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Optimal Power Allocation for Thermal Generators in Solving the Renewable-Based Economic Load Dispatch Using Novel Optimization Algorithms

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Abstract *– This research investigates the efficacy of two innovative meta-heuristic algorithms, the Newton-Raphson-based optimizer (NRBA) and the Starfish optimization algorithm (SFOA), in solving the Economic Load Dispatch (ELD) and Renewable-Based Economic Load Dispatch (RB-ELD), with the main objective function of minimizing the overall electricity production cost. Initially, both algorithms were deployed to optimize the power output of a 20-thermal Generator (ThG) system under a 2500 MW load demand. A comparative analysis of their performance on a variety of aspects revealed the superior performance of SFOA over NRBA across all evaluated aspects, particularly in its rapid convergence, ability to secure the best OEPC, and consistent stability while dealing with the ELD problem. Based on that, SFOA was then applied to the more complex RB-ELD problem, integrating a 200 MW Renewable-Based Generation Source (RBGS). The findings underscore the significant engineering and economic advantages of incorporating renewable energy, evidenced by a substantial reduction in the power output from the majority of ThGs, leading to decreased fuel consumption and a consequent lowering of the overall OEPC. The successful application of SFOA to this larger-scale, integrated problem further validates its capability in handling complex scenarios, establishing it as a highly effective and recommended search methodology for resolving intricate RB-ELD problems.*

Keywords*: Economic load dispatch, renewable-based economic load dispatch, thermal generators, renewable-based generating source, power loss, meta-heuristic algorithms, Newton-Raphson-based optimizer, Starfish optimization algorithm.*

I. INTRODUCTION

A fundamental problem that must be addressed early in power system operation is the economic load dispatch (ELD) [1]. The primary focus of solving the ELD problem is typically optimizing the allocation of power output among all the thermal generators within a given power system. This aims to meet the load demand while minimizing the overall electricity production cost (OEPC) [2-3]. Traditionally, thermal generators were the main sources of electricity, and their operation, which involved burning fossil fuels, caused environmental damage. Nowadays, fossil fuels have become more expensive and are nearing depletion. Coupled with increasing environmental concerns, the incorporation of renewable-based generating sources (RBGSs) has garnered significant attention and focus. In this context, the original ELD problem has also been modified to include the integration of various types of RBGSs, primarily wind and solar, leading to what is known as the Renewable-Based Economic Load Dispatch (RB-ELD) problem [4-5].

Recognizing the significant importance of tackling both the economic load dispatch (ELD) and the renewable-based economic load dispatch (RB-ELD) problem, a large number of publications have been proposed to solve both the mentioned problems using different approaches and methods. Among the applied methods, meta-heuristic algorithms have frequently been the chosen approach for addressing ELD and CE-ELD problems. For instance, various meta-heuristic techniques have been employed, including Growth Optimizer Algorithm (GOA) [6], Dandelion optimizer (DO) [7], improved fireworks algorithm (IFA) [8], One-to-One Optimization Algorithm (OOOA) [9], Modified Firefly Algorithm (MFA) [10], Modified Directional Bat Algorithm (MDBA) [11], Zebra optimization algorithm (ZOA) [12], War Strategy Optimization Algorithm (WSO) [13], moth-flame algorithm (MFA) [14], particle swarm optimization (PSO) [15], improved bacteria foraging optimization (IBFO) [16], Improved Harmony Search Algorithm (IHSA) [17], modified artificial bee colony algorithm (MABC) [18], hybrid salp swarm algorithm (HSSA) [19], Multi-swarm statistical particle swarm optimization (MSPSO) [20].

In this research, two novel meta-heuristic algorithms, the Newton-Raphson-based optimization algorithm (NRBA) [21] and the Starfish optimization algorithm (SFOA) [22], are applied to solve both the ELD (Economic Load Dispatch) and RB-ELD (Renewable-Based Economic Load Dispatch) problems for a 20-ThG (Thermal Generator) power system, with the primary objective of minimizing the overall electricity production cost (OEPC). In solving the RB-ELD problem, a 200 MW renewable-based generating source (RBGS) will be connected to the given system, maintaining the same objective function. Furthermore, the power loss in solving these two problems is also taken into account. Regarding the applied algorithms, SFOA is proposed based on simulating the foraging behavior of starfish in the ocean, while NRBA is developed based on the Newton-Raphson approach. Both NRBA and SFOA have undergone a variety of different tests, including theoretical and practical optimization problems.

