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REDUCING THE COST OF THE HYBRID SYSTEM OPERATION BY SKILL OPTIMIZATION ALGORITHM

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Abstract. *In the realm of energy networks, efficiently distributing the required load among all online generating units is crucial for meeting demand effectively. This is achieved through the Economic Load Dispatch Problem (ELD). ELD is problem of operating of thermal power plants; however, this operation can be opened by integrating renewable power plants, leading ELD problem turn into new one, called NELD problem. By employing various methods to solve ELD and NELD problems, we can create a strategic power distribution plan that optimally balances the output of online generating units. This study suggests three methods including Skill Optimization Algorithm (SOA), War Strategy Optimization Algorithm (WSO) and particle swarm optimization (PSO) to implement the optimal power distribution plan for these plants while minimizing the cost per unit of energy generated. Simulations are conducted to assess the effectiveness of the proposed algorithm in solving a variety of test systems, encompassing multiple load levels and diverse constraints. The results highlight the SOA's strong performance, demonstrating its potential to compete effectively with other advanced methods in the field.*

Key Words**:** *new economic load dispatch, Skill Optimization Algorithm, power system operation, renewable power plants.*

1. Introduction

Economic growth in the 21st century has led to increased electrical energy consumption through different activities such as production, services, and daily household needs. For the increase, traditional power plants such as thermal power plants (TPs) and hydropower plants (HPs) have generated a large amount of electricity. It is noticed that TPs use a significant amount of fossil fuels, leading to a total increase in the cost of the power system. Nevertheless, efficient fossil fuel exploitation is an extreme task for managers and operators of TPs. For dealing with such a challenge, Economic Load Dispatch (ELD) has become the focal point of attention for them. The ELD problem provides an optimal strategy to minimize fuel costs by assigning an optimal generation planning of units available in the power system while meeting operational requirements [1].

In the first time, the cost function is usually presented under quadratic or convex function forms; however, the constraints and characteristics of power systems must be considered in practical operations. As incorporating the actual constraints and characteristics, such as prohibited operating zones (POZ), transmission loss, ramp rate limits, valve-point effects (VP), and different fuel selections (FS), into natural power systems, the cost function becomes non-smooth, non-convex, and multi-modal [2–5], resulting to more challenges to the problem. With these characteristics, if operators incorrectly operate, economic losses or faults can be happened [6–8]. In determining the best solutions for ELD problem, conventional optimizations like Interior point method (IPM) [9], gradient method (GM) [10], lambda iteration method (LIM) [11], quadratic programming (QP) [12], hopfield model (HM) [13], enhanced lagrange artificial neural network (ELANN) [14] and enhanced augmented lagrange hopfield network (EALHN) [15] have been adopted. Among these methods, the neural network-based ELANN and EALHN methods effectively have solved the ELD problem with multiple fuel types represented by piecewise quadratic cost functions. However, these methods have struggled to address nonlinear constraints. Although they endured excessive numerical iterations, their convergences are slow, and their solutions are local. Similar to ELANN and EALHN methods, other methods are also suitable for ELD problems with a basic quadratic function and without FSs, POZs, and VPs. In other words, this group faces limitations in solving highly complex, non-linear, and non-convex optimization problems, making it challenging to identify the optimal solution [16].

To overcome such challenges, Artificial Intelligence (AI) based approaches and a variety of techniques inspired by natural phenomena or behaviors of animals were developed, including genetic algorithm (GA) [17], tabu search algorithm (TSA) [17], particle swarm optimization (PSO) [18], firefly algorithm (FA) [19], differential evolution (DE) [20], group search optimizer (GSO) [21], ray optimization (RO) [22]. These methods are adept at handling real-world constraints of the ELD problem and effectively solving optimization problems of any level of complexity within a reasonable timeframe. In this group, PSO has been introduced by James Kennedy and Russell C. Eberhart in 1995. This method can find optimal solutions in a variety of optimization fields with the significant performance and benefits of simplicity in implementation, adaptability, rapid convergence and less computational ability. Compared to algorithms in the literature, PSO has performed well thus far and has been used extensively to solve real-world problems [23–25]. In addition to PSO, DE is an algorithm with fewer parameters. The benefit makes DE find solutions fast, robust, easy to implement, and efficient to search in global spaces. For these advantages above, PSO and DE performance can be attributed to their natural capacity for processing a population of potential solutions, allowing them to conduct comprehensive exploration within the search space of the optimization problem [26]. However, both PSO and DE still have some disadvantages that scholars need to be noted as applying them to deal with optimal engineering problems. Namely, DE's drawbacks are the need for careful parameter tuning, the possibility of unstable convergence, suboptimal computational efficiency, and a tendency to get trapped in local optimums [26] and PSO's include premature convergence, sensitivity to parameters, and challenges with constrained optimization. Thus, to effectively improve the convergence and identify optimal solutions on a global scale within expansive spaces, numerous enhanced and modified versions of original methods have been put forward such as hybrid distributed Sobol PSO and TSA methods (DSPSO–TSA) [17], Anti-predatory PSO (APSO) [18], improved firefly algorithm (IFA) [19], quick GSO (QGSO) [21], one rank cuckoo search algorithm (ORCSA) [27], modified PSO (MPSO) [28], improved social spider optimization algorithm (ISSO) [29], improved antlion optimization algorithm (IALO) [30].

