



OPEN Investigating distributed generator high penetration in improving technical, emission and economic constraints of distribution network

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The widespread integration of distributed power generation plants (DGPs) into distribution networks has become a standard practice in many countries worldwide. The benefits gained from DGP deployment are heavily influenced by their optimal planning and placement. This study introduces an innovative approach that combines the Energy Valley Optimizer (EVO) with Fuzzy logic to determine the best access points and penetration levels for wind power plants (WTPs), solar power plants (SPPs), and micro-turbine power plants (MTPs) within the IEEE 69-node distribution network, while ensuring technical, economic, and environmental harmony. The research focuses on three key scenarios: (1) a single-objective optimization for maximum power loss reduction, (2) a multi-objective optimization aimed at simultaneously minimizing four sub-objectives, and (3) a multi-objective optimization considering seasonal variations in time-dependent generation and demand. Specifically, the multi-objective framework prioritizes reducing total power losses in distribution branches, improving the voltage deviation index, minimizing electricity procurement costs, and curbing CO₂, SO₂, and NO_x emissions. The proposed EVO-Fuzzy method was benchmarked against several robust optimization techniques. Results demonstrate the superior efficiency and reliability of the proposed approach compared to existing methods. In the third case study, which incorporates the simultaneous connection of WTPs, SPPs, and MTPs under time-varying conditions, the method yielded a fitness value of 0.2926—better than the sun flower optimization (SFO) method (0.2956) and the standalone EVO method (0.2936). This indicates an improved quality of solutions achieved through EVO-Fuzzy logic integration. Moreover, the study substantiated multiple advantages of DGP integration using this approach. By implementing the optimized solution, annual electricity procurement costs were reduced by \$1.36 million, with a DGP penetration level of 65.63%. Power losses in distribution branches fell by 84.64%, voltage levels improved from a range of [0.909, 1.00] to [0.965, 1.031], and emissions were reduced by 68.55%. Thus, connecting DGPs has proven to deliver significant financial, operational, and environmental benefits, affirming that EVO with Fuzzy logic represents an effective tool for tackling optimization challenges associated with DGP integration.

Keywords Energy valley optimizer, Fuzzy logic, Solar power plants, Wind power plants, Micro-turbine power plants

List of symbols

N_b, N_{ld}, N_n	The number of branches loads and nodes in the system
N_h, N_i	The number of hours (24 h per day) and distributed generation plants
N_j, N_{cv}	The number of solutions and control variables in each solution
$N_{WTP}, N_{SPP}, N_{MTP}$	The number of wind turbine, solar and micro-turbine-based power plants
$P_{w,h}^{WTP}, P_{s,h}^{SPP}, P_{m,h}^{MTP}$	Generated active power by the w^{th} WTP, s^{th} SPP and m^{th} MTP at the h^{th} hour
$Q_{w,h}^{WTP}, Q_{s,h}^{SPP}, Q_{m,h}^{MTP}$	Generated reactive power by the w^{th} WTP, s^{th} SPP and m^{th} MTP at the h^{th} hour

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$Q_{ld,h}, Q_{b,h}, Q_{sub,h}$	Reactive power from load, branch loss and main grid at the h^{th} hour
$I_{b,h}^{MAX}, I_{b,h}^{DGP}$	The maximum current and the current with DGPs of the b^{th} branch at the h^{th} hour
V^{MAX}, V^{MIN}	The highest and lowest allowable limit of node voltage
$V_{n,h}^{DGP}$	The voltage of n^{th} node at the h^{th} hour after connecting DGPs
$P_{WTP}^{MAX}, P_{SPP}^{MAX}, P_{MTP}^{MAX}$	The highest allowable limit of the rated power for each WTP, SPP and MTP
$P_{WTP}^{MIN}, P_{SPP}^{MIN}, P_{MTP}^{MIN}$	The lowest allowable limit of the rated power for each WTP, SPP and MTP
$\beta_{WTP}^{MAX}, \beta_{SPP}^{MAX}, \beta_{MTP}^{MAX}$	The highest allowable limit of the power factor for each WTP, SPP and MTP
$\beta_{WTP}^{MIN}, \beta_{SPP}^{MIN}, \beta_{MTP}^{MIN}$	The lowest allowable limit of the power factor for each WTP, SPP and MTP
$P_{RATED,w}^{WTP}, P_{RATED,s}^{SPP}, P_{RATED,m}^{MTP}$	The rated power for the w^{th} WTP, s^{th} SPP and m^{th} MTP
$\beta_{Ins,w}^{WTP}, \beta_{Ins,s}^{SPP}, \beta_{Ins,m}^{MTP}$	The power factor for the w^{th} WTP, s^{th} SPP and m^{th} MTP

To reduce fossil fuels-based resources and increase penetration of the renewable-based distributed generators (DGs), feasibility study of sitting and sizing of DGs in the distribution network is the main aim of the numerous studies. Wind turbine (WT), photovoltaic system (PV) and batteries are the common units of DGs.

System operators have developed various strategies to maintain the balance and stability of power systems, with one key approach being the use of energy storage solutions. Historically, pumped hydropower plants were the predominant choice for energy storage. However, in recent years, Battery Energy Storage Systems (BESS) have increasingly been adopted for such purposes. BESS offers numerous advantages to system operators¹, significantly aiding network operators in preserving system stability and balance. To maximize the economic and operational benefits of BESS, several critical factors must be taken into account: the system's energy and capacity requirements, as well as the optimal location of the BESS. When strategically located, BESS can provide operators with a highly flexible tool for maintaining system stability and equilibrium. Additionally, selecting appropriate BESS parameters is essential to meet operational needs while ensuring that investment costs remain reasonable. Beyond location and parameters, the effective scheduling of BESS operations—specifically its charging and discharging cycles—is equally important. Proper dispatching can substantially reduce energy procurement costs and further enhance system efficiency. Numerous studies have investigated these challenges, particularly focusing on optimizing the location and parameters of BESS to address issues arising from the integration of variable Renewable Energy Sources (RES) into power systems. A variety of optimization techniques have been employed to tackle these challenges. An overview of research efforts on this topic follows in the subsequent Sects²⁻⁵.

In subsequent studies, the determination of the location, parameters, and dispatching of Battery Energy Storage Systems (BESS) is tackled simultaneously. Paper⁶ introduces a mixed-integer non-linear programming model to optimize the location, parameters, and dispatching of BESS, aiming to minimize investment costs while maximizing Distribution System Operator (DSO) profits through energy arbitrage. Meanwhile⁷, expands on this by adopting a multi-criteria approach to address challenges in distribution systems (DSs) with BESS, including reverse power flow, voltage deviations, feeder power losses, annual energy losses, and load deviation indices. This methodology utilizes a multi-objective nested optimization framework. The study in⁸ focuses on locating BESS within DSs to reduce energy losses, environmental emissions, and transmission access fees by leveraging energy arbitrage. Similarly⁹, suggests using Particle Swarm Optimization (PSO) to identify the optimal location and size of BESS in order to minimize daily costs associated with peak demand, power losses, and voltage regulation. In¹⁰, a combination of Genetic Algorithms (GA) and PSO is employed for similar objectives. Authors in¹¹ compare optimization techniques such as PSO, GA, and the salp swarm algorithm in finding the ideal BESS location and parameters, addressing issues like voltage regulation, power loss reduction, and peak power demand costs. Conversely, in¹², an optimization algorithm incorporating quadratic programming and binary PSO is designed to determine optimal BESS placement and sizing in microgrids, aiming to lower operational costs. Paper¹³ proposes artificial ecosystem optimization to minimize DS costs associated with purchasing energy for load demands, while¹⁴ employs multi-objective equilibrium optimization to reduce costs related to energy not supplied, power losses, and CO₂ emissions. In¹⁵, a hybrid method combining GA and linear programming (LP) is applied to minimize costs linked to energy losses, transmission fees, environmental emissions, energy arbitrage, and both investment and operational expenses of BESS. An improved PSO algorithm is introduced in¹⁶ to address voltage deviations and active power losses in DSs. Lastly¹⁷, utilizes a multi-objective evolutionary algorithm based on decomposition to resolve issues involving energy not supplied, voltage deviations, power losses, and energy requirements for meeting load demand effectively. The primary limitation of the previously mentioned works lies in their failure to account for the variability of both energy consumption and PV production. This omission is critical, as these factors are inherently unpredictable. Treating them as constant values can result in inaccurate calculations and misguided conclusions. To address this, subsequent studies have incorporated the unpredictability of consumption and PV production into their analyses when determining the placement, parameters, and operation of Battery Energy Storage Systems (BESS). In study¹⁸, distributional robust optimization is utilized to account for uncertainties in identifying the optimal location and parameters for BESS. Meanwhile, the authors in¹⁹ introduce a framework that models uncertainties in consumption and wind energy production using Monte Carlo Simulations (MCS). They employ a chance-constrained stochastic optimization model to determine the ideal BESS location and parameters. Similarly, studies^{20,21} integrate the stochastic characteristics of both consumption and renewable energy production through the K-means clustering method, effectively reducing the number of scenarios required for calculations.

Thus, introducing a novel approach with high performance should be encouraged to maximize welfare. In this paper, the shortcomings of previous studies will be overcome. In summary, the main contributions of this work can be briefly listed as follows:

- The research endeavors to simulate the concurrent integration of Distributed Generation Plants (DGPs), encompassing wind turbine, solar, and micro-turbine-based power facilities within the IEEE 69-node distribution networks (DNs). This investigation examines three distinct scenarios of both fixed and time-varying generation and demand. Moreover, the study accounts for all four seasons within a year, with each representative day embodying a season and consisting of twenty-four hours. Consequently, a total of ninety-six data points were compiled for simulation purposes in this analysis.
- To thoroughly assess the integrated system, this research not only considers the single-objective function of loss reduction but also addresses the multi-objective problem. The goals include minimizing total power loss, improving the voltage deviation index, reducing electricity import costs from the power company, and minimizing emissions produced by power plant operations, all while adhering to strict technical constraints.
- This study examines and explores the key impacts of integrating distributed generation resources into distribution systems, highlighting the numerous benefits that can be achieved through the proper connection of DGPs.
- The study proposes using the forward/backward sweep method to tackle the power flow problem. Additionally, the weighted sum method is employed to identify the compromise solution for the multi-objective functions.
- This study presents a new method known as the Energy Valley Optimizer (EVO) with Fuzzy logic, designed to tackle the challenging issue of Distributed Generation Projects (DGPs) within power networks and improve solution quality. EVO is a meta-heuristic algorithm inspired by physical principles concerning particle stability and decay modes in the universe. The innovative EVO approach integrates Fuzzy logic to constrain the solution search area before employing EVO to address the optimization problem, substantially enhancing algorithm efficiency.

The rest of the paper could be structured into the following sections: Sect. 2 discusses the single-objective function (OF) and multi-objective function (OF), along with their technical constraints. Section 3 outlines the application of the proposed algorithm to the optimization problem. Section 4 provides simulation results accompanied by a detailed analysis. Lastly, Sect. 5 offers a summary of the key findings and overall content of this work.

Problem formulation

In this study, both of single and multi-objective function are presented to define DGPs sitting and sizing problem.

Single-objective function

In this work, single objective function is defined to minimize total power loss index by considering this index in both condition: with DGP and without DGP.