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The main novelties and contributions of this research are summarized as follows:

- Successfully applying two novel meta-heuristic algorithms to solve the original Economic Load Dispatch (ELD) problem and the Renewable-Based Economic Load Dispatch (RB-ELD) problem.
- Identifying the superior applied algorithm between the two using different criteria, including convergence speed, stability, and the minimum, average, and maximum OEPC values.
- Clearly demonstrating the impact of integrating the RBGS into the given power system in reducing the OEPC value when solving the RB-ELD problem.
- Providing a framework for implementing novel meta-heuristic algorithms to solve the RB-ELD problem and evaluating the role of renewable energy.

II. Problem Description

2.1. The main objective function

The main focus of this study is to minimize the overall electricity production cost (OEPC) to all the thermal generators (ThGs) in the system by using the following mathematical model:

$$Minimize\ OEPC = \sum_{n=1}^{N_{ThGs}} \gamma_{1,n} P_{ThG,n}^2 + \gamma_{2,n} P_{ThG,n} + \gamma_{3,n} \quad (1)$$
$$with\ i = 1, \dots, N_{ThGs}$$

Where $OEPC$ is the overall electricity production cost synthesized by all the existing ThGs in the power system; $\gamma_{1,n}$, $\gamma_{2,n}$, and $\gamma_{3,n}$ are, the fuel utilization factor of the ThGs n; $P_{ThG,n}$ is the power output of the ThG n with $n = 1, 2, \dots N_{ThGs}$ and N_{ThGs} is the number of ThGs in the power system.

2.2 The involved constraints

- *The power balance constraints:*

The power balance constraint is employed to ensure the equilibrium between the overall power provided by all generation sources and the level of power required by the load plus the quantity of losses, as illustrated below:

$$\sum_{n=1}^{N_{ThG}} P_{ThS,i} + \sum_{m=1}^{c} P_{RBGS,m} = P_{dm} + P_{lo} \quad (2)$$

Where, $\sum_{n=1}^{N_{ThG}} P_{ThG,i}$ is the total power output of all ThGs in the system ; $\sum_{m=1}^{N_{RBGS}} P_{RBGS,m}$ is the power output of all the renewable based generating source (RBGS) m with $m = 1, 2, \dots, N_{RBGS}$ and N_{RBGS} is the number of RBGSs in the system; P_{dm} and P_{lo} are the amount of demand and the loss power.

The value of power loss in Eq. (2) is determined using the following mathematical expression:

$$P_{lo} = \sum_{n=1}^{N_{ThG}} \sum_{q=1, q\neq n}^{N_{ThG}} P_{ThG,n} LF_{nq} P_{ThG,q} + \sum_{n=1}^{N_{ThG}} LF_{0n} P_{ThG,n} + LF_{00} \quad (3)$$

Where, ω_{nq}, ω_{0n}, and ω_{00} are the loss factors.

- *The operational constraint of ThGs*

This constraint is imposed to ensure that each of ThG in the system will be run safely and effectively as their design:

$$P_{ThG,n}^{Min} \leq P_{ThG,n} \leq P_{ThG,n}^{Max} \quad (4)$$

Where, $P_{ThG,n}^{Min}$ and $P_{ThG,n}^{Max}$ are the lowest and highest power output generated by ThG n.

