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Optimizing Distributed Energy Resources for Sustainable Solutions: A Multi-Objective Approach Based on Harmony Search Algorithm

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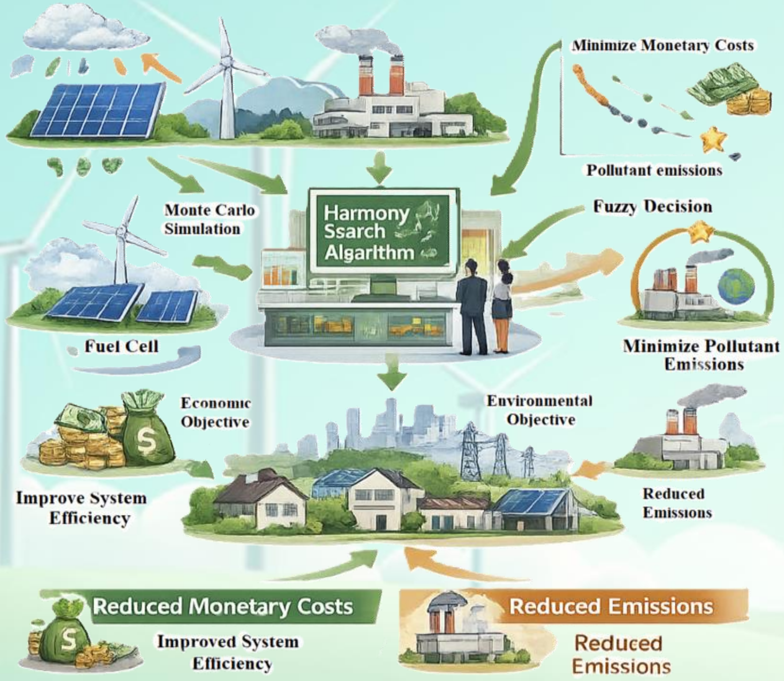
Highlights

- **A multi-objective harmony search algorithm with Monte Carlo simulation minimizes costs and emissions under load and price uncertainties.**
- **The model optimizes six diverse energy resources to balance economic and environmental trade-offs using fuzzy decision-making.**
- **Results confirm that higher renewable energy penetration significantly reduces losses, cuts emissions, and improves system efficiency.**

Graphical Abstract



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Optimizing Distributed Energy Resources for Sustainable Solutions: A Multi-Objective Approach Based on Harmony Search Algorithm

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A B S T R A C T

This study introduces a comprehensive multi-objective harmony search algorithm designed to simultaneously minimize total monetary costs and pollutant emissions while explicitly accounting for uncertainties associated with electrical load demand and electricity market prices. To effectively capture and model these inherent uncertainties, a Monte Carlo simulation (MCS) framework is employed, enabling a probabilistic assessment of system behavior under varying operating conditions. The formulated optimization problem integrates six distinct types of distributed energy resources (DER), namely wind turbines, photovoltaic systems, fuel cells, micro-turbines, gas turbines, and diesel generators. This diverse portfolio of DER technologies allows the model to accurately reflect the operational flexibility and heterogeneity of modern distributed energy systems. Within the proposed multi-objective harmony search framework, a non-dominated sorting mechanism is applied to systematically classify candidate solutions and extract the Pareto-optimal front, thereby revealing the trade-offs between economic and environmental objectives. To further support practical decision-making, a fuzzy decision-making methodology is incorporated to identify the most suitable compromise solution from the set of Pareto-optimal alternatives, taking into account decision-makers' preferences and system priorities. The simulation results demonstrate that higher penetration of renewable energy sources plays a crucial role in reducing energy losses, mitigating environmental impacts, and improving overall system efficiency. These findings highlight the effectiveness of the proposed optimization framework in enhancing the economic and environmental performance of distributed energy systems under uncertainty.

1. Introduction

1.1. Motivation and aim

Optimal planning of distributed energy resources (DERs) plays a pivotal role in the development and operation of modern energy distribution networks, particularly in response to the growing demand for sustainable, reliable, and environmentally friendly energy solutions, as well as the urgent need to reduce dependence on fossil fuel–based generation. The integration of renewable energy sources (RESs), such as solar photovoltaic and wind power systems, significantly contributes to lowering greenhouse gas emissions, mitigating environmental impacts, and advancing long-term energy sustainability objectives. Moreover, the strategic allocation and optimal sizing of DERs in close proximity to consumption points lead to a substantial reduction in transmission and distribution losses, thereby enhancing overall system efficiency. Such localized generation also strengthens grid resilience by improving voltage profiles, increasing supply reliability, and providing greater flexibility in accommodating load variations. By enabling the effective utilization of locally available renewable resources, optimal DER planning supports a more decentralized, robust, and sustainable energy infrastructure capable of meeting future energy challenges. Advanced forecasting and modeling techniques ensure the effective deployment of DERs while maintaining grid stability.

Additionally, optimal DER planning fosters consumer empowerment through energy independence, enabling participation in generation via rooftop solar panels or community wind projects, which also supports local economic development and job creation in the renewable sector [1,2]. The DERs planning is crucial for modern energy distribution networks, as it reduces dependence on fossil fuels, lowers air pollution, and mitigates climate change impacts. By integrating RESs, this approach enhances grid efficiency and resilience while promoting consumer participation and local economic growth. Ultimately, effective DER integration is essential for achieving a cleaner, sustainable energy future and addressing urgent environmental challenges.

