STM JOURNALS

Journal of
Thermal Engineering and
Applications

ISSN: 2349-8994
Volume 9, Issue 3, 2022
DOI (Journal): 10.37591/JoTEA

http://engineeringjournals.stmjournals.in/index.php/JoTEA/index

Review JoTEA

Reduction of Total Electricity Generation Cost for Complicated Power Systems Considering Renewable Energy Sources by Using a Sea Horse Optimizer

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Abstract

This paper focuses on solving the economic load dispatch (ELD) problem by incorporating the presence of wind and solar power plants alongside conventional thermal power plants (THs). Particle swarm optimization (PSO) and Sea horse optimizer (SHO) are applied to solve the problem with the main objective function of minimizing the total electricity generation cost (TEGC). SHO is a novel meta-heuristic method recently proposed, while PSO is one of the classical meta-heuristic methods proposed approximately three decades ago. The two applied methods are tested on the power system with twenty thermal power plants, one wind and one solar power plant. The results obtained by the two applied methods indicate that SHO is completely superior to PSO in all comparison criteria. Specifically, in terms of minimum, average, and maximum cost values, SHO obtains better values than those of PSO. Moreover, SHO also shows itself to be much more reliable than PSO by reporting a lower standard deviation than PSO. By evaluating this evidence, SHO is acknowledged as the powerful computing method to deal with ELD problems, which considers the presence of both wind and solar energy.

Keywords: Economic load dispatch; wind power plant; solar power plant; Sea horse optimizer; Particle swarm optimization.

INTRODUCTION

Solving the economic load dispatch problem (ELD) is one of the first priorities while operating the power system. Therefore, finding an optimal solution to ELD problems is a must because the optimal solution can either lower the total electricity generation cost (TEGC) and partly alleviate the negative effects on the environment [1]. Most previous researchers focused on solving the ELD problem with thermal power plants as the main generating source. But lately, the trend of using renewable energy sources (RESs) is widely considered [2]. The presence of RESs not only reduces the TEGC of thermal power plants but also mitigates the burden of meeting load demand at rush hours [3–4]. Nowadays, the damages caused by the global warming phenomenon are more severe, hence the use of RESs such as wind and solar energy is more encouraged than ever. Following the trend, this study proposes an alternative method for solving the ELD problem, considering the presence of both wind and solar energy.

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Received Date: October/27/2022
Accepted Date: November/18/2022
Published Date: November/24/2022

Citation: Nguyen Van Yen, Tran Trung Hieu. Reduction of Total Electricity Generation Cost for Complicated Power Systems Considering Renewable Energy Sources by Using a Sea Horse Optimizer. Journal of Thermal Engineering and Applications. 2022; 9(3): 1–8p.

At the present, conventional computing methods are not the best choice for dealing with ELD problems anymore because the scale, the number of needed variable, and the complicated degree of the problem are increased significantly. In these circumstances, meta-heuristic algorithms are most affordable replacement. There were a huge number of published paper using meta-heuristic algorithms to solve the ELD problem such as Particle swarm optimization (PSO) [5], Differential evolution (DE) [6], Slime mould algorithm (SMA) [7], Woodpecker mating algorithm (WMA) [8], Chaotic social group optimization (CSGO) [9], Harmony search algorithm (HAS) [10], Artificial fish swarm algorithm (AFSA) [11], Jaya algorithm (JA) [12], Sine Tree-Seed algorithm (STSA) [13], Efficient Chameleon swarm algorithm (EFSA) [14], Jellyfish search optimization (JSA) [15], Modified Krill Herd algorithm (MKHA) [16], Salp swarm optimization (SSO) [17], Improved Mayfly optimization algorithm (IMOA) [18], Firefly algorithm (FA) and its improved version [19–20], Grey Wolf optimization (GWO) [21], Dragonfly algorithm (DA) [22], Adaptive plant propagation algorithm (APPA) [23], Bat algorithm (BA) [24], and Crow search algorithm (CrSA) [25].

In this study, we apply Particle Swarm Optimization (PSO) [5] and Sea Horse Optimizer (SHO) [26] to determine the optimal solution of ELD problem. Besides, both wind and solar energy are simultaneously considered in the study. These considerations are aimed at reaching the minimum value of TEGC.