Over time, numerous algorithms have successfully tackled the ELD problem; however, each has unique strengths and weaknesses. As a result, researchers have strategically selected top-performing algorithms and integrated them to create innovative algorithms that deliver more promising results than their predecessors. There is considerable interest in various hybrid methods for solving the ELD problem, including Jaya algorithm with multi-population (Jaya-M) [31], Jaya algorithm with self-adaptive strategy and multi-population method (Jaya-SML) [31], Jaya algorithm with self-adaptive multi-population and Levy flights (Jaya-LF) [31], Greedy sine-cosine non-hierarchical grey wolf optimizer (G-SCNHGWO) [32], improved orthogonal design PSO (IODPSO) [33], imperialist competitive algorithm with PSO (PSO-ICA) [34]. In [31], authors have implemented Jaya on ELD because it stands out as an effective meta-heuristic due to its minimal requirement of algorithm-specific parameters for effective execution. However, Jaya still has drawbacks, and some techniques have been suggested to cover them. Namely, the multi-population (MP) technique is presented to enhance the population diversity of Jaya (called Jaya-M), or a self-adaptive strategy is used to cope with the tuning problem for extra parameters (called Jaya-SM). Lévy flight distribution is included in the population iteration phase to prevent getting trapped by local optima. Finally, self-adaptive multi-population and Lévy flights are integrated into the Jaya algorithm (called Jaya-SML) that can effectively solve various constraints such as power balance constraints, capacity limits, ramp rate limits, prohibited operating zones, valve-point effects, and multi-fuel options. In [34], PSO-ICA is shown as a new hybrid approach that combines ICA and PSO methods to find the feasible optimal solution for the non-convex ELD while considering the valve point effect. The outcomes demonstrate the applicability of PSO-ICA in resolving the power system economic load dispatch issue, especially in large-scale power systems. However, their successful implementation requires proper design, parameter adjustment, and integration to ensure that their advantages outweigh any drawbacks.

In modern society, the rapid development of renewable energies (RES) like wind and solar power has led to significant contributions to electricity generation. These resources have the potential to mitigate greenhouse gas effects effectively, address global warming, and replace the depletion of fossil energy sources. As a result, these energy sources are promising and viable alternatives to traditional fossil fuels globally. However, the RES have their limitations like climatic constraints resulting in a variation in resource disposal, ample source availability at far-off locations from the load, and system stability due to the integration of these intermittent resources into the existing power system [35, 36]. The integration of RES in power systems turns ELD problem to become new one called NELD problem. In the study referenced in [37], the authors address the ELD for different combinations of TPs, wind turbines, and PV systems. The authors considered the penalties associated with wind-based power generation but did not factor in the cost of the PV system. The authors in reference [38] propose a two-stage low-carbon economic scheduling model that considers the characteristics of wind, solar, and TPs and demand response at different time scales. This model addresses the challenges of large-scale renewable energy, mainly focusing on the high-demand periods for TPs.

This paper introduces Skill Optimization Algorithm (SOA) [39], a novel metaheuristic algorithm for optimization problems. SOA method draws inspiration from the human endeavor to acquire and enhance skills in problem-solving. The stages of SOA are embodied in two fundamental phases: exploration, in which people learn from experts, and exploitation, which involves enhancing one's skills through self-motivated practice. The efficiency of SOA in optimization applications is evaluated by testing on a set of twenty-three standard benchmark functions, including various unimodal, high-dimensional and fixed-dimensional multimodal types. The optimization results show SOA can provide good performance and appropriate solutions for optimization problems. This is a reason that SOA is introduced in this study for touching the solutions of two problems such as ELD and NELD. In addition to SOA, PSO [40] and War Strategy Optimization Algorithm (WSO) [41] are applied to search solutions of two problems.

