Research Article

A SOLUTION MAP FOR EXTENDED ECONOMIC LOAD DISPATCH PROBLEM BY SECRETARY BIRD ALGORITHM

Ly Huu PHAM[1], *Bach Hoang DINH*[1], *Tai Thanh PHAN*[1,*], *Tuu Kim DANG*[2], *Bao Thien LUONG*[3], *Trung Thanh Nguyen GIANG*[3]

[1]Power System Optimization Research Group, Faculty of Electrical and Electronics Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam
[2]Phuong Nam Prevent and Fight Fire Tech Company Limited
[3]Faculty of Electrical and Electronics Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam

phamhuuly@tdtu.edu.vn, dinhhoangbach@tdtu.edu.vn, phanthanhtai@tdtu.edu.vn, tuudk84@gmail.com, 41702016@student.tdtu.edu.vn, 01246154850trung@gmail.com

[*]Corresponding author: Tai Thanh Phan; phanthanhtai@tdtu.edu.vn

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Abstract. *The paper introduces three applied methods - Secretary Bird Optimization Algorithm (SBOA), Particle Swarm Optimization (PSO), and Tunicate Swarm Algorithm (TSA) - to address economic load dispatch problem (ELD) and the extended ELD problem with renewable energy resources (RES_ELD). These methods were rigorously evaluated using various test systems with complex restrictions and objective functions. The test cases were ranged from simple to complex, with the most challenging involving load demands ranging from the minimum to the maximum load demand based on the total power of all units. The study's results indicated that SBOA consistently outperformed PSO and TSA across all test systems, offering the best cost solutions in a shorter time. Also, SBOA demonstrates comparable or superior results as well as improved searchability compared to previous methods. Furthermore, comparing these results highlighted SBOA's effectiveness in solving these problems and its potential for addressing engineering problems beyond ELD. Finally, the study aimed to provide valuable insights for operators by suggesting solution map that operators can use it to make quick decisions to ensure safe and efficient system operation when generating capacity from power plants quickly meets load demand.*

Keywords

Economic Load Dispatch, Secretary Bird Optimization Algorithm, Tunicate Swarm Algorithm, Solution Map.

1. Introduction

Due to the rising energy demand for development in the residential, industrial, and commercial sectors, the fossil fuel consumption of power plants, especially thermal power plants (TPPs), to generate electricity for meeting these sectors will increase significantly, and the cost of TPP is huge, impacting on all power networks directly. This is one of the main concerns in the management and control of a power system, which must deal with. As we know, the financial prospects of the entire power system are significantly affected by even a slight increase in the cost of electric energy. Therefore, optimal load management strategy by the comparison of the power between the consummating side and generating side is crucial. The key task of the strategy in power system operation is to identify the correct generation among TPPs to satisfy the technical and economic requirements while meeting system reliability, compliance with operational constraints, and considering environmental and long-term planning factors. It is referred to as Economic Load Dispatch (ELD) problem. Normally, the primary functions of such a ELD problem can be presented as a quadratic or convex function. However, in practical operation, multivalve steam turbines introduce valve-point effects due to increasing and decreasing power that significantly distort the input-output curves of the generators. Consequently, the objective function becomes highly nonlinear and non-convex, posing a considerable challenge for resolution. Besides, the presence of faulty auxiliary systems or related machine issues can restrict generators from functioning in specific zones [1], resulting in a highly discontinuous feature in the solution space with lots of local optima. Furthermore, under stable power system conditions, transmission line loss is unavoidable. Clearly, with high dimensionality, nonlinearity, non-differentiability, and multi-constraint, ELD problem become challenging optimization problem. Up to now, there have been numerous popular methods for tackling ELD problems. These methods fall into three categories: exact methods, conventional mathematical programming methods, and approximation search methods.

The exact optimization techniques like lambda iteration (LI) [2], gradient based method [3], Newton's method, and Lagrange multiplier method [4] work effectively as long as the incremental cost curves of the generating units with piecewise-linear functions. However, in practice, the ELD problem is highly non-linear and non-convex functions or test systems are large-scale [5, 6], these methods fail to find the best solutions or only search for local solutions.

In the second group, these methods are widely used for solving ELD problems and offer effective structure ways to reach the best potential result while taking different restrictions into account. They are linear programming (LP) [7], quadratic programming (QP) [8], interior point method (IPM) [9], mixed-integer linear programming (MILP) [10], and dynamic programming (DP) [11]. All conventional methods have in common that they can only find the answer after running the ELD problem once. Furthermore, these methods possess the same benefits, such as a minimal standard deviation, quick execution, and few control parameters. Nevertheless, these approaches struggle to handle issues involving nonconvex objective functions and complicated constraints. For example, Dynamic programming can solve ELD problems, including discontinuous and intrinsically nonlinear cost curves. However, it is hampered by local optimality or the curse of dimensionality.

Over the past few decades, many techniques in the third group have been suggested to address the ELD problem, yielding promising results. They are considered powerful optimization techniques for solving the ELD problem. Most of the approaches have several benefits, including the capacity to work with large-scale systems, the ability to manage complicated constraints, and the ability to determine the global optimal solution for nonconvex objective function issues. Some of these methods can be divided into original methods and hybrid methods. Particle-swarm optimization (PSO) [12, 13], cuckoo search algorithm (CSA) [14], gravitational search algorithm (GSA) [15], biogeography-based optimization (BBO) [16], firefly algorithm (FA) [17], genetic algorithm (GA) [18], artificial bee colony (ABC) [19], simulated annealing (SA) [20], harmony search (HS) [21], etc are of original algorithms. These algorithms' advantages are effective at finding high-quality solutions for systems where fuel cost function of thermal units is nonconvex. However, their drawbacks are that they can sometimes get stuck in local optima, especially for complex, multimodal optimization problems. This can lead to suboptimal solutions, and the methods may need help to explore the search space to find the global optimum effectively. In addition, as the problem size and complexity increase, the performance of the original metaheuristic methods may deteriorate. This is due to the exponential growth of the search space, making it difficult for these methods to explore the space effectively. Combining the advantages of various techniques is to form a new method, called hybrid meta-heuristic approaches with the purpose of covering these drawbacks of original methods. They have a great deal of potential to improve the performance of optimization algorithms in solving the ELD issue such as particle swarm optimization - gravitational search algorithm (PSO-GSA) [22], cauchy-gaussian quantum-behaved bat algorithm (CGQBA) [23], comprehensive learning PSO-sequential quadratic programming (SQP-CLPSO) [24], quantum behaved artificial bee colony (QBA) [25], hybrid fuzzy adaptive chaotic ant swarm optimization (FCASO) algorithm and SQP method (FCASO-SQP) [26] and hybrid PSO and artificial fish swarm algorithm (PSO-AFSA) [27], etc. Hybrid meta-heuristic methods offer significant potential benefits despite their increased complexity and computing requirements. However, their successful implementation requires meticulous design, parameter adjustment, and integration to ensure their advantages outweigh the disadvantages.

