

Article

NSGA-II-Based Stochastic Multi-Objective Optimization for Demand Response–Enabled Smart Meter Placement in EVCS/PV-Integrated Distribution Networks

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Abstract

The growing penetration of electric vehicles (EVs) and distributed photovoltaic (PV) generation is increasing operational uncertainty in distribution networks and intensifying long-standing challenges such as higher power losses, rising peak demand, and voltage instability. To address these issues, this paper proposes a multi-objective optimization framework for the strategic placement of smart meters equipped with demand response (DR) capability in radial distribution systems. Unlike conventional placement approaches that mainly focus on monitoring or reducing non-technical losses, the proposed method integrates active load control into the planning stage and explicitly considers the stochastic behavior of loads, PV generation, and electric vehicle charging stations (EVCSs). The problem is formulated with four objectives: minimizing total power losses, substation peak demand, voltage deviation penalty, and installation cost. A scenario-based stochastic model is employed to represent operational variability across the network. The resulting nonlinear mixed discrete optimization problem is solved using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), an evolutionary multi-objective optimization technique that generates a set of Pareto-optimal solutions representing trade-offs among conflicting objectives. Smart meters are allowed to curtail a portion of controllable demand during critical loading conditions, which helps reduce feeder loading and improve voltage profiles. The proposed approach is evaluated on the IEEE 33-bus and IEEE 69-bus distribution systems. Simulation results demonstrate significant reductions in power losses and peak demand, with the IEEE 33-bus system achieving up to a 26.2% reduction in power losses and 52.5% reduction in substation peak demand compared with existing metaheuristic approaches. The results also indicate improved voltage stability and effective performance in the IEEE 69-bus system, confirming the importance of topology-aware DR-enabled planning. Overall, the findings show that embedding demand response capability within smart meter allocation can significantly enhance the resilience and operational efficiency of modern distribution networks with high EV and PV penetration.



Academic Editor: Grzegorz Sierpiński

Received: 20 May 2026

Revised: 10 June 2026

Accepted: 11 June 2026

Published: 12 June 2026

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conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.**Keywords:** smart meters; demand response; multi-objective optimization; NSGA-II; electric vehicles charging station; distribution networks; IEEE 33-bus; IEEE 69-bus

1. Introduction

1.1. Motivation

In recent years, distribution networks have been operating under conditions far more dynamic and uncertain than those for which they were originally designed. The accelerating adoption of electric vehicles and rooftop photovoltaic systems has introduced fluctuations that are both abrupt and spatially uneven, leading to demand surges, reverse power flows, and localized voltage instability across the feeders [1,2]. These disturbances are rarely gradual or predictable; instead, they emerge suddenly and propagate through radial structures where weaknesses—particularly at electrically distant buses—become amplified. Utilities now find themselves in a difficult position. Conventional reinforcement measures such as feeder upgrades or transformer replacements remain prohibitively expensive, yet failure to intervene results in increased technical losses, rising peak demand, and a greater frequency of voltage-related violations [1]. Compounding the issue is the limited visibility offered by traditional monitoring devices, which cannot capture the rapid and stochastic variations introduced by spatially concentrated EV charging and intermittent PV generation [2,3]. Consequently, certain buses repeatedly evolve into operational hotspots, exhibiting voltage drops, reverse flows, or thermal overloads.

In addition to acting as stochastic loads, electric vehicles are increasingly recognized as active elements in networked energy systems. Through coordinated charging strategies and Vehicle-to-Grid (V2G) integration, EVs can support energy balancing, peak load management, and improved operational flexibility in modern power networks [4,5]. Recent studies have explored advanced control and optimization frameworks for EV-integrated energy systems and microgrids, demonstrating their potential to enhance energy distribution efficiency and system resilience [6]. These developments further highlight the importance of intelligent monitoring and control infrastructures capable of supporting EV-integrated energy management in future distribution networks. Moreover, other emerging zero-emission transportation technologies, such as fuel cell vehicles (FCVs), are also attracting increasing attention due to their potential role in future sustainable energy–transportation systems. Unlike battery electric vehicles, FCVs rely on hydrogen-based energy conversion, which introduces additional uncertainties related to hydrogen production, storage, and refueling infrastructure. These factors may indirectly affect electricity demand patterns and energy management strategies in integrated energy systems. Recent studies have investigated advanced optimization and energy management frameworks for FCV-integrated transportation platforms, highlighting their potential to improve operational efficiency and energy utilization in next-generation energy–transportation networks [3]. These developments further emphasize the necessity of intelligent monitoring and control infrastructures capable of addressing the increasing uncertainty and operational complexity in modern distribution networks.

These challenges underscore the growing need for a more informed and adaptive monitoring framework. Strategically deployed smart meters can provide the high-resolution data and local observability required to understand real network behavior under uncertainty, while simultaneously enabling advanced functions such as demand response and flexible load control [4,5]. Without an optimized placement strategy, however, even large-scale smart meter deployment may fail to address the underlying operational issues. The combined pressure of uncertainty, uneven resource distribution, and escalating technical constraints provides the primary motivation for this study, which focuses on developing a systematic and effective approach for smart meter placement in modern distribution networks.

1.2. Literature Review

Over the past decade, the rapid electrification of transportation and the widespread integration of rooftop photovoltaic systems have substantially reshaped the operational landscape of distribution networks. These developments have heightened the need for improved visibility, enhanced situational awareness, and greater operational flexibility. As a result, optimal smart meter placement (SMP) has become a prominent research topic, with studies spanning various methodological and application-oriented perspectives. The existing body of work can be broadly classified into several research streams.

The first stream consists of comprehensive review papers that trace the evolution of meter placement and distribution system state estimation (DSSE). Lekshmana et al. (2018) documented the methodological progress from early transmission-oriented techniques to more recent distribution-focused approaches, emphasizing the longstanding trade-off between cost and estimation accuracy [4]. Zeraati et al. (2022) provided one of the most far-reaching surveys, categorizing existing placement algorithms into mathematical optimization, heuristic and metaheuristic methods, and hybrid formulations while highlighting unresolved challenges related to uncertainty, scalability, and active network operation [5]. Additional relevant surveys include those by Ahmad et al. (2017), who underscored the role of DSSE as a core smart-grid enabler [6]; Dehghanpour et al. (2018), who discussed practical barriers and emerging trends in state estimation for modern distribution systems [7]; and Primadianto and Lu (2017), who reviewed algorithmic advances and implementation issues [8]. Collectively, these studies show that traditional perspectives still tend to treat smart meters primarily as passive measurement units.

A second stream focuses on classical formulations aimed at enhancing observability and improving DSSE accuracy. Early contributions relied on Integer Linear Programming, greedy heuristics, and sensitivity-based procedures to minimize meter count while ensuring observability. Subsequent works employed semidefinite programming and circuit-theoretic models developed specifically for radial networks [9,10]. Techniques based on Fisher information measures [11] and global sensitivity analysis [12] also appear prominently in this line of research. Although these methods generally provide accurate estimates for standard IEEE benchmark feeders, including the 33-, 69-, and 123-bus systems, they typically assume deterministic operating conditions and do not account for the effects of flexible loads, EV charging demand uncertainty, and PV variability [13,14].

With the growing penetration of distributed energy resources (DERs), a more recent stream incorporates uncertainty directly into the placement problem. Scenario-based stochastic optimization, robust optimization, and probabilistic formulations have been employed to capture load, EV, and PV variability [15,16]. Some studies also consider meter placement in low-voltage networks with high DER penetration or jointly address it with distributed generation or EV charging station siting. Nevertheless, most of these works still regard smart meters as passive data-collection devices, while demand response is typically handled as an operational problem in a separate stage rather than being embedded into the planning model [17,18]. Another active research direction involves multi-objective formulations. Because meter placement naturally involves competing goals—such as installation cost, estimation accuracy, reliability, and network performance—various studies have adopted evolutionary algorithms, particularly the NSGA-II, to generate Pareto-optimal solutions [19,20]. Similar multi-objective frameworks have been successfully applied to μ PMU deployment, switching device placement, and energy storage planning in active distribution networks. Despite their effectiveness, applications that combine multi-objective evolutionary optimization with DR-enabled smart meter placement under stochastic EV/PV conditions remain relatively limited [21,22]. A final stream is related to demand response (DR), active load

management, and smart meter applications. Numerous studies propose stochastic DR scheduling models, real-time load curtailment strategies, and coordinated control mechanisms for flexible resources using smart meter data [23,24]. However, these works generally assume that an adequate metering infrastructure is already installed. Only a small number of studies have attempted to integrate active DR capabilities—such as controllable load curtailment—directly within the meter placement optimization framework itself. In particular, the combination of DR functionality, stochastic EV/PV behavior, and multi-objective planning has received comparatively limited attention in the literature [25,26].

1.3. Research Gap

Despite the substantial progress made in the field of smart meter placement, several critical gaps still persist in the existing literature. The majority of previous studies regard smart meters primarily as passive monitoring tools, designed to enhance network observability and improve the accuracy of distribution system state estimation [1,2,7,9]. Although a few recent publications incorporate stochastic elements arising from EV charging and PV uncertainties [14,15], their formulations rarely include active DR functions—such as direct or dynamic load curtailment—within the placement optimization itself. Consequently, smart meters are modeled either as fixed sensors or as static information sources, separated from the operational flexibility they can potentially offer.

Furthermore, existing optimization frameworks are often limited to single- or bi-objective structures, addressing cost and estimation accuracy under deterministic assumptions [8,10,11]. Only a handful of studies extend the scope to multiple technical and economic objectives that jointly consider power losses, peak demand reduction, voltage deviation mitigation, and installation cost trade-offs, especially within a stochastic setting [19,20]. Likewise, while DR has been thoroughly investigated in operational optimization—particularly in systems with high EV and PV penetration [23,24]—these approaches typically presume that the metering infrastructure already exists and focus solely on scheduling or curtailment decisions rather than on its optimal physical deployment. Another overlooked aspect concerns where DR-enabled smart meters should be installed to achieve the greatest system-wide impact. Topology-aware placement—especially in electrically remote or heavily loaded buses—has received minimal attention, despite its proven influence on both technical performance and DR effectiveness. Therefore, the strategic integration of active demand response capability into a stochastic, multi-objective optimization framework for smart meter placement remains largely unexplored. Table 1 summarizes the most relevant studies and highlights this research gap, emphasizing that combining DR functionality, stochastic uncertainty modeling, and multi-objective planning constitutes a necessary and timely direction for future investigation. In addition, while several existing studies adopt bi-objective formulations—typically minimizing installation cost and estimation error—such simplified structures cannot fully capture the complex trade-offs inherent in modern active distribution networks. In contrast, the proposed four-objective formulation enables simultaneous evaluation of technical efficiency (loss reduction), operational performance (peak demand mitigation), voltage regulation quality, and economic cost within a unified framework. This extended formulation provides a more comprehensive analytical perspective, allowing system planners to explicitly observe and quantify the interactions and trade-offs among operational flexibility, network stability, and investment decisions under uncertainty. Consequently, the proposed model offers enhanced decision-support capability compared with conventional bi-objective smart meter placement approaches.

Table 1. Comparison of selected studies on smart meter placement and related topics.

Reference	Year	Main Objectives	Method	Uncertainty Modeling	DR/Active Control	Test System	Key Limitations/Gap
Lekshmana et al. [4]	2018	Comprehensive review of meter placement	Review	No	No	-	Passive monitoring focus
Zeraati et al. [5]	2022	Review of meter placement for DSSE	Review	Partially discussed	No	-	Lack of active DR integration
Xygkis et al. [9]	2018	Observability and state estimation	Semidefinite Programming	No	No	IEEE 33, 69	Deterministic conditions
Ginocchi et al. [10]	2023	Optimal meter placement for DSSE	Global Sensitivity Analysis	No	No	Real LV network	No multi-objective, no DR
Nainar et al. [11]	2020	State estimation in LV networks	Smart meter data-driven	Low	No	Real Danish network	Passive approach
Athanasiadis et al. [17]	2024	Smart meter data applications	Review	Yes	Partially	-	DR considered separately from placement
Tiwari et al. [19]	2022	Multi-objective μ PMU placement	NSGA-II	No	No	IEEE 33, 69	No DR-enabled meters
Chintala et al. [20]	2021	Multi-objective meter placement	NSGA-II	No	No	IEEE 33-bus	No stochastic EV/PV modeling
Thomas et al. [23]	2020	DR scheduling with PV and EV	Stochastic Optimization	Yes	Yes	Building level	No meter placement
Sattarpour et al. [25]	2016	DG, capacitor and smart meter allocation	PSO	No	Limited	IEEE 33-bus	Limited DR, single/two-objective
Present Study	2026	Multi-objective DR-enabled SMP	NSGA-II + Scenario-based	Yes (EV, PV, Load)	Yes (Active Curtailment)	IEEE 33 and 69	-

1.4. Contributions of the Present Study

- An integrated multi-objective planning framework is developed for the optimal placement of smart meters with DR capability in radial distribution networks. Unlike conventional approaches that treat smart meters purely as passive monitoring devices, the proposed framework explicitly incorporates their active load curtailment capability within the planning model.
- A comprehensive four-objective optimization formulation is proposed to simultaneously minimize total active power losses, substation peak demand, voltage deviation across the network, and the installation cost of DR-enabled smart meters, enabling a balanced trade-off between technical performance and economic considerations.
- A scenario-based stochastic modeling approach is introduced to capture the uncertainties associated with load demand fluctuations, PV generation variability, and aggregate EVCS charging demand, providing a more realistic representation of modern distribution network operating conditions.
- The obtained results provide practical insights for distribution system planners by identifying critical buses where DR-enabled smart meters deliver the greatest operational benefits, particularly in electrically remote or heavily loaded sections of the feeder.