- *The operational constraint of RBGSs*

The power output generated by each RBGS in the system is also limited within their design capabilities as the ThGs:

$$P_{RBGS,m}^{Min} \leq P_{RBGS,m} \leq P_{RBGS,m}^{Max} \quad (5)$$

Where, $P_{RBGS,m}^{Min}$ and $P_{RBGS,m}^{Max}$ are the lowest and highest power output possibly generated by RBGS m;

III. Applied Algorithms

This section will shortly present the mathematical model of the Starfish optimization algorithm (SFOA). Note that SFOA is a meta-heuristic algorithm; therefore, the algorithm shares the same structure as many others in the same class. The only thing that differentiates SFOA from others is its update procedure, which will be presented in two phases as follows:

a. The exploration phase

In this first phase, the new solutions will be updated using the following model:

$$X_q^{new1} = \begin{cases} \begin{cases} X_q + AMF \times (X_{Best} - X_q) \times \cos\delta, & if\ \ rdn \leq \\ X_q + AMF \times (X_{Best} - X_q) \times \sin\delta, & \text{otherv} \end{cases} \\ NF \times X_q + rdn_1 \times (X_{R1} - X_q) + rdn_2 \times (X_{R2} - X_{(} \end{cases} \quad (6)$$

With

$$NF = \frac{MI^{max} - CI}{MI^{max}} \times \cos\delta \quad (7)$$

In Equations (6) and (7), X_q^{new1} is the new solution updated in phase 1 with $q = 1, 2, \dots NP$ and NP is the population size; X_q is the current solution q; AMF is the amplifying factor; X_{Best} is the best solution among the at current; δ is the phase angle of the current solution to the best solution; NF is the navigating factor; rdn_1, rdn_2 and rdn are the random factors between zero and one; X_{R1} and X_{R2} are the two random solution picked up from the population at given time.

b. The exploration phase

In this section, the new solutions are updated using the following expression:

$$X_q^{new2} = \begin{cases} X_q + rdn_1 \times dt_1 + rdn_2 \times dt_2, & \text{if } q \neq NP \\ exp\left(\frac{-MI^{max} \times NP}{MI^{max}}\right) \times X_q, & \text{if } q = NP \end{cases} \quad (8)$$

Where, X_q^{new2} is the new solution q updated in phase 2; dt_1 and dt_2 are the distance from the random two random solutions to the best solution.

IV. Results

Initially, in this section, the Starfish optimization algorithm (SFOA) and the Newton-Raphson-based optimizer (NRBA) are employed to address the traditional Economic Load Dispatch (ELD) problem. The primary goal is to minimize the Overall Electricity Production Cost (OEPC) within a 20-Thermal

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Generator (ThG) power system operating under a load demand of 2500 MW. Subsequently, the more effective of these two algorithms will be utilized again to tackle the Renewable-Based Economic Load Dispatch (RB-ELD) problem, aiming to highlight the impact of Renewable-based Generating Sources (RBGSs) on the system. The outcomes generated by both algorithms will be assessed using various metrics to determine which algorithm performs better. To ensure a fair comparison, both SFOA and NRBA are configured with identical control parameters across all experiments, specifically a population size of 100 and a maximum iteration count of 300. Furthermore, to ensure the reliability of the comparison, both SFOA and NRBA are executed for 50 independent trials to identify their respective best solutions before being compared.

The entire work was conducted on a personal computer that included an 8GB random access memory (RAM) and a central processing unit (CPU) with a clock frequency of 2.6 GHz. MATLAB programming language, version R2019a is the main platform supporting all the coding and necessary simulation.

a. The results of solving the original ELD problem

Figure 1 presents the OEPC values achieved by SFOA and NRBA after 50 trial runs. The observation from the figure indicates that the fluctuation of OEPC values obtained by SFOA across the 50 trial runs is significantly less than that of NRBA. This suggests that SFOA offers better stability than NRBA across all the trial runs when addressing the considered problem.

Figure 2 presents a comparison between SFOA) and NRBA across different criteria, including the Minimum OEPC, the Average OEPC, the Maximum OEPC, and the standard deviation (STD). Quantitatively, SFOA outperforms NRBA in all comparison criteria. Specifically, the application of SFOA can lead to savings of $4.987 for the minimum OEPC, $17.198 for the average OEPC, and $35.496 for the maximum OEPC compared to NRBA. Furthermore, SFOA demonstrates greater stability than NRBA by 92.768% based on the STD.