All the outstanding contributions of the whole study are briefly described as follows:

- Implement successfully a novel meta-heuristic algorithm called Sea-horse Optimizer (SHO) to discover optimal solutions for the ELD problem, considering the power supplied from both wind and solar energy.
- Demonstrate the outstanding performance of SHO over PSO by using particular evidence and discussions.
- Indicate and prove the effectiveness of utilizing the power produced by wind and solar sources while solving the ELD problem.

Besides the introduction, other sections of the study are described as follows: Section 2 presents problem descriptions; Section 3 provides a brief overview of the applied method; Section 4 shows the results and discussions; and Section 5 reveals the conclusions.

PROBLEM DESCRIPTIONS

The Main Objective Function

The main objective function is described following the expression below:

$$Minimize\ TEGC = \sum_{k=1}^{N_{TH}} \alpha_k + \beta_k TH_k + \gamma_k TH_k^2 \quad (1)$$

Where, N_{TH} is the number of thermal power plants in the system; α_k, β_k and γ_k is the fuel usage factor of thermal power plant *k*, with *k* = 1, 2, …, N_{TH} ; TH_k is the power generated by thermal power plant *k*

The Related Constraints

- *The power balance between supplying side and consuming side*: this constraint means that the total power supplied from all thermal power plants must equal the amount of power required by load demand plus the total power loss. The mathematical formulation of the constraint is presented as follows:

$$\sum_{k=1}^{N_{TH}} TH_k + PWD + PSL - (PD + PL) = 0 \quad (2)$$

Where, $\sum_{k=1}^{N_{TH}} TH_k$ is the total power supplied by all thermal power plants in the system; N_{TH} is the number of thermal power plants in the system; PWD and PSL are, respectively, the power generated by wind and solar power plants; and PD and PL are the total power demand and total power loss in the transmission lines, respectively.

- *The operational constraint of thermal generators*: This constraints is about limitations of power output of thermal power plants and they must locate inside the allowed range as described below:

$$TH_k^{min} \leq TH_k \leq TH_k^{max} \quad (3)$$

Where, TH_k^{min} and TH_k^{max} are the minimum and maximum power output values.

THE APPLIED METHOD

Sea Horse Optimizer (SHO) [26] is briefly presented as follows:

The Movement Behavior

In this behavior, the update of new solutions is conducted by using the Equation (4) below:

$$X_i^{new\_1} = \begin{cases} X_i + LV \times (X_{EL} - X_i) \times CF + X_{EL}, \text{if } \omega_1 > 0.5 \\ X_i + RnD \times 0.05 \times \mu \times (X_i - \mu \times X_{EL}), \text{if } \omega_1 \leq 0.5 \end{cases} \quad (4)$$

Where, $X_i^{new\_1}$ and X_i are, respectively the new and the current position of the sea horse *i* in the population with *i = 1, 2, ..., Pz* and *Pz* is the population size; LV is the value given by Levy distribution; CF is the cumulative factor; X_{EL} is the current best position in entire population; RnD is the random value between 0 and 1; μ is the results given by Brownian motion; and ω_1 is the selected factor and its value is between 0 and 1;

The Hunting Behavior

According to the authors, while hunting behavior is conducted, all solutions are updated by applying the mathematical model in Equation (5):

$$X_i^{new\_2} = \begin{cases} \sigma \times \left(X_{EL} - RnD \times X_i^{new\_1}\right) + (1-\sigma) \times X_{EL}, \text{if } \omega_1 > 0.5 \\ (1-\sigma) \times \left(X_i^{new_1} - RnD \times X_{EL}\right) + \sigma \times X_i^{new\_1}, \text{if } \omega_1 \leq 0.5 \end{cases} \quad (5)$$

Where, $X_i^{new\_2}$ is the new position of sea horse *i* while it performs the hunting behavior; σ is the decay factor.

The Reproducing Behavior

While the reproducing behavior takes place, all the current positions are updated following the expression below:

$$X_i^{new\_3} = \omega_1 \times X_i^{FT} + (1 - \omega_3) \times X_i^{MT} \quad (3)$$

In the Equations (7–8), $X_i^{new\_3}$ is the new position of the sea horse *i* as Reproducing behavior takes place; X_i^{FT} and X_i^{MT} are the random sea horses selected from the first part and the second part of the population.