Multi-objective function

To analyze economic, environment and technical constraints of this work, multi-objective functions are defined as follows:

Technical-based main function

Buses voltages and the active power loss in the branches are both of important technical constraints of distribution network which are considered as a technical function of this work as follows:

$$C_{TPL} = \frac{TPL_{DGP}}{TPL} \quad (1)$$

$$TPL = \sum_h^{N_h} \sum_b^{N_b} R_{b,h} I_{b,h}^2, \quad b \in N_b, h \in N_h \quad (2)$$

The C_{TPL} value serves as an indicator of power loss reduction. A smaller C_{TPL} value signifies greater effectiveness in minimizing losses. TPL_{DGP} and TPL represent the total branch power loss after and before the integration of DGPs respectively. In Eq. (2), $R_{(b, h)}$ and $I_{(b, h)}$ are defined as the branch resistance and branch current of the b th line at the h th hour, respectively.

$$C_{VDI} = \frac{VDI_{DGP}}{VDI} \quad (3)$$

$$VDI = \max \left(\frac{|V_{n,m} - V_{n,h}|}{V_{nom}} \right), \quad n \in N_n, h \in N_h \quad (4)$$

C_{VDI} represents the component that indicates improvements in the voltage deviation index within the distribution system. Minimizing the C_{VDI} value helps reduce voltage drops at the nodes. VDI_{DGP} and VDI denote the maximum values of the voltage deviation index with and without incorporating DGPs, respectively. Furthermore, $V_{(n, h)}$ refers to the voltage at the n th node during the h th hour, while V_{nom} , the nominal voltage, is set to 1 p.u. in this study.

Economic-based main function

In the investment project, impacts of new units on reducing distribution system dependency to main grid and reducing operating costs are analyzed. Therefore, economic index is considered as a second objective function.

$$C_{EPC} = \frac{EPC_{DGP}}{EPC} \tag{5}$$

$$EPC = \sum_h^{N_h} \left(Pri_{ld,h} \times \sum_{ld}^{N_{ld}} P_{ld,h} \right) + \sum_h^{N_h} \left(Pri_{ls,h} \times \sum_b^{N_b} P_{b,h} \right), \quad ld \in N_{ld}, b \in N_b \tag{6}$$

C_{EPC} represents the cost associated with purchasing energy from the grid, with lower values indicating a preferable outcome. Both EPC_{DGP} and EPC correspond to energy import costs incurred due to loads and branch losses. In Eq. (6), $Pri_{(ld,h)}$ and $Pri_{(ls,h)}$ denote the hourly electricity prices for imported energy related to loads and losses, while $P_{ld,h}$ and $P_{b,h}$ refer to the d th load power and the b th branch power loss during the h th hour, respectively.

Environmental-based main function

Another concern for energy administrators is the pollution associated with fossil fuel-based power plants. To address this issue, enhancing the distribution network with Distributed Generations (DGs) serves as a solution to avoid the need for new power plant installations and to minimize overall gas emissions.

$$C_{GER} = \frac{GER_{DGP}}{GER} \tag{7}$$

$$GER = \sum_h^{N_h} [P_{Sub,h} \times (E_{CO_2,h}^{Sub} + E_{SO_2,h}^{Sub} + E_{NO_X,h}^{Sub})] + \sum_h^{N_h} \sum_i^{N_i} [P_{DGP,i,h} \times (E_{CO_2,i,h}^{DGP} + E_{SO_2,i,h}^{DGP} + E_{NO_X,i,h}^{DGP})] \tag{8}$$

C_{GER} represents a component in the multi-OF that accounts for environmental factors, and its value is intended to be minimized. GER and GER_{DGP} correspond to the total emissions generated during operation, measured before and after the integration of DGPs, respectively. $P_{Sub,h}$ denotes the power generated by the substation during the h th hour, while $P_{DGP,i,h}$ represents the power generated by the i th DGP during the same hour.

Additionally, $E_{CO_2,h}^{Sub}$, $E_{SO_2,h}^{Sub}$, and $E_{NO_X,h}^{Sub}$ refer to the emission coefficients of CO₂, SO₂, and NO_X, respectively, from the primary grid source at the h th hour. Similarly, $E_{CO_2,i,h}^{DGP}$, $E_{SO_2,i,h}^{DGP}$, and $E_{NO_X,i,h}^{DGP}$ represent the emission coefficients of CO₂, SO₂, and NO_X produced by the i th DGP at the h th hour.

Finally, to address all aspects comprehensively, the multi-OF framework is implemented, and the weighted sum method is applied to determine the most suitable compromise solution as outlined below.

Minimize

$$MOF = (W_1 \times C_{TPL}) + (W_2 \times C_{VDI}) + (W_3 \times C_{EPC}) + (W_4 \times C_{GER}) \tag{9}$$

where : W_1, W_2, W_3 and W_4 are the weighted weights of the multi-OF that relates to total power loss, the voltage deviation, the electricity purchase cost and emission's reduction, respectively. These values of weighted weights are defined by user and they should be constrained by^{6,7}:

$$\sum_k^4 W_k = 1 \ \& \ 0 \leq W_k \leq 1, \quad k = 1, 2, 3, 4 \tag{10}$$

Equal and non-inequal constraints

equality constraints

In this study, DGPs generate both active and reactive power, so the power balance equations with the connection of DGPs are presented as :

$$P_{Sub,h} + \sum_{w=1}^{N_{WTP}} P_{w,h}^{WTP} + \sum_{s=1}^{N_{SPP}} P_{s,h}^{SPP} + \sum_{m=1}^{N_{MTP}} P_{m,h}^{MTP} = \sum_{ld=1}^{N_{ld}} P_{ld,h} + \sum_{b=1}^{N_b} P_{b,h} \tag{11}$$

$$Q_{Sub,h} + \sum_{w=1}^{N_{WTP}} Q_{w,h}^{WTP} + \sum_{s=1}^{N_{SPP}} Q_{s,h}^{SPP} + \sum_{m=1}^{N_{MTP}} Q_{m,h}^{MTP} = \sum_{ld=1}^{N_{ld}} Q_{ld,h} + \sum_{b=1}^{N_b} Q_{b,h} \tag{12}$$

Inequality constraints

The limits of branch current The current at each branch after connecting DGPs should be limited by :

$$I_{b,h}^{MAX} \geq I_{b,h}^{DGP} \quad b \in N_b, h \in N_h \tag{13}$$

The limits of node voltage The RMS voltage at each node should be maintained within below constraints:

$$V^{MIN} \leq V_{n,h}^{DGP} \leq V^{MAX}, \quad n \in N_n, h \in N_h \tag{14}$$

The limits of rated capacity The installed capacity is kept in the predetermined limits as :

$$P_{WTP}^{MIN} \leq P_{RATED,w}^{WTP} \leq P_{WTP}^{MAX}, \quad w \in N_{WTP} \tag{15}$$

$$P_{SPP}^{MIN} \leq P_{RATED,s}^{SPP} \leq P_{SPP}^{MAX}, \quad s \in N_{SPP} \tag{16}$$

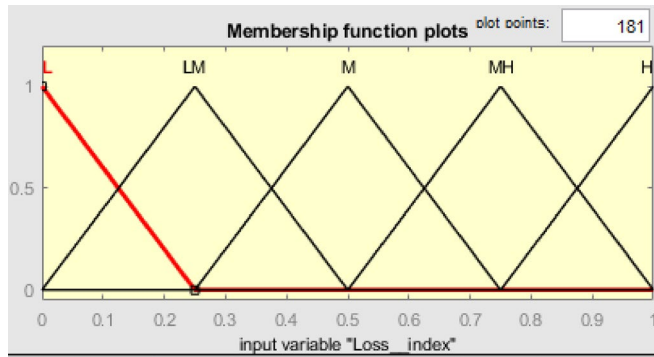


Fig. 1. Corresponding membership of node's power loss index.

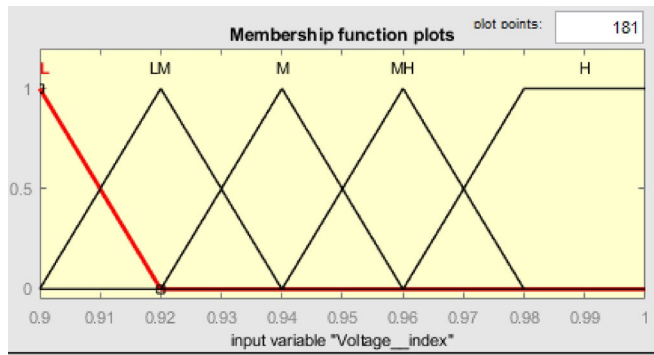


Fig. 2. Corresponding membership of node's voltage index.

$$P_{MTP}^{MIN} \leq P_{RATED}^{MTP}, m \leq P_{MTP}^{MAX}, \quad m \in N_{MTP} \tag{17}$$

The limits of dgp's power factor The power factor for WTPs, SPPs and MTPs should be bound by

$$\beta_{WTP}^{MIN} \leq \beta_{Ins,w}^{WTP} \leq \beta_{WTP}^{MAX}, \quad w \in N_{WTP} \tag{18}$$

$$\beta_{SPP}^{MIN} \leq \beta_{Ins,s}^{SPP} \leq \beta_{SPP}^{MAX}, \quad s \in N_{SPP} \tag{19}$$

$$\beta_{MTP}^{MIN} \leq \beta_{Ins,m}^{MTP} \leq \beta_{MTP}^{MAX}, \quad m \in N_{MTP} \tag{20}$$

Introduced methods for optimization problem

In this study, to optimal placement of the DGs in the distribution network, combination of EVO and fuzzy logic is used. The role of fuzzy logic is limitation the search regions and EVO is used to solve optimization problem and obtain the solutions.

Fuzzy logic

The primary challenge in applying optimization algorithms to problem-solving lies in handling the extensive search space. Various techniques exist to constrain this search space effectively. In this study, fuzzy logic is employed to limit the search area. The voltage of nodes and the power loss in branches are used as inputs within the fuzzy logic technique, while the relationship function between these inputs determines the output. This output is utilized to identify the optimal candidate bus for placing Distributed Generation (DGPs) within the distribution system. Figures 1, 2 and 3 illustrate, input and output indexes membership functions.

To decide the best solution for connecting DGPs, 25 certain rules are designed and the summary table is presented like the matrix in Table 1. Besides, the input and output relationships with certain rules are also illustrated as shown in Fig. 4.

Energy valley optimizer

This paper explores the application of a recently developed meta-heuristic algorithm, known as the Energy Valley Optimizer (EVO)²², to address the problem of optimal placement of Wireless Power Transfer Systems (WPTs), Solar Photovoltaic Panels (SPPs), and Medium-Voltage Transformers (MTPs) in the IEEE 69-node distribution network. EVO was designed based on advanced physical principles related to stability and varying

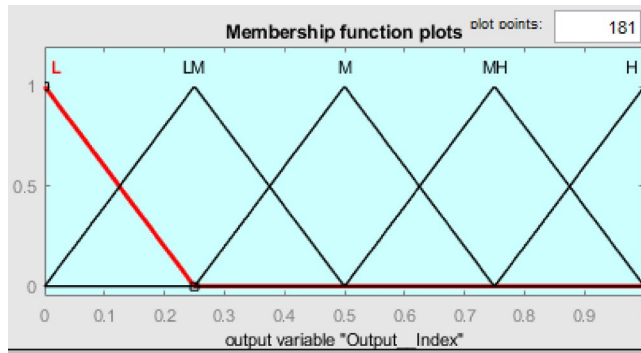


Fig. 3. Corresponding membership of output index.

