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Research Article

Determining solutions to new economic load dispatch problems by war strategy optimization algorithm

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Abstract. The paper applies three cutting-edge algorithms - War Strategy Optimization Algorithm (WSO), Egret Swarm Optimization Algorithm (ESOA), and Black Widow Optimization Algorithm (BWOA) - as potential tools to determining the optimal generation power of power plants in both the Economic Load Dispatch problem (ELD) and the New ELD problem (NELD), which incorporates renewable energy resources into the traditional power system. These algorithms underwent rigorous evaluation using various test systems with complex constraints, a multi-fuel objective function, and 24-hour load demands. In System 1, at various load levels, WSO method achieves a lower total minimum cost compared to BWOA and ESOA. Specifically, WSO outperforms BWOA and ESOA by \$0.68 and \$2.79 for a load of 2400 MW, by \$0.49 and \$4.41 for a load of 2500 MW, by \$0.79 and \$4.83 for a load of 2600 MW, and by \$0.54 and \$4.53 for a load of 2700 MW. In System 2, WSO method is less cost in a day than ESOA by \$ 80.92 and BWOA by \$ 46.73, corresponding to 0.39% and 0.23%, respectively. Additionally, WSO excels in response capability, providing a quicker reaction time than BWOA and ESOA across all four subcases while maintaining the same control parameters. Moreover, WSO demonstrated comparable or superior results and improved search capabilities compared to previous methods. The comparison of these results underscored WSO's effectiveness in addressing these challenges and its potential for resolving broader engineering issues beyond ELD. Ultimately, the study aimed to offer valuable insights into the role of renewable energy resources in the traditional power system, particularly in cost savings.

Keywords: Economic load dispatch, War Strategy Optimization, Egret Swarm Optimization Algorithm, Black Widow Optimization Algorithm

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1. Introduction

In today's modern age, the consumption of fossil fuels by power plants, particularly thermal power plants (TPP), is substantial enough to generate electricity to support the growth of industrial and commercial sectors. It is well established that higher fuel consumption by TPPs increases fuel costs. Among the available fuels for each unit, the primary goal reduces the overall fuel cost while adhering to generation and load constraints. Even a modest decrease in electricity costs can yield a substantial positive effect on the entire power system. Therefore, ensuring proper load sharing plan among generating units is essential for lower generation costs. In the power system, ELD problem addresses this challenge by determining the optimal generation allocation among all generating units, thereby minimizing the overall fuel cost while ensuring compliance with all necessary inequality and equality constraints (Nguyen *et al.,* 2016; Pham, An and Tam, 2018).

The functions of an ELD problem are usually expressed as quadratic or convex functions. However, in practical operation, the design and operating constraints of the generating units complicate the ELD problem. For instances, the introduction of valve-point effects by multi-valve steam turbines results in a highly nonlinear and non-convex function. Additionally, generators may be unable to operate in specific zones due to malfunctioning auxiliary systems or associated machine problems, which creates discontinuities in the solution space with multiple local optima (Pham *et al.,* 2017). Moreover, steady power system conditions cannot eliminate transmission line loss or multiple fuel options are applied. As a result, with high dimensionality, nonlinearity, non-differentiability, and multiple constraints, the ELD problem has become an more challenging optimization problem.

The conventional ELD problem with multiple fuel options has been addressed using traditional methods for several decades, disregarding environmental considerations. These methods include using gradient, base point, participation factors, and lambda-iteration methods. Compared to other solutions presented in (Thang, 2011), the lambda-iteration method was again employed and yielded the most significant result. This method is both simple and effective. However, a drawback of this method is the initial setup of the lambda value. The optimal solution was determined after many trial runs with different lambda values, and the fuel type k was initially selected. Although each trial's simulation period is brief, the overall time is extended. Despite its simplicity, implementing

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the Hopfield neural network (HNN) (Park *et al.,* 1993) has posed challenges when tackling large-scale problems with numerous specific inequality constraints. Moreover, the selection of penalty factors related to constraints affects the final solution of the HNN method. The dynamics of Lagrange multipliers, incorporating both equality and inequality constraints, have been refined to facilitate convergence to optimal solutions within the problem-solving framework of the enhanced Lagrangian neural network (ELANN) (Lee and Kim, 2002). Furthermore, the momentum technique was incorporated into its learning algorithm to achieve faster computational time. ELANN (Lee and Kim, 2002) and HNN (Park et al., 1993) necessitate numerous iterations for convergence. Two versions of HNN called augmented Lagrange Hopfield network (ALHN) (Dieu *et al.,* 2013) and enhanced augmented Lagrange Hopfield network (EALHN) (Vo and Ongsakul, 2012) were proposed by Dieu *et al*. (2011), by using energy function based on augmented Lagrangian function. ALHN and EALHN have been effectively designed to address ELD problem with multiple fuel types represented by piecewise quadratic cost functions. The findings suggest that both ALHN and EALHN outperformed HNN and ELANN in terms of total cost and CPU time. However, further evaluation is needed to compare the results of two algorithms and determine which one is superior. The mentioned methods face challenges related to system characteristics, high oscillations, and non-differentiable functions. Although some progress has been made with ALHN and EALHN, they are still unable to solve non-differentiable functions. As a result, recent developments have focused on the advancement and application of meta-heuristic algorithms for addressing these complex ELD problems. In fact, meta-heuristic algorithms have seen ongoing advancements in their application to solve complex ELD problems. This signifies a sustained effort in refining and adapting these algorithms to address the intricate challenges of ELD problems. One of the ancient methods is particle swarm optimization (PSO) (Jeyakumar et al., 2006). PSO draws inspiration from the social behaviors observed in bird flocks and fish schools. It is categorized as a swarm intelligence algorithm that harnesses collective behaviors to solve complex problems. However, the drawbacks of PSO consist of premature convergence, sensitivity to parameters, and challenges with constrained optimization, leading to the proposal of many improved versions of PSO like modified PSO (MPSO) (Park *et al.,* 2005), new adaptive PSO (NAPSO) (Park et al., 2005) and double weighted PSO (DWPSO) (Kheshti et al., 2018). In (Kheshti *et al.,* 2018), authors have recomened two inertia weights (wk_head and wk_end) for updating the velocity of particle, in which w_{k_head} is utilized at the start of the DWPSO iteration, while w_{k_end} is employed at the end of the DWPSO loop during each iteration. In (Park et al., 2005), NAPSO was enhanced by incorporating two improvements from conventional PSO. Improvement 1 involves a new formula for the inertia weight in the velocity updating equation, while Improvement 2 applies the mutation mechanism of the differential evolution technique (DE) to construct the position equation. The numerical results unequivocally demonstrated that NAPSO and DWPSO outperform PSO in superior robustness and reduced computational efforts. Others in the family of meta-heuristic algorithm such as DE (Noman and Iba, 2008), self-adaptive differential evolution (SDE) algorithm (Balamurugan, 2007), two-phase hybrid real coded genetic algorithm (HGA) (Balamurugan, 2007), real-coded genetic algorithm (RCGA) (Amjady and Nasiri-Rad, 2009), harmony search (HS) algorithm (Fesanghary and Ardehali, 2009), chaotic firefly algorithm (CFA) (Arul et al., 2013), improved FA (IFA) (Nguyen *et al.,* 2018a), adaptive cuckoo search algorithm (ACSA) (Pham et al., 2016), modified CSA (MCSA) (Nguyen et al., 2018b), improved social spider optimization algorithm (ISSO) (Kien et al., 2019), and improved antlion optimization algorithm (IALO) (Dinh et al., 2020) have been recommended for ELD problem. Among methods, IALO is the latest method by suggesting four modifications based on the standard ALO from Bach et al. in 2020. The performance of IALO was tested on different systems from 10 to 90 units together different constraints. Via obtained results, the method was better than ALO method. Its quicker computation times, faster convergence velocity, and more steady search capability explain this. Moreover, the IALO approach was noticeably better than almost every other approach to tackling difficulties for similar systems. It is noted that in most studies, authors have only focused on dealing with the allocation of power generation from TPPs available but not considered emissions from burning fossil fuels (e.g., coal, natural gas, oil). Components of TPP's emissions consist of carbon dioxide (CO2), sulfur dioxide (SO2), nitrogen oxides (NOx), particulate matter (PM), carbon monoxide (CO), heavy metals, ash, ect. As we know, these gases are the leading causes of a substantial increase in greenhouse gas (GHG) emissions, air pollution, global warming, and climate change. Taking proactive steps to reduce greenhouse gas (GHG) emissions and implementing effective carbon-lowering strategies is vital for successfully addressing climate change. Countries worldwide embrace diverse approaches tailored to their specific circumstances, resources, and commitments (Sebos et al., 2016; Losada-Puente et al., 2023; Martín-Ortega et al., 2024; Tsepi et al., 2024). By sharing best practices and collaborating on innovative solutions, we can collectively strengthen our efforts to combat this global challenge. In terms of air pollution, countries are aslo embracing innovative strategies to combat air pollution, united in their commitment to protect public health and preserve the environment for future generations (Progiou et al., 2023). Namely, specific strategies to cover these mentioned challenges, which are implemented by countries, include regulatory measures, renewable energy promotion, public transportation improvements, etc., for air pollution mitigation while renewable energy transition, energy efficiency improvements, afforestation, and reforestation, etc., for greenhouse gas mitigation and carbon lowering. Among strategies, the use of renewable energy resource is considered the best potential sollution. Other factors, such as epidemics or floods, can also affect the emissions that countries worldwide have recently experienced. Specially, the restrictions imposed during the COVID-19 pandemic resulted in significant short-term reductions in greenhouse gas emissions and improvements in air quality (Papadogiannaki et al., 2023; Yassine & Sebos, 2024)