PSO is an effective population-based optimization technique inspired by the natural behaviors of birds and fish. This approach offers a systematic way to tackle optimization challenges by continuously refining candidate solutions, known as particles. Each particle learns from its own experiences while benefiting from the insights the entire swarm shares. By adjusting its velocity and position based on both its personal best solution (pBest) and the global best solution (gBest), PSO enhances the search for optimal solutions. This method has proven to be highly valuable and applicable across various fields of scientific research, including hyperparameter tuning, neural network training, and data clustering [42]; gene selection, protein structure prediction, and medical image segmentation [43–45] and portfolio optimization, financial forecasting, and risk analysis [46]. WSO is an innovative metaheuristic algorithm grounded in military tactics and strategies. It perceives optimization as a strategic conflict in which candidate solutions compete like armies, executing attack, defense, reinforcement, and retreat maneuvers. WSO masterfully balances exploration and exploitation by dynamically adjusting its tactics based on performance. This capability not only prevents premature convergence but also enables adaptation to complex, multidimensional problem environments. The algorithm is effectively utilized across various fields to solve intricate optimization challenges by simulating strategic movements with precision. In the biomedical field, it has been utilized to improve treatment techniques for patients with autism spectrum disorder [47]. In energy forecasting, WSO helps to provide an effective and dependable energy supply [48], while in battery storage systems, it improves system performance and efficiency [49].

The key innovations and significant contributions of the study can be summarized as follows:

- The successful application of three novel meta-heuristic algorithms SOA, WSO, and PSO for optimizing power allocation of these available power plants in both ELD and NELD problems.
- A discussion and demonstration of the superior performance of SOA compared to WSO and PSO within these contexts.
- An examination of the relevance of solar power plants in two provinces of Vietnam concerning the ELD.

2. Problem Formulation

2.1. The Objective

The difference between ELD and NELD is that the ELD problem only focuses on allocating power among TPs, whereas the NELD problem concentrates on sharing power from TPs and renewable power plants (ie, solar power plant (SP)). However, two problems have the same objective: to minimize the system's total operating cost (TOC). In addition, the power generating scheduling of these power plants is implemented in one day. In the study, the objective can be defined as the following equation:

$$MinimizeTOC = \sum_{l=1}^{24}\sum_{i=1}^{N_i} C_{TP,i} + \sum_{l}^{24}\sum_{h=1}^{N_h} C_{SP,h} \quad (1)$$

In Eq.1, $C_{TP,i}$ and $C_{SP,h}$ denote cost function of ith TP and hth SP; N_i and N_h stand for a number of TPs and SPs. These costs are described in the following subsection.

Modelling TP cost

The C_{TP} of thermal power plant is definitively represented by a second-degree polynomial equation and formulated by:

$$C_{TP,i} = a_i + b_i P_{TP,i} + c_i P_{TP,i}^2;\ i = 1, ..., N_i \quad (2)$$

In some cases of increasing and decreasing load demand, TPs must be adjusted for power generation by control of the physical characteristics of steam boilers, leading the objective function in Eq.2 to become a new one, as shown in Eq.3 below.

$$C_{TP,i} = a_i + b_i P_{TP,i} + c_i P_{TP,i}^2 + \left| e_i \sin\left(d_i (P_{TP,i}^{\min} - P_{TP,i})\right)\right|;\ i = 1, ..., N_i \quad (3)$$

where a_i, b_i, c_i, e_i, and d_i denote the fuel burning factors for TP i.

The fuel cost function of TP with different fuel alternatives and VPs can be calculated mathematically using the following formula:

$$C_{\mathrm{TP},i} = \begin{cases} a_{i1} + b_{i1}P_{\mathrm{TP},i1} + c_{i1}P_{\mathrm{TP},i1}^2 \\ \quad + \left|e_{i1}\sin\left(d_{i1}(P_{\mathrm{TP},i1}^{\min} - P_{\mathrm{TP},i1})\right)\right|, \\ \quad \text{fuel } 1, \quad P_{\mathrm{TP},i1}^{\min} \leq P_{\mathrm{TP},i1} \leq P_{\mathrm{TP},i1}^{\max} \\ a_{i2} + b_{i2}P_{\mathrm{TP},i2} + c_{i2}P_{\mathrm{TP},i2}^2 \\ \quad + \left|e_{i2}\sin\left(d_{i2}(P_{\mathrm{TP},i2}^{\min} - P_{\mathrm{TP},i2})\right)\right|, \\ \quad \text{fuel } 2, \quad P_{\mathrm{TP},i2}^{\min} \leq P_{\mathrm{TP},i2} \leq P_{\mathrm{TP},i2}^{\max} \\ \vdots \\ a_{ik} + b_{ik}P_{\mathrm{TP},ik} + c_{ik}P_{\mathrm{TP},ik}^2 \\ \quad + \left|e_{ik}\sin\left(d_{ik}(P_{\mathrm{TP},ik}^{\min} - P_{\mathrm{TP},ik})\right)\right|, \\ \quad \text{fuel } k, \quad P_{\mathrm{TP},ik}^{\min} \leq P_{\mathrm{TP},ik} \leq P_{\mathrm{TP},ik}^{\max} \end{cases} \tag{4}$$

