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Research Article

Maximize the total electric sale profit for a hybrid power plant with fifteen thermal units and a 100-MW solar photovoltaic farm under a 20-year power generation project

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Abstract. This study investigates the effectiveness of two recently proposed meta-heuristic methods, the Weighted Average Algorithm (WAA) and Electric Eel Foraging Optimization (EEFO), to maximize the total profit of a hybrid power system. The considered system comprises fifteen thermal generating units (TGUs) and a 100-MW solar photovoltaic farm (SPP) operating over a 20-year period. Initially, the problem is solved under conditions of fixed load demand and rated power supply from the renewable energy source while accounting for prohibited operating zone constraint and system power losses. Comparative results obtained from both algorithms demonstrate that EEFO exhibits superior performance in terms of stability and convergence speed. Specifically, EEFO demonstrates a lower fluctuation in overall electricity generation cost (OEGC) across multiple independent runs compared to WAA. Furthermore, EEFO achieves better minimum, mean, and maximum OEGC values of \$0.266, \$58.890, and \$214.225, respectively. Subsequently, EEFO is reapplied to maximize the profit of the hybrid power system, incorporating load demand variations and real solar radiation data. This analysis includes the evaluation of initial capital expenditure (CAPEX) and operation and maintenance (O&M) costs for the SPP over the 20-year period. Current electricity and solar power prices are utilized to illustrate the cumulative profit over time. The results indicate that the hybrid system experienced the highest loss in the first year, with the minimum loss occurring after 9 years for the TGUs and 7 years for the SPP. Profitability is achieved after 10 years for the TGUs and 7 years for the SPP. The cumulative profit over 20 years amounts to \$14.2 billion for the TGUs and \$0.207 billion for the SPP, representing approximately 83% and 127% of their respective total costs.

Keywords: Economic load dispatch, thermal power plants, prohibited operating zones, fuel cost, total revenue, total profit.



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1. Introduction

Resolving the economic load dispatch (ELD) problem remains one of the first concerns in operational problems in power (Nguyen & Vo, 2015). The process of solving the ELD problem involves optimizing the power output of all thermal generating units (TGUs) in the system to achieve the target, which is minimizing the overall electricity generation cost (OEGC) in most cases (Dasgupta & Banerjee, 2014). Solving the ELD problem not only benefits the engineering aspects but also reduces the negative effects on the environment (Wu *et al.*, 2010). In the past, TGUs were in charge of the main generating sources in solving the ELD problem; however, clean energies, including solar and wind power, recently have been integrated more and more into the power system, and they also proved their role in partly reducing the use of conventional TGUs which consumed fossil fuel and caused toxic emissions. Based on that, the ELD problem has been modified to clean energies economic load dispatch (CE-ELD) (Kherfane *et al.*, 2014; Farag *et al.*, 1995; Reddy & Bijwe, 2015) with the integration of solar and wind energy for most cases.

By realizing the key role of solving ELD and its modern version, CE-ELD, much research has been conducted to unfold the problem. Moreover, while the scale of both ELD and CE-

ELD become larger and more complicated because of the consideration of constraints, meta-heuristic algorithms are acknowledged to be the most suitable computing tool for solving the mentioned problems. Specifically, the application particular meta-heuristic algorithm can be listed such as Squirrel search optimizer (SSO) (Suman *et al.*, 2020), Modified equilibrium algorithms (MEA) (Duong *et al.*, 2021), The Enhanced Firefly optimization algorithm (IFA) (Nguyen *et al.*, 2018), Double-weighted particle swarm optimization (DW-PSO) (Kheshti *et al.*, 2018), the Artificial algae algorithm (AAA) (Kumar & Dhillon, 2018), Improved bacterial foraging algorithm (IBFA) (Pandit *et al.*, 2012), search and rescue algorithm (SRA) (Said *et al.*, 2022), biogeography-based optimization (BBO) (Xiong & Shi, 2018), High-Performance Stochastic Fractal Search Algorithm (Pham *et al.*, 2019), Harmonic search algorithm (Fesanghary & Ardehali, 2009), Equilibrium optimizer (EO) (Duong *et al.*, 2021), Salp swarm optimization (SWO) (Alkoffash *et al.*, 2021), the Improved Jaya algorithm (Chen *et al.*, 2020), Modified moth swarm algorithm (MMSA) (Ha *et al.*, 2020), The enhanced Manta ray optimization algorithm (IMROA) (Hassan *et al.*, 2021), Ameliorated dragonfly algorithm (ADA) (Suresh *et al.*, 2019), Grey wolf optimal (GWO) (Pradhan *et al.*, 2016), Fire hawk optimization (FHO) (Tang & Cuong,

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Table 1
The summary of previous studies solving the ELD problem.

Reference	Applied method	Power sources			Objective function	
		Thermal	Wind	solar	Cost	Emission
(Mokarram <i>et al.</i> , 2019)	HOA	x	x	x	x	
(Zhang <i>et al.</i> , 2021)	MSPSO	x		x	x	
(Salim & Abdullah, 2022)	FA	x		x		
(Ahmed <i>et al.</i> , 2024)	ASSA	X	X	X	X	X
(Nagarajan <i>et al.</i> , 2024)	ECIA	x	x	x	x	
(Mishra & Shaik, 2024)	AVOA	X (Diesel)	X	x	X	X
(Kubicek <i>et al.</i> , 2024)	RDA	X	X		X	
(Ali <i>et al.</i> , 2024)	MOEAs	X	X	X	X	X
(Zhang <i>et al.</i> , 2024)	YALMIP toolkit	x	x	x		X
(Jiriwibhakorn & Wongwut, 2024)	ANN-ANFIS	x	x	x	X	
(Chaudhary <i>et al.</i> , 2024)	CJA	x	x	x	x	x

2023), Five phases algorithm (FHO) (Wang *et al.*, 2023), Social optimization algorithm (SOA) (Karimi & Khandani, 2020), Modified Krill Herd Optimization Algorithm (MKHOA) (Kaur *et al.*, 2022), and Modified Jaya algorithm (MJA) (Kumar *et al.*, 2021). These studies have applied different metaheuristic algorithms for ELD problems with single fuel option, multi-fuel options, fuel cost functions under convex or nonconvex forms, prohibited zone operation constraints, ramp rate limits, etc. Their purpose is to demonstrate that their applied or proposed algorithms could find global optimal solutions better or faster than others in previous studies could do. In the studies, renewable energy sources such as solar and wind have not been considered. On the contrary, other recent studies have been concerned with the importance of renewable power sources in reducing the generation of thermal power plants and cutting the emission and fuel costs from generating processes. Applied methods, renewable power sources, and objective functions of the recent studies are presented in Table 1.

Table 1 shows different algorithms were applied to solve wind and solar power-based ELD problem for a single objective function (cost or emission reduction) and a two-objective function with cost and emission reduction using different optimization tools. In general, the studies applied an existing optimization algorithm, such as FA (Salim & Abdullah, 2022), AVOA (Mishra & Shaik, 2024), MOEAs (Ali *et al.*, 2024) and YALMIP toolkit (Zhang *et al.*, 2024) or developed existing algorithms to improve their performance, such as HOA (Mokarram *et al.*, 2019), MSPSO (Zhang *et al.*, 2021), ASSA (Ahmed *et al.*, 2024), ECIA (Nagarajan *et al.*, 2024), RDA (Kubicek *et al.*, 2024), ANN-ANFIS (Jiriwibhakorn & Wongwut, 2024) and CJA (Chaudhary *et al.*, 2024). Existing algorithms were demonstrated to be effective for the ELD problem with renewable energies since the total emission and fuel cost were reduced. Modified algorithms could reach smaller costs and emissions than other existing algorithms. The contributions of the algorithms are related to cost and emission reduction and the high-performance proposed algorithms. These are two significant contributions of the studies; however, they have the same shortcomings: the need for more practical information on capital costs, operating and maintaining (O&M) costs, and the calculation of the payback period for a project.

