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Technoeconomic and Environmental Study of Multi-Objective Integration of PV/Wind-Based DGs Considering Uncertainty of System

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Abstract: For technological, economic, and environmental reasons, renewable distributed generators (RDGs) have been extensively used in distribution networks. This paper presents an effective approach for technoeconomic analysis of optimal allocation of REDGs considering the uncertainties of the system. The primary issue with renewable-based distributed generators, especially wind and photovoltaic systems, is their intermittent characteristic that results in fluctuating output power and, hence, increasing power system uncertainty. Thus, it is essential to consider the uncertainty of such resources while selecting their optimal allocation within the grid. The main contribution of this study is to figure out the optimal size and location for RDGs in radial distribution systems while considering the uncertainty of load demand and RDG output power. A Monte Carlo simulation approach and a backward reduction algorithm were used to generate a reasonable number of scenarios to reflect the uncertainties of loading and RDG output power. Manta ray foraging optimization (MRFO), an efficient technique, was used to estimate the ratings and placements of the RDGs for a multi-objective function that includes the minimization of the expected total cost, total emissions, and total system voltage deviation, in addition to enhancing predicted total voltage stability. An IEEE 118-bus network was used as a large interconnected network, along with a rural 51-bus distribution grid and the IEEE 15-bus model as a small distribution network to test the developed technique. Simulations demonstrate that the proposed optimization technique effectively addresses the optimal DG allocation problem. Furthermore, the results indicate that using the proposed method to optimally integrate wind turbines with solar-based DG decreases the expected costs, emissions, and voltage deviations while improving voltage stability by 40.27%, 62.6%, 29.33%, and 4.76%, respectively, for the IEEE 118-bus system and enhances the same parameters by 35.57%, 59.92%, 68.95%, and 11.88%, respectively, for the rural 51-bus system and by 37.74%, 61.46%, 58.39%, and 8.86%, respectively, for the 15-bus system.

Keywords: radial distribution system; renewable energy; uncertainties; distributed generators; solar and wind systems; optimum sizing and location; manta ray foraging optimization



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1. Introduction

1.1. Problem Statement

Uncertainty is a key issue in determining the best size and position for distributed generators (DGs) in electrical systems, and it is a big contributor to the problem's complexity, especially when it comes to load demand and renewable energy resources (RERs).

While much effort has been conducted to optimize the integration of DGs within electricity grids, few studies accounted for uncertainty. The optimal allocation of wind

turbine (WT) and photovoltaic (PV) systems within grids, along with the consideration of system uncertainty, plays a key role in maintaining system reliability. Electric power producers often employ DGs close to the load center for economic, technical, and environmental reasons. Integration of distributed renewable energy sources such as wind and photovoltaic within power systems has increased significantly over the last few years. Due to the intermittent characteristics of solar irradiance and wind speed, the output power of such systems exhibits continuous fluctuations, which contributes to the uncertainty of electric power systems. Thus, for optimal renewable distributed generator (RDG) sizing and location, the uncertainties of the system should be considered.

1.2. Literature Review

The fundamental purpose of DGs is to provide proper distribution network operation with reduced system losses, improved voltage profile, and higher system reliability [1]. DGs are now a clean and cost-effective source of energy, and RER production rates have recently fallen, despite the fact that the cost of generating electricity using traditional generators is rapidly increasing due to the rise of the fuel cost [2,3]. Lowering energy costs, reducing emissions, and improving voltage profiles are all advantages of a proper optimal DG allocation [4–6]. However, because of the uncertain nature of RERs, improper DG placement can cause system instability and voltage fluctuations [7,8]. The topic of optimal DG integration has been discussed in a number of studies from various perspectives. The firefly algorithm (FA) and particle swarm optimization (PSO) method were presented in [9] to achieve techno-economic and environmental benefits in electrical distribution networks. A PSO and hybrid enhanced gray wolf optimizer (EGWO-PSO) approach was presented in [10] for the optimal DG allocation in order to reduce system costs, emissions, active power losses, and voltage deviation index (VDI), as well as increase voltage stability index (VSI). For electrical power planning with load uncertainties, the authors of [11] suggested a Monte Carlo simulation-based bioinspired algorithm. To reduce the overall energy loss when sizing and deploying DG units, a method known as coefficient particle swarm optimization (CPSO) was used in [12]. In [13], the Salp swarm optimizer (SSO) was combined with the PSO method to improve the technical–economical–environmental performance of power plants. The authors of [14] introduced the equilibrium optimizer (EO) method, an efficient algorithm for solving the micro-grid energy management problem and optimizing the DG size and location within power systems. Monte Carlo simulation was employed in [15] for optimum DG allocation. The authors of [16] suggested a bilayer optimization technique for optimal battery energy storage system (BESS) and solar photovoltaic (SPVs) placement in the distribution system. In [17], a solution called strength Pareto evolutionary algorithm 2 (SPEA2) was presented for tackling the DGs and capacitor placement problem with load uncertainty. The manta ray foraging optimization algorithm (MRFOA) was proposed in [18] for the best control and operation of distribution networks with the least amount of lost energy. The manta ray foraging optimizer (MRFO) is a new and effective bioinspired algorithm for engineering applications that simulates the intelligent foraging behavior of manta rays in the environment [19]. The MRFO is used in this paper to determine the optimal solar and wind system allocation in a network based on IEEE 118-bus, rural 51-bus, and IEEE 15-bus systems for minimizing the expected total cost, emissions, and voltage deviation, and enhancing voltage stability while taking into account the uncertainties of load demand and solar and wind power generation.

1.3. Contribution of the Paper

The uncertainty of the RER output power and load demand is considered the most challenging issue related to optimal sizing and allocation of RDGs within power grids. As a result of the continuous increase in the penetration level of the RER to the power grids, the problem has grown significantly, forcing the construction of a more efficient solution. This paper is aimed at solving the optimal allocation of RDGs problem in a distribution

system using a backward reduction technique that takes into account uncertainties due to load demand and RER. The contributions of the paper can be summarized as follows:

- Presenting an effective backward reduction strategy to solve the optimal distribution system problem sizing and placement,
- Addressing the issue of the load and RER output power uncertainties,
- Adopting a Monte Carlo simulation approach and backward reduction algorithm to model electrical system uncertainty,
- Employing MRFO algorithm to solve the problem using the IEEE 118-bus, rural 51-bus, and the IEEE 15-bus distribution systems,
- Comparing the performance of MRFO with several well-known problem-solving algorithms.

2. Problem Formulation

Four objective functions were studied as part of a multi-objective function in this paper [20,21]. It is worth noting that, while modeling or assessing power system uncertainty, various scenarios must be considered. Each scenario has its own set of expected values, as elaborated below.

2.1. Proposed Objective Functions

2.1.1. Minimizing the Total Expected Cost (ETC_{Cost})

The total annual expected cost (ETC_{Cost}) includes the cost of the main substation's electric energy saving (EC_{Cost_{Grid}}), cost of the integrated PV (EC_{Cost_{PV}}), and cost of the WT (EC_{Cost_{WT}}), expressed as

$$ETC_{Cost} = EC_{Cost_{Grid}} + EC_{Cost_{PV}} + EC_{Cost_{WT}}. \quad (1)$$

The detailed items of Equation (1) are defined as follows:

$$ETC_{Cost_{Grid}} = \sum_{k=1}^{Ns} EC_{Cost_{Grid,k}} = \sum_{k=1}^{Ns} Cost_{Grid,k} \times \pi_{S,k}, \quad (2)$$

$$Cost_{Grid} = P_{Grid} \times K_{Grid}, \quad (3)$$

$$ETC_{Cost_{PV}} = \sum_{k=1}^{Ns} EC_{Cost_{PV,k}} = \sum_{k=1}^{Ns} \pi_{Solar,k} \times (a_{PV} + b_{PV} \times PG_{PV}), \quad (4)$$

$$a_{PV} = \frac{capital\ cost_PV \times P_{sr} \times Gr}{life\ time_PV \times 8760 \times LF}, \quad (5)$$

$$b_{PV} = Cost_PV_{O\&M} + Cost_PV_{Fuel}, \quad (6)$$

$$ETC_{Cost_{wind}} = \sum_{k=1}^{Ns} EC_{Cost_{wind,k}} = \sum_{k=1}^{Ns} \pi_{wind,k} \times (a_{wind} + b_{wind} \times PG_{wind}), \quad (7)$$

$$a_{wind} = \frac{capital\ cost_wind \times P_{wr} \times Gr}{life\ time_wind \times 8760 \times LF}, \quad (8)$$

$$b_{wind} = Cost_wind_{O\&M} + Cost_wind_{Fuel}, \quad (9)$$

where a_{PV} is the annual PV unit installment cost, and b_{PV} is the annual PV unit's operation and maintenance cost. The annual WT installment cost is a_2 , and the annual WT operating and maintenance cost is b_2 . LF is the load factor of DGs, and Gr is the annual rate of benefit (USD/h). The cost coefficients of PV in this study were chosen to be $capital\ cost_PV = 3985$ USD/kW, $Cost_PV_{O\&M} = 0.01207$ USD/kWh, and $Cost_PV_{Fuel} = 0$ USD/kWh. The wind cost coefficients were set to $capital\ cost_wind = 1822$ USD/kW, $Cost_wind_{O\&M} = 0.00952$ USD/kWh, and $Cost_wind_{Fuel} = 0$ USD/kWh. The operational lifetime of PV and WT was assumed to be 20 years, with $K_{Grid} = 0.096$ [20].

2.1.2. Minimizing the Total Expected Emissions ($ETEmission$)

Carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) are the most effective pollutants resulting from fossil fuels used in thermal power plants. The proposed objective function to minimize the emission of such toxic gases can be formulated as follows [20]:

$$ETEmission = \sum_{k=1}^{Ns} EEmission_k = \sum_{k=1}^{Ns} \pi_{Grid,k} \times E_{Grid,k}, \quad (10)$$

$$f_2(x) = \sum_{i=1}^{N_{DG}} E_{DG_i} + E_{Grid}, \quad (11)$$

$$E_{DG_i} = (CO_2^{DG} + NO_x^{DG} + SO_2^{DG}) \times PG_i, \quad (12)$$

$$E_{Grid} = (CO_2^{Grid} + NO_x^{Grid} + SO_2^{Grid}) \times P_{gGrid}, \quad (13)$$

where $ETEmission$ represents the total expected emission, and f_2 is the emission reduction from generation units. Grid NO_x , SO_2 , and CO_2 emission rates were set to 5.06 kg/MWh, 11.6 kg/MWh, and 2031 kg/MWh respectively [20].

2.1.3. Minimizing the Expected Voltage Deviation (EVD)

The expected total voltage deviation $ETVD$ of a radial distribution network (RDN) is expressed as follows [20,21]:

$$ETVD = \sum_{L=1}^{Ns} EVD_L = \sum_{L=1}^{Ns} \pi_{S,L} \times VD_L, \quad (14)$$

where

$$VD = \sum_{k=1}^n |V_k - 1|. \quad (15)$$

2.1.4. Enhancing the Expected Voltage Stability Index

The sum of the expected voltage stability indexes ($ETVSI$) can be formulated as

$$ETVSI = \sum_{L=1}^{Ns} EVSI_L = \sum_{L=1}^{Ns} \pi_{S,L} \times VSI_L, \quad (16)$$

$$VSI_n = |V_n|^4 - 4(P_n X_{nm} - Q_n R_{nm})^2 - 4(P_n X_{nm} + Q_n R_{nm})|V_n|^2. \quad (17)$$

2.1.5. Proposed Multi-Objective Function

The above objective functions were integrated into a multi-objective function. The weight approach method was utilized to prioritize the goals to be achieved. Furthermore, the objectives should be normalized on the basis of their base value (without WT and PV), to eliminate scaling concerns and make the objective function dimensionless. The multi-objective function F is given by Equation (18).

$$F = \Omega_1 F_1 + \Omega_2 F_2 + \Omega_3 F_3 + \Omega_4 F_4 \quad (18)$$

where Ω_1 , Ω_2 , Ω_3 , and Ω_4 are the weighing factors that should satisfy Equation (19).

$$|\Omega_1| + |\Omega_2| + |\Omega_3| + |\Omega_4| = 1 \quad (19)$$

where, $\Omega_1 = \Omega_2 = \Omega_3 = \Omega_4 = 0.25$ [20].