In recent years, renewable energies (RE) like wind and solar power have experienced rapid development and are making significant contributions to electricity generation. Their potential makes them promising resources for mitigating greenhouse gas effects, addressing global warming, and replacing the depletion of fossil energy sources. As a result, these energy sources are among the fastest-growing renewable ones and offer a viable alternative to traditional fossil fuels worldwide. The integration of renewable energy into the traditional power system transforms the economic load dispatch problem into a new one, named the new economic load dispatch (NELD) problem. For dealing with NELD problem, the author (Li et al., 2016) described a solution for a mechanism using virtual power plants, which were made up of wind farms. However, the authors overlooked the impact of penalty factors for over and underestimations by considering the cost of wind-based plants as zero. In (Liang et al., 2018), authors have adopted a random wind power model by considering three cost functions: direct, overestimation, and underestimation. As a result, the objective function of the NELD problem is the costs of TPP and wind power plant. Study (Ellahi and Abbas, 2020) has put forth three distinct combinations of power plants. These configurations involved the integration of RES with TPPs, the implementation of small-scale thermal power systems with constraints, and the operation of large-scale power systems with the valve point loading (VPL) effect in the aim at identifying the most effective operational parameters for these power plants. In (Basu, 2019), the cost formulation for integrating both photovoltaic (PV) power plant and wind-based power generation systems with TPPs was presented, with a primary emphasis on analyzing the cost of TPPs, while the authors in (Lai et al., 2017) have introduced a power system incorporating solar PV and biofuel as an alternative to fossil fuels. And their focus was on calculating the cost associated with the degradation of energy storage.

This research paper makes use of WSO, a population-based optimization algorithm by (Ayyarao et al., 2022) for solving ELD and NELD problems. This method models the strategic movement of army troops during war, focusing on attack and defense strategies. This work introduces an innovative weight-updating mechanism and a strategic approach for relocating underperforming soldiers, aiming to enhance convergence and robustness significantly, which help WSO get a balance between exploration and exploitation stages. Its efficacy is tested on 50 benchmark functions and four engineering problems, and its superiority is proven through experimental results. Since the algorithm appeared, it has been applied by many researchers to solve electrical engineering problems such as estimating parameters for solar PV models (Ayyarao and Kumar, 2022), enhancing the generated power for PV array (Alharbi et al., 2023), classifying air pollutant species (Gehad Ismail Sayed and Aboul Ella Hassanein, 2023), controlling load frequency for the power system (Ayyarao et al., 2023), and establishing an optimal configuration model for a voltage sag monitor (Shou et al., 2023). Along with WSO, Egret swarm optimization algorithm (ESOA) (Chen et al., 2022) and black widow optimization algorithm (BWOA) (Peña-Delgado et al., 2020) were also utilized for such problems. The application of WSO, BWOA, and ESOA to two types of ELD presents an opportunity to optimize the power output of power plants, ultimately reducing the overall operating costs of the system. Additionally, this approach provides a valuable framework for assessing the effectiveness of recently proposed metaheuristic methods. The results of the three applied methods were compared to those of other competitors.

The followings are the study's novelties and contributions :

a) The study successfully applies WSO (created in 2022) and takes into consideration the ESOA and BWOA algorithms (suggested in 2020 and 2022, respectively), to address ELD and NELD problems.
b) The study presents compelling numerical data and graphics that effectively demonstrate the advantages of the WSO algorithm compared to earlier techniques. Moreover, the results indicate that the WSO algorithm outperforms both the ESOA and BWOA in obtaining optimal and high-quality solutions, highlighting its potential for further advancements in the field.
c) The study provides how to compute the daily power production of solar power plants connected to the conventional power grid using accurate solar radiation data from two locations in Vietnam.
d) The study provides short discussions and strategies regarding greenhouse gas (GHG) emissions, air pollution, global warming, and climate change.

2. Problem Model

2.1 The objective

The paper carefully examines ELD and NELD problems. These problems are designed to minimize costs by meeting the load demand and various equality and inequality constraints. Specifically, the ELD problem focuses on minimizing the fuel cost of the TPP, while the NELD problem incorporates both the TPP fuel cost and the cost of photovoltaic power plant (PVP). The formulations for two problems are explicitly expressed in Eqs. (1) and (2), respectively.

$$Min\ (C_{TPP}) \tag{1}$$

$$Min\ (C_{TPP}, C_{PV}) \tag{2}$$

Subject to

Equality constraints

$$g(V_{TPP}, V_{PV}) = 0 \tag{3}$$

Inequality constraints:

$$h(V_{TPP}, V_{PV}) < 0 \tag{4}$$

- *Photovoltaic power plant:*

When the system operator has possession of the PVP, the cost function for a PVP may not be directly applicable because it does not apply fossil fuel. However, determining the cost of PVP generation becomes necessary through specific contracts if a state company does not possess the PVP (Huu Pham et al., 2021). This study undertakes an investigation into the total cost function of PVP (C_{PV}), which is represented linearly (Reddy, 2017).

$$C_{PV} = \sum_{v=1}^{P} \left(p.V_{PV,v}\ ; v = 1, \dots, P\right) \tag{5}$$

where p stands for the PV generator price in (\$/MWh); $\boldsymbol{V_{PV,v}}$ stands for the power ouput of the vth PV generator, which is given by

$$V_{PV}(PV_b) = \begin{cases} V_{PV,r} \times \dfrac{PV_b^2}{PV_{std} + R_c} & 0 < PV_b < R_c \\ V_{PV,r} \times \dfrac{PV_b}{PV_{std}} & PV_b > R_c \end{cases}; \tag{6}$$

$$b = 1, \dots, 8760\ hours$$

It is observed that solar radiation (PV_b) variations, including hourly, daily, monthly, and annual ones, are crucial for determining optimal placement and rated power of photovoltaic power systems. If Eq. (6) is applied to calculate the power output of PVP, then we need a powerful enough tool, which will take much time. This causes grid operators' decision-making to fail to keep up with load changes. In addition, current optimization methods need help handling the large data volume efficiently. To cover the obstacle, the study suggests using global solar data to analyze solar radiation patterns in two southern Vietnamese provinces, where two PVPs will be adopted to optimize the cost of the standard 10-unit IEEE system. The data accurately reports average radiation for each hour of every month, indicating the mean solar radiation for a year is 6 o'clock to 18 o'clock for every 12 months, with one year represented by 12 days instead of the standard 365 days. This approach will help determine the power output of PVPs integrated easily into traditional thermal power plant systems.

- *Thermal power plant:*

The formulation for TPP cost function (C_{TPP}) can be described mathematically as a second-order function. This means it can be represented by an equation involving a second-degree polynomial. This allows for a more detailed analysis of the fuel cost function, providing a deeper understanding of its behavior and implications. The function is formulated by (Ismaeel et al., 2023)

$$C_{TPP} = \sum_{t=1}^{T} \left(\rho_t + \sigma_t V_{TPP,t} + \tau_t V_{TPP,t}^2\right);\ t = 1, \ldots, T \tag{7}$$

The mathematical formula for TPP's cost with multiple fuel choices is shown in Eq. (8)

$$C_{TPP} = \begin{cases} \rho_{t1} + \sigma_{t1} V_{TPP,t} + \tau_{t1} V_{TPP,t}^2 \\ \text{For } fuel\ 1, V_{TPP,tmin} \le V_{TPP,t} \le V_{TPP,t1max} \\ \rho_{t2} + \sigma_{t2} V_{TPP,t} + \tau_{t2} V_{TPP,t}^2 \\ \text{For } fuel\ 2, V_{TPP,t2min} \le V_{TPP,t} \le V_{TPP,t2max} \\ \ldots\ldots\ldots \\ \rho_{tw} + \sigma_{tw} V_{TPP,t} + \tau_{tw} V_{TPP,t}^2 \\ For\ fuel\ w, V_{TPP,twmin} \le V_{TPP,t} \le V_{TPP,twmax} \end{cases} \tag{8}$$

Where, the cost coefficients for type wth of unit tth are denoted by ρ_{tw}, σ_{tw} and τ_{tw}

2.2. The considered constraints

This paper addresses ELD and NELD problems by ensuring that generators and systems meet various equality and inequality constraints as follows.