RESULTS AND DISCUSSIONS

In this section, we apply two meta-heuristic algorithms, including Particle swarm optimization (PSO) [5] and Sea horse optimizer (SHO) [26] to seek an optimal solution to the ELD problem, which considers the power supplied from both wind and solar power plants. The power system used in the study consists of 20 thermal power plants alongside one wind and one solar power plant. Suppose that power supplied by these power plants is 100 MW peak for wind power plants and 50 MW peak for solar power plants. In addition, the values are unchanged throughout the considered time period in the study. All the initial control parameters of the two applied methods about population size, maximum number of iterations, and maximum number of independent runs are set by 50, 200, and 50.

The whole work is performed on a personal computer with a 2.6 GHz central processing unit (CPU) accompanied by 8GB of random memory access (RAM). The related simulations and programming were completed using MATLAB software version R2018a.

Figure 1 shows the results obtained by the two applied methods after 50 independent runs. The red line stands for fitness values reported by PSO, while the blue one illustrates the fitness value obtained by SHO. Throughout all independent runs, the fitness values given by SHO are completely better than those of PSO. Of course, even after 50 independent runs, PSO cannot achieve optimal results.

In Figure 2, the minimum convergences given by both PSO and SHO are shown. In the figure, only SHO can achieve the optimal result, while PSO cannot perform the same effectivenss during its best runs. The superiority of SHO over PSO is undeniable and easy to observe in the figure.

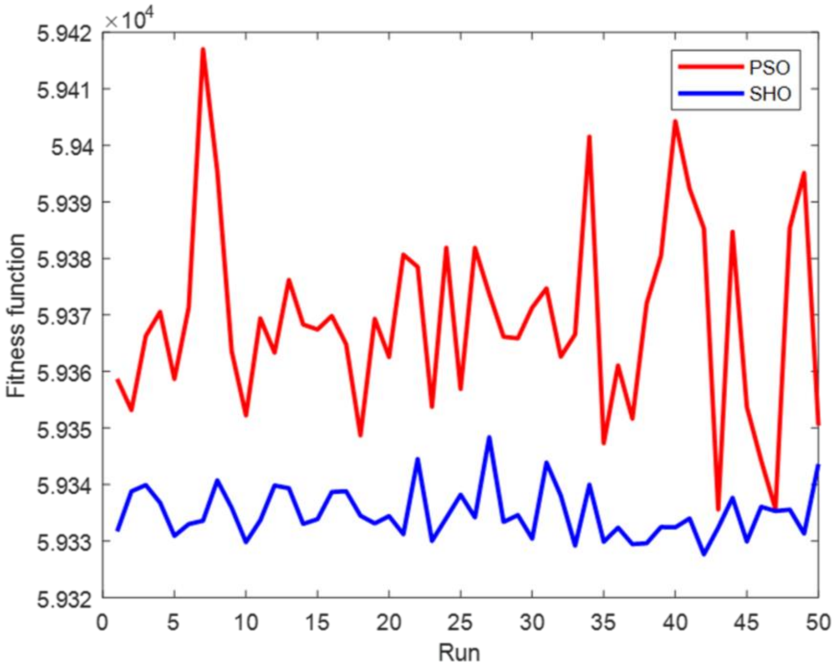

Figure 1. The results obtained by PSO and SHO after 50 independent runs.

