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## Optimizing the power outputs to all the thermal generators in the power system while solving the Generation Fuel Cost Optimization problem using Weighted Average Algorithm

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### Abstract

*This study presents the application of the recently proposed meta-heuristic algorithm, the Weighted Average Algorithm (WAA), to optimize the allocation of power output for a 20-thermal-generator power system, considering power losses in solving the Generation Fuel Cost Optimization (GFCO) problem. The optimization of the power output of all thermal generators aims to minimize the total generation fuel cost. A 100MW solar power plant and a 100MW wind power plant are integrated into the given system to support optimization, reducing the generation burden on all existing generators and lowering emissions. The performance of WAA is evaluated by comparing all results obtained by the algorithm with those of the Golf optimization algorithm (GOA) across different criteria. The comparison results show that for each hour of operation, WAA can save 22.955 \$ on the lowest total generation fuel cost (LGFC), 46.851 \$ on the average total generation fuel cost (AGFC), and 75.760 \$ on the maximum total generation fuel cost (MGFC). Moreover, WAA offers greater stability and faster convergence than GOA throughout the optimization process. All these results and superiority indicate that WAA is a highly effective search methods and the algorithm is highly considered utilizing to solve such the*

**Keywords:** Generation Fuel Cost Optimization problem; thermal generators; power loss; solar power plant; wind power plant; meta-heuristic algorithm; Weighted Average Algorithm; Golf optimization algorithm.

### 1. Introduction

The generation fuel cost optimization (GFCO) problem has a very important optimization task in power system operation, finding the optimal power generation for thermal units so as to minimize aggregate fuel cost while meeting power demand, transmission limits, and generation limit constraints [1]. In addition, Economic

and environmental benefits for grid operators are a major target for the power system [2].

Classical mathematical programming methods, such as linear programming and gradient-based techniques, were applied to the

GFCO problem. However, the non-convex fuel cost in the GFCO problems is not easy to solve, especially considering prohibited operating zones for these deterministic techniques [3]. In contrast, the sine cosine algorithm could solve the issues of the GFCO problem easily and effectively [4]. The Modified Krill Herd Algorithm [5] and the Stochastic Shaking Algorithm [6] were applied to the constrained GFCO problem, dealing with all constraints such as ramp-rate limits and transmission losses, showing robust exploration behaviour across systems of large scales and complexity conditions [6]. In addition, methods across multiple generator configurations [7] and the Five Phases Algorithm [8] could solve the GFCO problem with standard six- and ten-unit test cases. Multiple objective functions and power networks were also challenging for the GFCO problem [9-10]. The integration of renewable energy sources [11] and pumped storage hydropower plants [12] was suggested to reduce costs in the GFCO problems. Improved mayfly optimization was applied to economic-emission dispatch GFCO problem in renewable-integrated microgrids, achieving simultaneous reductions in fuel cost and pollutant emissions. Electric vehicle charge stations (EVCSs) are increasingly applied in the real system with renewable energy dispatch, making a more complicated GFCO problem formulation and solver requirements [13]. Uncertainty conditions of renewable power sources are critical for operating conditions [14]. The renewable penetration in the GFCO problems for the economic aspect was examined, confirming that high RE shares require fundamentally revised dispatch strategies to maintain system stability and cost efficiency [15]. The Dandelion Optimizer was an application for the problem with  $r$  multi-source scheduling [16]. Rooftop photovoltaic systems were considered with respect to their combined technical, economic, and environmental impacts on network performance [17]. The Pied Kingfisher Optimizer was successful in balancing voltage regulation improvement against capital investment [18]. Soft open points were added in distribution grids [19]. The enhancement of EVCSs was investigated to support load management and reduce peak-demand stress [20]. The GFCO problem can be expanded by considering flexible AC transmission system (FACTS) devices [21] and high-voltage direct current (HVDC) transmission [22].

