Resilience-Oriented Multi-Objective Optimization of PV and EV Charging Deployment in Unbalanced Distribution Networks

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***Abstract*—This paper presents a multi-objective, resilience-focused framework designed to determine the optimal location, capacity, and phase of photovoltaic systems and electric vehicle charging stations in a real 240-bus unbalanced distribution network. The model objectives include minimizing active power losses, reducing the voltage unbalance factor, and enhancing network resilience under various fault conditions. In this approach, a hybrid analysis and optimization framework is developed by integrating an evolutionary algorithm with accurate unbalanced power flow analysis in OpenDSS. This integration enables coordinated phase assignment, precise enforcement of voltage and power constraints, and real-time assessment of network resilience within an integrated Python-based platform. Simulation results indicate that the proposed framework achieves approximately 6.2% reduction in total power losses, 15.4% reduction in the unbalance factor, and a 5.1% improvement in the resilience index compared with the baseline, confirming its effectiveness and applicability in modern unbalanced distribution networks.**

***Index Terms*—Electric vehicle charging station (EVCS), Photovoltaic (PV) system, Resilience, Unbalanced distribution network, Voltage unbalance factor**

I. Introduction

In recent years, distributed energy resources (DERs) such as photovoltaic (PV) systems and electric vehicles (EVs) have been increasingly integrated into low-voltage (LV) distribution networks [1]. Although this expansion has improved energy efficiency and supported environmental sustainability, it has also introduced new challenges in the operation and management of power systems. Electrical distribution networks, which are responsible for stable and reliable energy delivery, often experience a three-phase unbalance in real-world conditions—a state in which the magnitudes or phase angles of voltages and currents differ among phases, leading to heterogeneous network behavior. This imbalance causes unequal active power distribution across phases, adversely affecting the power quality, reliability, and performance of critical equipment such as transformers. Under such conditions, the network experiences higher energy losses, voltage fluctuations, and reduced operational efficiency. Therefore, timely detection and intelligent management of unbalanced conditions are essential to maintain the stability, efficiency, and resilience of modern distribution networks.

In most previous studies, the primary focus has been on balanced distribution networks or simplified models. Consequently, the inherent three-phase imbalances and voltage variations present in real feeders have received limited attention [2], [3]. Although a number of studies have considered multi-objective approaches for DER location and sizing, most of them rely on a limited set of performance metrics and do not consider phase-level modeling or fault-related behavior in unbalanced distribution networks [4]. Furthermore, the issue of phase selection and its impact on power quality and voltage stability—despite its significance—has rarely been examined in the optimal allocation process of distributed resources [5]. Although numerous studies have explored the integration of DERs and EV charging stations (EVCS), the resilience of unbalanced distribution networks under fault conditions or critical events has not been comprehensively investigated [6]. This highlights the lack of integrated and efficient frameworks capable of jointly minimizing power losses, improving voltage imbalance, and enhancing the level of resilience of real distribution networks.

To address the identified research gaps, this paper presents a multi-objective, resilience-oriented framework for the co-planning of the location, capacity, and phase of PV systems and EV charging stations in a real 240-bus unbalanced distribution network. This study does not aim to introduce a new optimization algorithm. Instead, it formulates a phase-aware and resilience-oriented planning framework that is integrated with detailed unbalanced power flow analysis. The framework targets the reduction of active power losses, mitigation of voltage unbalance, and improvement of grid resilience under representative fault conditions.

The main contributions of this research can be summarized as follows:

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- A multi-objective planning framework is developed to enhance distribution network resilience by jointly determining the location, capacity, and phase of PV systems and EV charging stations in unbalanced networks subject to fault conditions.
- Creation of a synchronized environment between optimization and simulation in OpenDSS to enable accurate analysis of unbalanced three-phase power flow and realistic evaluation of distribution network performance.
- Validation of the proposed framework on a real 240-bus unbalanced distribution feeder, demonstrating its practical efficiency and effectiveness in modern distribution networks.

