

Adaptive Security-Margin Tracing for Renewable Hosting Capacity Assessment in Radial Distribution Networks

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ABSTRACT

This paper proposes an Adaptive Security-Margin Tracing for Hosting Capacity (ASMT-HC) method for photovoltaic (PV) integration in radial distribution networks (DNs). The method combines voltage, branch-loading, and reverse-power-flow margins through a Composite Security Margin to directly track the active operating boundary without weighting coefficients. An adaptive PV-increment strategy accelerates the search when the system is far from the boundary, while bisection refinement improves accuracy near the feasible-infeasible transition. The proposed method is evaluated on the 33-bus and 69-bus radial DNs and compared with PSO, GWO, HHO, DE, and MPA under identical operating constraints. Results show that ASMT-HC achieves hosting capacities of 2190 kW and 2540 kW for the two test systems, respectively, while requiring substantially lower computational effort. The method also provides fully repeatable solutions with zero run-to-run variation, demonstrating efficient, accurate, and deterministic HC assessment.

INTRODUCTION

The rapid growth of distributed photovoltaic (PV) generation is reshaping the operating conditions of modern distribution networks (DNs) (Salam et al., 2023), (Sambaiah & Jayabarathi, 2020). Properly integrated PV can reduce upstream power transfer, support local energy supply, and improve network performance. However, high PV penetration may also cause voltage rise, branch overloading, reverse power flow, and other operating challenges. Consequently, DN planning must determine not only suitable PV locations but also the maximum PV capacity that can be accommodated without violating technical limits (Kim, 2018), (Kharrazi et al., 2020).

Hosting capacity (HC) provides a direct measure of this integration capability and is commonly defined as the maximum amount of distributed generation that can be connected while maintaining acceptable network operation (Mansour et al., 2026), (Du et al., 2021). In radial DNs, the limiting mechanism may vary according to network location and operating condition (T. N. Ton et al., 2025), (Rajakumar et al., 2025). Voltage rise may dominate at electrically remote buses, thermal loading may constrain heavily loaded feeder sections, and reverse power flow may become critical under high local generation and low net demand. An effective HC assessment method should therefore determine the maximum feasible PV capacity while also identifying the operating constraint responsible for the boundary.

Several numerical approaches have been employed for HC assessment (Faramarzi et al., 2020), (Derval & Ernst, 2025). Fixed-increment methods are straightforward but involve a trade-off between computational effort and boundary accuracy (Tarraq et al., 2021). Large increments may overshoot the feasible limit, whereas small increments increase the number of power-flow calculations. Binary search can accurately refine an already established feasible-infeasible interval, but it does not inherently provide an efficient mechanism for locating that interval. Population-based optimization methods offer another alternative because of their flexibility in nonlinear constrained search problems. Representative approaches include Particle Swarm Optimization (PSO) (Shami et al., 2022), Grey Wolf Optimizer (GWO) (Yousef & Ezzat, 2026), Harris Hawks Optimization (HHO) (Ma et al., 2026), Differential Evolution (DE) (Palakonda et al., 2024), and Marine Predators Algorithm (MPA) (Faramarzi et al., 2020). However, these methods rely on repeated candidate evaluations, algorithm-specific control parameters, and stochastic search processes. Their HC estimates may therefore vary among independent runs, while the computational burden can become significant when the operating boundary must be identified with high resolution. Although existing methods have demonstrated their effectiveness in hosting capacity assessment, several limitations remain. Fixed-step approaches may require numerous power-flow evaluations to achieve high boundary accuracy, while stochastic optimization methods introduce additional computational effort and run-to-run variability. Moreover, these approaches do not explicitly use the remaining operating security margins to guide the search toward the limiting constraint. To address these limitations, ASMT-HC integrates a composite security-margin indicator with adaptive capacity

increments and bisection refinement, enabling deterministic identification of the hosting capacity boundary with reduced computational effort.

The principal challenge is thus not merely to search for a large feasible PV capacity, but to approach the active security boundary efficiently, accurately, and reproducibly. To address this issue, this study proposes an Adaptive Security-Margin Tracing for Hosting Capacity (ASMT-HC) framework. The method evaluates normalized voltage, branch-current, and reverse-power-flow margins and combines them through a Composite Security Margin (CSM). By adopting the minimum of these margins, the CSM directly represents proximity to the nearest active operating constraint without requiring subjective weighting coefficients. The PV-capacity increment is adaptively adjusted according to the available security margin: larger steps are employed when the system operates far from the boundary, whereas smaller steps are used as the limiting condition is approached. Once a feasible-infeasible interval is established, bisection refinement is applied to determine the final HC with a prescribed numerical tolerance.