Battery energy storage systems enhance HVDC grid stability to improve frequency regulation [23]. Voltage-source-converter-based HVDC systems reached reliable operation under diverse grid conditions [24]. The GFCO problem, considering renewable energy microgrids, has demonstrated the potential to smooth load profiles and reduce operational costs under diverse demand scenarios [25] and the conditions of EVCSs operation [26]. The digital infrastructure underpinning smart grids is increasingly exposed to cyber threats. A proactive intrusion detection and mitigation system has been developed for grid-connected photovoltaic inverters to counter coordinated cyberattacks that could disrupt renewable generation [27]. Transmission lines were considered very complicated in the GFCO problem [28]. Data-driven coordinated dispatch [29] and Deep reinforcement learning [30] were high-performance algorithms for optimization, such as searching for the maximum power point [30]. Among recently proposed general-purpose metaheuristics, the Greylag Goose Optimisation algorithm could solve the engineering benchmark functions effectively [31]. In addition, the Starfish Optimization, Sand Cat Swarm Optimization, Weighted Average, and Mirage Search Optimization algorithms provided good results in cutting costs [32]. For large scale GFCO problem, the Elk Herd Optimizer

[33] and the Skill Optimization Algorithm [34] have been applied successfully. The One-to-One Optimization Algorithm has recently been validated on large-scale renewable-integrated GFCO as a promising approach [35].

In this research, the Weighted Average Algorithm (WAA) [36] is applied to optimize the power output of 20 thermal generators (TGs) in the power system, aiming to minimize the overall total generation fuel cost. Throughout the optimization process, a 100 MWMW solar power plant (SPP) and a 100MW wind power plant are integrated into the given system along the TGs. Additionally, power loss is taken into account when establishing an optimal solution to the given problem. The actual effectiveness of WAA is then compared with another meta-heuristic, the Golf Optimization Algorithm (GOA) [37].

The main novelites and contributions of the entire study are as follows:

- Successfully applied a recent proposed meta-heuristic algorithm called the Weighted Average Algorithm (WAA) in solving the Generation Fuel Cost Optimization problem.
- Successfully considered the integration of both renewable and wind power plants in the entire optimization process to determine the optimal power output of all the TGs in the given power system
- Clearly demonstrate the superiority of the WAA over the Golf optimization algorithm (GOA) using specific comparison criteria.
- Provide a role model in applying the modern meta-heuristic algorithm in solving the large-scale optimization problem, which features many complicated constraints.

The remainder of this paper is organized as follows: Section 2 formulates the GFCO problem; Section 3 describes the proposed approach; Section 4 presents experimental results and comparisons; Section 5 concludes.

## 2. Problem description

The Generation Fuel Cost Optimization (GFCO) problem is formulated to determine the optimal operating power of the thermal generators while minimizing the total fuel cost under system operational constraints. The optimization process ensures that the total generated power satisfies the required load demand and that all generating units operate within their permissible operating ranges.

### 2.1. The main objective function

The objective of the GFCO problem is to minimize the total generation fuel cost (TGFC) of all thermal generating units (TGs), which can be mathematically expressed as:

$$TGFC = \sum_{j=1}^{NuTUs} (a_j OG_j^2 + b_j OG_j + c_j) \quad (1)$$

Where  $F_T$  denotes the total fuel generation cost (\$/h),  $NuTUs$  represents the total number of TGs,  $OG_j$  is the output generated power of the  $j^{th}$  unit (MW),  $a_j$ ,  $b_j$ , and  $c_j$  are the fuel cost coefficients of the  $j^{th}$  generating unit.

## 2.2. The considered constraint

### • Power Balance Constraint

To maintain system reliability and supply-demand equilibrium, the total generated power must satisfy the load demand and transmission losses. Therefore, the equality constraint is defined as:

$$\sum_{j=1}^{NuTUS} OG_j = LoadP + P_{Loss} \quad (2)$$

Where  $LoadP$  is the total load demand of the system (MW),  $P_{Loss}$  represents the transmission power losses (MW), and the  $P_{Loss}$  is determined as follows:

$$P_{Loss} = \sum_{j=1}^{NuTUS} \sum_{k=1, j \neq k}^{NuTUS} OG_j \theta_{jk} OG_k + \sum_{j=1}^{NuTUS} \theta_{0j} OG_j + \theta_{00} \quad (3)$$

Where  $\theta_{jk}$ ;  $\theta_{0j}$ ;  $\theta_{00}$  are, respectively the loss factors

### • Generation Operating Limits

Each generating unit is restricted by its minimum and maximum operating capacities. Hence, the operating constraint for each unit is expressed as:

$$OG_j^{LB} \leq OG_j \leq OG_j^{UB}, j = 1, 2, \dots, NuTUS \quad (4)$$

Where  $OG_j^{LB}$  is the lower bound generation limit of unit  $j$ ,  $OG_j^{UB}$  is the upper bound generation limit of unit  $j$ .