In general, the algorithms mentioned have been broadly and effectively utilized across a wide range of test systems. These systems include 6-unit test system with POZ and power loss constraints, 15-unit test systems with POZ and those without power loss constraints, 20-unit test system with power loss constraints, 40-unit test system with valve-point loading effects, 10-unit test systems with multiple fuels, and large-scale unit test systems with the complicated constraints. Additionally, IEEE systems with 30, 57, and

118 buses have also been part of the application scope. The applied or proposed algorithms have been assessed based on comparing fuel cost functions and other criteria such as population size, maximum iterations, and standard deviations. These detailed evaluations have offered valuable insights into the strengths and capabilities of these algorithms across different system configurations and constraints. After reviewing all mentioned references, the authors of studies have only investigated the electricity generating cost of these standard test systems with one or four load demand levels. However, the power consumption of a power system is always different and changes every minute, hour, or even day, leading to significant changes in the whole power system cost. The research gap should be covered by finding the solution map for each test system that helps operators and managers make the correct and quick decision on allocating power from the number of thermal power plants to ensure economical and efficient operation and safety.

Recently, there has been a significant increase in attention to addressing the dual challenges of energy scarcity and environmental impact by integrating renewable energy sources (RES) into the ELD problem to form e new problem, named RES_ELD problem. This new problem is being addressed by applying metaheuristic techniques, which are proving to be effective in finding solutions. In reference [28], the authors proposed a hybrid bat algorithm (HBA) to tackle the ELD problem with the integration of thermal power generators and renewable energy sources like wind power. The key feature of this algorithm is the combination of a chaotic map and a random black hole model, enabling the algorithm to mitigate premature convergence issues and effectively seek solutions within the global search space. An innovative study in [29] introduces a solution to optimize power distribution within interconnected microgrids. The study employs a probabilistic model to achieve balanced power-sharing while minimizing operating costs. It optimizes the objective function using PSO and the imperialist competitive algorithm (ICA). The results suggest that achieving optimal power distribution between the primary grid and microgrid can decrease the overall cost of distribution networks. Study [30] discusses the resolution of the RES_ELD problem through the application of a dynamic adaptive bacterial foraging algorithm (BFA). The study highlights the improved performance of the modified BFA in addressing challenges, such as poor convergence characteristics when dealing with high-dimensional complex problems, which were evident in the original BFA. The ELD problem with RESs is presented in [31]. In order to address the uncertainty associated with wind and solar energy, their stochastic behavior is represented using Weibull and Beta distributions. To tackle this highly constrained problem, an enhanced version of the Fireworks algorithm (FA) is utilized for optimization. Researchers in [32] have developed a cost-effective hybrid microgrid system incorporating RES, including wind power, hydrogen-based storage systems, and fuel cells. They tackled the optimal power problem using the PSO method, and the results from PSO were compared with those obtained by GA. In [33], the study addresses the ELD problem for a microgrid comprising solar and wind farms. The researchers employed the reduced gradient method to solve this complex problem. Furthermore, their conclusions highlight the importance of integrating solar energy with renewable energy credits for efficient energy management. The solution to the ELD problem, found in [34], involves the utilization of the BAT algorithm, which incorporates wind power. The objective function is designed to account for the stochastic nature of wind power. Moreover, it considers imbalance costs resulting from forecasting errors, such as overestimation and underestimation.

This study recommended a new method, called secretary bird optimization algorithm (SBOA) [35] for addressing ELD and RES_ELD problems. The method mimics the hunting and survival strategies of secretary birds to tackle real-world optimization problems. The method consists of two essential phases: exploration and exploitation. During the exploration phase, it thoroughly explores the search space and identifies potential solutions by simulating the hunting behavior of secretary birds. In the exploitation phase, it strategically selects the most optimal path for safety by emulating the escape strategies employed by secretary birds when evading predators. In [35], authors have implemented rigorous evaluations across multiple scenarios to demonstrate SBOA's superior performance in finding faster solutions and its potential in addressing complex real-world optimization problems such as the CEC-2017 and CEC-2022 benchmark suites, 12 constrained engineering designs, and three-dimensional path planning for Unmanned Aerial Vehicles when compared to alternative methods. In addition to SBOA, two methods like PSO [36] by Kennedy & Eberhart in 1995 and Tunicate Swarm Algorithm (TSA) [37] by Kaur et al in 2020 were also applied to such problems. The results from three applied methods were compared other competitors.

The novelties of the study are given as follows:

1. Propose a new model for establishing a solution data map to ELD problem.

2. Recommend how to use global solar atlas for determining solar radiation data to calculate power output of SP.

3. SBOA meta-heuristic algorithm, developed in 2024, and PSO and TSA algorithms, recommended in 1995 and 2020, are suggested to address ELD and RES_ELD issues with different constraints.

After applying these novelties, the study has made the following contributions below:

1. Demonstrate the superiority of the SBOA algorithm over previous algorithms by presenting specific numerical data and figures. Furthermore, the SBOA algorithm outperforms PSO and TSA in terms of identifying high-quality and optimal solutions.

2. Provide solution data for power system operators and managers, focusing on test systems with load demand varying from the minimum to the maximum levels of total generated power from all units.

3. Use precise solar radiation data from two southern provinces in Vietnam to calculate the power output of solar power plants (SP) connected to the conventional power system throughout the day. It is noteworthy that previous studies may have overlooked the opportunity to utilize the available natural solar radiation data from the global solar map.

The study is carefully structured as follows to provide a comprehensive understanding of the subject matter: Section 2 thoroughly presents the problem model in detail. Sections 3 and 4 meticulously introduces the applied methods and the implementation of SBOA, providing a comprehensive implementation overview. Section 5 extensively presents and thoroughly discusses the results of the applied methods, providing a deep analysis of the findings. Finally, Section 6 presents the conclusions, offering a comprehensive summary of the key insights derived from the study.

2. Problem Model

2.1. The objective function

The paper discusses the ELD and RES_ELD problems, which aim to minimize costs while satisfying the load demand and various equality and inequality constraints. In the ELD problem, the objective function is the fuel cost of the TPP, whereas in the RES_ELD problem, the objective function includes both the fuel cost and the solar power cost. The formulation for ELD and RES_ELD problems are shown in Eqs. (1) and (2) respectively:

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

$$Min(FC_{TPP}, FC_{SP}) \tag{2}$$

These objective functions are restricted by equality constraints and inequality constraints as shown in equations below:

$$m(P_{TPP}, P_{SP}) = 0 \tag{3}$$

$$n(P_{TPP}, P_{SP}) < 0 \tag{4}$$

Where P_{TPP} and P_{SP} represent the power outputs of TPP and SP, respectively.

Nextly, the models of thermal power plant and solar power plant are presented in Subsections as follows:

1) Modelling fuel cost of thermal power plant:

The fuel cost function of thermal power plants (FC_{TPP}) can be mathematically described as a second-order function, which signifies that it can be represented by an equation involving a second-degree polynomial. This allows for a more nuanced analysis of the fuel cost function, enabling a deeper understanding of its behavior and implications. It is formulated by:

$$FC_{TPP} = \sum_{t=1}^{T} (\varepsilon_t + \delta_t P_{TPP,t} + \gamma_t P_{TPP,t}^2; t = 1, \ldots, T) \tag{5}$$

Where, ε_t, δ_t, and γ_t are cost factors of TPP t and T is number of TPPs.