This framework establishes a coherent link between the optimization process and electrical power simulation, enabling coordinated planning and performance evaluation of PV system and EVCS under various network operating scenarios within an integrated platform.

II. Methodology and Problem Formulation

In this section, a multi-objective solution based on the concept of resilience is presented to enhance the performance of unbalanced distribution networks. The primary goal is to determine the optimal location and size of PV systems and EVCSs such that active power losses and the voltage unbalanced factor (VUF) are minimized, while the grid resilience index is simultaneously improved. To evaluate network performance under critical conditions, a set of failure scenarios is incorporated into the optimization process. The power generation from PV panels is estimated based on solar radiation and temperature, with natural fluctuations in these outputs simulated using a beta distribution model to preserve realism without increasing computational complexity [7]. The charging stations are modeled as constant power loads, with two power levels considered: 7–22 kW for Level 2 charging and 50–100 kW for Level 3 fast charging. Hourly profiles are incorporated to represent temporal variations. The decision variables include the location, capacity, and phase connection of PV systems and EV charging stations. Within the NSGA-II framework, these variables are encoded in each individual solution and are modified through selection, crossover, and mutation operators to generate a set of Pareto-optimal trade-offs among the defined objectives. Based on this modeling, three main objectives are defined: minimizing power losses, reducing VUF, and increasing the resilience index to ensure network stability, balance, and robustness under disturbances.

A. Objective function 1: Power losses

In this study, total network losses are defined as the sum of losses associated with lines, transformers, and control equipment. These losses are computed based on the current flowing through each phase and its corresponding resistance. Reducing total losses not only improves energy efficiency and peak load management, but also reduces system operating costs, thereby enhancing the stability and overall performance of the distribution network. The first objective function is expressed in (1).

$$\min(f_1) = \sum_{t=1}^{24} \sum_{\phi=1}^{3} P_{t,\phi}^{\text{loss}} \tag{1}$$

where $P_{t,\phi}^{\text{loss}}$ represents the active power loss in phase ϕ at hour t, and f_1 denotes the first objective function corresponding to the minimization of network power losses.

B. Objective function 2: Voltage unbalanced factor

One of the fundamental requirements for the reliable and efficient operation of distribution networks is maintaining voltage balance among the different phases. When a voltage imbalance occurs, energy losses increase, equipment temperatures rise, and overall power quality deteriorates. Therefore, in this study, the second objective function is formulated to minimize the VUF across all buses and over various time intervals [8], as presented in (2).

$$\min(f_2) = \frac{1}{24} \sum_{t=1}^{24} \frac{1}{N_b} \sum_{b=1}^{N_b} \left| \frac{V_{b,t}^{\text{neg}}}{V_{b,t}^{\text{pos}}} \right| \times 100 \tag{2}$$

where $V_{b,t}^{\text{neg}}$ and $V_{b,t}^{\text{pos}}$ denote the negative- and positive-sequence voltage components at bus b and time t, respectively; N_b is the total number of buses in the system.

C. Objective function 3: Resiliency

The third objective aims to enhance the distribution network's ability to maintain stable operation during fault conditions. For each hour t, the resilience index (R_t) is defined as the relative deviation of power losses from the reference state under normal operating conditions. Although resilience is often quantified using indicators such as unserved energy, a loss-based metric is adopted here to capture network-wide operational degradation observable through steady-state power flow analysis. This interpretation is consistent with the planning-level and steady-state focus of the study and avoids the need for explicit outage and recovery modeling beyond the scope of this work. A higher value of R_t indicates improved preservation of system performance under faulted conditions. Accordingly, the complement of the average resilience index over the 24-hour period is minimized, as expressed in (3).

$$\min(f_3) = 1 - \frac{1}{24} \sum_{t=1}^{24} R_t \tag{3}$$

where the hourly resilience index R_t is computed as:

$$R_t = 1 - \max\left(0, \frac{P_{t,\phi}^{\text{loss}} - P_{t,\phi}^{\text{base}}}{P_{t,\phi}^{\text{base}}}\right) \tag{4}$$

Where, $P_{t,\phi}^{\text{loss}}$ shows the network power loss at hour t and phase ϕ when a fault occurs, while $P_{t,\phi}^{\text{base}}$ represents the associated loss in the normal operating state. Objectives f_1 and f_3 both involve power losses but represent normal and faulted operating conditions, respectively, and are therefore not redundant. All objective functions are normalized with respect to their baseline values to ensure comparable scales.