where the fuel burning factors for type k^{th} of TP i are specified by a_{ik}, b_{ik}, c_{ik}, e_{ik} and d_{ik}.

Modelling SP cost

The cost function of SP can be ignored because the plant does not consume fossil fuel. However, most solar power plants belong to private entities, so the cost function should be considered as specific contracts of selling electricity [50]. The C_{SP} formulation of SP can be investigated by:

$$C_{SP,h} = f \cdot P_{SP,h} \tag{5}$$

In Eq.5, f denotes the price in (\$/MWh); $P_{\mathrm{SP},h}$ denotes the power output of SP h, which is calculated by:

$$P_{SP}(A_b) = \begin{cases} P_{SP,r}\dfrac{A_b^2}{A_{std} + R_c}, & 0 < A_b < R_c \\ P_{SP,r}\dfrac{A_b}{A_{std}}, & A_b > R_c \end{cases} \quad ; \quad b = 1, \ldots, 24 \text{ hours} \tag{6}$$

For calculating power from SP, the study recommends the application of global solar data of two SPs at two southern Vietnamese provinces to determine irradiation. After that, Eq. 6 will be used for computing power at each hour in one day.

Constraints

This study establishes that generators and systems must comply with equality and inequality constraints to address ELD issues effectively. This approach promotes a clear framework for optimal performance and system reliability.

Active power balance

The total real power output from all power plants is designed to effectively meet the total load demand (P_{LD}) while also accounting for system power losses (P_{Loss}). This ensures a reliable and efficient energy supply as given in Eq. 7:

$$\sum_{l=1}^{24}\left(\sum_{i=1}^{N_i} P_{TP,i} + \sum_{h=1}^{N_h} P_{SP,h}\right) = \sum_{l=1}^{24}(P_{LD} + P_{Loss}) \tag{7}$$

Generated power limitation

It is essential to strictly adhere to the minimum and maximum generation limits for the power plant to operate effectively. This practice promotes efficient and sustainable power generation while ensuring the power plant functions within its designated power range, reducing the risk of overload or underutilization.

$$P_{TP,i}^{\min} \leq P_{TP,i} \leq P_{TP,i}^{\max} \tag{8}$$

$$P_{SP,h}^{\min} \leq P_{TP,h} \leq P_{SP,h}^{\max} \tag{9}$$

3. Skill Optimization Algorithm

Implementing new solutions for SOA method involves two important phases: the acquisition phase and the self-improvement phase. These phases are designed to enhance the balance between exploration and exploitation capabilities. The mathematical models for each phase are described below.

3.1. Expert's acquisition phase

In the initial phase of the SOA algorithm, each member of the population develops a skill under the guidance of a community expert member.

The quality of each member is defined by the objective function value they achieve. The "experts set" consists of members with superior objective function values. A randomly chosen expert is assigned to train the member in question. The expert member leads the population to various positions in the search space, thereby improving the algorithm's global search and exploration capabilities. If a new position enhances the objective function value, it is deemed acceptable for each member. The best candidate solution becomes a permanent member of the experts set for all SOA members. Therefore, the first phase of the update can be modelled according to the mentioned concepts using Eq.10.

$$A_m^{\text{new1}} = A_m + R_1 \times (A_E - R_2 \times A_m) \quad (10)$$

In Eq. 10, the new and current positions of the mth solution are A_m^{new1} and A_m; A_E is the best solution among population; R_1 random number within 0 and 1; R_2 random number within 1 and 2.