The remainder of this paper is organized as follows. Section 2 presents the detailed mathematical formulation of the proposed problem, including the four objective functions and all technical and operational constraints. Section 3 describes the solution methodology and explains how NSGA-II is adapted and implemented to solve the stochastic multi-objective optimization problem. Section 4 introduces the IEEE 33-bus and IEEE 69-bus test systems and discusses the simulation results under different scenarios, including

deterministic and stochastic cases. Finally, Section 5 concludes the paper and suggests directions for future research.

2. Problem Formulation

This section describes the mathematical model developed for the optimal placement of smart meters equipped with demand response capability. The aim is to find the best locations for installing these meters in a radial distribution network while considering both technical performance and economic aspects under realistic uncertain operating conditions.

2.1. Decision Variables

The main decision variable is a binary vector $x \in \{0, 1\}^{N_b}$, where N_b is the number of buses in the system. If $x_i = 1$, a smart meter with demand response functionality is installed at bus i ; otherwise, $x_i = 0$.

2.2. Objective Functions

The optimization problem is formulated with four conflicting objectives:

f_1 : Minimization of Losses

The first objective aims to minimize the total power losses in the distribution network [3,27]. This objective consists of two components: technical losses obtained from load flow analysis and an estimation of non-technical losses. The technical losses are calculated for all network branches based on the line resistance and branch current obtained from the load flow simulation. The average value over all simulated scenarios is used.

The non-technical losses are modeled using a coefficient α (non_tech_coeff) and are assumed to decrease at buses where smart meters are installed. This objective includes technical power losses obtained from load flow analysis plus an estimation of non-technical losses. Non-technical losses are assumed to be higher at buses without smart meters.

$$f_1(x) = P_{loss}^{avg} + P_{NTL} \quad (1)$$

where P_{loss}^{avg} is the average technical loss obtained from load-flow simulations over all scenarios. $P_{NTL} = \sum_{i=1}^{N_b} (1 - OI_i)P_i$ is the estimated non-technical loss, reduced at buses equipped with smart meters and $(1 - OI_i)P_i$ represents the non-technical loss contribution of unmetered bus i , which is eliminated when a smart meter is installed at that bus. In this study, non-technical losses are modeled through a uniform distribution across unmetered buses as a simplified baseline assumption. This modeling choice provides a neutral and transparent basis for evaluating the proposed optimization framework in the absence of validated bus-level NTL data. Therefore, the adopted formulation should be interpreted as a methodological abstraction for consistent comparison rather than as an exact spatial representation of real-world NTL behavior.

f_2 : Minimization of Substation Peak Demand

This objective minimizes the peak power drawn from the substation across all simulated scenarios. Demand response actions are activated during high-load conditions, which helps reduce this peak.

$$f_2(x) = P_{peak} \quad (2)$$

where P_{peak} is defined as the maximum substation active power over all simulated scenarios. In the demand response model, when the load factor exceeds a predefined threshold, smart meters enable partial load disconnection at selected buses, which directly reduces the substation peak demand.

f_3 : Minimization of Voltage-Deviation-Weighted Penalty

$$f_3(x) = \sum_{i=1}^{N_b} (1 - x_i) w_i, w_i = \frac{\overline{\Delta v_i}}{\max_j (\overline{\Delta v_j}) + \varepsilon} \quad (3)$$

where x_i is the binary smart meter placement variable at bus i and w_i is the normalized importance factor derived from the average voltage deviation of bus i overall operating scenarios. Therefore, the third objective does not merely count the number of unmetered buses; instead, it assigns a higher penalty to buses without smart meters that experience more severe voltage deviations. Minimizing this objective promotes meter placement at voltage-critical buses and improves the voltage-related observability of the network.

f_4 : Minimization of Installation Cost

$$f_4(x) = \sum_{i=1}^{N_b} (x_i) \quad (4)$$

This objective represents the total number (and thus cost) of installed smart meters [18].

2.3. Optimization Constraints

To ensure the successful integration of smart meters in the distribution network, several operational constraints must be established:

1. Maximum Number of Meters:

Due to budgetary and implementation limits, only a predefined number of smart meters can be installed in the network. Let N_b denote the total number of buses in the system. The installation constraint is expressed as:

$$\sum_{i=1}^{N_b} x_i \leq \text{Max}_{\text{meter}} \quad (5)$$

where x_i is a binary decision variable indicating the installation of a meter at bus i (1 if installed, 0 otherwise).

2. Binary Decision Variables:

The decision variables are constrained to be binary, reflecting whether a smart meter is placed at each bus:

$$x_i \in \{0, 1\}, \quad \forall i = 1, \dots, N_b \quad (6)$$

3. Power Flow Constraints:

The operational reliability of the distribution network must be maintained across all scenarios. This includes adhering to AC power flow equations, ensuring that bus voltage magnitudes and line thermal limits are respected:

$$V_{\min} \leq V_i \leq V_{\max} \quad (7)$$

$$|S_{ij}| \leq S_{i,j}^{\text{Max}} \quad (8)$$

In these equations, V_i represents the voltage at bus i , while S_{ij} denotes the power flow through the line between buses i and j . These constraints are verified using a backward–forward load flow calculation, which ensures that the placement of smart meters does not compromise the grid's operational limits.

4. EV Charging Active Power Constraint

The active power demand of EV charging stations is constrained by their rated charging capacity. Let $P_{EV,k}$ denote the active charging power at EV station k , and $P_{EV,k}^{norm}$ represent its nominal capacity. The charging power must satisfy:

$$0 \leq P_{EV,k} \leq P_{EV,k}^{norm} \times EV_{scale} \quad (9)$$

where EV_{scale} is the EV penetration factor used to model different levels of EV integration in the network. The parameter EV_{scale} , bounded between 0 and 1, regulates the effective charging demand in accordance with the assumed EV penetration level. Equation (9) only defines the operational charging-power limits of EVCSs and does not represent the full stochastic EV charging model. The uncertainty of EVCS demand is modeled in Section 2.5 through scenario-based aggregate demand, while Equation (10) simply specifies the feasible charging range of the stations.

2.4. Demand Response Model

In this study, demand response (DR) is modeled as a localized and conditional load control mechanism, activated through smart meters installed at selected buses. Unlike idealized DR models that assume full controllability, here the response is both partial and scenario-dependent, reflecting practical operational limitations [28,29].

Specifically, when the system experiences high loading conditions (i.e., when the scenario load factor exceeds a predefined threshold), the smart meters at equipped buses temporarily reduce a portion of their controllable demand. This reduction is not continuous, but rather is triggered only under stressed operating states, which allows the model to capture realistic peak-shaving behavior rather than constant load curtailment [30].

Mathematically, the controllable demand at bus i is adjusted as:

$$P_i^{DR} = \begin{cases} P_i(1 - \delta), & \text{if } LF > LF_{th} \text{ and } x_i = 1 \\ P_i, & \text{Otherwise} \end{cases} \quad (10)$$

where P_i is the original load at bus i , P_i^{DR} is the load after demand response, δ is the load reduction factor (disconnect_fraction), LF is the system load factor, LF_{th} is the threshold for activating DR, and x_i is a binary variable indicating the presence of a smart meter at bus i . This mechanism allows partial load curtailment at selected buses during high-load conditions, which helps mitigate substation peak demand and reduce network losses. In this study, the controllable load reduction factor δ is assumed to be 0.2, meaning that up to 20% of the demand at equipped buses can be temporarily curtailed during high loading conditions. It should be noted that the adopted demand response model represents the aggregated flexibility potential at the distribution level rather than the detailed behavior of individual customers. In practice, DR effectiveness depends on factors such as participation rates, load composition, and response characteristics, and only a portion of the total demand is typically flexible. Therefore, the reduction factor ($\delta = 0.2$) is considered as an approximate share of controllable load available during peak conditions. This simplified representation is commonly used in planning-oriented studies to evaluate the system-level impact of demand-side flexibility while maintaining computational tractability.

2.5. Uncertainty and Scenario Generation

In modern distribution networks, the integration of distributed energy resources and flexible loads introduces significant stochasticity [30]. In this study, three primary sources of uncertainty are considered: load demand fluctuations, intermittent PV generation,

and aggregate scenario-based EVCS demand uncertainty. To evaluate the robustness of the proposed smart meter placement strategy, a scenario-based stochastic approach is employed.

The net power injection at each bus i under scenario s is determined by the individual contributions of demand, PV output, and EV charging, formulated as:

$$P_{i,s}^{net} = P_{i,s}^D + P_{i,s}^{EVCS} + P_{i,s}^{PV} \quad (11)$$

Each component is modeled as a stochastic variable around its nominal value:

$$P_{i,s}^D = P_i^D (1 + \epsilon_{i,s}^D) \quad (12)$$

$$P_{i,s}^{PV} = P_i^{PV} (1 + \epsilon_{i,s}^{PV}) \quad (13)$$

$$P_{i,s}^{EVCS} = P_i^{EV} (1 + \epsilon_{i,s}^{EVCS}) \quad (14)$$

where P_i^D , P_i^{PV} , and P_i^{EVCS} represent the nominal values of load PV generation and EVCS power consumption at bus i , respectively. The terms $\epsilon_{i,s}^D$, $\epsilon_{i,s}^{PV}$, and $\epsilon_{i,s}^{EVCS}$ denote the random variables representing the forecasting errors of load demand and PV generation, and the scenario-dependent aggregate uncertainty of EVCS charging demand, respectively. To capture the probabilistic nature of these variables, Monte Carlo Simulation (MCS) is utilized for scenario generation [30,31]. A set of S scenarios is generated by sampling from the probability distributions of the uncertain parameters. This allows the optimization algorithm to explore a wide range of operational conditions, from typical load patterns to worst-case peak demand and low PV generation periods. The final objective function is calculated as the expected value across all generated scenarios to ensure a robust solution:

$$F_{Total}^{avg} = \frac{1}{S} \sum_{s=1}^S (W_1 \times f_1^s + W_2 \times f_2^s + W_3 \times f_3^s + W_4 \times f_4^s) \quad (15)$$

where S is the total number of scenarios and f_1^s through f_4^s are the objective function values for scenario s . By incorporating this scenario-based framework, the smart meter placement remains effective under diverse and unpredictable network states.

The random deviations associated with load demand, PV generation, and aggregate EVCS charging demand are modeled using normally distributed random variables with zero mean and predefined standard deviations. These deviations represent forecasting errors and short-term variability commonly observed in practical distribution networks. Therefore, the stochastic variables are assumed to follow normal distributions centered around their nominal values. The standard deviations used for the random deviations are selected based on representative variability levels commonly reported in the literature for distribution system operation [30,31]. Specifically, load demand uncertainty reflects short-term forecasting errors typically observed in distribution networks, PV generation variability captures the intermittency caused by solar irradiance fluctuations, and EVCS charging variability represents the uncertain arrival and charging patterns of electric vehicles [18]. These assumptions allow the scenario generation process to realistically emulate practical operating conditions while maintaining computational tractability for the Monte Carlo simulation framework.

3. NSGA-II Optimization Framework

The smart meter placement problem developed in this study leads to a constrained, multi-objective, mixed-integer nonlinear optimization model. The combination of binary installation variables, nonlinear power flow relationships, and scenario-based uncertainty representation makes the problem difficult to solve using classical deterministic optimization techniques. These methods typically struggle with the model's high dimensionality and non-convex search space. To address these challenges, a population-based evolutionary algorithm—Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [32,33]—is adopted to compute a well-distributed set of Pareto-optimal solutions. NSGA-II has become one of the most widely used optimization tools in multi-objective power system studies due to its strong global search capability, robustness in handling nonlinear constraints, and effectiveness in generating diverse and representative Pareto fronts.

- Multi-Objective Formulation

The optimization problem can be expressed in the general multi-objective form:

$$\text{Min } F(x) = (f_1(x), f_2(x), \dots, f_M(x)) \quad (16)$$

subject to

$$x \in \Omega \quad (17)$$

where x denotes the decision vector and Ω represents the feasible solution space defined by the operational and installation constraints of the system [32]. In the proposed model, the decision vector consists of binary variables indicating the installation status of smart meters at candidate buses.

- Dominance Relation and Non-Dominated Sorting

Instead of aggregating objectives into a single scalar function, NSGA-II relies on the concept of Pareto dominance. A solution x_1 is said to dominate another solution x_2 if:

$$\forall m \in \{1, 2, \dots, M\}, \quad f_m(x_1) \leq f_m(x_2) \quad (18)$$

and

$$\exists m : f_m(x_1) < f_m(x_2) \quad (19)$$

Based on this dominance relation, the population is partitioned into a set of non-dominated fronts $F_1, F_2, \dots, F_k$. The first front F_1 contains the best non-dominated solutions, representing the current approximation of the Pareto front. Each solution is assigned a rank according to its front index:

$$\text{Rank}(x) = i \quad \text{If } x \in F_i \quad (20)$$

- Crowding Distance and Diversity Preservation

To maintain diversity among solutions within the same front, NSGA-II introduces a crowding distance measure in the objective space [32]. The crowding distance for solution i is defined as:

$$CD_i = \sum_{m=1}^M \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{\max} - f_m^{\min}} \quad (21)$$

where f_m^{i+1} and f_m^{i-1} represent the neighboring solutions in the sorted objective list [31]. Boundary solutions are assigned an infinite crowding distance to ensure their preservation in the population.