AND		Power loss of branches index				
		L	LM	M	MH	H
The index of node voltage	L	M	MH	MH	H	H
	LM	M	M	M	MH	H
	M	LM	LM	M	M	MH
	MH	L	L	LM	M	MH
	H	L	L	LM	M	M

Table 1. The rules matrix in search region of DGPs allocation.

modes of particle decay. In the natural world, unstable particles release energy during the decay process, and the rate of decay varies across different types of particles. The key factor lies in assessing the stability of particles, which depends on the number of protons and neutrons they contain.

During this decay process, three main types of particles—alpha, beta, and gamma—emerge, each possessing distinct stability levels. Inspired by the principle of decay across different particle types, the algorithm formulates optimization by determining stability points for these particles. EVO is built on this concept and has demonstrated its effectiveness compared to other available methods for solving various optimization challenges. The steps involved in applying EVO to an optimization problem are briefly outlined below.

Step no.1

Initialize the initial parameters and generate the first solutions. Initial solutions are generated randomly within predetermined limits.

$$S_j^{cv} = r_1 \cdot (S_j^{MAX,cv} - S_j^{MIN,cv}) + S_j^{MIN,cv}, \quad j \in N_j, cv \in N_{cv} \tag{21}$$

In Eq. (21), r_1 is a randomly generated number from 0 to 1; $S_j^{MAX,cv}$ and $S_j^{MIN,cv}$ are predetermined limits at the cv^{th} control variable of the j^{th} solution.

Step no.2

Determine the enrichment bound (EB) and stability level (SL) for solutions by.

$$EB = \frac{\sum_{k=1}^{N_k} NL_k}{N_k}, \quad k \in N_k \tag{22}$$

$$SL_k = \frac{NL_x - BL}{WL - BL}, \quad k \in N_k \tag{23}$$

In this case, the fitness value for each the solution is represented by the neutron enrichment level (NL). The NL value can be identified by using the objective function and the fitness value can be found by using Eq. (24). Besides, WL and BL in Eq. (23) are defined as the worst and best stability levels of the solutions in the population.

$$Fitness_j = MOF_j + \delta \cdot \Delta pen_j, \quad j \in N_j \tag{24}$$

where $Fitness_j$ is the value of the fitness function and MOF_j is the value of the objective function for the j^{th} solution. δ is the penalty coefficient which can be defined by user and Δpen_j is the penalty amount due to constraint violation of the j^{th} solution.

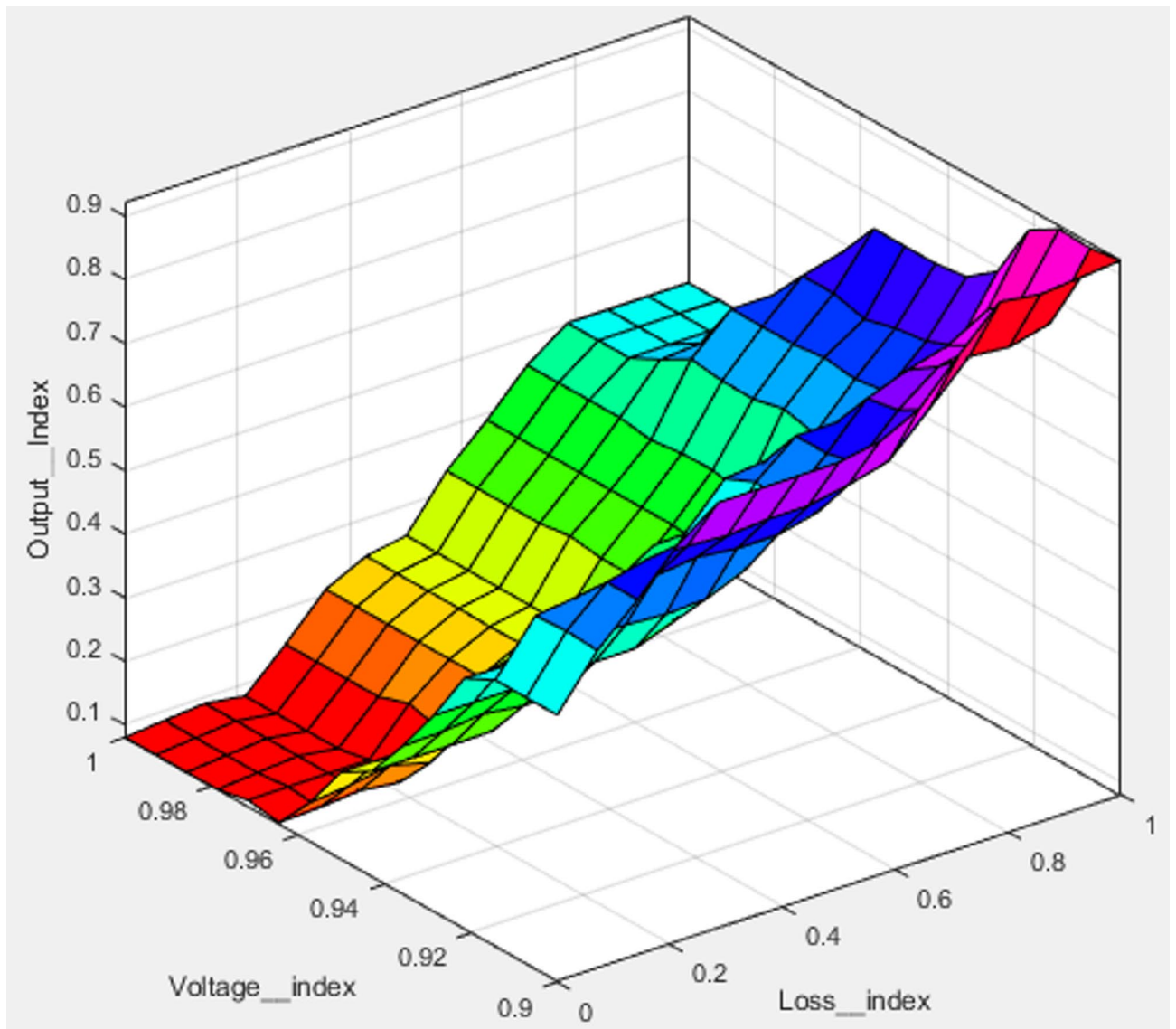


Fig. 4. The amount of output based on inputs values.

Step no. 3

In the original algorithm (EVO), new solutions are generated according to the established condition. At this stage, if $NL_k \leq EB$ then Eq. (25) is applied.

$$S_j^{NEW} = S_j + r_2, \quad j \in N_j \quad (25)$$

Here, r_2 is a random number in the range $[0, 1]$; S_j^{NEW} and S_j are defined as the new and current solutions. On the other hand, if $NL_k > EB$ then the stability bound (SB) in the universe will be determined and its value is a randomly generated number between 0 and 1.

Step no. 4

Update solution's new locations for case of $NL_k > EB$. At this stage, the separation of alpha and gamma particles is determined based on their stability. Specifically, if their stability level is higher than the stability bound ($SL_x > SB$), then the decay process occurs for heavy particles with higher stability level. In the decay of alpha particles, *alpha index 1* and *alpha index 2* are created in the limits of $[1, va]$ and $[1, \text{alpha index 1}]$, respectively. They are integers that are generated randomly within these ranges and the first position update equation for new solution is presented as Eq. (26).

$$S_j^{NEW(1st)} = S_j(S_{BS}(S_j^{cv})), \quad j \in N_j \& cv = \text{alpha index 2} \quad (26)$$

Similar to the decay of alpha particles, during the decay of gamma particles, two integers called *gamma index 1* and *gamma index 2* are also emitted in the limits of [1, *va*] and [1, *gamma index 1*]. In this case, the second position update equation is also described mathematically as Eq. (27).

$$S_j^{NEW(2nd)} = S_j (S_{Ne} (S_j^{cv})), \quad j \in N_j \& cv = \text{gamma index} \quad (27)$$

In the Eqs. (26, 27), $S_j^{NEW(1st)}$ and $S_j^{NEW(2nd)}$ are the new produced particles in the search space at the first and second stages, S_j is the current particle position vector, S_{BS} is considered as the position vector which accounts for the best level of stability, S_{Nei} is the position vector that is located around the j^{th} solution and S_j^{cv} represents the cv^{th} decision variable.

On the contrary, if the stability level is lower than or equal to the stability bound ($SL_x \leq SB$), the decay process of unstable particles occurs. These unstable particles tend to move with the most stable particle (S_{BS}) and the central particle (S_{Cent}). Therefore, the first position update equation is presented as below Eq. (28):

$$S_j^{NEW(1st)} = S_j + \frac{r_3 \cdot S_{BS} - r_4 \cdot S_{Cent}}{SL_j}, \quad j \in N_j \quad (28)$$

$$\text{where} \quad S_{Cent} = \frac{\sum_{j=1}^{N_j} S_j}{N_j}, \quad j \in N_j \quad (29)$$

Similarly, the second position update equation is also determined as:

$$S_j^{NEW(2nd)} = S_j + r_3 \cdot S_{BS} - r_4 \cdot S_{Nei} \quad j \in N_j \quad (30)$$

Step no.5

Keep new produced solutions within predetermined boundaries. Newly created solutions will be checked and calibrated within allowable limits as.

$$S_j^{NEW,cv} = \begin{cases} S_j^{MIN,cv} & \text{if } S_j^{cv} < S_j^{MIN,cv} \\ S_j^{MAX,cv} & \text{if } S_j^{cv} > S_j^{MAX,cv} \\ S_j^{cv} & \text{else} \end{cases}, \quad j \in N_j, \quad cv \in N_{cv} \quad (31)$$

Step no.6

Evaluate the quality of created solutions by using the fitness function as Eq. (24).

Step no.7

Check the condition for stopping iteration. This process is stopped and the best solution for the optimization problem is determined if the condition is satisfied ($Iter > Iter^{MAX}$), and vice versa, the above process is repeated from STEP No.2.

The flowchart for the process of finding the optimal solution by EVO is also briefly described in Fig. 5.

Simulation results

This study examines three simulation scenarios: a single-objective function (single-OF) case, a multi-objective function (multi-OF) case with fixed load demand and generation, and a multi-OF case with time-varying demand and generation. The IEEE 69-node distribution network, with a full load of 3.8019 MW/2.6941 MVar, is selected as the test network. Line and node data for the simulations are sourced from¹⁸. The planning issue has been analyzed and deliberated upon within a five-year timeframe. Results from applying fuzzy logic to identify potential solutions are presented in Fig. 6. Based on these results, locations with the lowest output indices (nodes 1 to 4 and nodes 28 to 52) are excluded from the search space, as shown in the network structure in Fig. 7. This narrows down the candidate locations for integrating distributed generation plants (DGPs) to nodes 5 through 27 and nodes 53 through 69. All simulations were conducted using MATLAB version R2017b on a desktop equipped with an i3-10105 F CPU @ 3.7 GHz and 16 GB of RAM.

Case 1: the single-OF with fixed load demand and generation

To demonstrate the effectiveness of the introduced method, the single objective function aimed at minimizing total power loss, as described in Eq. (1), is implemented. In this setup, three Distributed Generation Points (DGPs) are integrated into the Distribution Network (DN), considering their fixed output capacity at peak load times. For the simulation involving three algorithms—SFO, EVO, and EVO with Fuzzy Logic—the maximum number of iterations is set at 100, while the population size (N_j) is established at 30. Additionally, the penetration limits for the DGPs are chosen within a range from 0.0 MW to 2.0 MW. Due to the stochastic nature of the meta-heuristic algorithm, 40 test runs (N_{tri}) are conducted, and the best results obtained from these methods are compared with findings from previous studies.