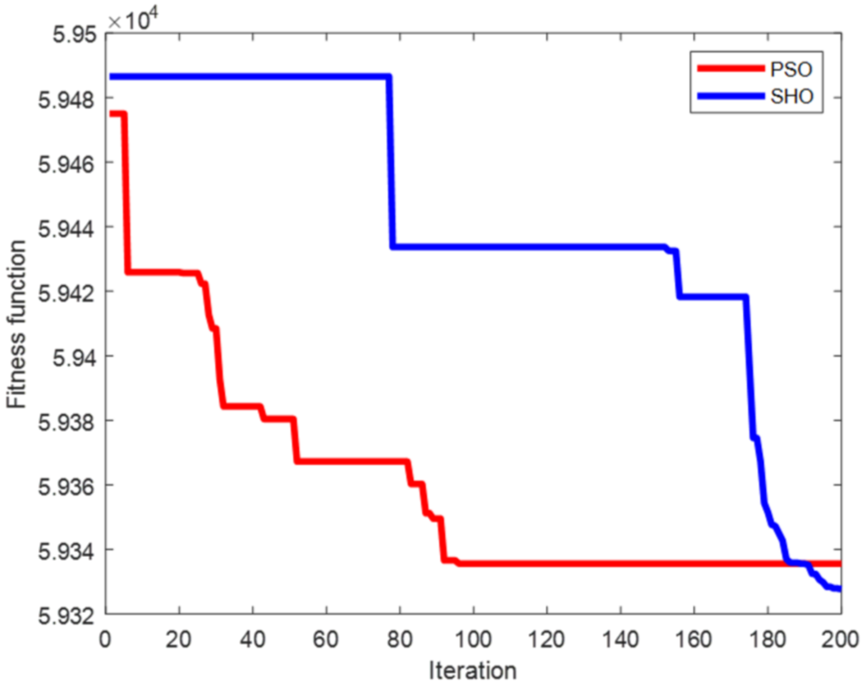

Figure 2. The best convergence curves given by PSO and SHO after 50 independent runs.

Journal of Thermal Engineering and Applications
Volume 9, Issue 3
ISSN: 2349-8994

In Figure 3, the maximum convergences of the three applied methods are described. In the figure, the outstanding performance of SHO over PSO is demonstrated once again. Specifically, SHO shows itself to be more effective than PSO by reaching a lower fitness value.

In Figure 4, comparison between SHO and PSO in terms of Minimum cost value (Min Cost), Average cost value (Aver Cost), Maximum cost value (Max Cost), and Standard deviation (Std) are shown. SHO outperforms PSO in all comparison criteria. Specially, while Min Cost and STD values reported by SHO is only 59327,650 ($) and 4.514. Those of PSO are up to 59335.584 ($) and 16.974. Other remaining criteria also indicate that SHO is more powerful than PSO.

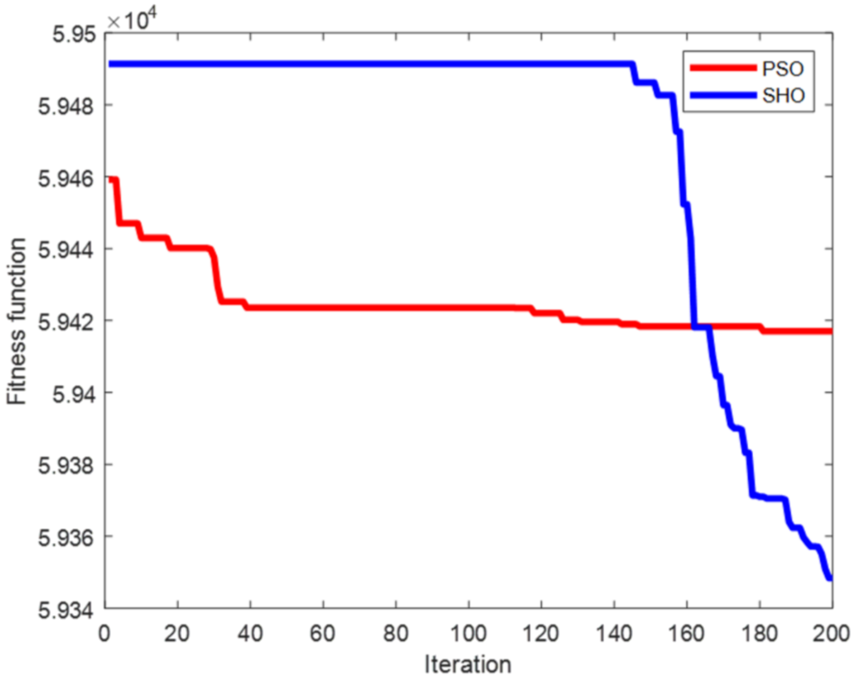

Figure 3. The maximum convergence curves given by PSO and SHO after 50 independent runs.