1.2. Literature review

The study presented in [3] introduces an advanced three-dimensional multi-objective optimization framework aimed at the optimal planning of distributed energy resources (DERs) alongside the effective management of electrical energy storage systems within distribution networks. This framework simultaneously considers multiple conflicting objectives, enabling a balanced trade-off between economic performance, technical reliability, and environmental impact. By incorporating the coordinated operation of DERs and storage systems, the proposed approach enhances operational flexibility, improves energy utilization efficiency, and supports more reliable and resilient distribution network planning under diverse operating conditions. In [4], a multi-objective planning strategy is introduced that takes into account the stochastic nature of customer-owned DERs. This approach concurrently tackles dynamic network reconfiguration, capacitor placement, and the dynamic adjustment of on-load tap changer transformers. The primary goal is to reduce power loss costs while enhancing the system's voltage profile by minimizing a newly proposed voltage consistency indicator presented in this study. Ref. [5] presents a comprehensive long-term stochastic mixed-integer single-level, single-stage nonlinear multi-objective optimization planning model specifically developed to facilitate the effective integration of distributed energy resources (DERs) into power distribution systems. This model captures the inherent uncertainties associated with long-term planning horizons while simultaneously addressing multiple conflicting objectives, thereby enabling more informed and robust decision-making for DER deployment. In [6], the authors investigate the coordinated and synergistic integration of RESs with battery energy storage systems, with the primary objective of improving the sustainability, operational reliability, and flexibility of modern power systems. By leveraging the complementary characteristics of renewables and storage technologies, the proposed approach enhances energy balancing capabilities and mitigates the adverse impacts of renewable intermittency. Furthermore, the study in [7] develops an optimization-based planning framework for the strategic placement and sizing of multiple DERs in conjunction with electric vehicle charging stations within distribution networks. This framework aims to accommodate the increasing penetration of electric vehicles while maintaining network performance, reducing operational costs, and ensuring efficient utilization of distributed energy assets. Additionally, [8] discusses various modeling and optimization methodologies for DERs, as well as control strategies for DERs and microgrids. Ref. [9] addresses stochastic energy management within a microgrid environment, taking into account RESs such as photovoltaic, wind, and tidal energy, along with demand response programs and storage solutions. In [10], a novel and comprehensive modeling approach is proposed that explicitly incorporates several practical and influential factors affecting distributed generation planning. These factors include pollutant emissions, capital investment costs, and operational expenses associated with distributed generators, as well as the cost of purchasing electricity from the main grid. In addition, the proposed framework accounts for dynamic planning aspects over the study horizon and addresses uncertainties arising from variations in load demand and electricity market prices. By integrating these considerations, the model provides a more realistic and robust decision-support tool for optimal planning and operation of distributed energy resources under real-world conditions. Ref. [11] focuses on establishing penetration limits for regulations within existing networks. As new electrification systems emerge, the integration of DERs necessitates new planning principles that consider the sizing and selection of network components such as feeder cables and transformer while accounting for various scenarios regarding DER uptake. Furthermore, it is crucial to address the uncertainties linked to the operation of these networks, particularly concerning the location and capacity of DERs. Ref. [12] proposes a comprehensive methodology for the optimal and coordinated allocation of wind farms, energy storage systems, and parking facilities for plug-in electric vehicles, while explicitly incorporating demand response programs and hourly distribution network reconfiguration under both normal operating conditions and severe contingency scenarios. In addition, this methodology evaluates the participation and behavior of different load types, providing a realistic representation of system demand dynamics and enhancing the operational flexibility and resilience of the distribution network. In [13], a multi-objective planning model for distributed energy resources is developed with the aim of achieving an effective trade-off between carbon emission reduction and economic cost minimization. By simultaneously addressing environmental and financial objectives, the proposed model supports sustainable planning decisions and promotes the integration of cleaner energy technologies within modern power systems. An innovative enhanced adaptive weighted-sum algorithm featuring a single sparse-preference parameter is introduced to generate a comprehensive Pareto front. Additionally, [14] proposes a three-objective capacity planning model for DERs that considers economic cost, carbon emissions, and voltage deviation. A comprehensive review about DER planning is stated in [15].

This paper presents a comprehensive probabilistic multi-objective framework designed to optimize the planning and deployment of DERs within distribution electricity networks. The proposed model is formulated from the viewpoint of the distribution company, ensuring that practical operational and economic considerations are fully reflected in the planning process. The mathematical formulation is based on nonlinear programming techniques, allowing the model to accurately capture the complex interactions and constraints inherent in modern distribution systems.

The proposed design aims to achieve an effective trade-off between minimizing total monetary costs and reducing pollutant emissions, while explicitly accounting for uncertainties associated with electrical load variations and fluctuations in electricity market prices. The monetary cost objective includes investment and operational costs of distributed generation (DG) units, compensation payments related to network losses, and expenditures incurred from purchasing electricity from the upstream grid.

To efficiently solve the resulting multi-objective optimization problem, the non-dominated sorting harmony search algorithm (NSHSA) is employed, enabling the identification of Pareto-optimal solutions. In addition, uncertainty analysis is conducted using the Monte Carlo simulation method, which provides a robust probabilistic assessment of system performance under varying stochastic conditions.

The NSHSA is a hybrid optimization technique that integrates two well-established and powerful methodologies [16], namely non-dominated sorting and the harmony search algorithm. This hybrid structure makes NSHSA particularly suitable for solving complex multi-objective optimization problems, in which the primary aim is to identify a set of optimal solutions that represent meaningful trade-offs among multiple, often conflicting, objectives. Rather than converging to a single solution, the algorithm seeks to generate a diverse collection of alternatives that collectively describe the Pareto-optimal front. Within NSHSA, the non-dominated sorting mechanism is employed to classify and rank candidate solutions according to the concept of Pareto dominance [17,18]. Under this framework, each solution is evaluated not only based on its individual objective values but also in comparison with other solutions in the population. A solution is defined as non-dominated if no other solution performs better across all objectives simultaneously. This ranking strategy enables the algorithm to preserve a diverse set of high-quality solutions, ensuring broad coverage of the Pareto front and facilitating a comprehensive exploration of the solution space. The harmony search component of NSHSA is inspired by the process of musical improvisation, in which musicians collaboratively seek harmonious sound patterns through experience, memory, and random variation [19]. Analogously, in the optimization context, new candidate solutions are generated by combining information from existing solutions, guided by harmony memory, pitch adjustment, and random selection mechanisms. This balance between exploitation of known good solutions and exploration of new regions of the search space enhances the algorithm's ability to avoid premature convergence. Furthermore, NSHSA dynamically adapts its search behavior based on solution performance, allowing for a flexible and efficient optimization process capable of handling nonlinear, multi-modal, and multi-objective problems effectively.

One of the primary advantages of the NSHSA lies in its strong capability to efficiently address multi-objective optimization problems. By simultaneously considering multiple conflicting objectives, NSHSA is able to generate a diverse set of Pareto-optimal solutions rather than converging to a single point. This feature allows decision-makers to clearly observe the trade-offs among objectives and select solutions that best align with technical, economic, or environmental priorities. Moreover, the integration of non-dominated sorting with the adaptive search mechanism of harmony search enhances both solution diversity and convergence speed, making NSHSA particularly effective for complex, nonlinear, and large-scale optimization problems. By combining non-dominated sorting with harmony search, NSHSA can effectively balance exploration and exploitation, leading to a robust search capability [20]. Additionally, the diversity maintained through non-dominated sorting helps prevent premature convergence to suboptimal solutions, ensuring that a wide range of potential solutions is considered. This makes NSHSA particularly suitable for complex real-world problems where multiple criteria must be optimized simultaneously, such as in engineering design, resource allocation, and scheduling tasks. Overall, NSHSA represents a significant advancement in multi-objective optimization techniques, leveraging the strengths of both non-dominated sorting and harmony search to achieve superior results. The novel contributions of this paper in comparison to prior research in the field can be outlined as follows:

- Introduction of a new multi-objective probabilistic framework for the planning of DERs by distribution companies operating in a competitive electricity market.
- Development of an effective scenario-based methodology to address uncertainties related to electricity prices and load demands.
- Simultaneous consideration of six distinct types of DERs, which include wind turbine (WT), photovoltaic (PV) system, fuel cell (FC), micro-turbine (MT), gas turbine (GT), and diesel engine (DE).
- Utilization of the NSHSA combined with a fuzzy decision-making approach to identify the optimal compromise solution from the set of Pareto optimal solutions.

1.3. Paper organization

The remainder of this paper is organized as follows. Section 2 describes the scenario-based modeling approach adopted to effectively address uncertainties associated with electricity pricing and load demand variations. Section 3 outlines the proposed probabilistic and multi-objective optimization framework developed for the optimal planning of distributed energy resources (DERs). The detailed mathematical formulation of the multi-objective optimization strategy and associated constraints is presented in Section 4. Section 5 provides a comprehensive analysis and discussion of the simulation results obtained from the studied primary distribution network. Finally, Section 6 concludes the paper by summarizing the main findings of the study and highlighting the practical implications and potential applications of the proposed approach.