Selection is then performed using the crowded comparison operator, defined as:

$$x_a < x_b \iff (\text{Rank}_a < \text{Rank}_b) \vee (\text{Rank}_a = \text{Rank}_b \wedge \text{CD}_a > \text{CD}_b) \quad (22)$$

This mechanism ensures that solutions with better rank are preferred, while diversity is preserved among solutions belonging to the same front.

- Evolutionary Optimization Process

The evolutionary search begins with a randomly generated population of candidate solutions. At each generation, offspring solutions are created through genetic operators such as selection, crossover, and mutation. The parent and offspring populations are then merged, and non-dominated sorting is applied to the combined set. The next generation is selected based on rank and crowding distance:

$$P_{t+1} = \text{select} (P_t \cup Q_t) \quad (23)$$

where P_t and Q_t denote the parent and offspring populations, respectively. This elitist strategy ensures that high-quality solutions are preserved across generations while maintaining diversity along the Pareto front.

After generating the Pareto-optimal set using NSGA-II, a representative best compromise solution (BCS) is selected in a post-optimization step. For this purpose, the objective values are normalized, and a compromise score is calculated for each Pareto solution based on its Euclidean distance from the normalized ideal point:

$$\text{BSC} = \text{Score}_i \sqrt{\sum_{m=1}^M \left(\frac{f_{m,i} - f_m^{\min}}{f_m^{\max} - f_m^{\min} + \varepsilon} \right)^2} \quad (24)$$

where $f_{m,i}$ is the value of the m -th objective for the i -th Pareto solution. The Pareto solution with the minimum Score_i is selected as the best compromise solution. This criterion is applied only after the NSGA-II search is completed and does not influence the Pareto-based optimization process.

The main steps of the NSGA-II-based optimization framework used in this study are summarized in Algorithm 1. The algorithm begins by generating an initial population of feasible smart meter placement configurations. Each candidate solution is then evaluated through a scenario-based simulation environment, where uncertain load demand, PV generation, and EV charging profiles are sampled. For every individual solution, a distribution load-flow analysis is carried out to obtain the corresponding objective function values. Following evaluation, the population is ranked through the non-dominated sorting procedure, and crowding distance is computed to maintain diversity across the Pareto front. Parent solutions are subsequently selected using binary tournament selection, and genetic operators—crossover and mutation—are applied to generate new offspring. The parent and offspring populations are combined, and an elitist selection mechanism is used to construct the next generation. This iterative process continues until the predefined maximum number of generations is reached, after which the final Pareto front is produced as the set of optimal smart meter placement solutions.

Algorithm 1: NSGA-II-based smart meter placement optimization

Input:

Network data, candidate locations, constraints, objective functions,
Npop, MaxGen, Pc, Pm

Output:

Pareto-optimal smart meter placement schemes

- 1: Generate the initial population P_t and set $t = 0$
- 2: Evaluate P_t through load flow analysis
- 3: Apply constraint handling and rank individuals using non-dominated sorting
- 4: Compute the crowding distance of individuals
- 5: while $t < \text{MaxGen}$ do
- 6: Generate offspring Q_t using selection, crossover, and mutation
- 7: Evaluate Q_t and apply constraint handling
- 8: Form $R_t = P_t \cup Q_t$
- 9: Rank R_t using non-dominated sorting and crowding distance
- 10: Select the best Npop individuals to construct P_{t+1}
- 11: Update $P_t = P_{t+1}$ and $t = t + 1$
- 12: end while
- 13: Return the first Pareto front as the optimal smart meter placement schemes

- Application in Smart Meter Placement

In the proposed framework, each individual in the optimization population represents a binary placement vector that specifies whether a smart meter is installed at each candidate bus. The quality of each candidate configuration is assessed through a scenario-based evaluation process designed to capture the inherent uncertainties in system operation. For a given placement pattern, multiple operating scenarios are generated to represent variations in load demand, PV output, and aggregate EVCS charging demand. For every scenario, a distribution load-flow analysis is performed using the backward–forward sweep method to calculate bus voltage magnitudes, branch currents, feeder loading levels, and network power losses. These operational results are then used to evaluate the objective functions of the optimization model, including total technical losses, peak demand indicators, network observability metrics, and the overall installation cost of smart meters. The final value of each objective associated with a candidate solution is obtained from its scenario-based performance over all simulated operating conditions. During the evolutionary search process, the NSGA-II algorithm progressively improves the population by favoring non-dominated solutions while maintaining diversity across the Pareto front. The final outcome of the optimization is a set of Pareto-optimal smart meter placement strategies, each representing a different trade-off between system performance enhancement and investment cost.

4. Simulation Results

This section evaluates the performance of the proposed NSGA-II framework in addressing the smart meter placement problem in radial distribution systems. The methodology is applied to two widely used benchmark networks—the IEEE 33-bus and IEEE 69-bus systems—under a variety of operating scenarios. To further demonstrate the effectiveness of the optimization process, the results obtained using the proposed approach are compared with those of several well-established population-based algorithms, including the Gravitational Search Algorithm (GSA), the Shuffled Frog Leaping Algorithm (SFLA) [3], the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [34], and the Whale Optimization Algorithm (WOA) [35]. The comparative analysis highlights the robustness, accuracy, and strong convergence behavior of the proposed NSGA-II-

based solution method for smart meter placement. All simulations were carried out in MATLAB 2023a on a computer equipped with an Intel Core i7 processor and 16 GB of RAM. The optimization framework is implemented in MATLAB using a custom-developed multi-objective genetic algorithm following the NSGA-II procedure. The algorithm uses a population size of 100 and a maximum of 200 generations. Parent solutions are selected using binary tournament selection, while crossover and mutation operators generate new offspring. The crossover probability is set to 0.8, and mutation is applied to maintain adequate diversity within the population. These parameter settings provide an effective balance between exploration and exploitation, yielding consistent and well-distributed Pareto-optimal solutions for the smart meter placement problem.

4.1. Justification of NSGA-II Parameter Settings

To justify the adopted NSGA-II parameter settings, the main parameters, including population size, maximum number of generations, and crossover probability, were selected based on preliminary examinations of convergence behavior, Pareto-front diversity, and computational effort.

Smaller population sizes reduced computational time but could decrease solution diversity and increase the risk of premature convergence, while larger populations only slightly improved the spread of the Pareto front at the cost of a noticeably higher computational burden. Therefore, a population size of 100 was selected as a balanced choice between solution quality and efficiency. Similarly, increasing the number of generations improved convergence mainly during the early stages of the search, whereas beyond 200 generations the improvement became marginal compared with the additional computational time required. For this reason, the maximum number of generations was set to 200. The crossover probability was also determined according to its influence on the balance between exploration and exploitation. Lower crossover probabilities limited the algorithm's ability to explore new regions of the search space, whereas higher values did not yield a meaningful further improvement in the obtained solutions. Accordingly, a crossover probability of 0.8 was adopted. Overall, these parameter settings provided stable convergence, satisfactory Pareto-front diversity, and acceptable computational efficiency for the considered optimization problem.

For a fair comparison, all optimization algorithms considered in this study were implemented under the same computational conditions. Specifically, the population size was set to 100 and the maximum number of iterations/generations was set to 200 for all algorithms. This setting ensured that the comparison among NSGA-II, GSA, SFLA, and WOA was conducted under equivalent computational effort, and that the observed differences in loss reduction and peak load improvement are mainly attributable to the search performance of the algorithms.

The optimization study is carried out under four operating scenarios designed to capture different levels of uncertainty, EV penetration, and smart meter deployment constraints.

Scenario 1—Base case (EVscale = 0):

This scenario represents the reference operating condition without EVCS demand, while the uncertainties in load demand and PV generation are still taken into account. It serves as the baseline for comparing total system losses and peak demand.

Scenario 2—Full uncertainty with EV penetration (EVscale = 1, non_tech_coeff = 0.08):

In this scenario, the uncertainties associated with **load demand**, EVCS charging and PV generation uncertainty are fully considered. This case evaluates the robustness of the optimization framework under increased operational variability and higher network loading conditions.

Scenario 3—EV penetration with a strict meter budget (Max_meters = 6):

This scenario investigates the impact of restricting the number of installable smart meters under conditions of combined load, PV, and EVCS uncertainties, reflecting realistic budgetary constraints faced by distribution system operators.

Scenario 4—EV penetration with reduced non-technical losses (non_tech_coeff = 0.05):

This scenario assesses the sensitivity of the optimization results to lower non-technical loss coefficients, while accounting for all three sources of uncertainty (load, PV, and EVCS). It provides insight into the interaction between technical loss reduction and non-technical loss mitigation. The optimization results for these scenarios are presented and discussed for the IEEE 33-bus and 69-bus test systems in Sections 4.2 and 4.3.

4.2. 33-Node Test System

To evaluate the effectiveness of the proposed method, the IEEE 33-bus distribution network is adopted as the primary test system. This radial feeder operates at a nominal voltage level of 12.66 kV and consists of 32 distribution lines connected to a single substation bus [35]. The total load demand of the system is 3715 kW of active power and 2300 kVar of reactive power, with all loads modeled as balanced three-phase demands representing a mixture of residential, commercial, and industrial consumers. The single-line diagram of the IEEE 33-bus system used in this study is shown in Figure 1. To reflect modern distribution network conditions, PV units are installed at buses 6, 18, and 33, each rated at 1000 kW. Additionally, EVCSs are integrated at buses 8, 25, and 30, with nominal charging capacities of 500 kW each, scaled according to the EV penetration factor (EVscale). This test configuration provides a realistic platform for examining the performance of the proposed optimization framework under high levels of renewable generation and EV charging demand.

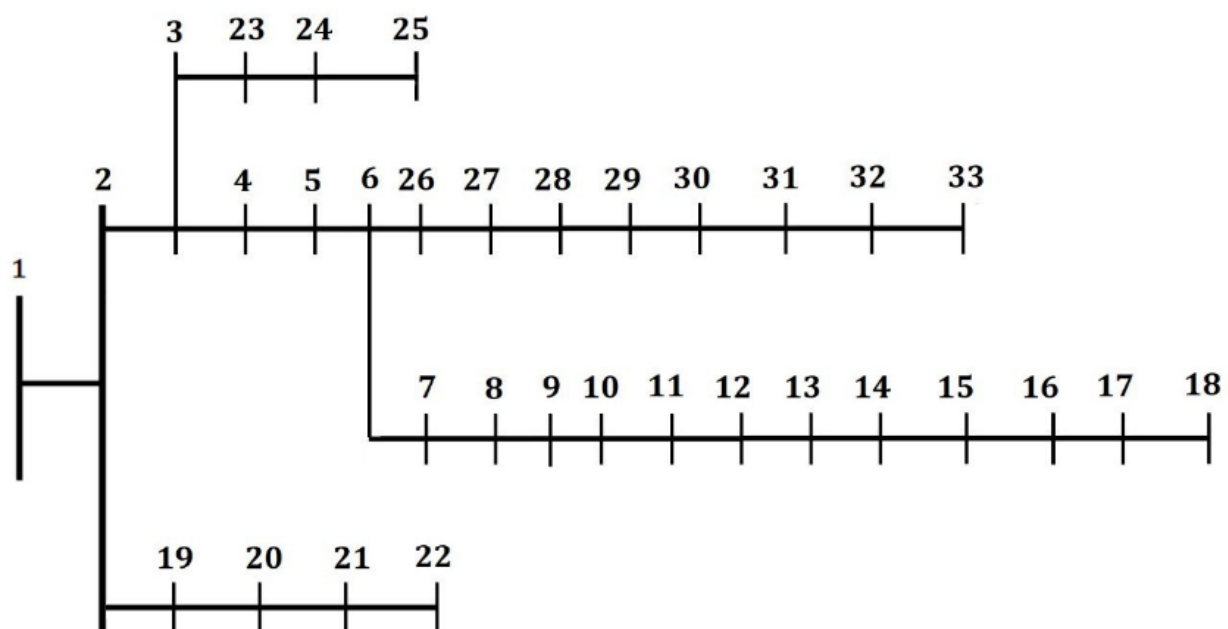


Figure 1. Single-line diagram of the 33-bus test system [27].

The simulation results for the multi-objective smart meter placement problem, considering the presence of PV units and EVCSs in the IEEE 33-bus network, are as follows:

Figure 2a–d illustrate the Pareto optimal fronts obtained using the proposed NSGA-II algorithm for the IEEE 33-bus system under Scenarios 1–4. Each front represents the set of non-dominated solutions reflecting the inherent trade-off between network losses, VDP and peak demand in each operational condition. As expected, solutions with lower total losses are often associated with higher peak demand values, indicating a clear trade-off between these objectives. At the same time, improving network observability (reflected by lower VDP values) and reducing investment cost introduce additional trade-offs among the objectives. Therefore, for each scenario, a best compromise solution (BCS) is selected from the Pareto front by simultaneously considering all four objectives, namely loss minimization, peak reduction, VDP, and investment cost. While the 3D Pareto fronts in Figure 3 provides an integrated overview of the four-objective optimization space, the precise evaluation of solution quality and trade-offs is further supported by the numerical results of the BCS presented in Table 2. This approach ensures a balance between visual conciseness and quantitative depth while avoiding the need for numerous 2D projections for each pair of objectives.

Table 2. Best compromise solutions for the IEEE 33-bus system.