2) Modelling cost of solar power plant:

When the system operator owns solar power plants, the cost function may not be applicable since SP does not require fuel. However, in cases where a utility does not own SP, the cost of SP generation needs to be determined based on specific contracts [38]. This paper discusses SP's total cost function (FC_{SP}), which can be represented as a linear function [38]:

$$FC_{SP} = \sum_{s=1}^{S} (a \cdot P_{SP,s}; s = 1, \ldots, S) \tag{6}$$

In Eq. (6), a is price of solar generators in (\$/MWh); $P_{SP,s}$ is the power output of the s^{th} SP and calculated by:

$$P_{SP}(A_b) = \begin{cases} P_{SP,rated} \times \frac{A_b^2}{A_{std}+R_c} & 0 < A_b < R_c \\ P_{SP,rated} \times \frac{A_b}{A_{std}} & A_b > R_c \\ b = 1, ..., 24 \text{ intervals} & \end{cases} ; \tag{7}$$

It is noted that solar radiation (A_b) varies greatly on an hourly, daily, monthly, and yearly basis. For optimal determination of location and rated power of photovoltaic systems, it is essential to collect solar radiation data for all 8760 hours in a year. However, the challenge lies in effectively managing the vast amount of data, as existing optimization algorithms struggle to address the issue. To efficiently address the challenge, we recommend leveraging global solar data to specify the locations of the solar power plants. These data set accurately report the average radiation for each hour of every month, providing valuable insights into solar radiation patterns. This approach allows for a more focused analysis, helping to optimize solar power generation strategies effectively. In the study, average radiation for each hour in a day collected from the global solar map in two southern provinces of Vietnam will be applied to determine the power output of SPs, which were integrated into traditional thermal power plant systems.

2.2. The considered restrictions

In addressing the ELD and RES_ELD problems, ensuring that the generators and systems meet a range of equality and inequality constraints is essential. This paper will focus on addressing these restrictions in the following manner:

1) Limitation on the real active power balance:

The total generated power from such power plants should be sufficient to meet demand load (PD) and transmission losses (P_{loss}), which can be expressed as follows:

$$\sum_{t=1}^{T} P_{TPP,t} + \sum_{s=1}^{S} P_{SP,s} = PD + P_{loss} \tag{8}$$

In Eq. (8), T and S are number of $TPPs$ and SPs; Ploss is determined by utilizing Krone's reduction model below:

$$\begin{aligned} P_{loss} = &\sum_{t=1}^{T}\sum_{j=1}^{T} P_{TPP,t} \times B_{tj} \times P_{TPP,j} \\ &+ \sum_{t=1}^{T} B_{0t} \times P_{TPP,t} + B_{00} \end{aligned} \tag{9}$$

2) Limitation on power generation:

In order to operate efficiently, every unit must adhere to the prescribed minimum and maximum generation capacities, as shown by:

$$P_{TPP,min} \leq P_{TPP,t} \leq P_{TPP,max} \tag{10}$$

$$P_{SP,min} \leq P_{SP,s} \leq P_{SP,max} \tag{11}$$

3. Secretary Bird Optimization Algorithm

The secretary bird optimization algorithm [35] is a nature-inspired optimization technique that mimics the hunting behavior of the Secretary bird, a large predatory bird of prey found in Africa. The secretary bird is known for its unique hunting strategy, using a combination of speed, agility, and intelligence to catch its prey. During the hunt, the bird uses its powerful legs to kick and stun its prey and then uses its sharp talons to grasp and kill it. SBOA was proposed by Fu et al in 2024 and has shown promise in solving optimization problems with complex search spaces, particularly those with multiple local optima. To simulate the optimization process of SBOA, the position of the secretary bird was assigned a potential candidate (a solution) in the search spaces for the considered problems and firstly initialized by:

$$\begin{aligned} X_i^{new} = X_i^{min} + r \times (X_i^{max} - X_i^{min}); \\ i = 1, 2, ..., PZ; \end{aligned} \tag{12}$$

Where X_i^{new} signifies the new position of the i^{th} secretary bird; X_i^{max} and X_i^{min} define the upper and lower limits, PZ is population size and r is a random number within [0, 1]. Next, all solutions in population size will be evaluated for the quality by calculating the objective function. From these fitness function values, the best solution with the lowest value for the optimization problem is selected. After that, two distinct natural behaviors of the secretary bird that correspond to two strategies for updating solutions have been used to revise the position of members. Two strategies are featured as follows:

1) Exploration strategy:

The strategy is devised by studying the hunting behavior of secretary birds, which involves seeking prey, consuming prey, and attacking prey. In other words, to effectively model the secretary bird's hunting behavior, the strategy has utilized its biological statistics and the highest iteration (HI) to divide the entire hunting process into three equal intervals: $t < 1/3HI$, $1/3HI < t < 2/3HI$, and $2/3T < t < HI$. These intervals correspond to the three distinct phases of the secretary bird's predation. As a result, the position of secretary birds is updated based on a comparison between the current iteration (t) and the maximum iteration using the following equations.

Phase 1: $t \leq \frac{1}{3}HI$

$$X_i^{new} = X_i + r_1 \times (X_{r1} - X_{r2}); \quad i = 1, 2, ..., PZ \tag{13}$$

Where X_i is the old position of the i^{th} secretary bird, r_1 is a random array within [0, 1], X_{r1} and X_{r2} are random solutions among population.

Phase 2: $\frac{1}{3}HI < t \leq \frac{2}{3}HI$

$$X_i^{new} = X_{best} + exp\left(\left(\frac{t}{HI}\right)^4\right) \times (X_{best} - X_i) \times (r_2 - 0.5); \quad i = 1, 2, ..., PZ \tag{14}$$

Where X_{best} is the best position of secretary bird, r_2 is a random array within [0, 1].

Phase 3: $t > \frac{2}{3}HI$

$$X_i^{new} = X_{best} + \left(\left(1 - \frac{t}{HI}\right) \Lambda \left(2 \times \frac{t}{HI}\right)\right)(X_i) \times 0.5 \times Levy(D); \quad i = 1, 2, ..., PZ \tag{15}$$

In Eq. (15), $Levy(D)$ stands for the Levy flight distribution function, which is determined by:

$$Levy(D) = 0.01 \times \frac{u \times \alpha}{(|v|)^{\frac{2}{3}}} \tag{16}$$

Where u and v are random number within [0, 1]; α is standard deviation, given by:

$$\alpha = 0\left(\frac{\Gamma(3.5) \times sin\left(\frac{3\pi}{4}\right)}{\frac{3}{4} \times \Gamma(1.25)}\right) \tag{17}$$

2) Exploitation strategy:

The strategy is constructed by simulating the secretary bird's behavior in avoiding threats from predators that may try to attack or steal its food. Secretary birds are known for employing a range of evasion strategies to protect themselves or their food when they face such threats. In brief, strategies for evasion can be represented mathematically by eq. (18):

$$X_i^{new} = \begin{cases} X_{best} + (2 \times r_2 - 1) \times \left(1 - \frac{t}{HI}\right)^2 \times X_i; \\ \quad \text{if } rand < 0.5 \\ X_i + r_3 \times (X_{r3} - k \times X_i); \\ \quad \text{otherwise} \end{cases} \tag{18}$$

In Eq. (18), r_3 is a random array within [0, 1], X_{r3} is random solution among population, and k is an integer of 1 or 2.