As presented in Table 2, the optimal solution derived from the proposed method is compared with the original method (EVO) and 12 other published active methods. Notably, the power loss reduction achieved by EVO with Fuzzy logic is the highest, reaching 69.14%. In contrast, the reductions by GA, AGA, TLBO, QOSIMBO-Q, LSFSA, MINLP, SGA, PSO, BFOA, SSA, KHA, SFO, and EVO alone range between 65.46% and

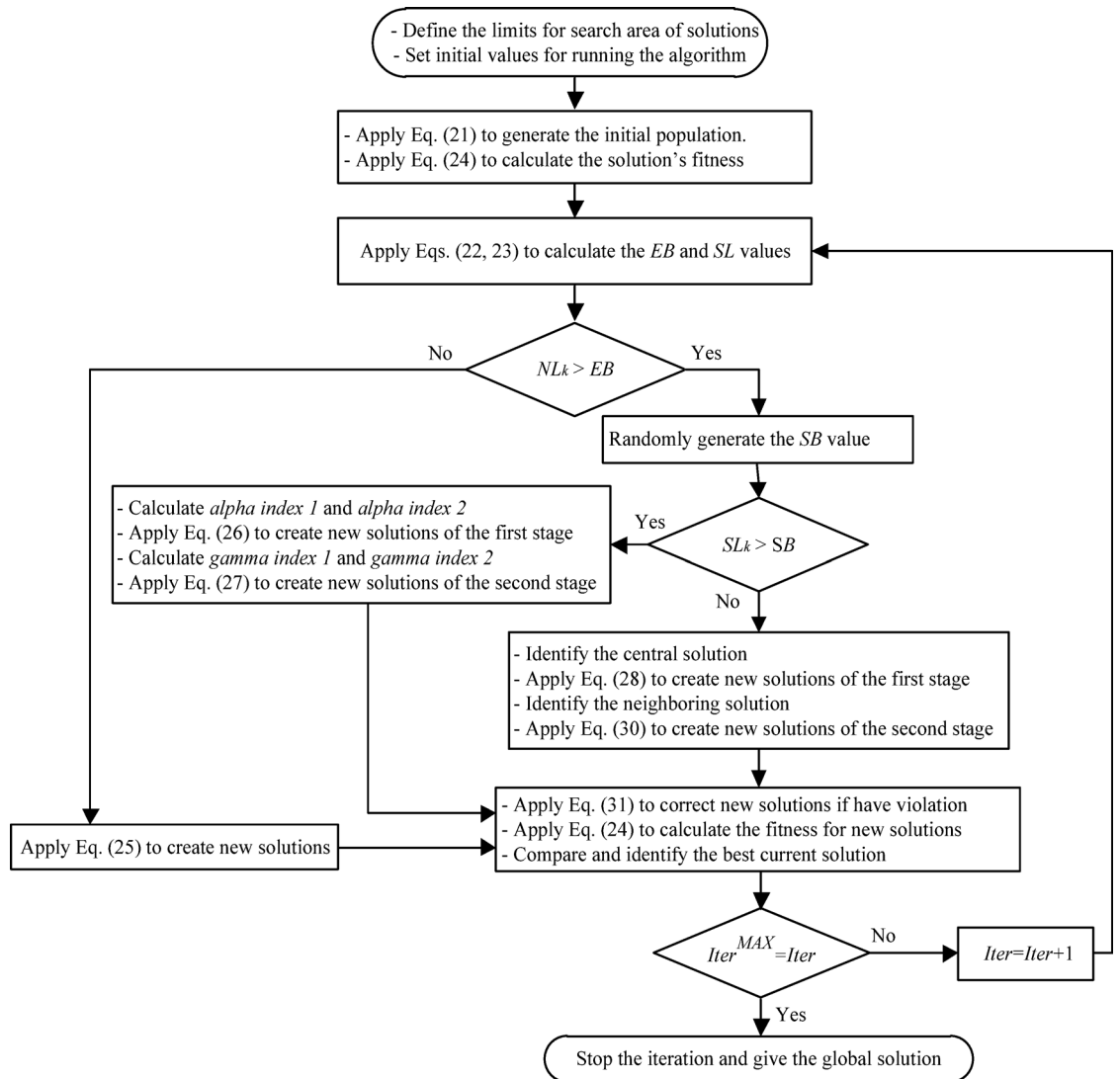


Fig. 5. The flowchart of EVO for optimization problem.

69.13%. This clearly demonstrates that the global solution identified by EVO with Fuzzy logic outperforms the other methods when pursuing the same objective. In essence, using Fuzzy logic to narrow the search space has significantly enhanced the efficiency of the proposed approach compared to others. In terms of practical benefits, applying the proposed method's optimal solution has led to a significant reduction in total power loss from 224.49 kW to 69.29 kW, which translates to a saving of 155.21 kW. This reduction directly impacts the cost of energy procurement during grid operation, emphasizing the substantial technical and economic advantages of integrating distributed generation sources into the distribution network. Additionally, the voltage profile benefits from this integration, as it ensures suitable connections for distributed generation points (DGPs). Specifically, with the proposed method, the voltage profile has markedly improved from a range of [0.909, 1.00] p.u. to [0.979, 1.00] p.u., as depicted in Fig. 8. This enhancement demonstrates that DGP penetration has greatly contributed to improving voltage stability while ensuring compliance with constraints of [0.95, 1.00] p.u. Thus, it can be concluded that the appropriate integration of DGPs not only significantly reduces power losses but also enhances voltage profiles within distribution systems.

Case 2: the multi-OF with fixed load demand and generation

In this scenario, three DGPs are evaluated for their connection to the DN, taking into account fixed generation and peak load demand, aligned with targets derived from the combination of economic, technical, and environmental factors as stated in Eq. (9). To simulate and identify the global solution, the parameters $\lceil \text{Iter} \rceil^{\text{MAX}}$, N_j , and N_{tri} are set to 120, 30, and 40, respectively. Additionally, detailed values relevant to the fitness evaluation of the solutions in the multi-objective function are provided in Table 3.

The results obtained from the methods implemented in SFO and EVO are summarized in Table 4. Evidently, the final evaluation value (MOF) for the solutions derived using the multi-OF approach with EVO and Fuzzy logic is the lowest at 0.1167, compared to 0.1248 for SFO and 0.1174 for EVO. This demonstrates that the optimal

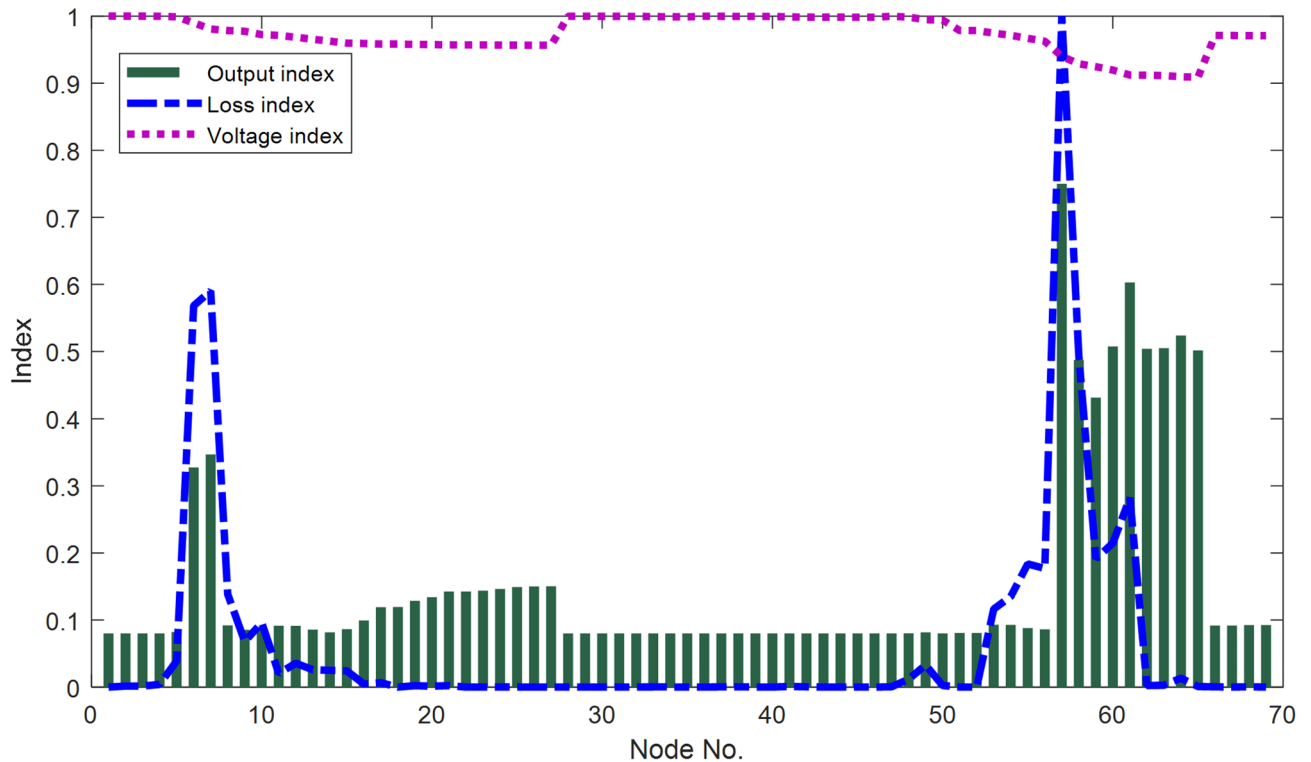


Fig. 6. Results for applying fuzzy logic to determine the potential locations of DGPs.

solution achieved through EVO with Fuzzy exhibits superiority, with a deviation index of 0.0081 relative to SFO and 0.0007 relative to EVO for solving this multi-OF problem. Additionally, the indexes for all single target components in the multi-OF function achieved through EVO with Fuzzy logic are lower than those obtained by the other methods. The indexes (C_TPL, C_VDI, C_EPC, and C_GER) for the proposed approach are measured at 0.3596, 0.0712, 0.0128, and 0.0231. In comparison, the corresponding values are 0.3800, 0.0815, 0.0136, and 0.0243 for SFO and 0.3622, 0.0712, 0.0130, and 0.0234 for EVO. Hence, it can be concluded that the proposed method outperforms both SFO and EVO in all evaluated aspects. In essence, incorporating Fuzzy logic to limit the search space for optimal solutions in determining DGP intrusions has proven beneficial and significantly enhanced the algorithm's performance relative to other approaches.

The solution of installing DGPs using the proposed method has proven to deliver significant technical, economic, and environmental benefits. As illustrated in Fig. 9, power losses in most distribution branches have been substantially reduced. The most notable reduction is observed in branch No. 56, which achieved a 69.30% decrease in losses. Overall, the total network power loss dropped from 224.49 kW to 80.72 kW, representing a 64.04% reduction, attributed to the optimal penetration of DGPs. Additionally, there has been a remarkable improvement in voltage profiles, as depicted in Fig. 10. In the original network, multiple nodes in the terminal branches recorded voltage levels below 0.950 p.u., with the lowest voltage being 0.909 p.u. at node No. 65. Following the integration of DGPs, the minimum voltage increased to 0.9935 p.u., while the highest reached 1.0002 p.u. This significant enhancement in voltage profile highlights the technical excellence achieved through proper DGP deployment. Economic and environmental benefits have also been noteworthy. Integrating DGPs has resulted in a dramatic drop in hourly electricity import costs from \$378.452 to \$4.852, equating to a 98.72% savings compared to the base network. Moreover, pollutant emissions, including CO₂, SO₂, and NO_x, have been considerably reduced from 2538.0 lb to 58.7 lb per hour, marking a 97.69% decrease. This substantial reduction in emissions underscores the environmental advantages of DGP operation and its contribution to ecological protection. In conclusion, the optimal integration of DGPs into the distribution network has delivered outstanding benefits across technical, economic, and environmental dimensions. The proposed optimization method demonstrated superior performance compared to other approaches under similar conditions, making it a highly effective solution for the problem of DGP installation in distribution networks.