- *Restriction on the actual active power balancing*

The constraint is one of these constraints in such a problem, in which the power produced by these power plants must be adequate to satisfy both the combined demand (*PD*) and transmission losses (*LP*) as stipulated by the specific equation. This means that the power generated should be capable of meeting the total power demand and accounting for any losses during transmission

$$\sum_{t=1}^{T} V_{TPP,t} + \sum_{v=1}^{P} V_{PV,v} = PD + LP \tag{9}$$

where, LP is determined in Eq. (9) using Krone's reduction model.

$$LP = \sum_{t=1}^{T}\sum_{j=1}^{T} V_{TPP,t} \times A_{tj} \times V_{TPP,j} + \sum_{t=1}^{T} A_{0t} \times V_{TPP,t} + A_{00} \tag{10}$$

- *Restriction on power generated:*

For the optimal functioning of the unit, it is crucial to adhere to the specified minimum and maximum generation capacities strictly. This ensures that the unit operates within its designated power, allowing for efficient and sustainable power generation while minimizing the risk of overloading or underutilization (Deb *et al.*, 2021).

$$V_{TPP,min} \le V_{TPP,t} \le V_{TPP,max} \tag{11}$$

$$V_{PV,min} \le V_{PV,v} \le V_{PV,max} \tag{12}$$

3. War Strategy Optimization

In 2022, Ayyarao *et al.* suggested an innovate revolutionary meta-heuristic algorithm called War Strategy Optimization (WSO). The algorithm models the strategic movement of army troops during war, focusing on attack and defense strategies. In the battlefield, every soldier constantly adjusts his positions based on the strategy's success influenced by King, Commander, and soldier rank. In order to replicate an optimization procedure, every soldier rushes dynamically to the target, which is the optimal position. When the war begins, each soldier holds the same rank and weight to them and depending on how well they perform in terms of assault force and fitness level, their weight is modified. Two common military strategies used to enhance soldier positions and solutions are the attack and defense strategies. To improve new solutions, two approaches will be described as below:

- *The attack strategy*

The fundamental strategy involves the king leading soldiers in a coordinated attack against the opposition, with the soldiers' positions adjusting based on the orders of the king and the commander. When the attacking force gains an advantage, the soldiers move forward; however, if the advantage diminishes, they return to their original positions. This approach enables the army to effectively cover the entire search area by making substantial progress initially and more incremental advances later.

The phase known as exploitation involves updating the soldier's position as follows:

$$\begin{aligned} A_i^{new} = A_i + 2 \times \mathcal{E} \times (A^K - A^C) \\ + rand \times (W_i \times A^K - A_i) \end{aligned} \tag{13}$$

In Eq. (13), the new and old locations of soldier i denote A_i and A_i^{new} are; A^K and X^C the location of the king and commander; $\mathcal{E}$ signifies a random value; W_i is the weight factor which is give by:

$$W_i = W_i \times \left(1 - \frac{B_i}{MX}\right)^{\alpha} \tag{14}$$

Where *MX* is the maximum iteration; B_i is the soldier's order which is formulated by:

$$B_i = \begin{cases} B_i + 1 & \text{If } (F_{new} \ge F_{old}) \\ B_i & \text{If } (F_{new} < F_{old}) \end{cases} \tag{15}$$

In Eq. (15), F_{new} and F_{old} stands for the fitness of A_i^{new} and A_i

- *The defense strategy*

The central aim of this strategic approach is to ensure the safety of the King. It involves a commander leading the way, with soldiers positioned in a chain formation to promptly respond to threats based on the King's movements.

The exploration phase is the name of the tactic. Equation (8) is applied to update the soldier's position during this phase.

$$A_i^{new} = A_i + 2 \times \mathcal{E} \times (A^K - A_{rand}) + rand \times W_i(A^C - A_i) \quad (16)$$

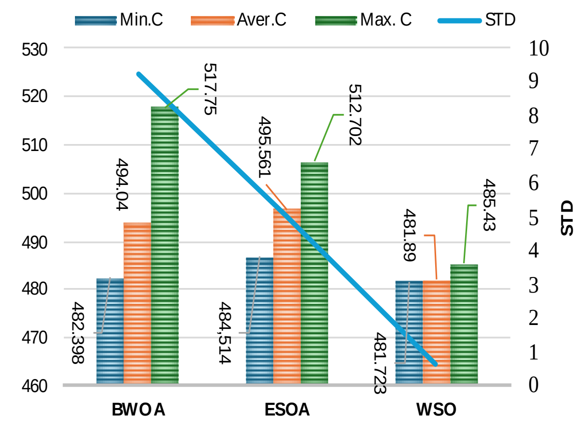
In Eq. (17), A_{rand} is a radom location of soldier among the army.

4. Results and Dicussion

In the section, two primary power systems – System 1 with ten TPPs and System 2 with TPPs and two PVPs – are utilized to assess the performance, resilience, and convergence rate of three applied methods. The details of these systems will be revealed in the following sub-sections, in which Section 4.1 gives information about the investigation of control parameters of WSO, BWOA, and ESOA, Section 4.2 discusses the results of System 1, and Section 4.3 discusses the results of System 2. The proposed algorithms-WSO, BWOA, and ESOA-will each be subjected to 50 independent trials for Systems 1 and 2. These trials will be conducted on a 2.4 GHz PC with 4 GB of RAM and a Matlab platform with R2018a version.

4.1. The investigation of control parameters:

To find the optimal solution for any problems, researchers must carefully implement the process of investigating control parameters for the applied methods. This work may be carried out based on various factors, including the mechanism of generating solutions (one or more times), the number of fitness evaluations, and the findings from previous researches. In this study, two parameters of WSO, BWOA and ESOA consisting of population size (PZ) and maximum iteration (MX) will be checked on the first system with PD of 2400 MW. In order to conduct a fair comparison, it is imperative to ensure that the total fitness evaluations (TFE) for all three methods are equivalent. The TFE for a method with solution generating once is calculated as (PZ × MX), where PZ represents a specific value, and MX represents another specific value. The TFE is calculated as (2 × PZ × MX) for a method with solution generating twice.



PZ	70	70	30
MX	100	100	100
TFE	7000	7000	3000

Fig 1. The investigated results obtained from three methods

In this study, three methods that were applied to such problems are a meta-heuristic algorithm with solution generating once.

For the survey, PZ is changed from 10 to 100, while MX varies from 50 to 150. Results from three methods: minimum cost (Min. C), average cost (Aver. C), maximum cost (Max. C), and standard deviation (STD) are collected and noted in Figure 1. Out of the four comparison criteria, the first one is crucial as it provides information about the performance of the applied method. If the method's Min. C is the smallest, it is considered the strongest. Otherwise, the method is considered the weakest. The second and fourth ones show the stable ability of the method in searching solutions. In Figure 1, the minimum costs of BWOA and ESOA are $ 482.398 and $ 484,514, respectively, and the value is the best that the ability of BWOA and ESOA can reach. To reach the Min. C, the *PZ*, *MX*, and TFE settings for the two methods are 70, 100, and 7000, respectively. If PZ is under 70, the method cannot find this value; otherwise, the Min. C remains unchanged. In terms of WSO, Min. C is $481.723 corresponding to PZ, MX, and TFE of 30, 100, and 3000, in turns. If the PZ of WSO continuously increases to 70, its costs, such as Min. C, Aver. C, Max. C and STD are $ 481.723, $ 481.765, $ 485.092, and 0.337, respectively. For PZ from 30 to 70, WSO's Min. C is the same value. From here, we conclude that the PZ significantly affects the speed and quality of each iteration's solutions. On the other hand, MX substantially affects both the time it takes to run independently and the quality of the solution. Therefore, setting high PZ value will increase the solutions' quality and time for each iteration. Similarly, setting a high MX value will improve the solution quality at the final independent runs but will also lead to longer run times. Notably, if both PZ and MX are set to high levels, the same optimal solutions will be produced, but it will take longer to achieve them.