3) Selection mechanism

After each strategy, the fitness function of the newly update solution (FF_i^{new}) is calculated and then the selection mechanism is applied to keep X_i^{new} or X_i as shown in Eq. (19):

$$X_i = \begin{cases} X_i^{new}; & \text{if } FF_i^{new} \leq FF_i \\ X_i; & \text{otherwise} \end{cases} \tag{19}$$

4. Applying SBOA to The Problem

The section offers a constructive approach of the proposed method to address the problems effectively as follows:

1) Initialization:

Solutions are X_i $(i = 1, ..., PZ)$, in which each solution is presented by X_i=$[X_{2,i}, X_{3,i}, \ldots, X_{T,i}]$. The power outcome of TPP from 2 to T in solutions is initially created, meeting the constraint in Eq. (10).

From the initialized solutions, the fitness function to each solution for the applied problem is formulated as follows:

$$FF_i = FC_{TPP,i}(X_i) + FC_{SP} + M \times (P_{1,i} - P_{1,i}^{limit})^2 \tag{20}$$

In Eq. (20), M is a penalty factor; and $P_{1,i}$ is the power outcome of slack TPP 1 and given by

$$P_{1,i} = \sum_{t=2}^{T} P_{TPP,t} + \sum_{s=1}^{S} P_{SP,s} - PD + P_{loss} \tag{21}$$

The limit for slack TPP 1 in Eq. (20) is constrained by

$$P_{1,i}^{limit} = \begin{cases} P_1^{max}; & \text{if } P_{1,i} > P_1^{max} \\ P_1^{min}; & \text{if } P_{1,i} < P_1^{min} \\ P_{1,i}; & \text{Else} \end{cases} \tag{22}$$

2) The first new updated solution by Exploration strategy

In the section, the first new updated solution is performed as shown in Section 3.1. It noted that each updated solution can be violated its limitations. Therefore, the power output of TPP must be checked violates its limitations as shown in Eq (23) below.

$$P_{i,t} = \begin{cases} P_{i,t}^{max}; & \text{if } P_{i,t} > P_{i,t}^{max} \\ P_{i,t}^{min}; & \text{if } P_{i,t} < P_{i,t}^{min} \\ P_{i,t}; & \text{Else} \end{cases} \tag{23}$$

After that, the slack TPP 1 is computed as Eq. (21) and FF$_i$ is obtained as Eq. (20). Finally, the selected mechanism is used to keep better solution as shown in Eq. (19).

3) The second new updated solution by Exploitation strategy

In the section, the second new updated solution is performed as shown in Section 3.2. It noted that each updated solution can be violated its limitations. Therefore, the power output of TPP must be checked violates its limitations as shown in Eq. (23). After that, the slack TPP 1 is computed as Eq. (21) and FF_i is obtained as Eq. (20). Finally, the selected mechanism is used to keep better solution as shown in Eq. (19).

The iterative algorithm for implementing the proposed method to solve the problem is outlined clearly.
Step 1: Set up PZ and HI
Step 2: Create random solutions

- Calculate and check $P_{1,i}$ using Eqs. (21) and (22).
- Calculate FF_i using Eq. (20)
- Select the best solution with the best fitness function
- Set t to 1

Step 3: Generate the first solutions using Section 3.1

- Check and repair solutions as violation
- Calculate and check $P_{1,i}$ using Eqs. (21) and (22)
- Compare old and new solution using Section 3.3

Step 4: Generate the first solutions using Section 3.2

- Check and repair solutions as violation
- Calculate and check $P_{1,i}$ using Eqs. (21) and (22)
- Compare old and new solution using Section 3.3

Step 5: If $t < HI$, set $t = t + 1$ and back to Step 3. Otherwise, stop the process and save results.

5. Numerical Results

In this section, we have tackled the ELD and RES_ELD problems by employing three different meta-heuristic methods: SBOA [35], PSO [36], and TSA [37]. Subsection 5.1 provides parameters selection of three methods. Subsection 5.2 details and discusses the outcomes of System 1 with twenty $TPPs$, catering to a power demand of 2500 MW. Subsection 5.3 has implemented the three methods to address the RE_ELD with twenty TPs and four SPs for 24 load levels spanning 24 hours. Finally, subsection 5.4 presents a solution map for System 1, which considers various load demands based on the total generating power of $TPPs$.

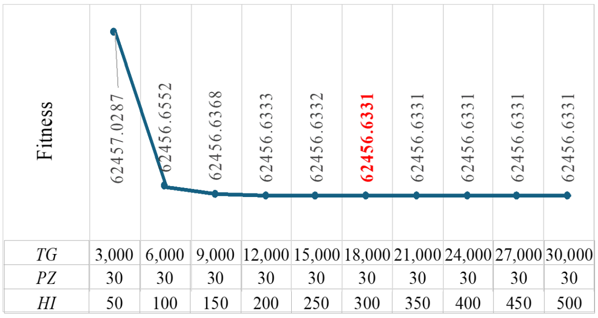

Fig. 1: The results obtained by SBOA as setting PZ of 30 and value of HI being changed.

Authors utilize a personal computer with 8GB of RAM and a 2.2GHz CPU for all our work and apply MATLAB software version R2018a for coding and simulations.

5.1. The parameters selection for applied methods to System 1

Before applying three applied methods for reaching the total cost of two problems, setting the decision parameters such as population size (PZ) and the highest iteration (HI) for these methods will be investigated carefully because the work acts important role in the fair comparison of these methods to specify the best one. Firstly, SBOA will be run by adjusting the value of PZ and HI based on previous studies to find the best couple value, which gives the best solution to the considered problem. After the couple value will be applied for PSO and TSA to reach more results for comparison. Figures 1, 2, and 3 show different cases for setting PZ and HI, in which Figure 1 is the case that 30 is for PZ and HI is changed from 50 to 500 iterations, Figures 2 and 3 are the cases that HI is fixed at 200 and 250 iterations and PZ is increased the small to big value. In addition to HI and PZ, the total generation (TG) of producing solutions and the corresponding fitness are shown in three figures. In Figure 1, the fitness provided by SBOA is from \$ 62457.0287 to the optimal one of \$ 62456.6331 as increasing HI from 50 to 500 iterations, corresponding to TG from 3,000 to 18,000 solutions. However, if TG continuously increases, the fitness will remain unchanged. As a result, PZ of 30 and HI of 300 are considered as the best parameters of SBOA for this investigation. Like Figure 1, 80 and 200 in Figure 2 and 40 and 250 in Figure 3 are the best for setting PZ and HI to reach the optimal fitness, highlighted in red. Although the fitness for both cases is the same, TG is different. Namely, TG is 32,000 solutions for Case 2, but that of Case 3 is 20,000 solutions.

