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Research Article

Strategic Sizing and Placement of Distributed Generation in Radial Distributed Networks Using Multiobjective PSO

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Distributed generators (DGs) offer significant advantages to electric power systems, including improved system losses, stability, and reduced losses. However, realizing these benefits necessitates optimal DG site selection and sizing. This study proposes a traditional multiobjective particle swarm optimization (PSO) approach to determine the optimal location and size of renewable energy-based DGs (wind and solar) on the Namibian distribution system. The aim is to enhance voltage profiles and minimize power losses and total DG cost. Probabilistic models are employed to account for the random nature of wind speeds and solar irradiances. This is used in an algorithm which eventually optimizes the siting and sizing of DGs using the nearest main substation as reference. The proposed method is tested on the Vhungu-Vhungu 11 kV distribution network in Namibia. Four cases were considered: base case with no DG, solar power, wind power, and a hybrid of both wind and solar. Optimal values for each case are determined and analyzed: 0.69.93 kW at 26 km for solar PV-based DG and 100 kW at 42 km for wind-based DG. These findings will serve as a valuable blueprint for future DG connections on the Namibian distribution network, providing guidance for optimizing system performance.

1. Introduction

Namibia faces a significant electricity demand, with 611 MW needed to meet its requirements. To fulfill this demand, the country heavily relies on imports, obtaining 60% of its electricity from South Africa and Zambia [1]. However, Namibia possesses a unique advantage due to its geographic location, as it boasts one of the highest solar irradiation levels in the world, reaching 3000 kWh/m^2 and an estimated maximum solar potential of 344 GW. Additionally, the country's 1600 km coastline experiences a yearly average wind speed of 10 m/s, offering a substantial wind energy potential of 27.201 GW. Furthermore, Namibia's terrain is covered with invader bush, which, if effectively utilized, has the potential to generate up to approximately 100 MW of power [2]. As Namibia looks to the future, there is an expectation of integrating numerous distributed generators (DGs) into its distribution networks. The integration of these renewable energy sources into medium voltage networks brings forth numerous benefits. However, it is crucial to emphasize that these benefits can only be fully realized if the size and location of these DGs are carefully determined and optimized. The optimal sizing and siting of DGs serve as the foundation for effective renewable energy planning in the country. The placement of DGs holds particular significance when considering the impact on power losses within the system. Addressing this issue requires careful consideration of the DGs' size and location, taking into account system losses, voltage stability, and overall network performance. Namibia's abundant solar irradiation, coastal wind resources, and potential utilization of invader bush present promising opportunities for renewable energy integration. However, optimizing the size and placement of DGs is paramount to ensure the realization of these benefits while mitigating potential challenges associated with power losses and voltage instability. By implementing effective planning strategies, Namibia can harness its renewable energy potential and pave the way for a sustainable and resilient energy future.

In residential distributed generation (DG) systems, the presence of voltage instability poses a potential challenge.

This is primarily due to the limitations of low voltage lines, typically operating at around 11 kV, which are unable to effectively accommodate the penetration of over 500 kW of generated electricity [3]. The voltage level at each bus, where both the DG units and loads are connected, further influences the extent of power losses experienced within the system [4]. The adverse impacts of DG integration on power losses have been extensively studied and documented [5]. To address the challenges associated with DG integration, researchers have solved the optimization problem of determining the optimal size and location of DG units within an existing distribution network [6]. By utilizing advanced optimization techniques such as multiobjective particle swarm optimization (PSO), researchers strive to identify the optimal configuration of distributed generation (DG) units that simultaneously minimize power losses and consider additional objectives such as voltage stability and cost. Extensive research and empirical studies have consistently demonstrated that a considerable portion of DGs, typically ranging from 10% to 50%, can be effectively integrated into distribution networks without compromising their overall performance [7]. However, achieving optimal integration and minimizing the impact on power losses require careful planning, taking into account factors such as network topology, load demand patterns, and available capacity.

Sizing and siting of distributed generators (DGs) in a radial distribution network pose a complex optimization problem. Single or a multiobjective approach is used. Single objective functions are aimed at minimizing system power losses, improving system voltage profiles, minimizing costs, enhancing system reliability, and more. On the other hand, multiobjective functions combine two or more single objective functions to capture multiple criteria simultaneously. Many articles in literature have worked on optimization techniques for DG integration; their main contribution and research gaps are individually analyzed in Table 1. Some literature focus on technical aspects [8–14], economic impacts [15–17], and environmental considerations [18]. Some literature considers a combination of both [16, 19, 20]. Various methods exist in the literature for solving the DG siting and sizing problem, each with its own advantages and disadvantages. Among them, particle swarm optimization (PSO) is widely utilized due to its simplicity, ease of implementation, and ability to explore a broad search space without being constrained by local optima. The weighted sum approach is commonly used in practical applications due to its simplicity and versatility in incorporating various constraints beyond the feasible region. This approach is indicated in [10, 11, 14, 20]. This approach involves assigning relative importance to different objectives based on their significance in the overall system performance. For instance, minimizing power losses or improving voltage profiles may be assigned higher priority compared to other objectives. Furthermore, it is crucial to consider the uncertainty associated with solar and wind resources [9, 10, 12, 13, 21, 22]. As solar and wind power generations exhibit intermittent characteristics, their output is subject to variability and uncertainty. Probabilistic or stochastic methods can be employed to model and analyze this uncertainty, enabling robust decisions in DG siting and sizing.

From the existing literature, it is evident that the majority of the researchers have focused on singular components of the objective functions, such as technical, economic, or environmental factors. However, this study takes a comprehensive approach by considering both technoeconomic aspects when addressing the optimal allocation of distributed generator (OADG) problem. One common limitation found in previous research is the assumption of dispatchable DGs, neglecting the stochastic nature of renewable energy-based DGs, specifically solar and wind. This assumption can lead to undesirable outcomes, as it fails to account for the intermittent and unpredictable nature of these energy sources. To overcome this limitation, this study acknowledges and incorporates the stochastic behavior of solar and wind resources into the analysis. Moreover, while some studies consider the random nature of renewable energy-based DGs, they often model it on a monthly or yearly basis [10, 13, 15]. This approach can potentially impact the accuracy of the results, as it overlooks the time-varying and hourly probabilistic characteristics of wind and solar resources. In contrast, this paper introduces an hourly probabilistic model that effectively captures the random nature of these energy sources, resulting in a more realistic representation of their behavior. The main contributions of this study can be summarized as follows:

(i) Development of an hourly probabilistic model: by incorporating an hourly probabilistic model, the study accurately captures the random characteristics of wind and solar resources, enabling a more precise analysis of their impact on the DG allocation problem

(ii) Consideration of technoeconomic parameters: in addition to system losses, this study takes into account important technoeconomic parameters such as DG investment cost and voltage profiles. By considering these factors, the proposed approach ensures that the DG sizing and siting decisions are not only technically sound but also economically viable

(iii) Introduction of a distance function: to determine the optimal distance of the DG from the slack, a distance function is introduced. This function helps in identifying the most favorable location for the DGs, considering factors such as power flow and voltage stability

(iv) Simultaneous siting of wind and solar DGs: unlike previous studies that often focus on either wind or solar DGs, this study considers the simultaneous siting of both types of DGs. This comprehensive approach allows for a more holistic and integrated analysis of renewable energy integration in the distribution system

(v) This study employed a traditional weighted multiobjective PSO approach. It utilizes relative weights to optimize multiple objectives effectively

Table 1: Literature review of use of MOPSO technique for optimizing DG sizing and placement in a distributed network.