Case 3: the multi-OF with time-varying load demand and generation

To address all technical, economic, and environmental considerations, the multi-objective function (Eq. 9) is utilized to integrate three types of power plants capable of generating both active and reactive power. These include two wind power plants (WTPs), two solar power plants (SPPs), and two micro-turbine power plants (MTPs). A dataset of 96 points, representing four days—each corresponding to a different season of the year—is analyzed. The output curves for WTPs and SPPs are sourced from Purlu et al. (2022), while the MTP output curve is assumed constant, with a power efficiency of 0.7, as shown in Fig. 11. Additionally, the power factor values ($\beta_{(Ins, w)}^{WTP}$, $\beta_{(Ins, w)}^{SPP}$, and $\beta_{(Ins, w)}^{MTP}$) for WTPs, SPPs, and MTPs are selected as 0.9

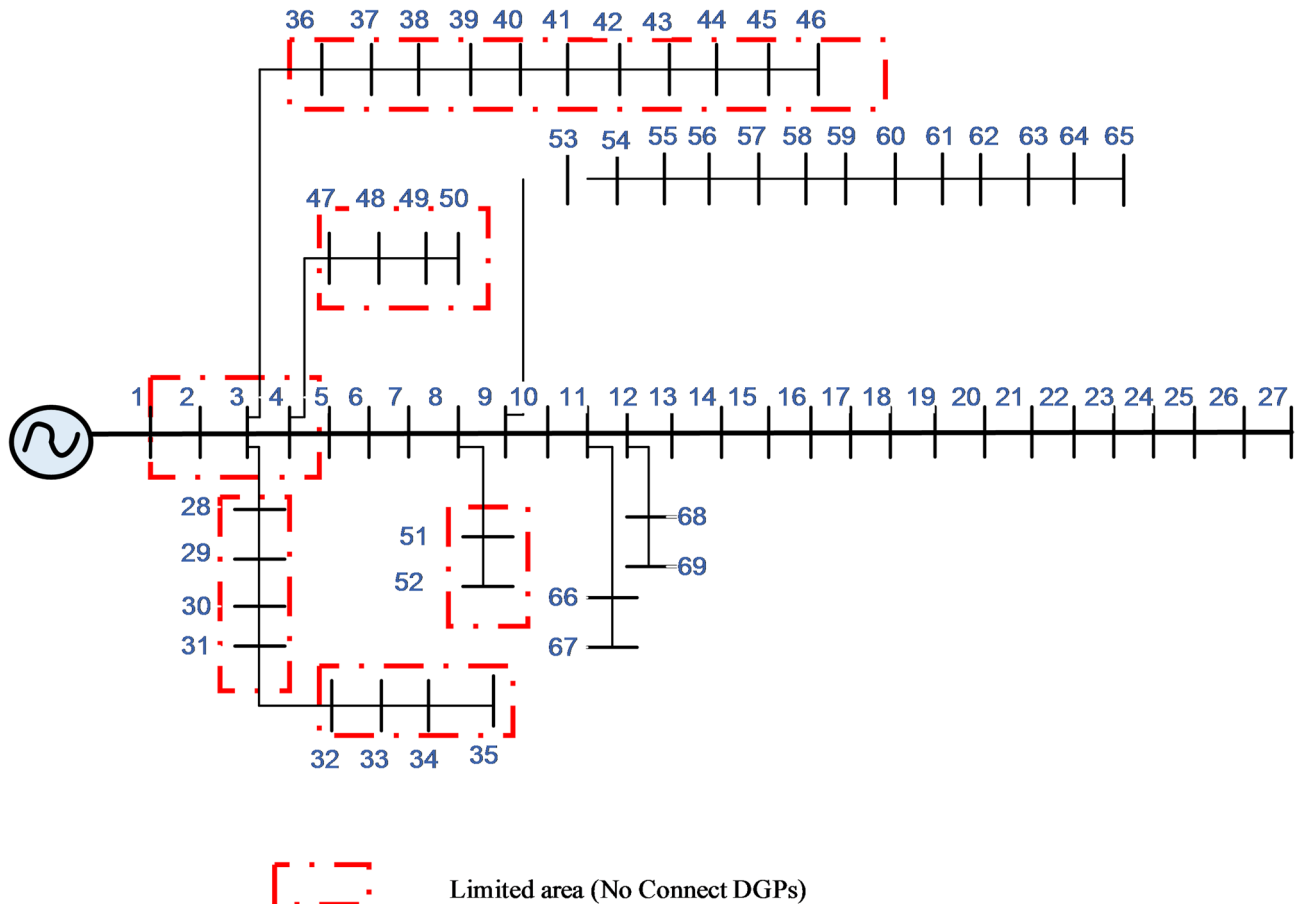


Fig. 7. IEEE 69-node DN.

based on Pham (2023). Furthermore, the IEEE RTS-96 standard is employed to model seasonal variations in load demand. This analysis focuses on the simultaneous integration of WTPs, SPPs, and MTPs into the distribution network alongside a conventional generator, which serves as the primary power source for the main grid, as depicted in Fig. 6. Under this scenario, emissions are generated by both the conventional power plant and the micro-turbine power plants. The emission coefficients for these components are detailed in Table 3 under Case 2. Key parameters required for running this simulation are also listed clearly in Tables 3 and 5.

As described, due to the stochastic nature of the implemented methods, 40 independent runs were conducted with $\text{Iter}^{\text{max}}=140$ and $N_r=30$ for this scenario. The optimal solution obtained through the proposed method was compared against two other active methods, EVO and SFO, as summarized in Table 6.

As outlined in Table 6, the fitness value (MOF) of the optimal solution using EVO with Fuzzy logic is 0.2926, which is lower than the values obtained from SFO (0.2956) and EVO (0.2936). In this context, a smaller MOF value indicates better performance. This implies that the proposed approach has successfully found a global solution that is of higher quality than those derived from the other methods. For clarification, the value of each component in the multi-OF is detailed in Table 6. Regarding the technical targets (CTPL and CVDI), SFO has values of 0.1950 and 0.3564, EVO has values of 0.1391 and 0.3939, and EVO with Fuzzy logic results in 0.1536 and 0.3865, respectively. Specifically, the CTPL value from the proposed method is considerably lower than SFO but marginally higher than EVO. Furthermore, the CVDI value from the proposed method (0.3865) surpasses EVO (0.3939) but falls short of SFO (0.3564). Consequently, the optimal solution found by the proposed method excels over SFO in terms of loss reduction but is inferior regarding voltage deviation enhancement, and vice versa for EVO. These trade-offs must be acknowledged when dealing with multi-OF considerations. On another note, concerning the objectives of decreasing electricity import costs and emissions, the values of CEPC and CGER from EVO with Fuzzy logic (0.3156 and 0.3145) are less than those of SFO (0.3158 and 0.3151) and EVO (0.3156 and 0.3145), indicating that the solution from the proposed method is economically advantageous and emits fewer emissions compared to the other methods. To summarize, aside from having a superior multi-OF value (MOF) compared to SFO and EVO, three out of four individual targets from the proposed method outperform those from the compared methods. Thus, it is evident that EVO with Fuzzy logic presents a more effective approach than SFO and EVO for addressing the multi-OF problem related to the penetration of DGPs in the DN.

As discussed, this study highlights the significant advantages of incorporating Distributed Generation Providers (DGPs) by simulating their connections, including Wind Turbine Plants (WTPs), Solar Photovoltaic

Method	Optimal result of installing DGPs (Node/capacity)	Power loss (kW)/ Loss reduction (%)
8	WTP Node 09/0.9600 MW;	77.54 kW/65.46%
	SPP Node 17/0.5120 MW;	
	MTP Node 61/2.0710 MW	
9	WTP Node 12/0.2720 MW;	70.67 kW/68.52%
	SPP Node 21/0.3100 MW;	
	MTP Node 61/1.8610 MW	
10	WTP Node 15/0.5919 MW;	72.41 kW/67.78%
	SPP Node 61/0.8188 MW;	
	MTP Node 63/0.9003 MW	
11	WTP Node 09/0.8336 MW;	71.00 kW/68.44%
	SPP Node 18/0.4510 MW;	
	MTP Node 61/1.5000 MW	
12	WTP Node 18/0.4204 MW;	77.10 kW/65.69%
	SPP Node 60/1.3311 MW;	
	MTP Node 65/0.4298 MW	
13	WTP Node 12/0.4962 MW;	69.56 kW/69.02%
	SPP Node 22/0.3113 MW;	
	MTP Node 61/1.7354 MW	
14	WTP Node 61/1.8259 MW;	69.80 kW/68.91%
	SPP Node 22/0.3284 MW;	
	MTP Node 66/0.4873 MW	
EVO	WTP Node 21/0.2990 MW;	69.31 kW/69.08%
	SPP Node 11/0.6210 MW;	
	MTP Node 61/1.7526 MW	
EVO with Fuzzy logic	WTP Node 11/0.5696 MW;	69.29 kW/69.14%
	SPP Node 18/0.3985 MW;	
	MTP Node 61/1.7345 MW	

Table 2. The optimal results from different methods for installing DGPs.

Plants (SPPs), and Micro Turbine Plants (MTPs) in the Distribution Network (DN). Using the optimal solution derived from the proposed method, the total penetration of DGPs during the analyzed period reached 150.975 MW, representing 65.63% of the total load demand and system losses, as shown in Fig. 12. Additionally, the annual cost of importing electricity from the grid was greatly reduced to \$0.627 million, delivering an annual saving of \$1.36 million compared to the original system, all due to the efficient integration achieved through the proposed solution. Furthermore, Fig. 13 illustrates the total power loss before and after integrating DGPs. The results demonstrate a substantial reduction in power losses, decreasing from 8.223 MW to 1.263 MW, equivalent to an 84.64% reduction. This underscores the considerable benefits of minimizing power losses across distribution branches, contributing to lower system operating costs through the strategic penetration of DGPs.

An additional advantage of appropriately connected DGPs is the improvement in the voltage profile. As demonstrated in Fig. 14, the voltage levels at all nodes in the base system originally fluctuate within a range of [0.909, 1.00] (p.u). However, this range has been significantly enhanced to [0.965, 1.031] (p.u), fully complying with the stated limits of [0.95, 1.05] (p.u). Moreover, a notable benefit is the reduction in emissions from conventional power plants. As illustrated in Fig. 15, prior to integrating DGPs, total emissions, including CO₂, SO₂, and NO_x over the considered hours, amounted to 145.01 klb. Following the integration of DGPs, this value drastically drops to 45.612 klb, representing a 68.55% reduction in emissions. This decrease contributes substantially to lowering emission costs and mitigating the greenhouse effect. In conclusion, optimizing the integration of DGPs yields significant technical advantages while also promoting economic and environmental benefits.

Employing the proposed approach on 119 bus IEEE system

In this section optimal siting and sizing of DGP in 119 bus IEEE system (which is illustrated in the Fig. 16) is studied. The multi-objective optimization problem demonstrates the effectiveness of the proposed EVO method by focusing on three optimization objectives: voltage variance, DGPs cost, and power loss reduction.