The respective normalized objective functions in Equation (18) are calculated as follows:

$$F_1 = \frac{ETCost}{ETCost_{base}} \quad (20)$$

$$F_2 = \frac{ETEmission}{ETEmission_{base}} \quad (21)$$

$$F_3 = \frac{ETVD}{ETVD_{base}} \quad (22)$$

$$F_4 = \frac{1}{ETVSI} \quad (23)$$

2.2. System Constraints

The above multi-objective function is solved subject to the below constraints.

2.2.1. Equality Constraints

The active and reactive powers flow in RDN are included in the equality constraints, which can be written as follows:

$$P_{Grid} + \sum_{j=1}^{NPV} P_{PV,j} + \sum_{j=1}^{NWT} P_{WT,j} = \sum_{j=1}^{NT} P_{loss,j} + \sum_{j=1}^{NB} P_{L,j}. \quad (24)$$

$$Q_{Grid} + \sum_{j=1}^{NWT} Q_{WT,j} = \sum_{j=1}^{NT} Q_{loss,j} + \sum_{j=1}^{NB} Q_{L,j}. \quad (25)$$

2.2.2. Inequality Constraints

The inequality constraints can be given as follows:

$$V_{min} \leq V_j \leq V_{max}. \quad (26)$$

$$\sum_{j=1}^{NWT} Q_{WT,j} \leq \sum_{j=1}^{NB} Q_{L,j}. \quad (27)$$

$$I_n \leq I_{max,n} \quad n = 1, 2, 3, \dots, NT. \quad (28)$$

where, V_{min} and V_{max} are the lower and the upper voltage limits.

3. Uncertainty Modeling of PV, Wind Turbine, and Load Demand

The continuous probability density function (PDF) is used to consider the uncertainty in load demand, WT, and PV systems.

3.1. WT Uncertainty Modeling

Wind speed uncertainty can be modeled using the Weibull PDF given by Equation (29) [22].

$$f_v(v) = \left(\frac{\beta}{\alpha}\right) \left(\frac{v}{\alpha}\right)^{(\beta-1)} \exp\left[-\left(\frac{v}{\alpha}\right)^\beta\right] \quad 0 \leq v < \infty. \quad (29)$$

The scaling and shaping factors for Weibull PDF are α , β that were set to $\alpha = 10.5$ and $\beta = 2.6$. A 1000 Monte Carlo wind speed distribution scenario utilizing Weibull PDF is depicted in Figure 1.

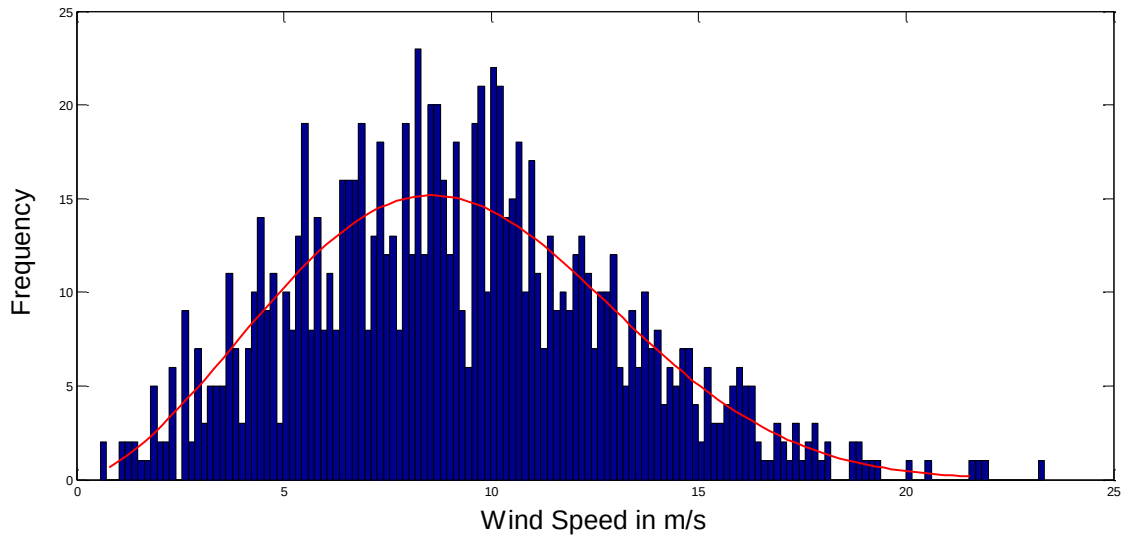


Figure 1. Weibull PDF ($\alpha = 10.5$, $\beta = 2.6$) for WT generator and a 1000 Monte Carlo scenario for wind speed distribution.

The output power of a WT is a function of wind speed expressed as follows [22]:

$$P_{\omega}(v_{\omega}) = \begin{cases} 0 & \text{for } v_{\omega} < v_{\omega i} \mid v_{\omega} > v_{\omega o} \\ P_{\omega r} \left(\frac{v_{\omega} - v_{\omega i}}{v_{\omega r} - v_{\omega i}} \right) & \text{for } (v_{\omega i} \leq v_{\omega} \leq v_{\omega r}) \\ P_{\omega r} & \text{for } (v_{\omega r} \leq v_{\omega} \leq v_{\omega o}) \end{cases}, \quad (30)$$

where, $P_{\omega r}$ is the rated output power of the WT, and $v_{\omega i} = 3$ m/s, $v_{\omega o} = 25$ m/s, and $v_{\omega r} = 16$ m/s are the cut-in, cut-out, and rated speed of the WT, respectively.

For each wind scenario, the probability of wind speed is computed using Equation (31).

$$\tau_{wind, L} = \int_{v_L^{min}}^{v_L^{max}} f_v(v) dv, \quad (31)$$

where v_L^{min} and v_L^{max} mark the beginning and end of the interval of wind speed for the L -th scenario, and $\tau_{wind, L}$ is the probability of WT speed being in the L -th scenario.

3.2. PV Uncertainty Modeling

The lognormal PDF can be used to specify the solar irradiance uncertainty [23].

$$f_G(G) = \frac{1}{G \sigma_s \sqrt{2\pi}} \exp \left[-\frac{(\ln G - \mu_s)^2}{2\sigma_s^2} \right] \text{ for } G > 0, \quad (32)$$

where μ_s , and σ_s represent the mean and standard deviation of the random variables, which were set to 5.5 and 0.5, respectively [23].

The solar irradiation scenarios using the Monte Carlo simulation are shown in Figure 2.

The output power of a PV array as a function of irradiance can be calculated as follows [22]:

$$P_s(G) = \begin{cases} P_{sr} \left(\frac{G^2}{G_{std} \times M_c} \right) & \text{for } 0 < G \leq M_c \\ P_{sr} \left(\frac{G}{G_{std}} \right) & \text{for } G \geq M_c \end{cases}, \quad (33)$$

where M_c represents a certain irradiance point which is set to 120 W/m², and G_{std} is the standard solar irradiance which is equal to 1000 W/m² [23].

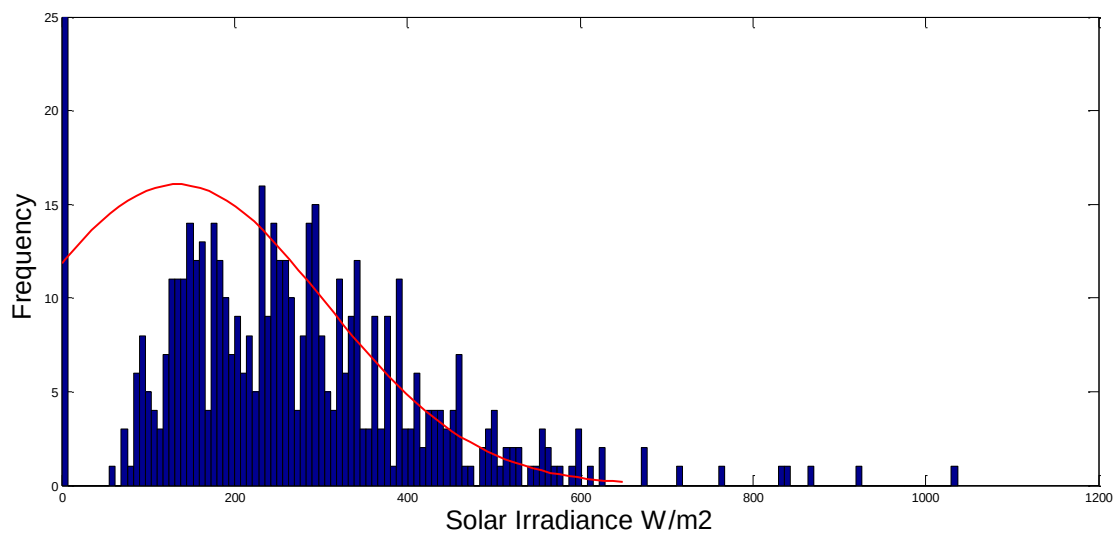


Figure 2. Solar irradiation scenarios for PV units (without zero irradiance).

The probability of solar irradiation can be calculated using Equation (34) [23].

$$\tau_{solar, m} = \int_{G_n^{min}}^{G_n^{max}} f_G(G) dG, \quad (34)$$

where G_n^{min} and G_n^{max} are the starting and ending points of the solar irradiance interval in the n -th scenario.

3.3. Load Demand Uncertainty Modeling

The normal distribution PDF can be used to simulate the uncertainty in the load demand as shown below [24].

$$f_d(P_d) = \frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right], \quad (35)$$

where the standard and mean deviation values are σ_d and μ_d , respectively. P_d represents the load normal distribution's probability density. Figure 3 shows the Monte Carlo scenarios of load demand formed with a normal distribution PDF ($\sigma_d = 10$, $\mu_d = 70$, and sample size = 1000).

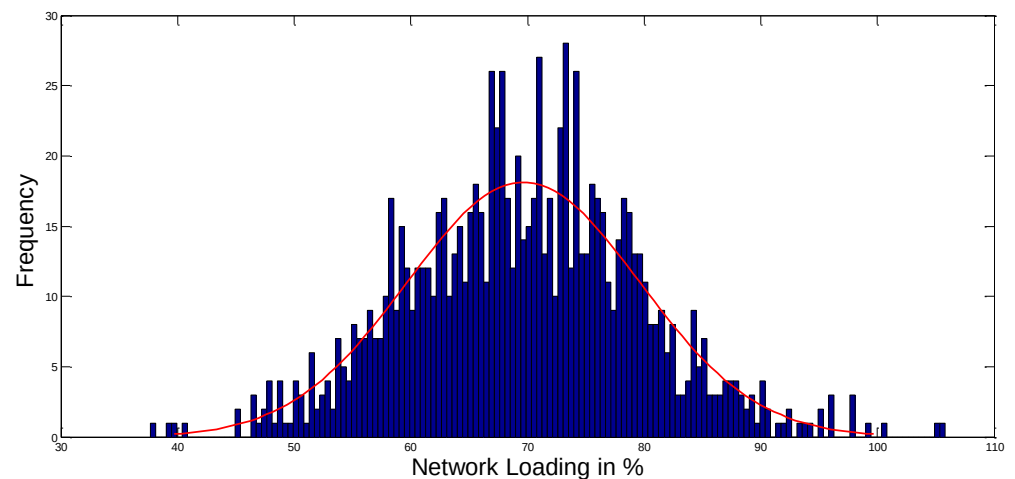


Figure 3. Demand scenarios using Monte-Carlo simulation.