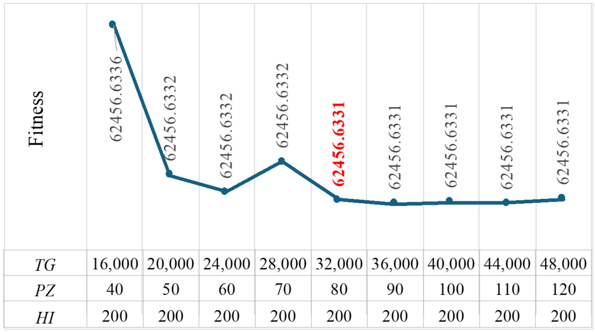

Fig. 2: The results obtained by SBOA as setting HI of 200 and value of PZ being changed.

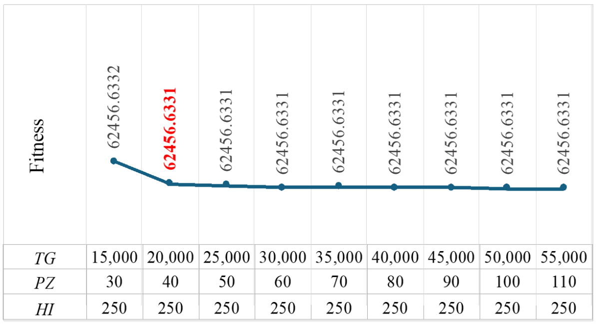

Fig. 3: The results obtained by SBOA as setting HI of 250 and value of PZ being changed.

In comparing three cases with the optimal fitness of \$ 62456.6331, Case 1 is less than Case 2 by 14,000 solutions and Case 3 by 2,000 solutions. From here, it can be concluded the best parameters of SBOA are 30 for PZ and 300 for HI.

PSO, TSA, and SBOA are each run fifty times with the parameters: PZ set to 30 and HI set to 300 for SBOA and PZ set to 60 and HI set to 300 for PSO and TSA. Fifty cost values for System 1, obtained through different methods, are detailed in Figure 4. The figure shows these costs in three colors: red for PSO, black for TSA, and blue for SBOA. The costs obtained by PSO are significantly fluctuating, with the highest being over \$ 62454 and the smallest being around \$ 62470; the black costs of TSA fluctuate slightly while these costs of SBOA are on the straight line.

To demonstrate the solution-reaching process of three methods, Figure 5 displays the search progress of these methods from the best run among 50 runs. Among the methods, the process from PSO is the least effective as it fails to reach the optimal solution for System 1, with the red line over the black and blue lines, and that of TSA is better than compared to PSO. In comparison to PSO and TSA, SBOA is the most effective because SBOA is easy to reach the best solution from the 45th to the end iteration. Besides, the time of SBOA running to each run is 1.53 s, which is faster than PSO (1.7s) and TSA (1,91s). These costs

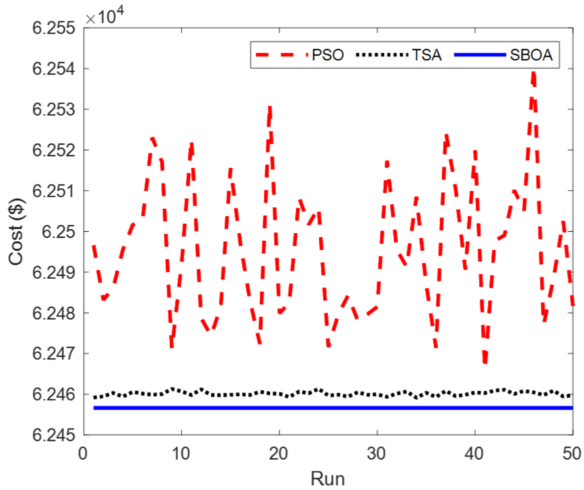

Fig. 4: Results obtained by three methods over 50 runs.

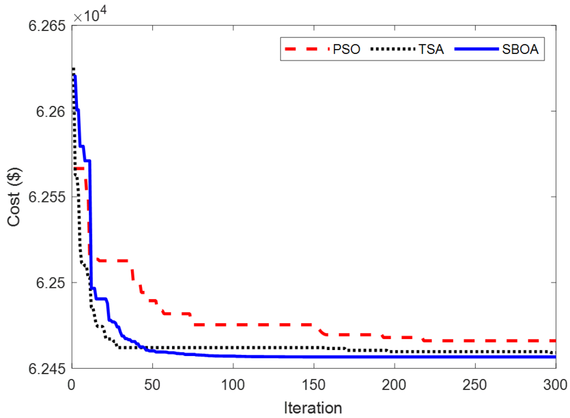

Fig. 5: Results obtained by three methods from the best run.

from Figure 5 will be presented under Minimum cost (Mi.C), Average cost (Av.C), Maximum cost (Ma.C), and standard deviation (SD), as shown in Figure 6.

The cost structures of SBOA, TSA, and PSO vary significantly. SBOA's Mi. C is \$ 62456.63309, the lowest among the three, while PSO's cost is the highest. Furthermore, it's noteworthy that Av. C and Ma. C of SBOA are identical to the Mi. C, whereas TSA and PSO costs differ. This leads to the conclusion that SBOA demonstrates superior performance compared to TSA and PSO.

5.2. Result discussion on System 1

This section utilizes information from reference [39, 40, 41, 42] to describe a power system of twenty thermal power plants. Sufficient power must be available for the system to accommodate the 2500 MW demand load. In addition, the system also takes transmission losses into account. The results obtained from the PSO, TSA, and SBOA methods in terms of Mi.C, Av.C,

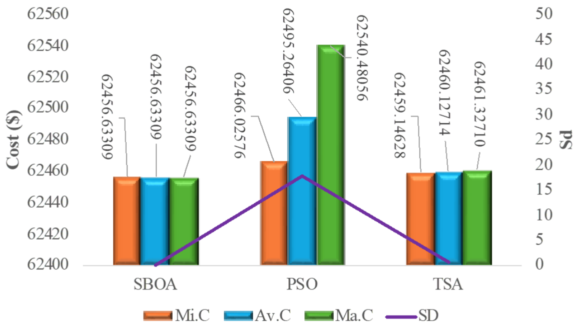

Fig. 6: The results given by three methods.

Ma.C, and SD are gathered by running 50 independent runs with the setting HI and PZ as Section 4.1 and then compared with results from other methods such as CSA [14], BBO [16], PSO-GSA [22], GQBA [23], CGQBA [23], backtracking search algorithm (BSA) [39], class topper optimization (CTO) [40], aggrandized CTO (ACTO) [40], improved stochastic fractal search algorithm (ISFS) [41], CSA [42] and one rank CSA (ORCSA) [42] as illustrated in Table 1. Moreover, population size and the number of iterations are presented in such a table for comparison. The minimum operating cost of three applied and compared methods is shown in the second column, which is the important criterion for proving the searchability. Regarding this criterion, PSO is the worst method with the Mi.C of $ 62,466.02576, while A-CTO [40] is the best method with the Mi.C of $ 62,452.5. The Mi.C of SBOA and the rest of the methods is $ 62,456.6331, except for TSA and CTO [40], which has a higher cost ($ 62,459.1463 and $ 62,457.9, respectively). Although the Mi.C of A-CTO is smallest, solutions in [40] did not report, leading to the unsure cost.