In this study, the ELD problem is expanded by considering solar power plants for a project of twenty years. In the study, real data on solar radiation in a zone of Viet Nam is collected to calculate the generation of a solar power plant. Real electric prices are applied to find the total revenues for thermal power plants and solar power plants, and then the total profit is calculated for the twenty-year project. The payback period is

analyzed for the project with the solar power plant. Weighted Average Algorithm (WAA) (Cheng & De Waele, 2024) and Electric Eel Foraging Optimization algorithm (EEFO) (Zhao *et al.*, 2024) are applied to determine the most optimal solution to the problem. The core objective of this study is to reduce the overall electricity generating cost (OEGC) for all TGUs in the power system. Besides, power loss from transmissison process and the prohibited working zones of TGUs are considered. Moreover, wind and solar energies are also integrated into the considered power system. The selection of the Weighted Average Algorithm (WAA) and the Electric Eel Foraging Optimization (EEFO) methods for this study was based on the following reasons:

- For the research field, both WAA and EEFO are relatively novel meta-heuristic algorithms.
- Prior to their application in this research, WAA and EEFO have been successfully tested on both theoretical and practical applications, as documented in (Cheng & De Waele, 2024) and (Zhao *et al.*, 2024).
- The update mechanisms of WAA and EEFO demonstrate high capabilities in addressing complex optimization problems, such as the one considered herein. Specifically, WAA utilizes the difference between the current, average, and best solutions to guide the search process during the exploitation phase. Subsequently, the solution is updated through a random process governed by Levy flight distribution. EEFO, in its initial phase, updates solutions based on the relationship between the current solution and its nearest neighbors, combined with a random component. In later phases, EEFO employs various update strategies, including Levy flight, to refine the search towards the optimal solution. The performance of EEFO compared to other metaheuristic algorithms is summarized in Table 2.

The novelties of the whole study focus on a realistic, long-term economic analysis of solar power plant (SPP) operation. Firstly, it moves beyond simplified models by incorporating actual, historical electric price and solar radiation data spanning a 20-year project timeframe. This approach allows for more accurate estimations of expenditure, revenue, and profit, providing a robust framework for visualizing the project's capital investment and economic benefits. This realistic data integration ensures that the results are directly applicable to

Table 2
The summary of comparisons between EEFO and previous metaheuristic algorithms

Test	Tested Optimization Problem/Suite	Problem Description	Compared Algorithms
Benchmark Function Suites	23 conventional benchmark functions	16 multimodal functions and 7 unimodal functions to test exploration, exploitation and local optimization avoidance	- Levy flight distribution(LFD). - Arithmetic optimization algorithm (AOA). - Whale optimization algorithm (WOA). - Sine-cosine algorithm (SCA). - Harris hawk optimization algorithm (HHO). - Butterfly optimization algorithm (BOA). - Wind driven optimization(WDO). - Moth flame optimization algorithm (MFO). - Adaptive evolution strategy algorithm (AESA). - Gravitational search algorithm (GSA). - Weighted differential evolution (WDE). - Atom search optimization (ASO).
	30 CEC 2017 benchmark functions	Rotated, hybrid composite, and shifted multimodal functions to evaluate exploitation, tradeoff , exploration, and the avoidance of local optimal solutions. Tested in 10, 30, and 50 dimensions.	
	CEC2011 Test Suite	Real-world optimization problems in engineering to evaluate exploitation, tradeoff , exploration, and the avoidance of local optimal solutions.	
Specific Engineering Problems	Three-bar truss optimization design	Engineering design problems likely focused on minimizing weight or stress under constraints.	LFD, AOA, WOA, SCA, HHO, BOA, AESA, WDO, MFO, GSA, ASO, WDE.
	Tension/compression spring optimization design	Optimizing coil and wire diameter of spring to minimize volume/weight under stress, surge frequency, and deflection constraints.	
	Welded beam design	Minimizing the welded beam cost consider conditions of bending stress, shear stress, end deflection and buckling load.	
	Pressure vessel design	Minimizing the cylindrical pressure vessel 's fabrication cost considering the thickness and material properties.	
	Speed reducer optimization design	Minimizing the speed reducer's weight considering surface stress, shaft stresses, deflections, and bending stress.	
	Brake design	Optimizing parameters for a multiple disc clutch brake, likely minimizing mass or stopping time under operational constraints.	
	Rolling element bearing design	Maximizing the rolling bearing's dynamic loading capacity subject to geometric constraints.	
	Cantilever beam design	Minimizing the cantilever beam's weight subject to stress constraints.	
	Car optimization design	Engineering problem related to weight reduction or injury criteria in a car side impact scenario under various constraints.	
	Compressor optimization design	Optimization design of a compressor station, likely minimizing cost under flow and pressure constraints.	

real-world scenarios, enhancing the practical value of the study. Secondly, the research provides a comprehensive visualization of the relationships between total cost, revenue, and profit for a 100 MW SPP operating over this extended period. This visualization serves as a crucial tool for planners and operators, enabling them to make informed adjustments in response to dynamic market conditions such as fluctuating government policies and potential engineering challenges. Furthermore, the analysis utilizes actual solar radiation data from reputable sources, ensuring that the power supply calculations are grounded in verifiable, real-world measurements, thereby enhancing the study's transparency and reproducibility. Finally, the study employs and compares novel meta-heuristic algorithms, specifically WAA and EEFO, to optimize the planning problem. By leveraging the superior-performing

algorithm, it maximizes the total profit of a hybrid power system, including the SPP, over the 20-year operational period. Additionally, the study determines the payback period for this hybrid system, providing critical economic insights for the long-term project viability of solar power plants integrating thermal power plants.

In summary, this study focuses on maximizing the profitability of a solar power project within a hybrid energy system. The study aims to assess and evaluate the effectiveness of a novel optimization algorithm (EEFO) in determining the optimal investment and operational strategies for both the solar plant and an existing thermal power plant. Subsequently, the main objective is to conduct a detailed economic analysis, including precise payback period calculations and sensitivity

analysis, to ensure the solar project yields the highest possible profit.

2. Problem modelling

2.1 The profit models

The profit model of TGU: Similar to other kinds of business on the market, in this regard, the supplied power from all the TGUs in the system is considered to be a good for selling. Profits are the key factor that decide the effectiveness of the particular model and lead to other important decisions which including, keeping moving, growing or terminated. For TGUs particularly, the profit of selling electricity is calculated by using the following equations.

$$Profit_{TPP} = Reve_{TPP} - (CAPEX_{TPP} + Cost_{TPP}^{O\&M} + FCost_{TPP}) \quad (1)$$

Where, **Profit_{TPP}** and **Reve_{TPP}** are the total profit and revenue of the TPP for 20 years; **CAPEX_{TPP}** is the CAPEX cost of the TPP; **Cost_{TPP}^{O&M}** is O&M costs for 20 years; and **FCost_{TPP}** is the total fuel cost of the TPP for 20 years. The parameters regarding the finance of the TPP are obtained by:

$$Reve_{TPP} = N_{year} \cdot N_{day} \sum_{h=1}^{24} (PG_{n,h} \cdot Pr_h) \quad (2)$$

$$CAPEX_{TPP} = CAPEX_{1MW} \cdot \sum_{n=1}^{N_{ThG}} (PG_n^{max}) \quad (3)$$

$$Cost_{TPP}^{O\&M} = Cost_{1MW}^{O\&M} \cdot \sum_{n=1}^{N_{ThG}} (PG_n^{max}) \quad (4)$$

$$FCost_{TPP} = N_{year} \cdot N_{day} \cdot OEGC_{1day} \quad (5)$$

Where **OEGC_{1day}** is the overall electricity generation cost all TGUs for one operating day and obtained by:

$$OEGC_{1day} = \sum_{h=1}^{24} \sum_{n=1}^{N_{ThG}} (\alpha_n + \beta_n PG_{n,h} + \gamma_n PG_{n,h}^2) \quad (6)$$

where N_{ThG} is the quantity of TGUs of the given system; α_n , β_n , and γ_n are coefficient factors while using particular fuel while operating TGU n ; and $PG_{n,h}$ is power output of the thermal power plant n at the hour h .

Figure 1 shows three costs of TPPs, including capital expenditures (CAPEX) for the initial time of projects, variable O&M costs for each produced MWh, and fixed O&M costs for every operating year. The three costs are based on the fossil energy technology characterization (National Renewable Energy Laboratory (NREL) for TGU - 2023). In the study, we used the variable O&M costs and CAPEX from the industry and historical data, whereas, the variable O&M costs is replaced with the fossil fuel costs as suggested in previous studies (Mokarram *et al.*, 2019; Zhang *et al.*, 2021).