Conclusions

This study presents an innovative approach combining Evolutionary Optimization (EVO) and Fuzzy Logic to address the challenge of optimally installing Distributed Generation Plants (DGPs) in Distribution Networks (DN). The analysis focuses on three scenarios: single-objective function (single-OF) with fixed generation and demand, multi-objective function (multi-OF) with fixed generation and demand, and multi-OF with time-

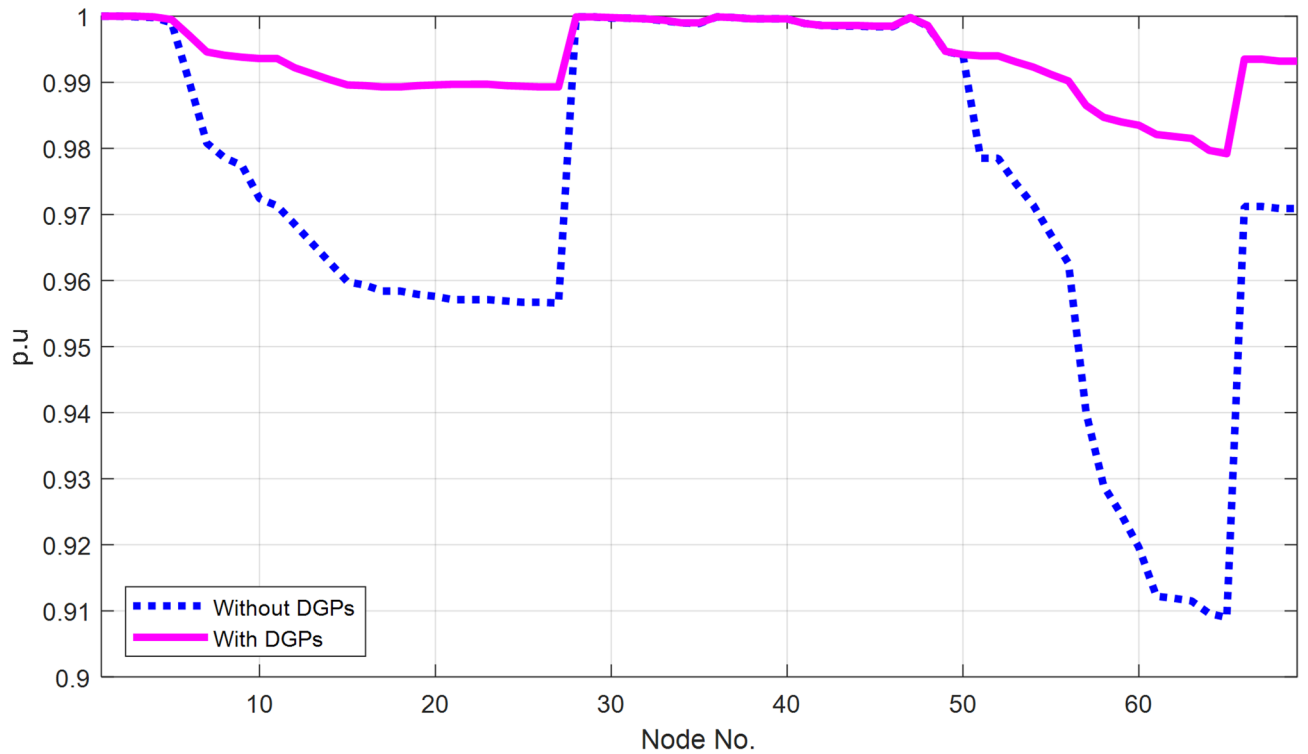


Fig. 8. The node voltage without and with DGPs.

Items	Values
$E_{CO_2}^{Sub}$, $E_{SO_2}^{Sub}$, and $E_{NO_X}^{Sub}$	621 lb/MWh, 6.465 lb/MWh and 2.875 lb/MWh
$E_{CO_2}^{DGP}$, $E_{SO_2}^{DGP}$, and $E_{NO_X}^{DGP}$	1.596 lb/MWh, 0.008 lb/MWh and 0.44 lb/MWh
Pri_{id} and Pri_{is}	96 \$/MWh and 60 \$/MWh
W_1, W_2, W_3 and W_4	0.25, 0.25, 0.25 and 0.25

Table 3. The parameters are used in evaluating multi-OF.

Method	Optimal result of installing DGPs in DN (Node/capacity)	C_{TPL}	C_{VDI}	C_{EPC}	C_{GER}	MOF
SFO	WTP Node 13/0.9013 MW SPP Node 55/1.0457 MTP MW Node 61/1.8548 MW	0.3800	0.0815	0.0136	0.0243	0.1248
EVO	WTP Node 09/1.2905 MW SPP Node 24/0.5020 MW MTP Node 62/2.0000 MW	0.3622	0.0712	0.0130	0.0234	0.1174
EVO with Fuzzy logic	WTP Node 09/1.2983 MW SPP Node 22/0.5035 MW MTP Node 62/2.0000 MW	0.3596	0.0712	0.0128	0.0231	0.1167

Table 4. The optimal results of implemented methods for penetrating DGPs.

varying generation and demand. Simulation results for Case 1 (single-OF) demonstrated exceptional efficacy of the proposed method in reducing power losses. By integrating three DGPs operating at a unity power factor, the approach achieved a power loss reduction of up to 69.14%, outperforming 13 compared methods whose reductions ranged from 65.46% to 69.13%. In Case 2 (multi-OF), the solution derived from EVO with Fuzzy Logic achieved a fitness value of 0.1167, which is superior to those obtained using SFO (0.1248) and standalone EVO (0.1174). This demonstrates the greater effectiveness of the proposed technique. Additionally, by applying this solution, power loss reduction reached 64.04%, the weakest voltage improved from 0.909 p.u. to 0.9935 p.u., the hourly cost of importing electricity decreased by 98.72%, and generated emissions dropped by 97.69%, underscoring the method's overall efficiency. In Case 3, involving the simultaneous integration of Wind Turbine Plants (WTPs), Solar Photovoltaic Plants (SPPs), and Micro Turbine Plants (MTPs) under time-

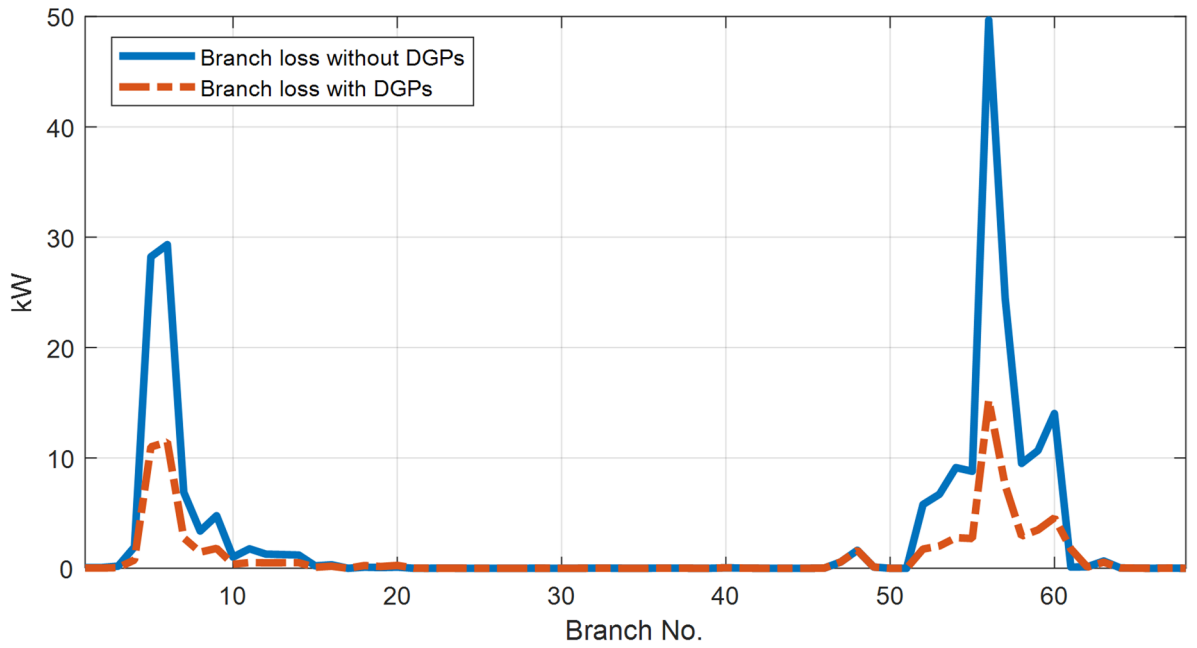


Fig. 9. The distributed line loss without and with DGPs.

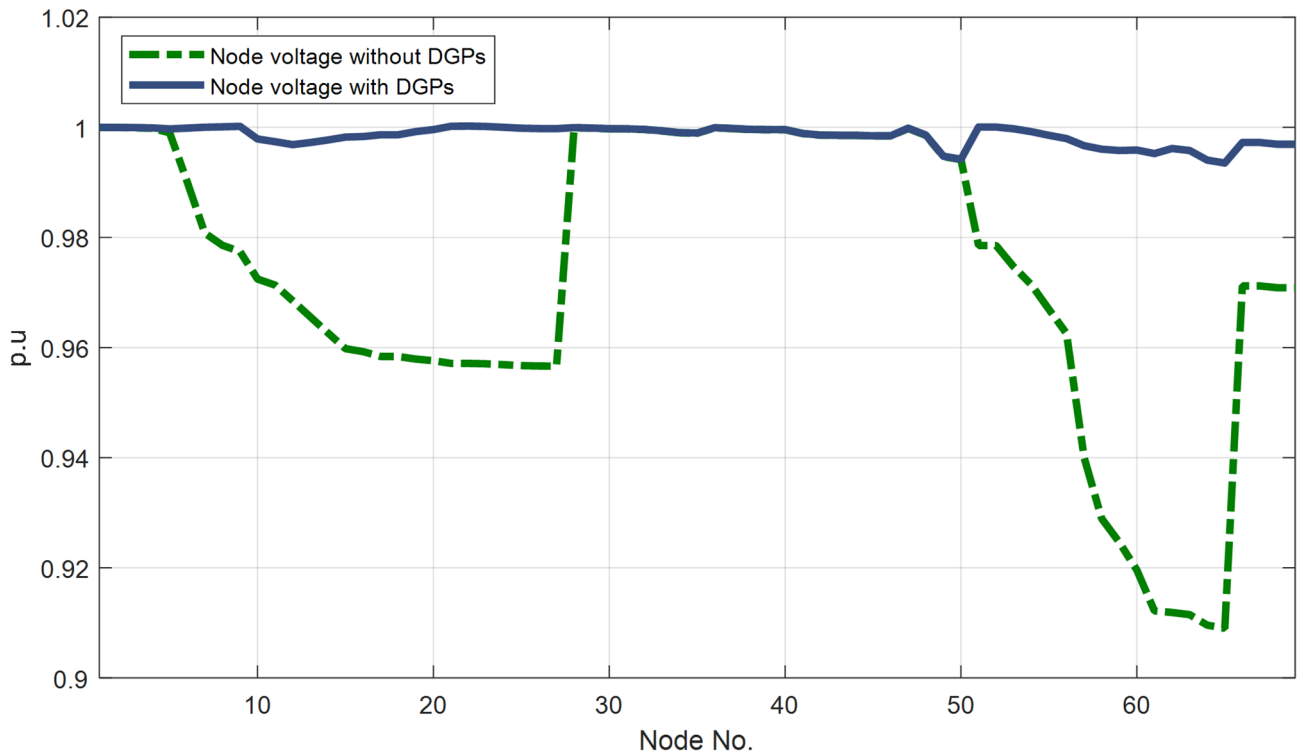


Fig. 10. The node voltage without and with DGPs.