Contribution	Ref.
(i) The study is aimed at reducing feeder losses and enhancing voltage quality. A Stamford generator, with a rated power of 1350 kW, was integrated into the network (ii) Research gaps: the analysis did not consider time-dependent loads and time-dependent generation. Additionally, renewable energy-based distributed generators (DGs) were not considered	[8]
(i) The modified voltage index (MVI) method was utilized to determine the optimal placement and size of DG units in order to enhance the voltage stability margin (ii) Research gaps: the study adopted a single DG placement approach, considering one DG at a time and assessing its placement at different buses. Economic variables such as investment and operational costs were not taken into consideration in the analysis	[9]
(i) The approach is aimed at minimizing power losses in the electrical network while improving voltage stability and network security. To address the stochastic nature of solar irradiance and wind speed, suitable probabilistic models were employed, allowing for realistic representation of their variability in the analysis (ii) Research gaps: the study focused solely on the technical aspects of optimal placement and sizing of solar and wind distributed generators (DGs) in the distribution territory; however, economic factors such as investment costs, operational costs, or financial considerations were not taken into account in the analysis	[10]
(i) Used weighted multiobjective voltage index to minimize real power loss and enhance the voltage profile within the system (ii) Research gaps: the study considers a general type of distributed generators (DGs) integrated into the network without specifying a particular DG type. The focus of the analysis is solely on technical aspects	[11]
(i) It employs a multistate modeling approach to account for the uncertain nature of wind and solar resources. The proposed model evaluates deviations in several key parameters, including annual energy losses (AEL), total DG penetration, loss of load expectation (LOLE), and loss of energy expectation (ii) Research gaps: the study primarily focuses on technical aspects and incorporates monthly, seasonal, and yearly models of solar and wind resources. It does not include hourly models, which means that the analysis does not account for the fine-grained variations and fluctuations in solar irradiance and wind speed throughout the day	[12]
(i) A methodology was proposed to optimize the allocation of different types of renewable distributed generation (DG) units within the distribution system with the objective of minimizing annual energy loss. This methodology involves the utilization of a multistate model for the hourly modeling of renewable energy sources (ii) Research gaps: the proposed methodology only focused solely on the technical aspects of optimally allocating different types of renewable distributed generation (DG) units within the distribution system	[13]
(i) Crow search algorithm (CSA) was used to determine the optimal size and allocation of distributed generators (DGs). A multiobjective function was formulated to address the objectives of reducing active power losses and improving the voltage profile (ii) Research gaps: the study solely focused on technical aspect only, and the algorithm was applied to IEEE 33-bus without incorporating real data	[14]
(i) Used time-varying and seasonal optimal placement and sizing of both intermittent renewable energy sources (such as wind energy) and nonintermittent renewable energy sources (such as solar energy). To account for the multistate and hourly probabilistic nature of wind speed and solar irradiance data, the study employed appropriate modelling techniques (ii) Research gaps: does not consider the economic aspects related to cost-benefit analysis or financial feasibility	[21]
(i) Uses multiobjective management approach that combines network reconfiguration with the allocation and sizing of renewable distributed generations (DGs) with the aim of minimizing active power loss, annual operation costs (including installation, maintenance and active power loss costs), and pollutant gas emissions. The optimization problem is solved by considering the time sequence variance in renewable DGs and load (ii) Research gaps: used simulation models (IEEE 33 bus) without validating the results against real-world data	[15]
(i) Incorporated both technical and economic aspects, with aim of minimizing power losses and maximizing profit. Additionally, it accounted for the stochastic nature of wind and solar resources (ii) Research gaps: the DG placement study lacked the use of real data and overlooked the significance of considering voltage profiles, which are crucial in DG placement studies	[16].
(i) An optimization model was developed to address the allocation of distributed generators (DGs) with the primary objective of minimizing the total planning cost (ii) Research gaps: the optimization model presented in the study focused solely on wind energy; integration challenges with other sources such as wind and solar were not tested and validated	[17]

Table 1: Continued.

Contribution	Ref.
(i) Multiobjective algorithm was applied to reduce power loss, maximizing the voltage stability index, minimizing voltage deviation, lowering real power loss costs, increasing real power loss savings, and reducing CO_2 emissions (ii) Research gaps: did not incorporate the potential effects of the intermittent nature of renewable distributed generations (DGs). The intermittent nature of renewable DGs, such as wind and solar, can introduce uncertainty and variability into the power system	[18]
(i) Three optimization techniques, PSO, variable constraint PSO (VCPSO), and GA algorithms, are applied to find the optimal size and placement of multiple DGs integrated into electrical power network. VCPSO was offered an improved solution for the optimal placement and size of DGs in terms of the accuracy of the global optimality (ii) Draw back: did not address the application of the hybrid PSO algorithm in real-world distribution networks	[19]
(i) Cost-based analysis was used on distributed generators (DGs), to determine installation costs, operational costs, and maintenance costs. The objective of the analysis was to minimize losses and maximize the loading capability of the system while ensuring that voltage stability is not compromised (ii) Research gaps: assumed a constant factor of 0.95 as power factor for DG operation which is not the case in real-life situations; the power factor of DGs may vary depending on various factors such as load conditions, system requirements, and control strategies	[20]
(i) Crisscross optimization algorithm and Monte Carlo simulation method (CSO MCS), used to address the optimal distributed generation allocation (ODGA) problem. This method considers the uncertainties associated with wind, solar, and load consumption (ii) Research gaps: does not consider an hourly resolution. This can lead to inaccurate results, as it fails to capture the time-varying nature of renewable energy generation	[22]
(i) PSO is used on IEEE 33 radial distribution system with different types of voltage-dependent load models. The results reveal that combination of active–reactive power DG is giving better results for power loss reduction and voltage profile improvement (ii) Research gaps: the study did not investigate the integration of renewable energy sources or consider uncertainties related to renewable generation	[23]
(i) Provided a review of optimization techniques used for DG sizing and placement in a distributed network (ii) Research gaps: did not consider different scenarios and constraints to identify the most appropriate techniques for specific applications	[24]
(i) MOPSO algorithm has been used to find the optimal solution of DG sizing and locating problem; this was tested on IEEE 33-bus reliability enhancement of the grid which was confirmed (ii) Research gaps: did not consider implementing renewable DGs with uncertain output power, such as PV panels or wind turbines	[25]
(i) Used multiobjective bat algorithm on IEEE 69-bus; from the obtained results, it is observed that the best localization and sizing of DG unit give more flexibility to the network (ii) Research gaps: did not cost function and the algorithm did not use real data	[26]
(i) A backtracking search optimization algorithm (BSOA) is developed to enhance voltage profile and reduce real network losses (ii) Research gaps: the study assumed that the output of renewable energy (RE) sources is dispatchable, hence did not consider intermittent nature of renewable energy sources	[27]

(vi) The study validates the proposed algorithm using real data of wind and solar applied to a practical distribution network as opposed to simulation models mostly used by researchers

2. Probabilistic Modelling of Renewable Energy Sources

2.1. Modeling of Wind Turbine Generator. Wind power exhibits a stochastic nature as it is influenced by the random and variable wind speeds. Modeling of such system at a particular hour t is achieved using the Weibull probability distribution function as given in [16]

$$f_v(v)^t = \frac{k^t}{C^t}\left(\frac{v}{C^t}\right)^{k^t-1} e^{-\left(v/C^t\right)^{k^t}} C^t, \tag{1}$$

where $f_v(v)^t$ is the Weibull PDF, C^t is the scale parameter, and k^t is the shape parameter at time period t hour.