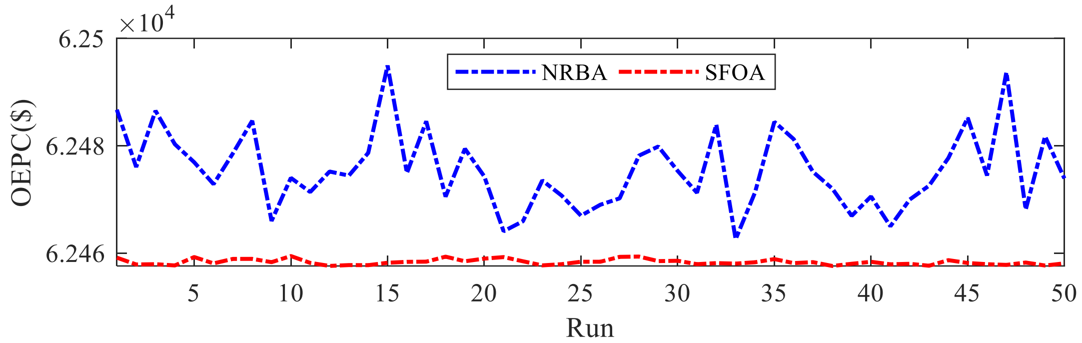

Figure 1. The OEPC values obtained by SFOA and NRBA after 50 trial runs.

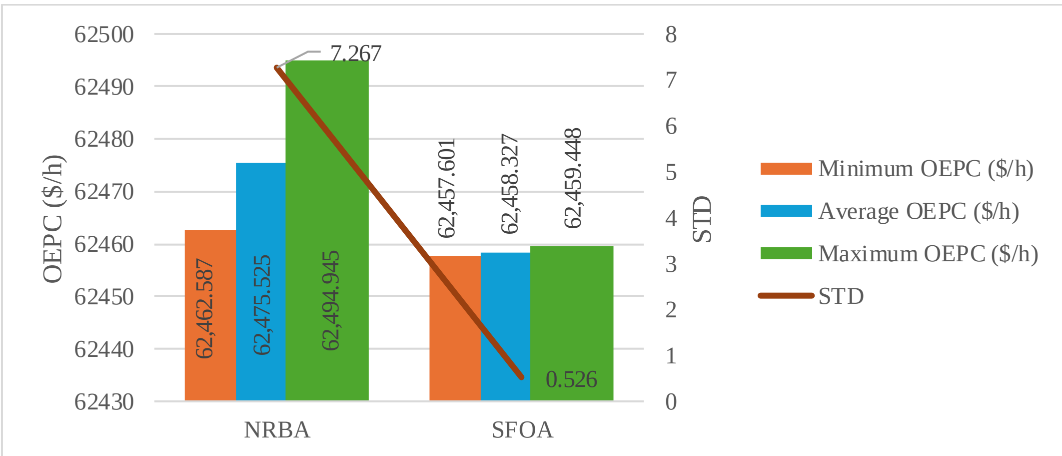

Figure 2. Three convergences were obtained by the two applied algorithms for their best-run.

Figure 3 illustrates the convergence behavior achieved by the two algorithms in their best runs across three metrics: minimum convergence, average convergence, and maximum convergence. Evidently, SFOA (Squirrel Fuzzy Optimization Algorithm) exhibits a faster convergence speed compared to NRBA in all three types of convergence. Specifically, SFOA reached the best OEPC value after approximately 250 iterations in its best run, a performance that NRBA could not match. Regarding the average and maximum convergence, SFOA also demonstrates a faster convergence speed than NRBA, particularly in the case of maximum convergence.

Figures 4 and 5 illustrate the power output and the corresponding EPC (Energy Production Cost) value for each ThG optimized by SFOA and NRBA. Additionally, Figure 5 displays the cost savings achieved for each ThG when driven by the power output optimized by SFOA compared to NRBA, represented by the green bars. The value of these green bars is calculated by subtracting the EPC obtained with SFOA from the

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EPC obtained with NRBA, denoted as "EPC_Diff". Upward-pointing green bars indicate that the EPC value resulting from the SFOA-optimized power output is better (lower) than that of NRBA. Conversely, downward-pointing green bars would signify that NRBA yields a better (lower) EPC value than SFOA.