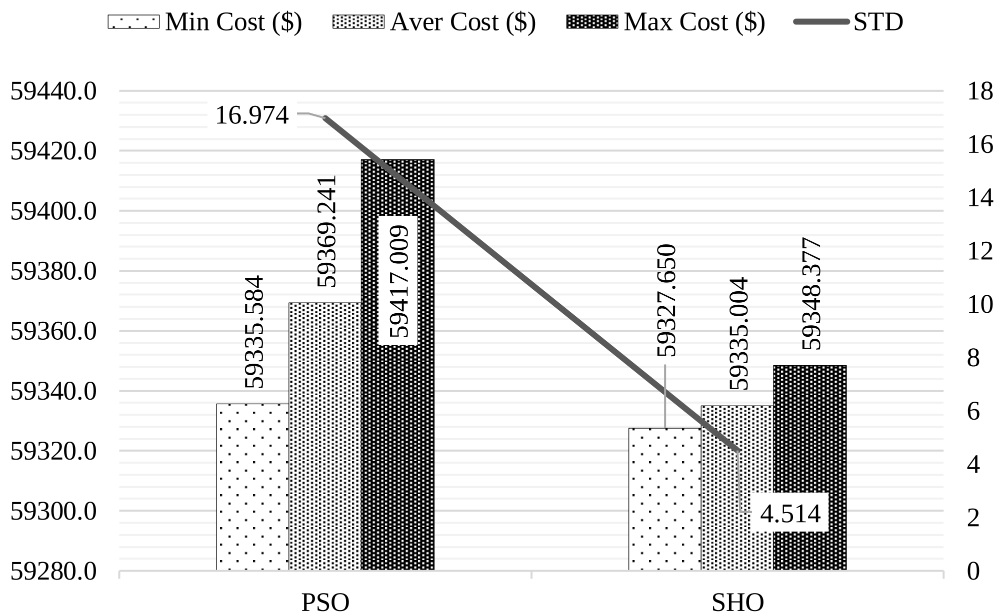

Figure 4. The summary of the results obtained PSO and SHO on different criteria.

In Figure 5, the power outputs obtained by the two applied methods are presented. The orange bars illustrate the power output reported by SHO, while the blue ones describe the similar values obtained by PSO. In addition, the power supplied by wind power plant (PW) and solar power plant (PSL) while operating two applied methods is the same.

Figure 6 shows the fuel cost values of twenty thermal power plants obtained the two applied methods. From the figure, we can see almost all thermal plants of SHO can reach smaller cost than those of PSO. So, SHO is more effecitve than PSO.