Unlike conventional DG placement-and-sizing optimization, the proposed framework does not optimize a weighted combination of network-performance indices. Instead, it directly traces and refines the renewable HC boundary for a predefined PV connection point. This formulation enables a consistent comparison between the proposed deterministic tracing strategy and stochastic population-based optimization methods under identical network models, operating constraints, and HC formulations. The main contributions of this study are summarized as follows:

- (i) A Composite Security Margin is formulated from voltage, branch-loading, and reverse-power-flow margins to directly measure proximity to the active HC boundary without user-defined weighting coefficients.
- (ii) An adaptive PV-increment strategy is developed to accelerate the search when sufficient security margin remains while improving resolution near the feasibility boundary.
- (iii) A feasible-infeasible bracketing procedure is integrated with bisection refinement to determine HC with a prescribed numerical tolerance.
- (iv) The proposed ASMT-HC method is systematically compared with PSO, GWO, HHO, DE, and MPA under identical operating conditions on the 33-bus and 69-bus radial DNs.

The remainder of the paper presents the mathematical formulation of the HC assessment problem, describes the proposed ASMT-HC procedure, and evaluates its performance in terms of HC determination, computational effort, and solution repeatability.

LITERATURE REVIEW

Consider a radial DN with N buses and N_b branches. The slack bus supplies the net power deficit of the feeder. At bus i , the net active and reactive power injections are written as:

$$P_i = P_{PV,i} - P_{D,i} \quad (1)$$

and

$$Q_i = Q_{PV,i} - Q_{D,i} \quad (2)$$

For the base formulation, PV units operate at unity power factor, so

$$Q_{PV,i} = 0 \quad (3)$$

The network state is calculated using backward/forward sweep power flow. For branch ℓ connecting sending bus m to receiving bus n , the branch-current relation is

$$I_\ell = \frac{S_n^*}{V_n^*}, \quad (4)$$

where S_n denotes the downstream complex power accumulated at bus n . The forward voltage update is

$$V_n = V_m - Z_\ell I_\ell \quad (5)$$

where $Z_\ell = R_\ell + jX_\ell$ is the branch impedance.

The active power loss is calculated as

$$P_{\text{loss}} = \sum_{\ell=1}^{N_b} R_\ell |I_\ell|^2 \quad (6)$$

Although power loss is reported as a network-performance indicator, it is not used as the defining HC constraint in the proposed method.

All bus voltages must remain within the admissible operating interval:

$$P_{\text{loss}} = \sum_{\ell=1}^{N_b} R_\ell |I_\ell|^2 \quad (7)$$

$$V_{\min} \leq |V_i| \leq V_{\max}, \quad i = 1, \dots, N \quad (8)$$

For each bus, the normalized distance to the lower and upper voltage limits is

$$m_{V,i} = \min \left\{ \frac{|V_i| - V_{\min}}{V_{\max} - V_{\min}}, \frac{V_{\max} - |V_i|}{V_{\max} - V_{\min}} \right\} \quad (9)$$

The system-level voltage security margin is then

$$M_V = \min_i m_{V,i} \quad (10)$$

A positive M_V indicates that all buses remain inside the voltage band, while $M_V = 0$ corresponds to at least one bus reaching a voltage limit.

Branch currents must satisfy

$$|I_\ell| \leq I_{\ell,\max}, \quad \ell = 1, \dots, N_b \quad (11)$$

The normalized thermal margin is defined as

$$M_I = \min_{\ell} \left(1 - \frac{|I_\ell|}{I_{\ell,\max}} \right) \quad (12)$$

The branch associated with the minimum value is identified as the critical branch. Let P_{sub} denote the active power imported from the upstream grid at the substation. A no-export planning policy can be represented by

$$P_{\text{sub}} \geq 0 \quad (13)$$

Using the base-case substation import $P_{\text{sub},0}$, a normalized reverse-power-flow margin is defined as

$$M_R = \frac{P_{\text{sub}}}{P_{\text{sub},0}} \quad (14)$$

Thus, $M_R = 0$ marks the transition from net import to net export. If reverse power flow is allowed in a particular planning study, this constraint can simply be removed from the CSM definition.