Scenario	Smart Meter Locations	Investment (No. of Meters)	Loss (kW)	Peak (kW)	VDP
1	7, 10, 16, 17, 24, 26, 27, 30, 31	9	156.4	2780	4.64
2	7, 8, 15, 23, 24, 25, 29, 30, 32	9	171.6	3500	7.15
3	9, 11, 27, 29, 31	5	209	3550	9.67
4	2, 8, 9, 10, 12, 31	6	171.4	3450	9.20

Across the four scenarios, the Pareto fronts reveal a clear trade-off among the three key objectives: power loss, peak demand, and VDP. In all cases, as the algorithm seeks to minimize total losses, the corresponding peak demand tends to increase, confirming the conflicting nature of these objectives. Conversely, solutions that achieve a lower VDP—indicating better network observability and voltage stability—often require slightly higher investment or result in moderate increases in losses and peak demand. This pattern highlights the inherent balance that must be maintained between efficiency, stability, and infrastructure cost in smart distribution systems.

When the four scenarios are compared, Scenario 4 exhibits the widest and most distinct Pareto front, suggesting greater variability in optimal meter placements under its operating conditions. This can be attributed to higher system dynamics caused by PV generation and EV charging interactions. In contrast, Scenario 1 displays a more compact and clustered Pareto set, indicating smoother trade-offs and more uniform performance across objectives. Overall, the consistent spread of Pareto solutions across all cases demonstrates the robustness of the optimization process and the adaptability of smart meter placement strategies to varying network stress levels. Overall, Figure 2a–d confirm that the proposed NSGA-II approach maintains strong adaptability and continues to produce balanced and meaningful compromise solutions across all operating scenarios. Table 2 summarizes the best compromise solutions (BCS) extracted from the Pareto fronts for the four scenarios. The table reports all objective values, including network power loss, peak demand, observability penalty, and installation cost measured by the number of smart meters deployed. Scenario 1 achieves the lowest power loss and peak reduction using nine smart meters, while Scenario 3 offers the minimum-investment configuration with only five meters, though at the expense of higher loss and peak values.

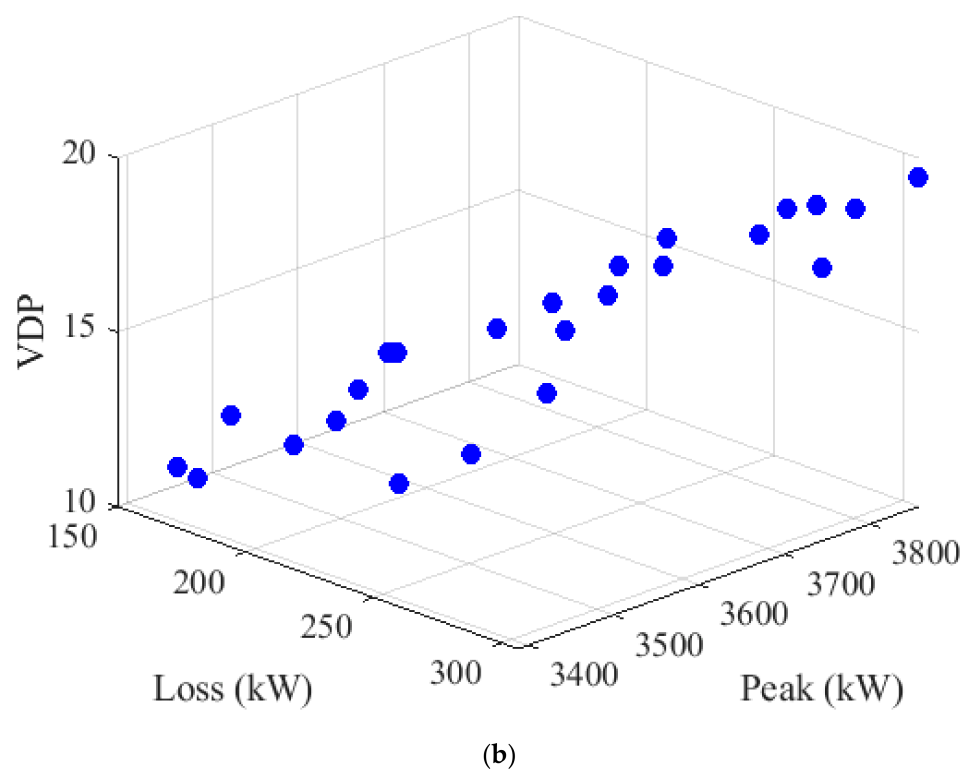
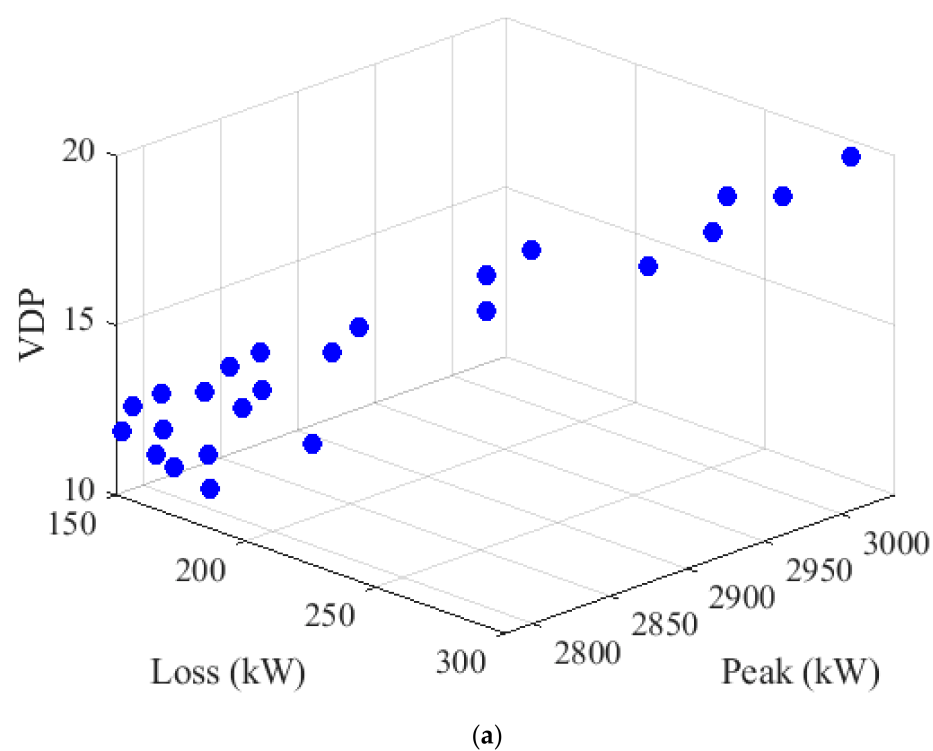


Figure 2. Cont.

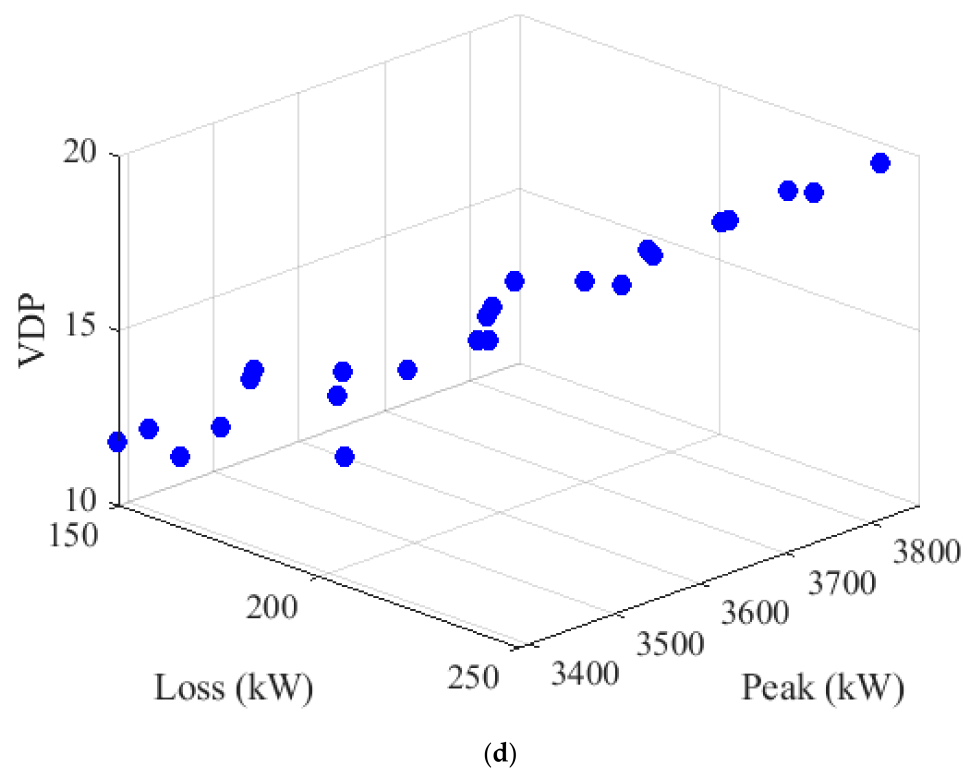
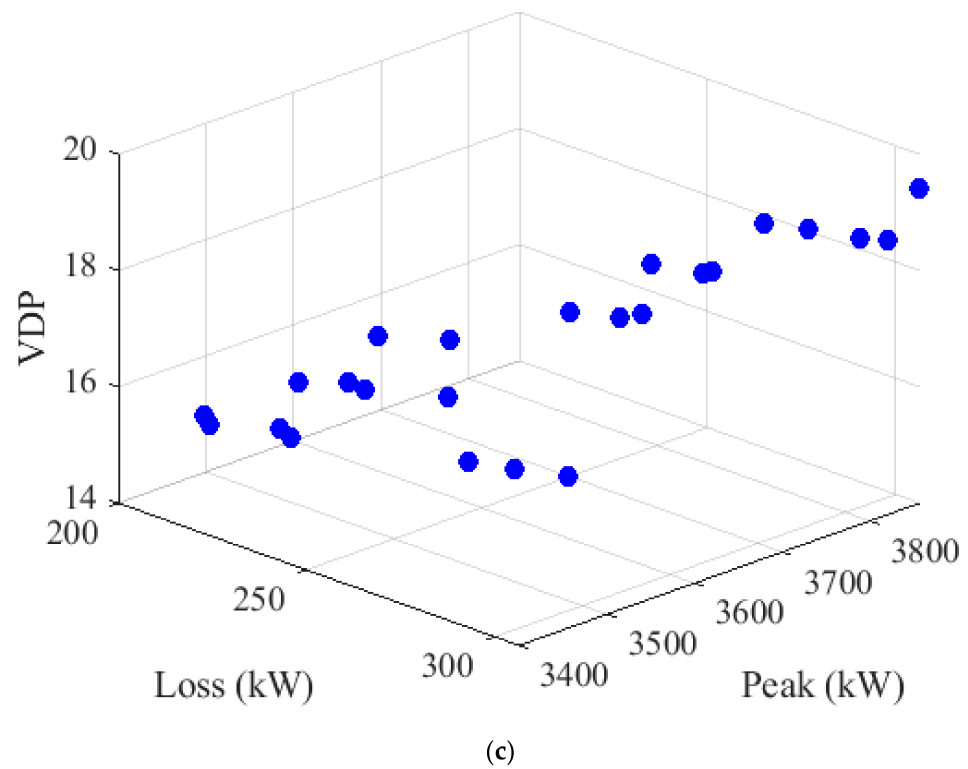


Figure 2. Pareto optimal front obtained by the proposed NSGA-II algorithm for the IEEE 33-bus system: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4.

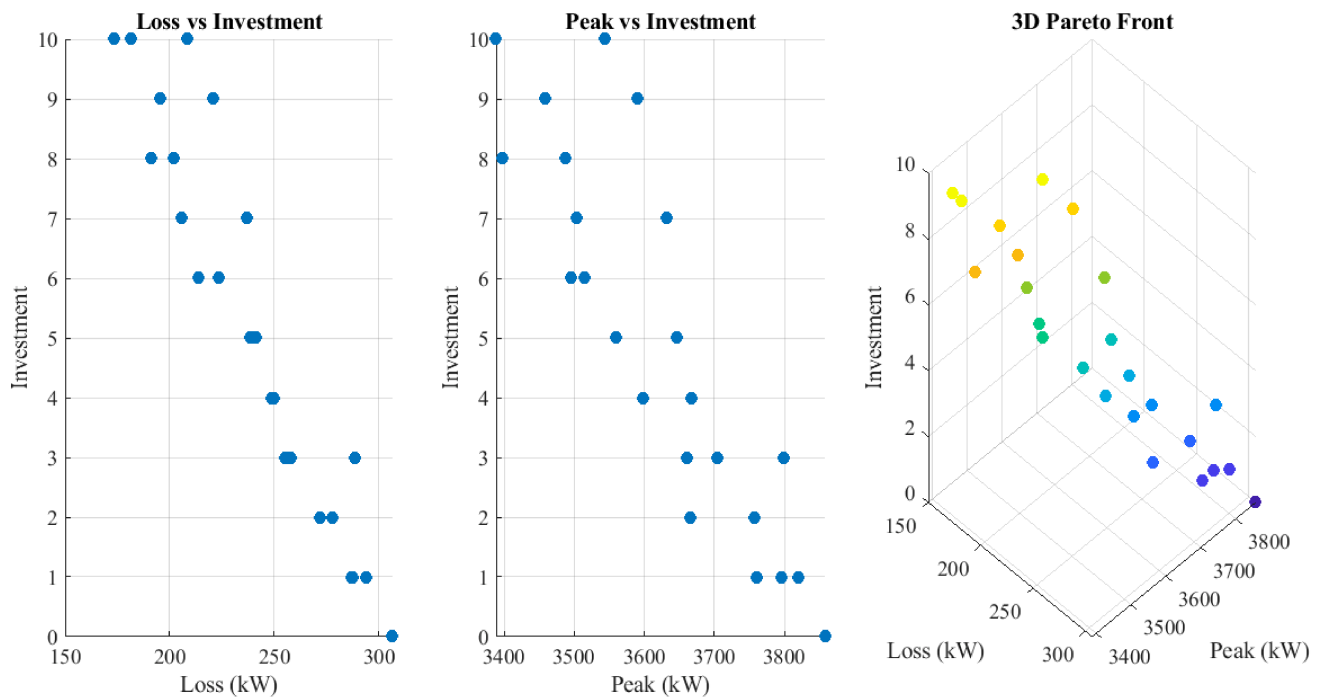


Figure 3. Two- and three-dimensional Pareto trade-off solutions for the first system.