2. Modeling uncertainties using scenario-based approaches

This paper focuses on various uncertainties that impact the planning of DERs, specifically addressing price and load uncertainties. The demand for electric power significantly influences the fluctuations in periodic electricity prices. Consequently, there is an increasing emphasis on analyzing the relationship between electricity prices and load demands.

A critical feature of electricity generated from RESs such as solar and wind is its intermittent availability, particularly during peak demand periods. From an economic perspective, ensuring system adequacy, defined as the ability to provide sufficient capacity to reliably meet peak demand, means that electricity holds greater value during these peak hours.

Therefore, it is essential to establish a correlation between electricity load profiles and price dynamics. However, it is important to note that this paper does not account for the correlation between load and price. The modeling strategy proposed herein is outlined as follows.

2.1. Modeling electricity prices based on different scenarios

In competitive electricity markets, distribution companies are obligated to purchase electrical energy directly from the market. Due to the highly dynamic and uncertain characteristics of these markets, electricity prices exhibit significant fluctuations over time, which introduces considerable uncertainty into operational and planning decisions. As a result, accurate anticipation of future market prices is essential for distribution companies to effectively schedule their short-term operations and long-term planning strategies. Nevertheless, the stochastic and volatile behavior of market prices makes reliable forecasting challenging, and prediction errors can substantially affect both operational performance and planning outcomes. To mitigate the impacts of price uncertainty, a scenario-based modeling approach that combines fuzzy C-means clustering with Monte Carlo simulation (FCM/MCS) is adopted to represent variations in electricity market prices. In this framework, the statistical properties of price behavior are captured through scenario generation rather than relying on a single forecast. It should be noted that the estimation of key statistical parameters, such as the expected value and variance of electricity prices, is commonly performed using advanced forecasting methods, including time series techniques and artificial neural network models.

Initially, using the forecasted mean and variance of prices, a set of np price samples is generated through Monte Carlo simulation, with each scenario assigned an equal probability of $1/n_p$. Although generating a large number of price samples enhances the representation of the uncertain model, it also results in a stochastic program that may become excessively large and difficult to solve. Therefore, a balance must be struck between achieving a good approximation and managing computational complexity. Consequently, various scenario reduction methods have been introduced in the literature to limit the total number of generated scenarios while maintaining the essential statistical properties of electricity price behavior. These techniques aim to improve computational efficiency by discarding scenarios with negligible occurrence probabilities and consolidating those that exhibit similar characteristics into representative groups, thereby preserving the overall stochastic structure of the problem. In this context, the FCM technique serves as the primary method for price scenario reduction. FCM is utilized to cluster n_p randomly generated samples into a specified number of clusters. By definition, a cluster comprises objects that are similar to one another but dissimilar to those in other clusters. Thus, the center of each cluster can effectively represent similar price scenarios within that cluster. Accordingly, FCM serves as an effective complement to the Monte Carlo simulation framework by transforming the initially generated set of n_p random price samples at each time interval into a smaller set of n_r representative and distinct scenarios. This reduction process retains the diversity of price behavior while significantly decreasing computational complexity. The occurrence probability assigned to each reduced price scenario is then calculated using the following approach [21]:

$$P_M = \frac{n_c}{n_p}, \quad M = 1, 2, \ldots, n_r \tag{1}$$

Consequently, a price scenario that serves as the center of a cluster with a greater number of members is considered to have a higher probability than other scenarios.

2.2. Scenario-based modeling of electrical loads

To properly reflect inaccuracies in load forecasting, it is necessary to explicitly model load-related uncertainties within the analytical framework. This requires identifying an appropriate probability distribution to represent load forecast errors. In this study, the load forecasting error is assumed to follow a Gaussian distribution, with its mean equal to the predicted peak demand that the distribution company is required to supply. Figure 1 depicts the continuous probability density function associated with the system load forecasting error, which is subsequently discretized into seven distinct intervals. Each interval spans a range equivalent to one standard deviation of the load forecast error, consistent with the methodology adopted in [22,23]. To produce representative load scenarios corresponding to different forecasted demand levels and their associated probabilities obtained from the defined probability distribution function, a roulette wheel selection technique is applied, as outlined in [24]. This probabilistic sampling approach enables the systematic generation of load scenarios in proportion to their likelihood of occurrence. At the first stage, the interval [0,1] is partitioned according to the normalized probabilities assigned to each load level, as illustrated in Figure 2. Next, a random value is drawn uniformly from the interval [0,1].

If the generated random value lies within the normalized probability segment associated with a particular load forecast level on the roulette wheel, that load level is selected as a representative scenario. By repeatedly applying this probabilistic selection procedure, a sufficient and diverse set of load scenarios is gradually constructed. The integration of the roulette wheel selection method with the Monte Carlo simulation framework forms a hybrid scenario generation approach, commonly referred to as the RW/MCS technique, which enables efficient and statistically consistent modeling of load uncertainties.

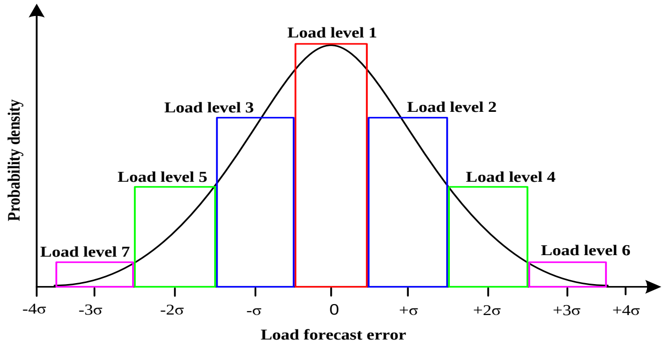

Figure 1. A standard approach involves discretizing the continuous probability distribution of the load forecast error into seven intervals.

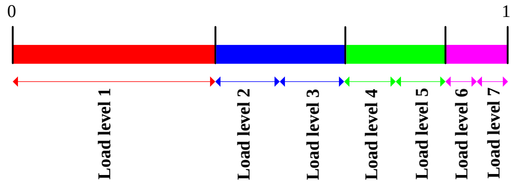

Figure 2. The roulette wheel mechanism is utilized for the normalized probabilities of load forecast levels.

3. Problem formulation

This section develops the formulation of a multi-objective optimal planning problem for distributed energy resources. The proposed framework is expressed as a nonlinear programming model, allowing for the accurate representation of the complex interactions and constraints inherent in the planning and operation of distributed energy systems.