The Weibull PDF parameters at a particular time t hour can be estimated by using the following equations [16]:

$$\begin{aligned} k^t &= \frac{{\sigma_v}^t}{{\mu_v}^t}, \\ C^t &= \frac{{\mu_v}^t}{\Gamma\left(1+\left(1/k^t\right)\right)}, \end{aligned} \tag{2}$$

where ${\sigma_v}^t$ and ${\mu_v}^t$ represent the standard deviation and the mean wind speeds at specific time t hour. $\Gamma()$ is a gamma function at time t hour.

2.2. Modeling of PV Generator. Solar irradiances vary throughout the day. Beta probability function is used to describe the uncertain nature of the solar resources [16].

Beta PDF at a time period t hour is defined by

$$f_s(s)^t = \begin{cases} \dfrac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} (s^t)^{\alpha^t+1}(1-s^t)^{\beta^t+1}, 0 \le s < 1, \alpha \ge 0, \beta \ge 0, \\ 0, \text{otherwise} \end{cases} \quad (3)$$

where α^t and β^t are the beta parameters. These parameters can be approximated using the following equations [14]:

$$\begin{aligned} \beta^t &= (1-\mu_s{}^t)\left[\frac{\mu_s{}^t(1+\mu_s{}^t)}{\sigma_s^2} - 1\right], \\ \alpha^t &= \frac{\mu_s{}^t \beta^t}{1-\mu_s{}^t}, \end{aligned} \quad (4)$$

where μ_s and α_s are the mean and variance of the solar irradiance.

2.3. Modeling of Electrical Loads. Modelling of loads in an electrical network is classified as follows:

(i) Constant power loads: there is no relationship between the voltage and the power drawn at each bus

(ii) Constant current loads: the voltage varies proportional with the active and reactive powers

(iii) Constant impedance loads: the active and reactive powers are directly proportional to the square of the voltage

To investigate the effect of changes in load demand over the year, this paper proposes modelling of loads as constant time-varying loads. This model considers the potential increase in loads that may occur during the planning horizon. The active and reactive power demands in year N_y are represented by the following [23]:

$$\begin{aligned} P_{L,i}(N_y) &= P_{L,i}(0) \times (1+r)^{N_y}, \\ Q_{L,i}(N_y) &= Q_{L,i}(0) \times (1+r)^{N_y}, \end{aligned} \quad (5)$$

where $P_{L,i}(N_y)$ and $Q_{L,i}(N_y)$ are the active and reactive power loads at bus i after N_y years, respectively. $P_{L,i}(0)$ and $Q_{L,i}(0)$ are the active and reactive power loads at bus i for the base year, respectively. r is the annual growth rate in the load. This value is calculated based on the historical data on the load profiles, and N_y is the number of years in the planning period.

2.4. Power Generation Models

2.4.1. Power Generation by PV Array. PV module power is a function of the temperature (T) and solar irradiance s and is determined by the following equations [12]:

$$\begin{aligned} T_c &= T_a + \frac{s}{800}(T_{NOCT} - 20), \\ I &= \frac{s}{s_{ref}}[I_{sc} + \gamma_{sc}(T_c - T_{c,ref})], \\ V &= V_{oc} - (\gamma_{oc} - T_c), \\ FF &= \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{sc}}, \\ P_{PV} &= FF \times V \times I, \end{aligned} \quad (6)$$

where P_{PV} is the power produced by the PV module (W), FF is the fill factor of the module, V is the module voltage output (V), I is the module current output (A), T_c is the cell temperature (°C), T_a is the ambient temperature (°C), T_{NOCT} is the normal operating temperature of the module, $T_{c,ref}$ is the reference temperature (25°C), s_{ref} is the reference insolation (1000 W/m^2), I_{sc} is the short circuit current of the module, V_{oc} is the open circuit voltage of the module (V), V_{mpp} is the voltage at maximum power point (V), I_{mpp} is the current at maximum power point (A), γ_{sc} is the current temperature coefficient (A/°C), and γ_{oc} is the voltage temperature coefficient (V/°C).

2.4.2. Power Generation by Wind Turbine. The output power of a WT at time t hour is given by [24]

$$P_{WT}(v) = \begin{cases} 0 & , V < V_{ci}, \\ \dfrac{V^2 - V_{ci}^2}{V_{rated}^2 - V_{ci}^2} P_{rated} & , V_{ci} < V \le V_{rated}, \\ P_{rated} & , V_{rated} < V \le V_{co}, \\ 0 & , V > V_{co}, \end{cases} \quad (7)$$

where $P_{WT}(v)$ is the power produced by the WT at speed v and P_{rated}, V_{rated}, V_{ci}, and V_{co} are the rated power, rated speed, cut-in wind speed, and cut-out wind speed, respectively.

To determine the power produced at each state, the probability of that specific state that gives its overall contribution to the total power produced in hour t should be known. The probabilities of solar insolation and wind speeds at state N_s are given by the following equations [12]:

$$\begin{aligned} p_s(N_s) &= \int_{s_1}^{s_2} f_s(s), \\ p_v(N_s) &= \int_{v_1}^{v_2} f_v(v), \end{aligned} \quad (8)$$

where $p_s(N_s)$ is the probability of solar irradiance in state N_s, $p_v(N_s)$ is the probability of solar irradiance in state N_s, and s_1 and s_2 are the lower and upper limit insolations for state N_s.

w_1 and w_2 are the lower and upper limit wind speeds for state N_s.

The power produced in an hour t by the PV module and the WT is the summation of the power produced at each state in that hour and is given by the following

Table 2: Weight factors.

	PLI	QLI	VPII	CFI
	α_1	α_1	α_1	α_1
Weight	0.3	0.2	0.3	0.2

equations [12]:

$$P_{\mathrm{pv}}^{t} = \sum_{n=1}^{n_s} p_{\mathrm{s}}(N_{\mathrm{s}}) \times P_{\mathrm{PV}}, \tag{9}$$

$$P_{\mathrm{wt}}^{t} = \sum_{n=1}^{n_s} p_{v}(N_{v}) \times P_{\mathrm{WT}}, \tag{10}$$

where P_{pv}^{t} is the power produced by the PV module at hour t and P_{wt}^{t} is the power produced by the WT at hour t.

3. Problem Formulation

The primary objective of this research is to strategically determine the optimal placement and sizing of distributed generators (DGs) to minimize total system losses and overall DG cost and enhance voltage profiles. The problem formulation incorporates a multiobjective function that considers these objectives while adhering to specified constraints [17]. To achieve optimal solutions, the algorithm leverages network performance indices. The formulated multiobjective function, considering the use of network performance indices, is expressed as follows:

$$\min (F) = \alpha_1 \mathrm{PLI} + \alpha_2 \mathrm{QLI} + \alpha_3 \mathrm{VPII} + \alpha_4 \mathrm{CFI}, \tag{11}$$

where α_1, α_2, α_3, and α_4 are the weights between [0,1] and $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$, PLI is the real power loss index, QLI is the reactive power loss index, VPII is the voltage profile improvement index, and CFI is the cost factor index.

