

# Congestion-Driven Dynamic Hosting Capacity Enhancement Framework using Distribution Network Reconfiguration

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## ABSTRACT

Traditional hosting capacity (HC) assessment methods for distribution networks commonly rely on static rule-of-thumb criteria, which often impose overly conservative limits leading to the underutilization of existing network assets. However, modern distribution networks operate under high dynamic load demand and power generation. Addressing these dynamics, this study proposes a congestion-driven framework to enhance HC through optimal radial network reconfiguration. An optimization-based network reconfiguration approach was employed to alleviate congestion and increase HC in the distribution network. Furthermore, the framework integrates the calculation of Dynamic Operating Envelopes (DOE) to allocate active power export and import limits for individual distributed generation (DG) and loads. Validated on a modified IEEE 33-bus system, the simulation results demonstrate that the proposed framework extends the allowable DG penetration from 280% in the static base case to 500%, while simultaneously reducing daily operational costs by up to 12.0%.

**Keywords:** Dynamic Operating Envelopes (DOE), Congestion Management, Network Reconfiguration, Dynamic Hosting Capacity

## 1. INTRODUCTION

The global energy transition toward sustainable power systems has necessitated the significant integration of Distributed Generation (DG) within distribution networks. Renewable Energy Sources (RES), particularly photovoltaic (PV) systems and wind turbines, are being deployed at unprecedented rates to meet decarbonization targets and mitigate greenhouse gas emissions. Concurrently, the electrification of the transportation sector has accelerated the deployment of Electric Vehicle (EV) charging infrastructure, introducing highly dynamic and variable loads into the grid. According to projections by

the International Energy Agency (IEA), global electricity demand is expected to grow at an average annual rate of approximately 4% between 2022 and 2027, whereas the installed capacity of renewable energy is anticipated to increase by more than 5,500 GW from 2024 to 2030 [1]–[3]. This simultaneous growth in both generation and demand creates complex operational challenges that traditional distribution network planning and operation paradigms were not designed to address. The integration of Distributed Energy Resources (DERs) introduces several technical challenges, including voltage rise, thermal overloading, reverse power flow, and network congestion [4]. When DG output exceeds local demand, surplus power flows upstream toward the substation, potentially causing voltage violations and equipment overloading. Consequently, the concept of Hosting Capacity (HC) has been defined as the maximum amount of DG that can be accommodated in a distribution network without violating operational constraints, such as voltage limits, thermal ratings, and power quality standards [5]–[7].

Conventionally, Distribution System Operators (DSOs) determine HC as a static value based on worst-case scenarios. This approach often results in conservative estimates that underutilize the available network capacity [8]. Such conservatism leads to the unnecessary curtailment of renewable generation, conflicting with global climate goals and diminishing the economic viability of DG investments. In contrast, the concept of Dynamic Hosting Capacity (DHC) has demonstrated that annual injectable energy can increase significantly by 62–76% in some cases when dynamic assessments are employed instead of static assessments [9]. Although HC can be enhanced through traditional network reinforcement, this requires substantial capital investment and lengthy implementation timelines, whereas energy curtailment reduces the overall efficiency of renewable energy systems [10], [11].

To address these limitations, various Active Network Management (ANM) techniques have been proposed. The authors of [12] investigated strategies such as power factor control and reactive power compensation to enhance HC. Among these, network reconfiguration is a particularly promising technique. Research in [13] demonstrated that reconfiguration can increase HC by up to 30% compared with static topology operations. Similarly, multiperiod network reconfiguration approaches utilizing optimization algorithms have been proposed to increase the HC while minimizing switching operations

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[14]–[16]. Moreover, combined approaches of network reconfiguration and phase load balancing using Genetic Algorithms (GA) have achieved significant increases in PV hosting capacity [17].

Dynamic network reconfiguration has received increasing attention owing to its ability to respond to time-varying network conditions. Risk-based approaches utilizing stochastic models have been proposed to account for uncertainties [18], whereas other strategies simultaneously consider both HC and system reliability [19]. Beyond mechanical switching, recent advances have introduced flexible alternatives such as Soft Open Points (SOPs) [20], robust optimization for SOPs and EVs [21], and extensions to hybrid AC/DC networks [22] or Hybrid Open Points (HOPs) [23]. Particle Swarm Optimization (PSO) [24] and its variants have been widely applied. Specifically, Binary PSO (BPSO) has proven to be especially suitable for determining switch statuses and analyzing location-dependent PV hosting capacity [25]–[26].

Despite extensive research, gaps remain in the literature on the operational implementation of these strategies. Most studies focus on maximizing the aggregate hosting capacity of the network but do not sufficiently address how this capacity is translated into the operational limits for individual users. The concept of “congestion-driven” reconfiguration, where topology changes are triggered specifically by detected violations rather than predetermined schedules, requires further exploration in conjunction with the allocation of Dynamic Operating Envelopes (DOE).

To address these gaps, this study proposes a congestion-driven dynamic HC enhancement strategy. The framework utilizes Binary Particle Swarm Optimization (BPSO) to identify optimal radial network topologies, specifically when technical violations are detected. Crucially, this study extends beyond aggregate analysis to calculate the DOE for both generation and load, providing a granular view of system capability.

The main contributions of this study are as follows:

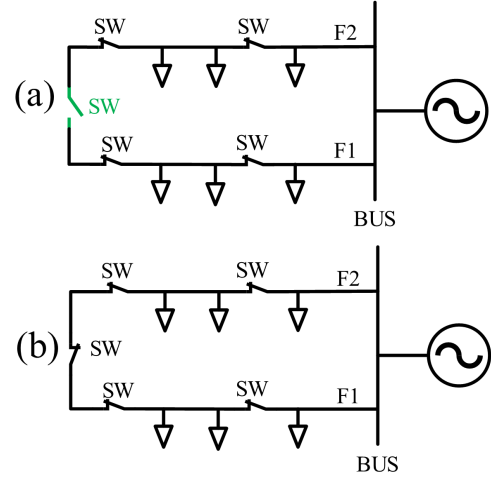
- 1) A congestion-driven framework that enhances DHC through optimal radial network reconfiguration.
- 2) An integrated methodology for allocating the DOE to individual generation and load points, enabling the DSO to manage specific customer export/import limits in coordination with the reconfigured network topology.
- 3) Application of the BPSO algorithm to solve the single-objective reconfiguration problem with efficient handling of discrete switch variables.

## 2. FACTORS AFFECTING HOSTING CAPACITY

This section summarizes the key technical factors that limit hosting capacity in distribution networks.

### 2.1 Topology of Distribution Networks

The radial topology of distribution networks is normally radial with open tie-line switches, as illustrated



**Fig. 1:** Illustrates the configurations of the distribution networks: (a) radial topology, (b) mesh topology.

in Figure 1(a), and is widely adopted because of its simplicity in the distribution network management for DSOs. This reduces the complexity of the protection system and facilitates easier control of the power flow.

The mesh topology, as shown in Figure 1(b), can be implemented either within the same feeder or across feeders and can be applied to both high-voltage and low-voltage systems. It is typically used in scenarios such as when the load exceeds the line capacity or during load transfer operations for maintenance of distribution networks. Each network topology exhibits a different level of HC, which is influenced by multiple factors, including the load profile and load density, feeder length, line impedance, and characteristics of in-line equipment, such as shunt capacitors.

### 2.2 Voltage Limit

The DSO is responsible for maintaining acceptable voltage levels at all buses within the distribution network. Under normal operating conditions, voltages must remain within 0.95–1.05 pu, whereas in emergency situations, a wider tolerance of 0.90–1.10 pu is permitted to ensure system stability. Typically, increasing the penetration of DG raises the voltage levels in the network; therefore, the voltage becomes a significant limit of HC.