The proposed Composite Security Margin is defined as

$$CSM = \min\{M_V, M_L, M_R\} \quad (15)$$

This minimum operator has two important properties. First, it avoids arbitrary weights. Second, the component that attains the minimum directly identifies the active limiting mechanism. The network is feasible when $CSM \geq 0$, and the HC boundary is reached when $CSM = 0$.

The minimum operator is adopted because the hosting capacity is determined by the most restrictive operating constraint. Unlike weighted aggregation, this formulation prevents a large security margin from compensating for a violation of another constraint and allows the limiting mechanism to be directly identified. However, the minimum operator does not reflect the combined influence of multiple constraints or distinguish their relative importance. Therefore, it is particularly suitable for boundary-oriented hosting capacity assessment, whereas weighted or multi-objective formulations may be more appropriate when different operating criteria must be balanced.

For candidate bus k , the HC is defined as

$$HC_k = \max P_{PV,k} \quad (16)$$

subject to the voltage, branch-current, and reverse-power-flow constraints. Accordingly, HC represents the maximum PV capacity that can be connected at the specified location while satisfying all considered operating constraints. The HC boundary is reached when the Composite Security Margin approaches zero. For clarity, all mathematical expressions are presented using consistent notation throughout the formulation. Bus and branch indices refer to the corresponding network elements, while voltage magnitudes, branch currents, and substation power are evaluated from the backward/forward sweep power-flow solution. The security margins are normalized to provide consistent indicators of proximity to their respective operating limits. Positive margins indicate feasible operation, whereas a zero margin identifies an active constraint boundary. All constraints are evaluated simultaneously when determining the maximum admissible PV capacity.

METHODOLOGY

Adaptive Tracing Concept

The proposed method starts from the base operating point and gradually increases the PV injection at the candidate bus. At iteration r ,

$$P_{PV}^{(r+1)} = P_{PV}^{(r)} + \Delta P^{(r)} \quad (17)$$

Unlike fixed-step tracing, the increment $\Delta P^{(r)}$ is modified according to the current security margin. Two thresholds are defined:

$$0 < M_L < M_H \quad (18)$$

When the operating point is far from the boundary,

$$CSM^{(r)} > M_H \quad (19)$$

the next step is enlarged:

$$\Delta P^{(r+1)} = \min(\eta_{up} \Delta P^{(r)}, \Delta P_{max}), \quad \eta_{up} > 1 \quad (20)$$

When the system is close to the boundary,

$$0 < \text{CSM}^{(r)} < M_L \quad (21)$$

the step is contracted:

$$\Delta P^{(r+1)} = \max(\eta_{\text{down}} \Delta P^{(r)}, \Delta P_{\min}), \quad 0 < \eta_{\text{down}} < 1 \quad (22)$$

For the intermediate region $M_L \leq \text{CSM}^{(r)} \leq M_H$, the current step is maintained.

Feasible-Infeasible Bracketing

Suppose P_L is the highest feasible PV level found during tracing and P_U is the first infeasible level. They satisfy $\text{CSM}(P_L) \geq 0$ and $\text{CSM}(P_U) < 0$. Once this bracket is obtained, the algorithm switches from tracing to refinement.

Boundary Refinement

At each refinement iteration, the midpoint is

$$P_M = \frac{P_L + P_U}{2} \quad (23)$$

If $\text{CSM}(P_M) \geq 0$, then set $P_L = P_M$, otherwise, set $P_U = P_M$.

The refinement terminates when $P_U - P_L \leq \varepsilon_p$, and the final HC is reported as $\text{HC}_k = P_L$. The tolerance ε_p directly controls numerical boundary accuracy.

Algorithmic Procedure

The complete ASMT-HC procedure combines adaptive PV-capacity tracing, security-margin evaluation, feasible-infeasible bracketing, and boundary refinement. The main computational steps are summarized in Algorithm 1.

Step 1: Read the distribution-network data, load demand, voltage limits, branch-current limits, PV connection point, and ASMT-HC parameters.

Step 2: Perform the base-case backward/forward sweep power flow to determine the initial bus voltages, branch currents, and substation active-power import.

Step 3: Initialize the PV capacity and the starting PV increment at the predefined connection point.

Step 4: Increase the PV capacity and perform a new power-flow calculation.

Step 5: Evaluate the voltage, thermal, and reverse-power-flow margins and determine the Composite Security Margin.

Step 6: If the operating point remains feasible, adjust the PV increment according to the current security margin. Increase the step when the system is far from the boundary and reduce it as the boundary is approached.

