Science and Technology for Energy Transition **81**, 17 (2026)
© The Author(s), published by EDP Sciences, 2026
https://doi.org/10.2516/stet/2026016

Available online at:
stet-review.org

Regular Article　　Open Access

Minimizing energy import cost for load demand with optimal penetration of renewable energy generation sources by using an efficient Walrus optimization algorithm

Nguyen Cong Chinh* Nguyen Nhat Tung

Faculty of Electrical and Electronics Engineering, Thuyloi University, Hanoi 11515, Vietnam

Received: 19 June 2025 / Accepted: 11 May 2026

Abstract. This paper presents a novel and effective approach for determining the optimal penetration of Renewable distributed Energy Resources (RESs) in Radial Distribution Networks (RDNs) considering time-varying generation and consumption. Walrus Optimization Algorithm (WaOA), which is inspired by the intelligent behaviors of walruses in the wild, is introduced to solve this optimization problem. The main target is to minimize the electricity generation cost by the main power source and the total power loss of the network. By determining appropriate installation parameters of access location, sizing, and operating power factor for solar Photovoltaics (PVs) and Wind Turbines (WTs), the cost from electricity purchase of the primary grid through the substation is reduced by 79.57%, and the power loss is cut by 95.06% compared to the original network. In addition, the bus voltage improvement and congestion reduction on branches are also greatly enhanced, with the weakest voltage being pulled from 0.9090 to 0.9785 pu, and the largest branch current also being sharply decreased from 387.1941A to 163.7125A. Moreover, the collected simulation results also prove the superiority of WaOA over other methods of particle swarm optimization algorithm (PSO) and Bacterial Foraging Optimization Algorithm (BFOA) in addressing the above problem under the same conditions.

Keywords: Walrus optimization algorithm, Metaheuristic algorithms, Renewable energies, Solar photovoltaics, Wind turbines, The distribution network.

Nomenclatures

N_{br}, N_{bs}, N_{ld}, N_{iter}	Total number of branches, buses, loads, and iterations
N_{pv}, N_{wt}	Totalnumber of connected photovoltaics and wind turbines
RP_h^{grid}, AP_h^{grid}	Reactive and active power, which are injected by main source at the h-th hour
$RP_{pv,h}$, $AP_{pv,h}$	Reactive and active power, which are generated by photovoltaics at the h-th hour
$RP_{wt,h}$, $AP_{wt,h}$	Reactive and active power, which are generated by wind turbines at the h-th hour
$RP_{load,ld,h}$, $AP_{load,ld,h}$	Reactive and active power of the ld-th load at the h-th hour
$RP_{loss,br,h}$, $AP_{loss,br,h}$	Reactive and active power loss of the br-th line at the h-th hour
I_{br}, V_{bs}	The br-th line current and the bs-th bus voltage
opf_{pv}^{MAX}, opf_{wt}^{MAX}	Upper bound for operating power factor of the pv-th photovoltaic and the wt-th wind turbine
opf_{pv}^{MIN}, opf_{wt}^{MIN}	Lower bound for operating power factor of the pv-th photovoltaic and the wt-th wind turbine
opf_{pv}, opf_{wt}	The operating power factor of the pv-th photovoltaic and the wt-th wind turbine
AP_{loss}^{base}, br, h	Active power loss of the br-th line at the h-th hour in the base system
Lo_{pv}^{MAX}, Lo_{wt}^{MAX}	Upper bound of access location of the pv-th photovoltaic and the wt-th wind turbine
Lo_{pv}^{MIN}, Lo_{wt}^{MIN}	Lower bound of access location of the pv-th photovoltaic and the wt-th wind turbine

*Corresponding author: chinhnc@tlu.edu.vn

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Lo_{pv}, Lo_{wt}	Access location of the pv-th photovoltaic and the wt-th wind turbine
$AP_{pv}^{MAX}, AP_{wt}^{MAX}$	Upper bound for installed active power of the pv-th photovoltaic and the wt-th wind turbine
$AP_{pv}^{MIN}, AP_{wt}^{MIN}$	Lower bound for installed active power of the pv-th photovoltaic and the wt-th wind turbine
$AP_{pv}^{rated}, AP_{wt}^{raed}$	The rated active power of the pv-th photovoltaic and the wt-th wind turbine
φ_2, φ_1	The coefficient of total reactive and active power generation of RESs

1 Introduction

The connection of distributed generation sources, mainly renewable energy, into the distribution networks has become popular in many countries around the world due to the great benefits from this penetration [1–3]. Several major countries have also made remarkable progress in promoting the integration of renewable energies into the national grid. Specifically, China has also announced that RESs, such as solar and wind power, have reached 50.90% (equivalent to 1330 GW) of the total installed power generation of the country in 2023. Thus, the target for 50% generation capacity from non-fossil fuel energy sources set by the government in 2021 has exceeded the plan earlier than the expected 2025 [4]. According to the report by the Ministry of New and Renewable Energy, 2024 [5], the total renewable energy generation is achieved 201.45 GW, accounting for 46.3% of India's total installed generation. In which significant contributions come from solar and wind power with 90.76 GW and 47.36 GW, respectively. Similarly, with the policy of promoting the use of renewable energies and carbon reduction, in 2022, Canada also produced 639 terawatt hours of electricity, of which 70% came from renewable energy sources. Investments in Canada's potential renewable energy market are enormous; the Canadian Center for Energy Information in 2024 estimated it at \$20 to \$150 billion by 2050 [6]. Thereby showing that the potential for the development of RES for reducing fossil energy use is huge. However, the connection of these energy sources requires appropriate planning to avoid negative impacts on the existing power grid. The penetration of RESs into the distribution grid has changed the original configuration of the grid and can lead to many problems, such as overvoltage, increased losses, harmonic distributions, and low reliability in operating the grid [7]. Therefore, to overcome above problems, it is necessary to consider the access location and capacity of RESs in the hybrid power grids [8, 9].

Many researchers in the world have also paid attention to these problems and proposed different approaches for integrating Distributed Generation Sources (DGSs) in general and RESs in particular to maximize benefits while meeting technical criteria. Like the authors in [10, 11] suggested, a Genetic Algorithm (GA) for determining the sizing and siting of DGSs in IEEE RDNs with 14 buses and 33 buses to cut total distribution line losses of active power. Besides, the other authors in [12, 13] also applied another long-standing algorithm of PSO for improving the voltage profile and maximizing loss reduction in different networks. Similarly, by using the same implemented method of PSO, [14] determines the appropriate connection locations for both DGSs and DSTATCOMs in systems of 12 buses, 34 buses, and 69 buses. Although both GA and PSO are popular and long-standing methods, their drawbacks are often related to convergence issues and control parameter sensitivity. Additionally, another interesting study in [15] has also succeeded in identifying the optimal integration of DGSs for cutting power loss as the main goal by using the Artificial Bee Colony algorithm (ABC). Likewise, [16] used an improved version of ABC, namely chaotic ABC (CABC), for reducing system losses as well as enhancing the stability of the voltage in three models of residential, industrial, and commercial loads. Another useful method is known as Biogeography-Based Optimization (BBO), used for solving the problem of connecting DGSs in the RDNs [17]. In that work, the researchers demonstrated the performance advantage of BBO over others such as GA, PSO, and ABC in minimizing power losses and harmonic distortions from nonlinear loads. Although both ABC and BBO are more positive than GA and PSO, their convergence is quite slow and easily falls into the area of local extremes for complex optimization problems. Obviously, the above studies have applied stochastic optimization algorithms with poor efficiency in mining and searching for feasible solutions. These traditional methods are widely used in many different optimization issues due to their simple algorithmic structure. The biggest common drawback of these algorithms is premature convergence, which results in performance not being guaranteed. Thanks to the rapid development of computer science, many newer optimization algorithms have also been introduced. Specifically, [18] has developed and applied the Butterfly Optimization Algorithm (BOA) for improving the system voltage stability in two different hypothetical RDNs of 33 buses and 69 buses. Besides, the authors in [19] also successfully implemented the Whale Optimization Algorithm (WOA) for finding an optimal solution to increase the voltage quality and minimize the power loss in the grid by properly connecting DGSs. With the same objective as [19], the study in [20] used another active method, named the Intelligent Water Drop Algorithm (IWDA), for tackling the optimal problem of DGSs in three RDNs, including IEEE 10 buses, 33 buses, and 69 buses. In that study, the performance and stability of IWDA have also been proven to outperform other methods. Moreover, recently published powerful algorithms have also attracted much attention in solving various optimization problems such as Derivative Search-based Political Optimization Algorithm (DSPOA) [21], Secretary Bird Optimization Algorithm (SBOA) [22], the OX optimizer [23], Egyptian Stray Dog Optimization (ESDO) [24], Walking Palm Tree Algorithm (WPTA)

[25], Single Candidate Optimizer (SCO) [26], Hippopotamus Optimization Algorithm (HOA) [27], Walrus Optimization Algorithm (WaOA) [28], etc. Although these new methods have been indicated to be more effective than previous algorithms in solving benchmark cases. However, these algorithms should also be applied to many different specific problems to demonstrate the effectiveness of each algorithm.