### 2.3 Thermal Limit of Distribution Line

The thermal limit of conductors in a distribution system is a direct constraint on the HC, as heat affects both the conductors and electrical insulation. Excessive heat may cause conductor damage and increase the sag length in overhead distribution networks.

In a real distribution network, various types and sizes of conductors are used in combination. Consequently, the overall current-carrying capacity limit of each circuit may vary depending on the specific types and sizes of conductors used in different segments of the circuit. Therefore, it is recommended to use an actual electrical

**Table 1:** Loading Planning Criteria for Distribution System Equipment.

| Equipment         | Normal Condition<br>[% of rated] | Emergency Condition<br>[% of rated]           |
|-------------------|----------------------------------|-----------------------------------------------|
| MV Conductor      |                                  |                                               |
| - Radial          | 80%                              | -                                             |
| - Mesh            | 50%                              | 100% (no time limit)                          |
| Power transformer | 80%                              | 100% (no time limit)<br>112% (within 4 hours) |

network model for HC analysis to ensure accuracy and reliability.

## 2.4 Loading Planning Criteria for Distribution System Equipment

The loading capacity of the distribution equipment is classified into two conditions: normal and emergency, as shown in Table 1. It can be observed that the loading capacity of a Medium Voltage (MV) distribution feeder operating in a radial configuration is limited to 80% of its rated capacity.

## 2.5 Reverse Power

Reverse power flow in distribution networks refers to the condition in which the electrical power generated by DG sources exceeds the local demand, causing surplus power to flow backward toward the upstream substation or transmission network. This phenomenon introduces several technical and operational challenges. One significant issue is the potential violation of the protection system settings. Conventional protective devices, such as breakers and relays, are typically configured to assume unidirectional power flow, and reverse flows can cause misoperation, leading to unnecessary outages or inadequate fault protection. Additionally, reverse power flow may conflict with regulatory agreements between DSOs and Transmission System Operators (TSOs), as it can impact the overall system stability and safety.

## 3. HOSTING CAPACITY PROBLEM FORMULATION

Unlike other studies, this research does not directly employ an objective function to maximize hosting capacity. Instead, it focuses on minimizing the daily operational cost of the DSO while incorporating a penalty term to assess the network's ability to accommodate additional DG units. In this study, HC is defined as the maximum DG penetration level at which the distribution network can operate without violating any technical constraints, including voltage limits, thermal ratings, and reverse power flow limits, under the optimal reconfigured topology. HC enhancement is achieved indirectly through the cost-based formulation: the penalty terms

impose prohibitively large costs on constraint violations, forcing the optimizer to find topologies that remain feasible at progressively higher DG penetration levels. As expressed in Equation (1), the total objective consists of: (i) active power loss costs ( $C_{loss}^t$ ), determined by the Time-of-Use (TOU) rates of the supplying substation; (ii) switching costs ( $C_{sw}^t$ ) associated with reconfiguration; and (iii) penalty costs ( $C_{penalty}^t$ ) related to optimization constraints and the congestion index when DG power exceeds the distribution network's capacity. By minimizing these operational costs alongside penalty terms, the framework identifies feasible bounds for higher DG integration. Consequently, the reported results (e.g., 500%) should be interpreted as these feasible penetration limits achieved via optimal topology, rather than values derived from a direct maximization formula. Notably, DG procurement costs are excluded to ensure the framework prioritizes maximizing renewable energy integration.

$$\min C_{Total} = \sum_{t=1}^{24} C_{loss}^t + C_{sw}^t + C_{penalty}^t \quad (1)$$

### 3.1 Operation Cost of DSO

The mathematical representation of each component of the overall operational cost is detailed as follows: the cost associated with grid active power loss cost ( $C_{loss}^t$ ), as described by Equation (2), ( $E_{loss}^t$ ) is the energy of power loss [Unit] at time  $t$ . This is multiplied by the energy price of electricity ( $K_p$ ).

$$C_{loss}^t = \sum E_{loss}^t \cdot K_p \quad (2)$$

In Equation (3), the cost of switching operations ( $C_{sw}^t$ ) at time step  $t$  is linked to the functioning of load break switches, which depends on the frequency of status changes between time of calculation. This relationship is measured using the Hamming Distance function, symbolized as  $d_h(\cdot)$ . This function determines the total number of switches that alter their state ( $S_{sw}$ ) (such as from open to closed or vice versa) between times  $t - 1$  and  $t$ , and this total is then multiplied by the unit switching cost ( $K_{sw}$ ).

$$C_{sw}^t = K_{sw} \cdot d_h(S_{sw}^t, S_{sw}^{t-1}) \quad (3)$$

### 3.2 Penalty & Constraints

When the DG injects power into the grid more than HC, the network experiences congestion. To ensure that the optimized network configuration operates within safe technical boundaries, the optimization process incorporates a strict penalty mechanism. This mechanism transforms a constrained optimization problem into an unconstrained one by adding penalty terms to the objective function whenever the operational limits are violated. Equation (??) represents the total penalty cost ( $C_{penalty}^t$ ) at time step  $t$ . This function is a critical indicator of network congestion. In the context of this study,

congestion is defined as the occurrence of any technical violation caused when the injected power from the DG exceeds the HC of the distribution network at that time. Consequently, when  $DG > HC$ , the penalty terms become high value, significantly increasing the total objective function value and signaling the algorithm to explore alternative topologies that more HC to reduce congestion.

$$C_{penalty}^t = C_{volt}^t + C_{ol}^t + C_{reverse}^t + C_{unsupply}^t \quad (4)$$

The components of the penalty function are as follows:

- Voltage violation penalty ( $C_{volt}^t$ ): Voltage stability is paramount for distribution networks. Deviations beyond the standard permissible range (0.95-1.05 pu) are penalized using (5).

$$C_{volt}^t = K_v \cdot N_V^t \quad (5)$$

Where:

$K_v$  is a large penalty coefficient assigned to voltage violations.

$N_V^t$  represents the number of buses violating the voltage limits at time  $t$ .

- Thermal overload penalty ( $C_{ol}^t$ ): To prevent equipment damage, line and transformer loadings must remain within their thermal ratings. The overload penalty is defined in (??), as follows:

$$C_{ol}^t = K_o \cdot N_{ol}^t \quad (6)$$

Where:

$K_o$  is a large penalty coefficient assigned to the overload.

$N_{ol}^t$  is the count of network branches (lines or transformers) that exceed the maximum thermal rating.

- Reverse power flow penalty ( $C_{reverse}^t$ ): High penetration of DG can lead to reverse power flow towards the primary substation, which may violate the protection settings or regulatory agreements with the transmission system operator. Equation (??) penalizes this condition, as follows:

$$C_{reverse}^t = K_{reverse} \cdot P_{reverse}^t \quad (7)$$

Where:

$K_{reverse}$  is the penalty factor for the reverse power flow.  $P_{reverse}^t$  is the active power flowing back to the substation at time  $t$  (considered only when reverse flow occurs)

- Unsupplied Constraint ( $C_{unsupply}^t$ ): This term ensures that any candidate solution resulting in a disconnected network or unsupplied customers is immediately discarded (assigned an infinite cost), thereby enforcing the connectivity of the distribution network. This is shown in (??).

$$C_{unsupply}^t = \begin{cases} \infty, & \text{if any bus is unsupplied} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

- Operational Strategy: The algorithm enforces a radial topology constraint.