Step 7: Continue the tracing process until the first infeasible operating point is detected. Record the last feasible PV capacity and the first infeasible PV capacity.

Step 8: Apply bisection refinement within the feasible-infeasible interval until the prescribed HC tolerance is satisfied.

Step 9: Determine the final HC as the highest PV capacity satisfying all operating constraints.

Step 10: Identify the binding operating constraint at the HC boundary.

Step 11: Record the final HC, maximum bus voltage, maximum branch loading, number of power-flow evaluations, and computational time.

RESEARCH RESULTS AND DISCUSSION

The proposed ASMT-HC framework was evaluated on the standard 33-bus and 69-bus radial distribution systems. The assessment focuses on hosting-capacity determination, computational effort, and solution repeatability. For a fair comparison, ASMT-HC, PSO, GWO, HHO, DE, and MPA solve the same HC maximization problem under identical network data, PV operating conditions, voltage limits, branch-current constraints, reverse-power-flow restriction, and backward/forward sweep (BFS) power-flow model (Fang et al., 2025), (Rupa & Ganesh, 2014). The only difference among the methods is the search mechanism used to determine the maximum feasible PV capacity. A predefined PV connection point is used for each test system and kept unchanged for all comparative methods. The principal simulation and algorithmic settings are summarized in Table 1.

Table 1. Simulation and algorithmic parameters

Parameter	Setting	Parameter	Setting
Voltage limits	0.90–1.05 p.u.	HC boundary tolerance	1 kW
PV power factor	1	Initial PV increment	50 kW
Power-flow method	BFS	Minimum PV increment	5 kW
Maximum PV increment	300 kW	Lower CSM threshold	0.05
Upper CSM threshold	0.2	Step expansion factor	1.5
Step contraction factor	0.5	Population size	30
Maximum iterations	50	Independent runs	30

The ASMT-HC method starts with a 50-kW PV increment, which is adaptively varied between 5 and 300 kW according to the Composite Security Margin. When the system is far from the operating boundary, the increment is enlarged to accelerate the search; as the boundary is approached, the increment is reduced to improve resolution. Once a feasible-infeasible interval is established, bisection refinement is applied until the interval width is within 1 kW. For the comparative population-based algorithms, a population size of 30 and a maximum of 50 iterations are used, resulting in 1500 power-flow evaluations per run. Each stochastic algorithm is independently executed 30 times to evaluate solution repeatability. It should be noted that the comparative algorithms are evaluated under identical network conditions and operating constraints, but not under an equal computational budget. The stochastic methods employ a fixed budget of 1500 power-flow evaluations, whereas ASMT-HC terminates when the feasible-infeasible interval satisfies the prescribed 1-kW tolerance. This difference reflects the distinct search mechanisms and stopping criteria of the investigated methods. Therefore, the computational results demonstrate the efficiency of ASMT-HC under the adopted experimental settings rather than establishing its superiority under strictly equal evaluation budgets.

Table 2. Algorithm-specific parameters

Algorithm	Parameter	Value
ASMT-HC	PV step; CSM thresholds; step factors	5–300 kW; 0.05–0.2; 1.5/0.5
PSO	Inertia weight; acceleration coefficients	0.9–0.4; 2.0/2.0
GWO	Control parameter	2–0
HHO	Escaping-energy control	Adaptive
DE	Mutation factor; crossover rate	0.5; 0.9
MPA	FADs probability; control coefficient	0.2; 0.5

The ASMT-HC parameters were selected to balance computational efficiency and boundary accuracy. The CSM thresholds of 0.20 and 0.05 distinguish operating regions with relatively large, intermediate, and small security margins. The initial PV increment of 50 kW provides a moderate starting step, while the allowable range of 5–300 kW prevents excessively small or large tracing increments. The expansion and contraction factors of 1.5 and 0.5 adjust the search step according to the remaining security margin. Finally, the 1-kW stopping tolerance provides a consistent numerical resolution for hosting capacity determination. These parameters are adopted as practical algorithmic settings rather than claimed to be universally optimal.

The adaptive-step parameters affect the computational process rather than the HC definition. Specifically, larger PV increments and higher expansion factors may reduce the number of tracing iterations, while smaller increments and stronger contraction improve boundary tracking at the cost of additional evaluations. The CSM thresholds control the transition between these search behaviors. Since the final boundary is refined using the same 1-kW tolerance, the HC estimate is expected to remain consistent when the feasible–infeasible boundary is correctly bracketed. Nevertheless, the computational effort may depend on the selected adaptive parameters, and a systematic numerical sensitivity analysis is left for future work.