3.2. Self-improving phase

During the second phase of the SOA algorithm, every member of the population is focused on refining their skills through dedicated individual practice and activity. This local search strategy is aimed at maximizing the use of their existing knowledge by elevating the value of their objective function, which is an indicator of their skill level. Any newly calculated position is deemed acceptable only if it results in an enhancement of the objective function value. The concepts of this phase of SOA updating are mathematically modelled using Eq.11.

$$A_m^{\text{new2}} = \begin{cases} A_m + \dfrac{1-2a}{I} \times A_m, & \text{if } a < 0.5 \\ A_m + \dfrac{A_m^{min} + \omega(A_m^{max} - A_m^{min})}{I}, & \text{otherwise} \end{cases} \quad (11)$$

Where, a is a random number; I is the current iteration; and A_m^{min} and A_m^{max} are the lower and upper boundaries of the m^{th} solution.

4. Results and discussion

Two test systems have been designed to showcase the effectiveness of the ELD problem-solving algorithm based on SOA, WSO, and PSO, in which System 2 is more complex than System 1 due to the inclusion of more power plants and additional constraints.

4.1. Discussion on System 1

In this section, ten thermal power plants are the power system under investigation. The data about the system is taken from [17, 18]. Enough power must be supplied by the system to satisfy the load requirement of 2700 MW. In order to determine the system's ideal power output, we have used SOA, WSO, and PSO while taking into account various constraints like power balancing, valve point effect, and several fuel options. To fairly evaluate these methods, some comparison criteria such as minimum cost (Min.c), mean cost (Mean.c), maximum cost (Max.c), and standard deviation (Sd) are recommended. These optimal costs are found by three methods via different investigations of the population size (PS), highest iterations (HI) and number of trial runs based on previous studies. As a result, PS of 50 and HI of 150 are selected for SOA, WSO and PSO to run for searching solutions of System 1.

Figure 1 shows the results of three methods based on 100 independent runs. The three-color lines in the figure – black for PSO, blue for WSO, and red for SOA – define the 100-cost of the three techniques. Basically, three lines fluctuate; however, the red line has lesser fluctuation, the black line has larger fluctuation, and the blue line has medium correspondingly. In addition, a lot of cost values from SOA are under those from WSO and PSO. From 100 cost values by running 100 times, we select the best run to show the process of touching the best solution with the best cost from three methods, as shown in Figure 2. As seen from such a figure, the solution searching process of SOA is considered the best because from about 45 to the final iterations, the red line is always below the blue line of WSO and the black one of PSO. For further evidence, from about 100 to 150 iterations, we zoom out the Figure 2 to display the positions of three methods. As a result, the red line is under the blue and black ones.

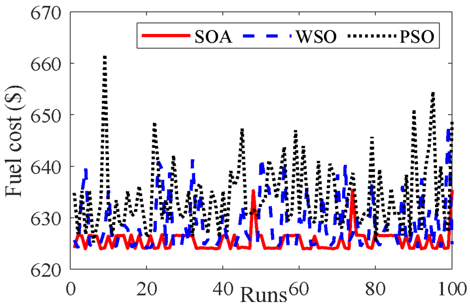

Fig. 1: The 100 results of SOA, WSO and PSO methods with 100 runs for System 1.

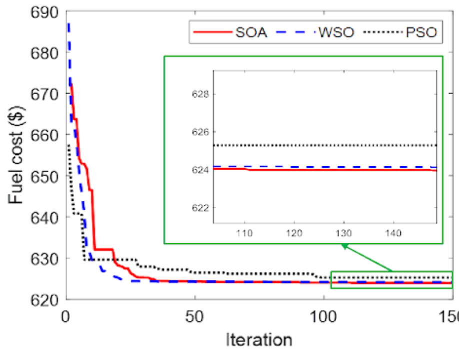

Fig. 2: The best run among 100 runs from three methods for System 1.

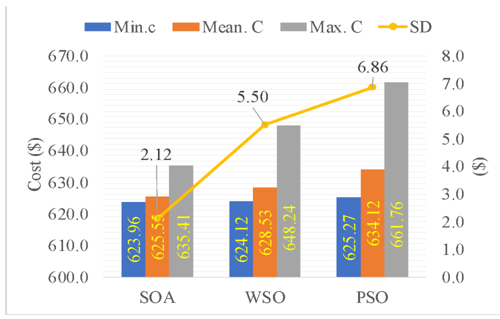

Fig. 3: The result comparison of three methods for System 1.

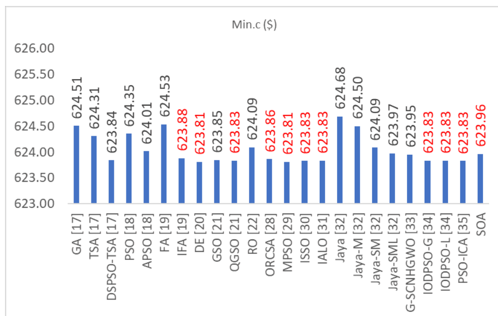

Fig. 4: The Min.c of three methods for System 1.