4.2. Discussion on System 1

This section evaluates the efficacy of three methods on a system comprising ten units, utilizing various fuel choices for 4 sub-cases: sub-case 1.a assesses a 2400 MW load, sub-case 1.b assesses a 2500 MW load, sub-case 1.c assesses a 2600 MW load, and sub-case 1.d assesses a 2700 MW load. The data source for System 1 is from (Dieu et al., 2013). To effectively run WSO, BWOA, and ESOA, it is important to configure PZ and MX with the parameters outlined in Section 4.1. Furthermore, it is essential to ensure that other control parameters, such as the step size factors of ESOA (*step$_a$* for Egret A and *step$_b$* for Egret C), float numbers of BWOA, and the weight of WSO, are adjusted to match the values of the original methods. In Table 1, the results from three methods are presented for comparison. Upon comparison with the BWOA and ESOA methods, it is evident that the WSO method demonstrates the smallest Min. C, the smallest Aver. C, and the smallest STD, except. for ESOA for 2700 MW load. This provides compelling evidence for the WSO method's superior performance in terms of search ability for the global optimal solution, stability in search ability, and quick convergence to the global solution. For further demonstrations, 50 fitness values of three methods for four demand loads are also found by running 50 trial runs and these values are then displayed in Figure 2a with 2400 MW, Figure 2b with 2500 MW, Figure 2c with 2600 MW, and Figure 2d with 2700 MW, respectively. In these figures, the results of WSO in red are under those from ESOA and BWOA in black and blue, respectively. In terms of fluctuation, both methods exhibit significant variability in their results. However, the variance between the worst and best WSO solutions is deemed

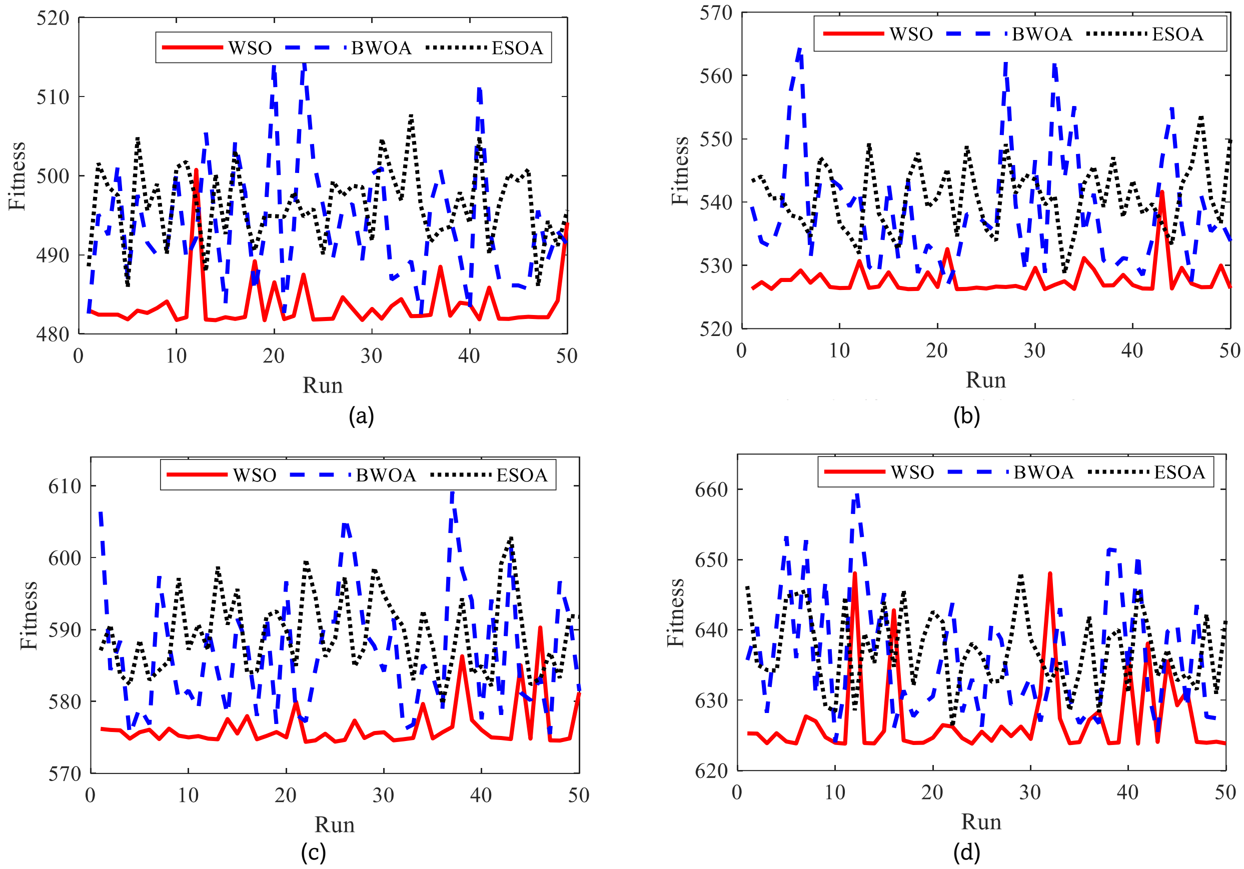


Fig 2. Fifty runs with PD (a) 2400 MW, (b) 2500 MW, (c) 2600 MW, (d) 2700 MW

Table 1

The results achieved by WSO, ESOA and BWOA for subcases of System 1.

PD (MW)	Methods	Min. C ($/h)	Aver. C ($/h)	Max. C ($/h)	STD ($/h)	TFE
2400	BWOA	482.398	494.036	517.754	9.273	7000
	ESOA	484.514	495.561	512.702	5.207	7000
	WSO	481.723	481.885	485.434	0.657	3000
2500	BWOA	526.731	538.419	569.321	10.510	7000
	ESOA	530.649	541.660	553.272	5.804	7000
	WSO	526.239	528.011	541.608	2.523	3000
2600	BWOA	575.180	588.039	614.528	11.695	7000
	ESOA	579.221	589.201	603.625	5.245	7000
	WSO	574.390	576.534	600.499	3.926	3000
2700	BWOA	624.363	635.365	659.332	9.155	7000
	ESOA	628.352	637.946	647.270	3.978	7000
	WSO	623.819	627.318	648.051	5.373	3000

negligible. The searchability of the optimal solutions for ESOA and BWOA has stabilized at a very high level.

In addition, the best run among 50 runs of three methods are collected and depicted Figure 3a with 2400 MW, Figure 3b with 2500 MW, Figure 3c with 2600 MW, and Figure 3d with 2700 MW, for showing the convergence features to global solutions. The data from the curves suggests that WSO consistently surpasses the other methods when the fitness function experiences a significant decrease in the initial five iterations. However, this decrease becomes almost negligible in the final iterations. On the other hand, the other methods exhibit only minor improvements in the initial iterations, with noticeable improvements still occurring in the final iteration.

For more explanation, in Figure 3a, most fitness values are on the straight line from 40 to 100 iterations, while those from Figures 3b, 3c, and 3d are from 20 to the end iterations. Consequently, WSO method outperforms the ESOA and BWOA ones in terms of effectiveness for System 1 with different choices of fuels and is a strong contender against previous methods.

To further illustrate the effectiveness of WSO, we have compared its performance with previous methods such as HNN (Park et al., 1993), ELANN (Lee and Kim, 2002), ALHN (Dieu et al., 2013), EALHN (Vo and Ongsakul, 2012), MPSO (Park et al., 2005), DE (Noman and Iba, 2008), SDE (Balamurugan, 2007), HGA (Baskar et al., 2003), HHS (Fesanghary and Ardehali,

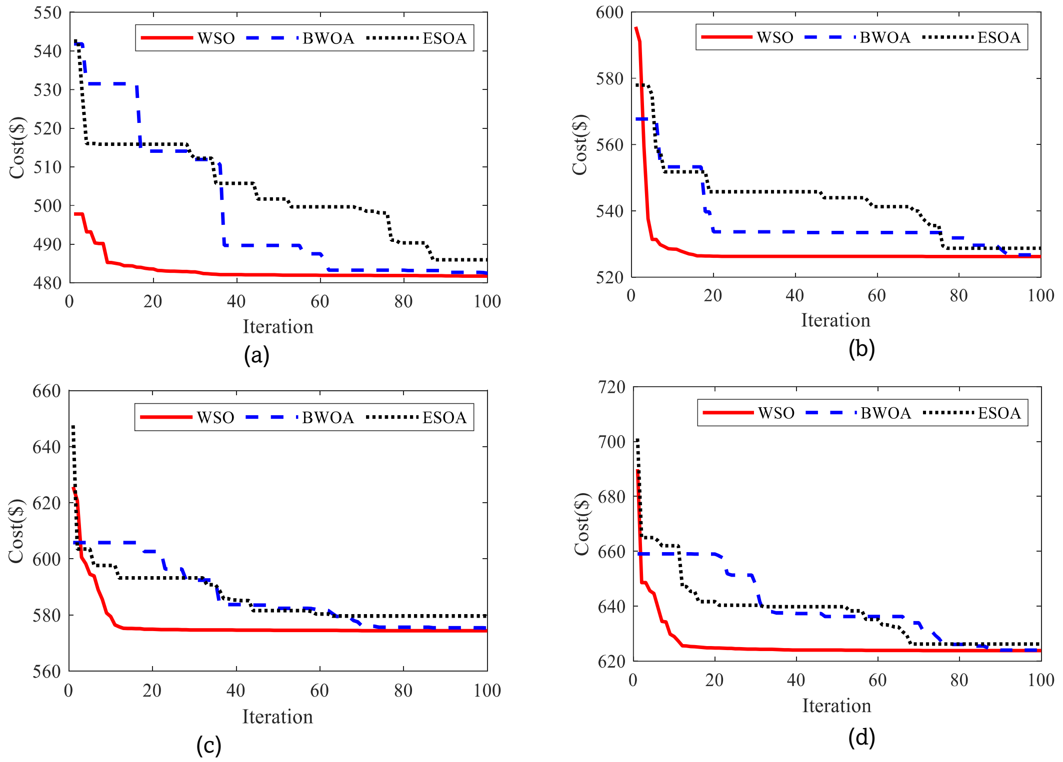


Fig 3. The best run with PD of (a) 2400 MW, (b) 2500 MW, (c) 2600 MW, (d) 2700 MW