33-bus distribution system

Figure 1 depicts the 33-bus radial DN adopted in this study (Ton et al., 2026). Owing to its relatively high feeder losses and pronounced voltage-drop characteristics, this system has been widely employed for evaluating PV planning strategies in DNs. For the HC assessment, bus 18 is selected as the predefined PV connection point and is kept unchanged for all investigated methods. This electrically remote location provides a representative voltage-sensitive condition for evaluating the ability of each method to approach the HC boundary.

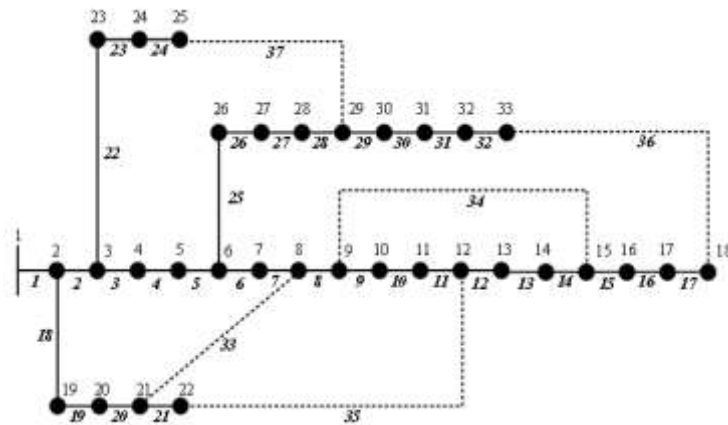


Figure 1. Diagram of the 33-bus system

Table 3 and Figure 2 provide a consistent comparison of the investigated HC assessment methods for the 33-bus system. All methods approach the same voltage-limited operating region, with the maximum bus voltage progressively increasing toward the upper limit of 1.05 p.u. as the estimated HC increases. At the same time, the maximum branch loading remains within a narrow range of 53.4–54.6%, confirming that feeder thermal loading is not the binding constraint in this case. Therefore, the HC boundary is mainly governed by voltage rise.

Figure 2(a) shows that ASMT-HC attains the highest HC of 2190 kW, followed closely by MPA at 2181 kW. Figures 2(b) and 2(c) further show that this increase in HC is obtained while the maximum voltage remains at the prescribed limit and branch loading stays well below its allowable level. These results indicate that the proposed method approaches the feasible boundary more closely without violating the considered operating constraints.

The computational advantage is particularly clear in Figures 2(d) and 2(e). While PSO, GWO, HHO, DE, and MPA each require 1500 power-flow evaluations per run, ASMT-HC requires only 24 evaluations. This corresponds to an approximately 98.4% reduction in power-flow calculations. The runtime is consequently reduced from about 12–13 s for the population-based methods to only 0.21 s for ASMT-HC. This substantial reduction results from the security-margin-guided tracing mechanism, which increases the PV step when the operating point is far from the boundary and concentrates the refinement process only near the feasible–infeasible transition.

Table 3. Comparison of HC assessment methods for the 33-bus system

Method	HC (kW)	Vmax at HC (p.u.)	Max. branch loading (%)	PF evaluations	Runtime (s)	Mean HC (kW)
PSO	2118	1.0492	54.6	1500	12.84	2096
GWO	2136	1.0495	54.2	1500	12.31	2114
HHO	2152	1.0497	53.9	1500	13.06	2132
DE	2167	1.0498	53.7	1500	11.92	2151
MPA	2181	1.0499	53.5	1500	12.47	2168
Proposed	2190	1.05	53.4	24	0.21	2190