Consequently, the GFCO problem is treated as a constrained optimization problem that aims to minimize the total fuel cost while satisfying both the power balance requirement and generator operating constraints.

## 3. The applied algorithm

The Weighted Average Algorithm (WAA) [36] is a recently proposed meta-heuristic that shifts the optimization focus by calculating how a population averages its positions. By utilizing two distinct coordinate search paths, it navigates the search space quite dynamically. The math behind the algorithm is tailored to balance two main tasks: scanning broad areas (exploration) and pinpointing precise local spots (exploitation), as explained below:

### • Stage 1: Exploration Phase

During the exploration phase, WAA applies three different candidate-generation strategies in order. This process updates the position of every individual  $t$  (where  $t = 1, 2, \dots, N_{pop}$  and  $N_{pop}$  represents the total population size:

$$SV_{cand1,t} = G_{rv}(SV_{avg} - SV_{gbest}) + G_{rv}SV_{avg} + G_{rv}(SV_{avg} - SV_{pbest,t}) + G_{rv}SV_{avg} \quad (5)$$

$$SV_{cand2,t} = G_{rv}(SV_{avg} - SV_{pbest,t}) + G_{rv}SV_{pbest,t} \quad (6)$$

$$SV_{cand3,t} = G_{rv}(SV_{avg} - SV_{gbest}) + G_{rv}SV_{gbest} \quad (7)$$

where  $SV_{cand1,t}$ ,  $SV_{cand2,t}$ ,  $SV_{cand3,t}$  refer to the candidate solution vectors created by the three sequential steps. The population's weighted average is captured by  $SV_{avg}$ , while  $SV_{pbest,t}$  tracks the best personal coordinates found so far by individual  $t$ . For global progress,  $SV_{gbest}$  holds the overall best position discovered across the entire group. Finally,  $G_{rv}$  represents a vector containing random values that are spread evenly between 0 and 1.

### • Stage 2: Exploitation Phase

For the exploitation phase, the algorithm refines its search locally. It randomly decides between two distinct mathematical models based on a simple stochastic threshold:

$$SV_{cand,t} = \begin{cases} SV_{gbest} \times LF, & \text{if } G_{rv} > 0.5 \\ G_{rv} \times (UB - LB) + LB, & \text{otherwise} \end{cases}$$

where,  $LF$  refers to the Lévy Flight (or Lévy Factor) drawn directly from the Lévy stable distribution. To guide this selection, we use  $G_{rv}$  as a vector of random values uniformly spread between [0, 1]. The boundaries of the valid search area are restricted by the upper ( $UB$ ) and lower ( $LB$ ) limit vectors.

## 4. Results

In this section, WAA will be implemented to determine the optimized power output for all 20 TGs in the power system to satisfy a load demand of 2700MW, with the main objective of minimizing the TGFC, accounting for transmission losses. Besides, a 100MW photovoltaic power plant and a 100MW wind power plant are also integrated into the given power system, aiming at reducing the generating pressure and environmental damage caused by the operation of all the TGs. Along with the implementation of WAA, the Golf optimization algorithm (GOA) [37] is also applied to solve the given problem, enabling comparison of WAA across different criteria. The comparison is ensured by using the same population size ( $N_{pop}$ ) and maximum iteration number for both algorithms across all comparisons. However, WAA will be executed with different  $N_{pop}$  and  $MI$  presets to determine the optimized values of these parameters. The entire process and the results of each pair of settings to WAA are presented in Tables 1 and 2. In particular, in Table 1,  $N_{pop}$  will be allowed to range from 10 to 100, while  $MI$  is set to 100. On the contrary,  $MI$  will be allowed to vary from 50 to 300 while  $N_{pop}$  is constantly set to 50. Furthermore, both WAA and GOA will undergo 50 trial test runs before any comparison.