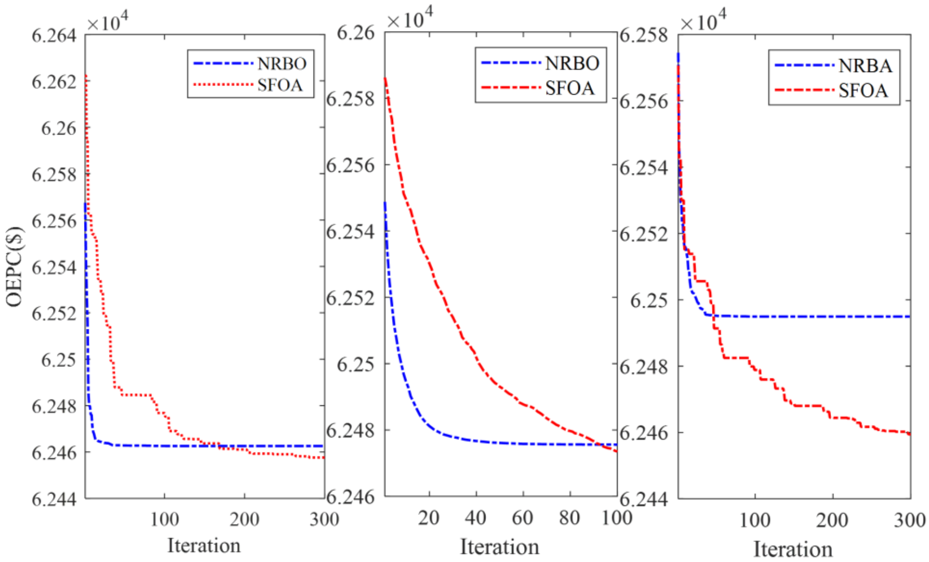

Figure 3. Three types of convergences obtained by the two applied algorithms for their best run.

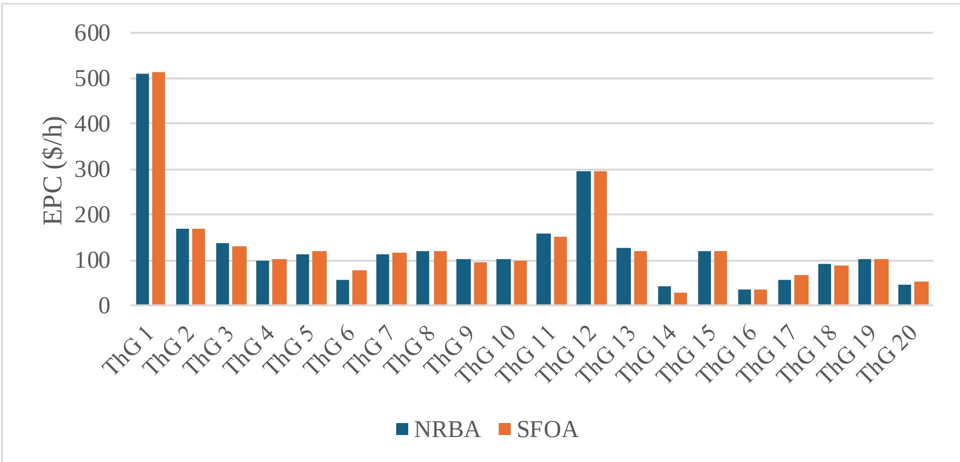

Figure 4. The optimal power output of each ThG optimized by the two applied algorithms.