To calculate the load demand probability and expected load scenarios, the following equations are used [24]:

$$\tau_{d,i} = \int_{v_{d,i}^{min}}^{v_{d,i}^{max}} \frac{1}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right] dp_d, \quad (36)$$

$$P_{d,i} = \frac{1}{\tau_{d,i}} \int_{P_{d,i}^{min}}^{P_{d,i}^{max}} \frac{P_d}{\sigma_d \sqrt{2\pi}} \exp \left[-\frac{(P_d - \mu_d)^2}{2\sigma_d^2} \right] dp_d, \quad (37)$$

where $P_{d,i}^{min}$ and $P_{d,i}^{max}$ represent the border limits of interval i .

3.4. Backward Reduction Algorithm

The authors of [21] demonstrated how to use the backward reduction technique to reduce possibilities. The probabilities associated with various scenarios are shown in Table 1. The probability of each scenario, the solar irradiation, the wind speed, and the percentage of loading are listed in the table.

Table 1. Reduced created scenarios, with associated uncertainties.

Scenario	π_s (Scenario Probability)	Irradiance of PV (W/m ²)	Speed of WT (m/s)	Loading %
S1	0.0010	825.1	5.7	82.1
S2	0.0030	665.8	8.1	85.9
S3	0.1050	311.2	9.3	72.8
S4	0.0060	80.3	4.6	58.2
S5	0.0040	744.2	7.1	75.4
S6	0.1040	201.8	7.7	68.4
S7	0.0110	585.5	4.3	73.8
S8	0.0470	360.5	10.6	63.7
S9	0.0330	406.5	8.2	78.1
S10	0.0010	909.6	5.7	64.5
S11	0.0530	250.6	13.6	66.1
S12	0.1210	133.4	8.8	72.9
S13	0.0160	504.8	8.8	64.4
S14	0.0100	455.6	10.3	65.4
S15	0.4850	0	10.3	72.1

4. Optimization Algorithms

The manta ray foraging optimizer (MRFO) is a new bioinspired optimization technique which was introduced in 2020 for solving engineering applications [19]. Manta rays are aquatic animals with two pectoral fins and a flat body. They are able to swim freely, as if they were birds. They also feature a pair of vertical lobes protruding from their massive terminal jaws. They do not have sharp teeth; therefore, they eat plankton (microscopic animals) [19]. The MRFO is similar to other optimizers that are based on developing the exploration and exploitation stages. For solving distinct optimization issues, three foraging strategies, i.e., chain foraging, cyclone foraging, and somersault foraging, can be used to define the development [25–27]. The mathematical models of the three foraging strategies are described below.

4.1. Chain Foraging

Manta rays may be able to identify plankton through MRFO and swim toward it. A larger concentration of plankton in a location results in a better identification process. The mathematical model of chain foraging can be expressed as

$$x_i^b(t+1) = \begin{cases} x_i^b(t) + A * (x_{best}^b(t) - x_i^b(t)) + \rho \times (x_{best}^b(t) - x_i^b(t)) & i = 1 \\ x_i^b(t) + A * (x_{i-1}^b(t) - x_i^b(t)) + \rho \times (x_{best}^b(t) - x_i^b(t)) & i = 2, \dots, N \end{cases} \quad (38)$$

$$\rho = 2 \times A \times \sqrt{|\log(A)|}, \quad (39)$$

where A is a random vector within the range $[0, 1]$, $x_i^b(t)$ is the position of the i -th individual at time t in b -th dimension, $x_{best}^b(t)$ is the plankton with the highest concentration, and ρ is a weight coefficient. The position update of the i -th individual is determined by the position $x_{i-1}^b(t)$ of the $(i - 1)$ -th current individual and the position $x_{best}(t)$ of the food.

4.2. Cyclone Foraging

When manta rays find plankton in deep water, they form a lengthy foraging chain and spiral their way to the food. Each manta ray swims in the same direction following the manta ray in front. Manta rays, in other words, hunt in swarms, spiraling around each other. The mathematical equation that can be used to model manta rays' spiral-shaped movement in 2D space is

$$\begin{cases} X_i(t+1) = X_{best}(t) + A \times (X_{i-1}(t) - X_i(t)) + e^{d\omega} \times \cos(2\pi\omega) \times (X_{best} - X_i(t)) \\ Y_i(t+1) = Y_{best}(t) + A \times (Y_{i-1}(t) - Y_i(t)) + e^{d\omega} \times \sin(2\pi\omega) \times (Y_{best} - Y_i(t)) \end{cases}, \quad (40)$$

where ω is a random number within the range $[0, 1]$. The mathematical model of cyclone foraging can be defined as

$$x_i^b(t+1) = \begin{cases} x_{best}^b(t) + A * (x_{best}^b(t) - x_i^b(t)) + \mu * (x_{best}^b(t) - x_i^b(t)) & i = 1 \\ x_{best}^b(t) + A * (x_{i-1}^b(t) - x_i^b(t)) + \mu * (x_{best}^b(t) - x_i^b(t)) & i = 2, \dots, N \end{cases}, \quad (41)$$

$$\mu = 2e^{r_1 \frac{T-t+1}{T}} \cdot \sin(2\pi r_1), \quad (42)$$

where r_1 is a rand number within the range $[0, 1]$, T is the maximum number of iterations, and μ is the weight coefficient.

This mechanism is primarily concerned with exploration and allows MRFO to conduct a comprehensive worldwide search; its mathematical equation is given by

$$x_{rand}^b = Lb^b + A \times (Ub^b - Lb^b), \quad (43)$$

$$x_i^b(t+1) = \begin{cases} x_{rand}^b + A \times (x_{rand}^b - x_i^b(t)) + \mu \times (x_{rand}^b - x_i^b(t)) & i = 1 \\ x_{rand}^b + A \times (x_{i-1}^b(t) - x_i^b(t)) + \mu \times (x_{rand}^b - x_i^b(t)) & i = 2, \dots, N \end{cases}, \quad (44)$$

where Ub^b , and Lb^b are the upper and lower limits of the b -th dimension, respectively, and x_{rand}^b is a random position produced in the search space. The Cyclone Foraging procedures are shown in Figure 4.

4.3. Somersault Foraging

The position of the meal is considered a pivot in this behavior. Each manta ray swims back and forth around the pivot, somersaulting to a new position. As a result, the manta rays constantly update their positions on the basis of the best position discovered thus far. The mathematical model of this process can be expressed as

$$x_i^b(t+1) = x_i^b(t) + S * (r_2 * x_{best}^b - r_3 * x_i^b(t)), i = 1, \dots, N, \quad (45)$$

where S is the somersault factor that decides the somersault range of manta rays ($S = 2$), and r_3 and r_2 are two random numbers within the range $[0, 1]$.

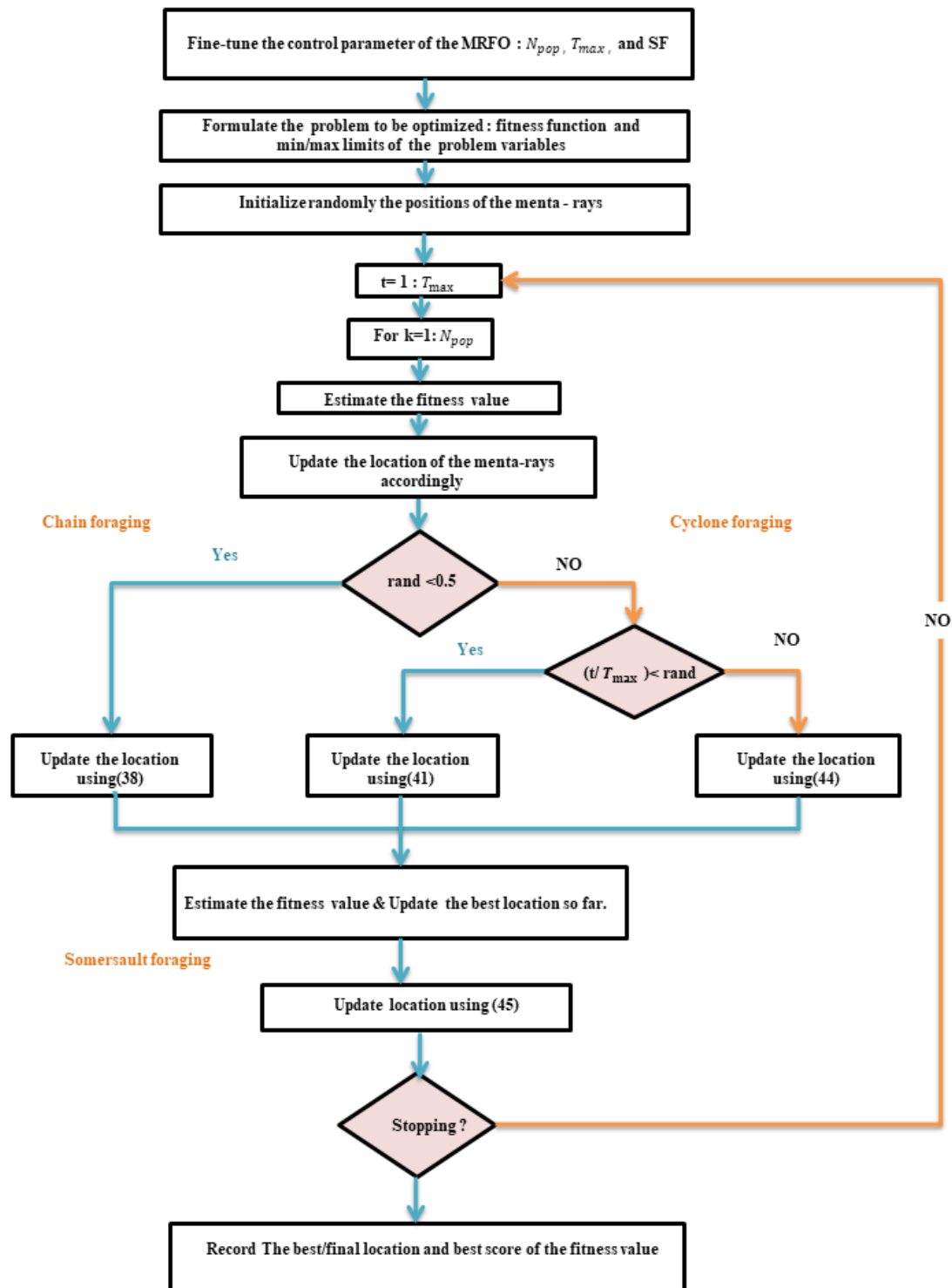


Figure 4. A flow chart of the MRFO.

5. Simulation Results, Comparison, and Discussion

5.1. Simulation Results and Comparison

In this section, the proposed approach is utilized to find the optimal RER allocations in two RDNs while considering the system's uncertainty. The installation of RERs is identified as a function of reducing the expected cost, the expected emissions, and the expected voltage deviation, while also improving the voltage stability index. These objectives were

integrated into a single multi-objective function in order to optimize them all at once. The MRFO was used to combine a solar PV and WT-based DGs within the IEEE 118-bus and a rural 51-bus systems as real distribution networks. The IEEE-15 bus system was also modeled as a small distribution network. Figures 5–7 show the single-line diagrams of these systems, respectively. The detailed parameters of the IEEE 118-bus, rural 51-bus, and the IEEE 15-bus test systems were provided in [28–30], respectively. Table 2 shows the initial power flow of these systems in the base case. The obtained results were compared with PSO, ALO, WOA, and SCA to verify the effectiveness of the suggested MRFO. Table 3 lists the parameters of the optimization techniques considered in this paper, whereas Table 4 lists the restrictions of the studied system, and Table 5 shows the characteristics of the generation resources. The proposed algorithms were developed using MATLAB software and applied to two case studies.