All the work in the entire research is performed on a personal computer with the following specifications: a Central processing unit (CPU) with a clock speed of 2.20 GHz paired with 16 GB of random-access memory (RAM). Moreover, MATLAB R2019a is selected as the primary foundation for all coding and related simulations.

**Table 1:** The various settings of  $N_{pop}$  with  $MI$  is constantly set by 100

$N_{pop}$	10	20	30	50	70	100
$MI$	100	100	100	100	100	100
$LGFC$ (\$/h)	62489.34	62458.92	62462.71	62456.81	62456.66	62456.64

**Table 2:** The variation of  $MI$  with  $N_{pop}$  is constantly set by 50

$MI$	50	100	150	200	250	300

$N_{pop}$	50	50	50	50	50	50
LGFC (\$/h)	62469.26	62456.81	62456.65	62456.64	62456.64	62456.64

Figure 1 and Figure 2 present the lower GFC (LGFC), the average GFC (AGFC), and the maximum GFC (MGFC) achieved by WAA across different settings, as described in Table 1 and Table 2.

Particularly, all the subfigures in Figure 1 show values when  $MI$  is constantly set to 100, while all the subfigures in Figure 2 do the same thing, but with  $N_{pop}$  constantly set to 50.

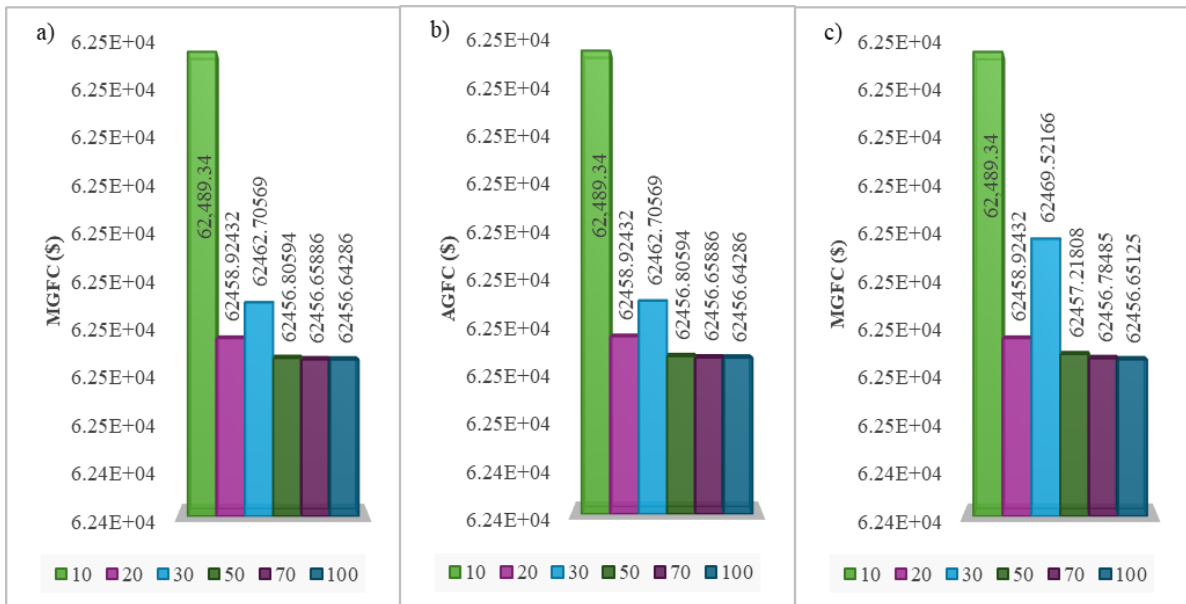


Figure 1. The LGFC, AGFC, and MGFC achieved by WAA with various presets of  $N_{pop}$  while  $MI$  is constantly set by 100.