The profit model of SPP: The profit model of an SPP is slightly different from that of a TGU in terms of the EGC. Particularly, the operation of SPP does not cause any value of EGC as the initial input. Therefore, the profit model of SPP is given as follows:

$$Profit_{SPP} = Reve_{SPP} - (CAPEX_{SPP} + Cost_{SPP}^{O\&M}) \quad (7)$$

where **Profit_{SPP}** and **Reve_{SPP}** are the total profit and revenue of the SPP for 20 years; **CAPEX_{SPP}** is the CAPEX cost of the SPP; **Cost_{SPP}^{O&M}** is O&M costs of the SPP for 20 years. The parameters regarding the finance of the SPP are obtained by:

$$Reve_{SPP} = N_{year} \cdot N_{day} \sum_{h=1}^{24} (P_{SPP,h} \cdot Pr_h) \quad (8)$$

$$CAPEX_{SPP} = CAPEX_{1MW} \cdot P_{SPP}^{max} \quad (9)$$

$$Cost_{TPP}^{O\&M} = Cost_{1MW}^{O\&M} \cdot P_{SPP}^{max} \quad (10)$$

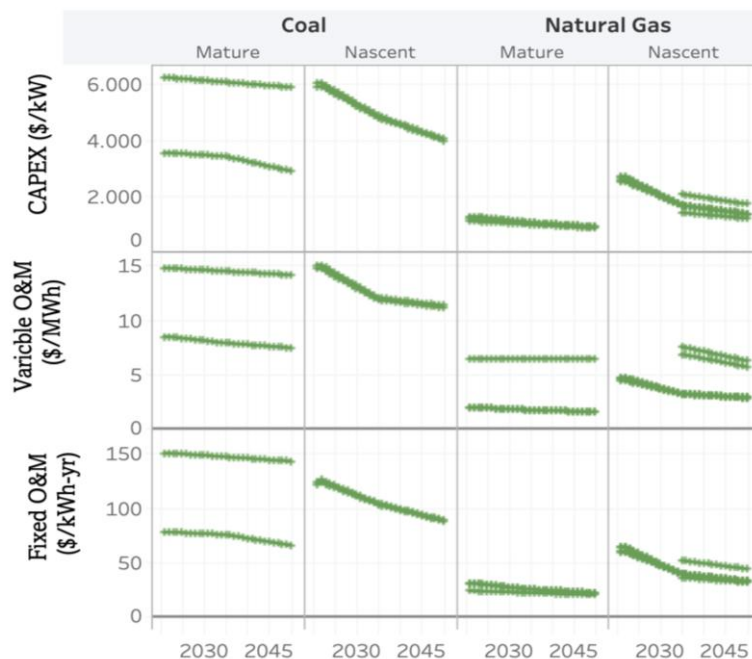


Fig. 1 The illustration of O&M cost considering the variable and fixed aspects, and CAPEX of TPPs



Fig. 2. The illustration of fixed O&M corresponding to CAPEX costs of a SPP.

A utility-sized solar photovoltaic (SPP) facility's CAPEX and fixed variable costs are depicted in Figure 2. Here, the SPP is modeled under the two cost types, benchmarked with industry and historical data (The SPP data – GAS, 2025). In the study, the two costs are applied to evaluate the investment effectiveness of renewable power sources under a utility-scale plant.

2.2 Main objective function.

The study considers a 20-year power generation project with a power system consisting of 15 TGUs and one solar photovoltaic farm. So, the core objective is to reach the maximum total profit of the hybrid power plant with TGUs and one SPP as follows:

$$\text{Maximize } Profit_{plant} = Profit_{TPP} + Profit_{SPP} \quad (11)$$

where $Profit_{plant}$ is the total profit of the hybrid power plant for 20 years.

2.3 The involved constraint

The power balance constraint: This constraint depicts the correspondence of the amount of power consumed by all loads plus the power loss, which must equal the overall supplied power of all the existing power sources as follows.

$$\sum_{n=1}^{N_{ThG}} PG_n + P_{SPP} - P_{LD} = 0 \quad (12)$$

where $\sum_{n=1}^{N_{ThG}} PG_n$ is the power output supplied by all existing TGUs in considered system configuration; $P_{SPP,s}$ is supplied power generated by the SPP; P_{LD} is the power required by loads.

The TGU's operational constraint: This constraint is applied to control the power supplied by each TGU in the given system must locate in the allowed ranges as follows (Nguyen & Vo, 2015).

$$PG_n^{min} \leq PG_n \leq PG_n^{max} \quad (13)$$

Prohibited operation zone constraint: This constraint refers to the sub-region of the power output supplied by TGUs, where the TGUs can be operated effectively and safely without risks to their physical limitation (Nguyen & Vo, 2015):

$$PG_n \in \begin{cases} PG_n^{min} \leq PG_n \leq TG_{n1}^i \\ TG_{nk-1}^k \leq PG_n \leq TG_{nk}^i; \\ TG_{nq}^k \leq PG_n \leq PG_n^{max} \end{cases} \quad (14)$$

$$k = 2, \dots, q; \forall n \in \Omega$$

where q is denoted as the quantity of prohibited operational zones of the TGU n .

The operational constraints of SPPs: Similar to the TGU mentioned above, this constraint is highly relevant to the physical limitations of a generator. That means that the power output of SPP is allowed to change in the operational ranges as follows (Kherfane *et al.*, 2014):

$$P_{SPP,s}^{min} \leq P_{SPP} \leq P_{SPP,s}^{max} \quad (15)$$

3. Applied method

3.1 Weighted Average Algorithm (WAA)

Introduced in 2024, the Weighted Average Algorithm (WAA) operates by determining the weighted average location of the entire population and selecting from two distinct movement strategies. The WAA's solution update process focuses on maintaining a delicate equilibrium between the exploitation and exploration stages, as detailed in the following sections:

The exploitation phase: In this phase, WAA executes three different strategies subsequently to update the new solution as follows:

$$X_n^{new1} = \mu_{0-1} \cdot (X_{Av} - X_{GB}) + \mu_{0-1} \cdot (X_{Av} - X_{PB,n}) + \mu_{0-1} \cdot X_{Av} \quad (16)$$

$$X_n^{new2} = \mu_{0-1} \cdot (X_{Av} - X_{PB,n}) + \mu_{0-1} \cdot X_{PB,n} \quad (17)$$

$$X_n^{new3} = \mu_{0-1} \cdot (X_{Av} - X_{GB}) + \mu_{0-1} \cdot X_{GB} \quad (18)$$

where, X_n^{new1} , X_n^{new2} , X_n^{new3} are, respectively, the n th new solution while executing the three strategies subsequently with $n = 1, 2, \dots, N_{ps}$; X_{Av} is the solution with average weight; and $X_{PB,n}$ is the so-far best of the solution n .

The exploration phase: In this phase, WAA executes the update process by selecting one out of two models as shown in the following equation.

$$X_n^{new} = \begin{cases} X_{GB} \cdot \mu_{Levy} & \text{if } \mu_{0-1} > 0.5 \\ \mu_{0-1} \cdot (UB - LB) + LB, & \text{else} \end{cases} \quad (19)$$

3.2 Electric Eel Foraging Optimization algorithm (EEFO)

Introduced in 2024, EEFO is an innovative optimization algorithm. It draws inspiration from the foraging behavior of electric eels in their natural habitat, specifically their distinct stages of searching, observing, maneuvering, and attacking. The position of the eel within each stage is dynamically adjusted and mathematically represented through the following equations.

The electric eel position in the first phase is obtained by:

$$E_q = \begin{cases} (E_p + \mu_{0-1} \cdot NF_1 \cdot (E_{RD} - E_q)), & \text{if } \varepsilon_1 > 0.5 \\ (E_p + \mu_{0-1} \cdot NF_2 \cdot (E_{RD} - E_q)), & \text{if } \varepsilon_1 \leq 0.5 \end{cases} \text{ if } FT_{E_p} < FT_{E_q} \quad (20)$$

$$= \begin{cases} (E_p + \mu_{0-1} \cdot NF_1 \cdot (E_{RD} - E_q)), & \text{if } \varepsilon_2 > 0.5 \\ (E_p + \mu_{0-1} \cdot NF_2 \cdot (E_{RD} - E_q)), & \text{if } \varepsilon_2 \leq 0.5 \end{cases} \text{ if } FT_{E_p} < FT_{E_q}$$

Where E_q is the position of the electric eel q in the first phase with $q = 1, 2, \dots, N_{ps}$; E_p is the electric eel having the nearest position with the considered electric eel; E_{RD} is a random individual picked up from the initial population.