Overall, past studies have focused on determining the sizing and siting of DGSs in RDNs to enhance the voltage profile and minimize total power loss as the primary objectives. However, this is not enough to prove the effectiveness of a project of integration of DGSs in the distribution power grid. In other words, besides the technical factor, the economic factor should also be considered. Furthermore, previous works only sought the optimal solution at a load level, which leads to the found solution having poor quality at other load levels. Therefore, it is necessary to consider the time-varying generation and load demand to determine the most suitable solution. Moreover, besides the placement and installed capacity, the operating power factor of inverter-based distributed generation sources should be considered to maximize the received welfare, but this has been neglected in the past research. Ultimately, the quality of the found solution mainly depends on the used optimization algorithm, so applying a robust algorithm for addressing the optimization problem should be encouraged. In this paper, the existing gaps in the past will be overcome. In short, the main contributions of this paper are summarized as follows:

- The study finds the optimal connection parameters for generation capacity, placement, and operating power factor of inverter-based renewable generators, such as solar photovoltaics and wind turbines, for minimizing the multi-Objective Function (multi-OF) considering techno-economic aspects.
- The research objective is to simultaneously reduce total power loss of the system and total cost of generating electricity from the primary grid for load demand, considering permissible limits of bus voltage, line current, and penetration of connected units.
- The study considers the simulation conditions of the time-varying generation and load demand to determine the most suitable solution.
- The study suggests applying the Weighted Sum Method (WSM) to identify the best compromise output of the multi-OF. Besides, the backward-forward sweep is also used for solving the load flow problem.
- A robust optimization algorithm, called the walrus optimization algorithm, is suggested to apply for determining the globally optimal solution for the problem of integrating RESs in the distribution grid.

The remaining contents of the paper are included in four sections: Section 2 covers the objective function and constraints. Section 3 describes the applied optimization algorithm. Section 4 shows the obtained simulation results. Section 5 summarizes all the main contents of the paper.

2 Problem statement

This study optimizes the connection of RESs in the RDNs to maximize techno-economic benefits. The system model with integrated PVs and WTs in this research is illustrated in Figure 1. Besides, the study objectives and technical constraints are also clearly stated in the sections below.

2.1 Objective function

The main objectives are to minimize: (1) the total losses on the distribution lines and (2) the total cost of generating electricity by the primary grid. The calculation process for the multi-OF's components is described below in the subsection.

2.1.1 The total power loss

Loss reduction is one of the primary criteria in evaluating the performance of a distribution network, and it is currently a challenge that needs to be addressed. Power loss cannot be completely eliminated, but it can be minimized. Therefore, reducing power losses is considered an important factor related to economic-technical aspects [17]. In this study, the power loss becomes the first component in the multi-OF and can be determined by:

$$TPL = \sum\nolimits_{br=1}^{N_{br}} R_{br}.(I_{br})^2; \quad br = 1 : N_{br} \tag{1}$$

Where, R_{br} is the resistance on the br-th branch and I_{br} is the current on the br-th branch.

Since each different target component has a different range, the value of each component should be normalized in the range of [0, 1]. In this case, the first component can be expressed as equation (2):

$$ObjF_A = \frac{TPL}{TPL^{base}} \tag{2}$$

In equation (2), TPL and TPL are denoted as total power loss with and without the connecting RDSs.

2.1.2 Cost of electricity generation by the primary grid

One of the important goals of integrating RESs in the distribution grid is to reduce the power generation from the main source, which uses fossil fuels. This will greatly contribute to cutting the cost of generating electricity of the main power grid as well as mitigating environmental pollution from the power grid operation [29]. Thus, in this study, the total cost of electric generation from the main source becomes a key component in the multi-OF, and it can be determined by:

$$EGC = \sum\nolimits_{h=1}^{N_h} Pri_h^{grid}.AP_h^{grid} \tag{3}$$

Here, Pri_h^{grid} is the electric generation price by the main source at the h-th hour, and AP_h^{grid} is the actual active power injected into the distribution grid through the substation after penetrating RESs at the h-th hour, respectively. Similarly, this component is also normalized to the

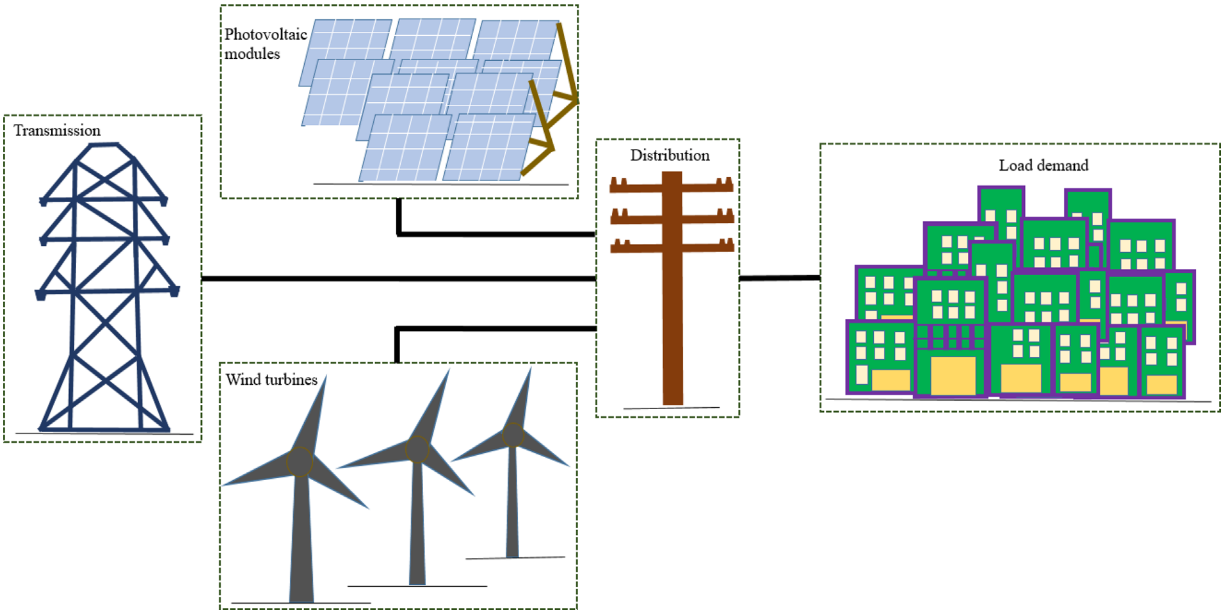

Figure 1. The hybrid power network model.

same range as the first target component for evaluation. The mathematical equation of this component is also placed in the range of [0, 1] as equation (4):

$$ObjF_B = \frac{EGC}{EGC^{base}} \tag{4}$$

Where, EGC and EGC^{base} are defined as the daily electricity generation cost to the distribution network by the main source before and after penetrating RESs.

For identifying the best compromise solution, the weighted sum method (Mohandas *et al.* 2015) is applied in the multi-OF, and it can be mathematically expressed by equation (5)

$$Minimize \;\; TOF = \omega_A . ObjF_A + \omega_B . ObjF_B;$$
$$\text{Where } \omega_A + \omega_B = 1 \& 0 < \omega_A, \;\; \omega_B < 1_B \tag{5}$$

In this paper, ω_A and ω_B are defined as the weighted factors of the target component related to the power loss $(ObjF_A)$ and the cost of generating electricity from the main source $(ObjF_B)$, respectively.

2.2 Technical constraints

To guarantee the satisfaction of the requirements, the constraints of the objective function are established as.