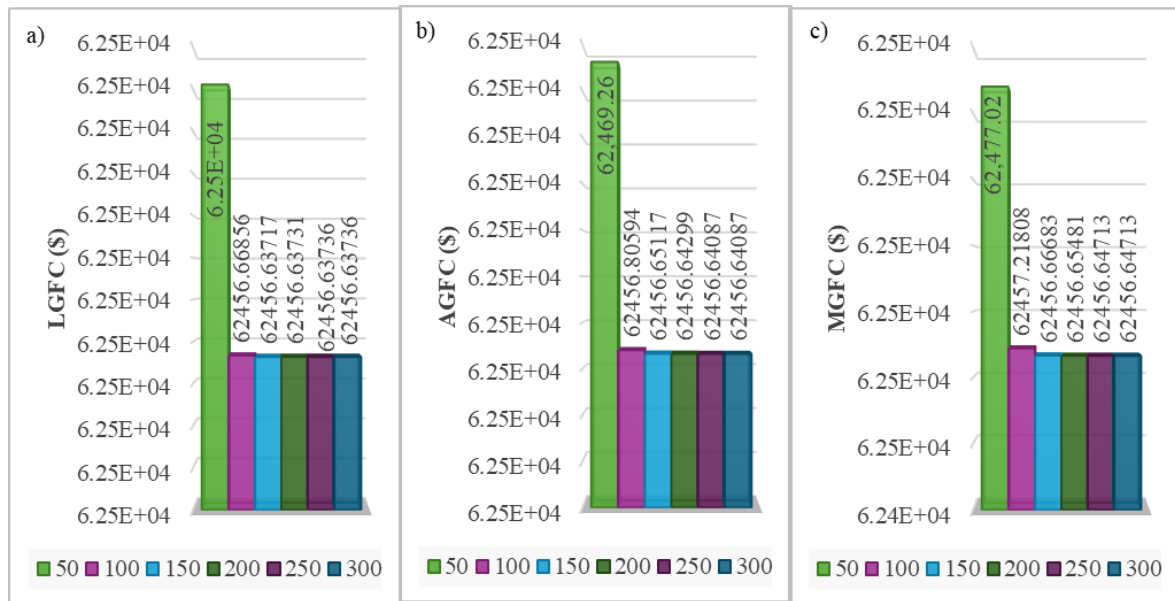
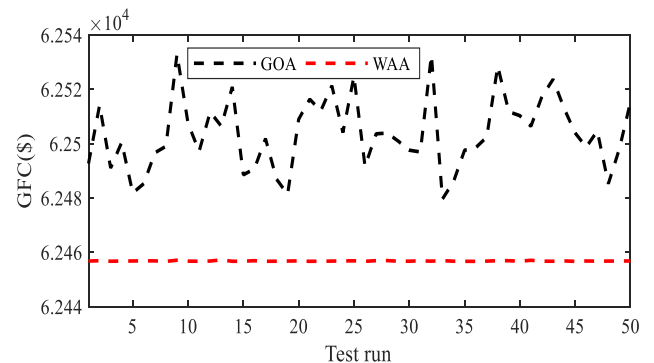


Figure 2. The LGFC, AGFC, and MGFC achieved by WAA with various presets of  $MI$  while  $N_{pop}$  is constantly set by 50.

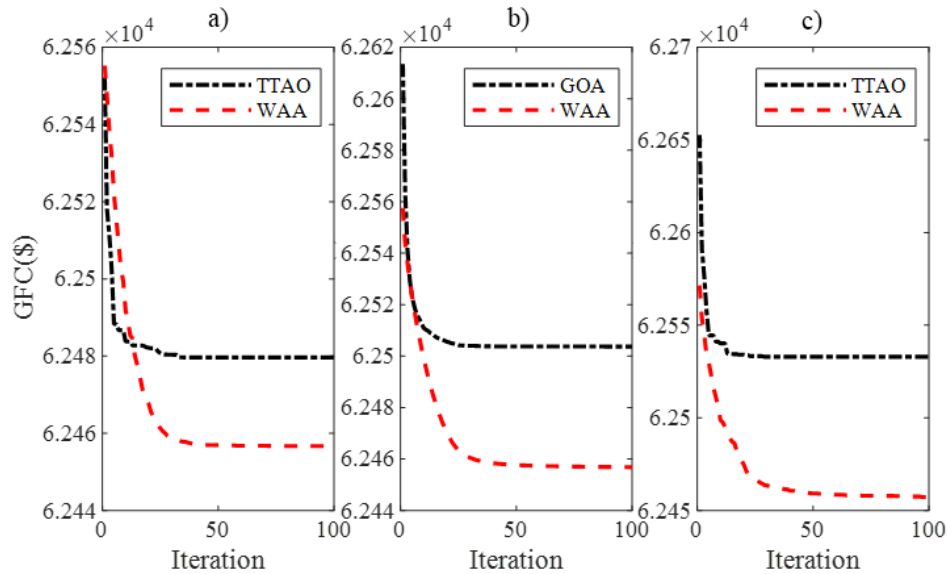
By observing the numerical results shown in Table 1, Table 2, Figure 1, and Figure 2, the optimized parameters of the  $N_{pop}$  and  $MI$  will be selected at 50 and 100. These parameters are also used to execute the GOA and assess the performance of WAA in solving the considered problem.