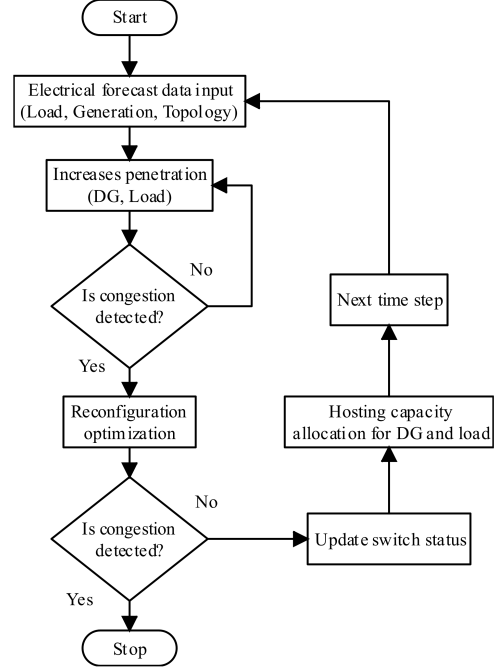


Fig. 2: Overall flowchart of the proposed framework.

#### 4. PROPOSED FRAMEWORK

This study proposes a congestion-driven dynamic hosting capacity enhancement framework that employs radial network reconfiguration to minimize DSO operational costs under high DG penetration while maintaining system security. Unlike conventional static hosting capacity assessments, the proposed approach operates based on real-time network congestion forecasts from load and generation profiles.

The proposed framework is designed for day-ahead operational planning under the following practical assumptions. First, regarding forecasting, the framework assumes that 24-hour load and generation profiles are available with reasonable accuracy, consistent with standard day-ahead forecasting practices employed by DSOs. Forecast errors are not explicitly modeled in this study. Second, regarding switching frequency, the switching cost parameter  $K_{sw}$  is incorporated into the objective function to naturally suppress excessive reconfigurations.

At high DG penetration levels, the increased switching frequency reflects a genuine operational requirement rather than an algorithmic artifact; the DSO may further limit switching operations by tightening  $K_{sw}$  or imposing a hard constraint on daily switching count. Third, regarding DER controllability, the framework assumes that the DSO has sufficient communication and control infrastructure, via SCADA, to enforce DOE limits and execute topology changes at each hourly interval. This assumption is consistent with modern distribution automation standards and is representative of a forward-looking operational setting rather than current universal practice.

The framework operates on a time-sequential basis, where, at each time step  $t$ , the system evaluates the current network conditions and executes the optimization strategy accordingly. The operational flow is illustrated in Figure 2, and the detailed procedures are outlined as follows:

#### 4.1 Initialization and Data Input

The process begins by loading electrical network parameters, including topology data, load profiles, and generation profiles for all buses at time  $t$ . Subsequently, the system progressively increases DG penetration and load demand separately until network congestion occurs. Congestion is identified when any of the following conditions are violated: voltage limits (undervoltage or overvoltage beyond the permissible range of 0.95–1.05 p.u.), thermal capacity limits of network branches, or reverse power flow to the upstream substations.

#### 4.2 Network Reconfiguration Optimization

During periods when the network operates within its hosting capacity limits, the framework finds the radial topology optimization to minimize operational costs, as defined in Equation (1), without congestion. The Binary Particle Swarm Optimization (BPSO) algorithm is employed to solve the discrete optimization problem, where each particle represents a binary vector of switch statuses  $S_i = [s_{i,1}, s_{i,2}, \dots, s_{i,M}]$ , with  $s_{i,j} \in \{0, 1\}$  indicating open or closed status for switch  $j$  and  $M$  is the number of all switches.

The BPSO algorithm maintains a population of  $N$  particles, where each particle's velocity and position are updated iteratively as shown in Equation (9).

$$\begin{aligned} V_{i,j}(k+1) &= w \times V_{i,j}(k) \\ &+ c_1 \times r_1 \times (P_{best,i,j} - S_{i,j}(k)) \\ &+ c_2 \times r_2 \times (G_{best,i,j} - S_{i,j}(k)) \end{aligned} \quad (9)$$

$$S_{i,j}(k+1) = \begin{cases} 1, & \text{if } rand() < \sigma(V_{i,j}(k+1)) \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

$$\sigma(v) = \frac{1}{(1 + e^{-v})} \quad (11)$$

where  $w$  is the inertia weight,  $c_1$  and  $c_2$  are cognitive and social coefficients respectively,  $r_1$  and  $r_2$  are random numbers in  $[0, 1]$ . In this study, the parameters are set to  $c_1 = 2.0$ ,  $c_2 = 2.0$ , and  $w$  varies linearly from 0.9 to 0.2 to ensure optimal convergence. Equation (10) is the position Update and  $\sigma(v)$  is the sigmoid function that maps continuous velocity to binary probability show in Equation (11).

The optimization continues until the convergence criteria are met, typically when the maximum iterations are reached or when the improvement in the global best solution falls below a predefined tolerance. The best solution obtained, represents the optimal radial configuration for time step  $t$ .

The cost and penalty parameters used in this study are summarized as follows. The energy price ( $K_p$ ) follows the TOU tariff structure defined in Table 2. The switching cost ( $K_{sw}$ ) is set to US\$16.67 per operation, derived from PEA asset management standards to reflect equipment depreciation. The penalty coefficients  $K_v$ ,  $K_o$ , and  $K_{reverse}$  are each set to US\$30,000, which are several orders of magnitude above typical operational costs, thereby enforcing hard constraints on voltage violations, thermal overloads, and reverse power flow within the single-objective formulation.

#### 4.3 Update Switch Status

Following the reconfiguration optimization, a comprehensive congestion assessment was performed. If the optimized configuration successfully eliminates all constraint violations, the new network topology is implemented by updating the switch status accordingly. Otherwise, the framework proceeds to terminate the simulation, indicating that the hosting capacity limit has been reached under the current operating conditions.

#### 4.4 DOE Allocation for each DG and Load

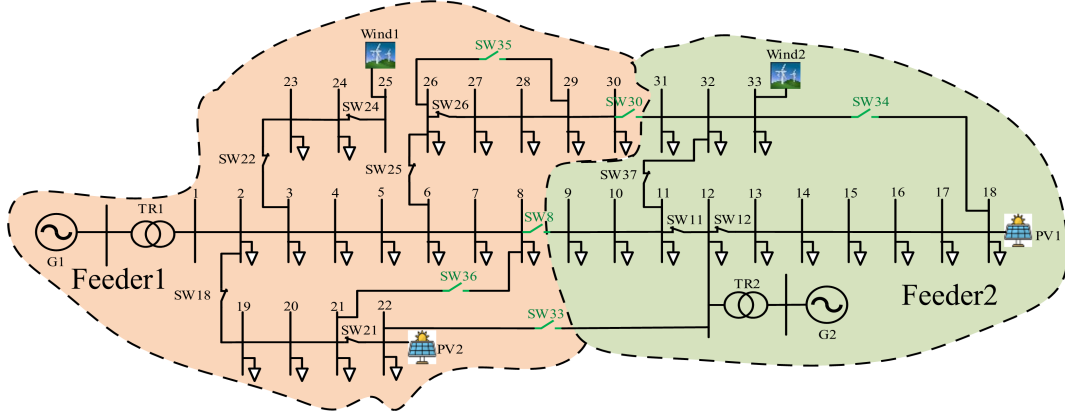
Following the determination of the optimal network topology, the framework calculates the DOE for individual generation and load points. This process is conducted separately for each feeder to ensure that the local network constraints are strictly respected. The allocation algorithm employs an iterative approach, incrementally scaling the active power injection (for generation DOE) or consumption (for load DOE) until network congestion occurs. To ensure equitable access to network capacity, the total available hosting capacity of a specific feeder is distributed among the connected DG units proportionally based on their rated active power.