2.2.1 The constraints of power balance

With the integration of RESs into the grid, the total power generation includes the main source, which is directly connected to the slack bus through the substation, solar photovoltaics, and wind turbines. Therefore, total generated power must equal total consumed power to maintain stability in the power grid [13]:

$$AP_h^{grid} + \sum\nolimits_{pv}^{N_{pv}} AP_{pv,h} + \sum\nolimits_{wt}^{N_{wt}} AP_{wt,h} = \sum\nolimits_{ld=1}^{N_{ld}} AP_{load,ld,h} + \sum\nolimits_{br=1}^{N_{br}} AP_{loss,br,h} \tag{6}$$

$$RP_h^{grid} + \sum\nolimits_{pv}^{N_{pv}} RP_{pv,h} + \sum\nolimits_{wt}^{N_{wt}} RP_{wt,h} = \sum\nolimits_{ld=1}^{N_{ld}} RP_{load,ld,h} + \sum\nolimits_{br=1}^{N_{br}} RP_{loss,br,h} \tag{7}$$

2.2.2 The overcurrent limits

To avoid changing the original network structure, the current on each branch with the penetration of RESs should not be higher than the permissible limit of each branch (I_{br}^{MAX}) [12]:

$$I_{br} \le I_{br}^{MAX}; \quad br = 1 : N_{br} \tag{8}$$

2.2.3 The constraints of bus voltage

The voltage range represents the voltage difference between the lowest and highest values. In this research, the voltage at each bus should also be maintained within the best voltage limits of V_{bs}^{MIN} (0.95 pu) and V_{bs}^{MAX} (1.05 pu) [17]

$$V_{bs}^{MIN} \le V_{bs} \le V_{bs}^{MAX}; \quad bs = 1 : N_{bs} \tag{9}$$

2.2.4 The operating power factor's limits

The operating power factor from inverter-based renewable generators can be taken as a positive or negative value to absorb or emit reactive power into the network. In this paper, the operating power factor of the units is set to the lower and upper limits between 0 and 1 for compensating the reactive power [29]:

$$opf_{pv}^{MIN} \leq opf_{pv} \leq opf_{pv}^{MAX}; \quad pv = 1 : N_{pv} \tag{10}$$

$$opf_{wt}^{MIN} \leq opf_{wt} \leq opf_{wt}^{MAX}; \quad wt = 1 : N_{wt} \tag{11}$$

2.2.5 Degradation of power loss

Proper integration of RES into the RDN will contribute to minimizing total losses. Therefore, total power loss with integrated RES in the system must be below that of the base case [30]:

$$\sum_{br=1}^{N_{br}} AP_{loss}^{base}, br, h > \sum_{br=1}^{N_{br}} AP_{loss}^{base}, br, h \tag{12}$$

2.2.6 The connection placement limits

The study determines the solution of the most suitable installation for the penetration of RESs, so the allowed connection locations in the system need to be predefined [17]:

$$Lo_{pv}^{MIN} \leq Lo_{pv} \leq Lo_{pv}^{MAX}; \quad pv = 1 : N_{pv} \tag{13}$$

$$Lo_{wt}^{MIN} \leq Lo_{wt} \leq Lo_{wt}^{MAX}; \quad wt = 1 : N_{wt} \tag{14}$$

2.2.7 The rated power limits

The limits for the generation capacity of RESs in the system should also be predetermined. They are constrained by [15]:

$$AP_{pv}^{MIN} \leq AP_{pv}^{rated} \leq AP_{pv}^{MAX}; \quad pv = 1 : N_{pv} \tag{15}$$

$$AP_{wt}^{MIN} \leq AP_{wt}^{rated} \leq AP_{wt}^{MAX}; \quad wt = 1 : N_{wt} \tag{16}$$

2.2.8 Power generation limits

In this study, to limit the reverse power flow, the total penetration of RESs should not be greater than the total load demand and branch losses [20]:

$$\sum_{pv}^{N_{pv}} AP_{pv,h} + \sum_{wt}^{N_{wt}} AP_{wt,h} \leq \varphi_1 \cdot \left(\sum_{ld=1}^{N_{ld}} AP_{load,ld,h} + \sum_{br=1}^{N_{br}} AP_{loss,br,h}\right) \tag{17}$$

$$\sum_{pv}^{N_{pv}} RP_{pv,h} + \sum_{wt}^{N_{wt}} RP_{wt,h} \leq \varphi_2 \cdot \left(\sum_{ld=1}^{N_{ld}} RP_{load,ld,h} + \sum_{br=1}^{N_{br}} RP_{loss,br,h}\right) \tag{18}$$

3 Applied optimization algorithm

The Walrus Optimization Algorithm (WaOA) is applied to solve the problem of optimizing the installation of RESs in the power network. WaOA is inspired and developed based on the three intelligent behaviors of walruses in nature, including (1) the leadership of the dominant walrus to guide the group members for finding food sources, (2) the migration of walruses to more suitable places due to warmer weather in summer, and (3) fighting and escaping from predators [28]. The implemented steps for applying WaOA to an optimization problem are briefly presented below:

Step No. 1: Initialize the initial population by generating random solutions within the predetermined upper bounds. The equation for producing the first solutions is described as equation (19):

$$S_{s,d} = S_{s,d}^{MIN} + r_{d1} \cdot \left(S_{s,d}^{MAX} - S_{s,d}^{MIN}\right); \quad s \in N_s \& d \in N_d \tag{19}$$

In equation (19), r_{d1} is a randomly created number in the allowable range of [0, 1], and $S_{s,d}^{MIN}$ and $S_{s,d}^{MAX}$ are the lower and upper search limits of the d-th control variable at the s-th solution, respectively.

Step No. 2: At this stage, the evaluation process to determine the best solution is implemented by comparing the obtained results from the fitness function. The best quality solution will be assigned as the leader (dominant) of the current population. The mathematical equation of the fitness function (f_s) is presented by equation (20):

$$f_s = TOF_s + Pen_s; \quad s \in N_s \tag{20}$$

Where, TOF_s and Pen_s are the found values by the objective function and the penalty function from violation of declared constraints at the s-th solution, respectively.

Step No. 3: Search and exploit food sources according to the instructions of the dominant. This stage is considered the first phase of the feeding strategy in WaOA, and it is mathematically described as:

$$S_{s,d}^{Ph1} = S_{s,d} + r_{d2} \cdot \left(S_d^{leader} - I_{s,d} \cdot S_{s,d}\right); \quad s \in N_s \& d \in N_d \tag{21}$$

Where, $S_{s,d}^{Ph1}$ is the s-th solution of the first phase at the d-th control variable, r_{d2} is a randomly created number in the allowable range of [0, 1], S_d^{grid} is the d-th control variable of the leader in the current population. $I_{s,d}$ is the integers that are taken randomly between 2, and 1, and this is applied to expand the search space for new possible solutions. Besides, the movement of the worst solution to around the best solution opens up better opportunities for finding new potential locations that promise better quality.

Like most other metaheuristic algorithms, comparison will be performed to eliminate the worst solution. In this

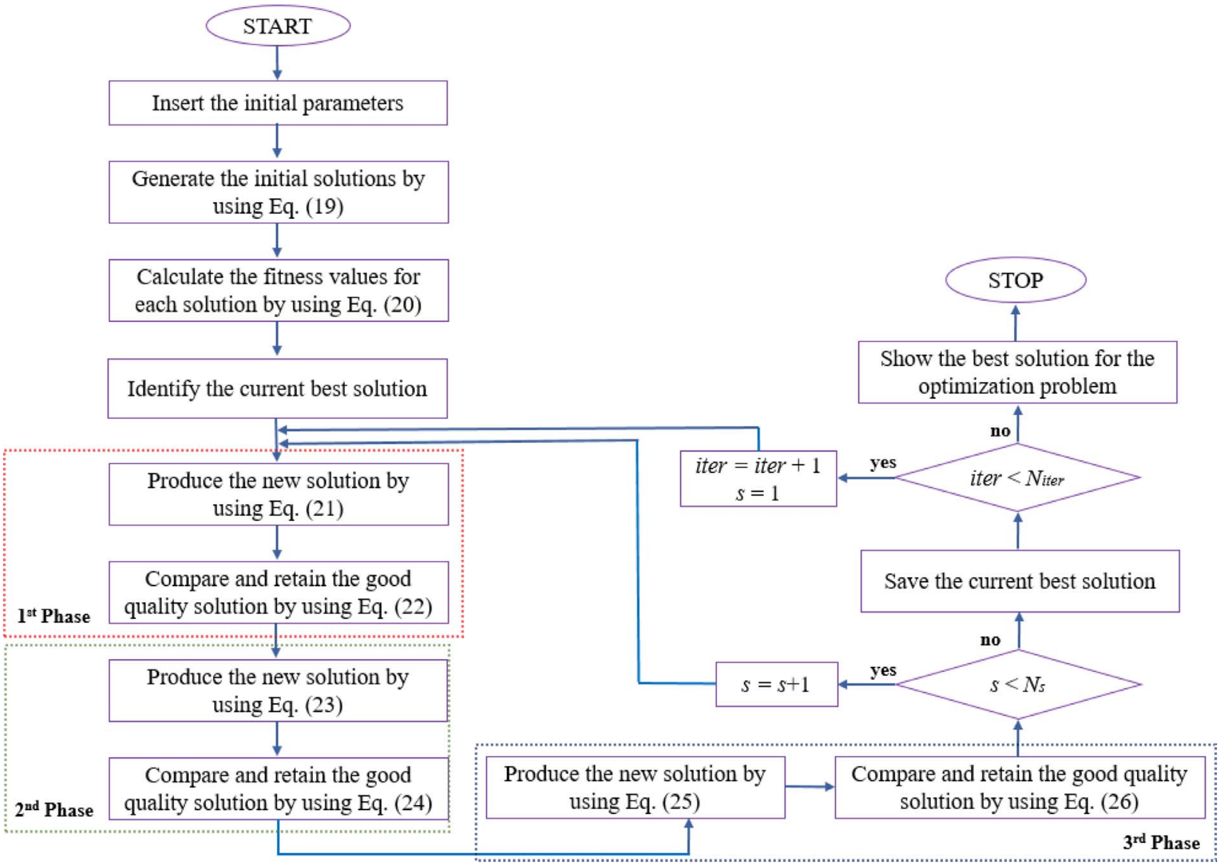

Figure 2. The flowchart of using WaOA for addressing the optimization problem.