The weights assigned to each impact index represent the relative importance of each index within the analysis. These weights are determined based on the specific analysis conducted. It is essential to acknowledge that these weight values may vary depending on the unique concerns and preferences of the engineer involved [24].

In this study, the significance of each performance index is assessed through a detailed technical analysis of the network. This analysis carefully evaluates the influence of each objective on the overall system performance. The weights assigned to each index, as presented in Table 2, reflect the outcomes of this analysis.

3.1. Objective Functions

3.1.1. Power Loss. The active and reactive power losses on any network are formulated as given by the following equation [16]:

$$\begin{aligned} P_{\mathrm{L}} &= \sum_{i=1}^{N_{\mathrm{bus}}} |I_i|^2 \times R_i, \\ Q_{\mathrm{L}} &= \sum_{i=1}^{N_{\mathrm{bus}}} |I_i|^2 \times X_i, \end{aligned} \tag{12}$$

$$\begin{aligned} P_{\mathrm{L},T} &= \sum_{y=1}^{N_y} \sum_{t=1}^{62} P_{\mathrm{L}}, \\ Q_{\mathrm{L},T} &= \sum_{y=1}^{N_y} \sum_{t=1}^{62} Q_{\mathrm{L}}, \end{aligned} \tag{13}$$

where P_{L} and Q_{L} are the active and reactive power losses, I_i and R_i represent the current and resistance of branch i, N_{bus} is the total number of buses in the network, N_y gives the number of years of the specified period, and t is time in hours.

3.1.2. Voltage Profile. The voltage profile function is derived from voltage magnitude at bus i given in the following equation [25]:

$$\mathrm{VP} = \sum_{y=1}^{N_y} \sum_{t=1}^{62} \sum_{i=1}^{N_{\mathrm{bus}}} (V_i - V_{\mathrm{rated}})^2, \tag{14}$$

where V_i is the voltage magnitude at bus i and V_{rated} is the desired steady-state voltage.

3.1.3. Total DG Cost. The total DG cost is the summation of the investment, maintenance, and operation cost.

(1) Investment Cost. The investment cost includes the start-up costs such as the amount of money spent on construction and installation of individual DG units. This can be calculated using the following equation [16]:

$$C_{\mathrm{investment}} = \sum_{n=1}^{N_{\mathrm{DG}}} P_{\mathrm{R}n} C_{\mathrm{inv}}, \tag{15}$$

where $P_{\mathrm{R}n}$ is the rated power of DG unit n, C_{inv} is the investment cost of DG n, and N_{DG} is the total number of DGs.

(2) Operation and Maintenance Costs. Operation and maintenance costs are the costs for generation, repairing, and renewable DG equipment. This cost is modelled using the following equation [16]:

$$C_{\mathrm{oper,maint}} = \sum_{y=1}^{N_y} \sum_{n=1}^{N_{\mathrm{DG}}} P_{\mathrm{R}n} C_{\mathrm{OM}} \left(\frac{1 + \mathrm{INFR}}{1 + \mathrm{INTR}} \right)^{p}, \tag{16}$$

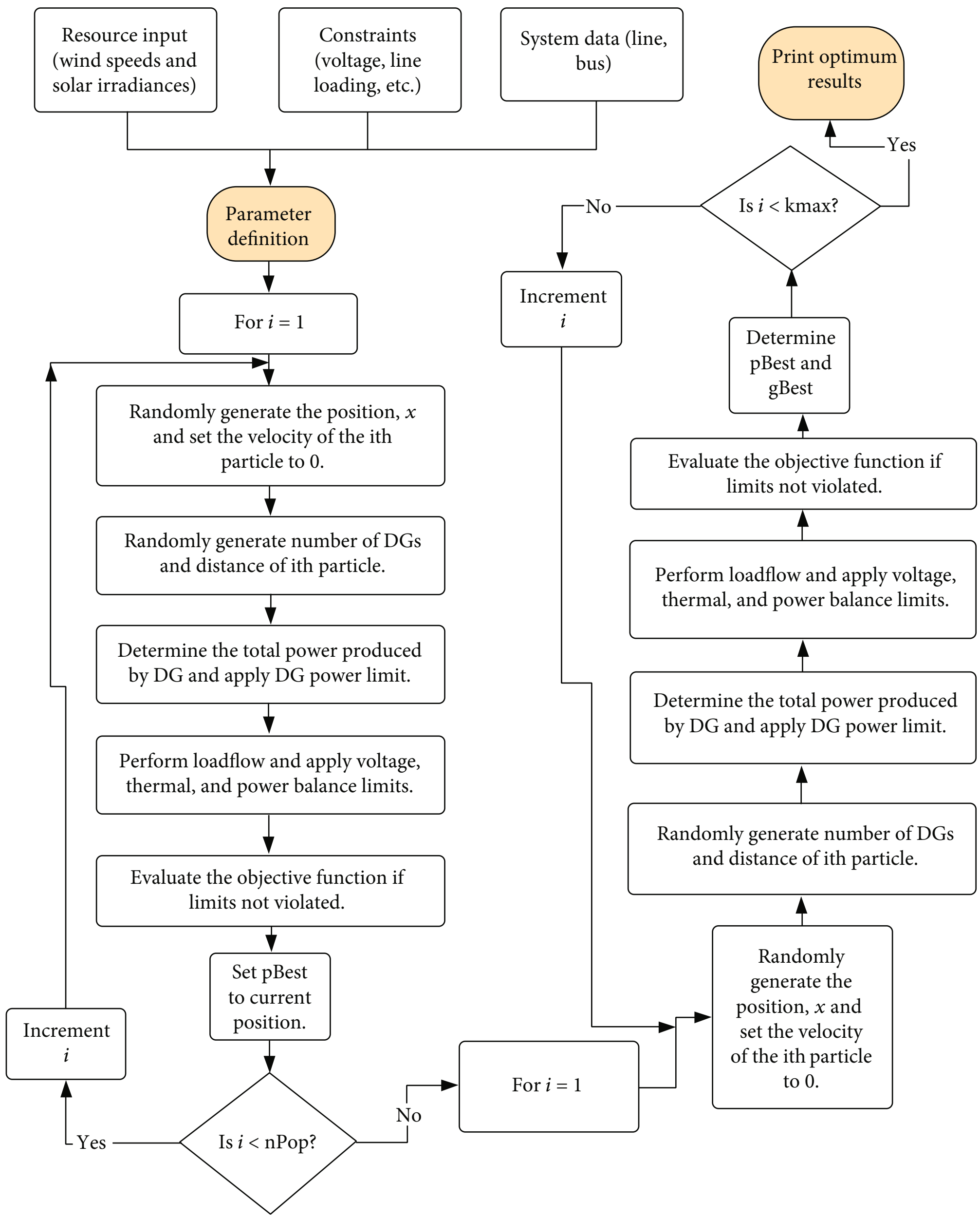

Figure 1: Algorithm for optimal sizing and placement of DGs on distribution network.

where C_{OM} is the operation and maintenance costs of DG unit n (N$/MWh), INFR is the inflation rate, INTR is the interest rate, and N_y is the number of years in the planning period.