Table 2
The optimal solution obtained by WSO for System 2

Unit	1	2	3	4	5	6	7	8	9	10	11	12
P1	218.33	214.84	214.08	207.48	207.53	215.57	218.98	228.21	243.08	241.15	244.09	236.58
P2	211.70	210.19	209.74	206.88	206.89	210.46	211.98	216.07	222.65	221.76	222.97	219.77
P3	280.94	276.39	275.42	267.05	267.08	277.31	281.64	500.00	500.00	500.00	500.00	500.00
P4	239.61	238.59	238.29	236.26	236.24	238.77	239.90	242.74	247.33	246.78	247.80	245.42
P5	278.40	272.57	271.08	259.65	259.79	273.56	279.83	295.82	350.46	318.43	351.62	310.40
P6	239.60	238.58	238.34	236.24	236.28	238.84	239.87	242.74	247.43	246.78	247.65	245.24
P7	288.76	282.92	281.46	270.64	270.48	284.16	289.89	305.27	354.40	351.14	356.16	343.78
P8	239.63	238.53	238.32	236.26	236.31	238.78	239.89	242.75	247.43	246.76	247.76	245.38
P9	428.29	418.28	415.43	332.81	332.63	342.12	430.62	440.00	440.00	440.00	440.00	440.00
P10	274.75	269.12	267.85	256.73	256.78	270.43	276.08	291.62	316.78	313.51	318.60	305.79
PVP1	0.00	0.00	0.00	0.00	0.00	0.00	0.64	7.58	16.05	23.24	28.49	30.96
PVP2	0.00	0.00	0.00	0.00	0.00	0.00	0.67	7.20	14.38	20.46	24.86	26.68

Unit	13	14	15	16	17	18	19	20	21	22	23	24
P1	242.46	239.23	238.81	238.95	244.49	236.71	240.65	244.64	236.84	243.27	227.46	228.32
P2	222.43	220.81	220.74	220.90	223.47	219.80	221.62	223.29	220.03	222.72	215.80	216.19
P3	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	293.55
P4	247.17	246.11	246.06	246.13	247.93	245.40	246.68	247.77	245.41	247.22	242.47	242.77
P5	320.66	314.58	314.27	314.64	324.43	310.60	317.72	352.18	311.44	350.54	294.51	296.08
P6	247.24	246.09	246.07	246.14	247.82	245.39	246.75	247.89	245.49	247.44	242.54	242.75
P7	489.81	463.67	462.45	463.84	356.36	446.66	477.05	356.81	449.27	354.39	304.24	305.63
P8	247.29	246.11	246.07	246.13	247.82	245.41	246.76	248.02	245.51	247.44	242.49	242.81
P9	440.00	440.00	440.00	440.00	440.00	440.00	440.00	440.00	440.00	440.00	440.00	440.00
P10	315.63	490.00	490.00	490.00	319.63	306.16	312.77	319.40	306.02	316.97	290.49	291.91
PVP1	31.00	28.77	24.16	17.55	9.35	1.97	0.00	0.00	0.00	0.00	0.00	0.00
PVP2	26.31	24.64	21.36	15.73	8.70	1.89	0.00	0.00	0.00	0.00	0.00	0.00

2009), IFA (Nguyen et al., 2018a), MCSA [21], and IALO (Dinh et al., 2020). The comparison results are presented in various Figures for a better understanding, in which the Min. C comparison is presented in Figure 4 and the Aver. C and Max. C comparisons are shown in Figure 5. From Figure 4, the Min. C of WSO is $ 481.723 for PD of 2400MW, $ 526.239 for PD of 2500MW, $ 574.381 for PD of 2600MW, and $ 623.810 for PD of 2700MW. These values are considered the best cost for System 1. From here, it can be concluded that WSO can find the same or less Min. C than other methods, excluding HHS

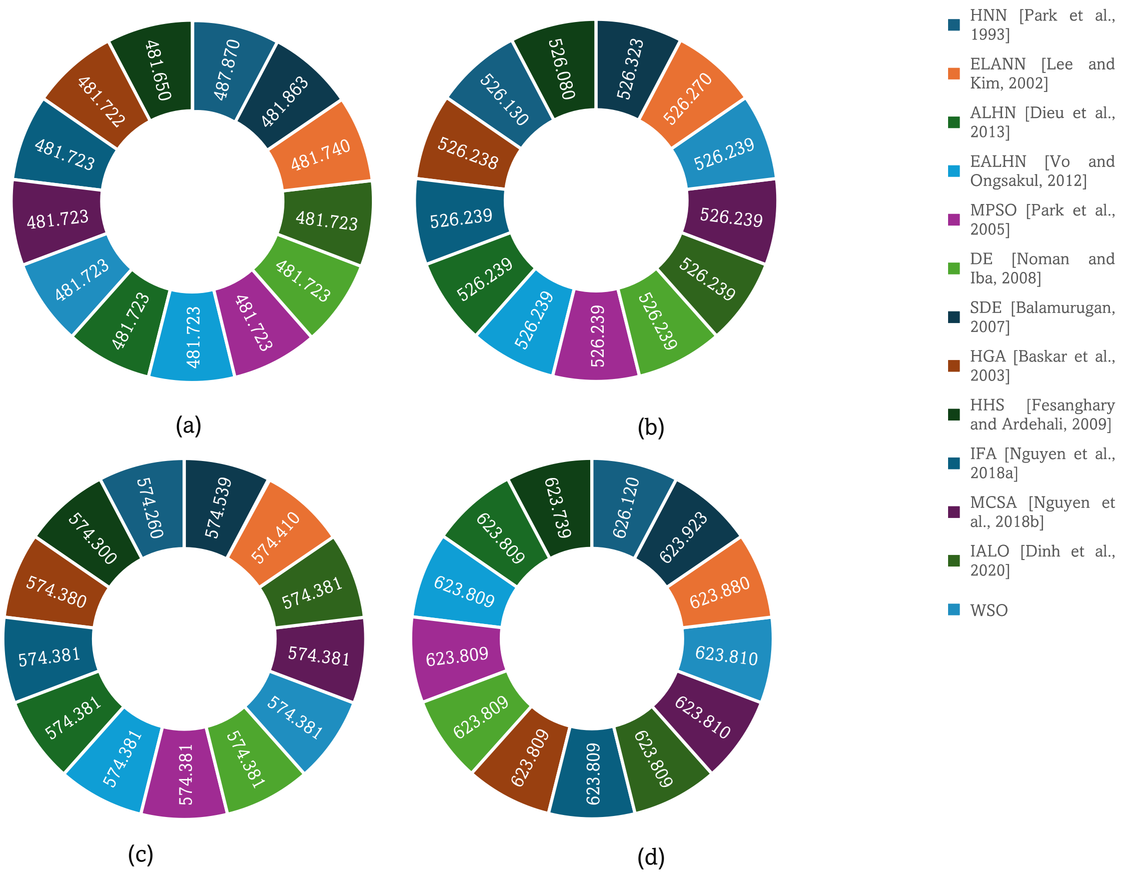


Fig 4. The minimum cost comparison from different methods with PD of (a) 2400 MW, (b) 2500 MW, (c) 2600 MW, (d) 2700 MW

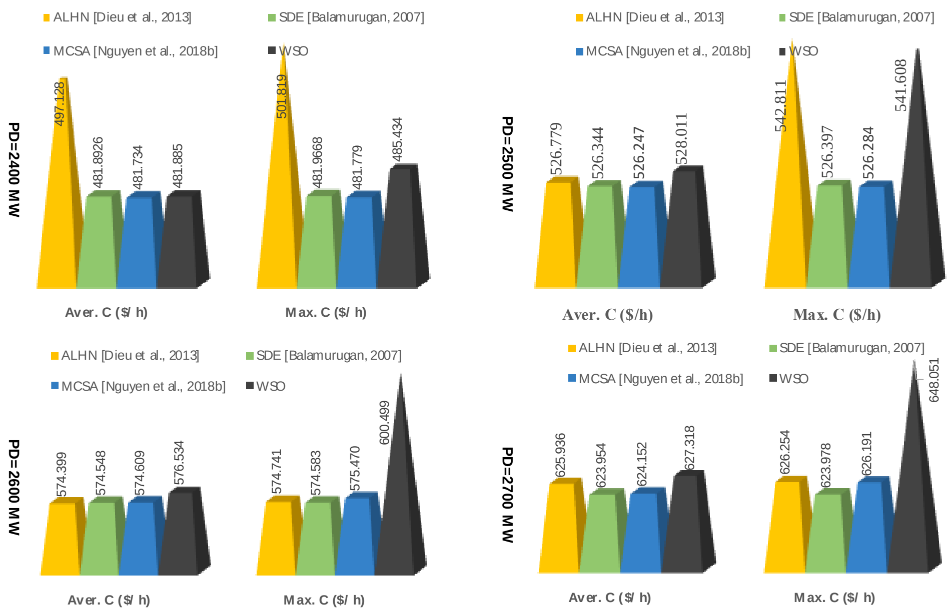


Fig 5. The average and maximum costs comparison from different methods

(Fesanghary and Ardehali, 2009) and HNN (Park et al., 1993), which have smaller Min. C than WSO. Namely, the Min. C of HHS is $ 481.650 for 2400 MW load, $ 526.080 for 2500 MW load, $ 574.381 for 2600 MW load, and $ 623.810 for 2700 MW load, and that of HHN is $ 526.130 for PD of 2500MW and $ 574.260 for PD of 2600MW. In Figure 5, only ALHN, SDE, MCSA, and WSO have reported the Aver. C and Max. C while others have not declared. This Figure showed the outstanding height of ALHN, corresponding to the highest value, while the height of others is the same. According to the analysis, WSO demonstrates a high degree of efficacy in solving the problem associated with System 1.