The position update of EEFO in the last three phases is obtained by:

$$E_q = \begin{cases} E_{Pr} + \mu_{0-1} \cdot (E_{Pr} - E_q); & \text{if } rf < 1/3 \\ -\mu_{0-1} \cdot E_q + \mu_{0-1} \cdot E_{RD} - \mu_{Levy} \cdot (E_{RD} - E_q); & \text{if } rf > 2/3 \\ E_{RD} + \omega \cdot E_{RD} \cdot E_q & \text{otherwise} \end{cases} \quad (21)$$

Where, E_{Pr} is the position of the potential prey; and ω is the scaling factor; rf is the reference factor in the interval between 0 and 1, $rf < 1/3$ is the observing phase, while the other two are corresponding to the maneuvering and the offensive phase.

4. Results

In this section, WAA and EEFO are utilized to solve a range of optimization problems initially. Afterward, these methods are applied to find optimal solutions for the specific problem described in Section 2. The results of these applications are discussed in the next two subsections.

All simulations and coding for the application of WAA and EEFO were conducted on a computer with a 2.4 GHz CPU and 16GB of RAM, using MATLAB R2018a.

4.1 The comparison criteria

This study applies WAA (Cheng & De Waele, 2024) and EEFO (Zhao *et al.*, 2024) to find the optimal solution for benchmark functions and one engineering problem. To conclude the performance of the applied algorithms, three criteria are employed to assess the effectiveness of the algorithms:

- 1) solution quality,
- 2) solution stability,
- 3) convergence characteristics.

Solution quality, representing the best solution obtained, is key criteria to assess the effectiveness of particular meta-heuristic methods in optimization problems. For example, when minimizing the overall electricity generation cost (OEGC), as mentioned in our manuscript, the algorithm achieving the lowest OEGC is considered superior. If multiple algorithms yield the same optimal value, solution stability is evaluated. This criterion assesses the consistency of fitness values across multiple independent trials. The algorithm with the least fitness value fluctuation and the lowest overall fitness value across these trials is deemed more stable and, therefore, better. In cases where solution stability does not differentiate performance, convergence characteristics are examined. This involves comparing the convergence speeds to the minimum, average, and maximum fitness values observed across the multiple trials. These convergence curves are plotted on the same axes for direct comparison. The algorithm exhibiting the fastest convergence to these values is considered the most efficient. Note that convergence speed is defined by the quantity of iteration needed to reach the optimal result. Fewer iterations indicate faster and more efficient convergence.

Table 3

Three benchmark functions

Function	Dimension (N)	Boundaries
Sphere	30	[-100; 100]
Schwefel	30	[-100; 100]
Rastrigin	30	[-5.12; 5.12]

Note that the advantage of a meta-heuristic method over others is not based on theoretical proofs. These algorithms operate through repeated steps and are significantly influenced by stochastic elements. Consequently, the determination of an algorithm's superiority is derived from a series of empirical tests and analyses of its optimal results across those tests. For instance, the authors in (Zhao *et al.*, 2024) conducted extensive tests, encompassing both theoretical and practical optimization problems, and subsequently compared EEFO's performance against other algorithms before introducing it to the academic community.

4.2. The simulations results for three benchmark functions

In this section, both WAA and EEFO are tested with three different theoretical functions, including the sphere, Schwefel, and Rastrigin functions. The mathematical expression, boundaries, and the number of dimensions of each function will be given as follows:

$$F_1(x) = \sum_{j=1}^N x_j^2 \quad (22)$$

$$F_2(x) = \sum_{j=1}^N (|x_j| + \prod_{j=1}^N |x_j|) \quad (23)$$

$$F_3(x) = A_N + \sum_{j=1}^N [x_j^2 - A \times \cos(2\pi x_j)] \quad (24)$$

The information regarding the different dimensions and the variable boundaries for the three benchmark functions will be given in Table 3. Both methods were run with 100 iterations and a population of 30 for a balanced comparison.

Figure 3 shows the minimum convergence achieved by WAA and EEFO while tested by the three benchmark functions as described above. Note that, the rows a), b), and c) represent the testing results of three different benchmark functions including the Sphere, the Schwefel, and the Rastrigin function, while the columns i), ii), and iii) show three convergence curves including the minimum, average, and maximum convergence of WAA and EEFO. The two algorithms can reach the optimal value of considered benchmark functions after less than 50 iterations for their best run. Besides, EEFO provides a better convergence speed than WAA while dealing with Sphere and Rastrigin benchmark functions; however, this method is slower than WAA when testing with the Schwefel test function.

In terms of the average and maximum convergences, EEFO still maintains the superiority while dealing with the Sphere and Rastrigin function and is slightly slower than WAA while tested with the Schwefel function.

4.3 The simulation results for the power system with 15 thermal units

This subsection applies WAA (Cheng & De Waele, 2024) and EEFO (Zhao *et al.*, 2024) to find an engineering problem's most optimal solutions. The optimal solution is comprised of the optimal power output for 15-TGU power systems so that the OEGC of all TGUs in the system reaches the minimum value. The system's load is 2650 MW. Besides, a 100 MW SPP and 200

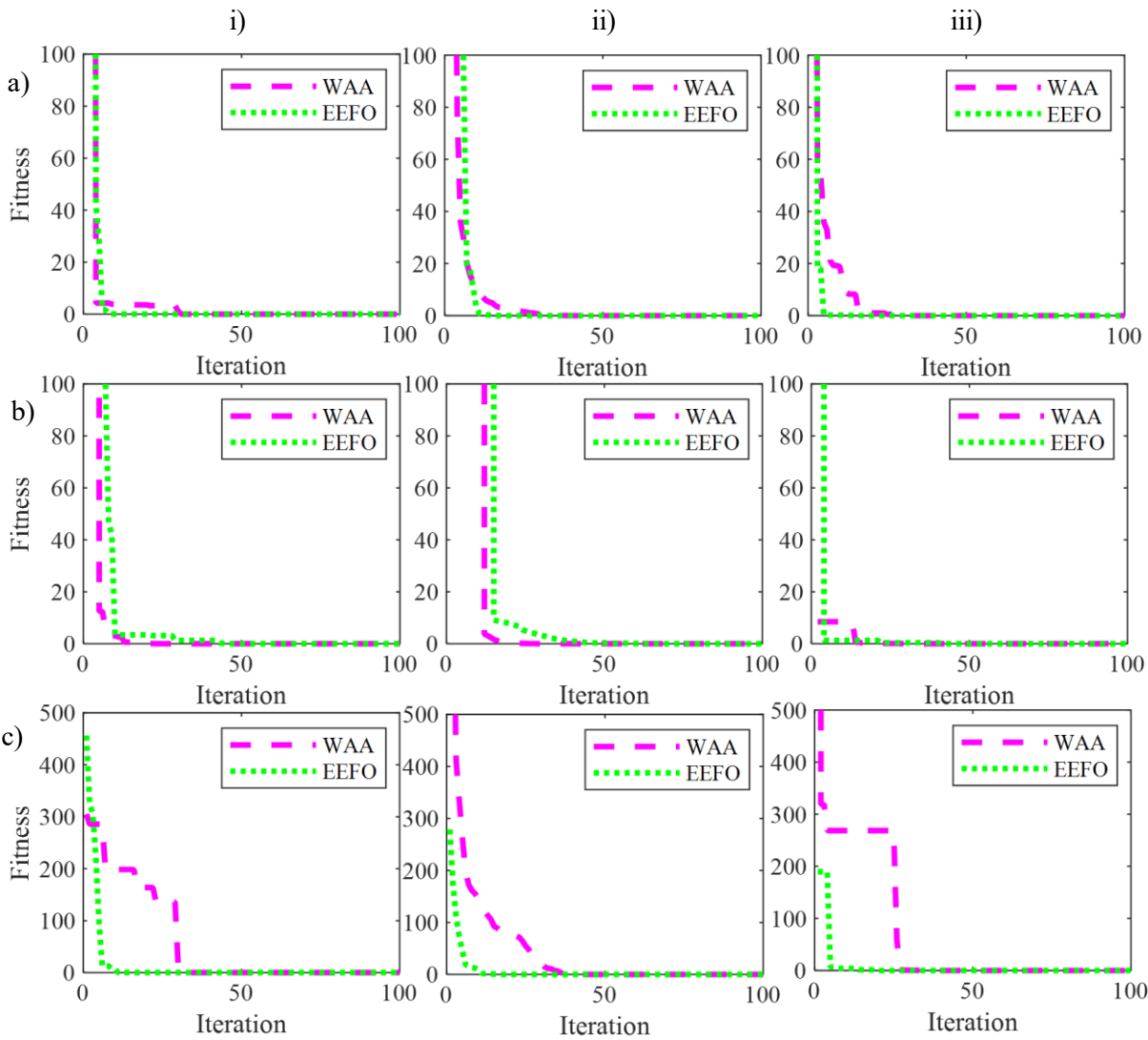


Fig. 3. Performance comparison of WAA and EEFO algorithms over 100 iterations. The plots show the convergence of fitness values for: a) Sphere, b) Schwefel, and c) Rastrigin test functions. Subfigures i), ii), and iii) represent the best, average, and maximum convergences achieved, respectively.