algorithm, equation (20) is applied to evaluate the fitness value of the current solution ($S_{s,d}$) and the new solution ($S_{s,d}^{Ph1}$). Comparison for retaining a good solution is implemented according to the following rules:

$$S_{s,d} = \begin{cases} S_{s,d}^{Ph1} & f(S_{s,d}) > f\left(S_{s,d}^{Ph1}\right) \\ & S_{s,d}\, else \end{cases} \quad s \in N_s \& d \in N_d \quad (22)$$

Step No. 4: Migrate to the other, more suitable environment. This action is also considered the second phase in the WaOA algorithm, and it is expressed by:

$$S_{s,d}^{Ph2} = \begin{cases} S_{s,d} + r_{d3}.(S_{k,d} - I_{s,d}.S_{s,d}) \text{ if } f(S_{k,d}) < f(S_{s,d}) \\ S_{s,d} + r_{d3}.(S_{s,d} - S_{k,d}) \; else \end{cases}$$

$$s \in N_s,\, d \in N_d \& k \in N_k \; (k \neq s) \quad (23)$$

In the equation (23), r_{d2} is a randomly created number in the allowable range of [0, 1] and $S_{k,d}$ is defined as the k-th randomly selected solution for migrating. In this step, there are two cases for updating the new position. Depending on the current solution quality compared to the randomly selected solution, different update equations will be taken as presented in equation (23). The process of retaining a good quality solution also follows the below mechanism, thanks to solution quality assessment by using the fitness function, such as equation (20):

$$S_{s,d} = \begin{cases} S_{s,d}^{Ph2} & f(S_{s,d}) > f\left(S_{s,d}^{Ph2}\right) \\ & S_{s,d} \; else \end{cases} \quad s \in N_s \& d \in N_d \quad (24)$$

Step No. 5: Fight and escape from the predator. This is the third phase in the WaOA algorithm.

$$S_{s,d}^{Ph3} = S_{s,d} + \left(\frac{L_{loc,d}}{iter} + \left(\frac{U_{loc,d}}{iter} - r_{d4}.\frac{L_{loc,d}}{iter}\right)\right);$$

$$s \in N_s,\, d \in N_d \;\&\; iter \in N_{iter} \quad (25)$$

Where, r_{d4} is a randomly created number in the allowable range of [0, 1], $iter$ is called the current iteration number, and $L_{loc,d}$ and $U_{loc,d}$ are respectively defined as the lower limit and upper limit for the d-th control variable. Similarly, like the two above phases, comparison and selection of good quality solutions are also implemented according to the following rules based on the result of the fitness function:

$$S_{s,d} = \begin{cases} S_{s,d}^{Ph3} \text{ if } f(S_{s,d}) > f\left(S_{s,d}^{Ph3}\right) \\ S_{s,d} \; else \end{cases} \quad s \in N_s \& d \in N_d \quad (26)$$

Step No. 6: Determine the best quality solution in the present population. If the loop exit condition of ($iter < N_{iter}$) is

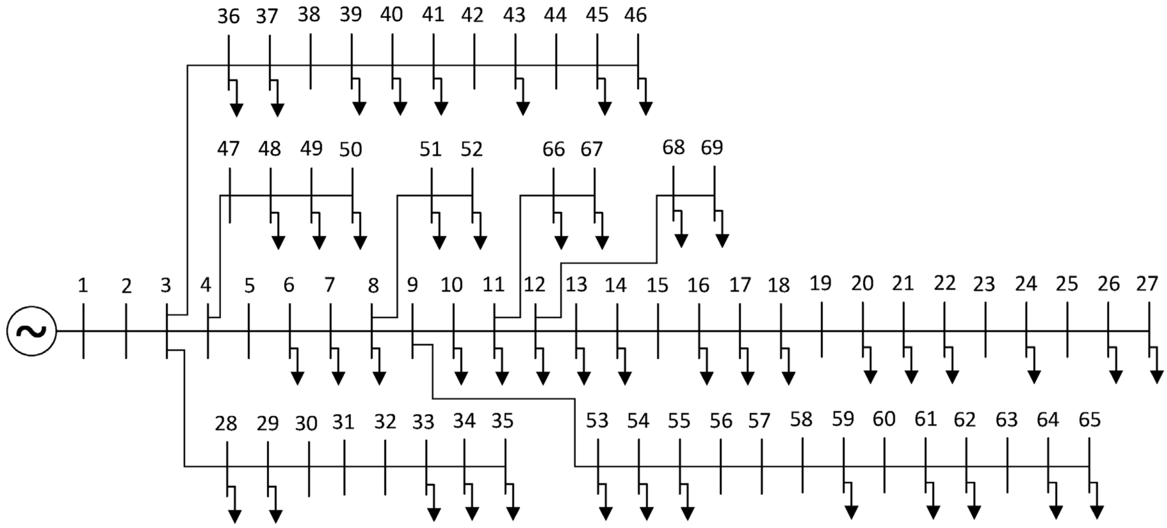

Figure 3. The IEEE 69-bus RDN.

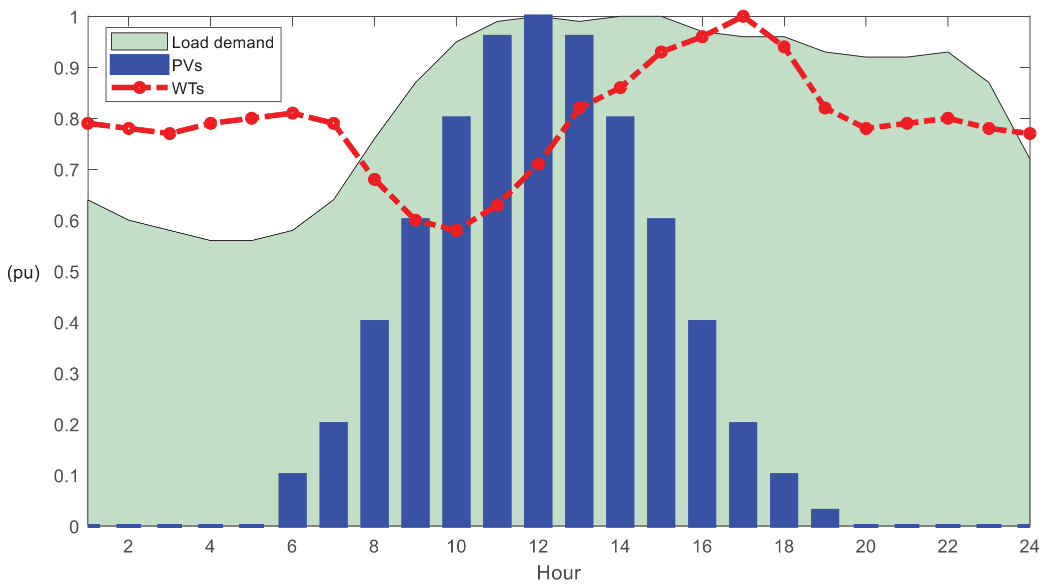

Figure 4. The output power curves of loads, solar photovoltaics, and wind turbines.

satisfied, then return to Step No. 3. Otherwise, end the iteration and show the global optimal solution for the optimization problem.

The application of WaOA for the optimization problem is briefly presented in the following flowchart:

4 Simulation results

In this paper, WaOA is suggested to address the optimization problem for access location, sizing, and operating power factor of PVs and WTs in the IEEE 69 bus RDN. This network has 12.66 kV base voltage with total power consumption at the peak load stage of 3.802 MW/2.694 MVar. The single-line diagram is plotted as Figure 3 and the network data is referenced from [17]. Moreover, the study considers the time variation of generation and consumption simultaneously. Therefore, the data of output curves for PVs and WTs, as well as loads, are taken in [31] and these values are illustrated in Figure 4. Besides, the electricity generation price from the main power grid during off-peak hours (22 h00–04 h00), normal hours (04 h00–09 h00, 11 h00–17 h00 and 20 h00–22 h00) and peak hours (9 h00–11 h00 and 17 h00–20 h00) are also stated as 45.4 \$/MWh, 70.0 \$/MWh and 128.9 \$/MWh, respectively [32]. As mentioned, the study also used WSM for identifying the suitable compromise output for the multi-OF, so the weighted factors such as ω_A and ω_B are

Table 1. The optimal results for connecting RESs in the distribution network.