The mathematical formulation for the allocated generation DOE for the  $i$ -th DG unit located in feeder  $k$  at time  $t$ , denoted as  $P_{DOE,i}^{gen}(t)$ , is expressed in Equation (12):

$$P_{DOE,i}^{gen}(t) = P_{HC}^{Feeder}(t) \times \left( \frac{P_{rated,i}^{DG}}{\sum_{j \in \Omega_k} P_{rated,j}^{DG}} \right) \quad (12)$$

Where  $P_{HC}^{Feeder}(t)$  is the total available hosting capacity of feeder  $k$  at time  $t$ .  $P_{rated,i}^{DG}$  is the rated active power output of the  $i$ -th DG unit.  $\Omega_k$  represents the set of all DG units connected to feeder  $k$  under the current topology.  $\sum_{j \in \Omega_k} P_{rated,j}^{DG}$  is the sum of the rated capacities of all DG units within the same feeder  $k$ .

The proportional DOE allocation based on DG rated capacity is simple and suitable for systems with uniform DG sizes. However, it does not consider network location or sensitivity, which may lead to inefficient allocation. Larger DG units may dominate the available capacity, limiting smaller units even if they are less constrained. Therefore, this approach is less suitable for systems with heterogeneous DG sizes, where network-aware or



**Fig. 3:** Modified IEEE 33 bus test systems with 2 feeders.

**Table 2:** Grid TOU Import Price.

| Period   | Time Range (Hours) | G1 Substation Price (USD/MWh) | G2 Substation Price (USD/MWh) |
|----------|--------------------|-------------------------------|-------------------------------|
| Off-peak | 22:00 – 09:00      | 77.8                          | 78.6                          |
| Peak     | 09:00 – 22:00      | 120.7                         | 140.8                         |

optimization-based allocation methods would provide more efficient results.

#### 4.5 Temporal Progression

Upon completion of the DOE allocation, the framework advances to the next time step ( $t + 1$ ) and repeats the entire process. In this study, a one-hour time resolution was employed for all simulations, enabling the framework to capture both intra-day variations in load and generation patterns while maintaining computational tractability. While the current study employs a 1-hour time step to maintain computational efficiency and mitigate mechanical stress on switching assets, adopting a 30-minute resolution could provide a more granular response to rapid fluctuations in load and generation. This higher resolution may lead to more frequent reconfigurations to precisely manage short-term congestion, though it would increase the total number of switching operations and computational demand.

### 5. TEST SYSTEM

In this study, the proposed framework was validated on a modified IEEE 33-bus distribution network [27]. Unlike the standard single-feeder topology, this test system was reconfigured to be supplied by two distinct substations, creating a dual-feeder network structure. To enable flexible congestion management and topology optimization, the network was equipped with 15 switching devices. These switches are classified into nine sectionalizing switches (Normally Closed) for isolating faulted or congested areas and six tie-lines (Normally

Open) for load transfer capabilities. The network also has a DG to simulate a modern active distribution network. As illustrated in Figure 3, two Wind Turbine (WT) units are installed at Buses 25 and 33, whereas two photovoltaic (PV) units are located at Buses 18 and 22. The maximum generation capacity of each DG unit was 0.2 MW. The DG penetration level is defined as a multiplier applied to the rated capacity of each unit. The actual DG output at each time step is obtained by multiplying the rated capacity (0.2 MW) by the penetration multiplier and the normalized 24-hour generation profile. For example, at 300% penetration, each DG unit produces up to three times its rated capacity following its hourly profile. Furthermore, to realistically evaluate the system performance under varying operating conditions, 24-hour dynamic profiles were utilized for both the electrical load demand and the renewable generation outputs, as shown in Figure 4.

Distribution networks normally receive power from multiple import sources, where electricity prices vary based on the connection voltage level and time-of-use (TOU) rates. This study considers a scenario in which the tariff for Source 1 (G1) is lower than that for Source 2 (G2), as shown in Table 2.

### 6. SIMULATION RESULTS AND DISCUSSION

This section presents the validation results of the proposed framework, which was applied to the modified IEEE 33-bus test system.

#### 6.1 Reconfiguration Topology Result

The proposed framework was validated on a modified IEEE 33-bus radial distribution system to evaluate its effectiveness in enhancing HC. In the base-case scenario with a fixed topology, the HC was limited to a maximum of 280% DG penetration. As illustrated in Figure 5, the primary physical constraint restricting the HC is the reverse power flow from the distribution network to the G2 substation, which is the dominant limiting factor. The simulation results indicate a significant surge in reverse power flow at noon, driven by PV generation exceeding

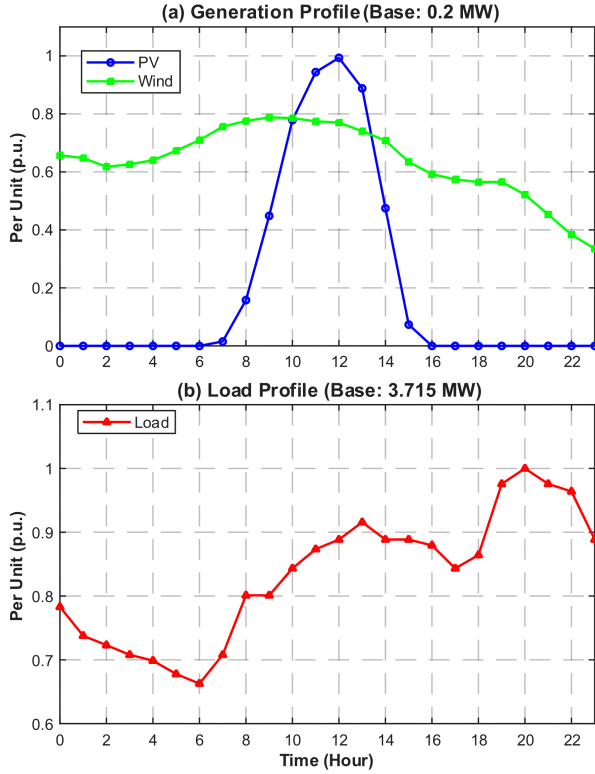


Fig. 4: 24-hour profiles of the modified IEEE 33-bus test system: (a) generation profile and (b) load profile.

local load demand, which rose substantially from 62.42 kW at 300% DG penetration to 752.34 kW at 500% DG penetration. Figure 6(a)–6(d) compare the maximum and minimum voltage profiles of the base case (red line) with those of the proposed framework (green line). Although voltage violations also occur as a secondary constraint, they manifest at higher penetration levels than the reverse power flow limit. The base case exhibited overvoltage violations exceeding the 1.05 p.u. limit at all DG penetration levels above 300%, specifically reaching 1.0509 p.u. at 350% and escalating to 1.0600 p.u. at 500%. Although voltage issues contribute to limiting the HC below 350%, reverse power flow emerges as the binding constraint that fundamentally caps the system at a 280% penetration.

The implementation of dynamic reconfiguration successfully mitigates both constraints simultaneously, maintaining voltage levels within the standard limits of 0.95–1.05 p.u. and effectively managing reverse power flow. This capability extends the allowable DG penetration up to 500% without experiencing any violations of either constraint.

The switching operations and quantitative performance metrics are shown in Figure 7 and Table 3, respectively. An analysis of the 24-hour switching profiles indicated that topology changes occur predominantly during peak PV generation hours (09:00–14:00) to mitigate congestion. As the DG penetration increases, the frequency of the required reconfigurations increases

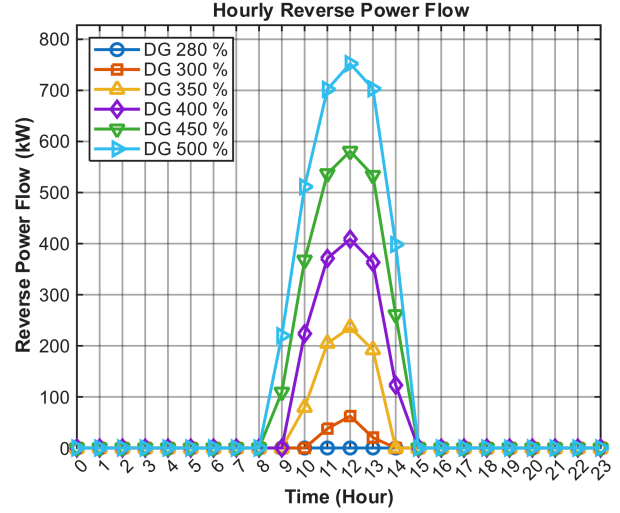


Fig. 5: Reverse power flow of base case under various DG penetration levels.