The repeated selection of certain buses across different scenarios can be explained by their electrical significance in the IEEE 33-bus distribution system. These buses are generally located in downstream sections or lateral branches where voltage drops and power losses are more pronounced. Since power flow variations in these areas have a stronger effect on the voltage profile and loss behavior of the network, installing smart meters at these locations improves the observability of critical operating points. Furthermore, buses connected through relatively high-impedance branches or located near heavily loaded sections tend to exhibit higher voltage sensitivity. Therefore, their repeated appearance in the optimal solutions indicates that the optimization algorithm identifies electrically influential buses rather than selecting deployment nodes randomly.

The scenario-based results indicate a clear trade-off between smart meter investment and technical performance. Scenario 1 delivers the best overall performance, achieving the lowest power loss, peak demand, and VDP because of its more effective meter deployment under the baseline condition. Although Scenario 2 uses the same number of meters, its loss, peak demand, and VDP are all higher, showing that system performance depends not only on the number of meters but also on their placement and the operating condition. A similar pattern can be seen when comparing Scenarios 3 and 4. With one additional meter, Scenario 4 improves both loss and VDP compared with Scenario 3 and also slightly reduces peak demand. Overall, the results confirm that greater or better-targeted observability generally improves network performance, but peak demand reduction is still strongly influenced by scenario conditions and meter allocation strategy.

Overall, the results demonstrate that the optimal number and placement of smart meters strongly depend on the operating scenario and the associated network stress level. Increasing the number of meters generally improves observability and reduces VDP, but the extent of improvement in loss and peak demand remains scenario-dependent. These findings provide useful guidance for distribution system operators in planning cost-effective smart meter deployment strategies under varying network conditions.

In addition to the three-dimensional Pareto representations, this section examines the two-dimensional Pareto fronts obtained for solving the problem. In Scenario 2, Figure 3

presents the Pareto-optimal solutions obtained from the proposed multi-objective optimization framework, illustrating the trade-off among three objective functions: network loss, VDP, and investment in terms of the number of installed smart meters. The results indicate that increasing the number of smart meters generally provides greater potential for loss reduction and voltage-profile improvement; however, these improvements do not follow a strictly uniform trend, highlighting the conflicting nature of the objectives. Moreover, the simultaneous visualization of the solutions in both two-dimensional and three-dimensional forms demonstrates that no single solution can achieve the best value for all objectives at the same time. Therefore, Figure 3 confirms the ability of the proposed method to generate a set of balanced non-dominated solutions for selecting an appropriate smart-meter placement strategy.

For clarity, the performance improvement percentages reported in Table 3 are calculated using a scenario-specific but consistently defined base case. For each scenario, the corresponding base case is obtained under the same operating conditions, including the same load level, PV generation, EV charging demand, and scenario-related assumptions, but without optimized smart meter deployment and without demand response control. Therefore, the numerical base-case values may differ across scenarios; however, the baseline definition is applied consistently within each scenario.

Table 3. Performance improvement achieved by optimal smart meter placement.

Scenario	Base Loss (kW)	Optimized Loss (kW)	Loss Reduction (%)	Base Peak (kW)	Optimized Peak (kW)	Peak Reduction (%)
1	222.6	156.4	29.74	3035	2780	8.40
2	301.5	171.6	43.08	3857	3500	9.26
3	275.2	209	24.06	3857	3550	7.96
4	229.3	171.4	25.25	3857	3450	10.54

The loss reduction and peak reduction percentages are calculated as follows:

$$\text{Loss reduction (\%)} = [(P_{\text{loss,base}} - P_{\text{loss,algorithm}}) / P_{\text{loss,base}}] \times 100$$

$$\text{Peak reduction (\%)} = [(P_{\text{peak,base}} - P_{\text{peak,algorithm}}) / P_{\text{peak,base}}] \times 100$$

where $P_{\text{loss,base}}$ and $P_{\text{peak,base}}$ denote the network loss and peak demand of the corresponding scenario-specific base case, while $P_{\text{loss,algorithm}}$ and $P_{\text{peak,algorithm}}$ denote the values obtained by each optimization algorithm under the same scenario. This definition ensures that the reported improvements are based on a consistent scenario-matched baseline.

The comparative results summarized in Table 3 demonstrate that the strategic placement of smart meters can considerably reduce both power losses and peak demand under all examined operating conditions. Among the studied cases, Scenario 2 achieves the highest efficiency improvement, with optimized meter deployment leading to a 43.08% decrease in power losses. This pronounced improvement indicates that under highly stochastic loading conditions, the optimized meter configuration can effectively identify critical feeder sections and enhance operational efficiency.

In contrast, Scenario 3 exhibits more moderate gains, achieving a 24.06% reduction in losses. This result can be attributed to the stricter meter installation constraint in this scenario, which limits network observability and therefore reduces the achievable loss mitigation. In terms of peak load management, the proposed optimization framework also delivers consistent improvement across all scenarios, although with more moderate percentages than those observed for loss reduction. The largest peak reduction is obtained in Scenario 4, with a decrease of 10.54%, followed by Scenario 2 and Scenario 1 with reductions of 9.26% and 8.40%, respectively. Scenario 3 shows the smallest peak improvement, with

a reduction of 7.96%. These results confirm that the proposed approach is effective in reducing peak demand under different operating conditions, while also indicating that the extent of peak mitigation is strongly influenced by the specific scenario characteristics, meter budget, and optimal placement strategy.

Table 4 presents a comparative evaluation of the proposed NSGA-II-based optimization strategy against four well-known metaheuristic algorithms, namely GWO, SFLA, GSA, and MOEA/D, for the IEEE 33-bus distribution system. The comparison is based on the optimal trade-off solutions obtained from the corresponding Pareto fronts. It should be noted that, due to differences in network conditions and component configurations—such as the number and capacity of PV units and EV charging stations—direct quantitative comparison with previously published studies is not practically meaningful. Therefore, the comparison is carried out among the considered optimization methods under the same simulation framework. To ensure statistical reliability, each algorithm was executed over 20 independent runs, and the average (AVG) and standard deviation (STD) values of both power loss and peak demand were recorded.

Table 4. Comparison of the proposed method with other optimization algorithms (IEEE 33-bus system).

Method	Loss (kW)		Peak (kW)		Number of Meters	Best Meter Locations	CPU Time (s)
	AVG	STD	AVG	STD			
GSA	189.7	1.94	2993	15.64	9	6, 10, 14, 17, 23, 26, 28, 30, 31	39
SFLA	177.9	1.88	2925	15.15	9	7, 10, 15, 17, 23, 26, 27, 30, 31	45
GWO	166.4	1.56	2880	14.66	9	7, 9, 16, 17, 24, 26, 27, 30, 31	37
MOEA/D	159.5	1.49	2849	14.25	9	7, 15, 17, 23, 24, 25, 28, 30, 32	31
NSGA-II	156.4	1.45	2780	13.85	9	7, 10, 16, 17, 24, 26, 27, 30, 31	33

As shown in Table 4, NSGA-II achieves the best overall performance among all compared methods, with the lowest average power loss of 156.4 kW and the lowest average peak demand of 212 kW. In addition, it provides the smallest standard deviation values for both loss (1.45) and peak demand (1.69), indicating superior convergence accuracy and solution stability.

A direct comparison with MOEA/D further confirms the effectiveness of the selected NSGA-II algorithm. Although MOEA/D provides competitive results, with an average loss of 159.5 kW and an average peak demand of 2849 kW, NSGA-II achieves superior objective values under the same smart meter investment level. Both algorithms use nine smart meters; however, NSGA-II obtains a lower average loss of 156.4 kW and a lower average peak demand of 2780 kW, indicating better technical performance. In terms of computational effort, MOEA/D requires 31 s, while NSGA-II requires 33 s. This shows that the improved optimization performance of NSGA-II is achieved with only a marginal increase in CPU time. Overall, the comparison demonstrates that the proposed multi-objective NSGA-II framework outperforms GSA, SFLA, GWO, and MOEA/D in determining optimal smart meter placement for the IEEE 33-bus system, while maintaining a balanced trade-off between loss reduction, peak demand mitigation, and computational efficiency.

As illustrated in Figure 4, the proposed NSGA-II scheme demonstrates clear improvements over the other optimization algorithms. In terms of power loss reduction, the proposed method achieves approximately 6.01%, 12.08%, and 17.55% improvements compared with GWO, SFLA, and GSA, respectively. A similar trend is observed for peak demand mitigation, where the proposed method provides performance gains of 2.70%, 5.35%, and 7.62% relative to GWO, SFLA, and GSA, respectively. These results further confirm the superior capability of the proposed optimization framework in identifying smart meter placement strategies that effectively reduce both network losses and peak demand.

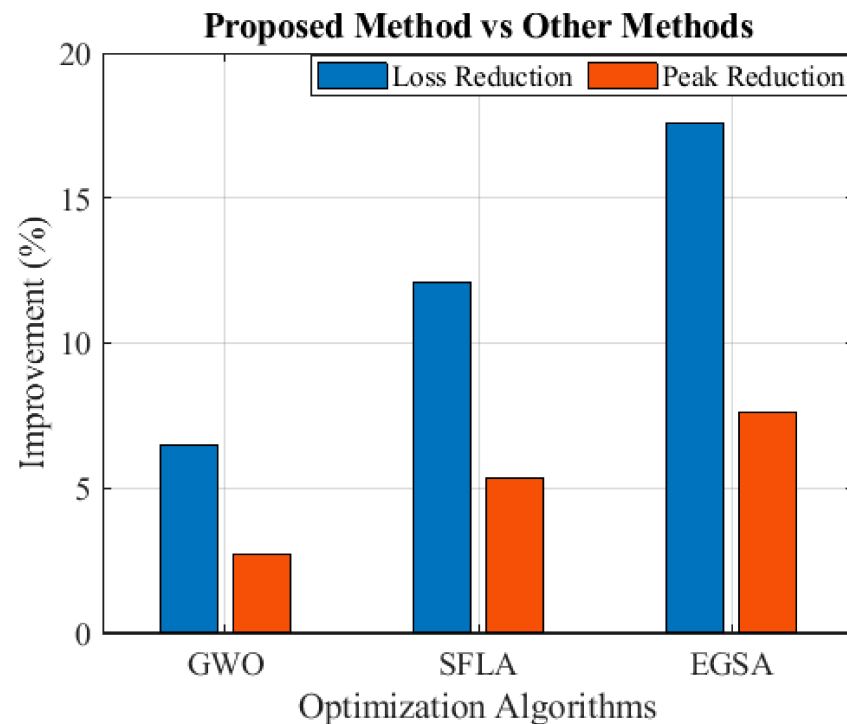


Figure 4. Improvement of proposed method over other algorithms.

Figures 5 and 6 present the boxplot distributions of the power loss and peak demand obtained from 20 independent runs of each optimization algorithm. As illustrated in Figure 5, the NSGA-II algorithm achieves the lowest median power loss with the smallest variability, indicating a more stable and reliable convergence compared with GWO, SFLA, and GSA. A similar pattern is observed in Figure 6 for peak demand, where NSGA-II again outperforms the other methods by yielding both lower central values and narrower spread. These results collectively demonstrate the superior performance and robustness of the proposed optimization framework in achieving consistent and high-quality solutions for smart meter placement in the IEEE 33-bus distribution system.

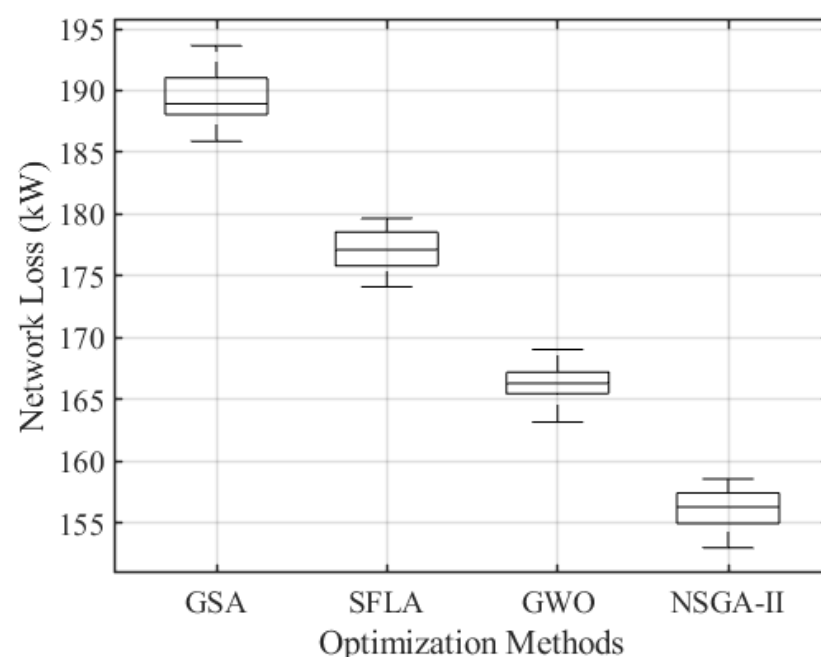


Figure 5. Boxplot of network loss for different algorithms.