So, the total cost is

$$C_{DGT} = C_{oper,maint} + C_{investment}. \quad (17)$$

3.2. Performance Index Formulation

3.2.1. Real Power Loss Index. The real power loss index based on network with DG placement and without DG placement is modeled as given in the following equation [25]:

$$\text{PLI} = \frac{P_{L,\text{with DG}}}{P_{L,\text{without DG}}}, \quad (18)$$

where $P_{L,\text{with DG}}$ is the active power losses after DG placement and $P_{L,\text{without DG}}$ is the real power losses of the network without DG.

3.2.2. Reactive Power Loss Index. The real power loss index is given by [18]

$$\text{QLI} = \frac{Q_{L,\text{with DG}}}{Q_{L,\text{without DG}}}, \quad (19)$$

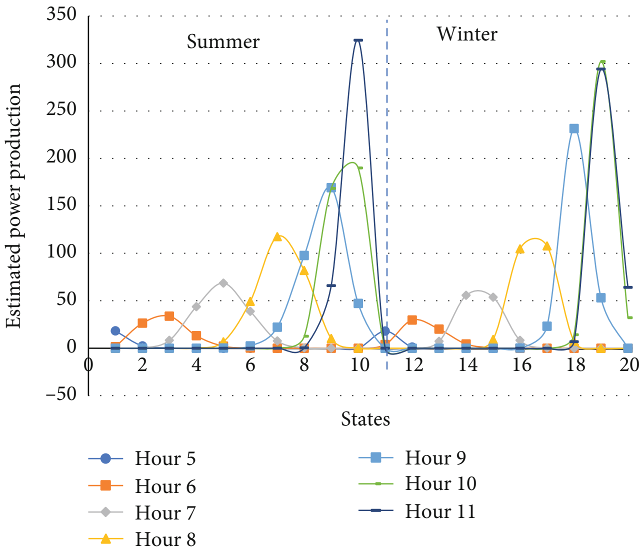

Figure 2: Estimated power produced by PV module at different states (kW).

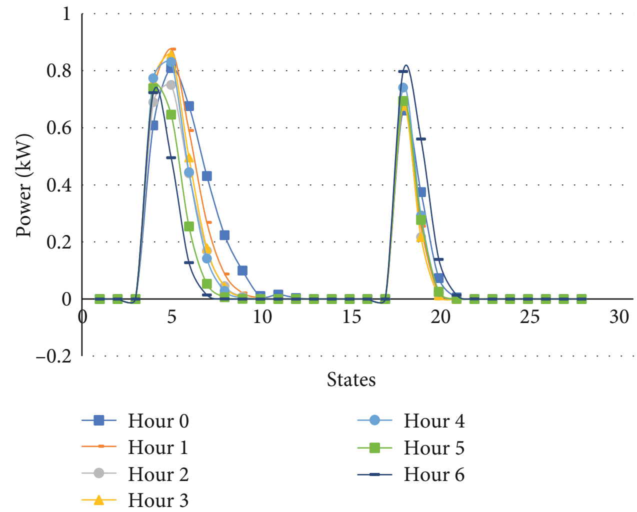

Figure 3: Estimated power produced by WT module at different states (kW).

where $Q_{\mathrm{L,with\,DG}}$ is the reactive power losses after DG placement and $Q_{\mathrm{L,without\,DG}}$ is the reactive power losses of the network without DG.

3.2.3. Voltage Profile Improvement Index. The voltage profile improvement index (voltage stability index) is an indication of how stable a distribution network is. In this paper, VPII is modeled using equation (20), which compares voltage profile of a network with DG with that without DG [26].

$$\mathrm{VPII} = \frac{\mathrm{VP}_{\mathrm{with\,DG}}}{\mathrm{VP}_{\mathrm{without\,DG}}}. \tag{20}$$

3.2.4. Cost Factor Index. The index of the total DG cost is expressed as given by the following equation [26]:

$$\mathrm{CFI} = \frac{\mathrm{Cost}_{\mathrm{DG}}}{\mathrm{Cost}_{\mathrm{DG}}^{\max}}, \tag{21}$$

where $\mathrm{Cost}_{\mathrm{DG}}$ is the cost of the selected DG and $\mathrm{Cost}_{\mathrm{DG}}^{\max}$ is the maximum cost of DG at maximum DG penetration.

3.3. Constraints. In optimization problems, constraints define a region that is feasible within the search space. The minimization problem is subjected to the following equality and equality constraints.

3.3.1. Power Balance Constrain. Complex power injected at each bus should be equal to complex power drawn at that particular bus. This constraint is shown in the following equations [9]:

$$P_{\mathrm{G}i} - P_{\mathrm{L}i} = |V_i| \sum_{j=1}^{N_{\mathrm{bus}}} |Y_{ij}||V_j| \cos\left(\delta_i - \delta_j - \theta_{ij}\right), \tag{22}$$

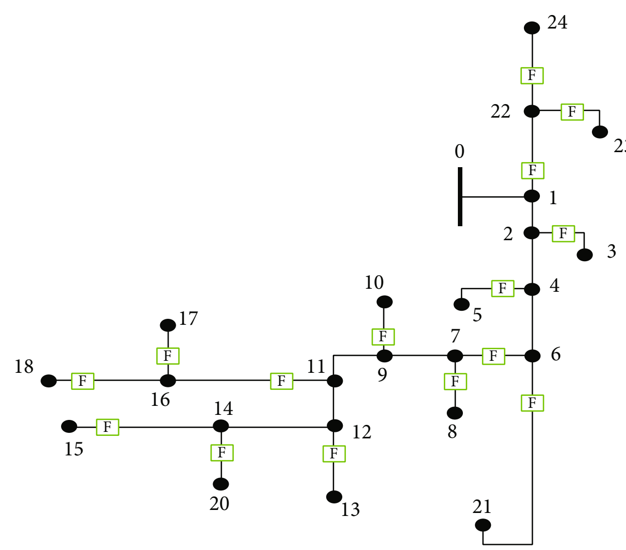

Figure 4: Vhungu-Vhungu distribution network (11 kV).

$$Q_{\mathrm{G}i} - Q_{\mathrm{L}i} = |V_i| \sum_{j=1}^{N_{\mathrm{bus}}} |Y_{ij}||V_j| \sin\left(\delta_i - \delta_j - \theta_{ij}\right), \tag{23}$$

where $P_{\mathrm{G}i}$ is the active power output of the generator at bus i, $P_{\mathrm{L}i}$ is the active power load at bus i, $Q_{\mathrm{G}i}$ is the reactive power output of the generator at bus i, $Q_{\mathrm{L}i}$ is the reactive power load at bus i, Y_{ij} and θ_{ij} are the magnitude and angle of the admittance related to bus i and j.

3.3.2. Generation Capacity. The size of the DGs should be within the following size limits [19]:

$$P_{\mathrm{DG}i}^{\min} \le P_{\mathrm{DG}i} \le P_{\mathrm{DG}i}^{\max}, \tag{24}$$

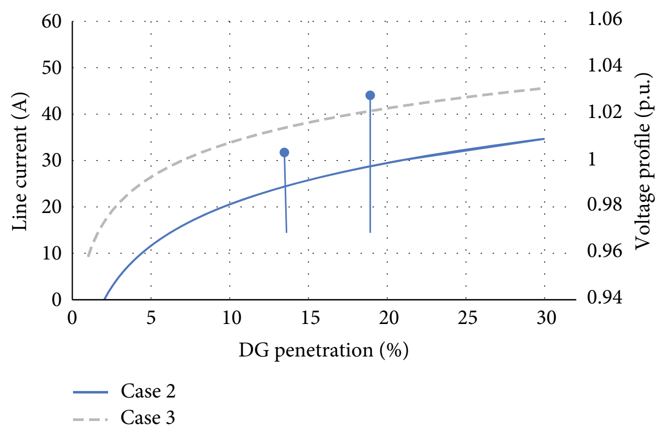

Figure 5: Optimum sizing for Vhungu-Vhungu network (Cases 2 and 3).

where $P_{\mathrm{DG}i}^{\min}$ and $P_{\mathrm{DG}i}^{\max}$ are the minimum and maximum power outputs injected at bus i.