3.1. Objective functions

The economic objective function in the planning problem of DERs aims to minimize the investment and operational costs associated with DERs, as well as the expenses related to loss compensation services and payments for purchased power by the distribution company. The monetary objective function is represented by Equations (2) and (3) [21]:

$$f_1 = \sum_s \pi_s \left(\begin{array}{l} \sum_i \sum_k \left(C_k^{INV} S_B P_{s,i,k}^{OP} \right) + 8760 \times \sum_t \sum_i \sum_k \left(\left(\frac{1}{1+d} \right)^t C_k^{OP} S_B P_{s,i,k}^{OP} \right) + \\ 8760 \times \sum_t \left(\left(\frac{1}{1+d} \right)^t P_{s,ij}^{Loss} S_B \rho_s \right) + 8760 \times \sum_t \left(\left(\frac{1}{1+d} \right)^t \sum_n P_{s,n}^{PP} S_B \rho_s \right) \end{array} \right) \tag{2}$$

$$\forall s \in \{1,\ldots,NS\},\ \forall t \in \{1,\ldots,NT\},\ \underset{i \neq j}{\forall} i \in \{1,\ldots,NB\}$$

$$\forall k \in \{\mathrm{WT,PV,FC,MT,GT,DE}\},\ \forall n \in \{1,\ldots,NSS\}$$

where

$$P_{s,ij}^{Loss} = \sum_i \sum_j \left(\frac{\left(|V_{s,i}| - |V_{s,j}| \right)^2}{|Z_{ij}|} \right) \times \cos\varphi \tag{3}$$

$$\underset{i \neq j}{\forall} i \in \{1,\ldots,NB\},\ \underset{i \neq j}{\forall} j \in \{1,\ldots,NLB\}$$

In Equation (2), C_k^{OP} encompasses both fixed and variable components of operating costs. The fixed components consist of the costs associated with operation and maintenance, while the variable components pertain to fuel expenses. Furthermore, to appropriately capture the trade-off between locally generated electricity, especially the variable and emission-free power produced by solar and wind–based DERs, and energy purchased from the upstream grid, the emission minimization objective function is defined as shown in Equation (4) [21]:

$$f_2 = \sum_s \pi_s \left(\begin{array}{l} \sum_i \sum_k \left(8760 \times P_{s,i,k}^{OP} \times S_B \times \sum_m E_{k,m}^{DER} \right) + \\ \sum_n \left(8760 \times P_{s,n}^{PP} \times S_B \times \sum_m E_m^G \right) \end{array} \right) \tag{4}$$

$$\forall s \in \{1,\ldots,NS\},\ \forall n \in \{1,\ldots,NSS\},\ \forall i \in \{1,\ldots,NB\}$$

$$\forall k \in \{\mathrm{WT,PV,FC,MT,GT,DE}\},$$

$$\forall m \in \{SO_2, NO_x, CO, CO_2, PM_{10}\}$$

In modern energy system planning and operation, a wide range of effective measures are available to mitigate pollutant emissions. These measures include shifting energy production away from fossil fuel–based technologies toward RESs, improving overall energy efficiency across generation and consumption sectors, adopting market-based mechanisms such as carbon taxation, and enabling emission trading schemes between public and private stakeholders. Such approaches provide both regulatory and economic pathways for controlling emissions while maintaining system performance.

Within optimization-based planning frameworks, marginal emission abatement costs can be estimated directly from the optimization outcomes, offering valuable insight into the economic trade-offs associated with emission reduction strategies. In multi-objective planning models, the weighting factors assigned to the emission-related objective function can be carefully tuned so that the resulting marginal abatement costs are consistent with long-term emission price targets and policy expectations defined by decision makers. As a result, planners are required to determine the appropriate level of clean energy deployment or procurement by balancing the operational and societal benefits of electricity generation against the financial penalties associated with surpassing allowable emission thresholds. This process enables informed decision-making that aligns environmental goals with economic feasibility.

3.2. Constraints

The objective functions associated with DER planning are optimized subject to a set of technical and operational constraints to guarantee realistic and feasible planning solutions. These constraints encompass limitations related to the operational capacities of DER units, the maximum allowable capacities of distribution substations, the thermal loading limits of distribution feeders, and the fundamental requirements of power balance and conservation within the network. Each of these constraints plays a critical role in maintaining system reliability and operational security and is described and analyzed in detail in the following subsections [21].

a) Operational capacity of DER: This constraint, as shown in Equation (5), refers to the maximum power output that the DER can deliver under normal operating conditions. It ensures that the generation from the DER does not exceed its rated capacity, which is crucial for maintaining grid stability and reliability.

$$P_{s,i,k}^{OP} \times S_B \leq P_k^{CAP} \tag{5}$$

$$\forall s \in \{1,\ldots,NS\}, \quad \forall i \in \{1,\ldots,NB\}$$

$$\forall k \in \{\mathrm{WT}, \mathrm{PV}, \mathrm{FC}, \mathrm{MT}, \mathrm{GT}, \mathrm{DE}\},$$

b) Distribution substation capacity: This constraint, as shown in Equation (6), defines the maximum load that a distribution substation can handle. It limits the total amount of power that can be supplied to the distribution network from the substation, ensuring that it does not exceed its designed capacity and avoiding potential overloads.

$$P_n^{SS} \leq P_n^{SS-MAX}, \quad \forall n \in \{1,\ldots,NSS\} \tag{6}$$

c) Thermal capacity of distribution feeder: This constraint, as shown in Equation (7), refers to the maximum current that a distribution feeder can carry without overheating. It ensures that the thermal limits of the feeder are not exceeded, which could lead to equipment damage or failure.

$$P_{s,ij} \times S_B \leq P_{ij}^{MAX}, \tag{7}$$

$$\forall s \in \{1,\ldots,NS\}, \ \underset{i \neq j}{\forall} i \in \{1,\ldots,NB\},$$

$$\underset{i \neq j}{\forall} j \in \{1,\ldots,NLB\}$$

d) Power balance limits: This constraint, as shown in Equation (8), ensures that the total power generated in the system equals the total power consumed, maintaining equilibrium in the network. It is essential for preventing over-generation or under-generation scenarios, which can affect system stability.

$$\left\{\sum_j \left\{P_{s,ij} - P_{s,ji}^{Loss}\right\} - \sum_j P_{s,ij} + \sum_k P_{s,i,k}^{OP}\right\} \times S_B = D_{s,i} \tag{8}$$

$$\forall s \in \{1,\ldots,NS\}, \ \forall i \in \{1,\ldots,NB\}, \ \underset{i \neq j}{\forall} j \in \{1,\ldots,NLB\},$$

$$\forall k \in \{\mathrm{WT},\mathrm{PV},\mathrm{FC},\mathrm{MT},\mathrm{GT},\mathrm{DE}\},$$

4. Solution methodology

4.1. NSHSA

In this study, the proposed multi-objective optimization framework is addressed using the Harmony Search Algorithm enhanced with a non-dominated sorting mechanism. This approach is particularly well suited to distribution network expansion planning problems, as it retains high computational efficiency when dealing with non-convex and complex solution spaces. Moreover, one of its key strengths is the ability to generate the entire Pareto-optimal front within a single execution of the algorithm, eliminating the need for repeated runs with different weighting factors. The underlying principle of this algorithm relies on organizing candidate solutions into multiple hierarchical levels based on their degree of optimality. Solutions assigned to the first level represent quasi-optimal outcomes over the entire feasible solution space, as they are not dominated by any other alternatives.