The Min.c, Mean.c, Max.c and SD of SOA, WSO and PSO from the best run are collected and given in Figure 3. As seen from the blue bars, we observe that the Min.c of SOA is \$623.96, which is less than that of WSO and PSO by \$0.16 and \$1.31, respectively. From the orange and gray bars, the Mean.c and Max.c of SOA are also lower than those from WSO and PSO. In terms of SD, SOA has a value of 2.12, the lowest among the three methods. From the comparison of the four terms, we can conclude that SOA is more effective than WSO and PSO.

The costs of SOA are compared with previous methods shown in Table 1. In the table, Min.c of these methods is reported in column 1, and it is a key criterion for proving the performance of the compared methods. If the method's Min.c is smaller than others, the method is considered the best. Otherwise, the method is the worst. The Min.c is divided into two groups: Group 1 is under \$624, and another is over \$624. For easy viewing, Min.c in Table 1 is presented under different bars displayed in Figure 4. SOA is allocated in group 1, which is marked in red.

In a comparison of Mean.c and Max.c, IODPSO-G [33] and IODPSO-L [33] are the best, while FA [19] is the worst. Regarding SD, SOA is 2.12, and others are from 0.01 to 1.1593. Considering PS and HI, SOA has values of 50 and 150, while others have different values.

4.2. Discussion on System 2

The applied methods (PSO, WSO, and SOA) will be carefully examined in this part to determine how effective they are at finding the optimum solution and how reliable their search process is on System 2. System 2 contains ten thermal power plants and two solar power plants. The data of ten TPs is from [28, 29], and the data of two SPs is accessed from a global solar map [51].

SP1 is located at Vu Bon commune with geographical coordinates of $(12.660647°, 108.420719°)$ and SP2 is located at Yang Mao commune with geographical coordinates of $(12.407423°, 108.508808°)$. Moreover, SP1 and SP2 have a rated power of 50 MVA and 45 MVA, respectively. By accessing the geographical coordinates of SP1 and SP2, the output power over one day can be obtained and reported in Table 2. The mission of three methods is to recommend the optimal output power of these plants while considering the operation cost of System 2 at a lower level, satisfying all constraints and meeting loads over one day. Namely, load demand over one day with 24 different levels is also presented in Table 2.

For implementing three methods to System 2, the population size and maximum iterations are set to 50 and 150, respectively. With 100 runs, Min.c, Mean.c, and Max.c obtained by three methods every 24 hours are collected and shown in Figures 5, 6, and 7. Figure 5 shows the Min.c while Figures 6 and 7 show the Mean.c and Max.c. The shape of the three figures is similar; however, the height bar of SOA, WSO, and PSO at the same load level is different. To prove this, the cost of PSO at the 12th hour of three figures will be boxed and marked in red.

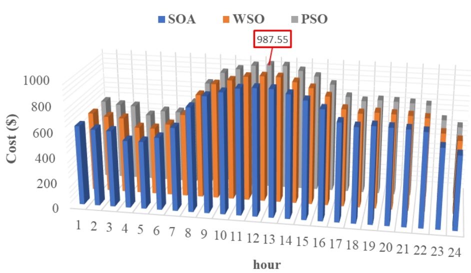

Fig. 5: The hourly Min.c of three methods over 24 hours for System 2.

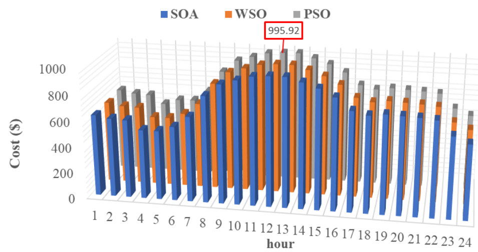

Fig. 6: The hourly Mean.c of three methods over 24 hours for System 2.

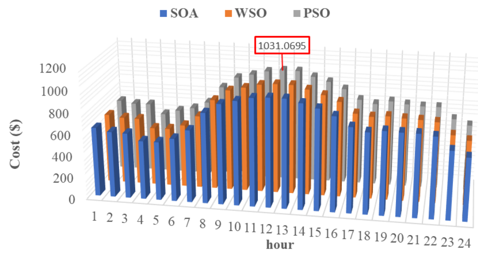

Fig. 7: The hourly Max.c of three methods over 24 hours for System 2.