The third and fourth columns are the Av.C and Ma.C of methods, in which six methods, including CSA [14], BBO [16], CTO [40], A-CTO [40], CSA [42], and ORCSA [42] were not available. Regarding the two criteria, only SBOA and PSOGSA [22] have the same values of $ 62,456.63309 and $ 62,456.63311, respectively, which are equal to the Mi.C. As a result, it can be indicated that SBOA and PSOGSA have robust searching ability. To further prove SBOA's stability, we can see that the SD of SBOA is approximately zero while the value of PSOGSA is not present. The table also shows two parameters-HI and PZ-that represent the search speed of approaches based on the number of fitness evaluations (FE). FE is defined by multiplying HI, PZ, and ω, in which ω represents the frequency of generating a new solution in an iteration. Noted that ω is different from different methods and it is dependent the solution producing structure of each method. The table shows that ω is equal to 1 for BBO [16], PSOGSA [22], GQBA [23], CGQBA [23], BSA [39], PSO, and TSA, and 2 for CSA [14, 42], ORCSA [42], and SBOA, and 2.5 for ISFS [41]. Namely, FE of SBOA is 18,000 is less than that of CSA [14], PSOGSA [22], GQBA [23], CGQBA [23], and BSA [39] but higher than CSA [42], ORCSA [42], and ISFS [41]. The results validate SBOA's potential as a workable solution for the system with 20 units in light of the quadratic fuel cost function and the limit of power loss in line.

5.3. Result discussion on System 2

This section will offer a thorough analysis of the proposed approaches (PSO, TSA, and SBOA) in order to ascertain how well they work in locating the best solution and how stable their search procedure is on System 2. The combined functioning of the thermal power plants of System 1 and four solar power plants are built to form System 2. In System 2, the data of TPP is comparable to that of System 1 and data of four SPs are collected by accessing the map of global solar [43]. Namely, $SP1$ is Binh Nguyen project with geographical coordinates of (15.333270°, 108.709070°), $SP2$ is Lac Dien project with geographical coordinates of (12.967340°, 109.096410°), $SP3$ is Phuoc Huu project with geographical coordinates of (11.540740°, 108.872940°), and $SP4$ is Tien Hanh project with geographical coordinates of (10.905840°, 108.010450°). The rated power of four SPs is 50MW, 45MW, 40MW, and 49MW, respectively. From accessing the location of these solar power plants from global solar, the power output of SP in MW for 24h can be calculated and shown in Figure 7. In such a figure, some hours do not have irradiation, resulting in a zero power output; however, the remaining hours in the day have power because of existing irradiation. In one day, the power output of SP is changed from the minimum power at the 6th hour to the maximum power at the 12th or 13th hour. The load demands of System 2 within a day are established using data from the electricity national control center, as depicted in Figure 8, in which PD in black is the case without SPs while PD called $PDnew$ in red is the case with SPs. In addition, $PDnew$ is applied to System 2 as the required load for power plants, and the task of these power plants is to find the suitable power so that the total cost of System 2 is as minimal as possible while meeting $PDnew$.

We configure PZ and HI parameters specifically for PSO, TSA, and SBOA in the initial stage, as presented in System 1. Subsequently, we execute each of the three methods 50 times to comprehensively obtain the costs for comparison. As a result, the most favorable costs in one day from the best-performing run are carefully aggregated and visually presented in Figure 9. The figure shows the 24 values of Mi. C from three methods over 24 hours in three bar colors: the blue bar is for SBOA, the orange bar is for TSA, and the green bar

Tab. 1: The result comparison of three applied methods and other methods for System 1.

Method	Mi.C ($/h)	Av.C ($/h)	Ma.C ($/h)	*PZ*	*HI*	*SD*
CSA [14]	62,456.63	NA	NA	50	500	NA
BBO [16]	62,456.7926	NA	NA	NA	NA	NA
PSOGSA [22]	62,456.6330	62,456.63311	62,456.63310	100	500	NA
GQBA [23]	62,455.86154	62,455.8921	62,471.521	20	1000	1.73
CGQBA [23]	62,455.41276	62,455.4912	62,469.123	20	1000	1.65
BSA [39]	62,456.6925	62,457.1517	62,458.1272	20	20000	NA
CTO [40]	62,457.9	NA	NA	NA	1000	NA
A-CTO [40]	62,452.5	NA	NA	NA	1000	NA
ISFS [41]	62,456.633	62,456.6331	62,457.94	10	100	0.2
ORCSA [42]	62,456.6331	NA	NA	10	500	NA
CSA [42]	62,456.6331	NA	NA	10	500	NA
PSO	62,466.02576	62,495.26406	62,540.48056	60	300	17.78
TSA	62,459.14628	62,460.12714	62,461.3271	60	300	0.573
SBOA	62,456.63309	62,456.63309	62,456.63309	30	300	0.0000007

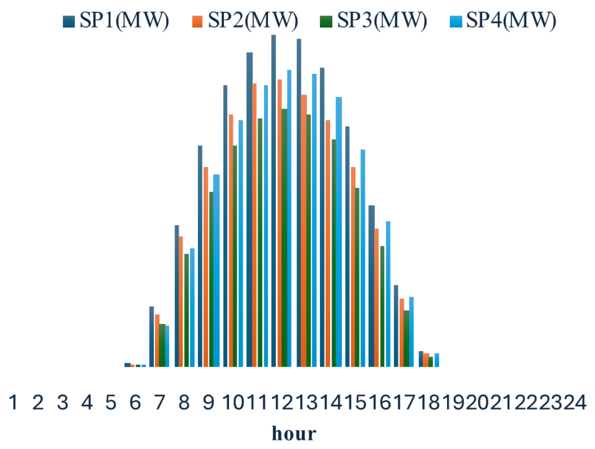

Fig. 7: Power from SPs.

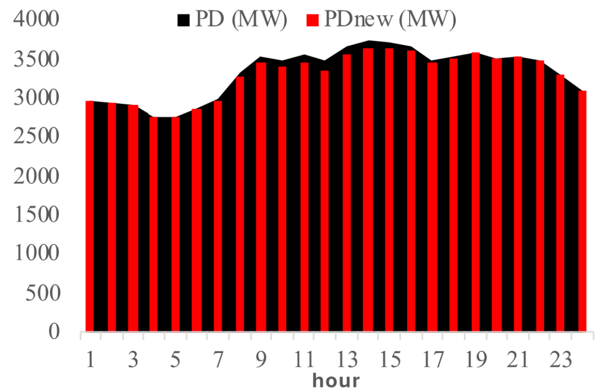

Fig. 8: Load demand levels of System 2.

is for PSO. The height of each bar from methods is different because the load demand level of each hour is different. Moreover, cost savings of SBOA over TSA and PSO cannot show clearly due to the values being much smaller than the value of the vertical axis. To cover this issue, Figure 10 is plotted with the aim of giving more details about the cost difference of SBOA over TSA and PSO.