(1) Bus Voltage Limits. The voltage at each bus should be maintained within their upper and lower limits. These limits are specified by the network operator [20].

$$V_{i,\min} \leq V_i \leq V_{i,\max}, \tag{25}$$

where $V_{i,\min}$ and $V_{i,\max}$ are the minimum and maximum voltage magnitudes at bus i, respectively. For this work, these limits are taken to be

$$0.95 \leq V_i \leq 1.05. \tag{26}$$

(2) Line Loading Limit. The current through any feeder (I_i) should be within the maximum thermal capacity ($I_{i,\max}$) of that particular feeder. This limit is given by [20]

$$I_i \leq I_{i,\max}. \tag{27}$$

4. Proposed PSO for DG Placement

The proposed algorithm as given in Figure 1 is designed to optimally size and place DGs in a distribution network in order to implement and to minimize total system losses, improve voltage profiles, and minimize total DG cost. PSO parameters such as maximum number of iterations, $k_{\max}$, swarm size, nPop, inertia weight, acceleration coefficients, c_1 and c_2, velocity limits, $v_{\min}$ and $v_{\max}$, and position limits, $x_{\min}$ and $x_{\max}$. The number of DGs (N) and the distance from the main bus d are randomly generated.

Power produced by two DGs is given by

$$P_{\mathrm{DG,PV}} = N \times P_{\mathrm{pv}}^{t}, \tag{28}$$

$$P_{\mathrm{DG,WT}} = N \times P_{\mathrm{wt}}^{t}. \tag{29}$$

Optimal power and site are then evaluated by first performing load flow analysis within the constraints given in

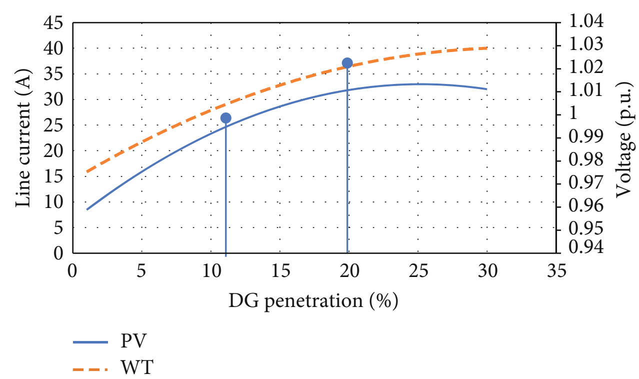

Figure 6: Optimum sizing for Vhungu-Vhungu network (Case 4).

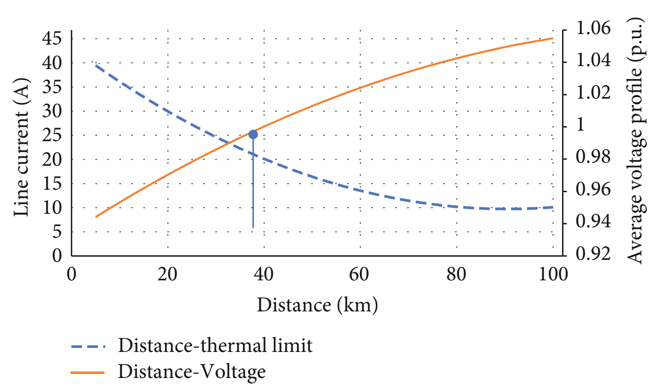

Figure 7: Optimum siting for Vhungu-Vhungu network (Case 2).

Section 3.3. Finally, the objective functions are evaluated using the following steps:

(1) Parameter definition: $k_{\max}$, nPop, c_1, c_2, $v_{\min}$, $v_{\max}$, $x_{\min}$, $x_{\max}$, and w

(2) Define control variables (number of WT and number of PV, distance from the main bus)

(3) Set g_{best} to infinity

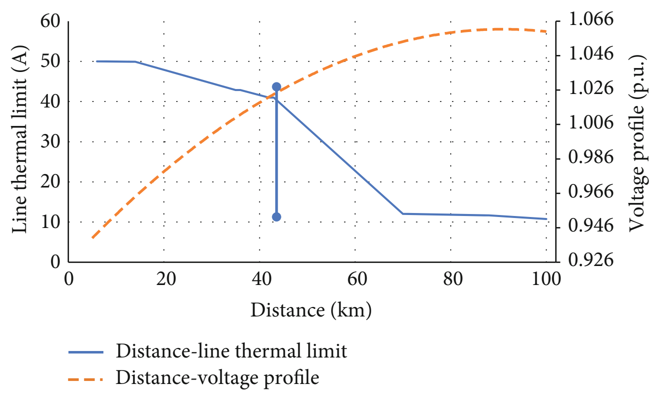

Figure 8: Optimum siting for Vhungu-Vhungu network (Case 3).

(4) For $i = 1$: nPop
  - (i) Initialization: randomly initialize position x and set velocity $v = 0$ for each particle
  - (ii) Randomly generate the number of WT and PV and distance from the main bus
  - (iii) Input system data, line data, bus data, and constraints
  - (iv) Input solar and wind resources
  - (v) Run load flow
  - (vi) Evaluate the objective function of each month in every season
  - (vii) Update personal best (p_{best}) and global best (g_{best})

(5) For $i = 1$: k_{max}
  - (i) Update velocity and apply velocity limits v, and apply velocity limits, v_{min} and v_{max}
  - (ii) Update position x, and apply position limits, x_{min} and x_{max}
  - (iii) Randomly generate the number of WT and PV and distance from the main bus
  - (iv) Input system data, line data, bus data, and constraints
  - (v) Input solar and wind resources
  - (vi) Run load flow
  - (vii) Apply constraints
  - (viii) Evaluate objective function each month in every season
  - (ix) Update personal and global best
  - (x) Print the optimum size and location

4.1. Wind, Solar Data, and Load Data Analysis. Strategic integration of renewable energy in the network appropriate analysis of wind, solar, and load data is important. Seasonal model where a year is divided in winter (May to October) and summer (November to April) is used in data collection. The seasons are further classified in 24 hours for one day and 182 days per season. Solar irradiance data is collected for 2 years giving 362 days of analysis, while wind speed is data collected for one year making 182 days of analysis.

Solar irradiance was modelled using beta PDF, and the wind speed was fitted with the Weibull PDF.

The solar irradiances each hour t were divided into 10 states with each state adjusted to 1 kW/m^2. Wind speeds were divided into 14 states with each state adjusted by 1 m/s. For each hour, the mean and standard deviations, probabilities, and power produced were evaluated. Total power produced in an hour t was determined as the summation of the power produced at different states. The results obtained and the ratings of the PV module and WT are shown in Figures 2 and 3.