Figure 3 describes the GFC values obtained by GOA and WAA after 50 test runs. The figure clearly shows that WAA completely outperforms GOA in terms of stability and robustness in reaching the minimum of the main objective function. Particularly, all the GFC values after 50 test runs achieved by WAA are almost flat, indicating lower fluctuation, and all those GFC values are always located in the lower position compared to those of GOA.



Figures 4a), 4b), and 4c) provide more proof about the advantages in solving the given problem offered by WAA over GOA through the minimum, average, and maximum convergence. WAA has

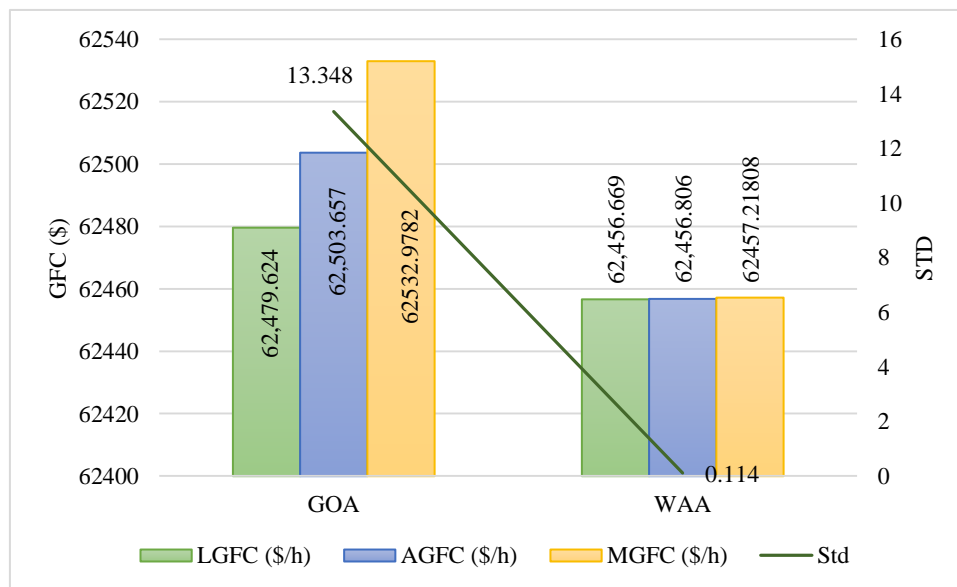
proven that, in addition to the surprising stability over GOA, the algorithm also offers faster convergence and the ability to reach higher optimal values across all three convergences.



**Figure 4.** a) the minimum, b) the average, and c) the maximum convergence achieved by GOA and WAA in their best runs.

Unlike Figures 3 and 4, Figure 5 provides the specific measurement of how much better the WAA is compared to GOA on certain criteria, including the lowest GFC (LGFC), average GFC (AGFC), maximum GFC (MGFC), and standard deviation (STD). As shown in the figure, WAA has offered a clear superiority in economic aspects compared to GOA across the first three criteria. Specifically, WAA obtains the lower LGFC value over GOA by 22.955 \$/h, equivalent to a savings of 0.0367%. On the AGFC, WAA achieves a cost reduction of 46.851 \$/h, which translates to a 0.0750% improvement. The most significant

improvement is observed in the maximum fuel cost (MGFC), where WAA cuts expenses by 75.760 \$/h, representing a savings of 0.1212% over GOA. Finally, WAA completely outperforms GOA in terms of the last criterion, which is STD. In particular, WAA demonstrates a greater deviation than GOA. While GOA exhibits a high standard deviation (13.348), indicating scattered results and lower reliability across trial tests, WAA achieves a near-zero standard deviation of 0.114. This drastic reduction proves that WAA is highly stable, reliable, and capable of consistently converging to high-quality global optimal solutions.