Applied method	The best fitness value	Optimal solution for installing RESs	
		Solar photovoltaics	Wind turbines
PSO	0.1673	Bus 09 – 9590 modules (opf: 0.765)	Bus 61– 15 turbines (opf: 0.765)
		Bus 60 – 17015 modules (opf: 0.978)	Bus 04 – 08 turbines (opf: 0.916)
		Bus 14 – 9322 modules (opf: 0.920)	Bus 18 – 02 turbines (opf: 0.767)
BFOA	0.1667	Bus 67 – 8921 modules (opf: 0.843)	Bus 15 – 04 turbines (opf: 0.824)
		Bus 60 – 2087 modules (opf: 0.812)	Bus 61 – 15 turbines (opf: 0.758)
		Bus 04 – 24784 modules (opf: 0.750)	Bus 10 – 06 turbines (opf: 0.908)
WaOA	0.1634	Bus 05 – 23339 modules (opf: 0824)	Bus 61 – 15 turbines (opf: 0.849)
		Bus 64 – 7633 modules (opf: 0839)	Bus 21 – 03 turbines (opf: 0.851)
		Bus 18 – 4818 modules (opf: 0872)	Bus 10 – 07 turbines (opf: 0.906)

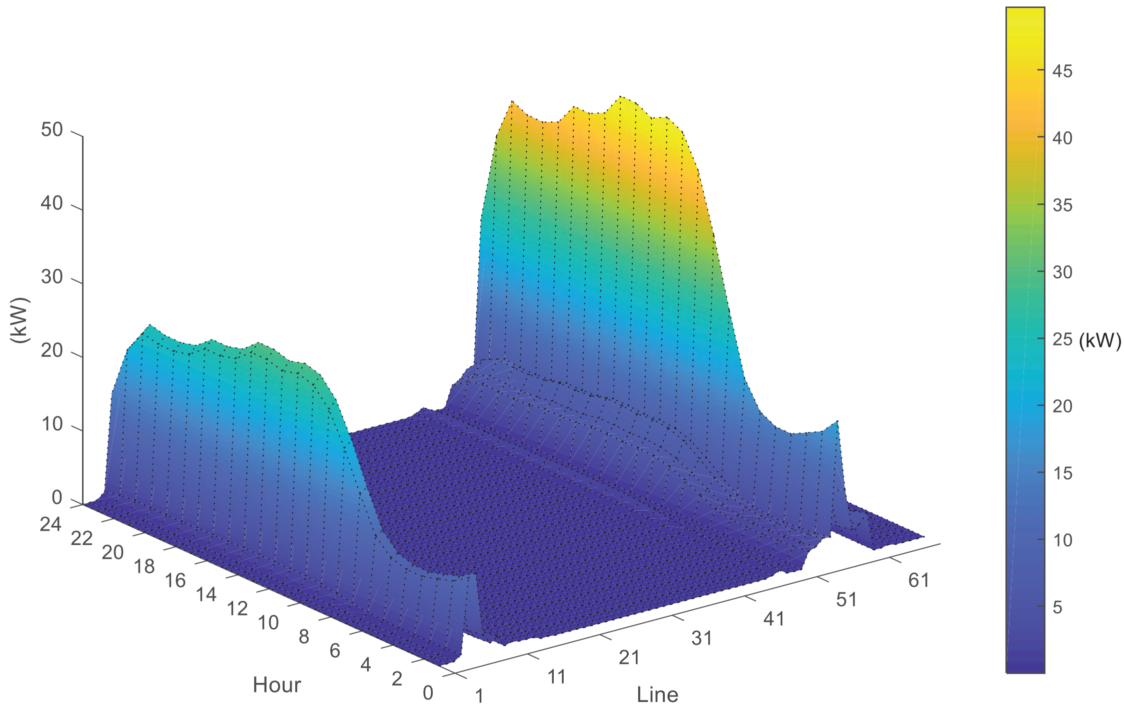

Figure 5. The distribution line power losses without connecting PVs and WTs.

chosen according to the importance level of each single target component. In this work, the minimization of the daily cost of generating energy by the main source is more important than total power loss reduction of the grid; thus, the weighted factor of ω_B is larger than ω_A. Specifically, these factor should be assigned as 0.7 and 0.3 for ω_B and ω_A, respectively. This study determines the optimal integration solution for 03 PVs and 03 WTs with the smallest and largest allowable output power of (2000 modules and 30000 modules) and (02 turbines and 15 turbines), respectively. In which the rated power of each module is 50 W, and each turbine is 100 kW as assumed. The penetration coefficient of RESs (φ_1 and φ_2) are assigned the same value of 1.0. Besides, the grid-connected units are allowed to generate appropriate reactive power, so the operating power factor is also determined to have the optimal value between 0 and 1. In addition, this study also supposes that all locations in the test distribution grid (except the slack bus) have the ability to connect PVs and WTs.

For the simulation of three implemented methods, the individual control parameters for each algorithm of PSO, BFOA, and WaOA are referenced from [33, 34], and [28], respectively. Additionally, the common control parameters for the algorithms in this study are determined through surveys to ensure convergence. Specifically, the number of iterations (N_{iter}) is surveyed from 80 to 160, with each step

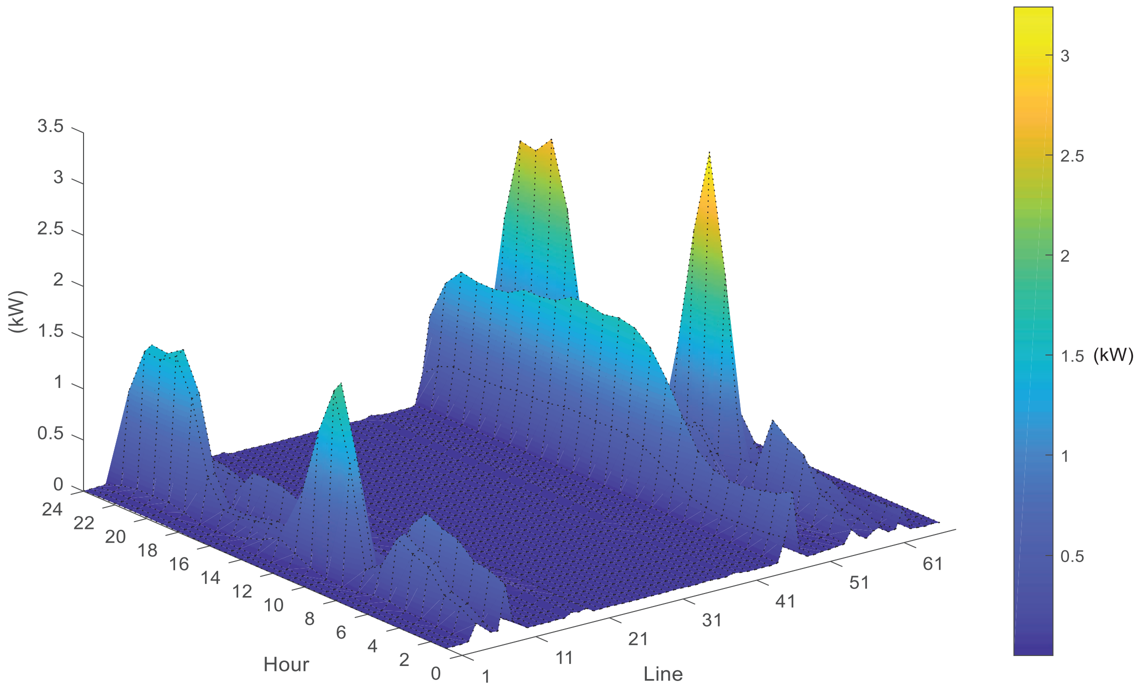

Figure 6. The distribution line power losses with connecting PVs and WTs.