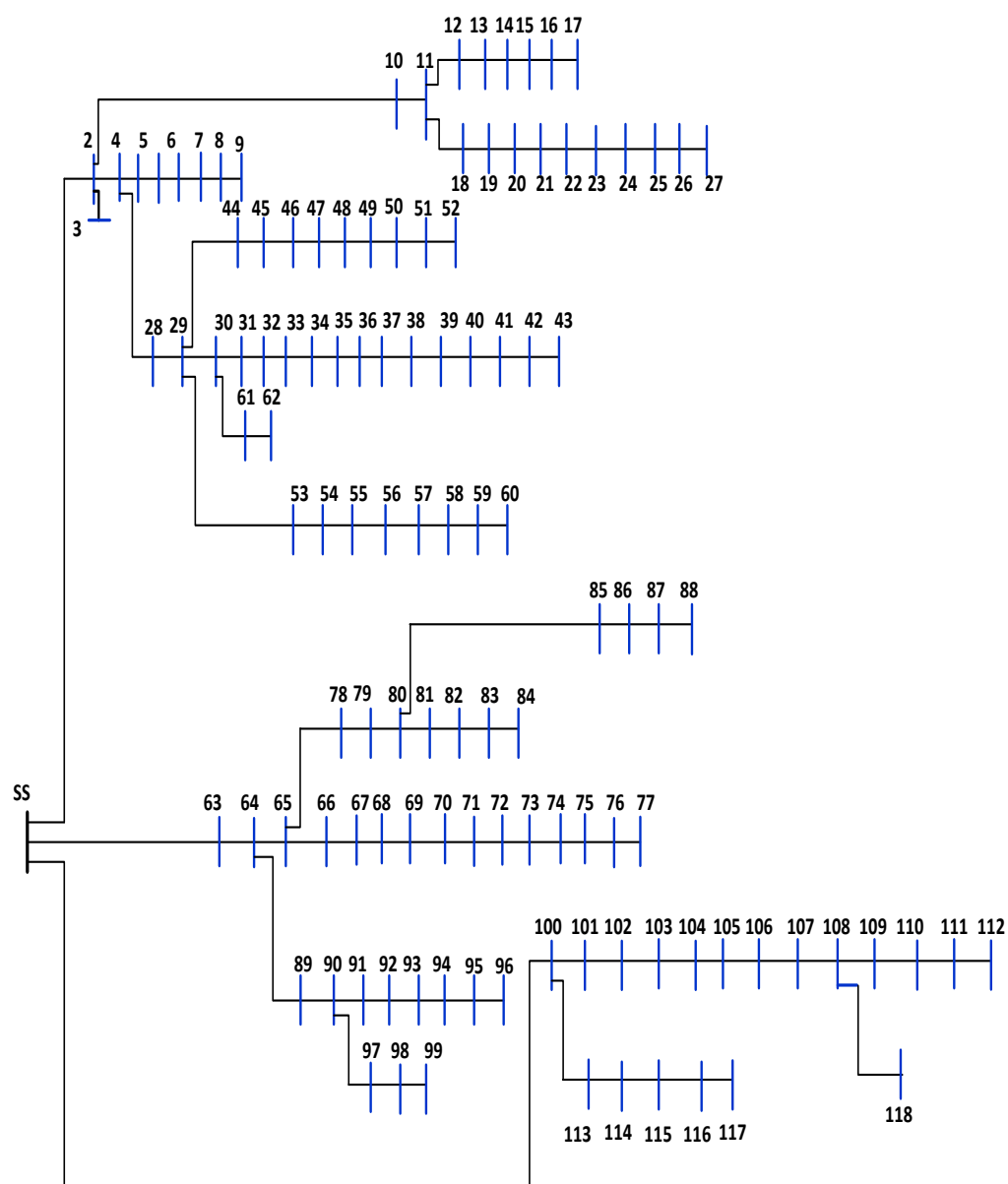


Figure 5. Single-line diagram of the IEEE 118-bus system.

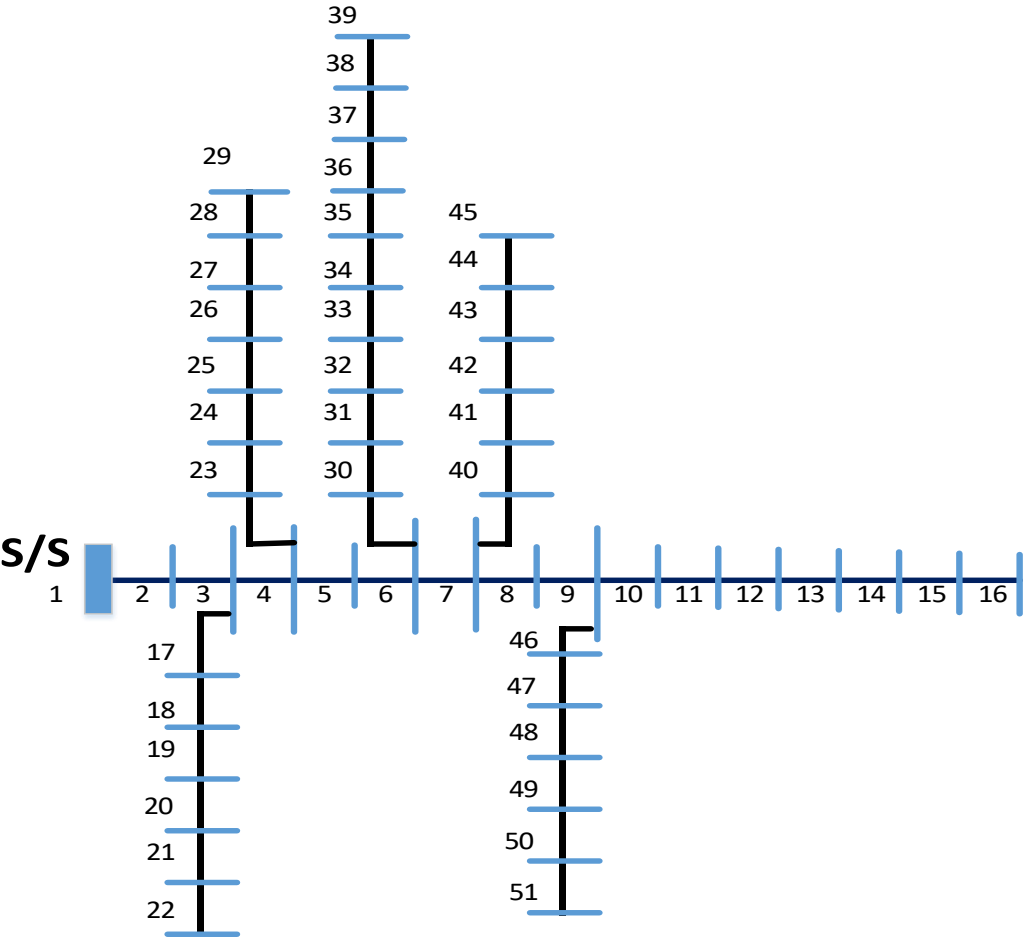


Figure 6. Rural 51-bus system.

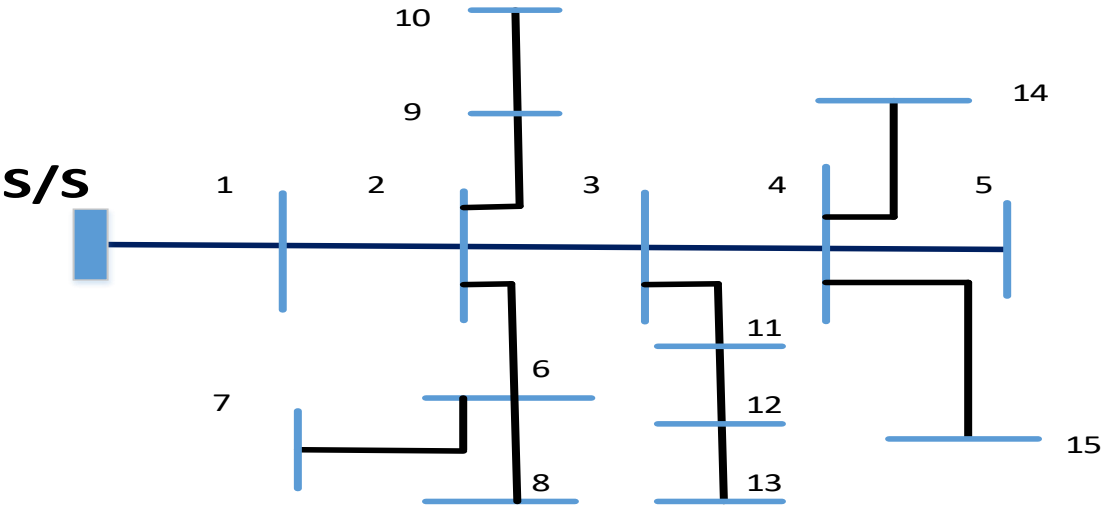


Figure 7. IEEE 15-bus system.

Table 2. Specifications of the studied networks.

Item	IEEE 118-Bus	Rural 51-Bus	IEEE 15-Bus
Minimum voltage (p.u.)	0.86882 @ bus 77	0.90812 @ bus 16	0.94452 @ bus 13
Excluding the slack bus, maximum voltage (p.u.)	0.99629 @ bus 100	0.98919 @ bus 2	0.97128 @ bus 2
Total reactive load (kVAR)	17,041.068	1569	1251.179
Total active load (kW)	22,709.720	2463	1226.400
Total Reactive Loss (kVAR)	978.649	111.679	56.538
Total Active Loss (kW)	1297.869	129.550	60.668

Table 3. Parameters used in each optimization technique.

Optimizer	Parameter Configuration
MRFO	$T_{\max} = 100$, populations = 25.
ALO	$T_{\max} = 100$, populations = 25.
WOA	$T_{\max} = 100$, populations = 25.
SCA	$T_{\max} = 100$, populations = 25.
PSO	$T_{\max} = 100$, populations = 25, $b1 = 2$, $b2 = 1$, $w = 0.7$

Table 4. The limitations of the system.

Parameter	Value
Limits of DG size	$0 \leq P_{WT, PV} \leq P_L$ kW
Limits of power factor	$0.65 \leq PF_i \leq 1$
Limits of voltage	$0.90 \leq V_i \leq 1.05$ p.u.

Table 5. Characteristics of the generation resources.