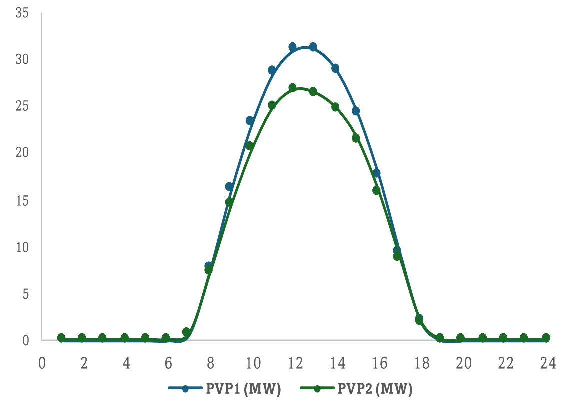


Fig 6. Output power of PVPs

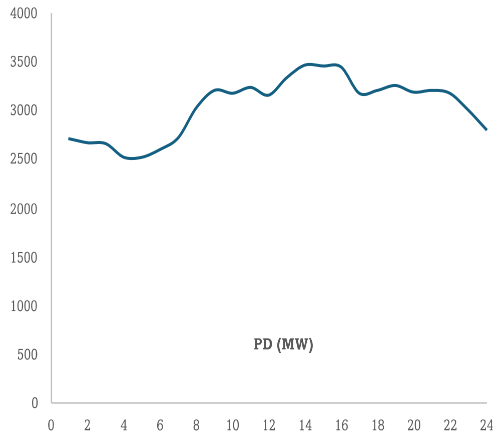


Fig 7. Load demand

4.2. Discussion on System 2

In this section, we will conduct an in-depth evaluation of the suggested methods (BWOA, ESOA, and WSO) to determine their effectiveness in finding the optimal solution and assess the stability of their search process on System 2 as the basis for our evaluation. System 2 is built from System 1, which is the combination operation of thermal power and photovoltaic power plants. In the system, data of TPPs is similar to those from System 1; data for calculating the power output of PVPs, located in two provinces of Vietnam, are accessed from Solar Global as displayed in Figure 6. Load demands of System 2 in one day are built from data of the electricity national control Centre as shown in Figure 7.

Firstly, we set PZ and MX for BWOA, ESOA, and WSO as the setting of System 1. Next, three methods are run 50 trial times to reach the cost for comparison. The best costs from the best run are then collected and presented in Figure 8 while the average and the maximum costs are showed in Figures 9 and 10. Figure 8 shows the Min. C from three methods under three colors (green for WSO, orange for ESOA, and blue for BWOA) over 24 hours. In Figure 8, the height of orange bars is higher than that of green bars and blue bars, and that of green bars is lower than that of blue bars at each hour. In other words, the best cost of WSO is always less than ESOA and BWOA's over 24 hours. As a result, the saving cost of WSO compared to ESOA is from \$ 0.56 at the 16th hour to \$ 6.08 at the 4th hour and as compared to BWOA is from \$ 0.29 at the 4th hour to \$ 4.91 at the 13th hour. Figures 9 and 10 report the Aver. C and Max. C of three methods. The shape of such figures is similar to that of Figure 8; however, the values of the three methods in Figures 9 and 10 are always bigger. To show the difference, 24 numbers above orange bars (ESOA) are outlined. Figure 11 shows one day costs from WSO, ESOA, and BWOA, in which the one-day Min. C of WSO is \$ 20,542. 190 and less than ESOA by \$ 80.92 and BWOA by \$ 46.73. These values converted in % are 0.39% and 0.23%, respectively. Like Min. C, the rest of costs of WSO are smaller than those from ESOA and BWOA methods. Once again, it demonstrates that WSO has a high degree of efficacy in solving the problem associated with System 2 with the presence of RE, more constraints and load demands.

The optimal solution obtained by WSO is given in Table 2. In the table, the best solution consisting of power output from TPPs and PVPs, which is given by WSO in one day, is reported. Additionally, the power values of these power plants are within their boundaries as shown in Eqs. (11) and (12).

5. Conclusion

The study effectively employed three methods (WSO, ESOA, and BWOA) to attain optimal solutions for ELD and NELD problems. Two testing systems were used in the analysis: System 1 focused on thermal power plant operation. In contrast,