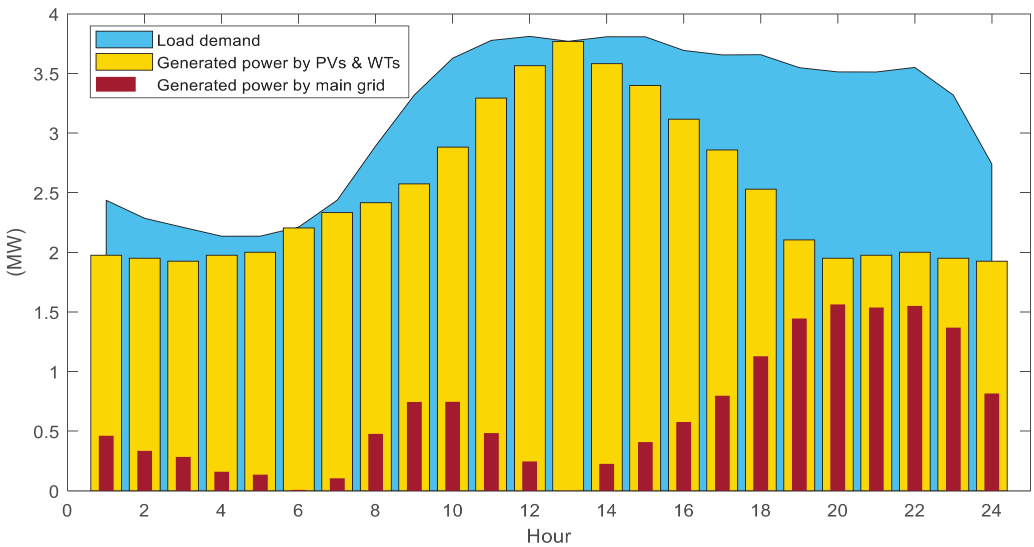

Figure 7. Load demand and power generation by RESs and main source at each hour.

being 20, and the population (N_s) is also surveyed from 20 to 50, with each step being 10. The survey results indicated that N_{iter} is 140 and N_s is 30; the used algorithms can be converged completely. Moreover, due to the random characteristics of the metaheuristic algorithms, 40 trials (N_{tri}) with the randomly generated initial population are also performed. The best results from three different implemented methods for the simultaneous installation of RESs are presented in Table 1. In optimization problems, the fitness value of the objective function is used to determine the optimal solution's quality. Therefore, the evaluation of the effectiveness of each algorithm is based on the calculated fitness value. As presented in Table 1, the best fitness values in 40 random runs of PSO, BFOA, and WaOA are 0.1673, 0.1667, and 0.1634, respectively. Obviously, the found fitness function value of WaOA is the lowest compared to the other methods, with the fitness value difference up to 2.39% for PSO and 2.02% for BFOA. In other words, the

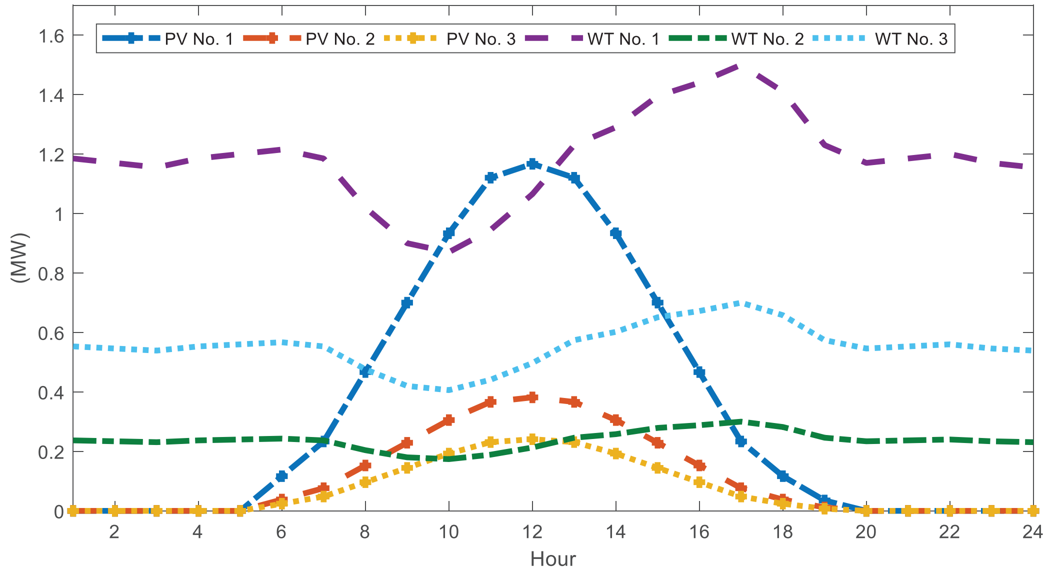

Figure 8. Power generation of each unit at each hour.

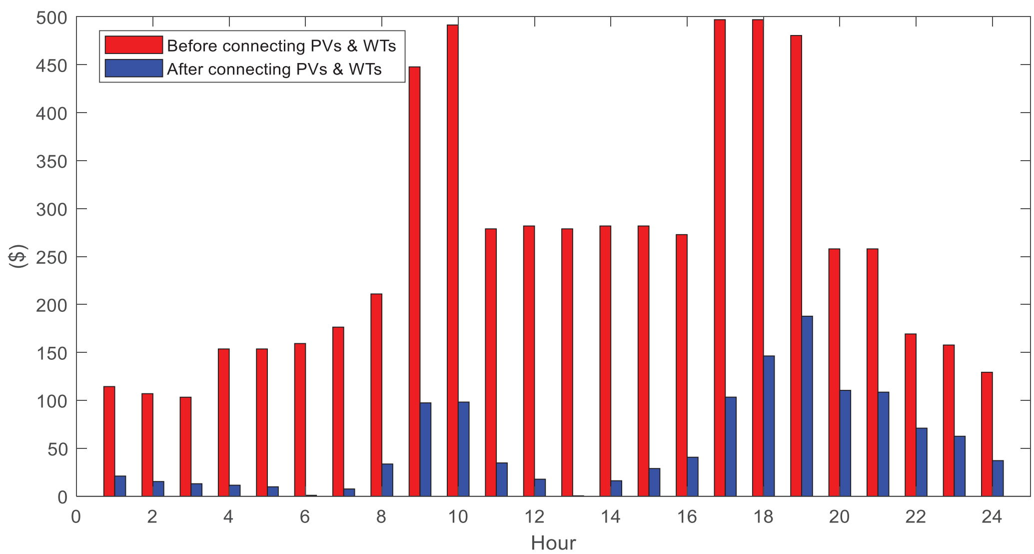

Figure 9. The hourly cost for generating electricity from main source without and with RESs.

suggested algorithm, WaOA, is more effective than PSO and BFOA, and among them, BFOA is better than PSO in tackling the optimization problem of connecting RESs in the RDN. Besides, based on the optimal solution's results from the used methods, it indicated that the total number of proposed wind turbines for installation is 25 turbines (equivalent to 2.50 MW) for all three methods. However, the number of solar panel modules is different between the methods. The number of proposed modules by PSO, BFOA, and WaOA is 35,927 modules (equivalent to 1.7964 MW), 35,792 modules (equivalent to 1.7896 MW), and 35,790 modules (equivalent to 1.7895 MW), respectively. Obviously, the found optimal solution of the suggested method in terms of the number of wind turbines is on par with the other methods, but the number of solar modules is lower than that of the other compared methods, leading to the lower investment, maintenance, and operation costs with the solution of WaOA. This also contributes to affirming the excellent efficiency of the suggested method compared to others in optimal integration of RESs in RDNs.

In this work, the optimal solution from the suggested method (WaOA) is applied to demonstrate the multi-benefits from the connection of PVs and WTs in the distribution grid. As presented in Figures 5 and 6, thanks to the integration of RESs with suitable installation parameters for access placement, sizing, and operating power factor, total daily loss on the distribution lines has been reduced significantly from 3.7778 MW to 0.1868 MW. Power loss reduction of up to 95.06% (corresponding to 3.591 MW) has demonstrated

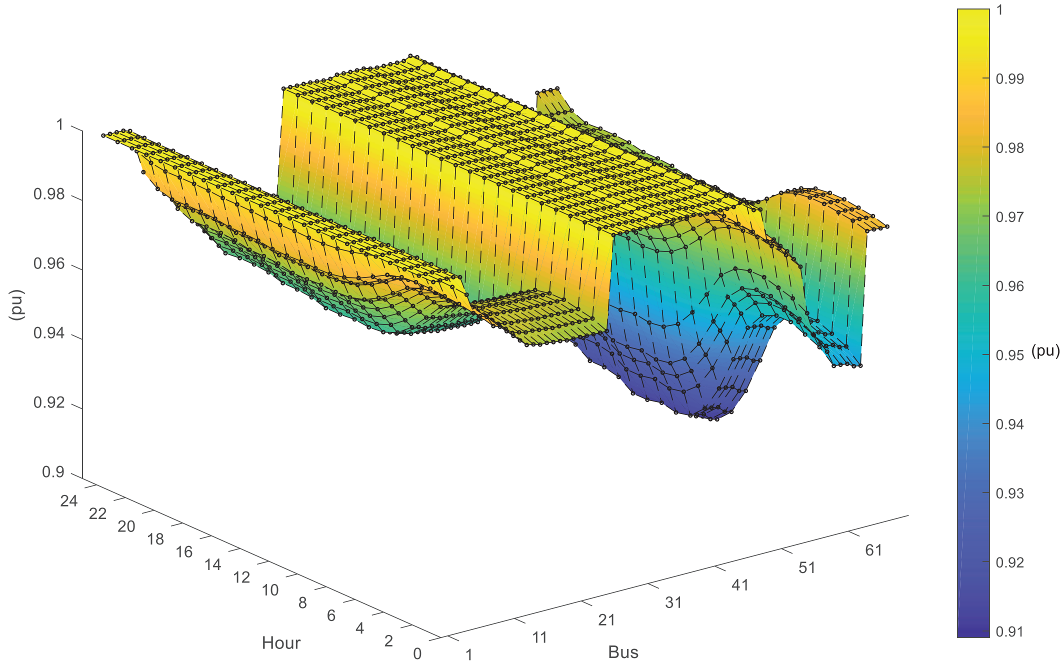

Figure 10. The voltage profile at each hour without connecting RESs.