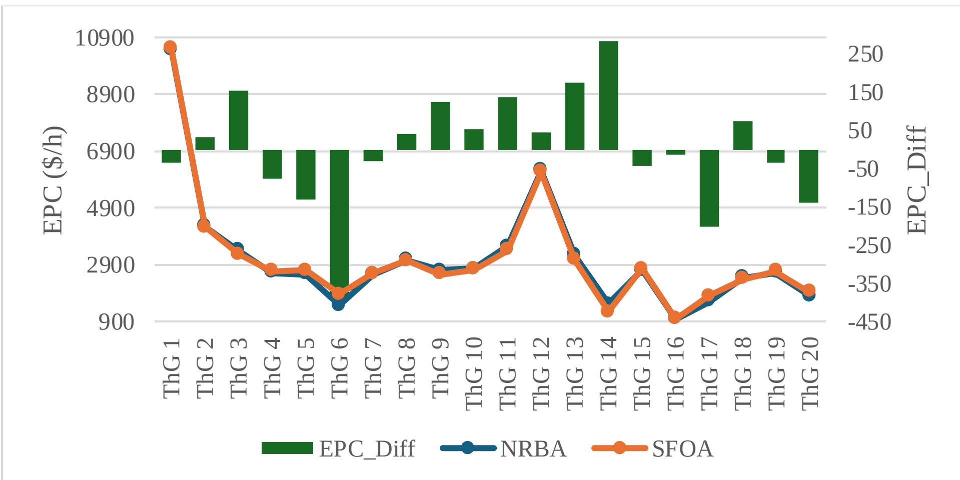

Figure 5. The difference on the EPC value of each ThG obtained by the two applied algorithms.

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b. The results of solving the RB-ELD problem

In this section, SFOA (Squirrel Fuzzy Optimization Algorithm), the superior algorithm identified in the previous section, will be reapplied to optimize the allocation of power output among all the ThGs when solving the RB-ELD problem for a system connected to a 200 MW RBGS. Figure 6 illustrates the difference in power output for each ThG in the system with and without the RBGS connection. Furthermore, the specific power output reduction for each ThG is also determined. Generally, the presence of an RBGS leads to a noticeable reduction in the power output of almost all ThGs in the system, with the exception of the 11th ThG. As previously mentioned, lower power output from the ThGs corresponds to minimal environmental damage. It's important to note that all the values presented in Figure 6 represent the results obtained by SFOA for only 1 hour of operation. When considering a larger operational timeframe, such as a day, a month, a year, or even 20 years, this power reduction will amount to a significant quantity.

Figure 7 illustrates the cost savings for each ThG in the scenario with and without an RBGS. In this figure, the savings for each ThG are represented by the blue bars. Evidently, the integration of an RBGS noticeably reduces the EPC values for almost every ThG, with the exception of the 11th ThG, which aligns with the data presented in Figure 6. Specifically, the 11th ThG is the only ThG that experiences an increase in power output when an RBGS is present, while all other ThGs show a reduction in their power output. It's important to note that the EPC values for the scenario without an RBGS are derived from the previous section's application of SFOA for 1 hour only As mentioned previously, considering a large operational timeframe highlights the significant role of incorporating an RBGS in both engineering and economic aspects.

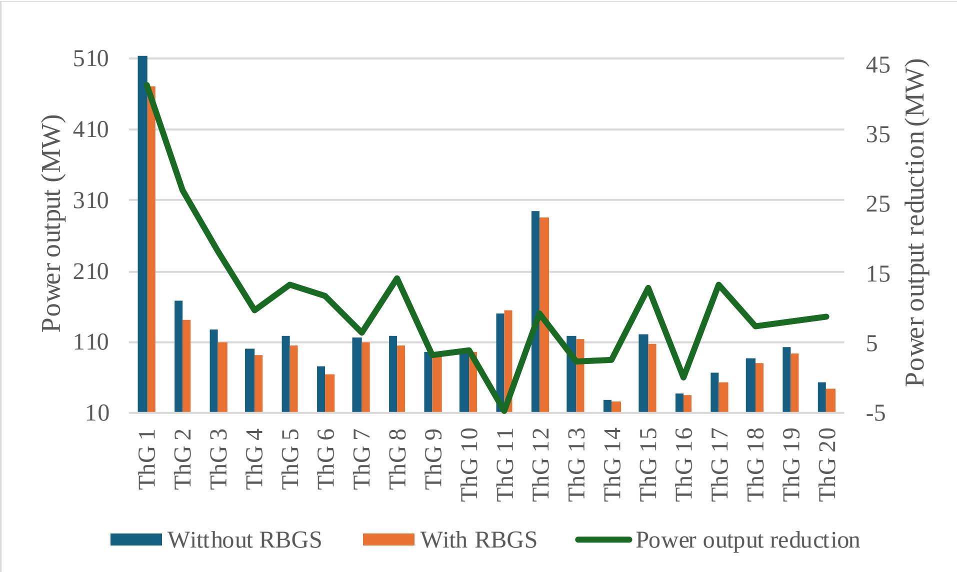

Figure 6. The power output of all the ThGs for the case with/without RBGS and the corresponding power output reduction.