Table 3: Switching Sequence Result.

| DG (%) | Hour | Switching Sequence                                                      |
|--------|------|-------------------------------------------------------------------------|
| 300    | 11   | CLOSE SW30, OPEN SW26                                                   |
| 350    | 10   | CLOSE SW30, OPEN SW25                                                   |
| 400    | 10   | CLOSE SW30, OPEN SW25                                                   |
| 400    | 12   | CLOSE SW34, OPEN SW12                                                   |
| 450    | 9    | CLOSE SW30, OPEN SW25                                                   |
| 450    | 11   | CLOSE SW35, OPEN SW22                                                   |
| 450    | 12   | CLOSE SW34, OPEN SW12                                                   |
| 500    | 9    | CLOSE SW30, OPEN SW25                                                   |
| 500    | 10   | CLOSE SW34, OPEN SW12<br>CLOSE SW25, OPEN SW37<br>CLOSE SW37, OPEN SW11 |
| 500    | 11   | CLOSE SW35, OPEN SW18<br>CLOSE SW08, OPEN SW22<br>CLOSE SW36, OPEN SW26 |
| 500    | 12   | CLOSE SW26, OPEN SW25                                                   |
| 500    | 13   | CLOSE SW22, OPEN SW35                                                   |
| 500    | 14   | CLOSE SW11, OPEN SW08                                                   |

significantly, escalating from two operations per day at 350% penetration to 20 operations per day at 500%. Consequently, dynamic reconfiguration extends the HC limit from 280% (base case) to 500%. From an economic perspective, Table 4 shows that the daily operational costs decrease across all scenarios. Savings ranged from US\$96 at 300% penetration to US\$604 at 500%, representing cost reductions of 2.5% and 12.0%, respectively. Notably, while the active power losses decrease by 16.6%–23.7% at moderate DG levels (350%–400%), they increase by 14.3%–15.0% at higher penetration levels (450%–500%). This trend is attributed to the hierarchy of objectives of the optimization algorithm: it must primarily satisfy technical constraints to eliminate congestion, which forces the selection of feasible topologies, even if they entail higher active power losses. Ultimately, the

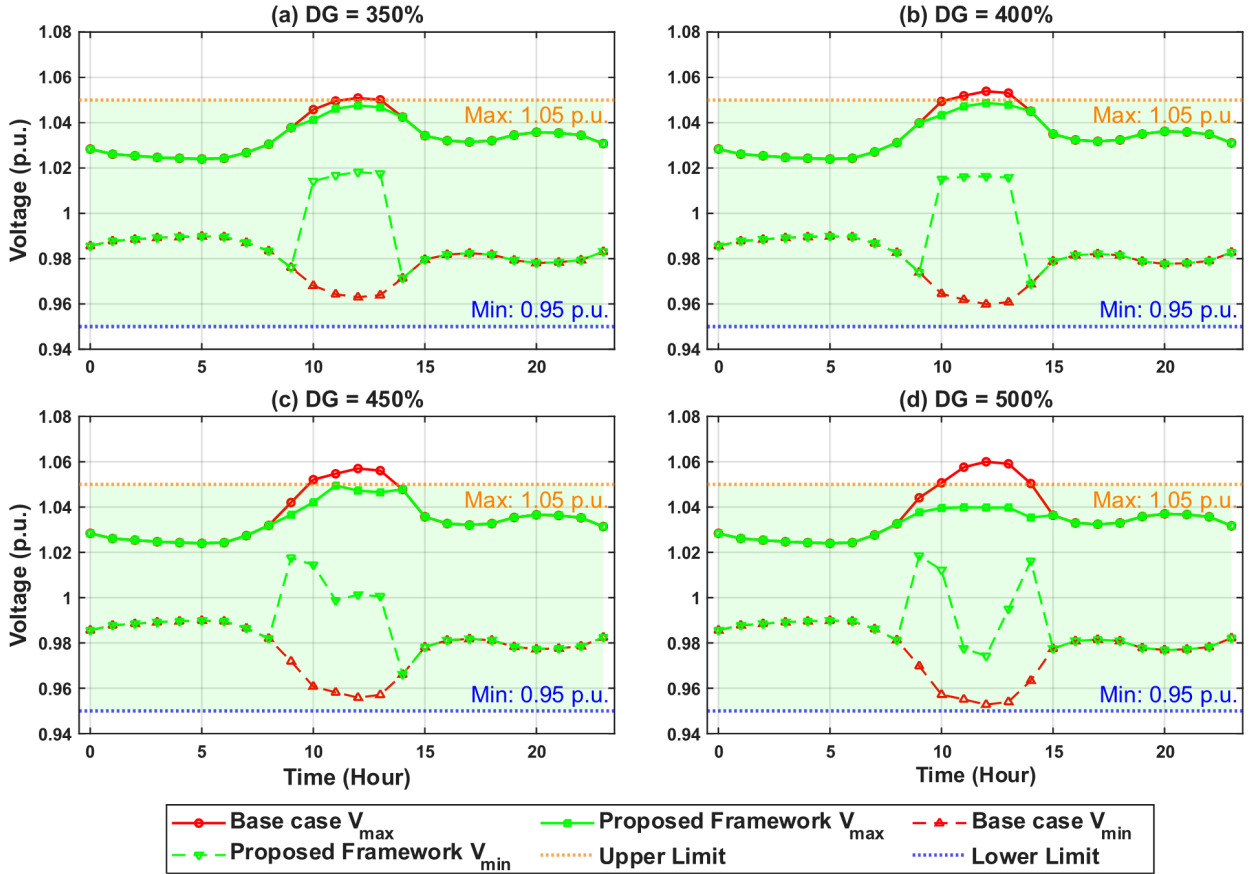


Fig. 6: Voltage profile of distribution network (a) DG 350% (b) DG 400% (c) DG 450% (d) DG 500%.

sharp increase in switching operations at 500% penetration, combined with substantial reverse power flow at substation G2, indicates that the system is approaching its physical limits, suggesting that reconfiguration alone cannot further enhance HC beyond this threshold.