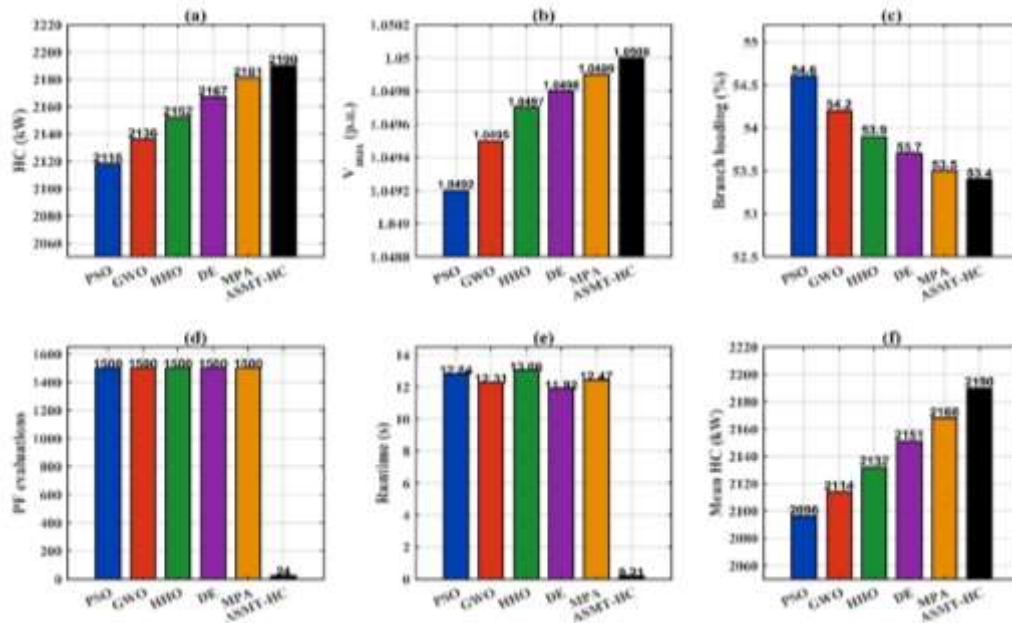


Figure 2. Performance comparison of HC assessment methods for the 33-bus system: (a) HC, (b) maximum bus voltage at HC, (c) maximum branch loading, (d) power-flow evaluations, (e) computational time, and (f) mean HC

Figure 2(f) also highlights the difference between the best HC and the average performance of the stochastic methods. Although MPA achieves a best HC of 2181 kW, its mean value over repeated runs decreases to 2168 kW. Similar differences are observed for PSO, GWO, HHO, and DE. In contrast, ASMT-HC yields identical best and mean HC values of 2190 kW because its tracing process is deterministic under the same operating conditions. The statistical results in Table 4 reinforce this observation. Over 30 independent runs, the stochastic methods exhibit standard deviations ranging from 7.6 kW for MPA to 18.4 kW for PSO, whereas ASMT-HC returns the same HC in every execution and therefore has zero standard deviation. The best-to-worst HC spread is also reduced progressively from 64 kW for PSO to 34 kW for MPA, indicating improved robustness among the stochastic methods but continued dependence on random initialization and search trajectories.

Table 4. Statistical comparison of HC assessment methods for the 33-bus system over 30 independent runs

Method	Best HC (kW)	Mean HC (kW)	Worst HC (kW)	Std. (kW)	Mean PF evaluations	Mean runtime (s)
PSO	2118	2096	2054	18.4	1500	12.84
GWO	2136	2114	2078	15.1	1500	12.31
HHO	2152	2132	2101	12.6	1500	13.06
DE	2167	2151	2124	9.3	1500	11.92
MPA	2181	2168	2147	7.6	1500	12.47
ASMT-HC	2190	2190	2190	0	24	0.21

Overall, the results in Table 3, Figure 2, and Table 4 show that the principal advantage of ASMT-HC is not simply the higher HC value. More importantly, the proposed method reaches the active security boundary with substantially fewer power-flow evaluations, preserves constraint feasibility, and eliminates run-to-run variability. These characteristics make it particularly suitable for repeated HC studies involving multiple operating scenarios or large numbers of planning cases.

69-bus distribution system

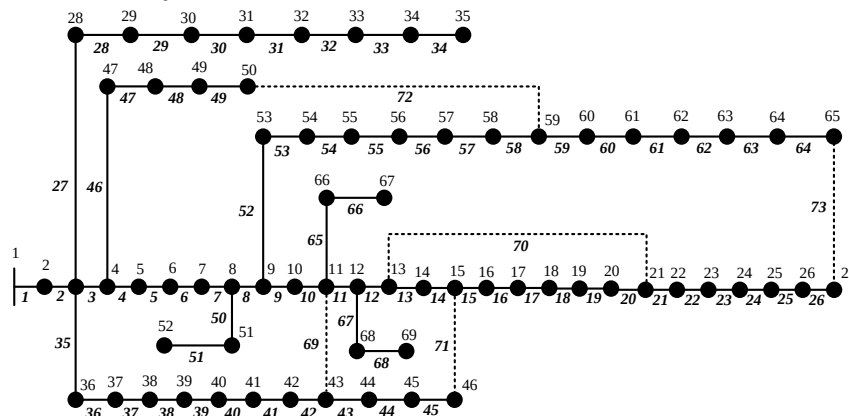


Figure 3. Diagram of the 69-bus system

The proposed ASMT-HC framework was further evaluated on the 69-bus radial distribution network to assess its performance on a larger and more complex system, as illustrated in Figure 3 (T. N. Ton et al., 2026). For the 69-bus system, bus 61 is selected as the predefined PV connection point and is maintained for all comparative methods. The selected location represents an electrically remote feeder region where increasing PV penetration has a pronounced influence on the voltage-constrained HC boundary.