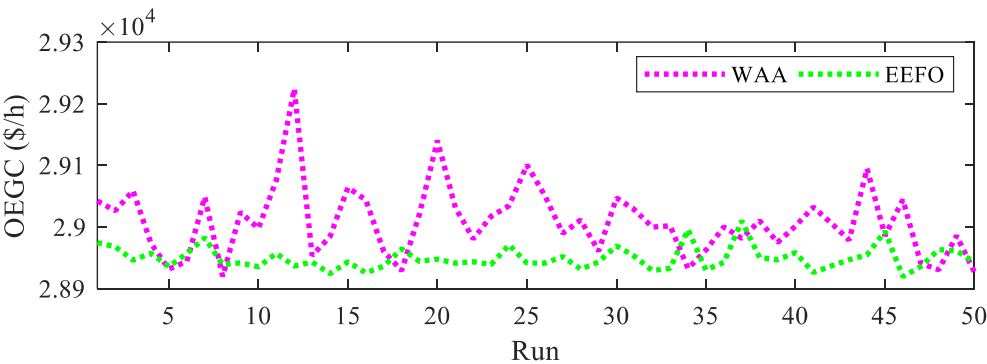


Fig. 4 The results after 50 test runs of the two applied methods

MW WPP are also connected with the given power system to reduce the emissions caused by the operation of TGUs. The load demand and data of thermal generating units are taken from the study (Vo *et al.*, 2013). The two applied methods are evaluated for their performance while solving the RE-ELD by using 100 for maximum iteration and 40 for population size.

Moreover, both methods are executed for 50 test runs for optimal solutions before comparisons

Figure 4 shows the results after 50 test runs achieved by WAA and EEFO. In the figure, it is very easy to recognize that EEFO can reach many more optimal solutions than WAA. On the other hand, the fluctuation of the fitness value achieved by

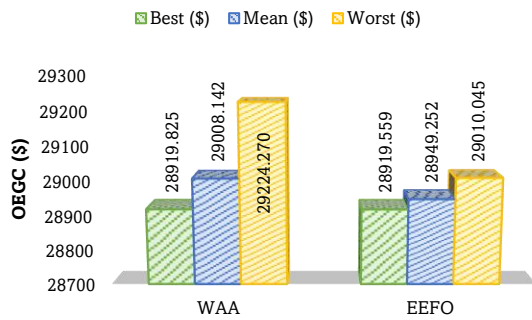


Fig. 5 A comparative analysis of WAA and EEFO on different aspects.

Figure 6 displays the worst, mean, and best convergences obtained by WAA and EEFO after solving the CE-ELD problem. The observation of the three figures indicates that EEFO performs better in determining the minimum value of OEGC, which is presented in Figure 6a, while WAA cannot even in its best run. Furthermore, the magnified view in Figure 6a demonstrates that EEFO exhibits a faster response time compared to WAA. This rapid response capability is a significant advantage of EEFO in managing the operational scenarios of the problem, as it can reduce waiting times and facilitate timely decision-making by dispatchers in response to fluctuating power system load demands. Additionally, while the difference in the optimal OEGC obtained by the two algorithms is relatively small, and the exact number is 0.226 \$, as can be defined by the data provided in Figure 5, this represents the cost savings achieved by EEFO compared to WAA for a single operational period. That means that for the realistic scenario, s

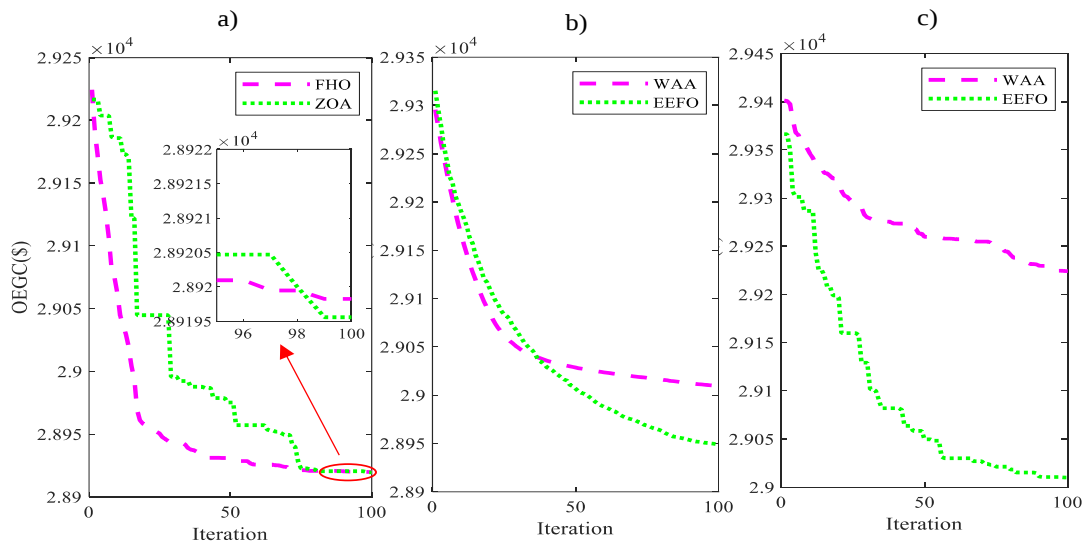


Fig. 6 The presentation of minimum, average, and maximum convergence characteristics of WAA and EEFO

EEFO is noticeably less than WAA. In fact, Standard deviation (STD) is a commonly used statistical measure to quantify the fluctuation of fitness values across multiple independent runs of an algorithm. A smaller STD indicates greater stability, while a larger STD suggests instability. By analyzing the STD in conjunction with the fitness values presented in the figure, EEFO is more stable and effective than WAA in solving the considered problem.

Figure 5 compares WAA and EEFO results, such as the best, mean and maximum OEGC. The comparison observation indicated that EEFO not only offers a better finding of the best OEGC value, but the method is also superior to WAA on other criteria, such as the mean OEGC and the worst OEGC. Particularly, EEFO can save \$0.266 per hour compared to WAA on the best OEGC. While the difference in optimal energy generation cost (OEGC) savings between EEFO and WAA is relatively small, this difference indicates that EEFO yields a more optimized solution. Specifically, an hourly saving of \$0.266, though seemingly marginal, accumulates significantly over extended periods such as daily, monthly, annual, and the 20-year operational lifespan. On the two remaining criteria, the savings cost by EEFO over WAA is more noticeable, at \$58.890 for the mean OEGC and \$214.225 for the worst OEGC corresponds to approximately 0.2% and 0.73%.

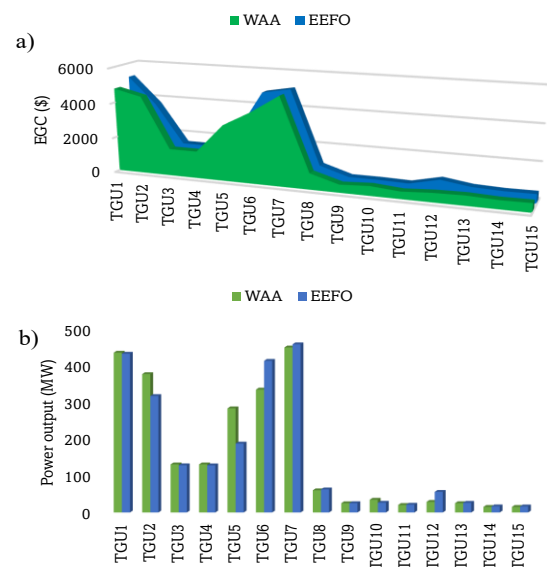


Fig. 7. a) The power output and b) the EGC values for each TGU achieved by WAA and EEFO