## 6.2 DOE Allocation Result

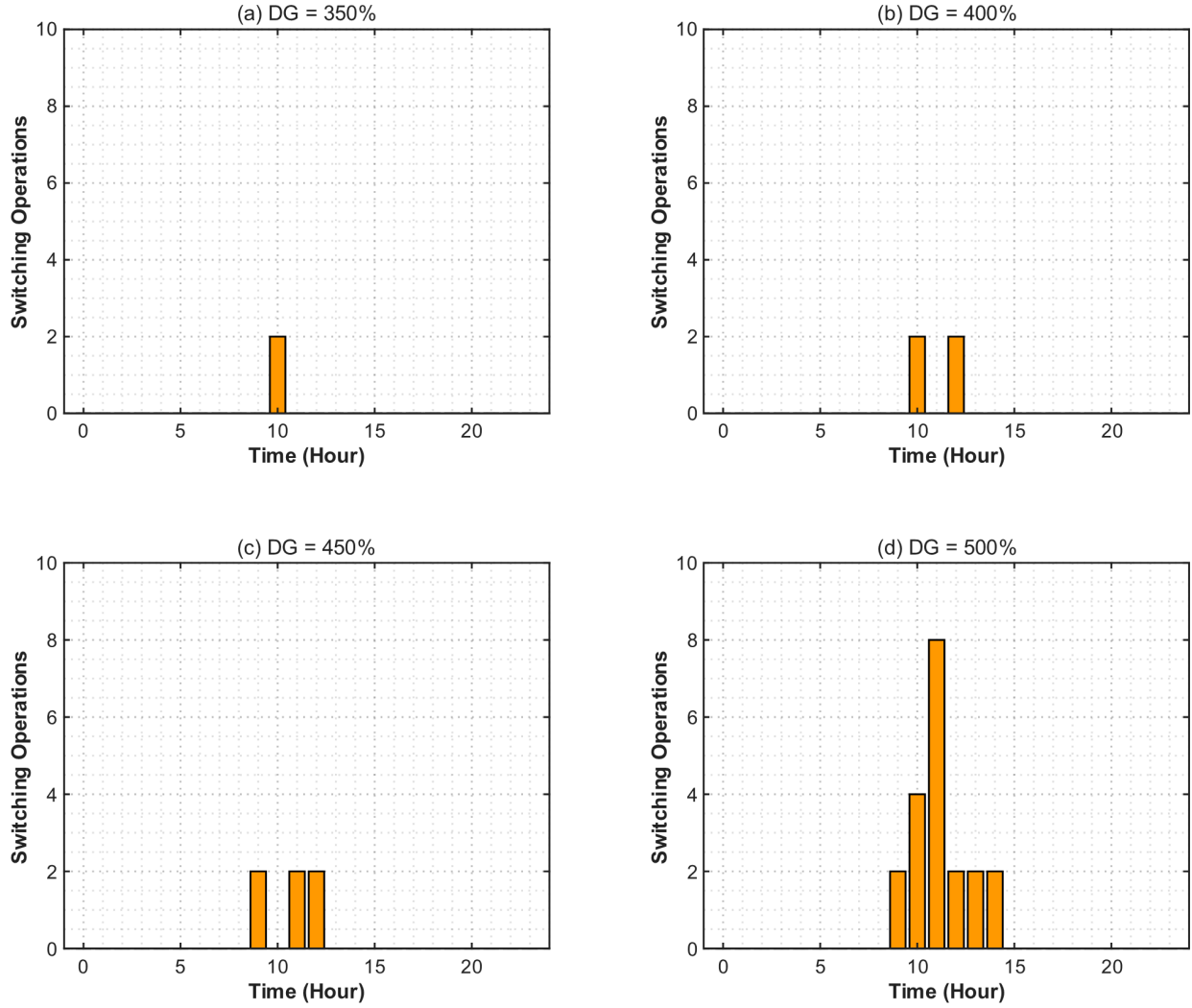
The reconfiguration results obtained by varying the DG penetration levels (300%–500%) were utilized to determine the DOE for both the generation and load at Buses 18, 22, 25, and 33. The DOE for generation is allocated based on the number of DG units present in the same feeder during each time step, utilizing their rated power output. In this study, all DG units were rated at 0.2 MW; therefore, in feeders containing multiple DG units, the allocated export limit was distributed equally among them. Figure 8 illustrates the 24-hour DOE allocation profiles for the optimized network topologies at the four representative buses. These profiles demonstrate the temporal variations in the generation (solid lines) and load (dashed lines) hosting capacities across different DG penetration scenarios.

### 6.2.1 Generation DOE Analysis

- **Early Morning Period (Hours 0-8):** Under light-load conditions, the system demonstrates divergent

hosting capacity characteristics among buses. Buses 18 and 33, which are primarily connected to Feeder 2 during this period, exhibit limited generation hosting capacity (0.37–0.47 MW) owing to reverse power flow constraints. Conversely, Buses 22 and 25, connected to feeder 1, face overvoltage limitations with generation capacities ranging from 0.875–0.96 MW. The overvoltage constraint emerges from the voltage rise effect caused by DG injection in the presence of low load consumption, where the voltage at the bus exceeds the upper limit of 1.05 p.u.

- **Transition Period (Hours 9-13):** This critical window witnesses significant network reconfiguration as the system transitions from light-to high-load conditions, coinciding with peak PV generation. The DOE allocation undergoes substantial modifications as the optimization algorithm dynamically reassigns buses to different feeders to maximize the overall hosting capacity. At hour 9 in the DG 300% penetration scenario, Buses 18 and 33 transitioned from reverse power flow limitations to overvoltage constraints (increasing capacity from 0.445 MW to 0.595–0.625 MW), whereas Buses 22 and 25 maintained their overvoltage-limited operation. This shift reflects the increasing load demand, which alleviates reverse power flow concerns while simultaneously amplifying the voltage rise sensitivities.



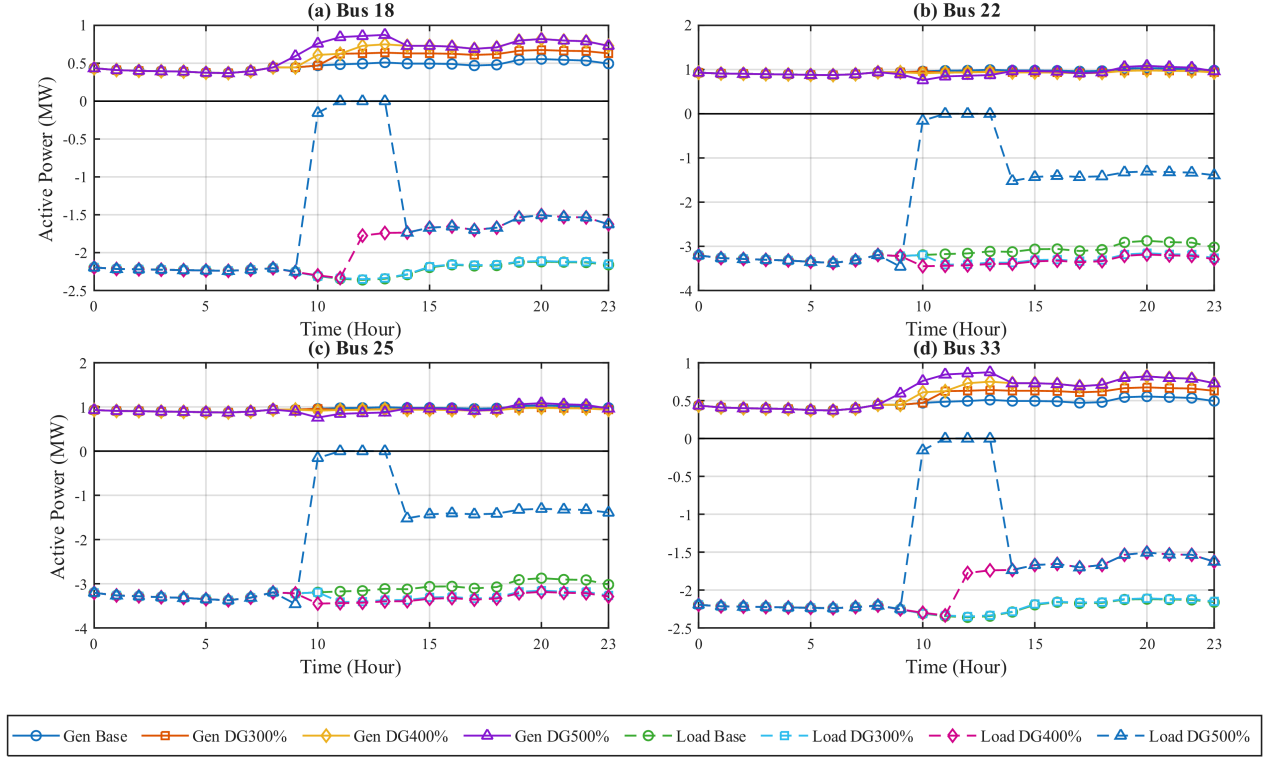
**Fig. 7: 24-hr switching profile**  
result (a) DG 350% (b) DG 400% (c) DG 450% (d) DG 500%.