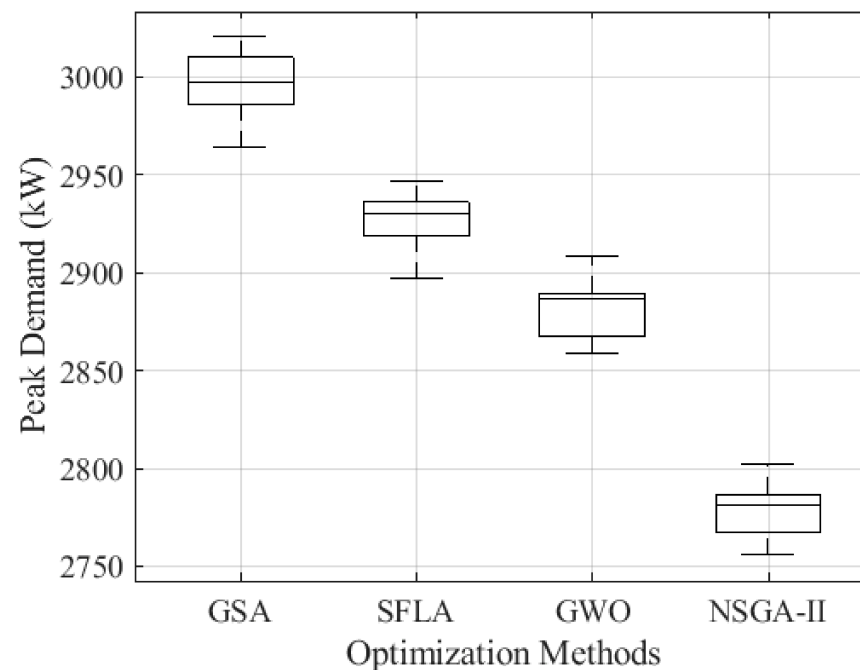


Figure 6. Boxplot of peak demand for different algorithms.

- **Impact of the Revised Demand Response Model on Simulation Results**

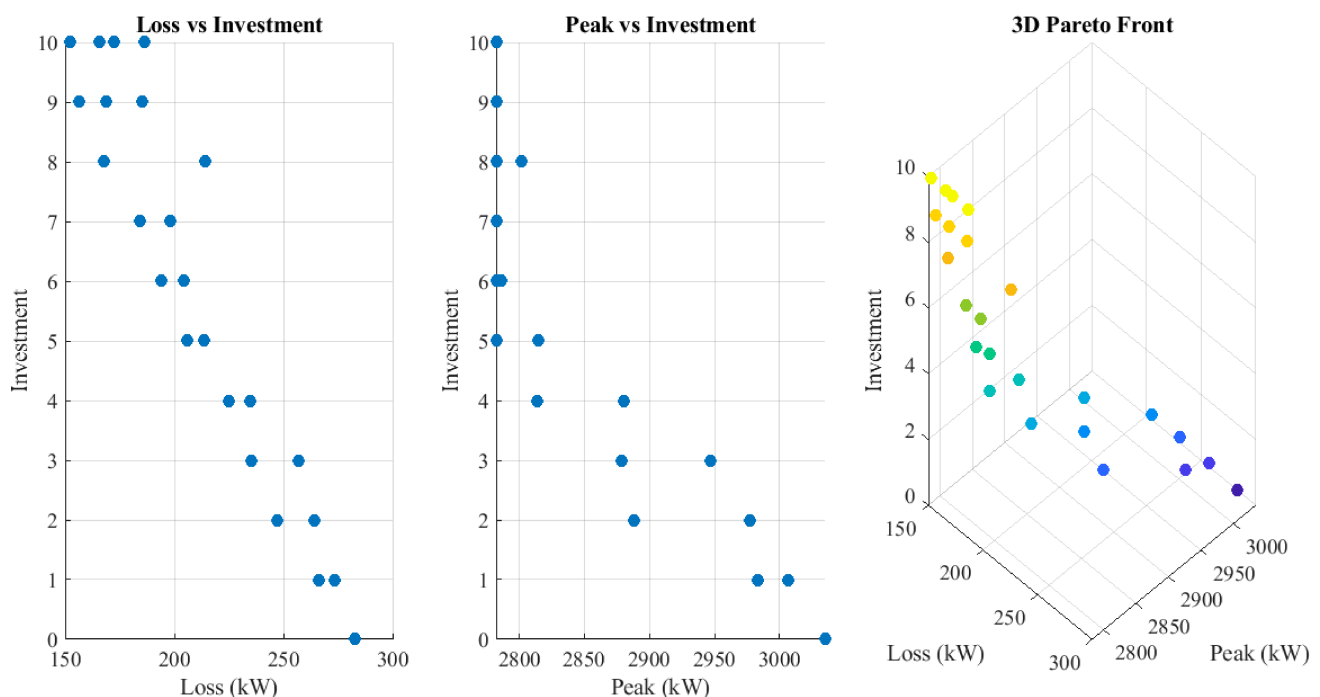
In order to enhance the realism of the demand response (DR) representation, the model adopted in this study was modified to account for dynamic participation rates and the rebound effect. Unlike the previous formulation, which assumed a fixed and fully effective load reduction, the revised model reflects the fact that customer participation is not always uniform and that part of the reduced demand may return after the DR event. In this updated representation, the effective load reduction is calculated as $P_{\text{red}}(t) = \alpha(t) \cdot P_{\text{cut}}(t)$, where $\alpha(t)$ represents the dynamic participation rate. To account for the recovery of the shifted demand, a rebound component is introduced as $P_{\text{reb}}(t) = \beta \cdot P_{\text{red}}(t)$, where β is the rebound factor. Consequently, the final net load is determined by $P_{\text{DR}}(t) = P_{\text{base}}(t) - P_{\text{red}}(t) + P_{\text{reb}}(t)$. By capturing the practical uncertainty and imperfect effectiveness of demand response, the updated model provides a more realistic and defensible basis for assessing the effectiveness of smart meter placement strategies. As a consequence, the resulting values for power loss, peak demand, and voltage deviation penalty are generally more conservative than those obtained from the previous simplified model. However, these results are more practically meaningful, as they avoid overly optimistic assumptions and instead offer a robust estimation of the technical impacts on the distribution system.

Table 5 presents the best compromise solutions for the IEEE 33-bus system considering the revised demand response model. The reported solutions were identified from the obtained Pareto fronts based on an equal-weight normalization of the objective functions, including power loss, peak demand, voltage deviation penalty, and number of installed smart meters. Owing to the incorporation of dynamic customer participation and rebound effect in the revised DR formulation, the obtained results are more practically representative than those derived from the previous simplified model. Therefore, the solutions listed in Table 5 can be regarded as the most balanced and technically defensible planning options for the examined scenarios.

Table 5. Best Compromise Solutions for the IEEE 33-bus system considering the revised demand response model.

Scenario	Smart Meter Locations	Investment (No. of Meters)	Loss (kW)	Peak (kW)	VDP
1	5, 8, 9, 10, 12, 16, 21, 24, 30	8	170.4	2840	7.08
2	9, 10, 11, 25, 28, 29, 30	7	198.6	3635.5	8.35
3	13, 17, 30, 32, 33	5	218	3695	11.27
4	2, 8, 9, 16, 24, 25, 29, 33	8	161.62	3440.2	8.13

Figure 7 illustrates the output of the proposed optimization method for Scenario 1 under the revised demand response model. As shown, the obtained Pareto solutions represent the trade-off between investment, expressed as the number of installed smart meters, and the technical performance indices including power loss, voltage deviation penalty, and peak demand. The two-dimensional plots indicate that lower values of loss and voltage deviation penalty are generally associated with higher investment levels, whereas solutions with fewer installed meters tend to show weaker technical performance. The three-dimensional Pareto front also highlights the inherent conflict among loss, peak demand, and investment, confirming that no single solution can simultaneously achieve the best values for all objectives. Therefore, Figure 8 clearly demonstrates the ability of the proposed method to generate a diverse set of non-dominated solutions for Scenario 1, from which the best compromise solution can be identified.

**Figure 7.** Two- and three-dimensional Pareto trade-off solutions considering the revised demand response model.

Compared with the results obtained under the previous demand response formulation in Table 2, the best compromise solutions reported in Table 5 are generally associated with higher loss, peak demand, and voltage deviation penalty values. This difference is mainly attributed to the fact that the previous DR model relied on a simplified fixed load reduction assumption, which tended to overestimate the effectiveness of demand response. In contrast, the revised DR model incorporates dynamic participation behavior and rebound effect, thereby reducing the net amount of curtailed load and yielding more practically representative outcomes. However, the comparison also reveals that the revised model does not uniformly degrade performance; in some cases, such as Scenario 4, improved

smart meter placement under the revised formulation leads to better overall technical performance despite a higher investment level.

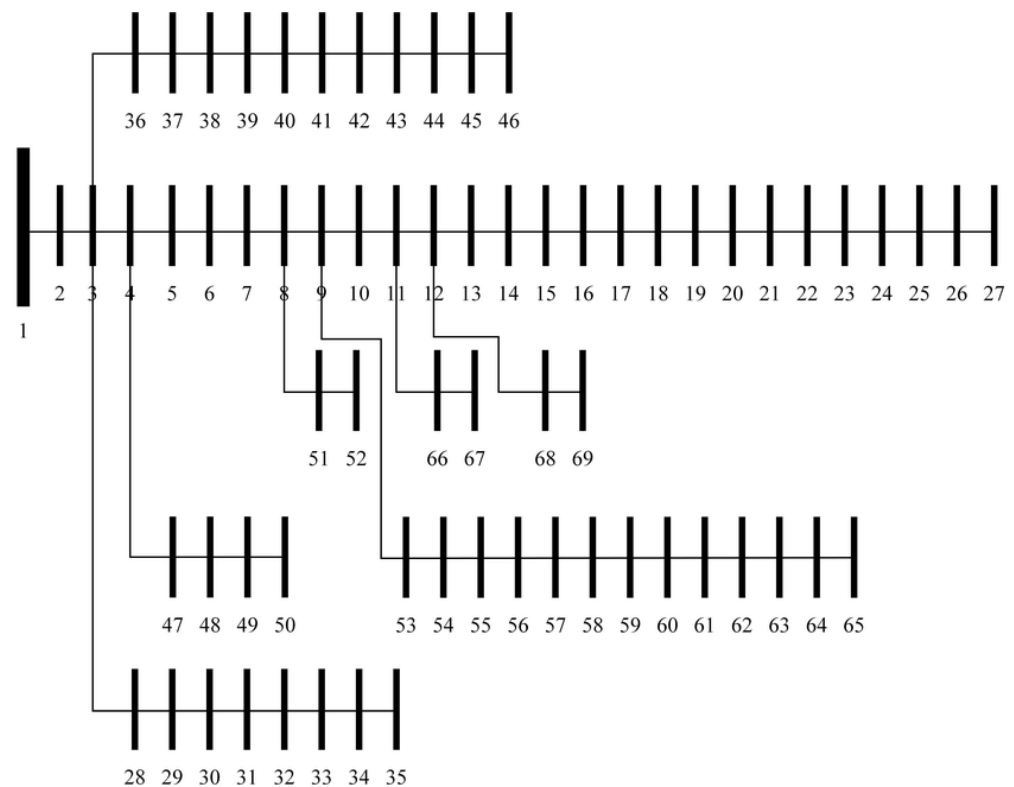


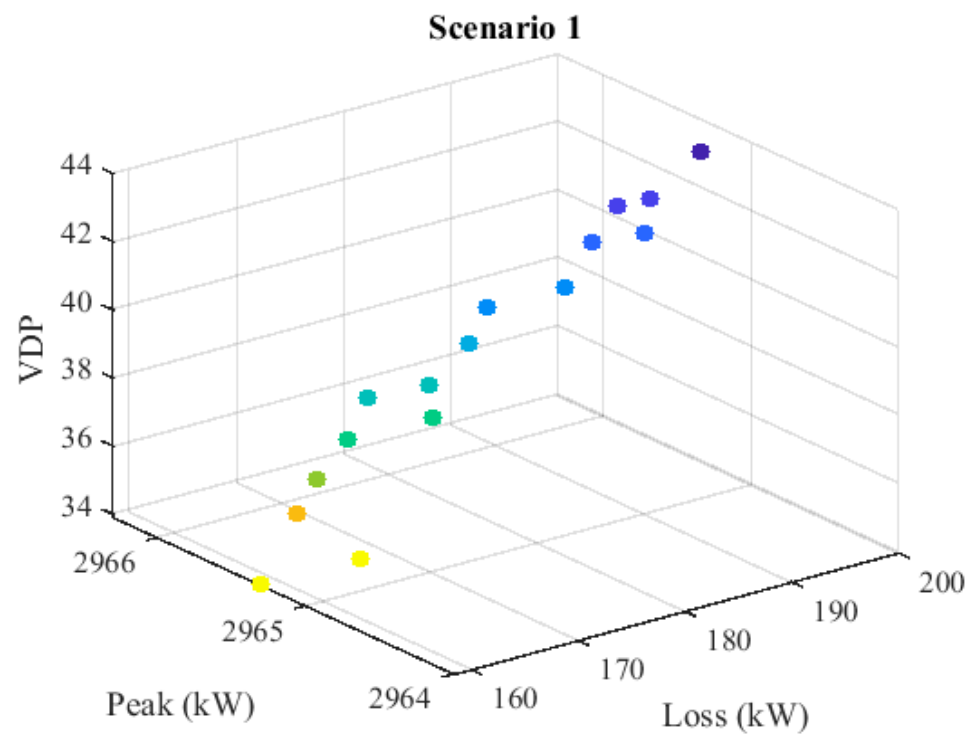
Figure 8. Single-line diagram of the 69-bus system.