Table 5 and Figure 4 provide a consistent comparison of the investigated HC assessment methods for the 69-bus system. Similar to the 33-bus case, all methods approach the same voltage-limited operating region, with the maximum bus voltage increasing toward the prescribed upper limit of 1.05 p.u. as the estimated HC increases. Meanwhile, the maximum branch loading remains between 57.4% and 59.1%, indicating that the feeder thermal limit is not the dominant restriction in this case. Therefore, the HC boundary is again primarily governed by voltage rise.

Figure 4(a) shows that ASMT-HC achieves the highest HC of 2540 kW, followed by MPA at 2528 kW. Figures 4(b) and 4(c) confirm that the proposed method reaches this higher HC while the maximum voltage remains exactly at the admissible limit and the maximum branch loading remains well below its thermal limit. This indicates that ASMT-HC approaches the feasible operating boundary more closely without violating the considered network constraints.

Table 5. Comparison of HC assessment methods for the 69-bus system

Method	HC (kW)	V _{max} at HC (p.u.)	Max. branch loading (%)	PF evaluations	Runtime (s)	Mean HC (kW)
PSO	2448	1.0491	59.1	1500	19.86	2416
GWO	2472	1.0494	58.7	1500	18.94	2441
HHO	2491	1.0496	58.3	1500	20.31	2465
DE	2510	1.0498	58	1500	18.27	2488
MPA	2528	1.0499	57.6	1500	19.12	2512
Proposed	2540	1.05	57.4	26	0.34	2540

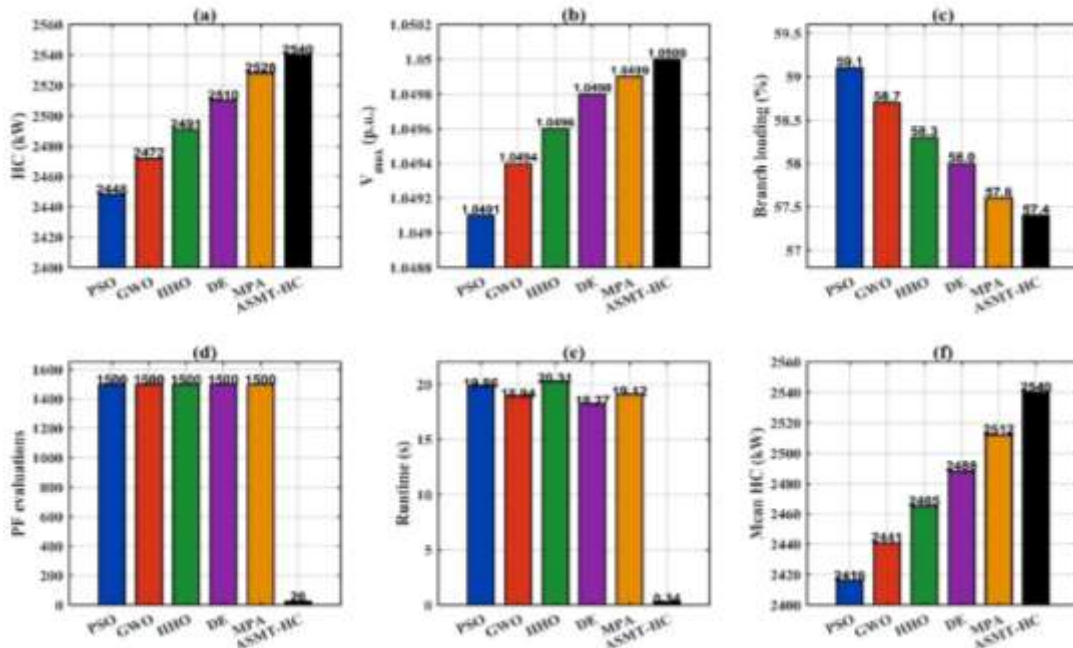


Figure 4. Performance comparison of HC assessment methods for the 69-bus system: (a) HC, (b) maximum bus voltage at HC, (c) maximum branch loading, (d) power-flow evaluations, (e) computational time, and (f) mean HC