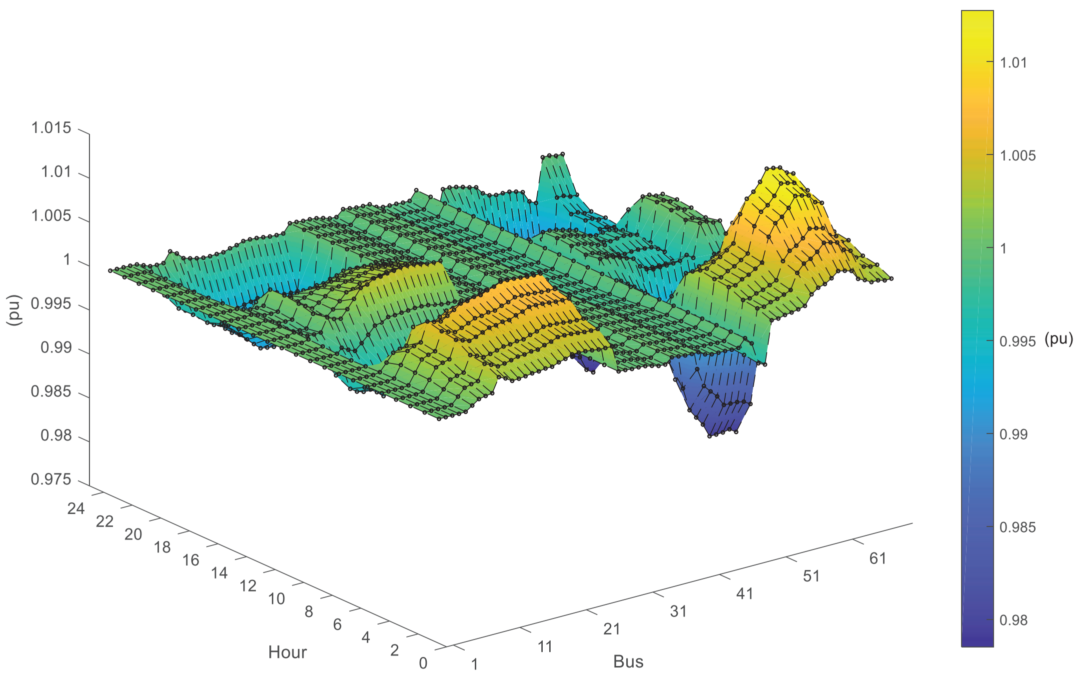

Figure 11. The voltage profile at each hour with connecting RESs.

the great benefit in determining the appropriate integration of RESs in the system. In addition, another huge benefit from the penetration of RESs is the cost minimization of electricity generation from the main power grid. Specifically, the total daily demand in the original network is 75.8444 MW and is completely supplied through the substation by the main power grid. However, after connecting RESs, the main grid only supplies 15.5995 MW per day, and the remaining demand is compensated by RESs as plotted in Figure 7. Thanks to the planning of daily power generation from the grid-connected units as presented in Figure 8, the total grid generation is only 20.57% of the

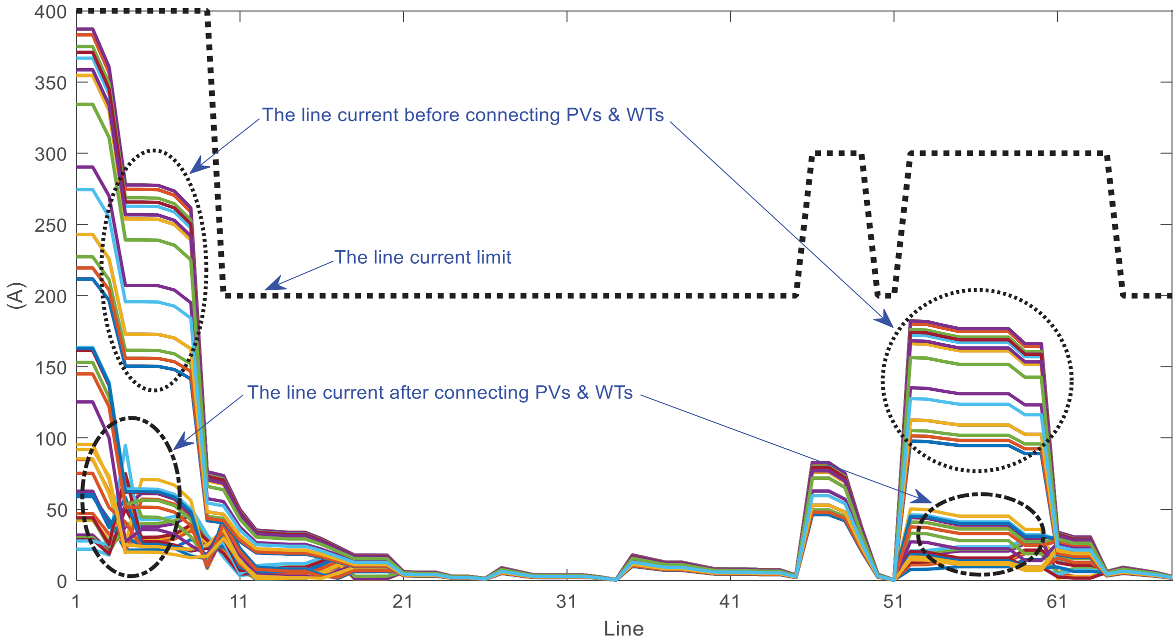

Figure 12. The current on distribution lines at each hour without and with connecting RESs.

total demand. This mainly contributes to cutting the cost of generating energy from the primary source. As shown in Figures 7 and 8, the total daily generation of RESs is up to 60.2449 MW (corresponding to 79.43% of total demand), leading to significant cost reduction of importing electricity from the primary grid. In this scenario, the total daily cost for generating energy by the main source is only $1274.9, a saving of up to 79.57% compared to the original case. As presented in Figure 9, during the stages of favorable natural conditions such as high irradiation and strong wind, PVs and WTs supply electricity to the load demand almost completely. This high penetration of RESs not only contributes mainly to minimizing electricity import at the peak hours but also reduces the use of electricity from fossil fuels. In short, the above numerical results demonstrated the enormous economic–technical benefits from determining the appropriate integration of RESs in the distribution grid.

Furthermore, other great benefits of voltage improvement and current congestion reduction on the distribution branches due to the integration of RESs are also demonstrated. As plotted in Figure 10, the voltage at the buses without RESs is in the voltage range of 0.909 to 1.0 pu. This obviously violates the voltage constraint of [0.95, 1.05] pu. However, due to the suitable integration of RESs, the profile voltage is sharply improved to [0.9785, 1.0127] pu as shown in Figure 11. As mentioned, thanks to the proper penetration of RESs, the current on the branches has also strongly decreased. In which the highest branch current is 387.1941A at the original case, and it is reduced to 163.7125A with connecting RESs as shown in Figure 12. This current reduction has significantly mitigated the congestion on the distribution branches of the system. These have contributed to demonstrating multiple economic and technical benefits from connecting suitable RESs in the distribution grids.

5 Conclusion

This study has successfully applied a novel and powerful algorithm, called the walrus optimization algorithm, for determining installation parameters of placement, sizing, and operating power factor for PVs and WTs. The main target of the research is to minimize both the total system power loss and the total cost of generating electricity from the primary source. The collected results demonstrated the outstanding performance of WaOA compared to other algorithms of PSO and BFOA under the same conditions. Moreover, thanks to the integration of RESs in the RDN, total system power loss is cut by 95.06%, and total cost of power generation from the primary grid is also cut by 79.57% compared to the original case. Besides, the profile voltage is also pulled from [0.9090, 1.00] pu to [0.9785, 1.0127] pu, and the maximum branch current is reduced from 387.1941A to 163.7125A, thanks to the penetration of RESs. These indicated the huge benefits of properly connecting RESs in the RDN. In the future, the research will consider the integration of smart inverters to maximize the penetration of RESs while still ensuring the satisfaction of technical criteria. Not only that, consideration for WaOA improvement is also necessary to further enhance the performance and stability of the algorithm, especially in tackling complex optimization problems with many control variables and large search spaces.

References

1 Mahmoud K., Yorino N., Ahmed A. (2015) Optimal distributed generation allocation in distribution systems for loss minimization, *IEEE Trans. Power Syst.* **31**, 2, 960–969. https://doi.org/10.1109/TPWRS.2015.2418333.

2 Siddiqui A.S. (2022) Optimal location and sizing of conglomerate DG-FACTS using an artificial neural network and heuristic probability distribution methodology for modern power system operations, *Protect. Control Modern Power Syst.* **7**, 1, 1–25. https://doi.org/10.1186/s41601-022-00230-5.