Subsequent levels consist of solutions that are quasi-optimal within the reduced solution space obtained after excluding solutions from higher-ranked levels. This ranking procedure continues iteratively, progressively categorizing solutions according to their relative performance across the multiple objectives. Figure 3 provides a graphical illustration of this Pareto-based classification process, highlighting the distribution of solutions across different optimality levels.

As shown in Figure 3, only three Pareto levels are depicted for illustrative purposes. Once all candidate solutions are classified into their respective Pareto levels, a fitness value is assigned to the solutions within each level using randomly generated numbers. These fitness values serve as a quantitative measure for guiding the search process of the algorithm. Solutions located on the first Pareto level are given the highest fitness values, while progressively smaller fitness values are allocated to solutions in the subsequent levels. It should be noted that there is no strict rule governing the exact numerical assignment of these fitness values; the only requirement is that solutions in higher-ranked Pareto levels receive larger fitness values than those in lower-ranked levels, thereby preserving the dominance hierarchy among solutions.

In addition to Pareto ranking, a secondary control parameter used for evaluating and ranking candidate solutions is the crowding distance metric. This concept is introduced to preserve diversity among solutions by measuring the density of neighboring solutions surrounding a particular option. Specifically, when a solution is located in a densely populated region of the Pareto front, its fitness value is reduced, whereas solutions situated in sparsely populated regions are favored. As illustrated in Figure 4, consider a set of Pareto-optimal solutions in which the $(i-1)$th and $(i+1)$th solutions are the immediate neighbors of the ith solution along the Pareto front. The crowding distance associated with the ith solution is then calculated using Equation (9), which quantifies the relative spacing between adjacent solutions and ensures a well-distributed and diverse Pareto front.

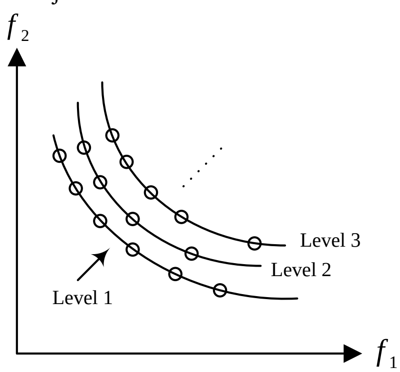

Figure 3. Dividing options into multiple Pareto levels.

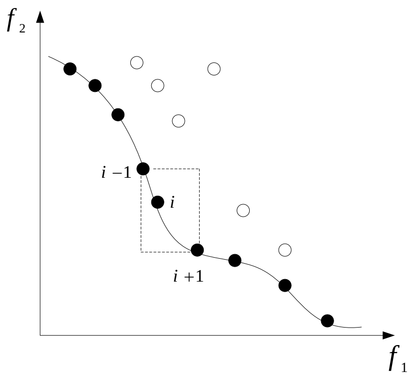

Figure 4. Definition of crowding distance.

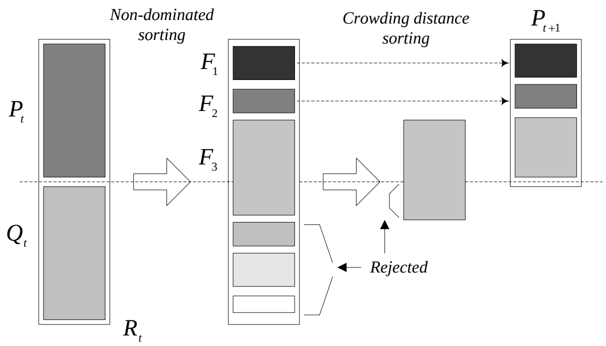

Figure 5. The process of selecting the best vector from among the alternatives.

$$d_i = d_i^1 + d_i^2,\quad d_i^1 = \frac{f_1(x_{i+1}) - f_1(x_{i-1})}{f_1^{\max} - f_1^{\min}},\quad d_i^2 = \frac{f_2(x_{i-1}) - f_2(x_{i+1})}{f_2^{\max} - f_2^{\min}} \tag{9}$$

In a bi-objective competition, solution i is considered superior to solution j if any of the following conditions are met:

• The rank of i is lower than the rank of j ($r_i < r_j$).

• If solution i has the same rank as j, then solution i is superior to solution j if the crowding distance of solution i is greater than the crowding distance of solution j ($d_i > d_j$).

Following the completion of the Pareto ranking process and the computation of crowding distances, a new population vector of candidate solutions is constructed. This updated set of options reflects both solution optimality and diversity and serves as the basis for subsequent stages of the optimization procedure. Then, using common methods employed in harmony search algorithms, new options are generated from this new harmony, and the previous steps are repeated. Figure 5 illustrates the process of selecting the superior vector from among the options.

According to the above figure, at the beginning of each iteration, a vector from the harmony memory (Q_t) is generated using conventional methods of the harmony search algorithm. Then, all vectors ($R_t = P_t \cup Q_t$) are sorted and divided into different levels of Pareto. The number of members in this combined vector is equal to $2N$, where N is the number of members in the initial vector selected by the planner. From the vector R_t, the top N options are selected based on priority and sent to the $(t+1)$-th iteration, and this process continues until the stopping condition is met. Given the method used to form the new vector, it is evident that an elitist approach is employed, as suitable solutions from the previous iteration are carried over unchanged to the next iteration. The stopping condition can be defined in various ways, including setting a maximum number of iterations.

Non-dominated sorting is a fundamental mechanism in multi-objective optimization frameworks. A candidate solution is regarded as non-dominated when no other solution outperforms it simultaneously across all objective functions. This procedure entails assessing an entire population of solutions and organizing them into multiple layers, or fronts, according to their dominance relationships. The first front comprises solutions that are not dominated by any others in the population, representing the best trade-offs among objectives. The second front includes solutions that are dominated only by those in the first front, while remaining mutually non-dominating, and this hierarchical sorting continues for subsequent fronts. Such a structured classification plays a crucial role in directing the optimization process toward the Pareto-optimal region while ensuring sufficient diversity among the generated solutions.

4.2. Harmony Search Mechanism

The harmony search algorithm is inspired by the musical improvisation process, in which musicians collaboratively strive to achieve a harmonious sound by continuously tuning and adjusting their instruments based on experience, memory, and creative variation. In NSHSA, a harmony memory (HM) stores a set of potential solutions (harmonies), and new solutions are generated through a combination of existing harmonies. The generation process involves three main operations: pitch adjustment, harmony memory consideration, and random selection.

1. Pitch Adjustment: This operation allows for fine-tuning of solutions by making small perturbations, helping to explore the solution space more thoroughly.

2. Harmony Memory Consideration: Solutions from the harmony memory are selected based on a probability distribution, promoting the retention of high-quality solutions.

3. Random Selection: Occasionally, new random solutions are introduced to maintain diversity and avoid premature convergence.

4.3. Important Parameters

Several parameters significantly influence the performance of NSHSA:

1. Harmony Memory Size (HMS): This parameter determines the number of solutions stored in the harmony memory. A larger HMS can provide a richer set of solutions but may slow down convergence, while a smaller HMS may lead to faster convergence but less diversity.