D. Constraints

The proposed optimization model is subject to operational and technical constraints to ensure the secure and reliable operation of the unbalanced distribution network. The power balance between generation and demand is maintained at each time step, as stated in (5). Voltage magnitudes must remain within the permissible limits, as expressed in (6). The power outputs of PV units and EVCSs are limited by their rated capacities, as indicated in (7) and (8). Furthermore, the resilience index and voltage unbalance factor are constrained by $0 \leq R_t \leq 1$ and $VUF_{b,t} \leq 2\%$, respectively.

$$P^{\text{PV}}_{t,\phi} + P^{\text{grid}}_{t,\phi} = P^{\text{L}}_{t,\phi} + P^{\text{EVCS}}_{t,\phi} + P^{\text{loss}}_{t,\phi}, \quad (\forall\, t, \phi) \tag{5}$$

$$0.9 \leq V^{\text{pu}}_{b,\phi,t} \leq 1.1, \quad (\forall\, b, \phi, t) \tag{6}$$

$$0 \leq P^{\text{PV}}_{i,t} \leq P^{\text{PV,max}}_{i}, \quad (i = 1, \ldots, N_{PV}) \tag{7}$$

$$P^{\text{EVCS,min}}_{j} \leq P^{\text{EVCS}}_{j,t} \leq P^{\text{EVCS,max}}_{j}, \quad (j = 1, \ldots, N_{\text{EVCS}}) \tag{8}$$

where, $P^{\text{PV}}_{t,\phi}$ and $P^{\text{grid}}_{t,\phi}$ represent the active power generated by PVs and imported from the upstream grid, respectively; $P^{\text{L}}_{t,\phi}$ and $P^{\text{EVCS}}_{t,\phi}$ represent the load demand and charging power of EVCSs; while $P^{\text{loss}}_{t,\phi}$ corresponds to the active power losses in the network.

All constraints are incorporated into the optimization framework to ensure that network performance remains physically valid and reliably stable. The optimization process is carried out using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), an effective method for solving multi-objective problems with nonlinear, non-convex characteristics and discrete variables. This algorithm produces a set of Pareto-optimal solutions that simultaneously minimize power losses, voltage imbalance, and improve the grid resilience index. Each member of the initial population represents a potential configuration of PV systems and EVCSs, defined by bus location, connection phase, and nominal capacity. Through the sequential execution of selection, crossover and mutation operators, the population gradually evolves toward the optimal Pareto front while maintaining genetic diversity among solutions. To evaluate the performance of each configuration, the OpenDSS simulation engine is integrated with the Python environment through a COM interface. The engine performs unbalanced three-phase power flow analyses considering hourly load variations, PV generation, and EV charging demand. At each time step, Python dynamically generates the required input files describing system components—photovoltaic systems, charging stations, and loads—and executes OpenDSS to compute key network performance indicators such as voltage profiles, line currents, and total losses. The resulting data are then used to calculate the objective functions and assess the operational constraints. This integrated framework enables time-based simulations over a 24-hour period, accurately capturing network behavior under normal and fault conditions.