3 Elattar E.E., Elsayed S.K. (2020). Optimal location and sizing of distributed generators based on renewable energy sources using modified moth flame optimization technique, *IEEE Access* **8**, 109625–109638. https://doi.org/10.1109/ACCESS.2020.3001758.

4 SolarPACES (2023) *Available online*: https://www.solarpaces.org/chinas-51-renewable-energy-target-was-achieved-early/.

5 Ministry of New and Renewable Energy (2024) *Available online*: https://pib.gov.in/PressNoteDetails.aspx?NoteId=153279&ModuleId=3&reg=3&lang=1.

6 Canadian Centre for Energy Information (2024). *Available online*: https://energy-information.canada.ca/en/energy-facts/clean-power-low-carbon-fuels.

7 Eid A., Kamel S., Korashy A., Khurshaid T. (2020) An enhanced artificial ecosystem-based optimization for optimal allocation of multiple distributed generations, *IEEE Access* **8**, 178493–178513. https://doi.org/10.1109/ACCESS.2020.3027654.

8 Ali A., Keerio M.U., Laghari J.A. (2020) Optimal site and size of distributed generation allocation in radial distribution network using multi-objective optimization, *J. Modern Power Syst. Clean Energy* **9**, 2, 404–415. https://doi.org/10.35833/MPCE.2019.000055.

9 Hamad Y.K., Hussain A.N., Lafta Y.N., Al-Naji A., Chahl J. (2024) Multi-objective optimization of renewable distributed generation placement and sizing for technical and economic benefits improvement in distribution system, *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3492119.

10 Ayodele T.R., Ogunjuyigbe A.S.O., Akinola O.O. (2015) Optimal location, sizing, and appropriate technology selection of distributed generators for minimizing power loss using genetic algorithm, *J. Renew. Energy* **1**, 832917. https://doi.org/10.1155/2015/832917.

11 Sattianadan D., Sudhakaran M., Dash S.S., Vijayakumar K., Ravindran P. (2013) Optimal placement of DG in distribution system using genetic algorithm, in *Swarm, Evolutionary, and Memetic Computing: 4th International Conference, SEMCCO 2013, Chennai, India, December 19–21, 2013, Proceedings, Part II 4*, Springer International Publishing, pp. 639–647. https://doi.org/10.1109/ICAECT49130.2021.9392496.

12 Pandey D., Bhadoriya J.S. (2014) Optimal placement & sizing of distributed generation (DG) to minimize active power loss using particle swarm optimization (PSO), *Int. J. Scient. Technol. Res.* **3**, 17. https://doi.org/10.1016/j.egypro.2013.06.759.

13 Pushkarna M., Ashfaq H., Singh R., Kumar R. (2024) An optimal placement and sizing of type-IV DG with reactive power support using UPQC in an unbalanced distribution system using particle swarm optimization, *Energy Syst.* **15**, 1, 353–370. https://doi.org/10.1007/s12667-022-00551-2.

14 Devi S., Geethanjali M. (2014) Optimal location and sizing determination of Distributed Generation and DSTATCOM using Particle Swarm Optimization algorithm, *Int. J. Elect. Power Energy Syst.* **62**, 562–570. https://doi.org/10.1016/j.ijepes.2014.05.015.

15 Khorasany M., Aalami H. (2016) Determination of the optimal location and sizing of DGs in radial distribution network using modified PSO and ABC algorithms, *Int. J. Mod. Trends Eng. Res* **3**, 429–436.

16 Mohandas N., Balamurugan R., Lakshminarasimman L. (2015) Optimal location and sizing of real power DG units to improve the voltage stability in the distribution system using ABC algorithm united with chaos, *Int. J. Elect. Power Energy Syst.* **66**, 41–52. https://doi.org/10.1016/j.ijepes.2014.10.033.

17 Duong M.Q., Pham T.D., Nguyen T.T., Doan A.T., Tran H. V. (2019) Determination of optimal location and sizing of solar photovoltaic distribution generation units in radial distribution systems, *Energies* **12**, 1, 174. https://doi.org/10.3390/en12010174.

18 Mohanty P.K., Lal D.K. (2020) Voltage stability index and butterfly optimization algorithm-based DG placement and sizing in electrical power distribution system, in *Green Technology for Smart City and Society: Proceedings of GTSCS 2020*, Springer, Singapore, pp. 311–326. https://doi.org/10.1007/978-981-15-8218-9_27.

19 Subbaramaiah K., Sujatha P. (2023) Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm & its techno-economic analysis, *Elect. Power Syst. Res.* **214**, 108869. https://doi.org/10.1016/j.epsr.2022.108869.

20 Prabha D.R., Jayabarathi T., Umamageswari R., Saranya S. (2015) Optimal location and sizing of distributed generation unit using intelligent water drop algorithm, *Sustain. Energy Technol. Assess.* **11**, 106–113. https://doi.org/10.1016/j.seta.2015.07.003.

21 Chen X., Lu Q., Yuan Y., He K. (2024) A novel derivative search political optimization algorithm for multi-area economic dispatch incorporating renewable energy, *Energy* **300**, 131510. https://doi.org/10.1016/j.energy.2024.131510.

22 Fu Y., Liu D., Chen J., He L. (2024) Secretary bird optimization algorithm: a new metaheuristic for solving global optimization problems, *Artif. Intel. Rev.* **57**, 5, 1–102. https://doi.org/10.1007/s10462-024-10729-y.

23 Al Hwaitat A.K., Fakhouri H.N. (2024) The OX optimizer: a novel optimization algorithm and its application in enhancing support vector machine performance for attack detection, *Symmetry* **16**, 8, 966. https://doi.org/10.3390/sym16080966.

24 ElMessmary M.H., Diab H.Y., Abdelsalam M., Moussa M.F. (2024) A novel optimization algorithm inspired by Egyptian stray dogs for solving multi-objective optimal power flow problems. *Appl. Syst. Innov.* **7**, 6, 122. https://doi.org/10.3390/asi7060122.

25 Zitouni F., Harous S., Mirjalili S., Bouaicha A.M., Houari H. A., Mohamed A.W., Limane A., Lakbichi R., Ferhat A. (2024, August). The Walking Palm Tree algorithm: a new metaheuristic algorithm for solving optimization problems, in *Proceedings of the International Conference on Advanced Intelligent Systems for Sustainable Development (ICEIS 2024)*. Advances in Intelligent Systems Research, Vol. **184**, p. 19. https://doi.org/10.2991/978-94-6463-496-9_3.

26 Shami T.M., Grace D., Burr A., Mitchell P.D. (2024) Single candidate optimizer: a novel optimization algorithm, *Evol. Intel.* **17**, 2, 863–887. https://doi.org/10.1007/s12065-022-00762-7.

27 Amiri M.H., Mehrabi Hashjin N., Montazeri M., Mirjalili S., Khodadadi N. (2024) Hippopotamus optimization algorithm: a novel nature-inspired optimization algorithm, *Scient. Rep.* **14**, 1, 5032. https://doi.org/10.1038/s41598-024-54910-3.

28 Trojovský P., Dehghani M. (2023) A new bio-inspired metaheuristic algorithm for solving optimization problems

based on walruses behavior, *Scient. Rep.* **13**, 1, 8775. https://doi.org/10.1038/s41598-023-35863-5.

29 Hung D.Q., Mithulananthan N., Lee K.Y. (2014) Determining PV penetration for distribution systems with time-varying load models, *IEEE Trans. Power Syst.* **29**, 6, 3048–3057. https://doi.org/10.1109/TPWRS.2014.2314133.

30 Ouali S., Cherkaoui A. (2020) Optimal allocation of combined renewable distributed generation and capacitor units for interconnection cost reduction, *J. Elect. Comput. Eng.* 2020, **1**, 5101387. https://doi.org/10.1155/2020/5101387.

31 Muthusamy T., Meyyappan U., Thanikanti S.B., Khishe M. (2024) Enhancing distribution system performance by optimizing electric vehicle charging station integration in smart grids using the honey badger algorithm, *Scient. Rep.* **14**, 1, 27341. https://doi.org/10.1038/s41598-024-78569-y.

32 Pham T.D., Nguyen T.T. (2024) Minimize renewable distributed generator costs while achieving high levels of system uniformity and voltage regulation, *Ain Shams Eng. J.* **15**, 6, 102720. https://doi.org/10.1016/j.asej.2024.102720.

33 Dahal S., Salehfar H. (2016) Impact of distributed generators in the power loss and voltage profile of three phase unbalanced distribution network, *Int. J. Elect. Power Energy Syst.* **77**, 256–262. https://doi.org/10.1016/j.ijepes.2015.11.038.

34 Devabalaji K.R., Ravi K. (2016) Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using bacterial foraging optimization algorithm, *Ain Shams Eng. J.* **7**, 3, 959–971. https://doi.org/10.1016/j.asej.2015.07.002.