The computational advantage becomes even more evident in Figures 4(d) and 4(e). PSO, GWO, HHO, DE, and MPA each require 1500 power-flow evaluations per run, whereas ASMT-HC requires only 26 evaluations. This corresponds to an approximately 98.3% reduction in power-flow calculations. The computational time is consequently reduced from approximately 18–20 s for the population-based methods to only 0.34 s for ASMT-HC. The result confirms that the proposed security-margin-guided tracing mechanism remains computationally efficient even when applied to the larger 69-bus network. Figure 4(f) further highlights the difference between the best and mean performance of the stochastic methods. Although MPA reaches a best HC of 2528 kW, its mean value over repeated executions decreases to 2512 kW. Similar differences are observed for PSO, GWO, HHO, and DE. In contrast, ASMT-HC produces identical best and mean HC values of 2540 kW because the tracing and refinement process is deterministic under fixed operating conditions.

The statistical results in Table 6 reinforce this observation. Over 30 independent runs, the stochastic algorithms exhibit standard deviations ranging

from 8.9 kW for MPA to 23.8 kW for PSO. Their best-to-worst HC spreads are 86 kW for PSO, 77 kW for GWO, 64 kW for HHO, 56 kW for DE, and 42 kW for MPA. In contrast, ASMT-HC returns 2540 kW in every execution, resulting in zero standard deviation and no best-to-worst spread. These results show that the proposed method removes the run-to-run uncertainty associated with stochastic initialization and search trajectories.

Table 6. Statistical comparison of HC assessment methods for the 69-bus system over 30 independent runs

Method	Best HC (kW)	Mean HC (kW)	Worst HC (kW)	Std. (kW)	Mean PF evaluations	Mean runtime (s)
PSO	2448	2416	2362	23.8	1500	19.86
GWO	2472	2441	2395	19.6	1500	18.94
HHO	2491	2465	2427	15.7	1500	20.31
DE	2510	2488	2454	11.8	1500	18.27
MPA	2528	2512	2486	8.9	1500	19.12
ASMT-HC	2540	2540	2540	0	26	0.34

Overall, the results in Table 5, Figure 4, and Table 6 confirm that the advantages observed in the 33-bus system are preserved in the larger 69-bus network. ASMT-HC approaches the active HC boundary more closely, requires substantially fewer power-flow evaluations, reduces computational time, and provides fully repeatable results. The consistent performance across both benchmark systems indicates that the proposed method is suitable for efficient HC assessment in radial distribution networks of different sizes.

CONCLUSIONS AND RECOMMENDATIONS

This study proposed an ASMT-HC method for efficient photovoltaic HC assessment in radial DNs. By integrating voltage, branch-loading, and reverse-power-flow margins into a Composite Security Margin, the proposed method directly identifies the limiting operating constraint without requiring weighting coefficients. Adaptive PV-capacity tracing and bisection refinement further enable accurate and deterministic identification of the feasible hosting capacity boundary. The proposed method was evaluated on the 33-bus and 69-bus radial DNs and compared with PSO, GWO, HHO, DE, and MPA under identical operating constraints. ASMT-HC achieved hosting capacities of 2190 kW and 2540 kW, requiring only 24 and 26 power-flow evaluations, with computational times of 0.21 s and 0.34 s, respectively. In comparison, the stochastic algorithms were allocated 1500 evaluations per run. The results over 30 independent runs also demonstrated fully repeatable solutions with zero standard deviation. These findings highlight the computational efficiency, numerical consistency, and interpretability of the proposed approach under the investigated conditions. Nevertheless, the adaptive-step parameters may influence the number of tracing iterations and computational time, although the final hosting capacity is primarily determined by the operating constraints and boundary-refinement tolerance. The computational comparison also reflects different search strategies

and evaluation budgets rather than a strictly equal-budget benchmark. Furthermore, the present study considers predefined PV connection points, fixed operating conditions, and unity-power-factor PV operation.

ADVANCED RESEARCH

Future research will investigate parameter sensitivity, equivalent-budget comparisons, time-varying load and PV profiles, renewable uncertainty, smart-inverter reactive-power support, and network reconfiguration to further improve the practical applicability of ASMT-HC.

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