III. Numerical Results and Discussions

This study is based on a real unbalanced distribution network located in the Midwest region of the United States, as described in [9]. The network comprises three feeders and 240 buses. To conduct a realistic assessment of the system's performance under both normal and fault conditions, detailed specifications network components—including overhead lines, underground cables, and distribution transformers—were incorporated. For performance evaluation of the proposed model, the winter season was selected as the study period, and simulations were performed over a 24-hour horizon. Figures 1 and 2 present the time profiles of load, solar radiation, and ambient temperature during a typical winter day, which were used as inputs to the network model. Initially, the base case without PV systems and EVCSs was considered as a reference for comparison. To analyze network resilience, three failure scenarios were defined. The fault scenarios are selected as representative disturbances to demonstrate the adaptability of the proposed framework, rather than to exhaustively assess all possible contingencies. In this context, the reported resilience results describe changes in steady-state network performance under faulted conditions.

- **Scenario 1:** Complete disconnection of the third feeder and removal of all connected loads and equipment from the circuit.
- **Scenario 2:** Disconnection of transformers associated with loads 2008, 2041, and 2052 in the second feeder.
- **Scenario 3:** Failure of the first feeder lines, including lines 1006–1007, 1016–1017, and 1014–1015.

In all scenarios, the multi-objective NSGA-II algorithm was implemented with the goals of minimizing power losses, improving voltage balance, and enhancing network resilience, and the results were compared with the baseline. The optimization is carried out separately for each operating scenario to examine how planning decisions adapt to different fault conditions. Each scenario includes a fixed number of

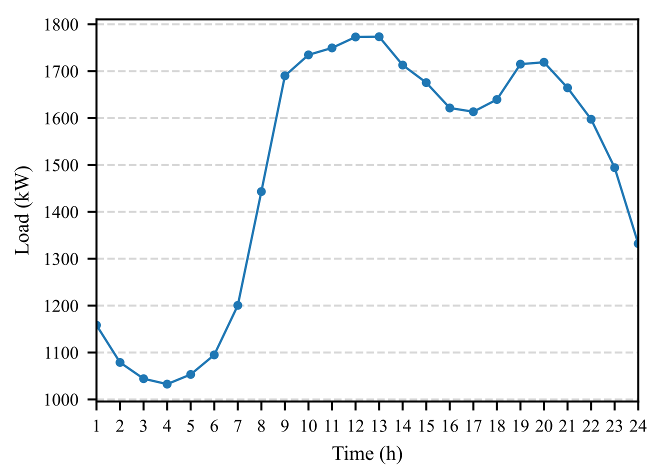

Fig. 1. Hourly load profile during the winter day.

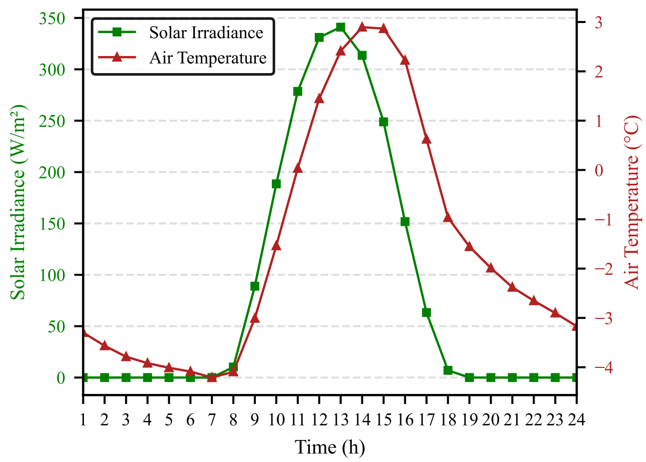

Fig. 2. Hourly solar irradiance and ambient temperature profiles.

distributed resources, which includes eight PV systems and four EVCSs. However, the optimal bus, phase, and capacity of each resource vary depending on the fault type and network condition. The final configurations of the PV systems and EVCS units for all grid scenarios are summarized in Table I and Table II, respectively. The obtained results indicate that both the phase-bus selection and the total installed capacity change according to the fault type, demonstrating the adaptability of the proposed framework. Table III presents the results for two selected points on the Pareto front for each network operating mode. Under normal network operating conditions, the losses and voltage fluctuations remain stable, confirming the efficient operation of the system. When faults occur in different scenarios, slight variations are observed in these indicators, but their values remain within acceptable and reliable limits. Furthermore, the consistently high resilience index across all cases indicates that the network has the capability to maintain stable performance and quickly return to normal conditions following a fault.