DG Type	Fuel Cost (USD/kWh)	Capital Cost (USD/kW)	O&M Cost (USD/kWh)	Life Time (Year)	Rated Capacity (MW)	Emission Factors (lb/MWh)		
PV	-	3985	0.01207	20	1	NO _x	SO ₂	CO ₂
WT	-	1822	0.00952	20	5	-	-	-
Grid	0.044	-	-	25	25	5.06	11.6	2031

5.1.1. Case Study 1: IEEE 118-Bus System

MRFO was utilized to determine the optimal RER placements and ratings in the IEEE 118-bus system shown in Figure 5. Without any penetration of RERs, the expected cost, emissions, voltage deviations, and the expected voltage stability index were 1633.5 USD/h, 34,842,000 kg/MWh, 4.2157 p.u., and 101.4379 p.u., respectively. In the case of optimal insertion of WT- and solar PV-based DGs, these calculations became 975.7504 USD/h, 13,029,000 kg/MWh, 2.9794 p.u., and 106.5046 p.u., respectively. In other words, these values are enhanced by 40.27%, 62.6%, 29.33%, and 4.76%, respectively. The optimal sites of the PV units and the WT-based DGs were buses 72 and 64, respectively. These DGs should be of the following optimum sizes: 2589.53 kW and 20,029.39 kW. Table 6 shows the PV unit and WT-based DG output powers, as well as the expected values for each scenario. It can be seen that the numbers changed in each scenario due to the differences in the RER output power and load demand. Furthermore, it can be observed that scenario number 15 had the highest projected expenses, expected emissions, and predicted voltage variation. This was due to the out power of the solar PV being 0 kW. As a result, the majority of the required power would be provided by the grid, causing these values to rise. Cost, emissions, VDs, and the VSIs for each scenario with and without the integration of the RERs are shown in Figures 8–11, respectively. According to these figures, the cost, emissions, and VDs were reduced significantly in each scenario with the inclusion of RERs, while the VSI at

each scenario was enhanced considerably. Figures 12 and 13 depict the voltage profiles of the IEEE 118-bus system for each situation. It is obvious that the insertion of RERs can improve the voltage profile for each scenario. Table 7 lists the statistical findings of the objective function calculated using several optimization techniques, namely, WOA (whale optimization algorithm) [30], PSO (particle swarm optimization) [31], ALO (ant lion optimizer) [32], and SCA (sine cosine algorithm) [33]. It can be observed that the MRFO surpasses other methods for solving this problem.

Table 6. The IEEE 118-bus system simulation results.

Scenario	π_{τ_s}	Loading %	P_w (kW)	P_s (kW)	ETCOST (USD/h)	ETEmission (kg/MWh)	ETVD (p.u.)	ETVSI (p.u.)
S1	0.0010	82.1	4180	2136.9	1.6	26,800	0.0033	0.1045
S2	0.0030	85.9	7765	1724.5	4.2	66,600	0.0096	0.3156
S3	0.1050	72.8	9696	806	107.5	1,465,700	0.301	11.1894
S4	0.0060	58.2	2460	139.2	8.3	138,600	0.0204	0.6253
S5	0.0040	75.4	6227	1927.5	5.1	79,400	0.0118	0.424
S6	0.1040	68.4	7290	522.6	119.9	1,798,900	0.317	10.9873
S7	0.0110	73.8	2036	1516.4	18.1	313,900	0.0387	1.1417
S8	0.0470	63.7	11,735	933.8	29.9	248,000	0.1215	5.112
S9	0.0330	78.1	8056	1052.9	41.6	635,600	0.1027	3.4809
S10	0.0010	64.5	4179	2356	1.2	17,900	0.0027	0.1069
S11	0.0530	66.1	16,287	649.1	17.9	0	0.1559	5.8439
S12	0.1210	72.9	8878	345.6	137.5	2,014,500	0.3737	12.7797
S13	0.0160	64.4	8890	1307.4	13.7	167,600	0.0405	1.7251
S14	0.0100	65.4	11,281	1179.9	6.9	64,500	0.0255	1.0866
S15	0.4850	72.1	11,201	0	462.2	5,990,800	1.455	51.5818
Summation	1				975.7503	13,028,800	2.9793	106.5047

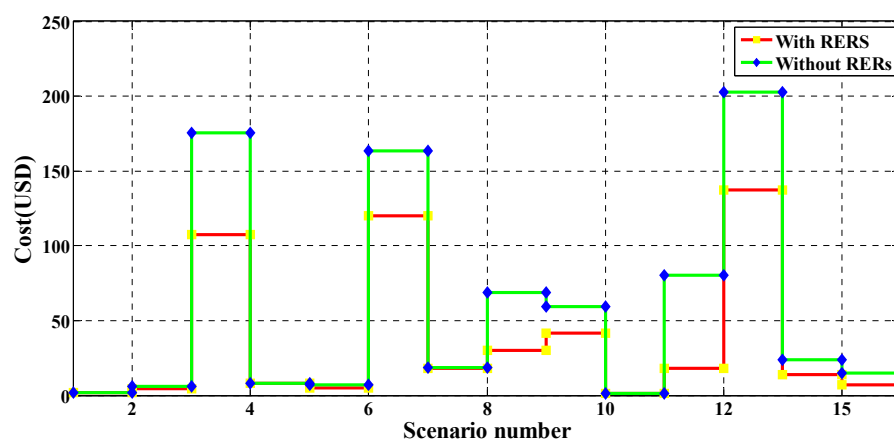


Figure 8. The IEEE 118-bus system total costs.

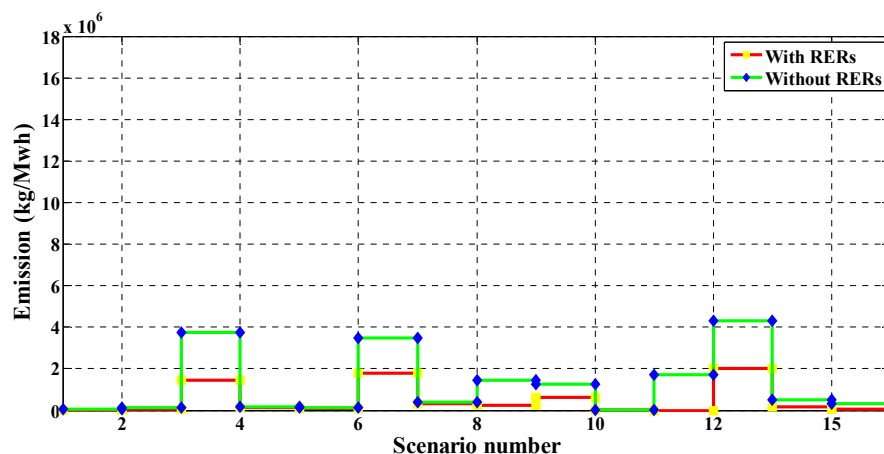


Figure 9. The IEEE 118-bus system emissions.

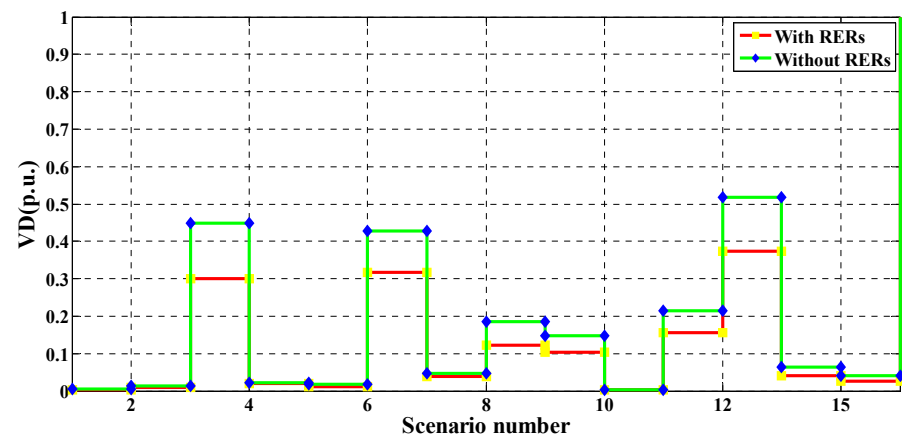


Figure 10. The IEEE 118-bus system VDs.

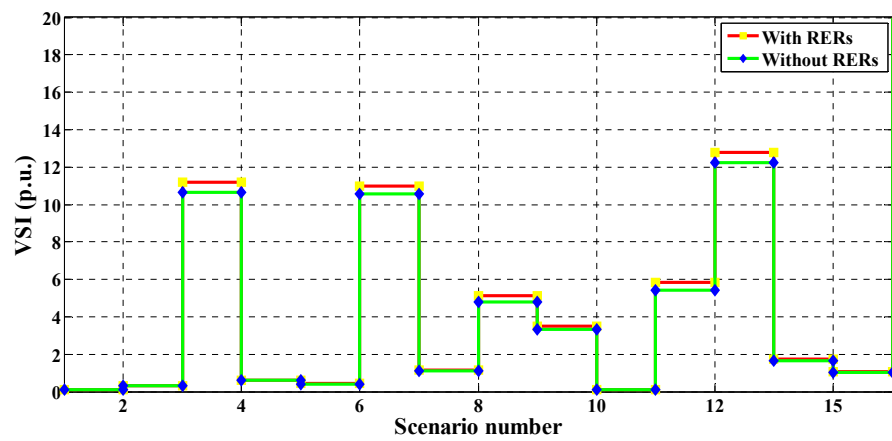


Figure 11. The IEEE 118-bus system VSIs.

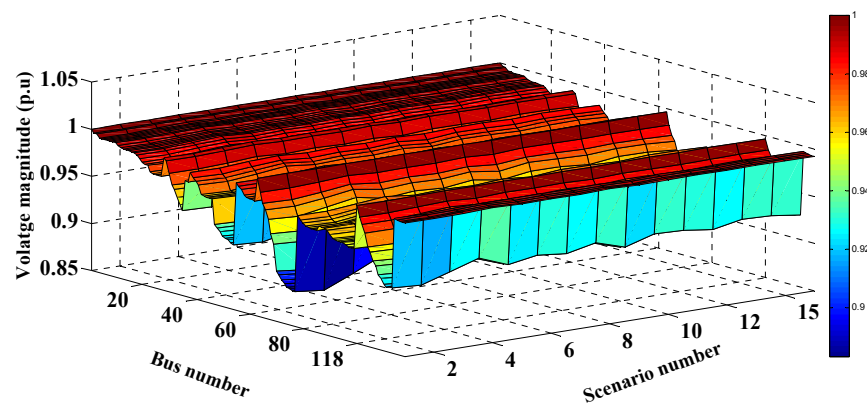


Figure 12. Bus voltage magnitudes of the IEEE 118-bus system without RERs.

Table 7. The statistical results in the IEEE 118-bus system with the use of several optimizers.

Optimizer	Best Values	Average Values	Worst Values	SD
MRFO	0.6820	0.7087	0.7655	0.0253
PSO	0.7097	0.7547	0.8333	0.0374
ALO	0.7323	0.7985	0.8625	0.0358
WOA	0.7745	0.8132	0.8903	0.0175
SCA	0.6942	0.7351	0.7905	0.0306

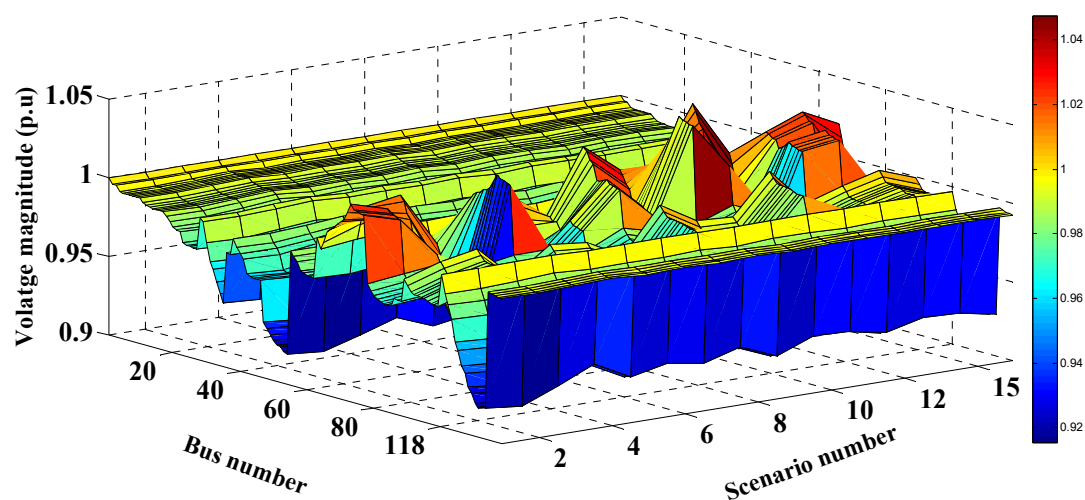


Figure 13. Bus voltage magnitudes of the IEEE 118-bus system with RERs.