4.3. 69-Bus Network

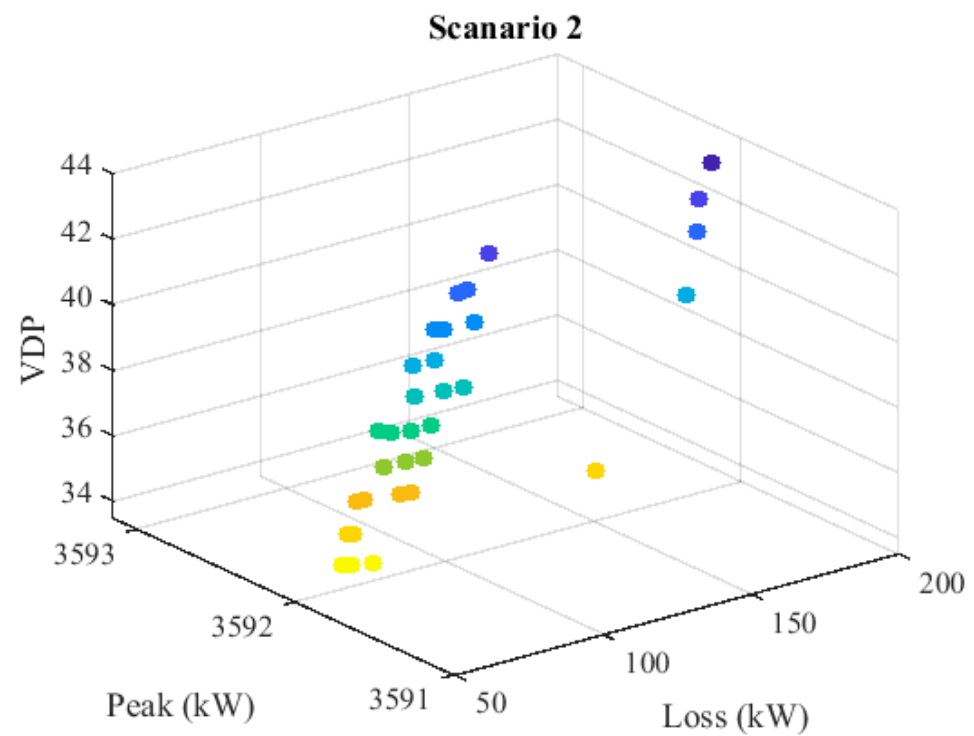
A typical 69-bus distribution network, which includes 68 branches, is shown in Figure 8. The system has a total load of 3.8 MW and 2.69 MVAR. Detailed line and load data are available in [36]. The network operates with a base voltage of 12.66 kV and a base power of 10 MVA. The results obtained from the multi-objective optimization of the smart meter placement problem in the distribution network are presented and analyzed in this section. To emulate contemporary operating conditions in distribution networks, four units are deployed at buses 18, 31, 50, and 61, each with a rated capacity of 1000 kW. In addition, three EVCSs are incorporated at buses 12, 35, and 64, each having a nominal charging capacity of 500 kW which is adjusted according to the EV penetration factor (*EV_scale*). Figure 9a–d show the three-dimensional Pareto fronts obtained for the four studied scenarios, highlighting the trade-offs among network loss, peak demand, and VDP.

Each subfigure represents one scenario and illustrates how the non-dominated solutions are distributed in the objective space. Although the numerical ranges differ from one scenario to another, a similar trend can be seen in all cases. In general, the spread of solutions along the penalty dimension is more limited, while the variations in loss and peak demand are more pronounced. This suggests that the penalty remains within a relatively narrow range, whereas the trade-off between loss reduction and peak demand mitigation leads to a wider distribution of feasible solutions. The shape and distribution of the Pareto fronts also reflect the impact of EVCS and PV uncertainty on the optimization results. Scenarios with higher uncertainty tend to produce a wider spread in the loss–peak plane, indicating a larger set of feasible trade-offs and a more complex search space. By contrast, scenarios with more stable operating conditions show more compact clusters of solutions, which points to a more consistent optimization behavior. Overall, these figures

help visualize how the proposed multi-objective framework behaves under different operating conditions and provide a clearer view of the solution space before selecting the best compromise solution.



(a)



(b)

Figure 9. *Cont.*

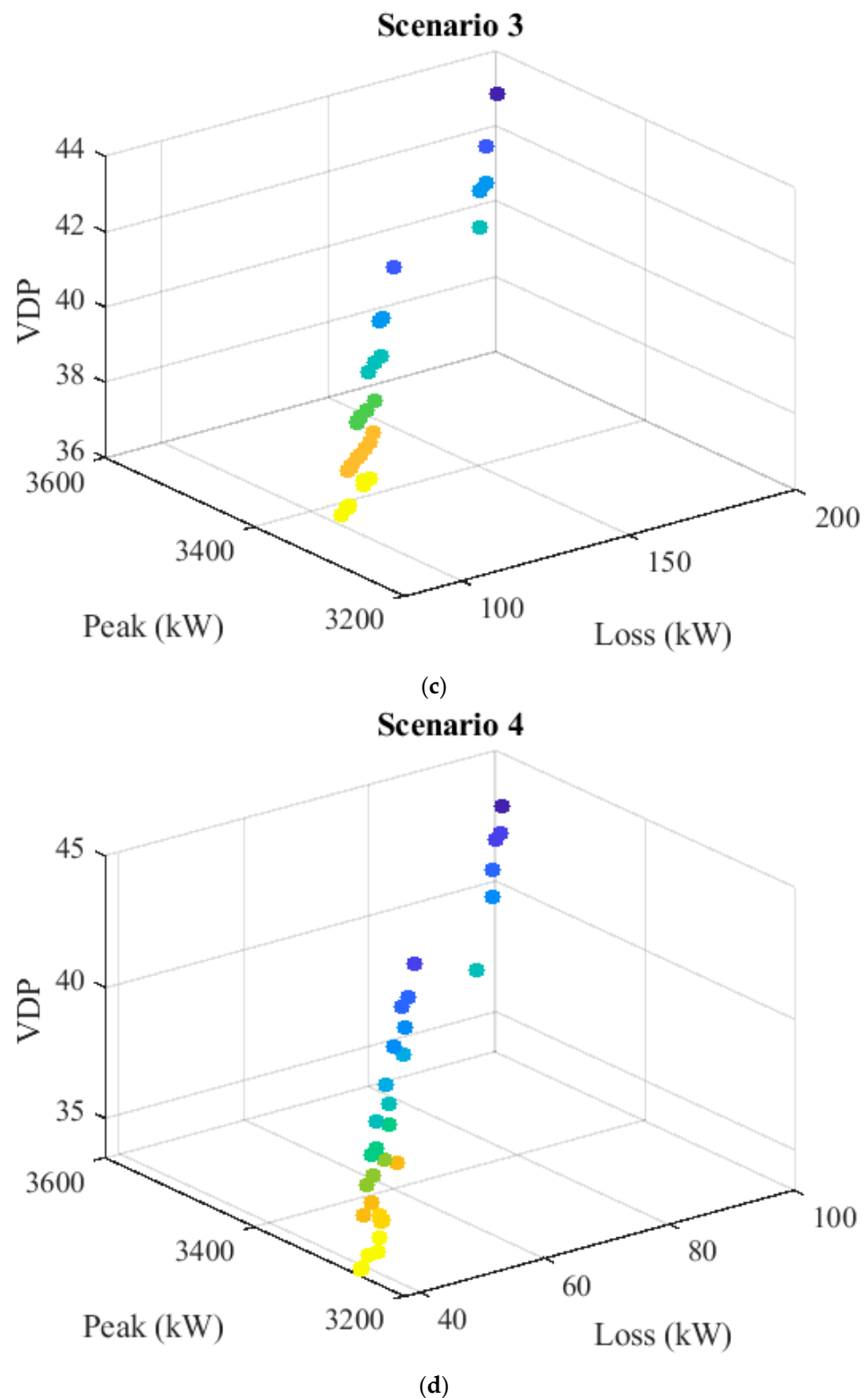


Figure 9. Pareto front solutions generated by the proposed NSGA-II algorithm for the IEEE 69-bus system: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4.

Table 6 summarizes the best compromise solutions obtained for the IEEE 69-bus distribution system under four different operating scenarios. These solutions are selected from the Pareto fronts as the best compromise solutions for each scenario, considering the trade-off among network power loss, peak demand, and smart meter investment cost. The

results clearly show that the optimal meter placement pattern changes across scenarios, highlighting the strong influence of operating conditions on both the required number of meters and their installation locations. In Scenario 1, the best compromise solution is obtained by installing five smart meters at buses 11, 12, 59, 65, and 69. This configuration results in a network loss of 153.61 kW, a peak demand of 2653.27 kW, and a VDP value of 32. Scenario 2 requires six smart meters, installed at buses 11, 12, 35, 37, 58, and 65, and leads to a network loss of 163.45 kW, a peak demand of 3258.00 kW, and a VDP value of 33. Scenario 3 uses only three smart meters at buses 11, 12, and 35; however, this lower investment level results in a higher network loss of 169.15 kW, a peak demand of 3315.00 kW, and the highest VDP value of 36. Scenario 4, with five smart meters installed at buses 11, 12, 35, 59, and 65, achieves the lowest network loss of 79.34 kW. Nevertheless, it has the highest peak demand of 3500.21 kW and a VDP value of 34, indicating that the lowest-loss solution is not necessarily the most balanced solution when peak demand and voltage performance are also considered.

Table 6. Optimal compromise solutions for the IEEE 69-bus system.

Scenario	Smart Meter Locations	Investment (No. of Meters)	Loss (kW)	Peak (kW)	VDP
1	11, 12, 59, 65, 69	5	153.61	2653.27	32
2	11, 12, 35, 37, 58, 65	6	163.45	3258	33
3	11, 12, 35	3	169.15	3315	36
4	11, 12, 35, 59, 65	5	79.34	3500.21	34

In the IEEE 69-bus system, the optimal deployment nodes also show a consistent pattern across the investigated scenarios. This behavior is mainly related to the radial structure of the network, where buses located far from the substation or near highly loaded laterals are more affected by voltage drops and loss variations. These buses are therefore more sensitive to changes in active and reactive power flows. In addition, branches with relatively high impedance increase the electrical impact of downstream buses on voltage deviation and power losses. As a result, the repeated selection of these buses reflects their importance for monitoring power flow distribution, voltage sensitivity, and line-impedance-related effects in the network.

Scenario 2 deploys six smart meters at buses 11, 12, 35, 37, 58, and 65, yielding a network loss of 163.45 kW, a peak demand of 3258.00 kW, and a VDP value of 33. In comparison, Scenario 3 installs only three meters at buses 11, 12, and 35, but records the highest loss value of 169.15 kW among the first three scenarios, along with a peak demand of 3315.00 kW and the highest VDP value of 36. These observations show that the effectiveness of smart meter placement depends not only on the number of deployed meters, but more importantly on their locations and the spatial distribution of network stress. Scenario 4 involves five meters installed at buses 11, 12, 35, 59, and 65 and achieves the lowest loss value of 79.34 kW. This indicates that an appropriate meter configuration can substantially improve loss reduction without increasing the investment level. Nevertheless, Scenario 4 also exhibits the highest peak demand of 3500.21 kW and a VDP value of 34, showing that its overall performance is less balanced when peak demand and voltage deviation are considered simultaneously. Overall, the comparison confirms that the proposed optimization framework effectively identifies deployment strategies that reflect the trade-off between investment cost, loss reduction, peak demand mitigation, and voltage performance under different operating scenarios.

In Scenario 2, Figure 10 provides a clearer interpretation of the feasible compromise solutions by depicting the Pareto fronts associated with the smart-meter placement problem. As the investment level increases when installing more meters, both network loss and VDP tend to decrease, which reflects the positive impact of improved system

observability and monitoring on operational performance. However, the behavior of the solutions also indicates that the achieved benefits are not perfectly proportional to the added investment, and beyond certain points the technical improvements become more limited. This distribution of solutions highlights the existence of a trade-off region in which decision-makers must balance economic cost against loss reduction and voltage-quality enhancement, making the Pareto front an effective tool for identifying practically attractive planning options.