Fig. 3 illustrates the daily trend of power losses for the base case and the three fault scenarios. As shown, in the base case, losses fluctuate between approximately 20 and 33 kW, reaching their maximum during peak load hours. In the first scenario, disconnection of the third feeder redistributes power among the other feeders, leading to a slight increase in losses. In the second scenario, removal of the specified transformers in the second feeder causes voltage instability and a noticeable rise in losses during peak demand periods. In the third scenario, where several lines in the first feeder fail, the highest losses are observed because the alternative current paths become more heavily loaded. Overall, despite these structural disturbances, the level of losses remains within an acceptable range, demonstrating the effectiveness and robustness of the proposed approach in maintaining network performance under critical operating conditions.

Fig.4 shows the statistical distribution of the VUF for different operating conditions. In the base case, the VUF value is approximately 0.13%, indicating stable and uniformly distributed voltages under normal conditions. When the third feeder is disconnected in the first scenario, only minor fluctuations are observed, and the network maintains its ability

TABLE I
OPTIMIZED PLACEMENT AND TOTAL CAPACITY OF PV UNITS UNDER DIFFERENT STATES

States	PVs Bus–Phase	Total PV (kW)
Base	3132–1, 3137–1, 3109–2, 3097–2, 3111–1, 3148–1, 3110–2, 3157–2	524.522
S1	1006–1, 2046–2, 2047–2, 2052–3, 2002–2, 2040–1, 2040–2, 1003–1	510.960
S2	3132–2, 3111–2, 3134–1, 3104–2, 3095–1, 3043–2, 3134–2, 3136–1	423.073
S3	3095–2, 3012–1, 3148–2, 1006–1, 3112–1, 3097–1, 3085–1, 3149–1	398.059

TABLE II
OPTIMIZED PLACEMENT AND TOTAL CAPACITY OF EVCS UNITS UNDER DIFFERENT STATES

States	EVCSs Bus–Phase	Total EVCS (kW)
Base	3125–3, 3112–2, 2060–3, 3144–3	44.531
S1	2023–3, 1015–3, 2043–3, 2009–1	138.582
S2	1015–1, 3084–3, 3152–3, 2002–1	95.182
S3	1012–2, 2015–2, 3117–3, 2020–3	211.359

TABLE III
REPRESENTATIVE PARETO-OPTIMAL SOLUTIONS FOR ALL OPERATING STATES

States	Pareto Point	Normalized Power Loss	Normalized VUF	Resilience Index
Base	1	0.9553	0.0123	1
	2	0.9444	0.0126	1
S1	1	0.9870	0.0130	0.9979
	2	0.9815	0.0131	0.9974
S2	1	0.9840	0.0105	0.9914
	2	0.9620	0.0107	0.9979
S3	1	0.9696	0.0106	0.9944
	2	0.9595	0.0107	0.9979

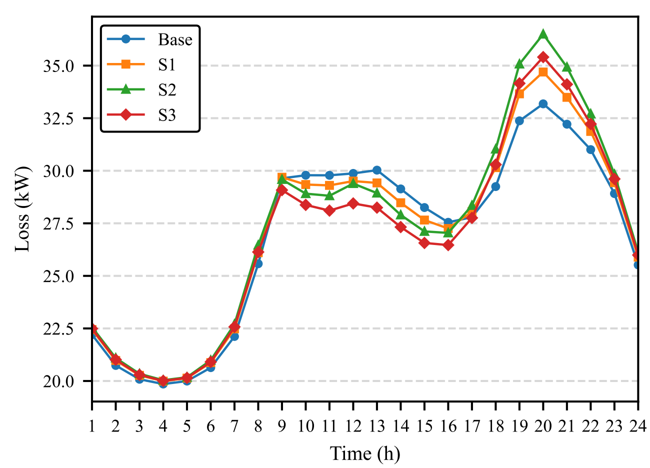

Fig. 3. Hourly variation of power losses under different states.