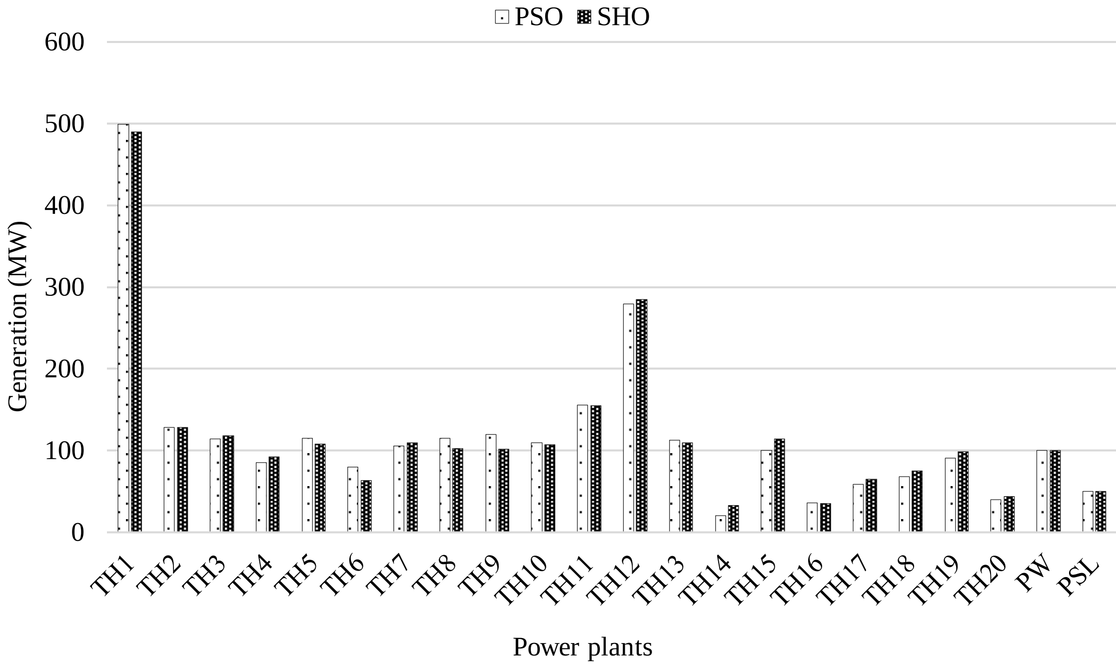

Figure 5. The power output obtained by PSO and SHO from the best runs.

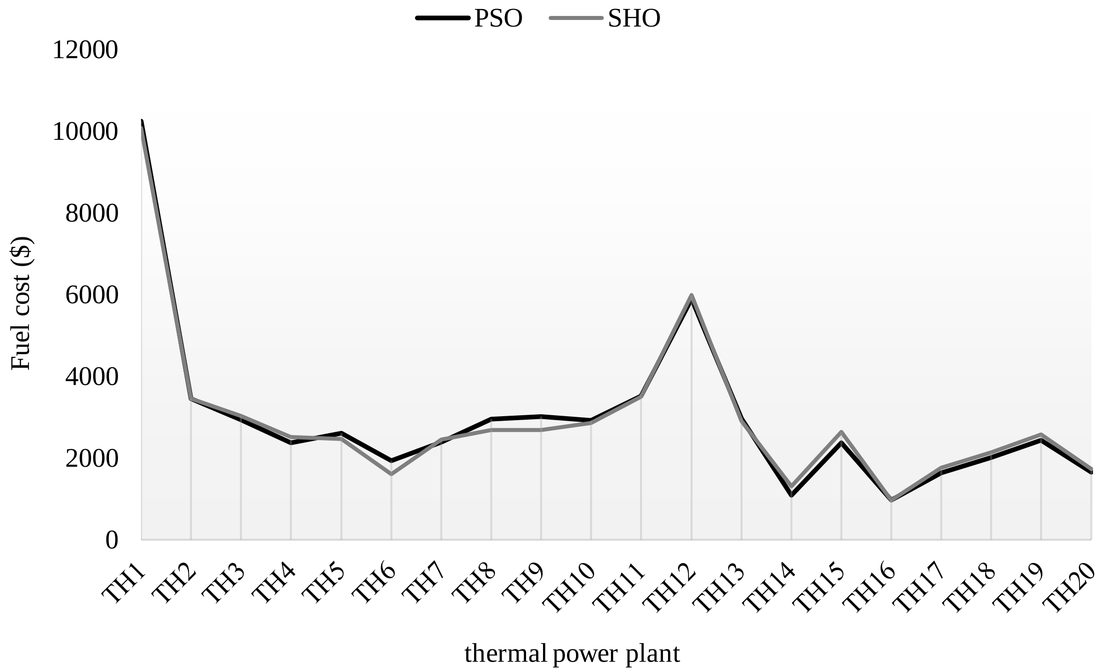

Figure 6. The fuel cost of each thermal power plant obtained by PSO and SHO.

CONCLUSIONS

In this study, a novel meta-heuristic method called the Sea Horse Optimizer was successfully applied to solve the ELD problem, considering the presence of both wind and solar power plants. The results obtained by SHO are compared with those of PSO on different criteria, including minimum cost value (Min Cost), average cost value (Aver Cost), maximum cost value (Max Cost), and standard deviation (STD). All comparisons indicate that SHO is completely superior to PSO. In particular, the optimal solution achieved by SHO not only satisfies all related constraints with zero violation but also keeps the TEGC value significantly better than the similar one reached by PSO. Therefore, SHO is acknowledged as the most powerful searching method, and we highly suggest using SHO to deal with such ELD problems. In the future, the ELD problem should be expanded with the consideration of more complicated constraints such as prohibited operation zones, multiple fuels, valve point effects, and load demand variation within 24 hours. Besides, SHO is also needed to modify or improve to reach a higher degree of performance while dealing with large-scale optimization problems.

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