Table 4
SPP's information

Location	Dong Hai Ward, Phan Rang Thap Cham City, Ninh Thuan Province, Vietnam
Geographical coordinates	11.550392°, 109.028377° (11°33'01", 109°01'42")
The configuration of PV systems	Ground-mounted large scale*
System size (MWp)	100
The PV panels' applied tilt	11°
The PV panels' applied azimuth	180°

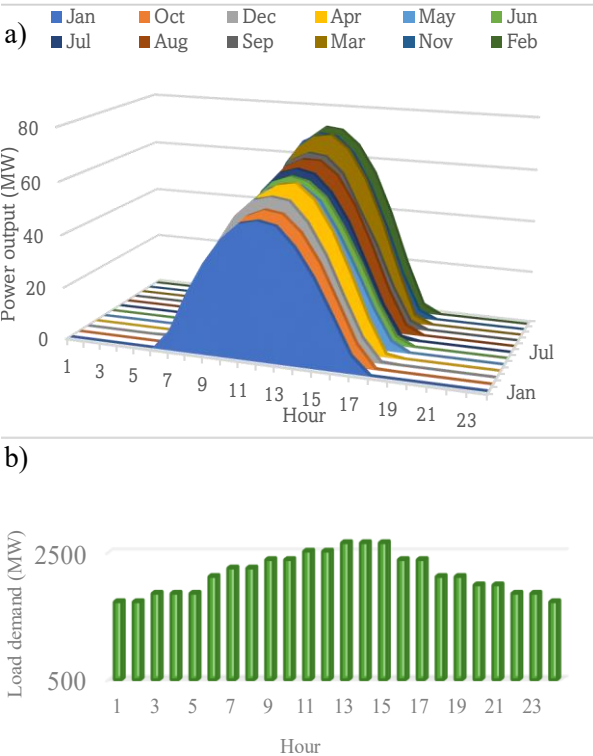


Fig. 8 a) The power supplied by SPP in a year and b) The load demand variation within a day.

uch as a day, a month, a year, or a ten-year operation. The cumulative savings costs will be noticeable and cannot be ignored. Besides, the superiority of EEFO over WAA can be viewed more vividly in Figure 6b and Figure 6c. These figures show that EEFO is far more effective than WAA in these two regards. Figure 7 displays each TGU' generation and electricity generating cost (EGC). In Figure 7a, the power output of the TGUs with high EGC found by EEFO is lower than those of WAA. The extra output required by the load is allocated to the TGUs with lower than EGC, so the OEGC found by EEFO is less than WAA overall.

4.4 The results of performing optimization to the system with 15 TGUs and one solar farm for a 20-year project

In this section, the CE-ELD problem is resolved considering the demand variations and actual data from the SPP within 24 hours. Besides, the economic profit of having an SPP in the system will be calculated after twenty years of operation. As stated in the previous section, the sole SPP's basic information is reported in Table 4 (The SPP data – GAS, 2025). The electric

prices in Vietnam are used to calculate the hybrid power plant's total revenue (Nguyen *et al.*, 2022).

Figure 8 shows the 24-hour power supply from the SPP (Subfigure 8a) and the 24-hour load demand (Subfigure 8b) across twelve months.

4.5. The evaluation of the reduction cost with SPP

Figure 9a) compares each month's EGC values for the case where the system with power is supplied by SPP. The reduction cost of an average day of each month will be determined by the subtraction between the cases without SPP and the cases with SPP of each month. It should be noted that the reduction in EGC is only observed from the 6th to the 18th hour daily. This limitation is due to the physical constraints of the SPP, which can only generate power during daylight hours, thereby offsetting the EGC during this period. During the remaining hours, the EGC remains unchanged, as the SPP does not contribute. The "No_SPP" scenario demonstrates a substantial increase in EGC from the 10th hour, peaking at the 13th and 14th hours, followed by a sharp decrease after the 17th hour.

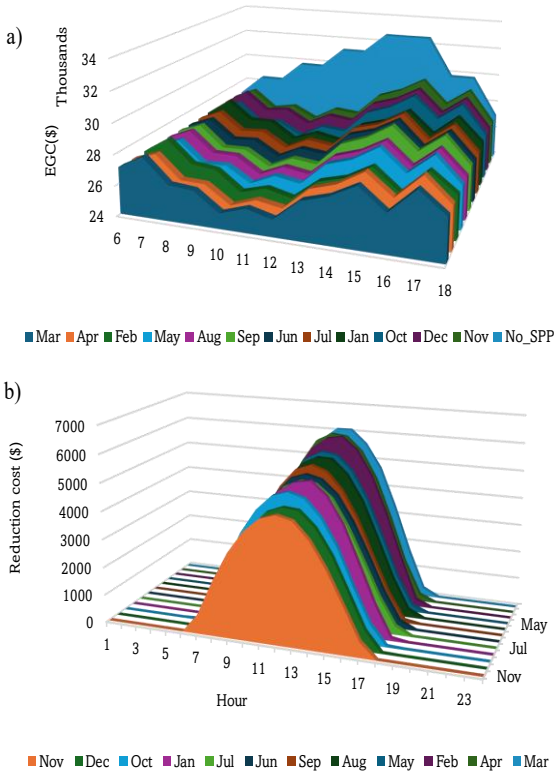


Fig. 9 a) The OEGC value for twelve 12 compared to the case without SPP and b) The corresponding cost reduction for each months.

However, these peak hours coincide with periods of high solar radiation, resulting in significant power output from the SPP. This correlation leads to a noticeable reduction in EGC, consistently observed across all twelve months. The observation from the figure indicated that the lowest reduction cost is in November, while the highest is in May.

Figure 9b presents the reduction cost of EGC each month for the case where the system with power supplied from SPP. The reduction cost of an average day of each month is determined by the subtraction between the cases without SPP and those with SPP of each month. While Figure 9a illustrates the comparative reduction of Electricity Generation Costs (EGC) for scenarios with and without SPPs, Figure 9b provides a quantitative measure of the EGC reduction for an average day of each month across the entire year. Consistent with Figure 9a, the reduction is observed from the 6th to the 17th hour daily. The observation from the figure indicated that the lowest reduction cost is in November, while the highest reduction cost is in March.

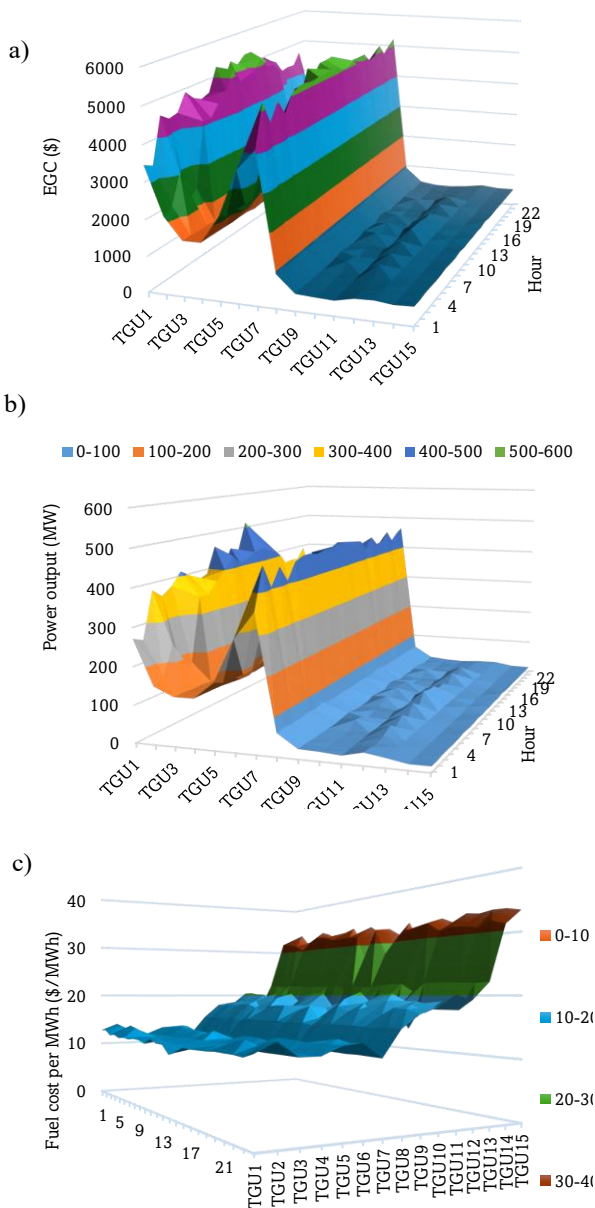


Fig. 10 The illustration in 24 hours of a) the EGC for each TGU, b) Power output of TGUs over 24 hours, and c) Fuel price per MWh without SPP

4.6. The evaluation of profit of the whole system

This section investigates the profit generated by incorporating a Solar Photovoltaic Plant (SPP) and Thermal Generation Units (TGUs) into the system. Based on the mathematical model described in Eqs. (8)-(10), Figure 10 presents the components necessary for determining the operational profit of the TGUs. Specifically, Figure 10a shows the 24-hour Energy Generation Cost (EGC) for each TGU. Figure 10b depicts the 24-hour electricity supply from each TGU. Using the data from these figures and Eq. (9), Figure 10c displays the calculated cost per MW of electricity generated by each TGU.