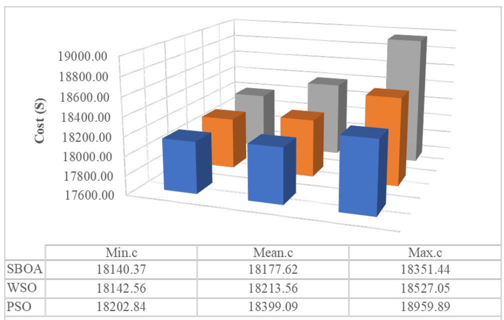

Fig. 8: The total cost for one day of SOA, WSO and PSO.

The total cost for one day of SOA, WSO and PSO is presented in Figure 8. In the figure, Min.c, Mean.c and Max.c of SOA are $18,140.37, $18,177.62, and $18,351.44, respectively. These are lower than those from WSO and PSO. For one day, a cost saving of SOA over WSO and PSO is $2.19 and $62.47 for Min.c, $35.93 and $221.46 for Mean.c, and $175.62 and $608.46 for Max.c. If we consider cost for one year, the cost saving of SOA over WSO and PSO is significant. Optimal solutions suggested by SOA are reported in Table 3.

Tab. 1: Result comparison of SOA and other methods for System 1

Methods	Min.c ($)	Mean.c ($)	Max.c ($)	SD	PS	HI
GA [17]	624.5050	624.7419	624.8169	0.1005	NA	100
TSA [17]	624.3078	624.8285	635.0623	1.1593	NA	100
DSPSO-TSA [17]	623.8375	623.8625	623.9001	0.0106	10	100
PSO [18]	624.3506	625.8198	629.1037	NA	NA	200
APSO [18]	624.0145	627.3049	624.8185	NA	20	200
FA [19]	624.5306	675.5344	679.4260	NA	10	100
IFA [19]	623.8768	625.2704	629.2765	NA	10	100
DE [20]	623.8090	NA	NA	NA	10	40
GSO [21]	623.8465	623.9829	624.2570	NA	NA	300
QGSO [21]	623.8349	623.8276	623.8501	NA	400	300
RO [22]	624.0922	625.2564	627.1189	NA	100	2000
ORCSA [27]	623.8608	623.8963	623.9353	NA	NA	1000
MPSO [28]	623.8090	NA	NA	NA	NA	NA
ISSO [29]	623.8286	623.8490	624.1641	NA	40	50
IALO [30]	623.8347	623.9930	626.4434	0.4232	40	200
Jaya [31]	624.6819	626.1531	637.5108	1.6584	30	1000
Jaya-M [31]	624.4959	625.9222	630.7652	0.8578	30	1000
Jaya-SM [31]	624.0850	624.2788	624.9105	0.1139	30	1000
Jaya-SML [31]	623.9738	624.0468	624.1300	0.0327	30	1000
G-SCNHGWO [32]	623.9491	623.9914	624.7415	0.0418	30	NA
IODPSO-G [33]	623.8300	623.8400	623.8300	0.0100	40	NA
IODPSO-L [33]	623.8300	623.8300	623.8300	0.0000	40	NA
PSO-ICA [34]	623.8257	NA	NA	NA	NA	300
SOA	623.9600	625.5500	635.4100	2.1200	50	150

Tab. 2: The output power of SP1 and SP2 for System 2

Hour	Output Power (MW)							
	1	2	3	4	5	6	7	8
SP1 (MW)	0.00	0.00	0.00	0.00	0.00	0.17	4.62	13.17
SP2 (MW)	0.00	0.00	0.00	0.00	0.00	0.16	4.29	12.61
PLD	2700	2660	2650	2510	2510	2590	2710	2926
Hour	Output Power (MW)							
	9	10	11	12	13	14	15	16
SP1 (MW)	21.80	28.63	32.63	34.01	33.46	30.30	23.85	15.49
SP2 (MW)	20.47	25.96	29.19	30.17	29.63	25.40	19.14	12.19
PLD	3012	3015	3042	3049	3053	3031	3023	2993
Hour	Output Power (MW)							
	17	18	19	20	21	22	23	24
SP1 (MW)	7.38	1.46	0.00	0.00	0.00	0.00	0.00	0.00
SP2 (MW)	4.96	0.92	0.00	0.00	0.00	0.00	0.00	0.00
PLD	2902	2902	2940	2930	2920	2900	2700	2600