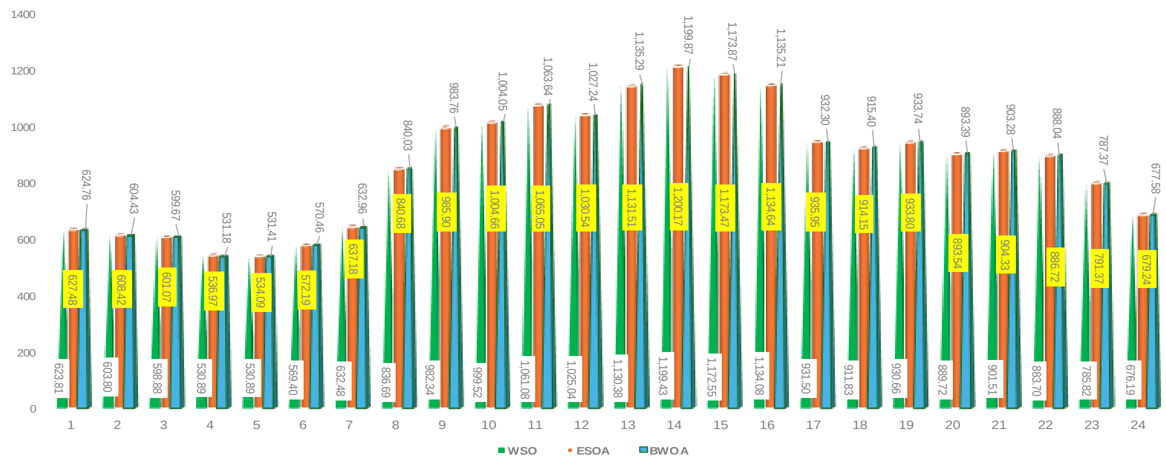


Fig 8. The Min. C comparison from three methods over 24 hours

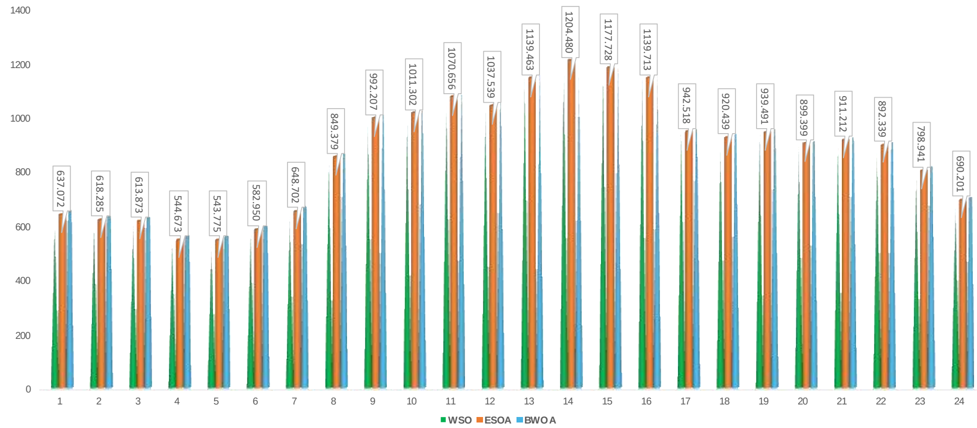


Fig 9. The Aver. C comparison from three methods over 24 hours

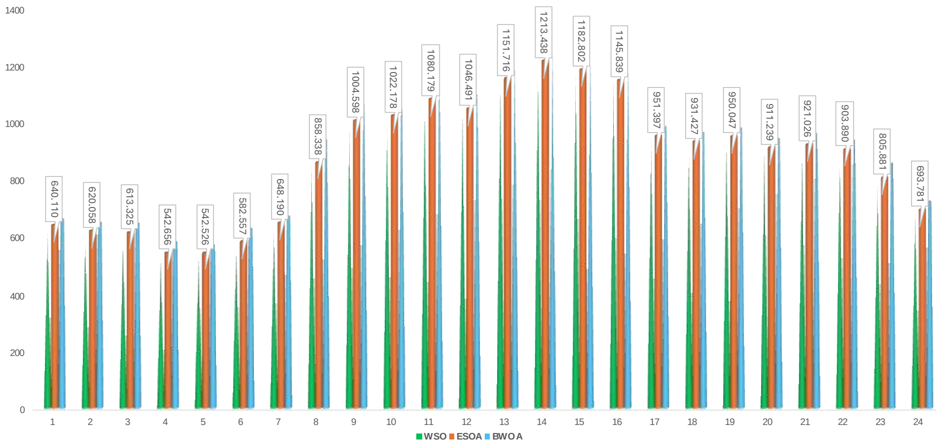


Fig 10. The Max. C comparison from three methods over 24 hours

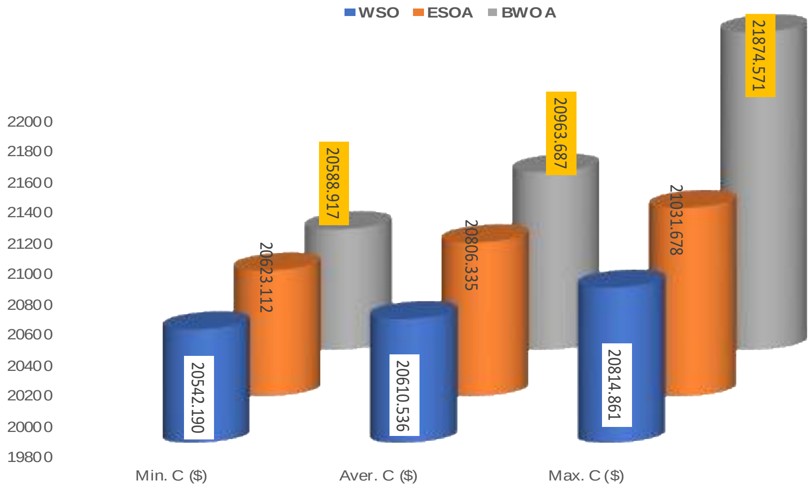


Fig 11. The one day Min. C, Aver. C and max. C from three methods

System 2 addressed the combined operation of thermal and photovoltaic power plants, taking into account fluctuating load demands over 24 hours. When examining the solutions to ELD problem in System 1, it was found that the WSO method outperformed both ESOA and BWOA in terms of minimum cost, average cost, maximum cost, and standard deviation. Notably, WSO consistently produced results equaling to or better than other methods, confirming its effectiveness as a reliable search technique. In the solutions to the NELD problem for System 2, the minimum cost achieved by WSO, ESOA, and BWOA varies each hour. Notably, the minimum cost for WSO is consistently the lowest, while this is not the case for ESOA and BWOA. Consequently, WSO incurs costs that are lower than those of ESOA and BWOA over the course of a day. Furthermore, WSO has demonstrated a high degree of effectiveness in addressing problems associated with systems, whether or not they involve RE. As a result, we see that RE has an important role in dealing with decreasing fossil fuel use. To do this, the manager must correctly adjust the power generation allocation from power plants by exploring more power from renewable power plants. The strategy of more RE use not only applies in the power system but also implements in different fields, leading to reduce carbon emission and air pollution and improved life quality. This requires collaboration and commitment at both national and international levels with resolutions and laws calling on individuals and organizations to participate.

Moving forward, we can improve WSO's performance by updating how it integrates new solutions. The updated version of WSO will be applied to address the ELD problem and other issues.

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References

Alharbi, A. G., Fathy, A., Rezk, H., Abdelkareem, M. A., & Olabi, A. G. (2023). An efficient war strategy optimization reconfiguration method for improving the PV array generated power. *Energy*, *283*, 129129. https://doi.org/10.1016/j.energy.2023.129129

Amjady, N., & Nasiri-Rad, H. (2009). Nonconvex Economic Dispatch With AC Constraints by a New Real Coded Genetic Algorithm. *IEEE Transactions on Power Systems*, *24*(3), 1489–1502. https://doi.org/10.1109/TPWRS.2009.2022998

Arul, R., Velusami, S., & Ravi, G. (2013). Chaotic firefly algorithm to solve economic load dispatch problems. *2013 International Conference on Green Computing, Communication and Conservation of Energy (ICGCE)*, 458–464. https://doi.org/10.1109/ICGCE.2013.6823480

Ayyarao, T. S. L. V, L V, S. K., Sasapu, P., & Padi, H. S. (2023). Optimal Load Frequency Control of Renewable Integrated Multi-Area Power System using War Strategy Optimization Algorithm. *2023 First International Conference on Cyber Physical Systems, Power Electronics and Electric Vehicles (ICPEEV)*, 1–5. https://doi.org/10.1109/ICPEEV58650.2023.10391921

Ayyarao, Tummala. S. L. V., & Kumar, P. P. (2022). Parameter estimation of solar models with a new proposed war strategy optimization algorithm. *International Journal of Energy Research*, *46*(6), 7215–7238. https://doi.org/10.1002/er.7629

Ayyarao, Tummala. S. L. V., Ramakrishna, N. S. S., Elavarasan, R. M., Polumahanthi, N., Rambabu, M., Saini, G., Khan, B., & Alatas, B. (2022). War Strategy Optimization Algorithm: A New Effective Metaheuristic Algorithm for Global Optimization. *IEEE Access*, *10*, 25073–25105. https://doi.org/10.1109/ACCESS.2022.3153493

Balamurugan, R. , & S. S. (2007). Self-adaptive differential evolution based power economic dispatch of generators with valve-point effects and multiple fuel options. *International Journal of Electrical and Computer Engineering*, *1*(1), 543–550.

Baskar, S., Subbaraj, P., & Rao, M. V. C. (2003). Hybrid real coded genetic algorithm solution to economic dispatch problem. *Computers & Electrical Engineering*, *29*(3), 407–419. https://doi.org/10.1016/S0045-7906(01)00039-8

Basu, M. (2019). Squirrel search algorithm for multi-region combined heat and power economic dispatch incorporating renewable energy sources. *Energy*, *182*, 296–305. https://doi.org/10.1016/j.energy.2019.06.087

Chen, Z., Francis, A., Li, S., Liao, B., Xiao, D., Ha, T., Li, J., Ding, L., & Cao, X. (2022). Egret Swarm Optimization Algorithm: An Evolutionary Computation Approach for Model Free Optimization. *Biomimetics*, *7*(4), 144. https://doi.org/10.3390/biomimetics7040144

Deb, S., Houssein, E. H., Said, M., & Abdelminaam, D. S. (2021). Performance of Turbulent Flow of Water Optimization on Economic Load Dispatch Problem. *IEEE Access*, *9*, 77882–77893. https://doi.org/10.1109/ACCESS.2021.3083531

Dieu, V. N., Ongsakul, W., & Polprasert, J. (2013). The augmented Lagrange Hopfield network for economic dispatch with multiple fuel options. *Mathematical and Computer Modelling*, *57*(1–2), 30–39. https://doi.org/10.1016/j.mcm.2011.03.041

Dinh, B. H., Pham, T. Van, Nguyen, T. T., Sava, G. N., & Duong, M. Q. (2020). An Effective Method for Minimizing Electric Generation Costs of Thermal Systems with Complex Constraints and Large Scale. *Applied Sciences*, *10*(10), 3507. https://doi.org/10.3390/app10103507

Ellahi, M., & Abbas, G. (2020). A Hybrid Metaheuristic Approach for the Solution of Renewables-Incorporated Economic Dispatch Problems. *IEEE Access*, *8*, 127608–127621. https://doi.org/10.1109/ACCESS.2020.3008570

Fesanghary, M., & Ardehali, M. M. (2009). A novel meta-heuristic optimization methodology for solving various types of economic dispatch problem. *Energy*, *34*(6), 757–766. https://doi.org/10.1016/j.energy.2009.02.007

Gehad Ismail Sayed, & Aboul Ella Hassanein. (2023). Air Pollutants Classification Using Optimized Neural Network Based on War Strategy Optimization Algorithm. *Automatic Control and Computer Sciences*, *57*(6), 600–607. https://doi.org/10.3103/S0146411623060081

Huu Pham, L., Hoang Dinh, B., Trung Nguyen, T., & Phan, V.-D. (2021). Optimal operation of wind-hydrothermal systems considering certainty and uncertainty of wind. *Alexandria Engineering Journal*, *60*(6), 5431–5461. https://doi.org/10.1016/j.aej.2021.04.025