5.1.2. Case Study 2: Rural 51-Bus System

In this case study, MRFO was employed to identify the optimal RER locations and ratings in the 51-bus system shown in Figure 6. Without RERs, the expected cost, emissions, voltage deviation, and the expected voltage stability index were 176.0419 USD/h, 3,754,900 kg/MWh, 2.1514 p.u., and 41.9992 p.u., respectively. In the case of the optimal insertion of WT and solar PV-based DGs, these respective values improved to 113.4299 USD/h, 1,504,600 kg/MWh, 0.6678 p.u., and 47.6629 p.u. with a percentage improvement of 35.57%, 59.92%, 68.95%, and 11.88%, in each respective parameter. The optimal sites of the PV units and the WT were buses 43 and 9, respectively. The optimum sizes of these DGs were found to be 574.58 kW and 1884.61 kW, respectively. Table 8 shows the PV and WT output powers, as well as the expected values for each studied scenario. Similar to the above case study, the values in Table 8 changed for each scenario due to the changes in RER generation and the variation of the load demand. It can be seen that the highest values of the expected cost, emissions, and voltage deviation occurred in scenario number 15, where no solar-based power is generated. The values of the cost, emissions, VDs and the VSIs for each scenario with and without the integration of RERs are shown in Figures 14–17, respectively. These figures reveal that the cost, emissions, and VDs were reduced significantly in each scenario with the inclusion of RERs, along with a considerable enhancement in the VSI. In addition, Figures 18 and 19 depict the voltage profiles of the 51-bus system for each situation. It is obvious that the integration of RERs at a proper location and with an optimum sizing can improve the voltage profile at each bus for all scenarios. Table 9 shows the statistical results of the objective function calculated using different optimization algorithms. Results in Table 9 attest to the superiority of the proposed MRFO technique over all other optimization methods, namely, PSO, WOA, SCA, and ALO.

Table 8. The 51-bus system simulation results.

Scenario	π_s	Loading %	P_w (kW)	P_s (kW)	ETCost (USD/h)	ETEmission (kg/MWh)	ETVD (p.u.)	ETVSI (p.u.)
S1	0.0010	82.1	393.4	474.4	0.1574	2460	0.0013	0.0451
S2	0.0030	85.8	730.8	82.8	0.4317	6380	0.0028	0.1393
S3	0.1050	72.8	912.5	78.9	11.9328	157,040	0.0653	4.9954
S4	0.0060	58.2	231.5	0.9057	0.9118	14,940	0.0092	0.2651
S5	0.0040	75.4	586.1	27.9	0.5107	7190	0.0037	0.1857
S6	0.1040	68.4	686.1	16.1	13.3313	194,260	0.0973	4.8225
S7	0.0110	73.8	191.6	36.7	1.8425	30,250	0.0174	0.4842
S8	0.0470	63.7	1104.4	07.3	3.4467	27,710	0.0163	2.3186
S9	0.0330	78.1	758.2	33.8	4.4574	65,000	0.0292	1.5367
S10	0.0010	64.5	393.3	23.1	0.1111	1460	0.001	0.0463
S11	0.0530	66.1	1532.8	44.1	2.6	90	0.0277	2.7232
S12	0.1210	72.9	835.5	6.7	15.6	226,480	0.1	5.661
S13	0.0160	64.4	836.7	90.3	1.5	15,890	0.008	0.7691
S14	0.0100	65.4	1061.7	261.9	0.7632	6480	0.0037	0.4917
S15	0.4850	72.1	1054.2	0	55.8	748,990	0.285	23.1788
Summation	1				113.4299	1,504,620	0.6679	47.6627

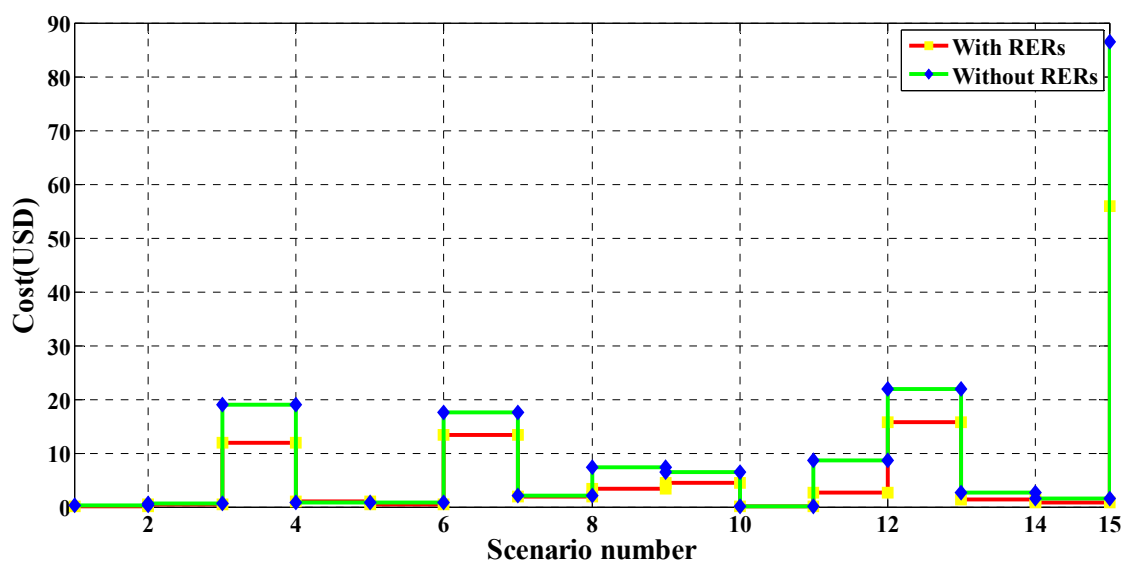


Figure 14. The 51-bus system total costs.

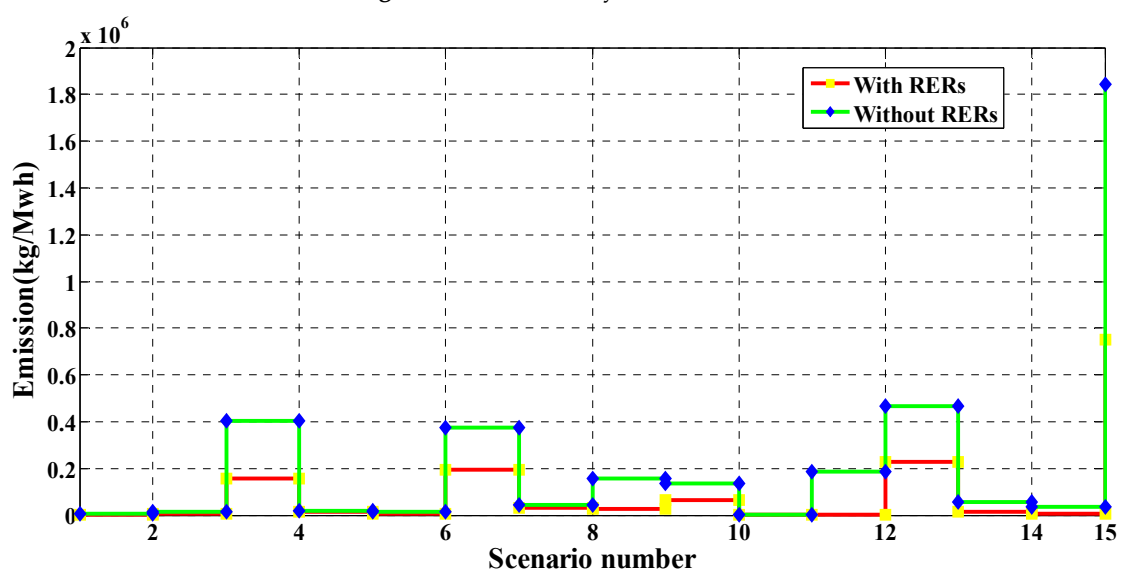


Figure 15. The 51-bus system emissions.

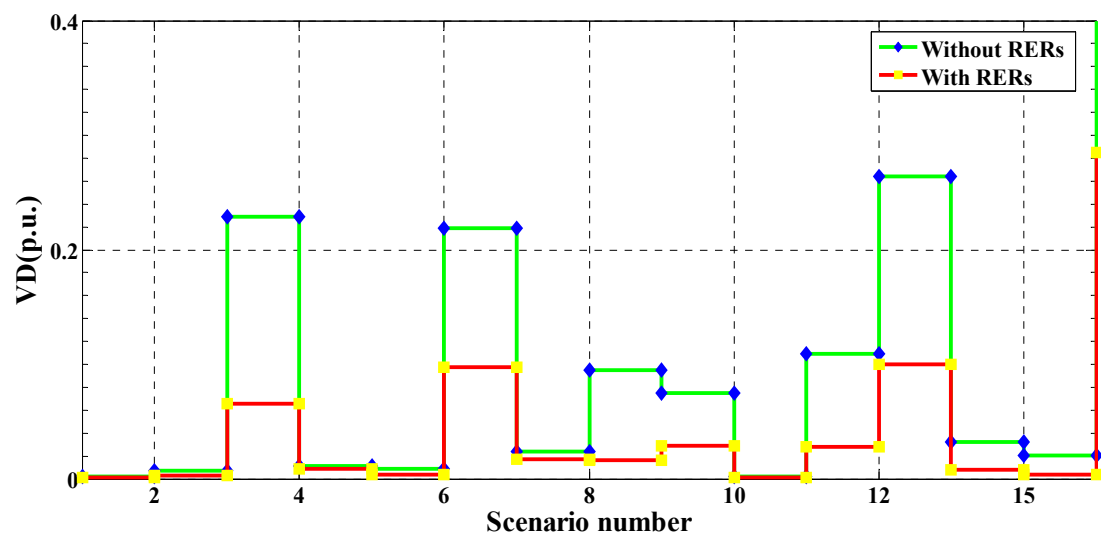


Figure 16. The 51-bus system VDs.

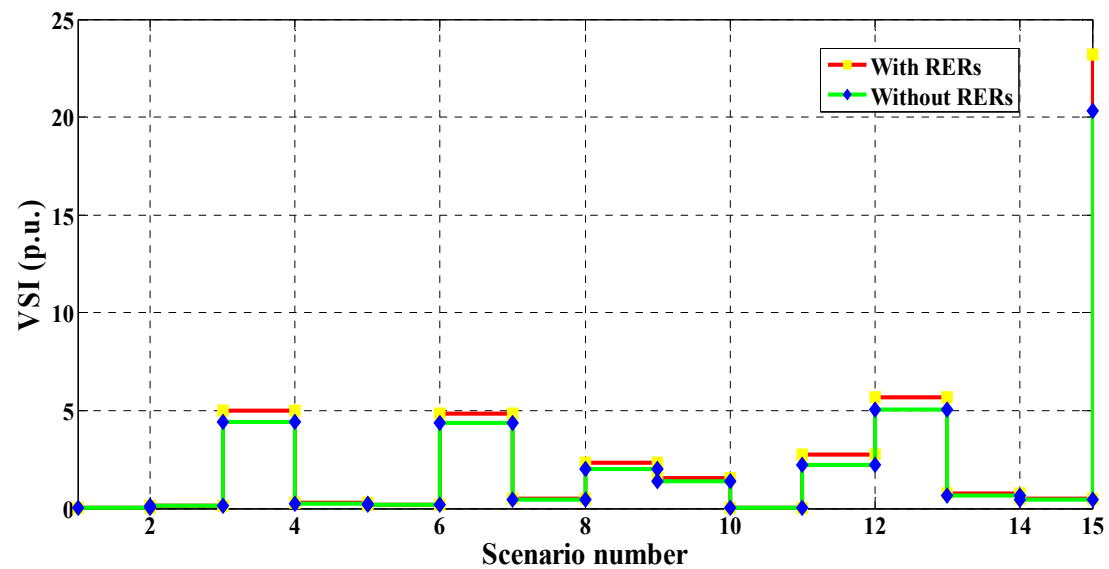


Figure 17. The 51-bus system VSIs.