**Table 4: Reconfiguration results.**

| Metric               | DG 300% | DG 350% | DG 400% | DG 450% | DG 500% |
|----------------------|---------|---------|---------|---------|---------|
| <b>Max Voltage</b>   |         |         |         |         |         |
| - Base (p.u.)        | 1.0478  | 1.0509  | 1.0539  | 1.0570  | 1.0600  |
| - Optimized (p.u.)   | 1.0446  | 1.0476  | 1.0487  | 1.0495  | 1.0440  |
| <b>Power Loss</b>    |         |         |         |         |         |
| - Base (kWh)         | 1,043   | 1,037   | 1,041   | 1,054   | 1,076   |
| - Optimized (kWh)    | 808     | 791     | 868     | 1,212   | 1,231   |
| - Reduction (%)      | -22.5%  | -23.7%  | -16.6%  | +15.0%  | +14.3%  |
| <b>Cost Saving</b>   |         |         |         |         |         |
| - Daily (USD)        | 96      | 144     | 320     | 486     | 604     |
| - Reduction (%)      | 1.5%    | 2.5%    | 5.8%    | 9.2%    | 12.0%   |
| <b>Switching Ops</b> | 2       | 2       | 4       | 6       | 20      |

- **Peak and evening periods (Hours 14-23):** During high-load conditions, the system exhibited maximum hosting capacity across all buses. In the baseline and low DG penetration scenarios (DG300), all buses became overvoltage-limited, with capacities reaching 0.610–0.675 MW for Buses 18 and 33, and 0.92–0.985

MW for Buses 22 and 25. The system maintains these elevated capacity levels throughout the evening as the load consumption remains high, effectively utilizing the available network capacity through an optimal feeder configuration.



**Fig. 8:** 24-hour DOE allocation for the optimized topologies at (a) Bus18, (b) Bus 22, (c) Bus 25 and (d) Bus 33.

**Table 5:** Statistics of DOE Allocation under Different DG Penetration Levels.

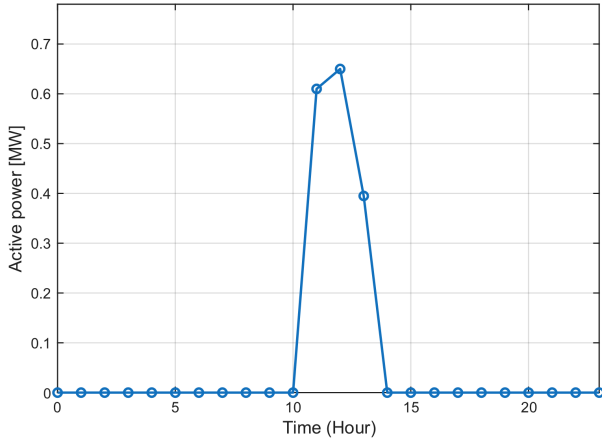
| Metric         |                     | Optimized reconfiguration topology |                   |                   |                   |                   |                    |
|----------------|---------------------|------------------------------------|-------------------|-------------------|-------------------|-------------------|--------------------|
|                |                     | Base case                          | DG300%            | DG350%            | DG400%            | DG450%            | DG500%             |
| Generation DOE | Sum of Energy [MWh] | 68.06                              | 70.37<br>(+3.39%) | 70.44<br>(+3.50%) | 73.08<br>(+7.38%) | 72.01<br>(+5.81%) | 74.76<br>(+9.85%)  |
|                | Maximum [MW]        | 3.18                               | 3.32<br>(+4.40%)  | 3.31<br>(+4.09%)  | 3.60<br>(+13.21%) | 3.57<br>(+12.26%) | 3.81<br>(+19.81%)  |
|                | Average [MW]        | 2.84                               | 2.93<br>(+3.52%)  | 2.94<br>(+3.52%)  | 3.05<br>(+7.39%)  | 3.00<br>(+5.63%)  | 3.12<br>(+9.86%)   |
| Load DOE       | Maximum [MW]        | 11.23                              | 11.52<br>(+2.58%) | 11.56<br>(+2.94%) | 11.55<br>(+2.85%) | 11.50<br>(+2.40%) | 11.42<br>(+1.69%)  |
|                | Minimum [MW]        | 9.99                               | 10.53<br>(+5.41%) | 10.59<br>(+6.01%) | 9.38<br>(-6.11%)  | 5.05<br>(-49.50%) | 0.00<br>(-100.00%) |
|                | Average [MW]        | 10.73                              | 11.00<br>(+2.46%) | 11.05<br>(+2.92%) | 10.50<br>(-2.19%) | 8.17<br>(-23.88%) | 7.14<br>(-33.49%)  |

### 6.2.2 Load DOE Analysis

The analysis of the load DOE, represented by the dashed lines in Fig. 8 (negative active power), reveals a fundamental trade-off between maximizing generation export and maintaining load hosting capability. In scenarios with base-to-moderate penetration (DG300%–DG350%), the reconfiguration strategy exerts a minimal impact on the Load DOE. The selected network topologies remained robust, accommodating the maximum load demand without violating the under-voltage constraints.

However, substantial reductions in load DOE were observed under high penetration scenarios (DG400%–DG500%), particularly during peak solar irradiance (Hours 10–14). As detailed in Table 5, the minimum

Load DOE for the DG500% case dropped drastically to 0.00 MW. Specifically, the minimum Load DOE declines progressively from 9.38 MW (−6.11%) at DG400%, to 5.05 MW (−49.50%) at DG450%, and reaches 0.00 MW (−100.00%) at DG500%, indicating a complete loss of load hosting capability under worst-case conditions. This decline stems from the conservative nature of the Load DOE calculation, which assumes a worst-case scenario with zero active DG power injection. The proposed framework selects topologies that are specifically optimized for massive power export. Consequently, without the auxiliary voltage support provided by DG injection, these configurations become highly susceptible to under-voltage violations under heavy loading.



**Fig. 9:** 24-hour minimum active power injection by all DG for voltage support in the 500% DG case study.

From a practical perspective for the DSO, the DG450% scenario was identified as the optimal operational limit. This represents the maximum topological configuration that maintains system robustness without necessitating complex constraints.

Unlike the DG500% case, DG450% facilitates high renewable energy integration without compromising power quality or load hosting capabilities.

If operation at the DG500% level is required, a minimum active power injection constraint must be enforced. As illustrated in Fig. 9, mandating a minimum output level from the DG units during the reconfigured periods provides essential voltage support. This strategy effectively mitigates the under-voltage risks, thereby restoring the system's ability to accommodate the load.

Table 5 summarizes the statistical performance of our proposed framework. The results demonstrate a consistent enhancement in the total energy accommodated by the network, increasing from 68.06 MWh (Base Case) to 74.76 MWh in the DG500% scenario (+9.85%). Although the generation DOE benefits significantly from dynamic reconfiguration, the load DOE statistics underscore the necessity of either selecting an appropriate operational setpoint (e.g., DG450%) or implementing coordinated voltage support strategies to prevent the under-utilization of load capacity in highly reconfigured networks.