Tab. 3: Solutions reached by SOA of System 2

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
TP1 (MW)	219.68	215.99	213.53	207.62	208.83	217.12	219.12	237.17
TP2 (MW)	210.91	208.93	209.42	206.69	205.96	211.41	212.65	219.83
TP3 (MW)	283.16	277.58	273.59	269.09	265.62	275.65	282.41	310.39
TP4 (MW)	239.28	239.82	238.34	236.19	235.79	236.46	239.69	245.46
TP5 (MW)	279.67	274.36	277.05	260.61	262.60	277.05	280.06	310.74
TP6 (MW)	238.86	238.59	237.78	236.03	235.36	236.84	239.80	244.90
TP7 (MW)	288.63	283.38	284.00	267.06	271.79	285.83	290.19	344.07
TP8 (MW)	239.55	240.63	238.48	235.25	237.00	239.28	239.96	245.06
TP9 (MW)	424.42	415.25	408.19	330.95	328.65	340.99	423.47	439.97
TP10 (MW)	275.84	265.47	269.61	260.51	258.39	269.04	273.75	302.61
SP1 (MW)	0.00	0.00	0.00	0.00	0.00	0.17	4.62	13.17
SP2 (MW)	0.00	0.00	0.00	0.00	0.00	0.16	4.29	12.61
Hour	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
TP1 (MW)	222.53	222.87	223.46	228.25	227.05	225.90	223.02	224.28
TP2 (MW)	212.66	213.65	212.40	213.64	214.11	214.63	214.38	212.14
TP3 (MW)	499.57	499.80	499.98	499.76	499.71	499.53	499.73	499.96
TP4 (MW)	241.03	239.15	241.70	242.64	241.96	241.43	241.97	240.49
TP5 (MW)	287.18	291.96	290.02	292.04	293.47	286.53	290.77	283.87
TP6 (MW)	241.68	241.81	241.14	241.81	242.21	241.14	241.41	241.01
TP7 (MW)	301.34	295.05	304.04	302.35	300.43	301.01	300.13	299.57
TP8 (MW)	240.90	239.28	242.11	242.91	241.43	240.09	241.84	241.43
TP9 (MW)	436.43	437.73	439.91	440.00	439.96	439.79	439.50	439.93
TP10 (MW)	286.42	279.11	285.41	281.41	289.56	285.26	287.25	282.62
SP1 (MW)	21.80	28.63	32.63	34.01	33.46	30.30	23.85	15.49
SP2 (MW)	20.47	25.96	29.19	30.17	29.63	25.40	19.14	12.19
Hour	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
TP1 (MW)	236.23	236.56	213.92	217.81	219.35	236.61	216.05	218.67
TP2 (MW)	218.84	221.29	213.11	211.41	211.16	220.55	210.19	208.69
TP3 (MW)	301.70	304.08	499.71	498.00	497.76	304.76	284.79	279.74
TP4 (MW)	245.33	243.58	241.57	238.88	239.42	245.33	238.88	238.61
TP5 (MW)	310.57	310.82	279.01	282.32	283.13	315.84	277.09	277.87
TP6 (MW)	244.50	246.52	239.80	239.93	239.93	243.96	239.12	237.64
TP7 (MW)	341.38	344.19	290.14	293.65	293.20	341.09	291.15	282.93
TP8 (MW)	243.31	244.79	241.97	239.41	240.23	245.06	240.09	238.21
TP9 (MW)	439.43	439.88	438.73	429.67	424.91	439.95	423.75	344.32
TP10 (MW)	308.36	307.91	282.04	278.92	270.91	306.86	278.89	273.32
SP1 (MW)	7.38	1.46	0.00	0.00	0.00	0.00	0.00	0.00
SP2 (MW)	4.96	0.92	0.00	0.00	0.00	0.00	0.00	0.00

5. Conclusions

This paper proposes a Skill Optimization Algorithm (SOA) to address non-convex economic dispatch problems involving solar power plants. The performance of SOA is compared with that of the Water Strategy Optimization (WSO) and Particle Swarm Optimization (PSO) algorithms by analyzing the costs associated with System 1, which consists of ten thermal power plants. The analysis demonstrates that SOA outperforms the two other methods. Additionally, SOA is benchmarked against other methods found in the literature. Three methodologies are also tested on System 2, which includes varying load levels and constraints. The results indicate that SOA remains more effective than WSO and PSO, with significant cost savings over one day—specifically, SOA saves \$2.19 compared to WSO and \$62.47 compared to PSO. To enhance SOA performance moving forward, refining its mechanisms for integrating new solutions to the method is important. Additionally, this study will investigate the uncertainties associated with renewable energy sources, highlighting how energy instability influences the power system's technical and economic dimensions.

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