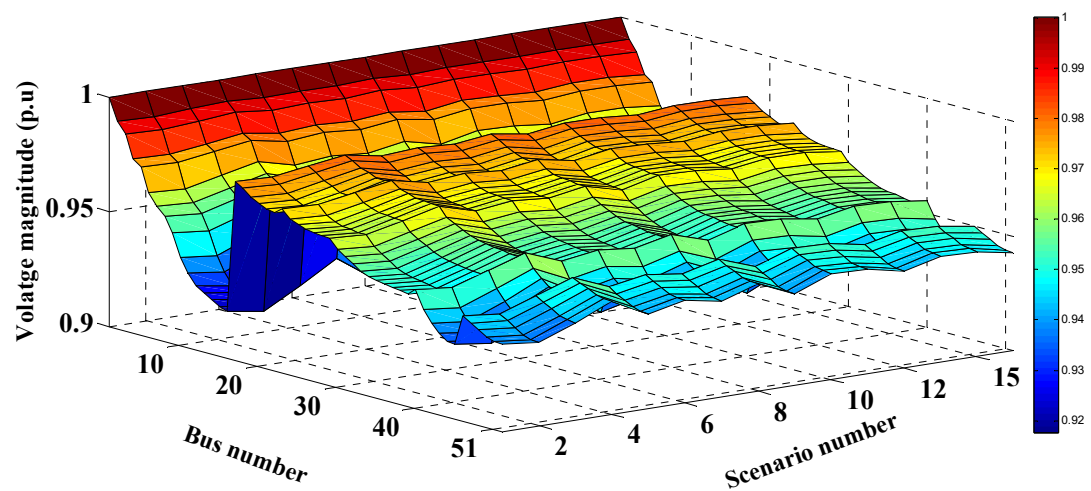


Figure 18. Bus voltage magnitudes of the 51-bus system without RERs.

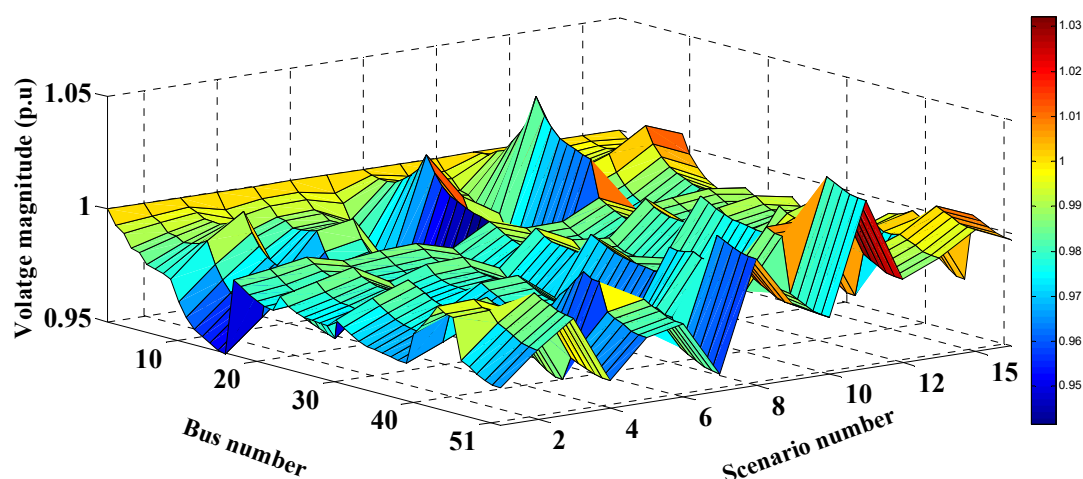


Figure 19. Bus voltage magnitudes of the 51-bus system with RERs.

Table 9. The statistical results in the rural 51-bus system with the use of several optimizers.

Optimizer	Best Values	Average Values	Worst Values	SD Values
MRFO	0.6226	0.6367	0.6562	0.0093
PSO	0.6478	0.7367	0.8431	0.0545
ALO	0.6318	0.7220	0.8824	0.0534
WOA	0.6530	0.7138	0.8002	0.0412
SCA	0.6418	0.6686	0.7018	0.0178

5.1.3. Case Study 3: Small 15-Bus System

In this case study, MRFO was employed to identify the optimal RER locations and ratings within the 15-bus system shown in Figure 7. Without RERs, the expected cost, emissions, voltage deviation, and the expected voltage stability index were 88.1005 USD/h, 1,879,200 kg/MWh, 0.5313 p.u., and 12.0005 p.u., respectively. In the case of the optimal insertion of WT and solar PV-based DGs, these respective values improved to 54.8523 USD/h, 724,180 kg/MWh, 0.2211 p.u., and 13.1670 p.u., with a percentage improvement of 37.74%, 61.46%, 58.39%, and 8.86%, in each respective parameter. The optimal sites of the PV units and the WT were buses 14 and 11, respectively. The optimum sizes of these DGs are found to be 249 kW and 977 kW, respectively. Table 10 shows the PV and WT output powers, as well as the expected values for each studied scenario. Similar to the above case studies, the values in Table 10 changed for each scenario due to the changes in RER generation and the variation of the load demand. It can be seen that the highest values of the expected cost, emissions, and voltage deviation occurred in scenario number 15, where no solar-based power is generated. The values of the cost, emissions, VDs, and the VSIs for each scenario with and without the integration of RERs are shown in Figures 20–23, respectively. These figures reveal that the cost, emissions, and VDs were reduced significantly for each scenario with the inclusion of RERs, along with a considerable enhancement in the VSI. In addition, Figures 24 and 25 depict the voltage profiles of the 15-bus system for each situation. It is obvious that the integration of RERs at a proper location and with an optimum sizing can improve the voltage profile at each bus for all scenarios. Table 11 tabulates the statistical results of the objective function calculated using different optimization algorithms. Results in Table 11 attest to the superiority of the proposed MRFO technique over all other optimization methods, namely, PSO, WOA, SCA, and ALO.

Table 10. The 15-bus system simulation results.

Scenario	π_s	Loading %	P_w (kW)	P_s (kW)	ETCost (USD/h)	ETEmission (kg/MWh)	ETVD (p.u.)	ETVSI (p.u.)
S1	0.0010	82.1	203.9	205.4	0.0801	1280	0.0004	0.0125
S2	0.0030	85.9	378.8	165.8	0.2165	3250	0.0009	0.0386
S3	0.1050	72.8	472.9	77.5	5.852	77,200	0.0237	1.3783
S4	0.0060	58.2	119.9	13.4	0.4542	7500	0.0025	0.0746
S5	0.0040	75.4	303.8	185.3	0.2589	3740	0.0012	0.0513
S6	0.1040	68.4	355.6	50.3	6.5761	96,310	0.0301	1.34
S7	0.0110	73.8	99.3	145.8	0.9357	15,610	0.0048	0.1358
S8	0.0470	63.7	572.4	89.8	1.6609	13,010	0.0067	0.6332
S9	0.0330	78.1	392.9	101.2	2.2128	32,570	0.0093	0.426
S10	0.0010	64.5	203.9	226.5	0.0574	790	0.0003	0.0128
S11	0.0530	66.1	794.5	62.4	1.148	0	0.0063	0.7375
S12	0.1210	72.9	433.1	33.3	7.638	110,400	0.0317	1.5715
S13	0.0160	64.4	433.6	125.7	0.7221	8070	0.0033	0.211
S14	0.0100	65.4	550.3	113.4	0.3721	3150	0.0015	0.1343
S15	0.4850	72.1	546.4	0	26.6676	351,300	0.0983	6.4095
Summation	1				54.8524	724,180	0.2211	13.1669

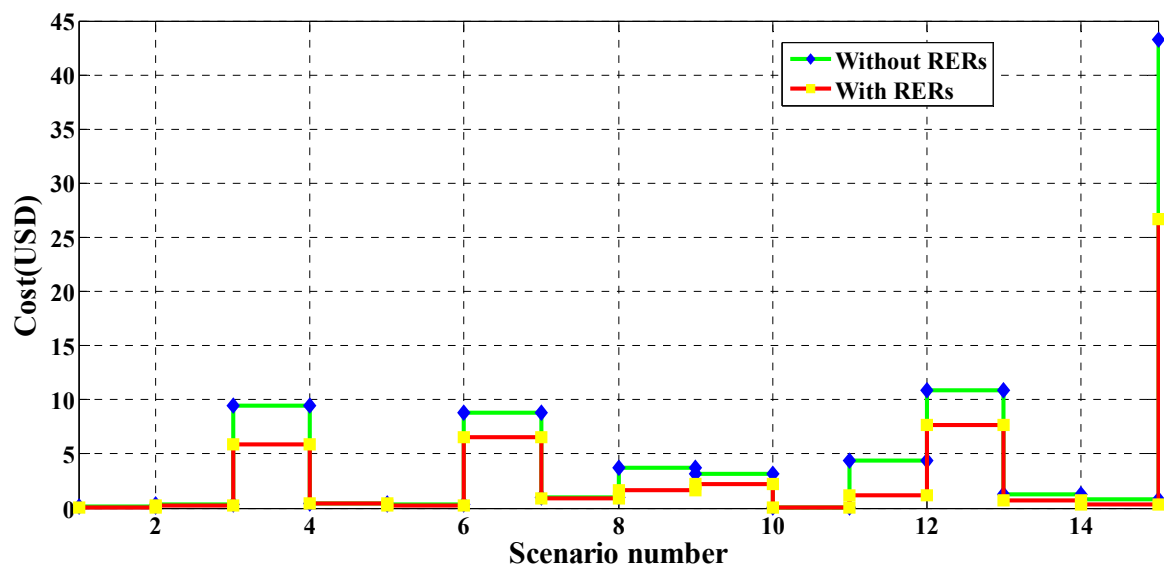


Figure 20. The 15-bus system total costs.

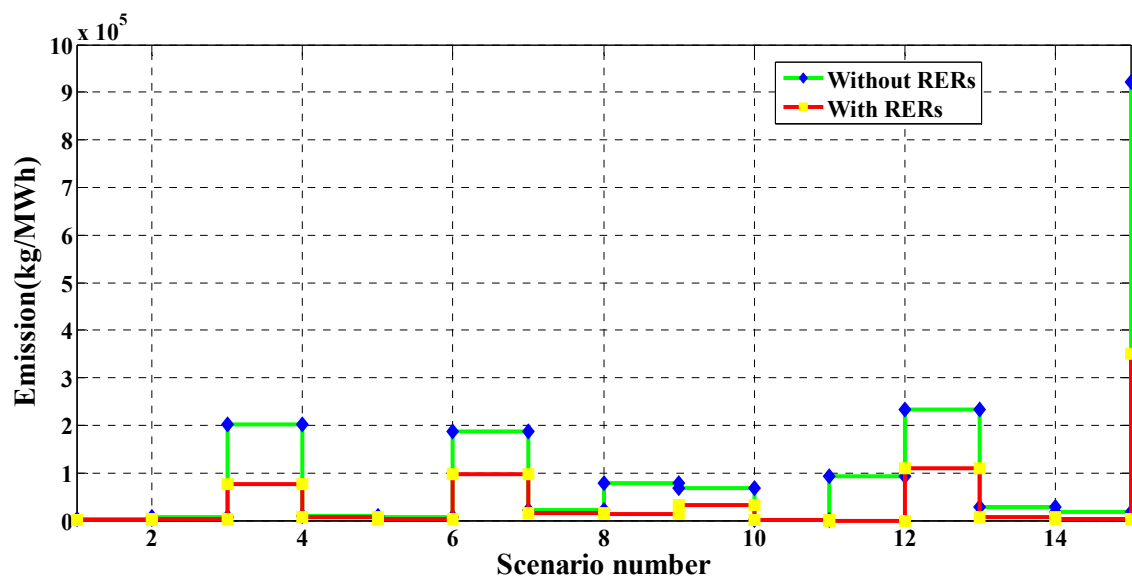


Figure 21. The 15-bus system emissions.