2. Harmony Memory Considering Rate (HMCR): This rate indicates the probability of selecting a solution from the harmony memory when generating new solutions. A higher HMCR encourages exploitation of known good solutions, while a lower HMCR promotes exploration.

3. Pitch Adjustment Rate (PAR): This parameter defines the likelihood that a generated solution will undergo pitch adjustment. A higher PAR allows for more exploration around existing solutions, while a lower PAR may focus more on exploitation.

4. Number of Iterations: The total number of iterations or generations affects the algorithm's ability to converge to optimal solutions. More iterations can lead to better results, but at the cost of increased computational time.

5. Diversity Maintenance: Techniques such as crowding distance or niche formation can be incorporated to maintain diversity among non-dominated solutions in the population, preventing convergence to a single solution.

In conclusion, the NSHSA provides a powerful and reliable framework for addressing multi-objective optimization problems through the seamless integration of non-dominated sorting techniques with the adaptive search mechanisms of the harmony search algorithm. By appropriately adjusting its control parameters and systematically applying non-dominated sorting, NSHSA is capable of thoroughly exploring the feasible solution space and producing a well-distributed set of Pareto-optimal solutions that clearly reflect the inherent trade-offs among competing objectives.

4.4. Fuzzy decision-making

Fuzzy-based decision-making offers a practical and flexible framework for managing multi-objective problems, especially in situations where objectives are inherently conflicting and subject to uncertainty. In the context of multi-objective optimization, decision-makers are frequently confronted with the difficulty of choosing a single preferred alternative from a collection of Pareto-optimal solutions, each of which embodies a different balance among competing objectives. Fuzzy decision-making provides a framework to incorporate subjective preferences and imprecise information into the decision-making process. By utilizing fuzzy logic, decision-makers can express their preferences more flexibly, allowing for the representation of vague or ambiguous criteria that may not be easily quantifiable. This is particularly important in multi-objective scenarios where stakeholders may have differing priorities or values. To select a satisfactory solution from the Pareto front using fuzzy decision-making, decision-makers can define fuzzy membership functions for each objective, reflecting their level of satisfaction with different outcomes. These functions help to evaluate and rank the Pareto-optimal solutions based on how well they align with the decision-makers' preferences.

The incorporation of fuzzy logic allows for a more nuanced understanding of trade-offs and helps to identify solutions that are acceptable to all planners involved. Ultimately, fuzzy decision-making facilitates a collaborative approach, ensuring that the selected solution not only meets the objectives but also resonates with the diverse perspectives of all stakeholders, leading to a more widely accepted and robust decision.

To determine the most appropriate compromise solution from the Pareto-optimal set produced by the NSHSA method, a fuzzy-based decision-making strategy is applied. Within this framework, a linear fuzzy membership function is constructed for each objective of the multi-objective optimization model. For objective functions formulated as minimization problems, the corresponding membership function is expressed according to Equation (10) [21]:

$$\mu_i^k = \begin{cases} 1 & f_i^k \le f_i^{\min} \\ \dfrac{f_i^{\max} - f_i^k}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \le f_i^k \le f_i^{\max} \\ 0 & f_i^k \ge f_i^{\max} \end{cases} \tag{10}$$

For objective functions formulated with a maximization goal, the associated fuzzy membership function is defined as given in Equation (11).

$$\mu_i^k = \begin{cases} 0 & f_i^k \le f_i^{\min} \\ \dfrac{f_i^k - f_i^{\min}}{f_i^{\max} - f_i^{\min}} & f_i^{\min} \le f_i^k \le f_i^{\max} \\ 1 & f_i^k \ge f_i^{\max} \end{cases} \tag{11}$$

In this framework, f_i^k and μ_i^k represent the value of the ith objective function and its associated membership degree for the kth Pareto-optimal solution, respectively. The membership function quantifies the level of satisfaction or desirability of the ith objective within the corresponding Pareto solution. The comprehensive membership degree of the kth Pareto-optimal solution, denoted by μ_k, is obtained by combining its individual objective membership values in accordance with Equation (12) [21]:

$$\mu^k = \frac{\sum_{i=1}^{p} w_i \times \mu_i^k}{\sum_{i=1}^{p} w_i} \tag{12}$$

The weight factors w_i utilized in Equation (12) play a crucial role in the decision-making process. For the multi-objective DER planning problem, these weight factors can be determined by the distribution company according to the significance of both monetary costs and emissions. The Pareto solution that exhibits the highest membership function μ^k is deemed the most favorable option based on the selected weight factors, and therefore, it is chosen as the final solution to the multi-objective optimization problem.

5. Numerical results

5.1. 9-Node primary distribution system

This paper reports simulation outcomes obtained from a 9-node primary distribution benchmark network. The structural layout of the test system is depicted in Figure 6. The network consists of a single 132 kV/33 kV substation situated at node 9, which has a rated capacity of 40 MVA and supplies eight aggregated load points connected to nodes 1 through 8 under normal operating conditions.

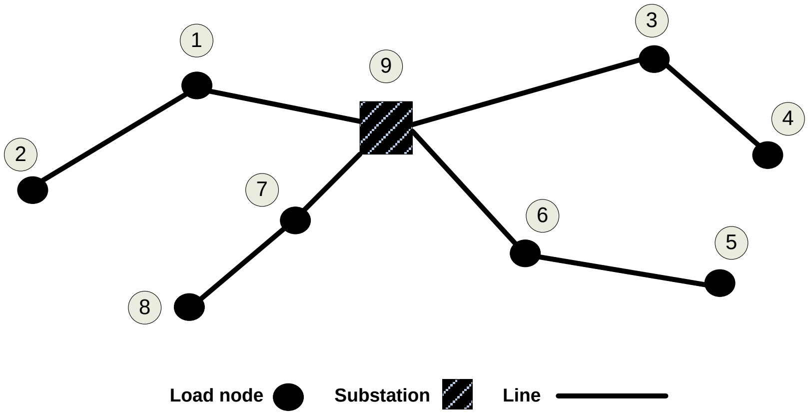

Figure 6. The 9-bus test distribution network.

The numerical simulations conducted for this test system utilize data sourced from [25]. A peak load of 51.1 MVA is projected and must be accommodated. Six different types of DERs are considered in the analysis, including wind turbines, photovoltaics, fuel cells, micro turbines, gas turbines, and diesel engines. The specifications for these DERs are derived from [21], and they are detailed in Tables 1 and 2.

To construct representative scenarios for load demand and electricity prices, the procedure described in Section 2 is applied. In this study, the electricity market price during peak load hours is assumed to be fixed at 70 USD per MWh. Furthermore, for all subsequent simulation cases, the system power factor is considered to be unity in order to simplify the analysis and focus on active power exchanges. At the initial stage of the assessment, the emission factor corresponding to electricity purchased from the upstream grid is assumed to be insignificant.

To extract the set of Pareto-optimal solutions, the NSHSA is executed using the following parameter settings: harmony memory size (HMS) equal to 40, harmony memory consideration rate (HMCR) of 0.99, pitch adjustment rate (PAR) of 0.001, and a maximum iteration number $N$of 200. The obtained non-dominated solutions are presented in Figure 7, which clearly illustrates the trade-off relationship between the economic objective and the environmental objective, highlighting the balance between cost minimization and emission reduction.