Ismaeel, A. A. K., Houssein, E. H., Khafaga, D. S., Abdullah Aldakheel, E., AbdElrazek, A. S., & Said, M. (2023). Performance of Osprey Optimization Algorithm for Solving Economic Load Dispatch Problem. *Mathematics*, *11*(19), 4107. https://doi.org/10.3390/math11194107

Jeyakumar, D. N., Jayabarathi, T., & Raghunathan, T. (2006). Particle swarm optimization for various types of economic dispatch problems. *International Journal of Electrical Power & Energy Systems*, *28*(1), 36–42. https://doi.org/10.1016/j.ijepes.2005.09.004

Kheshti, M., Ding, L., Ma, S., & Zhao, B. (2018). Double weighted particle swarm optimization to non-convex wind penetrated emission/economic dispatch and multiple fuel option systems. *Renewable Energy*, *125*, 1021–1037. https://doi.org/10.1016/j.renene.2018.03.024

Kien, L. C., Nguyen, T. T., Hien, C. T., & Duong, M. Q. (2019). A Novel Social Spider Optimization Algorithm for Large-Scale Economic Load Dispatch Problem. *Energies*, *12*(6), 1075. https://doi.org/10.3390/en12061075

Lai, C. S., Jia, Y., Xu, Z., Lai, L. L., Li, X., Cao, J., & McCulloch, M. D. (2017). Levelized cost of electricity for photovoltaic/biogas power plant hybrid system with electrical energy storage degradation costs. *Energy Conversion and Management*, *153*, 34–47. https://doi.org/10.1016/j.enconman.2017.09.076

Lee, S. C., & Kim, Y. H. (2002). An enhanced Lagrangian neural network for the ELD problems with piecewise quadratic cost functions and nonlinear constraints. *Electric Power Systems Research*, *60*(3), 167–177. https://doi.org/10.1016/S0378-7796(01)00181-X

Li, M., Hou, J., Niu, Y., & Liu, J. (2016). Economic dispatch of wind-thermal power system by using aggregated output characteristics of virtual power plants. *2016 12th IEEE International Conference on*

Control and Automation (ICCA), 830–835. https://doi.org/10.1109/ICCA.2016.7505381

Liang, H., Liu, Y., Shen, Y., Li, F., & Man, Y. (2018). A Hybrid Bat Algorithm for Economic Dispatch With Random Wind Power. *IEEE Transactions on Power Systems*, *33*(5), 5052–5061. https://doi.org/10.1109/TPWRS.2018.2812711

Losada-Puente, L. et al. (2023) 'Cross-Case Analysis of the Energy Communities in Spain, Italy, and Greece: Progress, Barriers, and the Road Ahead', Sustainability, 15(18), p. 14016. https://doi.org/10.3390/su151814016

Martín-Ortega, J.L. et al. (2024) 'Enhancing Transparency of Climate Efforts: MITICA's Integrated Approach to Greenhouse Gas Mitigation', Sustainability, 16(10), p. 4219. https://doi.org/10.3390/su16104219

Nguyen, T. T., Quynh, N. V., & Van Dai, L. (2018). Improved Firefly Algorithm: A Novel Method for Optimal Operation of Thermal Generating Units. *Complexity*, *2018*, 1–23. https://doi.org/10.1155/2018/7267593

Nguyen, T. T., Vo, D. N., Dinhhoang, B., & Pham, L. H. (2016). Modified Cuckoo Search Algorithm for Solving Nonconvex Economic Load Dispatch Problems. *Advances in Electrical and Electronic Engineering*, *14*(3). https://doi.org/10.15598/aeee.v14i3.1633

Nguyen, T. T., Vo, D. N., Vu Quynh, N., & Van Dai, L. (2018). Modified Cuckoo Search Algorithm: A Novel Method to Minimize the Fuel Cost. *Energies*, *11*(6), 1328. https://doi.org/10.3390/en11061328

Niknam, T., Mojarrad, H. D., & Meymand, H. Z. (2011). Non-smooth economic dispatch computation by fuzzy and self adaptive particle swarm optimization. *Applied Soft Computing*, *11*(2), 2805–2817. https://doi.org/10.1016/j.asoc.2010.11.010

Noman, N., & Iba, H. (2008). Differential evolution for economic load dispatch problems. *Electric Power Systems Research*, *78*(8), 1322–1331. https://doi.org/10.1016/j.epsr.2007.11.007

Papadogiannaki, S. et al. (2023) 'Evaluating the Impact of COVID-19 on the Carbon Footprint of Two Research Projects: A Comparative Analysis', Atmosphere, 14(9), p. 1365. https://doi.org/10.3390/atmos14091365

Park, J. H., Kim, Y. S., Eom, I. K., & Lee, K. Y. (1993). Economic load dispatch for piecewise quadratic cost function using Hopfield neural network. *IEEE Transactions on Power Systems*, *8*(3), 1030–1038. https://doi.org/10.1109/59.260897

Park, J.-B., Lee, K.-S., Shin, J.-R., & Lee, K. Y. (2005). A Particle Swarm Optimization for Economic Dispatch With Nonsmooth Cost Functions. *IEEE Transactions on Power Systems*, *20*(1), 34–42. https://doi.org/10.1109/TPWRS.2004.831275

Peña-Delgado, A. F., Peraza-Vázquez, H., Almazán-Covarrubias, J. H., Torres Cruz, N., García-Vite, P. M., Morales-Cepeda, A. B., & Ramirez-Arredondo, J. M. (2020). A Novel Bio-Inspired Algorithm Applied to Selective Harmonic Elimination in a Three-Phase Eleven-Level Inverter. *Mathematical Problems in Engineering*, *2020*, 1–10. https://doi.org/10.1155/2020/8856040

Pham, L. H., An, N. H., & Tam, D. T. (2018). *Modified Flower Pollination Algorithm for Solving Economic Dispatch Problem* (pp. 934–942). https://doi.org/10.1007/978-3-319-69814-4_90

Pham, L. H., Ho, T. H., Nguyen, T. T., & Vo, D. N. (2017). *Modified Bat Algorithm for Combined Economic and Emission Dispatch Problem* (pp. 589–597). https://doi.org/10.1007/978-3-319-50904-4_62

Pham, L. H., Nguyen, T. T., Vo, D. N., & Tran, C. D. (2016). Adaptive Cuckoo Search Algorithm based Method for Economic Load Dispatch with Multiple Fuel Options and Valve Point Effect. *International Journal of Hybrid Information Technology*, *9*(1), 41–50. https://doi.org/10.14257/ijhit.2016.9.1.05

Progiou, A., Liora, N., Sebos, I., Chatzimichail, C.,, Melas, D. (2023) Measures and Policies for Reducing PM Exceedances through the Use of Air Quality Modeling: The Case of Thessaloniki, Greece, *Sustainability,* 15(2), p. 930. https://doi.org/10.3390/su15020930

Reddy, S. S. (2017). Optimal scheduling of thermal-wind-solar power system with storage. *Renewable Energy*, *101*, 1357–1368. https://doi.org/10.1016/j.renene.2016.10.022

Sebos, I., Progiou, A., Kallinikos, L., Eleni, P., Katsavou, I., Mangouta, K. and Ziomas, I (2016) Mitigation and Adaptation Policies Related to Climate Change in Greece. In: Grammelis, P. (eds) Energy, Transportation and Global Warming. Green Energy and Technology. Springer, Cham, pp. 35–49. https://doi.org/10.1007/978-3-319-30127-3_4

Shou, S., Luo, H., Zhang, R., Ji, T., Liu, Q., & Su, L. (2023). Optimal Configuration of Voltage Sag Monitoring Points Considering Branch Current based on War Strategy Optimization Algorithm. *Journal of Physics: Conference Series*, *2659*(1), 012009. https://doi.org/10.1088/1742-6596/2659/1/012009

Thang, N. T. (2011). Solving Economic Dispatch Problem with Piecewise Quadratic Cost Functions Using Lagrange Multiplier Theory. In *International Conference on Computer Technology and Development, 3rd (ICCTD 2011)* (pp. 359–363). ASME Press. https://doi.org/10.1115/1.859919.paper62

Tsepi, E., Sebos, I. and Kyriakopoulos, G.L. (2024) 'Decomposition Analysis of CO2 Emissions in Greece from 1996 to 2020', Strategic Planning for Energy and the Environment, pp. 517–544. https://doi.org/10.13052/spee1048-5236.4332

Vo, D. N., & Ongsakul, W. (2012). Economic dispatch with multiple fuel types by enhanced augmented Lagrange Hopfield network. *Applied Energy*, *91*(1), 281–289. https://doi.org/10.1016/j.apenergy.2011.09.025

Yassine, C. and Sebos, I. (2024) 'Quantifying COVID-19's impact on GHG emission reduction in Oman's transportation sector: A bottom-up analysis of pre-pandemic years (2015–2019) and the pandemic year (2020)', Case Studies on Transport Policy, 16, p. 101204. https://doi.org/10.1016/j.cstp.2024.101204