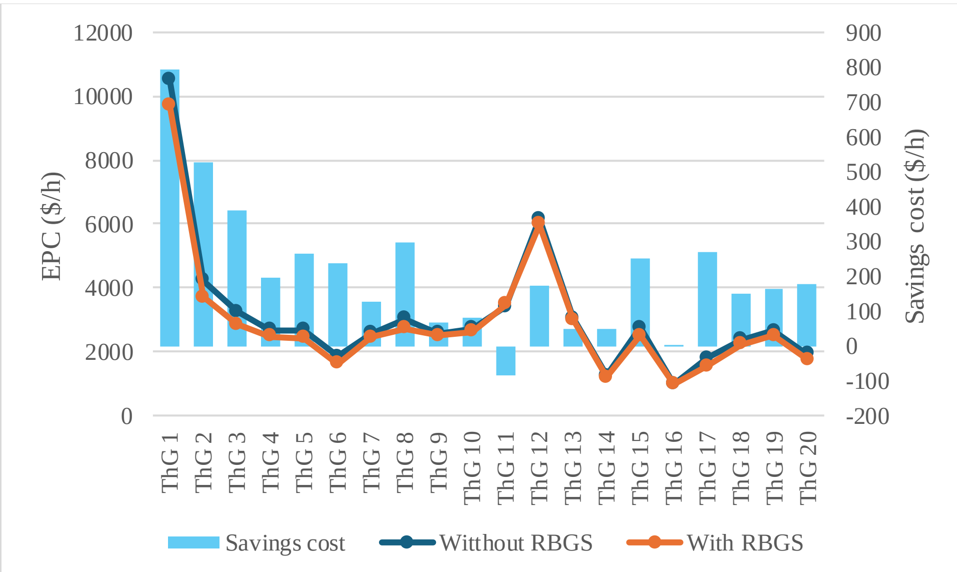

Figure 7. The savings cost for each ThG of the case with RBGS compared to the case with no RBGS connection.

V. Conclusions

In this study, two novel meta-heuristic algorithms, the Newton-Raphson-based optimizer (NRBA) and the Starfish optimization algorithm (SFOA), are successfully applied to solve the ELD (Economic Load Dispatch) and RB-ELD (Renewable-Based Economic Load Dispatch) problems, with the primary objective of minimizing the overall electricity production cost. Initially, these two algorithms are used to optimize the power output for a 20-ThG (Thermal Generator) power system with a load demand of 2500 MW. The results obtained by both algorithms are evaluated across various aspects, including the convergence speed towards the optimal OEPC (Overall Electricity Production Cost) values, and quantitative criteria such as the Minimum OEPC, the average OEPC, the Maximum OEPC, and the standard deviation (STD). The analysis of these results indicates that SFOA outperforms NRBA in all considered aspects and comparison criteria, particularly in convergence speed, the ability to achieve the best OEPC, and stability when addressing the ELD problem. Consequently, SFOA is reapplied to solve the RB-ELD problem, incorporating a 200 MW RBGS (Renewable-Based Generation Source). The results demonstrate that the integration of the RBGS offers benefits in both engineering and economic terms. Specifically, the presence of an RBGS leads to a noticeable reduction in power output from almost all ThGs in the system, resulting in less fuel utilization and, consequently, a lower overall OEPC. After successfully solving the RB-ELD problem, SFOA further proves its capability to handle large-scale and complex problems. Therefore, SFOA is considered an effective search method and is highly recommended for resolving such RB-ELD problems.

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