The Pareto optimal solutions presented in Figure 7 indicate that a reduction in daily emissions correlates with an increase in the total cost of DER planning, and conversely, an increase in emissions results in lower planning costs. This suggests that the adoption of clean DER technologies aimed at reducing emissions will lead to higher overall DER planning costs. The overall cost associated with DER planning is observed to vary between 163.02 and 225.025 million USD across the set of Pareto-optimal solutions. The normalized fuzzy membership function defined in Equation (12) provides a systematic tool to support decision-makers in identifying the most appropriate compromise solution among these alternatives. It should be emphasized that the weighting coefficients used in the fuzzy membership aggregation can be flexibly adjusted to reflect the relative importance assigned to each objective by the decision-maker. One commonly adopted approach for determining such weights is the analytical hierarchy process (AHP). Nevertheless, in the present analysis, equal importance is assigned to the economic and environmental objectives, resulting in weighting factors of $w_1 = w_2 = 0.5$.

Table 1. Data of six DG technologies.

DG	Unit size (kW)	Installed capacity Limit (kW)	Investment cost ($/kW)	Operation cost ($/kWh)
DE	1000	2000	500	0.045
FC	1500	3000	3500	0.050
GT	1000	4000	1000	0.040
MT	200	2000	1500	0.050
PV	100	2000	5000	0.005
WT	1000	4000	4500	0.010

Table 2. Emission of pollutant rates of six DG technologies.

DG	NOX (kg/kWh)	SO2 (kg/kWh)	CO2 (kg/kWh)	CO (kg/kWh)	PM10 (kg/kWh)
DE	0.00213	0.00125	0.625	0.0028	0.00036
FC	0.000015	0.000024	0.447	0	0
GT	0.00029	0.000032	0.625	0.00042	0.000041
MT	0.0002	0.000037	0.725	0.00047	0.000041
PV	0	0	0	0	0
WT	0	0	0	0	0
Grid	0.0022952	0.0035834	0.92125	-	-

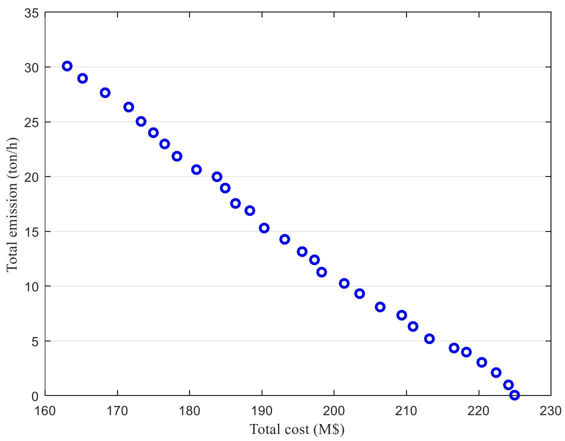

Figure 7. Pareto front of case study.

By applying the fuzzy decision-making framework described in Equation (12) with equal weights for both objectives, the optimal compromise solution for DER planning is obtained, as reported in Table 3. For this selected solution, the total economic cost, encompassing investment and operational expenditures of DER units, electricity procurement costs, and network energy losses, is estimated to be 185.6 million USD. Simultaneously, the corresponding environmental performance is evaluated at 13.1 tons per hour, reflecting a balanced trade-off between economic efficiency and emission mitigation.

To demonstrate the effectiveness of the proposed method, a comparison is made with the NSGA II (population size = 300, Mutation rate = 0.95, crossover rate = 0.8) and NSPSO (number of particles = 300, cognitive learning rate = 1.5, social learning rate = 1.1, inertia weight = 0.85) methods, as illustrated in Figure 8. For evaluating the Pareto solutions of the multi-objective methods, two indices are employed: the diversity measure and the ideal distance mean. The first index, as defined in Equation (13), indicates the diversity of the solutions; a larger value signifies better diversity. The second index, according to Equation (14), reflects the quality of the solutions in relation to their proximity to the average optimal solution, where a smaller value indicates superior quality of the Pareto solutions.

$$\mathrm{DM}=\sqrt{\sum_{i=1}^{M}\left(\max_{j=1,\ldots,N_P}\{f_i^j\}-\min\{f_i^j\}\right)^2} \tag{13}$$

$$\mathrm{MID}=\frac{\sum_{j=1}^{N_P}C_j}{N_P},\quad C_j=\sqrt{\sum_{i=1}^{M}\left(f_i^j-f_{i,\mathrm{m}}\right)^2} \tag{14}$$

In this context, N represents the number of Pareto solutions, M denotes the number of objective functions, f_i^j is the value of the objective function i for solution j, and $f_{i,m}$ indicates the average value of the Pareto solutions for objective function i. Table 4 presents a comparison of the proposed method's solutions with those obtained from the mentioned algorithms. As shown in Table 4, the parameters for the proposed method outperform those of the other algorithms, demonstrating the effectiveness of the proposed approach.

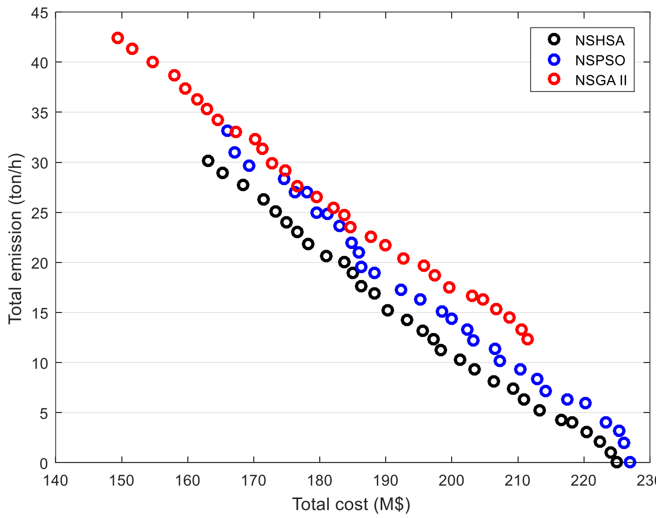

Figure 8. Pareto solutions of other algorithms used in solving the applied multi-objective model.

Table 3. The best compromised solution.

	Type, size (MW), and location of planned DERs					
	WT	PV	FC	MT	GT	DE
Total planned capacity	2,1	1,1	-	-	3,1,1,1,1,1,1,2	2,2,2,2,2,2,2,2
Bus	1,7	1,7	-	-	1,2,3,4,5,6,7,8	1,2,3,4,5,6,7,8

Table 4. Comparison of the parameters of diversity size and ideal mean distance in the multi-objective model.

Algorithm	Diversity size	Ideal mean distance
NSHSA	163.312	59.3277
NSPSO	161.987	60.6121
NSGA-II	161.691	61.8124

5.2. A real distribution system in Iran

The effectiveness of the proposed methodology is further demonstrated through its application to a real-world segment of the Iranian distribution power system, where it is used to compare the existing historical expansion strategy with a newly developed expansion plan derived from the proposed framework. A simplified schematic of the selected portion of the Iranian 20 kV distribution network is presented in Figure 9.

