 200 to the end iteration. All discussions mentioned prove that EHO has very potential in dealing with the problem with more challenges.

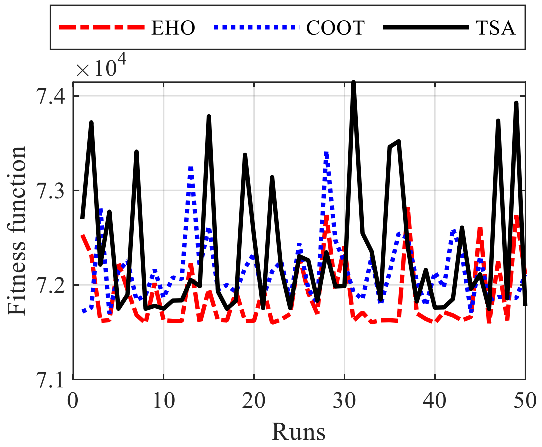

Figure 3. Results of 50 runs obtained by the methods

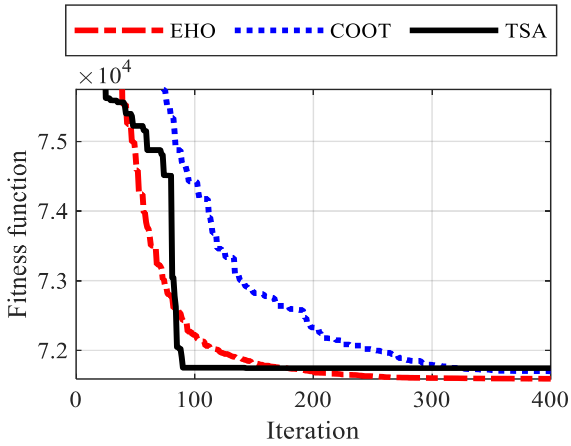

Figure 4. Convergence features obtained by the methods

4.3. Discussion on the results of the two systems

Figure 5 shows three costs of EHO for Systems 1 and 2, in which blue color bars are for System 1 and orange color bars are for System 2. As seen in the figure, *Mi.c*, *Av.c*, and *Ma.c* for System 1 are \$96024.34, \$96024.37, and \$96024.43, and these costs are less than those from System 2 by \$24431.03, \$24149.12, and \$23201.62, respectively. The cost reduction of System 2 compared to System 1 is shown to be the contribution of renewable energy resources. To meet the load demand of 13904 (MW) in 24 hours, System 1 requires two power plants to supply 5928.08 (MW) for *HPP* and 8398.25 (MW) for *TPP*, with a power loss of 422.33 (MW) as presented in Table 3. With the same load demand, System 2 requires power plants to supply 5929.78 (MW) for *HPP*, 5284.78 (MW) for *TPP*, 989.04 (MW) for *SPP*, and 2012.38 (MW) for *WPP,* with a power loss of 311.98 (MW).

Table 3. Contribution power output of power plants vs load demand and power loss

System	P_d (MW)	P_h (MW)	P_t (MW)	P_s (MW)	P_w (MW)	P_l (MW)
1	13904	5928.08	8398.25	N/A	N/A	422.33
2	13904	5929.78	5284.78	989.04	2012.38	311.98

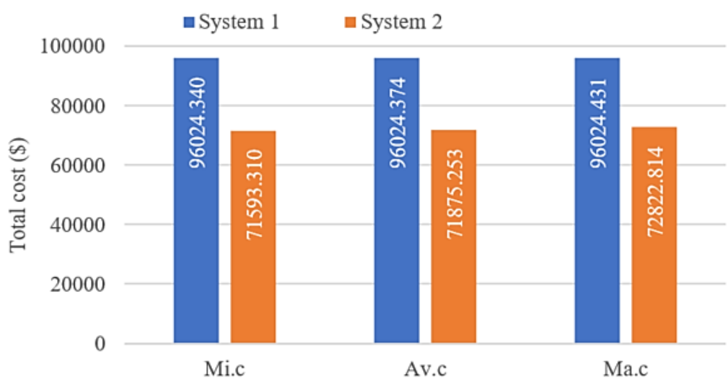

Figure 5. Costs of EHO to Systems 1 and 2

Figures 6 and 7 show the distribution of power output generated by various power plants across each hour in 24 intervals as indicated by EHO. In the figures, the power outputs from *HPP*, *TPP*, *SPP*, and *WPP* are represented by different colored bars. From analyses, it can be seen that the presence of renewable energy resources plays an important role in reducing the fuel cost of TPP, leading to significant cost savings for the system.

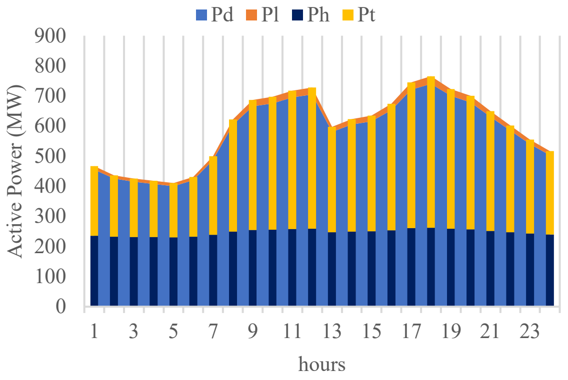

Figure 6. Optimal obtained by EHO for System 1

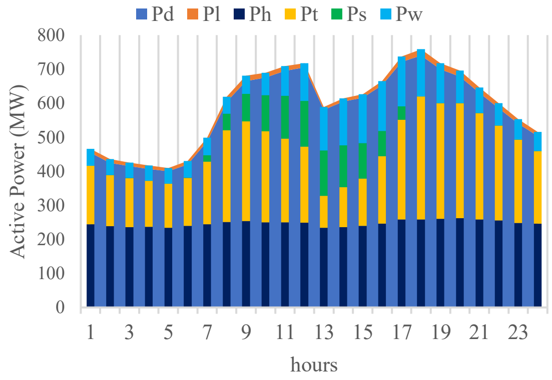

Figure 7. Optimal obtained by EHO for System 2

5. CONCLUSION

This paper explores some exciting optimization method specifically the elk herd optimizer, coot optimization algorithm, and tunicate swarm algorithm, to find the best operational parameters for various types of power plants, including thermal, hydro, wind, and solar. These methods are investigated on two different systems. The second system builds on the first one, making things a bit more challenging by including *SPP*, *WPP*, and the uncertainties that come with solar radiation and wind speed. The results from systems 1 and 2 show that the EHO method outperforms the other applied methods because the minimum, average, maximum costs, and standard deviation from the EHO method are all superior to those of COOT and TSA. Additionally, EHO surpasses nearly all previously published optimization methods. EHO has shown great potential in optimizing electricity generation costs from both thermal and renewable power plants while adhering to all system and generator constraints. In the future, the problem will be resolved by considering a large-scale system with the presence of renewable energy resource located in Vietnam. In addition, set of solution for the problem will be investigated.

ACKNOWLEDGMENTS

We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [HDN], upon reasonable request.

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