In the figure, SBOA can identify costs as low as $ 0.0023 at the 14th hour, increasing to $ 110.0 at the 9th hour. Meanwhile, PSO ranges from $ 1.7 in the 5th hour to $ 18.6 in the 22nd hour. The hourly cost of SBOA is on average $ 8.5 less than that of TSA and $ 41.6 less than that of PSO. The total one-day cost from the three methods is indicated in Figure 11, in which the height of SBOA is lower than that of TSA and PSO. Namely, SBOA, TSA, and PSO costs $ 1,917,450.3, $ 1,917,649.0, and $ 1,918,426.3, respectively. It means that the one day cost of SBOA is less than TSA by $ 198.68 and PSO by $ 976.04, in turn. Solutions obtained by SBOA is given in Table 2.

5.4. Discovering solution data with step size of 1 MW to System 1

The section utilized SBOA to derive solution data for System 1 by adjusting the load demand from 1010 MW to 3650 MW with a step size of 1 MW. These values represent the system's smallest and largest load demands. It's worth noting that the minimum and maximum generated power output of all TPPs fall within the range of 1010 MW to 3865 MW. However, it's important to acknowledge that the maximum load demand cannot match the maximum power output of all TPPs due to power loss in the transmission line. The results obtained through SBOA are depicted in Figure 12, with solutions corresponding to each PD being represented by different color lines. With every load value, we can systematically analyze the cost and power of 20 TPPs, as well as the power loss, as illustrated in Figure 13. The green line represents the

Tab. 2: Solutions obtained by SBOA of System 2.

Unit (MW)	1	2	3	4	5	6	7	8
TPP_1	600.00	600.00	599.99	570.04	570.01	589.92	600.00	600.00
TPP_2	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
TPP_3	169.28	166.89	165.36	151.09	151.08	159.27	169.69	199.60
TPP_4	135.51	131.09	130.23	120.03	120.03	125.76	134.18	173.13
TPP_5	135.79	133.83	132.68	125.20	125.20	129.25	134.78	159.63
TPP_6	98.62	95.64	95.46	86.40	86.41	91.21	97.92	100.00
TPP_7	125.00	125.00	125.00	120.59	120.60	123.71	125.00	124.98
TPP_8	149.43	144.37	144.32	132.98	132.97	139.09	147.92	150.00
TPP_9	124.58	121.35	120.28	112.55	112.54	116.68	123.64	164.42
TPP_{10}	140.54	134.80	133.14	119.20	119.22	126.62	138.55	150.00
TPP_{11}	163.91	160.52	159.90	155.25	155.26	156.98	163.31	189.22
TPP_{12}	313.86	311.20	310.75	303.32	303.30	306.78	315.20	352.80
TPP_{13}	132.38	130.40	130.04	125.95	125.95	127.82	132.04	158.35
TPP_{14}	38.45	35.72	35.30	32.38	32.39	33.20	37.26	62.73
TPP_{15}	142.24	138.96	137.59	128.93	128.95	133.47	142.20	184.30
TPP_{16}	38.51	37.82	37.85	37.18	37.18	37.50	38.08	41.53
TPP_{17}	85.00	85.00	85.00	80.07	80.06	84.75	85.00	85.00
TPP_{18}	110.70	108.29	107.30	100.30	100.31	103.76	111.44	119.99
TPP_{19}	119.98	120.00	119.56	112.17	112.18	116.14	119.98	120.00
TPP_{20}	80.55	76.41	75.81	67.19	67.17	71.60	79.31	99.99
SP_1	0.00	0.00	0.00	0.00	0.00	0.43	5.82	13.87
SP_2	0.00	0.00	0.00	0.00	0.00	0.37	5.24	12.60
SP_3	0.00	0.00	0.00	0.00	0.00	0.26	4.21	10.89
SP_4	0.00	0.00	0.00	0.00	0.00	0.22	4.10	11.45

Tab. 3: Solutions obtained by SBOA of System 2 (cont).

Unit (MW)	9	10	11	12	13	14	15	16
TPP_1	600.00	600.00	600.00	600.00	600.00	600.00	600.00	600.00
TPP_2	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
TPP_3	200.00	200.00	199.97	199.99	200.00	200.00	200.00	200.00
TPP_4	199.93	200.00	199.99	194.50	200.00	200.00	200.00	199.99
TPP_5	160.00	159.99	159.95	160.00	160.00	160.00	160.00	160.00
TPP_6	100.00	99.99	99.99	100.00	100.00	100.00	100.00	100.00
TPP_7	124.96	125.00	125.00	125.00	125.00	125.00	125.00	125.00
TPP_8	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00
TPP_9	199.95	193.22	199.99	176.58	200.00	200.00	200.00	200.00
TPP_{10}	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00
TPP_{11}	223.90	205.05	218.57	201.87	260.19	300.00	300.00	287.47
TPP_{12}	398.40	384.99	401.51	374.13	467.52	500.00	500.00	499.74
TPP_{13}	159.98	159.96	159.97	159.93	159.97	160.00	160.00	160.00
TPP_{14}	108.44	87.40	111.88	79.84	129.90	130.00	130.00	130.00
TPP_{15}	185.00	185.00	185.00	185.00	184.98	185.00	185.00	185.00
TPP_{16}	46.35	43.13	45.21	42.90	50.28	76.51	77.26	53.05
TPP_{17}	85.00	84.98	85.00	85.00	84.99	85.00	85.00	85.00
TPP_{18}	119.99	120.00	120.00	119.94	119.99	120.00	120.00	120.00
TPP_{19}	120.00	120.00	120.00	119.95	120.00	120.00	120.00	120.00
TPP_{20}	100.00	99.96	99.97	99.99	99.99	100.00	100.00	100.00
SP_1	21.42	27.25	30.54	32.12	31.87	28.99	23.28	15.65
SP_2	19.48	24.47	27.44	27.89	26.40	23.94	19.40	13.32
SP_3	17.06	21.56	24.12	25.07	24.42	22.11	17.34	11.73
SP_4	18.58	23.95	27.32	28.77	28.44	26.09	21.11	14.16

Tab. 4: Solutions obtained by SBOA of System 2 (cont).