4.2. Wind, Solar Data, and Load Data Analysis. The proposed algorithm was tested on a Namibian distribution network, *Vhungu-Vhungu* 11 kV, as detailed in Section 5.

5. Simulation Results

As stated during the algorithm's development, the primary objective behind strategically positioning and sizing the DGs is to minimize losses and enhance voltage profiles. To analyze the networks, simulations were conducted using the DIgSILENT Power Factory software. The Newton-Raphson method was employed to assess the load flows. Moreover, the multiobjective particle swarm optimization (PSO) algorithm was created and executed using MATLAB.

This is done by considering varying loads and renewable sources. For placement, DGs are injected at the main bus bar (substation), where the number of DG units and the distance (in a range of 5-100 km) from the main substation are randomly generated. The output power of the DGs and distance are adjusted to give a minimum fitness value. This is to balance the total losses and power consumed by loads to

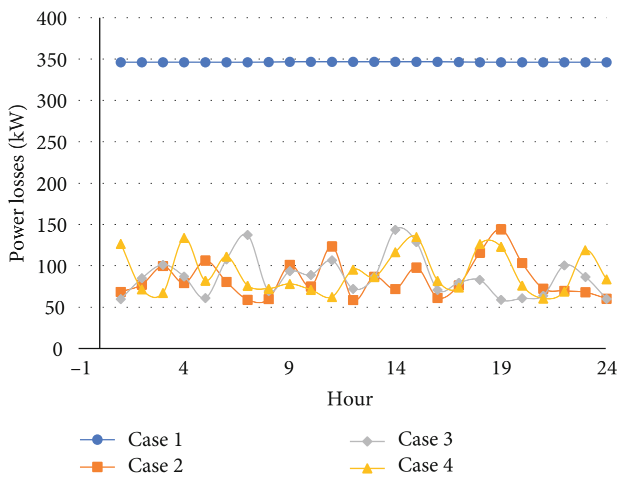

Figure 9: Hourly power losses for Vhungu-Vhungu network in summer.

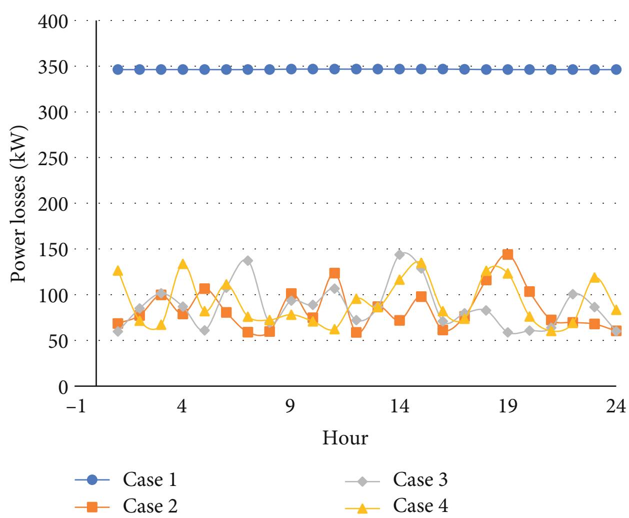

Figure 10: Vhungu-Vhungu network's hourly reactive power losses for winter.

the DG output and the power fed by the grid, thus reducing the supply burden on the grid.

For each test network, the following scenarios are considered:

(i) Case 1: no DG (base case)

(ii) Case 2: only PV is connected

(iii) Case 3: only wind-DG is connected

(iv) Case 4: combination of wind and PV units

5.1. Test System: Vhungu-Vhungu. The PSO algorithm proposed in this study is evaluated using the Vhungu-Vhungu 11 kV distribution feeder, as depicted in Figure 4. The distribution network consists of 24 buses (1 is slack bus, 11 PV buses, and 12 load buses), peak of hourly load of 577 KVA, and maximum feeder capacity of 53 A. The distribution

Table 3: Total power losses for Vhungu-Vhungu network (MW).

Region	Before placement Case 1	After placement Case 2	Case 3	Case 4
Summer	49.89	14.33	14.47	13.99
Winter	49.91	14.06	14.19	14.48
Total	99.8	28.39	28.66	28.47

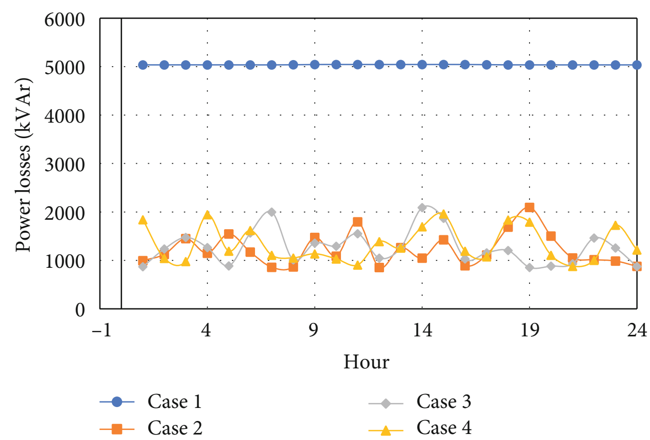

Figure 11: Vhungu-Vhungu network's hourly reactive power losses for summer.

feeder is situated in the Uvhunghu-Vhungu area of the Okavango East Region. It serves a peak load of 496.22 kW, mainly composed of agricultural and residential consumers. The maximum allowable integration of distributed generation (DG) into the network is limited to 148.87 kW, representing 30% of the peak load.

Case 2. The optimum fitness value was achieved with 189 PV modules rated at 69.93 kW and placed at 26 km from the main substation.

Case 3. The optimum fitness value was achieved with 1 wind turbine rated at 100 kW and placed at 42 km from the main substation.

Case 4. The optimum fitness value was achieved with 179 PV modules rated at 65.12 kW and placed at 26 km from the main substation and 1 wind turbine rated at 100 kW placed at 26 km from the main substation.

For each case, variations in DG penetration were plotted where the optimum size and location of the DGs were achieved based on two constraints: thermal limit and voltage profile limit. Simulation results for increased DG penetration and optimum sizing and siting based on the proposed algorithm are as shown in Figures 5–8

In Figure 5, it is observed that, for each case that thermal limit and voltage profile are within the limit of maximum thermal capacity of 53 A and voltage limit of $0.95 \leq v_i \leq 1.05$, for Case 2 (69.96/496.22 = 14%) and Case 3 (100/496.22 = 20%), the same applies to Case 4 in Figure 6. For optimum siting

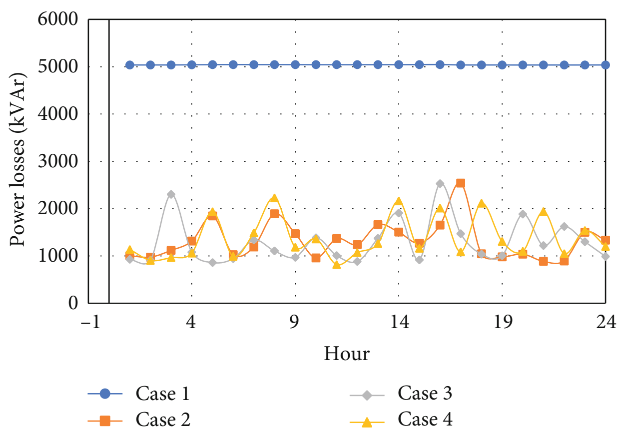

Figure 12: Hourly reactive power losses for Vhungu-Vhungu network in winter.