varying conditions, the proposed method again produced superior results. The fitness value of the method (0.2926) was marginally better than SFO (0.2956) and EVO (0.2936), indicating an optimally refined solution. Using this methodology, annual electricity import costs were reduced by \$1.36 million with a DGP penetration level of 65.63%. Total power losses decreased by 84.64%, voltage stability was improved from a range of [0.909, 1.00] to [0.965, 1.031], and generated emissions fell by 68.55%. These outcomes highlight the multifaceted benefits of DGP integration through the proposed approach. In conclusion, this study underscores the potential of combining EVO with Fuzzy Logic as a robust method for solving optimization problems related to DGP

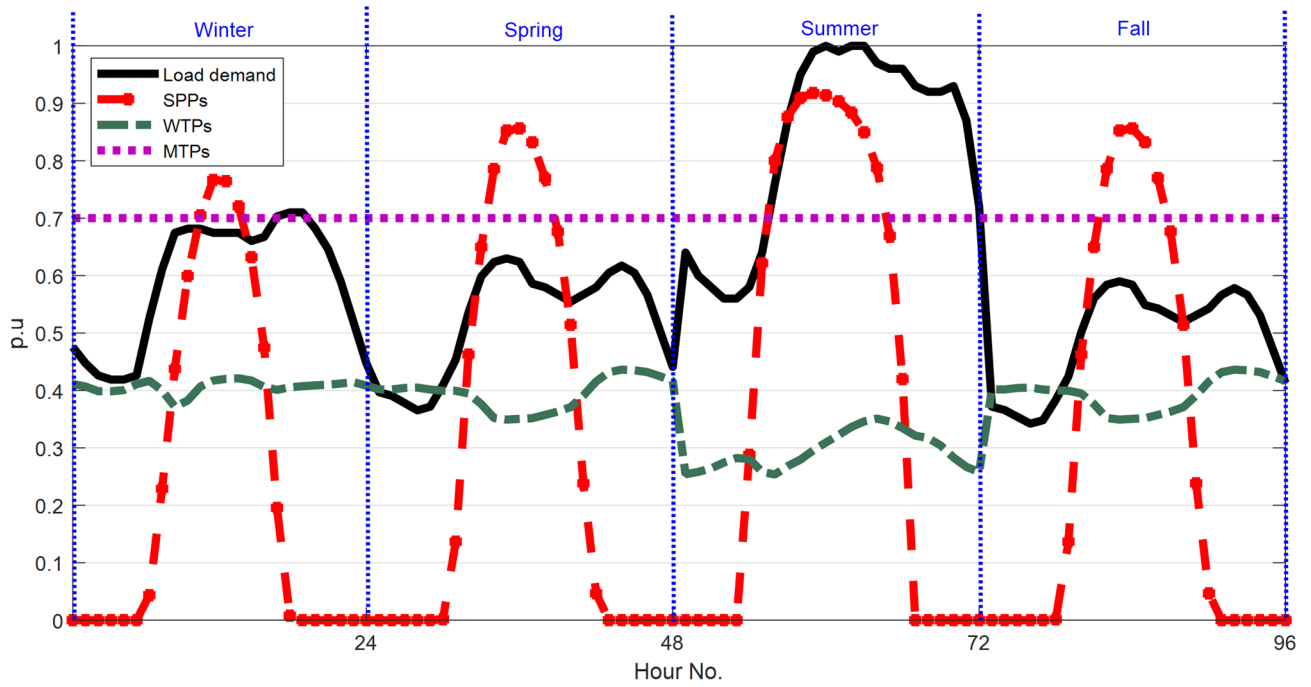


Fig. 11. The output curves of load demand, WTPs, SPPs and MTPs.

Items	Values
P_{WTP}^{MAX} and P_{WTP}^{MIN}	15 turbines and 02 turbines (100 kW/turbine)
P_{SPP}^{MAX} and P_{SPP}^{MIN}	30,000 modules and 2000 modules (50 W/module)
P_{MTP}^{MAX} and P_{MTP}^{MIN}	30 units and 02 units (50 kW/unit)

Table 5. The parameters are used in this study.

Method	Optimal result of installing PDGs (Node/number of connected generators)			0.1950	0.3564	0.3158	0.3151	0.2956
	WTPs	SPPs	MTPs					
SFO	- Node 44/ 02 turbines	- Node 32/ 11,469 modules	- Node 62/ 13 units	0.1391	0.3939	0.3213	0.3201	0.2936
	- Node 61/14 turbines	- Node 55/9406 modules	- Node 65/07 units					
EVO	- Node 49/03 turbines	- Node 61/ 11,345 modules	- Node 63/ 21 units	0.1536	0.3865	0.3156	0.3145	0.2926
	- Node 56/04 turbines	- Node 24/9666 modules	- Node 61/07 units					
EVO with fuzzy	- Node 61/07 turbines	- Node 18/ 6027 modules	- Node 58/ 03 units	0.1536	0.3865	0.3156	0.3145	0.2926
	- Node 22/05 turbines	- Node 63/15,174 modules	- Node 64/20 units					

Table 6. The optimal result of implemented methods for integrating WTPs, SPPs and MTPs in the DN.

integration in distribution networks. For future work, the research aims to incorporate energy storage systems (BES) and smart inverters into power networks to enhance distributed generation penetration while maintaining system constraints. Moreover, simultaneous network reconfiguration will also be explored to further maximize overall network welfare.

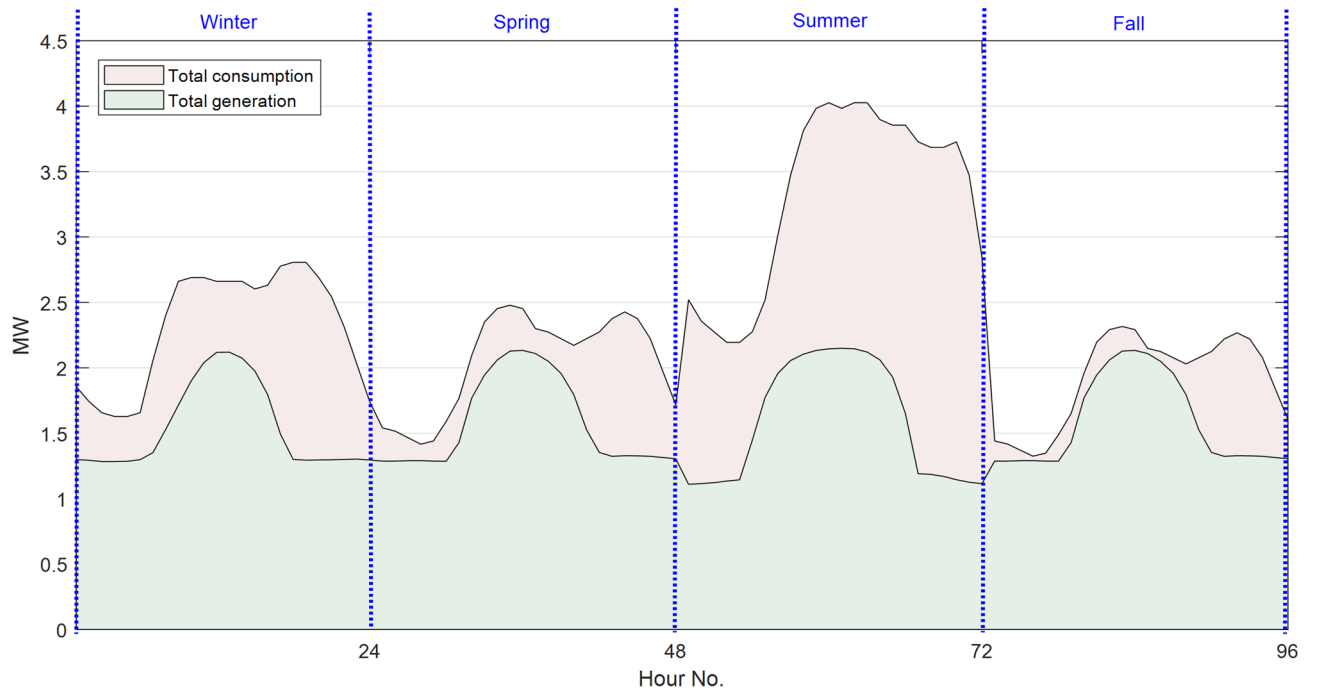


Fig. 12. Total generation from DGPs and total consumption.

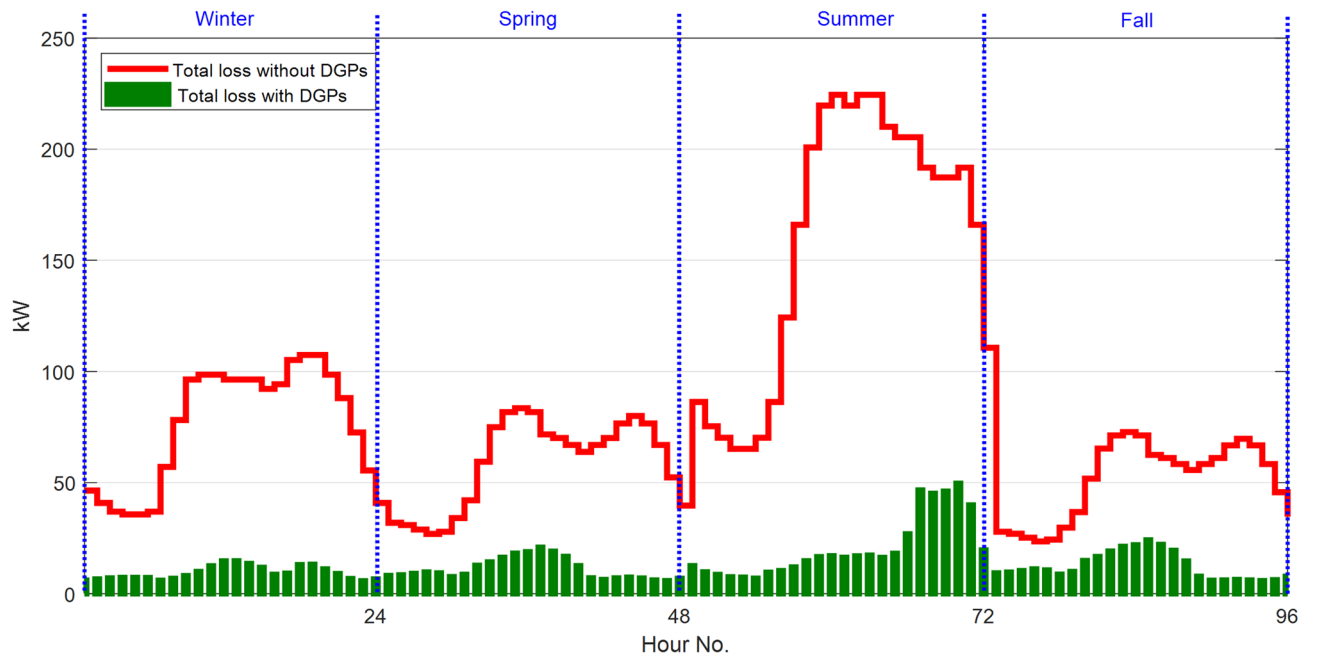


Fig. 13. Total power loss without and with DGPs.