**Figure 5.** The statistical results obtained by GOA and WOA after 50 trial tests.

Figure 6 illustrates the optimal power output of all the TGs in the system and the corresponding GFC values for all 20 TGUs obtained by GOA and WAA. The results indicated that both algorithms produce nearly identical power output allocations; however, there are still some differences in the results obtained by the two algorithms. In particular, WAA achieved lower power

outputs for TG3, TG4, TG9, and TG14 than GOA did. All these lower power output values of the TGs largely contribute to the lower LGFC, as shown in the figure, and are considered the main foundation for the effectiveness of WAA in solving the given problem.

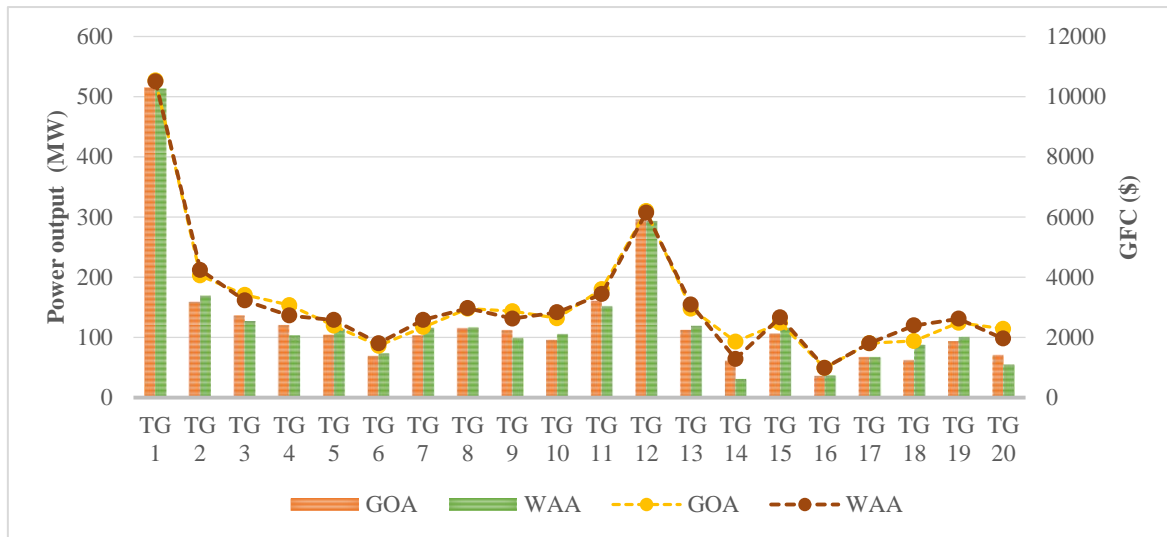


Figure 6. The optimal power output of all the TGs in the given system with their GFC values obtained by GOA and WAA

## 5. Conclusions

In this study, the Weighted Average Algorithm (WAA) has been successfully applied to determine the optimal allocation of power output to 20 thermal generators in the power system, aiming to minimize the total generation fuel cost (TGFC). Throughout the optimization process, a 100MW solar power plant and a 100MW wind power plant have been integrated directly into the system as an initial effort to reduce the generation burden on all the thermal generators in the given power system and to alleviate environmental emissions. Additionally, power loss is considered when determining an optimal allocation for all thermal generators. WAA is responsible for determining the optimal power output for all thermal generators to achieve the lowest overall generation fuel cost for the system. The results achieved by WAA were then compared to those obtained by the Golf optimization algorithm (GOA). The comparison across different criteria has clearly shown the significant superiority of WAA over GOA in solving the given problem, especially in overall stability and convergence speed across the three convergences.

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