The studied system consists of a single distribution substation, 72 distribution lines, and 47 network nodes. The planning problem is formulated over a five-year horizon, during which a total load increase of 15% is anticipated. One candidate distribution substation with a rated capacity of 4 MVA is available for potential installation, while all existing feeders are considered eligible for either reinforcement or new construction, depending on the planning outcomes. As indicated in Figure 9, four candidate sites for distributed generation installation are identified and labeled as “a,” “b,” “c,” and “d.”

For the purposes of this case study, several system parameters are specified. The power factor is assumed to be 0.992, the system base power is set to 100 MVA, the discount rate is taken as 10%, and the electricity price is fixed at 0.07 USD per kWh. In addition, the thermal capacities of the lines connecting nodes “a”–“b,” “b”–“c,” and “c”–“d” are each assumed to be 4 MW. Additional technical and network-related data for this distribution system are available in [10]. The resulting optimal expansion plan obtained using the proposed approach is summarized in Table 5.

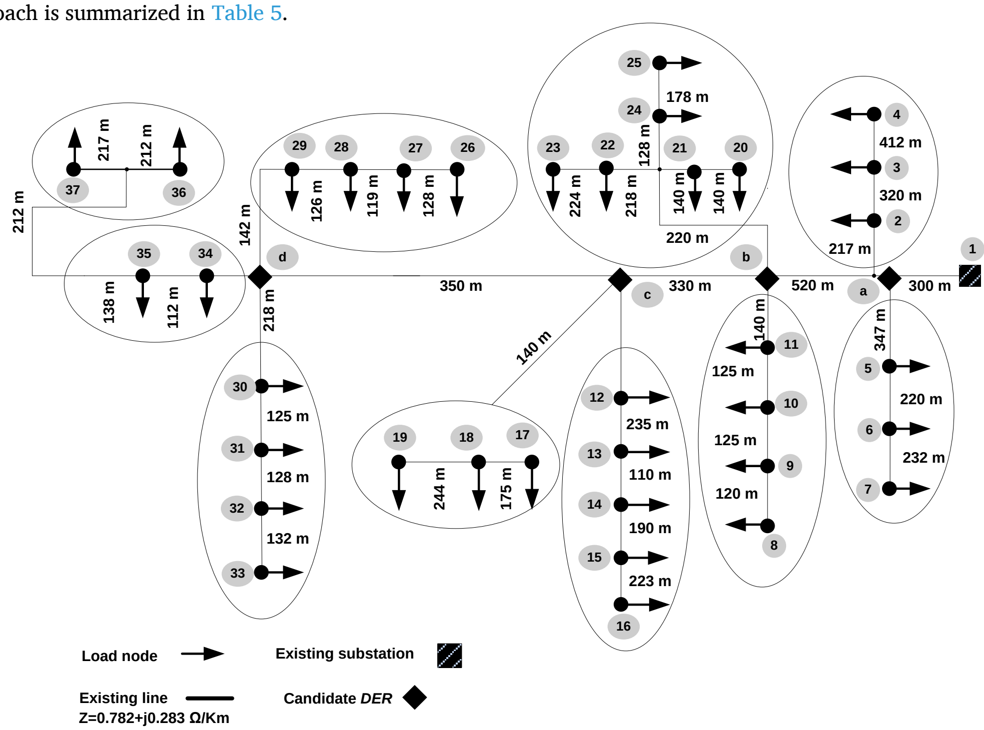

Figure 9. Single-line diagram of part of the 20 kV distribution network.

Table 5. Optimal expansion planning for system (6).

Node	DG	Type, size, and location of planned DGs					
		WT	PV	FC	MT	GT	DE
a	OG*	2000	-	-	-	-	1000
	PC*	2 × 1000	-	-	-	-	1 × 1000
b	OG	-	-	-	-	-	-
	PC	-	-	-	-	-	-
c	OG	-	-	-	-	-	2000
	PC	-	-	-	-	-	2 × 1000
d	OG	-	-	-	-	-	1000
	PC	-	-	-	-	-	1 × 1000

Investment cost (M$): 11
Operation cost (M$): 8.7864
Cost of purchased power (M$): 0.0025
Pollution (ton/h): 2.4262
Losses (p.u.): 0.011227
Losses without DGs: 0.001154
* OG: operating generation
* PC: planned capacity

6. Conclusion

In conclusion, this paper introduces a novel probabilistic multi-objective framework for optimizing DERs in distribution electricity networks. It utilizes nonlinear programming to address the needs of distribution companies in a competitive market, balancing monetary costs and pollutant emissions while managing uncertainties in electrical load and market prices. The model employs an NSHSA for efficient solution exploration, combining non-dominated sorting with harmony search to enhance multi-objective problem management and ensure a diverse set of solutions representing the Pareto front. Key contributions include a scenario-based approach for uncertainty management, simultaneous consideration of various DER types, and a fuzzy decision-making method for identifying optimal compromise solutions from the Pareto set. Overall, the framework demonstrates effectiveness and potential applicability in real-world scenarios, advancing multi-objective optimization techniques in the energy sector.

Nomenclature

i, j	Index for buses
k	Index of DERs technologies
m	Index of gaseous emissions
s	Index of scenarios
n	Index of substations
t	Index of times
np	Number of randomly generated price samples
nc	Number of members at cluster c
nr	Number of clusters
NB	Total number of buses
NLM	Total number of load buses
PM	The probability of each price reduction scenario
SB	Base kVA of the network
P_{ij}^{MAX}	The thermal capacity of the feeder that connects bus i to bus j
P_k^{CAP}	The capacity limit associated with the kth DER technology
Ps,ij	The power flow within the feeder that links bus i to bus j during scenario s
f1, f2	The monetary and environmental objective functions, respectively
$f_i^{\max}$, $f_i^{\min}$	The maximum and minimum values of the objective function i, respectively
$E_{k,m}^{DER}$	The emission factor for type m in the kth DER technology
E_m^G	The emission factor for type m related to electricity sourced from the grid
Ds,i	The demand present at the ith load bus during scenario s
d	The applicable discount rate
$\cos\varphi$	The power factor of the overall system
C_k^{OP}	The operational cost associated with the kth DER technology
C_k^{INV}	The investment cost linked to the kth DER technology
$P_{s,ij}^{Loss}$	The total power loss occurring in the feeder that connects bus i to bus j during scenario s
$P_{s,i,k}^{OP}$	The operational generation of the kth DER technology at bus i in scenario s
$P_{s,n}^{PP}$	The power purchased from substation n in scenario s
P_n^{SS}	The power output of the distribution substation
P_n^{SS-MAX}	The capacity limit of the distribution substation
Vs,i	The voltage level at bus i in scenario s
Zij	The impedance of the feeder that connects bus i to bus j
ρ_s	The electricity market price during scenario s
π_s	The probability associated with each scenario
μ_i^k	The membership function corresponding to the ith objective function in the kth Pareto optimal solution
μ^k	The overall membership function for the kth Pareto optimal solution

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

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