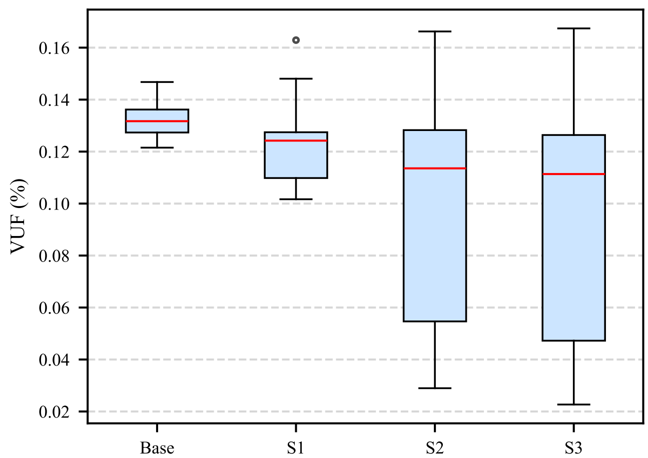

Fig. 4. Distribution of VUF across different states.

to redistribute the load among the active feeders. For the second and third scenarios, the median VUF drops below the base-case level, which indicates that phase balance is largely preserved despite the removal of some lines or transformers. Although a wider variation is observed, the unbalance level remains within acceptable limits. Fig. 5 shows the average resilience index for all operating states, which stays close to 1 and remains above 0.9 across all scenarios, demonstrating stable network performance under disturbances.

IV. Conclusion

This work examined the behavior of an unbalanced distribution network under normal operating conditions as well as three disturbance scenarios, using power losses, VUF, and a resilience index as evaluation metrics. The analysis was carried out on a publicly available unbalanced distribution test system, and the considered fault scenarios and modeling assumptions were explicitly defined to allow transparent interpretation of the results. Under baseline operating conditions, total network losses ranged roughly from 20 to 33 kW, while the VUF remained around 0.13%. In the first disturbance scenario, where the third feeder was disconnected, power losses increased by about 3–5%. Even with this increase, the average resilience index stayed close to 0.987, showing that the overall system behavior was not noticeably degraded. In the second scenario, disconnecting three transformers led to a further rise in losses, with values approaching 36.5 kW. At the same time, a lower average VUF was observed. This change is mainly associated with load redistribution among the remaining feeders and phases. For the third scenario, losses rose slightly, but voltage levels remained acceptable, and the resilience index was above 0.97. When all scenarios are considered together, the resilience index does not drop below 0.9. In this context, resilience is evaluated as the ability of the network to preserve acceptable steady-state operating conditions under faulted scenarios.

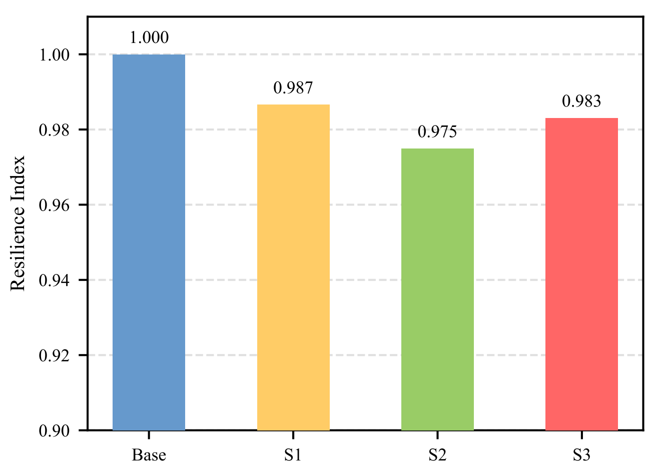

Fig. 5. Comparison of the average resilience index under different states.

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