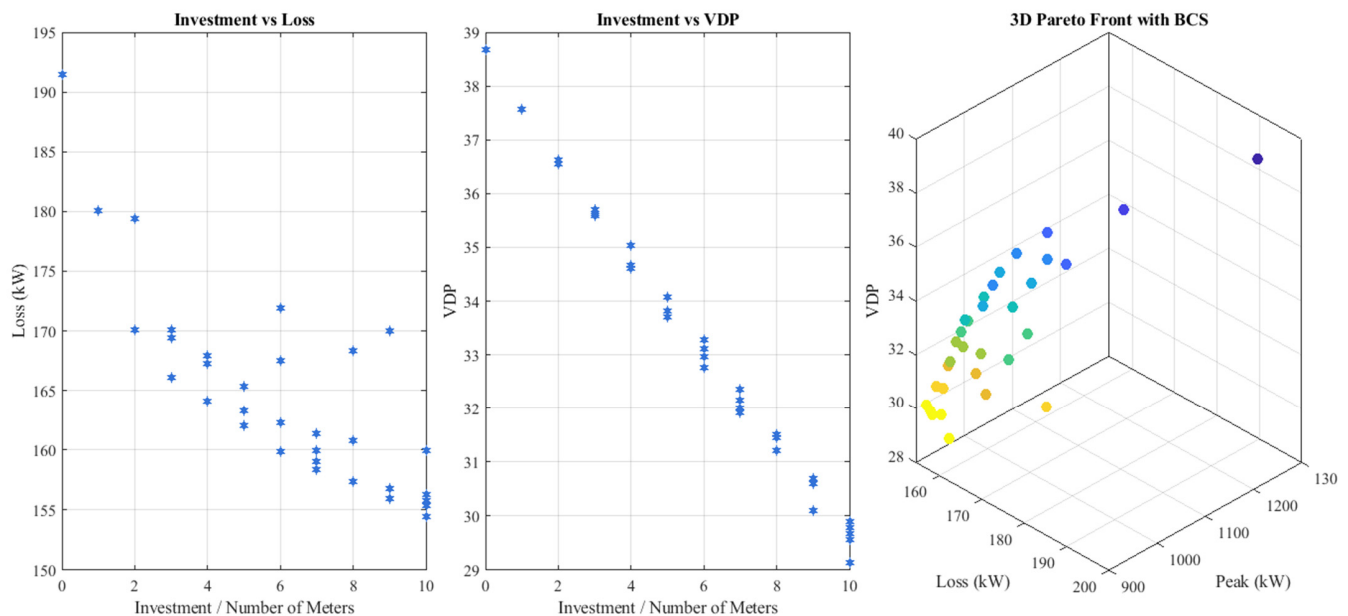


Figure 10. Two- and three-dimensional Pareto trade-off solutions.

The dispersion observed in the investment vs. loss plot reflects the influence of optimal placement strategies; for a given number of meters, different spatial configurations result in varying levels of loss reduction, and the algorithm effectively identifies the non-dominated configurations that provide the most efficient loss mitigation.

Figure 11 further illustrates the performance improvements achieved in the IEEE 69-bus distribution system after applying the optimized smart meter placement strategy. As shown, both power loss and peak demand are reduced across all four scenarios, confirming the effectiveness of the proposed optimization framework under different operating conditions. The largest loss reduction is observed in Scenario 4, reaching 24.10%, followed by Scenario 3 with 20.50%, Scenario 2 with 16.80%, and Scenario 1 with 12.60%. In terms of peak demand reduction, Scenario 4 also provides the highest improvement, with a reduction of 10.51%. Scenario 3 and Scenario 1 achieve peak demand reductions of 8.65% and 8.53%, respectively, while Scenario 2 shows the lowest peak reduction of 6.87%. Overall, these results confirm that the proposed method can identify effective smart meter locations and provide consistent technical benefits in terms of both loss reduction and peak demand mitigation across diverse operating scenarios.

Table 7 summarizes the statistical performance of the proposed NSGA-II approach and four benchmark metaheuristic algorithms, including MOEA/D, for the IEEE 69-bus distribution system under Scenario 1. The results are reported based on 20 independent runs using the average (AVG) and standard deviation (STD) values of network power loss and peak demand. As shown in Table 7, the proposed NSGA-II method achieves the best overall performance among all compared techniques. It records the lowest average power loss of 153.61 kW and the lowest average peak demand of 2653 kW. In addition, NSGA-II provides the smallest standard deviation values for both objectives, with an STD of 2.85

kW for power loss and 14.35 kW for peak demand. These results indicate that NSGA-II not only improves the objective function values but also demonstrates more stable and robust convergence behavior over repeated runs. A direct comparison with MOEA/D further confirms the advantage of the proposed method. Although MOEA/D shows competitive performance, with an average loss of 157.25 kW and an average peak demand of 2670 kW, it requires seven smart meters located at buses 3, 8, 15, 24, 34, 36, and 56. In contrast, NSGA-II achieves lower loss and peak demand values using only five smart meters located at buses 11, 12, 59, 65, and 69. Therefore, NSGA-II provides a more efficient trade-off between technical performance and meter deployment cost. Compared with the other benchmark algorithms, NSGA-II also outperforms GSA, SFLA, and GWO in both objective functions. The reduction in average loss relative to GSA, SFLA, GWO, and MOEA/D is approximately 21.55%, 15.41%, 9.27%, and 2.32%, respectively. Similarly, the average peak demand obtained by NSGA-II is lower than those of GSA, SFLA, GWO, and MOEA/D by about 6.23%, 3.61%, 1.60%, and 0.64%, respectively. Overall, these findings verify that the proposed NSGA-II-based framework provides superior solution quality, higher robustness, and better allocation efficiency compared with the other optimization techniques considered in this study.

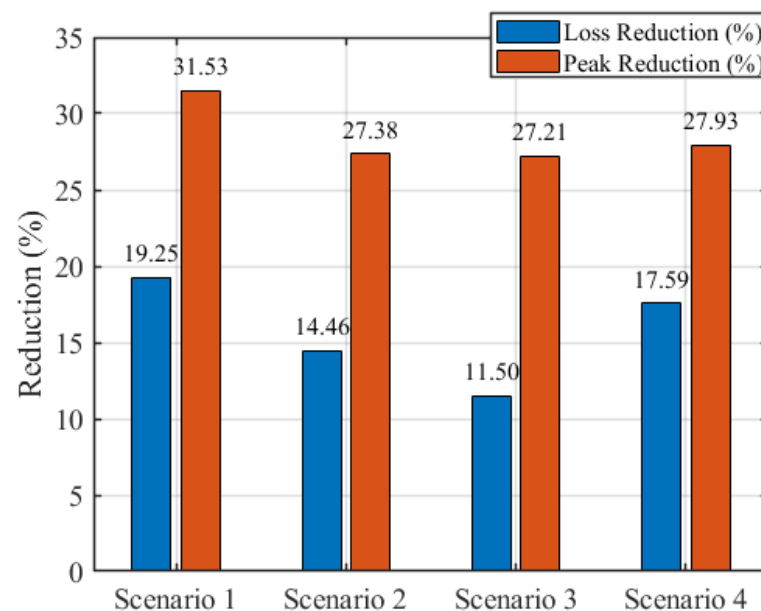


Figure 11. Reduction percentages of loss and peak demand for the 69-bus system under four optimized.

Table 7. Comparison of optimization techniques, including the proposed approach, on the IEEE 69-bus test system.

Method	Loss (kW)		Peak (kW)		Number of Meters	Best Meter Locations
	AVG	STD	AVG	STD		
GSA	195.8	5.98	2829.23	17.20	5	11, 12, 55, 62, 69
SFLA	181.6	4.66	2752.23	16.35	6	10, 11, 12, 59, 65, 69
GWO	169.3	3.76	2696.25	15.85	6	11, 12, 16, 59, 65, 69
MOEA/D	157.25	2.89	2670	14.88	7	3, 8, 15, 24, 34, 36, 56
NSGA-II	153.61	2.85	2653	14.35	5	11, 12, 59, 65, 69

Figures 12 and 13 present the boxplot distributions of network loss and peak demand obtained from 20 independent runs of the compared optimization algorithms for the IEEE 69-bus system. The boxplots provide a visual representation of the variability, median values, and dispersion of the solutions produced by each algorithm. As observed, the NSGA-II algorithm consistently achieves the lowest median values for both network loss

and peak demand. Moreover, the interquartile range and overall spread of the NSGA-II results are noticeably smaller than those of GSA, SFLA, and GWO, indicating a more concentrated distribution of solutions. This suggests that NSGA-II not only produces better solutions on average but also maintains higher solution stability across multiple runs. In contrast, the other algorithms exhibit wider distributions and greater variability, reflecting less consistent performance. Overall, the statistical distributions illustrated in these figures further confirm the reliability and effectiveness of the NSGA-II approach for the smart meter placement optimization problem.

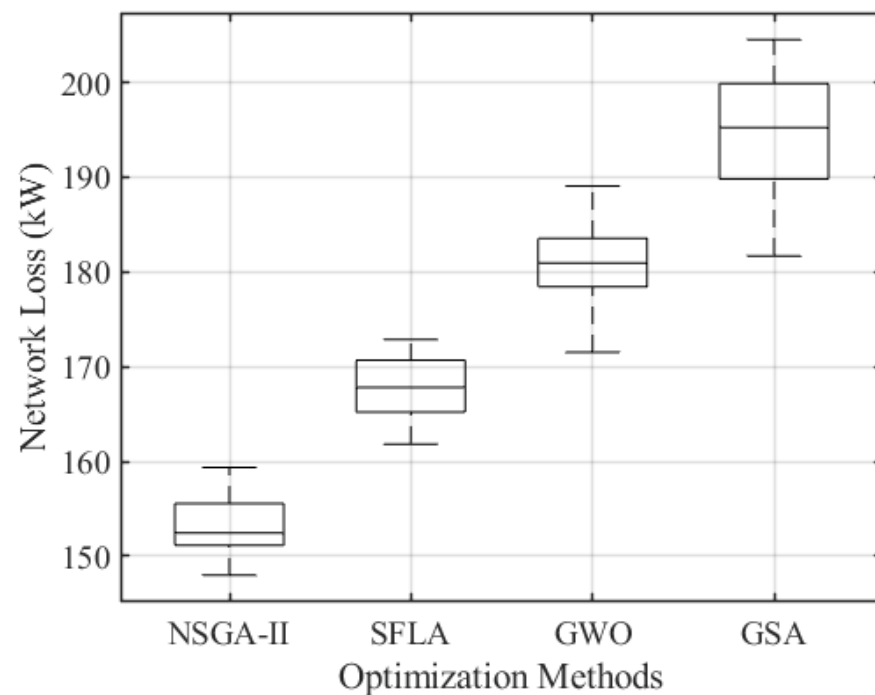


Figure 12. Boxplot of network loss for IEEE 69-bus system.

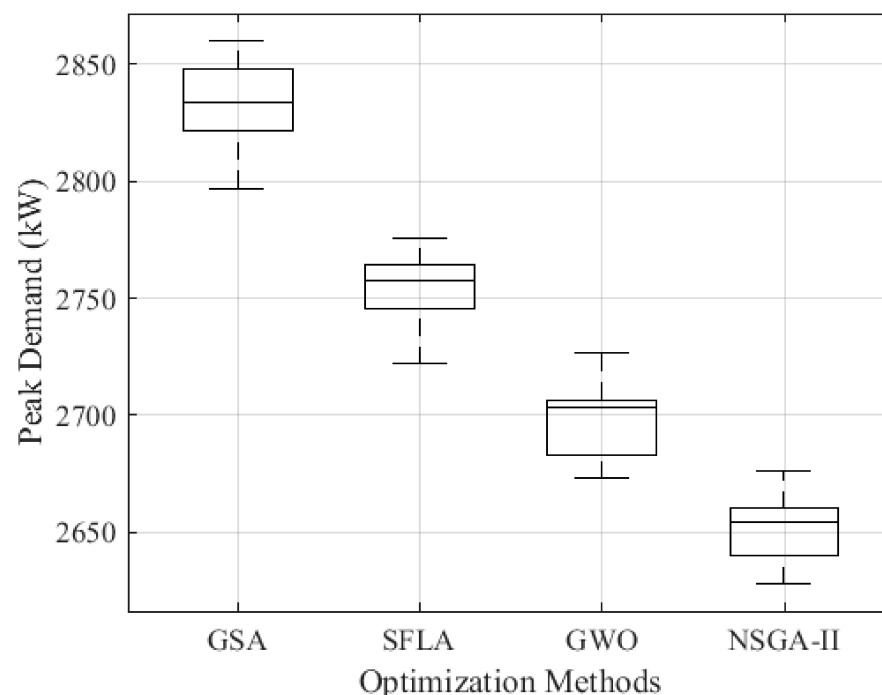


Figure 13. Boxplot of peak demand for IEEE 69-bus system.

5. Conclusions

This study developed a multi-objective framework for smart meter placement in distribution networks with integrated PV units and EV charging stations, where smart meters were considered not only as monitoring devices but also as enablers of limited demand-side control. The results showed that the proposed NSGA-II-based approach can identify well-balanced placement schemes that improve multiple technical performance indices simultaneously, including power loss, peak demand, and voltage deviation profile, while avoiding excessive meter deployment. The comparative analysis on the IEEE 33-bus and 69-bus systems confirmed that the proposed method consistently outperformed the benchmark algorithms in the studied scenarios. Beyond the numerical improvements, the results also indicate that the most effective meter locations are generally associated with electrically remote and more heavily loaded buses. This suggests that smart meter placement should be guided by network topology and operational sensitivity rather than by uniform installation patterns. From a practical perspective, the findings highlight that incorporating a simple rule-based load curtailment capability into the placement model can enhance the operational value of smart meters under stressed conditions, especially in networks with simultaneous PV penetration and EV charging demand. Therefore, smart meter deployment can be interpreted not only as an observability enhancement measure, but also as a flexible support mechanism for improving network performance.

Author Contributions: Conceptualization, H.L. and H.P.; methodology, H.L.; software and formal analysis, H.L.; validation, H.L. and H.P.; investigation, H.L.; writing—original draft preparation, H.L.; writing—review and editing, H.L. and H.P.; supervision, H.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ongoing research and model development.

Conflicts of Interest: The authors declare no conflicts of interest.

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