## 7. CONCLUSION

This study proposed a congestion-driven framework for enhancing the hosting capacity of distribution networks through optimal radial reconfiguration and a DOE assessment. Validated on a modified IEEE 33-bus system, the BPSO-based strategy effectively managed voltage violations and reverse power flows, enabling the network to accommodate a DG penetration increase from 280% to 500%. Furthermore, the approach achieved a 12% reduction in daily operational costs compared with the static baseline. However, the analysis of the

load DOE reveals a critical trade-off: maximizing the generation export capacity significantly diminishes the network's ability to support the load, particularly in extreme penetration scenarios (DG 500%), where the load hosting capability drops to zero. Consequently, a penetration level of 450% was identified as the optimal operational limit for ensuring system robustness. To operate feasibly at 500% penetration, a minimum active power injection constraint must be enforced to provide the necessary voltage support. These findings offer a viable decision-support tool for DSO to manage the complexities of modern active distribution networks. Future work will focus on integrating adaptive protection relay coordination to address relay setting changes caused by topology reconfiguration, incorporating time-varying weather-dependent line outage probabilities into the load transfer decision, and extending the framework toward a stochastic optimization approach that jointly considers operational cost and reliability risk under probabilistic contingency scenarios.

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## REFERENCES

- [1] IEA, World Energy Outlook 2024. Paris, France: IEA, 2024. [Online]. Available: <https://www.iea.org/reports/world-energy-outlook-2024>
- [2] W. Deng, D. Xiao, M. Chen, S. Chen and D. Zhu, "OLTC-Driven Network Reconfiguration for Enhanced Renewable Hosting Capacity," *2025 7th Asia Energy and Electrical Engineering Symposium (AEEES)*, Chengdu, China, 2025, pp. 579-583.
- [3] Sayed, E.T.; Olabi, A.G.; Alami, A.H.; Radwan, A.; Mdallal, A.; Rezk, A.; Abdelkareem, M.A. "Renewable Energy and Energy Storage Systems". *Energies*, vol. 16, no. 1415, Feb 2023.
- [4] S. M. Ismael, S. H. E. Abdel Aleem, A. Y. Abdelaziz, and A. F. Zobaa, "State-of-the-art of hosting capacity in modern power systems with distributed generation," *Renewable Energy*, vol. 130, pp. 1002-1020, Jan. 2019.
- [5] R. Torquato, D. Salles, C. Oriente Pereira, P. C. M. Meira and W. Freitas, "A Comprehensive Assessment of PV Hosting Capacity on Low-Voltage Distribution Systems," *IEEE Transactions on Power Delivery*, vol. 33, no. 2, pp. 1002-1012, April 2018.
- [6] H. Al-Saadi, R. Zivanovic and S. F. Al-Sarawi, "Probabilistic Hosting Capacity for Active Distribution Networks," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2519-2532, Oct. 2017.
- [7] F. Ding and B. Mather, "On Distributed PV Hosting Capacity Estimation, Sensitivity Study, and

- Improvement," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 3, pp. 1010-1020, July 2017.
- [8] S. Wang, S. Chen, L. Ge and L. Wu, "Distributed Generation Hosting Capacity Evaluation for Distribution Systems Considering the Robust Optimal Operation of OLTC and SVC," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 3, pp. 1111-1123, July 2016.
- [9] L. Herding, L. Carvalho, R. Cossent, and M. Rivier, "A security-aware dynamic hosting capacity approach to enhance the integration of renewable generation in distribution networks," *International Journal of Electrical Power & Energy Systems*, vol. 229, 2024.
- [10] Fatima S, Püvi V, Lehtonen M. "Review on the PV Hosting Capacity in Distribution Networks," *Energies*, vol. 13, no. 4756, Sep 2020.
- [11] Z. M. Zenhom et al., "A comprehensive review of renewables and electric vehicles hosting capacity in active distribution networks," *IEEE Access*, vol. 12, pp. 3665-3693, 2024.
- [12] J. Xiao et al., "Enhancing hosting capacity of uncertain and correlated wind power in distribution network with ANM strategies," *IEEE Access*, vol. 8, pp. 189116-189127, 2020.
- [13] F. Capitanescu, L. F. Ochoa, H. Margossian, and N. D. Hatziargyriou, "Assessing the potential of network reconfiguration to improve distributed generation hosting capacity in active distribution systems," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 346-356, Jan. 2015.
- [14] Y.-Y. Fu and H.-D. Chiang, "Toward optimal multi-period network reconfiguration for increasing the hosting capacity of distribution networks," *IEEE Transactions on Power Delivery*, vol. 33, no. 5, pp. 2294-2304, Oct. 2018.
- [15] D. Jakus, R. Čadenović, J. Vasilj and P. Sarajčev, "Maximizing distribution network hosting capacity through optimal network reconfiguration," *2019 16th International Conference on the European Energy Market (EEM)*, Ljubljana, Slovenia, 2019, pp. 1-5.
- [16] M. Alturki and A. Khodaei, "Increasing Distribution Grid Hosting Capacity through Optimal Network Reconfiguration," *2018 North American Power Symposium (NAPS)*, Fargo, ND, USA, 2018, pp. 1-6.
- [17] B. B. Navarro and M. M. Navarro, "Increasing Distribution System PV Hosting Capacity Using Network-Based Optimization Techniques," *2023 13th International Conference on Power, Energy and Electrical Engineering (CPEEE)*, Tokyo, Japan, 2023, pp. 501-505.
- [18] Z. N. Popovic and S. D. Knezevic, "Dynamic Reconfiguration of Distribution Networks Considering Hosting Capacity: A Risk-Based Approach," *IEEE Transactions on Power Systems*, vol. 38, no. 4, pp. 3440-3450, July 2023.
- [19] Ž. Popović, S. Knezević, B. Brbaklić and M. Glogovac, "Dynamic Reconfiguration Considering Hosting Capacity in Active Distribution Networks," *2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Novi Sad, Serbia, 2022, pp. 1-5.
- [20] W. Cao, J. Wu, N. Jenkins, C. Wang, and T. Green, "Operating principle of soft open points for electrical distribution network operation," *Applied Energy*, vol. 164, pp. 245-257, Feb 2016.
- [21] S. Zhang, Y. Fang, H. Zhang, H. Cheng and X. Wang, "Maximum Hosting Capacity of Photovoltaic Generation in SOP-Based Power Distribution Network Integrated With Electric Vehicles," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 11, pp. 8213-8224, Nov. 2022.
- [22] M. Taghavi, H. Delkhosh, M. P. Moghaddam, and A. S. Fini, "Hosting capacity enhancement of hybrid AC/DC distribution network based on static and dynamic reconfiguration," *IET Generation, Transmission & Distribution*, vol. 17, no. 17, pp. 3765-3780, Sep 2023.
- [23] M. Deakin et al., "Hybrid Open Points: An Efficient Tool for Increasing Network Capacity in Distribution Systems," in *IEEE Transactions on Power Delivery*, vol. 37, no. 2, pp. 1340-1343, April 2022.
- [24] S. Hermawan, L. M. Putranto, H. R. Ali and F. Saputra, "Determination of PV Hosting Capacity on the 20 kV Distribution Network considering Network Configuration," *2023 International Conference on Smart-Green Technology in Electrical and Information Systems (ICSGTEIS)*, Badung, Bali, Indonesia, 2023, pp. 202-207.
- [25] V. Panchalogaranjan and P. Moses, "Utilizing PSO Technique for Locational-Dependent Feeder PV Hosting Capacity Evaluation," *2023 IEEE 50th Photovoltaic Specialists Conference (PVSC)*, San Juan, PR, USA, 2023, pp. 1-5.
- [26] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of the IEEE International Conference on Neural Networks.*, vol. 4, 1995, pp. 1942-1948.
- [27] S. H. Dolatabadi, M. Ghorbanian, P. Siano and N. D. Hatziargyriou, "An Enhanced IEEE 33 Bus Benchmark Test System for Distribution System Studies," *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 2565-2572, May 2021.



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