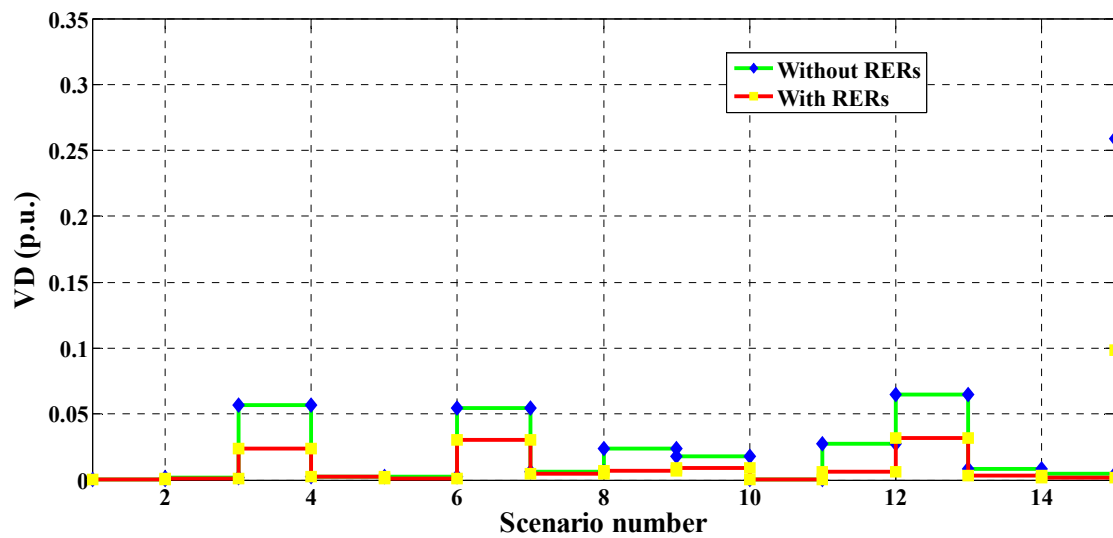


Figure 22. The 15-bus system VDs.

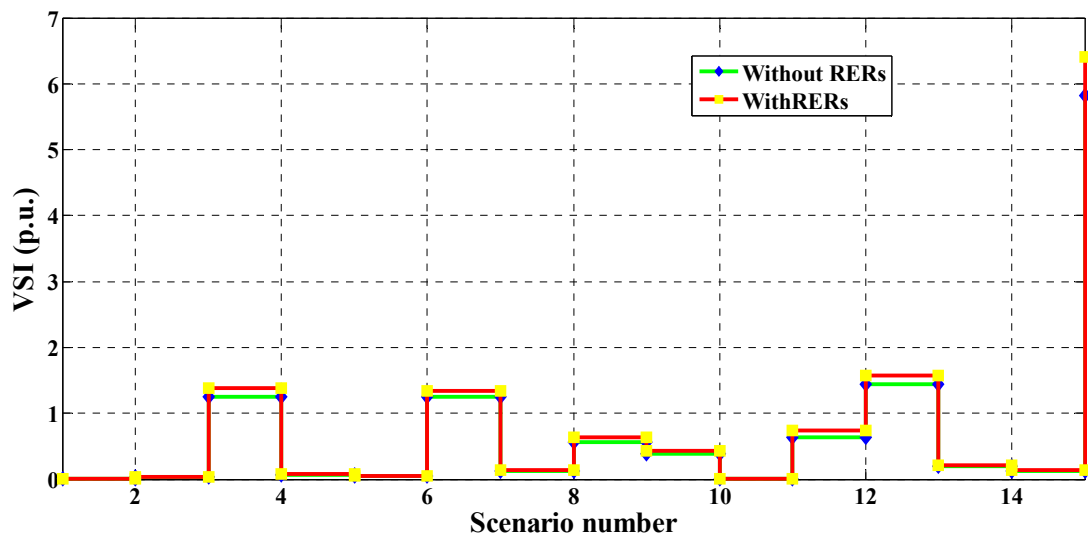


Figure 23. The 15-bus system VSIs.

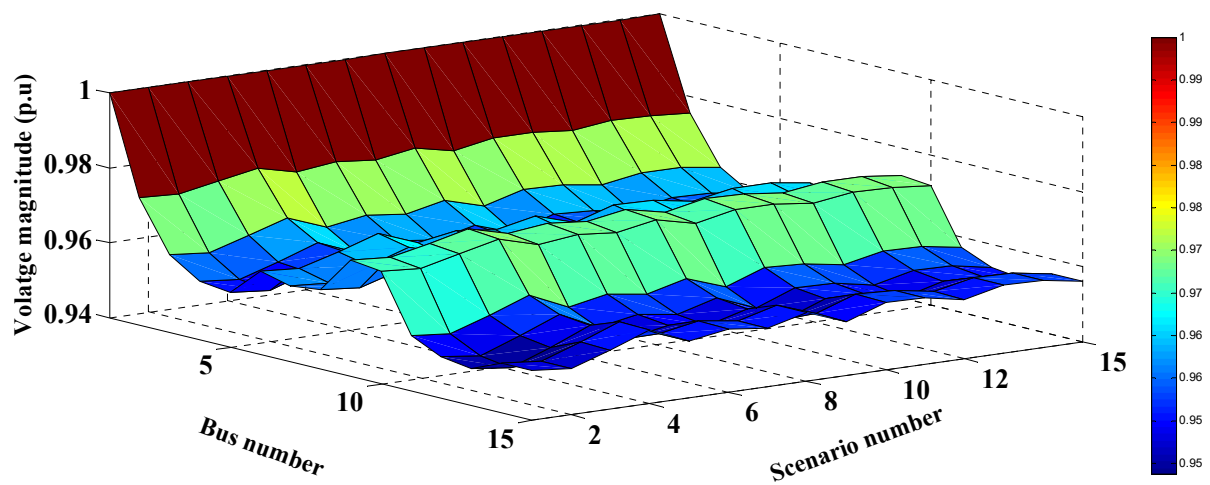


Figure 24. Bus voltage magnitudes of the 15-bus system without RERs.

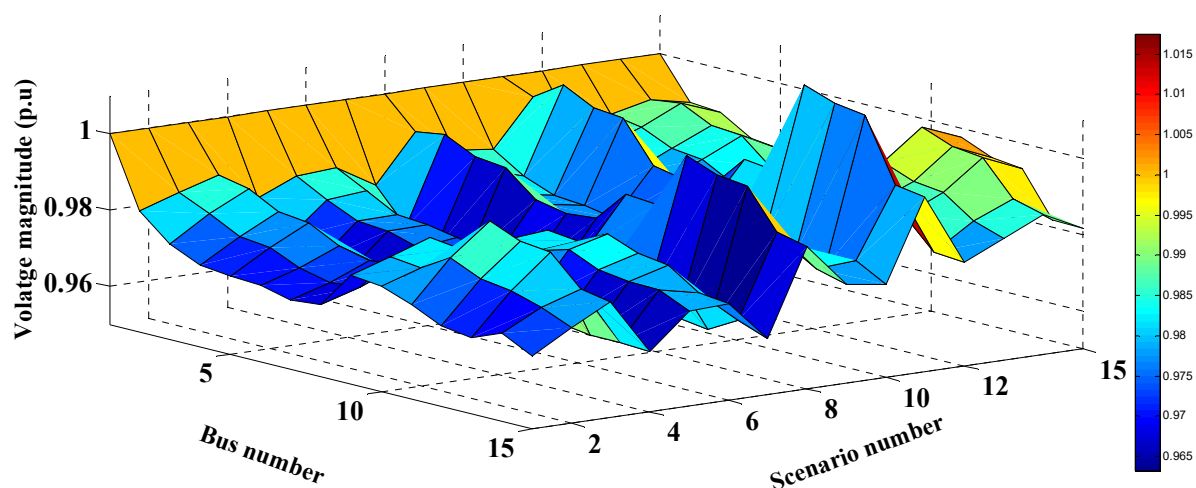


Figure 25. Bus voltage magnitudes of the 15-bus system with RERs.

Table 11. The statistical results in the 15-bus system with the use of several optimizers.

Optimizer	Average Values	Best Values	Worst Values	SD Values
MRFO	0.6345	0.6303	0.6426	0.0030
PSO	0.7201	0.6482	0.9301	0.0676
ALO	0.6832	0.6367	0.7515	0.0357
WOA	0.6695	0.6339	0.7917	0.0444
SCA	0.6485	0.6355	0.6665	0.0107

5.2. Discussions

From the results of the above three studied systems, the key conclusion points can be summarized as follows:

- The MFRO is an efficient algorithm for solving the allocation problem of the DGs in distribution systems that comprise uncertainty of the load demand and power generation from intermittent renewable energy sources.
- The cost, emissions, and VDs are significantly reduced with the inclusion of RERs, while the VSI is significantly enhanced.
- The Monte Carlo simulation approach and backward reduction algorithm were successfully applied for modeling electrical system uncertainty.

6. Conclusions

This paper introduced the manta ray foraging optimizer (MRFO) as an efficient optimizer for identifying the optimal sizing and location of renewable-based DGs in RDN. A multi-objective function comprising total cost, emission, voltage deviation, and system stability was proposed and solved using the MRFO with consideration of the uncertainty of solar irradiance, load demand, and wind speed. The lognormal and normal Weibull PDFs were employed to emulate these uncertainties. Furthermore, Monte Carlo simulation was used to generate a set of scenarios (1000 scenario), which was reduced to 15 dominant scenarios using the backward reduction method. The robustness of the proposed optimization method was assessed through its applications on three radial distribution networks: IEEE 118-bus, rural 51-bus, and IEEE 15-bus distribution systems. Results show that, when considering the uncertainties and optimal insertion of solar PV- and wind turbine-based DGs, the expected cost, emission, voltage deviation, and the voltage stability index were improved by 40.27%, 62.6%, 29.33%, and 4.76%, respectively, for the IEEE 118-bus case study. For the 51-bus case study, if the uncertainties were taken into account, and the solar PV- and WT-based DGs were optimally allocated, these values were improved by 35.57%, 59.92%, 68.95%, and 11.88%, respectively. For the 15-bus case

study, if the uncertainties were taken into account, and the solar PV- and WT-based DGs were optimally allocated, these values were improved by 37.74%, 61.46%, 58.39%, and 8.86%, respectively. Compared to other optimization techniques (PSO, ALO, WOA, and SCA), the results reveal the superiority of the proposed algorithm in solving the allocation and sizing problem of the renewable-based DGs under deterministic and probabilistic states.

Author Contributions: Conceptualization, A.R., M.E. and S.K.; data curation, M.I.M. and A.A-S.; formal analysis, A.R., M.E. and S.K.; resources, M.I.M. and A.A-S.; methodology, M.I.M. and A.A-S.; software, A.R., M.E. and S.K.; supervision, A.R., M.E. and S.K.; validation, M.I.M. and A.A-S.; visualization, M.I.M. and A.A-S.; writing—original draft, A.R., M.E. and S.K.; writing—review and editing, M.I.M. and A.A-S. All authors read and agreed to the published version of the manuscript.

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