Unit (MW)	17	18	19	20	21	22	23	24
TPP_1	600.00	600.00	600.00	600.00	600.00	600.00	600.00	600.00
TPP_2	200.00	199.97	200.00	200.00	200.00	200.00	200.00	181.84
TPP_3	200.00	200.00	199.99	199.98	200.00	200.00	200.00	200.00
TPP_4	199.99	199.80	199.98	200.00	199.98	200.00	179.74	145.85
TPP_5	160.00	159.99	160.00	160.00	160.00	160.00	160.00	145.62
TPP_6	100.00	99.99	100.00	100.00	99.98	100.00	100.00	99.99
TPP_7	125.00	125.00	124.99	125.00	125.00	125.00	124.93	124.97
TPP_8	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00
TPP_9	200.00	200.00	199.96	200.00	200.00	199.91	171.66	134.73
TPP_{10}	150.00	149.97	150.00	150.00	149.99	150.00	149.97	149.78
TPP_{11}	287.47	225.51	270.07	235.35	244.27	230.79	191.28	172.31
TPP_{12}	499.74	410.16	485.40	429.79	446.70	421.65	356.99	323.52
TPP_{13}	160.00	159.91	159.99	160.00	159.99	159.99	158.92	140.18
TPP_{14}	130.00	114.93	129.99	130.00	129.99	129.62	71.02	46.94
TPP_{15}	185.00	185.00	184.99	185.00	185.00	185.00	184.84	155.76
TPP_{16}	53.05	46.14	50.45	46.53	47.47	46.37	41.34	38.75
TPP_{17}	85.00	85.00	85.00	84.99	85.00	85.00	84.96	85.00
TPP_{18}	120.00	120.00	120.00	120.00	120.00	120.00	119.96	118.92
TPP_{19}	120.00	120.00	120.00	120.00	119.99	119.97	120.00	120.00
TPP_{20}	100.00	100.00	100.00	100.00	100.00	100.00	100.00	88.81
SP_1	7.88	1.68	0.00	0.00	0.00	0.00	0.00	0.00
SP_2	6.62	1.32	0.00	0.00	0.00	0.00	0.00	0.00
SP_3	5.61	1.05	0.00	0.00	0.00	0.00	0.00	0.00
SP_4	6.85	1.36	0.00	0.00	0.00	0.00	0.00	0.00

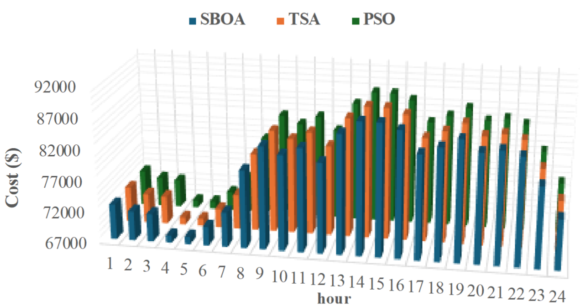

Fig. 9: Costs obtained by three methods of System 2 over 24 hours.

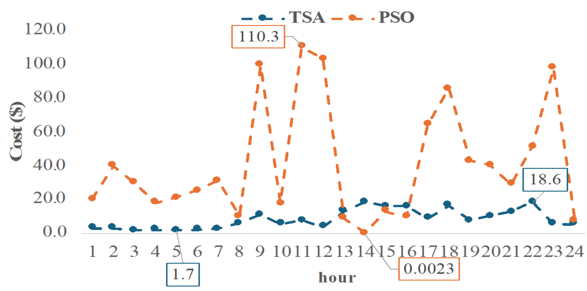

Fig. 10: Cost saving of SBOA compared TSA and PSO on System 2 over 24 hours.

cost in \$, the orange array displays P_{loss} in MW, and the dark blue array indicates the load demand in MW. From the figure, when PD increases, P_{loss} significantly escalates, and this is true for the cost. It means that the financial prospects of the entire power system are significantly affected by even a slight decrease in the cost of electric energy because of increasing load demand. Nowadays, the penetration of renewable energy resources is increasing, and the fluctuation of PD is different. Therefore, operators of power systems must make a quick decision to require suitable power allocation from power plants with the aim of reducing the cost of electric energy as small possible as. As a result, creating solution data with a step size of 1 MW to System 1 plays a vital role because if load demand is given, system operators can receive detailed information such as power generated by all thermal power plants, power loss, and system cost immediately as importing the PD into the solution map. This ensures that the supply side always meets the consumption side, allowing the system to operate efficiently and safely.

6. Conclusions

The study has successfully utilized three methods (SBOA, PSO, and TSA) to achieve optimal solutions

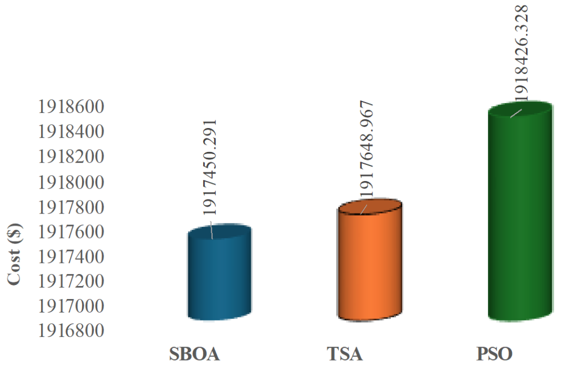

Fig. 11: One day cost of three methods on System 2.

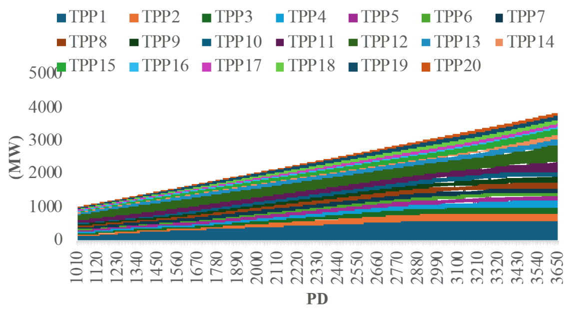

Fig. 12: Solutions given by SBOA for System 1 with step size of 1 MW.

for ELD problems with the hybrid operation of traditional power plants and renewable power plants. Three study cases were examined to serve two primary purposes: firstly, to evaluate the effectiveness of the three methods by implementing the first two study cases, and secondly, to offer solution data for operators by implementing the last study case. The results revealed that SBOA outperforms TSA and PSO in solving the ELD problems for Systems 1 and 2. These findings demonstrate that SBOA is an effective search method, capable of achieving the same best cost or better than the other methods. Furthermore, by adjusting the load from the lowest to the highest demand of System 1, SBOA can identify a set of solutions that can aid operators in making informed decisions for power plants when loads are provided. Going forward, SBOA's performance can be enhanced by refining its mechanism to update itself with new solutions. Additionally, the study will explore the uncertain aspects of renewable energy sources to illustrate how energy instability impacts the technical and economic considerations of the power system.

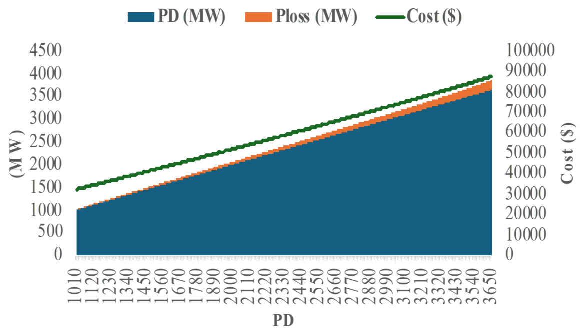

Fig. 13: The cost, load demand and power loss obtained by SBOA for System 1.

Author Contributions

T. T. P. carried out the analytic calculations and numerical simulations, providing valuable insights for the study. L. H. P. took the lead in writing the entire paper and B. H. D. contributed significantly by revising the final manuscript to enhance its clarity and coherence. While T. K. D., B. T. L. and T. T. N. G. help us to support the data in the revised version.

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