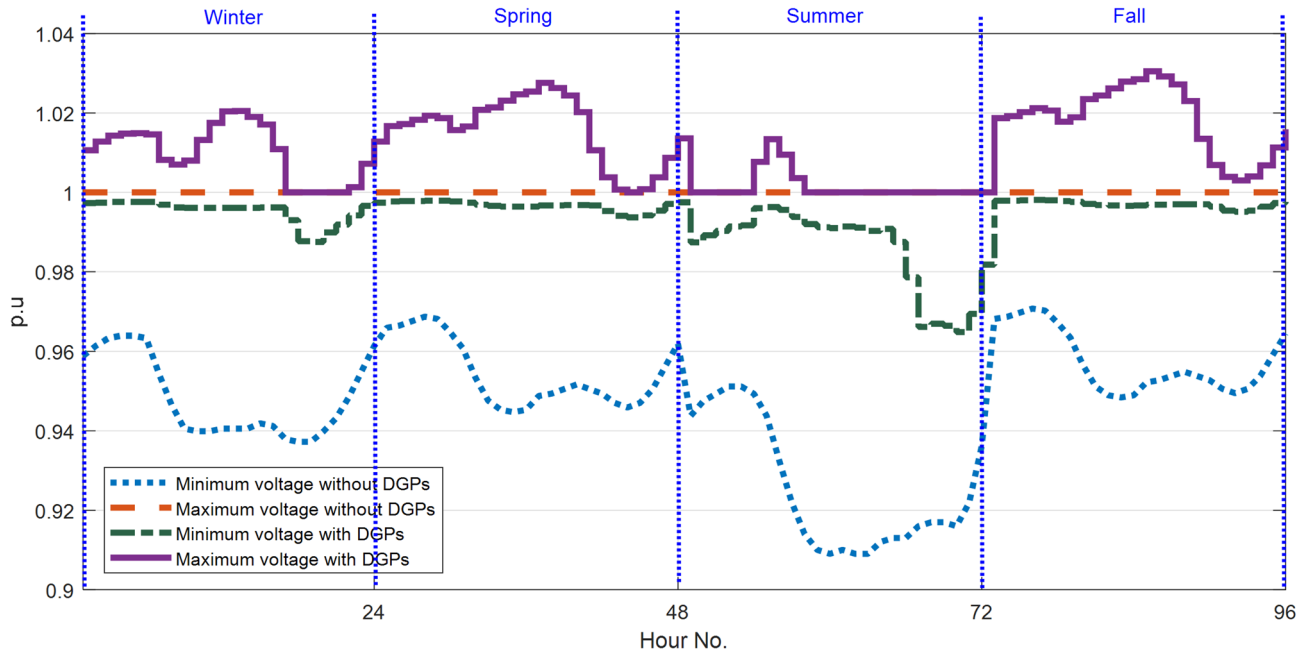


Fig. 14. Minimum and maximum node voltage values without and with DGPs.

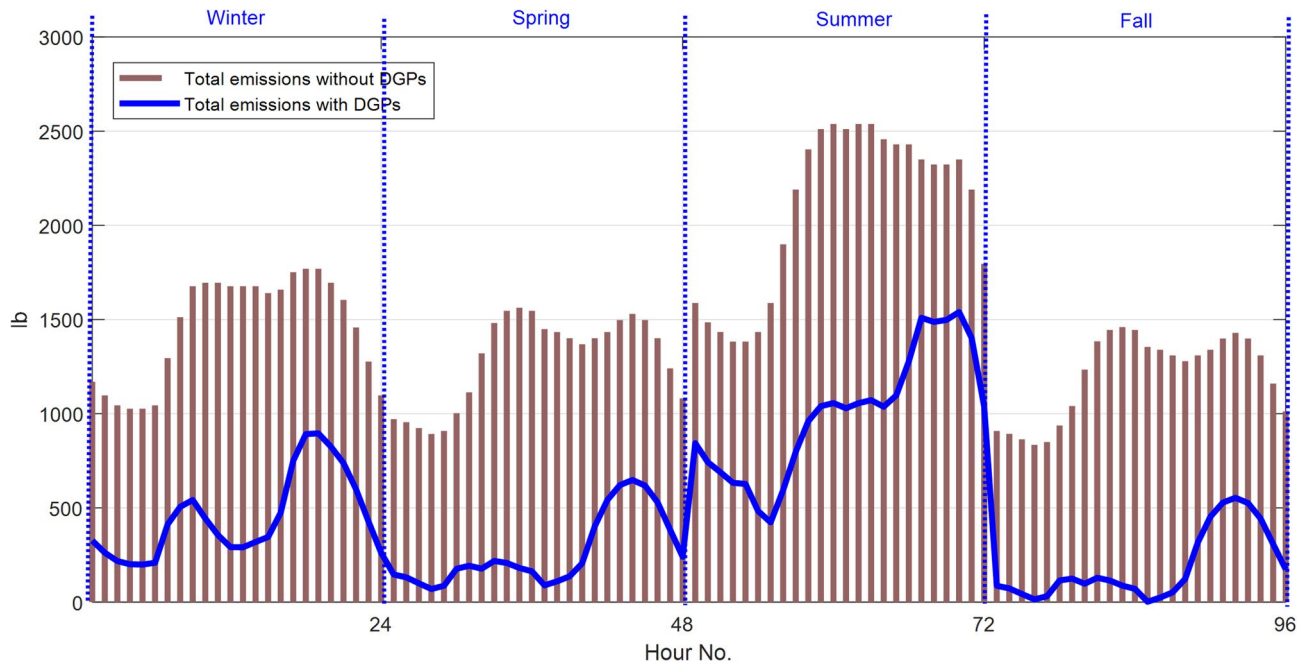


Fig. 15. Total generated emissions without and with DGPs.

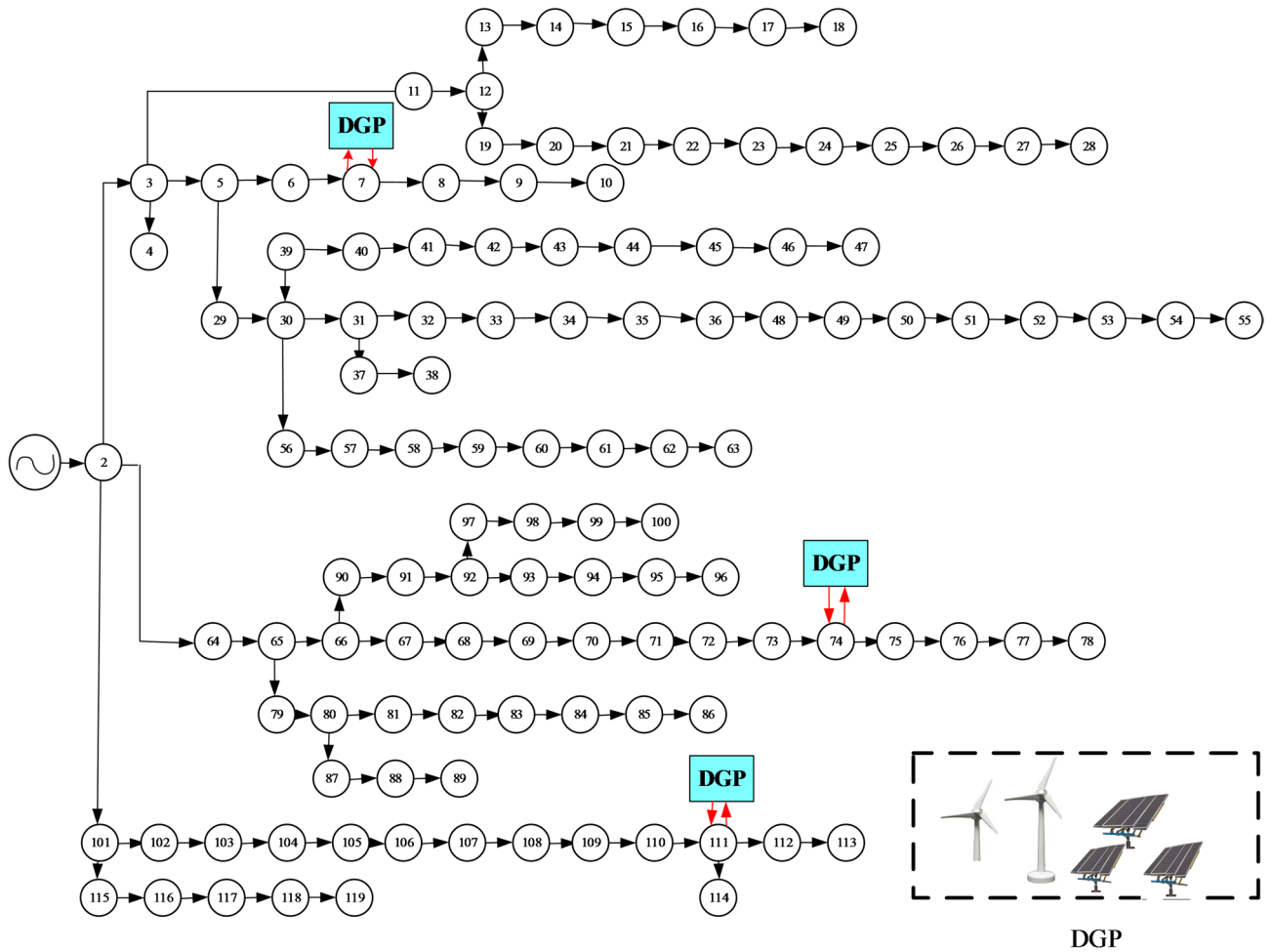


Fig. 16. 119 bus IEEE system.

Power factor #	method	DGP size (location)	$F_1(KW)$	$F_2(P.U)$	$F_3(\$/h)$
Without DGP			1298.1	0.3577	
unity power factor	Proposed algorithm	0.26481(70);1.137(74) 0.4308(76); 0.89018(111) 0.17768(96); 0.18977(7) 0.65209(51)	842.23800	0.18994	153.01761
	MODE	0.79752(77) 1.0862(54) 0.74976(72) 0.087507(5) 0.16504(83) 0.51814(33) 0.68433(107)	878.23578	0.20303	169.45525
0.86 power factor	Proposed algorithm	0.59982(52) 0.92096(77) 0.50941(110) 0.32416(71) 0(43) 0.56832(54) 0.42213(73)	737.13665	0.16640	141.091
	MODE	0.60453(71) 0.66382(99) 0.77869(76) 0.30481(70) 0.60189(68) 0.86773(54) 0.71376(72)	752.19278	0.15174	189.11617

Table 7. Records the optimal distribution of DGPs Attained using different optimization techniques under a constant load model, factoring in two DGPs operational conditions—unity and 0.87 lagging power factor. It is noteworthy that system performance shows significant improvement when DGPs operate at a 0.87 lagging power factor. In terms of minimizing power losses, the EVO algorithm proves highly effective, achieving a 35.1176% reduction at unity power factor and an even greater improvement of 43.2098% at the 0.87 lagging power factor. Similarly, the cost associated with DGPs operation drops to \$153.01761 per hour at unity power factor and further reduces to \$141.091 per hour under the 0.87 lagging power factor condition. Additionally, voltage profiles benefit from reduced deviation, with values improved to 0.16640 p.u. at 0.87 lagging power factor and 0.18994 p.u. at unity power factor. Table 7. optimal sitting and sizing of DGP in 119 bus system.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Author contributions

1 Fares suliaman alromithy : Validation; visualization; writing—original draft. 2 Hamed Hosseinnia: Conceptualization; data curation; formal analysis; funding acquisition; investigation; resources; software. 3 Rana Rostami: Validation; visualization; writing—original draft. 4 Mohammad Rashed M Altmania : Validation; visualization; writing—original draft.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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