The power outputs of thermal power plants in Figure 10b and the electric prices are substituted into Eq. (7) to calculate the total fuel cost and profit. Figure 11a presents the total cumulated cost, cumulated revenue, and cumulated profit after each year from 2024 to 2043. The total revenue for twenty years is \$31,356,508,271; meanwhile, the total cost and total profit are \$26,607,299,625 and \$4,749,208,646, respectively. The TGUs optimization operation can reach a total profit of \$4,749,208,646 for 20 operating years. On the other hand, power plants have CAPEX and O&M costs (CAPEX and O&M of TGU, NREL - 2023). The CAPEX per kW in 2024 is \$3492.254 per kW, and O&M costs for the period from 2024 to 2043 are given in (CAPEX and O&M of TGU, NREL - 2023). To calculate the CAPEX for 15 TGUs, the total capacity of the fifteen thermal power plants is calculated, equaling 3542 MW. Finally, the total CAPEX is \$12,369,563,668.

Figure 11b presents the total cumulated cost, total cumulated revenue, and total cumulated profit from 2024 to 2043. Here, the total cost is the sum of total CAPEX, total fuel cost, and total O&M cost. The calculations of the total cost and profit is based on Eq. (1). The total cumulated profit in Figure 11a is reused and put in Figure 11b. The total cost is shown in blue points. The total cumulated profit after the first year, 2024, is minus and equal to about -11 billion dollars. The total cumulated profit can be increased from 2024 to 2032, and the total cumulated profit is the smallest minus value, with the total cumulated profit of -0.3987 billion dollars after 2032. After 2033, the total cumulated profit becomes positive, with 0.931 billion dollars. The total cumulated profit continues to increase and reach about 14.2 billion dollars after 2043. The total cumulated cost after 2043 is 17.1 billion dollars. See Figure 11a; the total cumulated cost and profit for the case, neglecting the O&M and CAPEX costs, are about 4.75 and 26.6 billion dollars. So, for an actual project considering the O&M and CAPEX costs, the total cumulated profit after 20 years is $14.2/26.6=53.4\%$. Next, the profit from having an SPP in the system is investigated. As seen from Equation (20), besides the Revenue, CAPEX and O&M costs must be determined before calculating the profit. According to (CAPEX and O&M of SPP, NREL - 2023), the CAPEX value is 1289.51\$ per kW; therefore, this value of a 100MW SPP is 128950700 \$.. The solar power plant's total cumulated cost and the cumulated profit after each year can be calculated. Figure 11c presents the total cumulated cost, revenue and profit of the SPP after 20 years. After 2024, the solar power plant project suffers the highest loss, with about -0.112 billion dollars. The loss can be reduced gradually seven years later, from 2024 to 2030. 2030 is the last year that the project suffered a loss, with the smallest value of about -13.23 million dollars. After 2031, the project started getting a small profit, with 3.5 million dollars. The total cumulated profit continues to increase and reach about 0.207 billion dollars after 2043. The total cost after 2043 is 0.163 billion dollars. So, for an actual project considering the CAPEX and O&M costs, the total cumulated profit after 20 years is $0.207/0.163=127\%$.

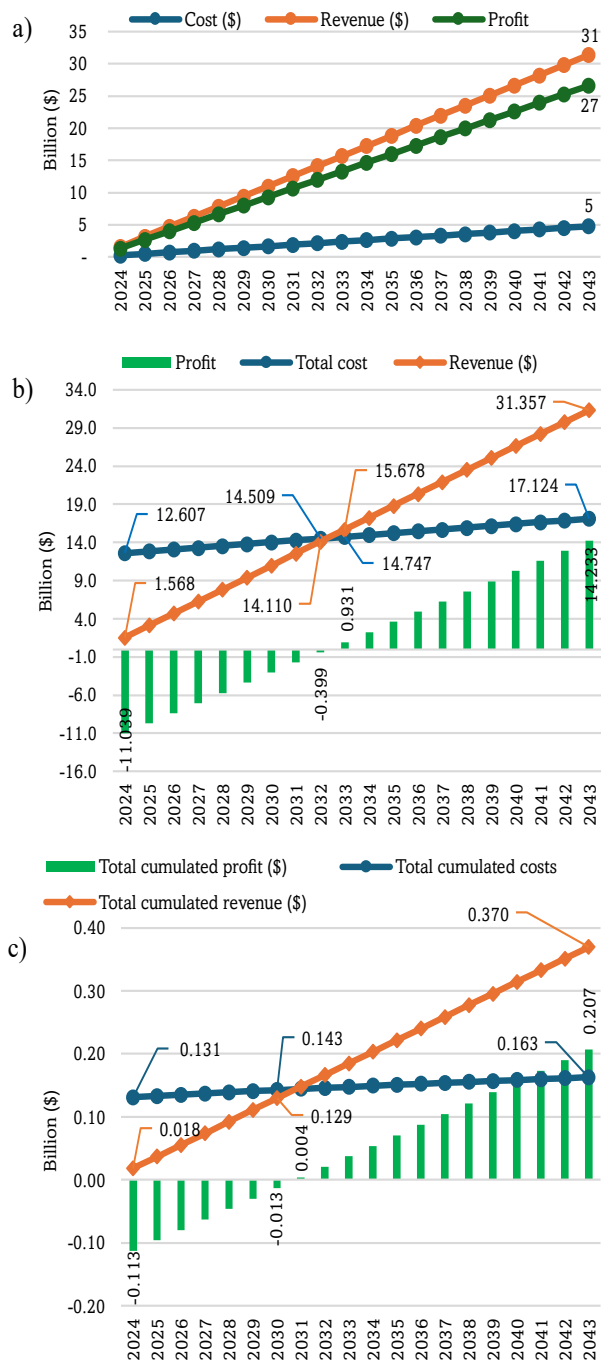


Fig. 11 a) Total cumulative fuel cost, revenue and profit from 2024 to 2043, b) The total cost, revenue and profit after using CAPEX and O&M costs, and c) The total cumulative cost, revenue and profit of the SPP after 20 years.

In summary, a project with 15 TGUs and the 100-MW SPP suffered the highest loss after the first year, and the loss is the smallest after 9 years for TGUs and 7 years for the SPP. The loss disappears, and the profit comes after 10 years for the TGUs and 7 years for the SPP. The total cumulative profit is about 83% of the total costs for the TGUs and 127% of the total costs for the SPP after 20 years.

5. Discussion on Factors Affecting Project Output

The results presented in the previous sections were derived from calculations incorporating various economic factors,

including electricity prices, solar power prices, and fixed costs such as the O&M and CAPEX costs. CAPEX and O&M costs were estimated based on Annual Technology Baseline of the National Renewable Energy Laboratory (CAPEX and O&M of TGU, NREL – 2023; CAPEX and O&M of SPP, NREL - 2023) and are illustrated in Figures 1 and 2 for both thermal generating units (TGUs) and solar photovoltaic plants (SPPs). However, electricity and solar power prices are subject to significant market and economic fluctuations, contributing to the output variations observed in the previous section. This section will briefly describe three key elements, not previously evaluated, that are acknowledged to have a major influence on the time at which profitability is achieved:

5.1. Fuel Price Fluctuations

The fundamental operational dependence of TGUs on fuel consumption renders them particularly vulnerable to price volatility. A rapid increase in natural gas or coal prices will directly a significant change in operating costs. To deal with this situation, the generation company's owner must execute the electricity price regulation, avoiding losses or at least keeping their marginal profit. To address this issue, the authors (Wang *et al.*, 2013) introduced a two-stage probabilistic model for independent power producers (IPPs), known as price-based unit commitment (PBUC), designed to optimize profits in a deregulated electricity market where their role as price takers. This model accounts for the unpredictable nature of market prices and wind energy production. The initial stage involves decisions regarding unit commitment of thermal and hydroelectric generators and the quantity of electricity offered in the day-ahead market. The subsequent stage focuses on the real-time market, encompassing generation dispatch, actual wind power utilization, and the discrepancy in energy between day-ahead bids and real-time generation, which can incur penalties. Beyond fossil fuel prices, other factors like geopolitical instability and supply chain disruptions pose significant financial risks to project owners. Specifically, rising oil import costs can influence political outcomes in democracies, as public dissatisfaction with fuel prices fuels protests and impacts elections (Arezki *et al.*, 2022). Furthermore, efficient supply chains are crucial for converting raw materials such as coal, liquefied natural gas, and oil into electricity through transportation, acquisition, and trade. Disruptions caused by geopolitical events, natural disasters, or economic instability can lead to shortages of these materials, consequently driving up electricity prices across the market (Yang & Fu, 2025). In general, long-term profitability is contingent upon accurate fuel price forecasting and the implementation of effective risk mitigation strategies, such as hedging or the securing of favorable long-term supply agreements. Conversely, TGUs possessing fuel flexibility or advantageous supply agreements are positioned to capitalize on market volatility, thereby gaining a competitive advantage during periods of heightened prices.