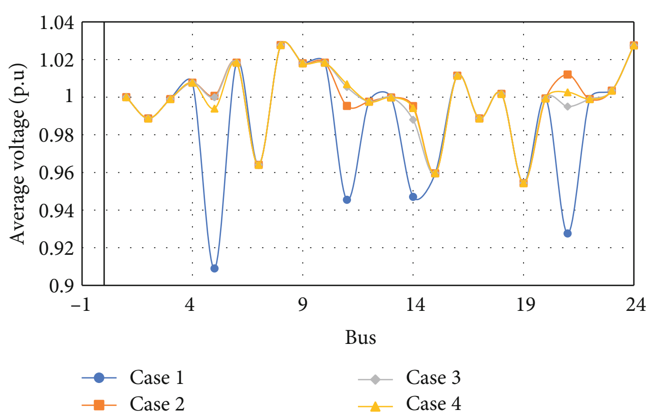

Figure 13: Average bus voltages for Vhungu-Vhungu network.

Table 4: Average voltages at sensitive buses got Vhungu-Vhungu (bus voltages in p.u.).

Bus	Case 1	Case 2	Case 3	Case 4
5	0.909	0.9999	0.9999	0.9939
11	0.94545	0.9953	1.007	1.0071
14	0.947	0.9947	0.9880	0.9942
21	0.9276	1.0121	0.999	1.0026

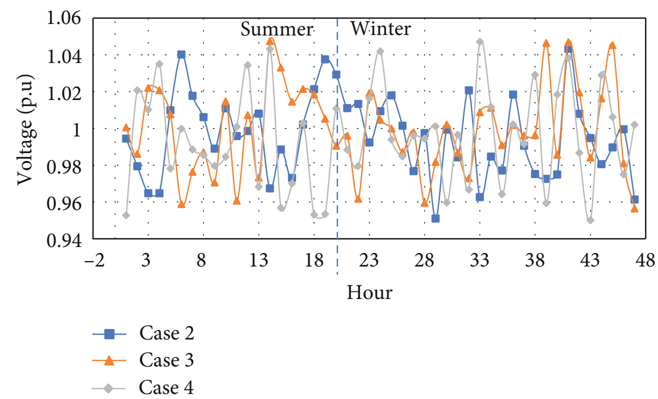

Figure 14: Variation of voltage at bus 5 for Vhungu-Vhungu network.

given in Figures 7 and 8, the line current decreases with increase in distance and voltage profile increases with increase in distance. So, the optimum site becomes the intersection between the graphs of distance-line current and distance-voltage profile.

5.1.1. Active Power Loss Reduction. Integration of DG units into the system results in significant reduction in power losses with highest of 71.55% (from 99.8 MW to 28.29 MW) recorded in Case2. For Cases 3 and 4, the total power losses were reduced by 71.25% and 71.46%, respectively. The variation of these power losses with respect to time for both summer and winter is presented in Figures 9 and 10.

The proposed algorithm has successfully determined the optimal sizes and locations for the integration of distributed generation (DG) units. The resulting active power losses for each of the four cases are presented in Table 3.

5.1.2. Reactive Power Loss Reduction. While the distributed generators (DGs) in the system are designed to supply active power exclusively, they also contribute to a substantial reduction in reactive power losses. The network under analysis is a rural distribution network primarily catering to agricultural and residential loads. In such a network, the presence of inductive devices, such as induction motors, leads to reactive power consumption. Consequently, voltage drops and fluctuations may occur, compromising the stability and reliability of the electrical system. The reduction in reactive power losses is visually represented in Figures 11 and 12.

5.1.3. Voltage Profile Improvement. The integration of distributed generation (DG) units has a positive impact on the voltage profiles of the network, as demonstrated in Figure 13. Comparing Case 1 with Cases 2, 3, and 4, it is evident that Case 1 exhibits a relatively poorer voltage profile. With DG penetration, the voltages at each bus remain within the permissible limits of 0.95 p.u. and 1.05 p.u. Significant voltage changes are only observed at buses 5, 11, 14, and 21, which are considered weaker buses. The analysis of voltage variation at these weaker buses is presented in Table 4. Among them, bus 5 is identified as the weakest, and its voltage variation is further examined in Figure 14. Notably, both Case 1 and Case 2 exhibit a 7.9% improvement in voltage profile at bus 5 (from 0.909 p.u to 0.9999 p.u). Although Case 2 shows a greater voltage improvement, the disparity in voltage enhancement across buses in each case is not significant. The higher voltage change observed at bus 5 can be attributed to its larger number of induction motors, resulting in a higher consumption of reactive power.

5.1.4. Total Cost Analysis. By using the proposed algorithm on cost analysis and applying the cost factor index as given

Table 5: Technical and economical indices for 5 years for Vhungu-Vhungu.

Indices	Case 1	Case 2	Case 3	Case 4
Investment cost PV ($M)		0.06993		0,06512
Investment cost WT ($M)			0.11	0.11
Total investment cost ($M)		0.06993	0.11	0.17512
Operation and maintenance cost PV ($M)		0.003556		0.003329
Operation and maintenance cost WT ($M)			0.005717	0.005717
Total operation and maintenance cost ($M)		0.003556	0.005717	0.009046
Total active energy losses (MWh)	9731	5181.175	5193.95	5199.425

in equation (21), technical and economical indices are shown in Table 5.

Table 5 shows the operational cost, the investment cost, and the total energy losses after a period of 5 years for each case; it can be shown that the cost of active power loss decreases with DG penetration. This improves economic efficiency eventual reduction in carbon emission.

The total cost given is optimized cost since the DG size and placement are determined based on the optimized algorithm given. This eventually reduces feeder losses, hence reduction in total active power loss.

6. Conclusions

A weighted multiobjective PSO was presented in this work to site and size renewable energy-based DGs on a distribution network. PSO is implemented to minimize total system losses, improve voltage profiles, and minimize total DG cost. Stochastic nature of solar irradiances and wind speeds was modelled using appropriate probabilistic models. Seasonal model was utilized. To effectively analyze the hourly data for each season, a multistate model was employed. This model divided the data into different states, enabling a comprehensive assessment of the system's performance. The control variables for DG placement and sizing were determined based on the number of DG units, including both photovoltaic (PV) and wind turbine (WT) units. The sizes of the DG units were randomly generated and injected at the slack bus to assess their impact on the system.

The proposed optimization technique was tested on one of Namibian's distribution network, and results obtained showed improved voltage profile, minimized active power loss, and reduced cost of the total power supplied.

To realize the benefit of voltage profile improved, total cost reduction, and minimized power loss, the optimized placement and sizes of DG integration in the network were found: For Case 2, the optimum size of PV was found to be 69.93 kW and placed at a distance of 26 km from the main substation. For Case 3, the optimum size of WT was found to be 100 kW and placed at a distance of 42 km from the main substation. For Case 4>, the optimum size for both PV and wind-based DGs was found to be 65.12 kW and 100 kW, respectively. The PV farm was placed at a distance of 37 km from the main substation and the wind farm at 20 km from the substation. By achieving these positive outcomes, the study underscores the potential benefits of DG integration and emphasizes the importance of carefully determining the appropriate sizes and locations for optimal performance.

Data Availability

The data supporting the results can be found in references [2].

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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