5.2. Inflation (Affecting Both TGUs and SPPs):

This is the second factor not previously evaluated. For both thermal generating units (TGUs) and solar photovoltaic plants (SPPs), inflation directly impacts initial capital expenditures (CAPEX), increasing the costs of construction materials, equipment, and labor. Consequently, payback periods are extended, and returns on investment are reduced. Furthermore, operational costs, including regular maintenance, wages, and administrative expenses, also rise with inflation. If electricity prices do not adequately adjust to inflationary pressures, profit

margins will significantly decrease. Inflation significantly impacts financial modeling by influencing discount rates. As evidenced by (Shea & Ramgolam, 2019), increased discount rates diminish the current worth of future cash inflows, negatively affecting project valuations. The discount rate represents the concept of the time value of money, and its fluctuations, influenced by inflation and perceived risk, are pivotal for determining net present value and informing investment strategies. Therefore, careful selection of an appropriate discount rate, tailored to the specific project context, is essential to avoid significant miscalculations and flawed financial forecasts. In the case of solar power plants (SPPs) and other renewable energy projects, if power purchase agreements (PPAs) lack inflation adjustments, the real value of revenue streams will diminish over time (Guaita-Pradas & Blasco-Ruiz, 2020).

5.3. Policy Changes:

This factor affects both TGUs and SPPs' operations. Particularly, the regulatory framework plays a key role in shaping the economic viability of energy projects. The rigorous environmental regulations such as emissions trading schemes or carbon taxes, impose substantial financial burdens on TGUs, increasing their operating costs and potentially rendering them less competitive. Conversely, these policies can bolster the economic attractiveness of SPPs, as they are inherently low-carbon. Soon, decarbonization has become a large trend in almost all countries in the EU. By following the trend, many countries have soon begun to transit their economy-oriented green and low to zero carbon with the support of the whole society, leaders of administrations, and the maturity of related technologies (Jarosławska-Sobór, 2021). Government also support for renewable energy development, reducing feed-in tariffs, tax benefits, and renewable portfolio standards, significantly boosts the economic viability of Solar Photovoltaic Plants (SPPs). In China, for instance, the government has implemented four key strategies to accelerate the expansion of renewable energy sources, including fostering research and development, providing rapid financial and tax support for renewable energy projects, facilitating the development of policies that allow for the integration of renewable energy into the grid, and finally, expanding the market for renewable energy (Zhao *et al.*, 2016). However, abrupt policy shifts can cause significant uncertainty and increase the risks of long-term investments. The unexpected modifications in grid connection regulations and permitting procedures can also impede project progress and escalate costs for both Thermal Generating Units (TGUs) and SPPs. Furthermore, energy market deregulation can create both opportunities and risks, potentially lowering electricity prices but also introducing greater volatility. Changes to fuel import or export rules can dramatically affect the cost and availability of fuel, which directly affects TGUs.

6. Conclusions

This study applied two novel meta-heuristic algorithms, including WAA and EEFO, developed in 2024 to maximize the total profit over 20 operating years for a hybrid power plant with 15 thermal generating units and a 100-MW solar farm. In the first study case, the two algorithms were applied to reach the optimal solution for the 15 TGUs at one peak load hour. In the second study case, the TPP was integrated into one 100-MW solar photovoltaic farm for a 20-year operating project. The CAPEX, O&M, and fuel costs for real thermal power plants and the CAPEX and O&M costs for real solar photovoltaic power

plants were considered. In addition, the electric prices and solar radiation were also taken from an electric power company and a real zone in Vietnam, respectively. Results from the simulation can be summarized as follows:

1. For the first study case, EEFO could find smaller minimum, mean, and maximum costs than WAA by \$0.266, \$58.890, and \$214.225, respectively. So, EEFO is more suitable than WAA for the study.
2. For the second study case, the 15 thermal units and the 10-MW SPP could reach a greater revenue than the total costs after nine years and seven years, respectively. The TPP could reach a profit of 14.2 billion dollars, and the SPP could reach a total profit of 0.207 billion dollars after 20 years. The total profit was about 83% of the total costs for the TPPs and 127% of the total costs for the SPP.

The results above indicated the noteworthy contributions of the study. EEFO was a powerful algorithm to solve the problem, and the results from the algorithm were validated. The total costs of a real thermal power plant and a real solar power plants were considered in addition to the real electric prices. The optimization operation of the hybrid power plant could bring a high profit after nine years, and the profit after 20 years was significant. This information can show the overview to investors for developing power sources when the load demand is really high nowadays. While this study offers valuable contributions, it also presents several limitations that warrant careful consideration to enhance practical applicability. These limitations are outlined below:

1. Market Price Fluctuations: The study does not account for market-driven electricity and solar power price variations. In reality, these prices are subject to supply and demand dynamics, and applying constant prices is not close to what happens in real-world scenarios.
2. Static Load Demand: The assumption of constant load demand constitutes another significant limitation. In practice, load demand is expected to increase proportionally with population and economic growth.

As mentioned above, future research should assess the impact of price variations and load demand growth. Furthermore, a comprehensive evaluation of other factors influencing the operation of a solar power plant (SPP) over 20 years is necessary. This evaluation should include, but not be limited to, the plant's ability to maintain designed operational characteristics, regulatory policy changes affecting SPP operation, and operational costs such as staff salaries. Additionally, In future work, load demand, solar radiation, and electric prices will be predicted by using modern techniques or software to obtain more exact results for the project with the combination of thermal power plants and solar power plants.

Abbreviation

HOA	Hybrid optimization algorithm
MSPSO	Modified symbiosis particle swarm optimization
FA	Firefly Algorithm
ASSA	Adaptive salp swarm algorithm
ECIA	Enhanced Cheetah-inspired algorithm
AVOA	African vulture optimization algorithm
RDA	Robust Distributed Algorithm
MOEAs	Multi-objective evolutionary algorithms
ANN-	Artificial Neural Network and Adaptive Neuro-Fuzzy
ANFIS	Inference System

CJA Chaotic Jaya algorithm

Nomenclature

N_{year}	The number of (20) years for the project
N_{day}	The number of days in one year (selected to be 360 days)
$CAPEX_{1MW}$	The capital expenditure per MW (\$/MW)
$Cost_{1MW}^{O\&M}$	The operating and maintenance cost per MW per year (\$/MW-year)
$PG_n; PG_m$	The power output of the TGU n and m
$PG_n^{min}; PG_n^{max}$	The highest and lowest value of power output supplied by TGU n
$P_{SPP,s}^{min}; P_{SPP,s}^{max}$	The minimum and maximum power output of SPP s
$P_{WPP,w}^{min}; P_{WPP,w}^{max}$	The minimum and maximum power output of WPP w
N_{ps}	The initial population size
μ_{0-1}	A random value between 0 and 1
X_{GB}	The best solution of the whole population at current iteration
X_n^{new}	The new solution updated in the exploration phase
μ_{Levy}	A random value based on Levy flight distribution
$UB; LB$	The upper and lower boundaries of the search space
$NF_1; NF_2$	The navigation factors
$\varepsilon_1; \varepsilon_2$	The reference factors
$FT_{Ep}; FT_{Eq}$	The fitness values of the electric eels p and q

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