Data Center Spatiotemporal Flexibility for Enhancing Distributed PV Hosting Capacity with Transformer Reverse Power Flow Limits

Shibo Zhou, Zhaoyuan Wu, Ming Zhou
School of Electrical and Electronic Engineering
North China Electric Power University
Beijing, China
{zhoushibo, wuzy, zhouming} @ ncepu.edu.cn

Hao Yue, Bingqing Wu
Economic and Technological Research Institute
State Grid Jibei Electric Power Co., Ltd.
Beijing, China
{yue.hao, wu.bingqing} @ jibei.sgcc.com.cn

***Abstract*—With the rapid expansion of distributed photovoltaics (DPVs), low-voltage networks face increasing challenges in local absorption, especially under reverse power flow (RPF) limits. The emerging spatiotemporal flexibility of data centers (DCs) offers new potential to alleviate such challenges, yet its contribution to enhancing DPV hosting capacity remains insufficiently quantified. This study develops a coordinated evaluation framework centered on flexible DC scheduling. Critically, detailed transformer modeling under bidirectional flow is incorporated as a prerequisite for accurately assessing DC flexibility impacts. By jointly optimizing DCs with soft open points (SOPs) and energy storages (ESs), the framework enables spatiotemporal reshaping of power demand and improves local absorption. Case studies confirm the effectiveness of DC-enabled flexibility in increasing DPV hosting capacity and mitigating RPF occurrences.**

***Index Terms*--Data centers, distributed photovoltaics, hosting capacity, reverse power flow.**

I. Introduction

A. Background

In recent years, the deployment of distributed photovoltaics (DPVs) in low-voltage distribution networks has expanded rapidly. When the installed DPV capacity, local load characteristics, and network parameters such as nodal voltages and transformer impedances are poorly coordinated, a paradox emerges: rather than improving efficiency, excessive DPV penetration may lead to operational challenges. During periods of strong solar irradiance and low electricity demand, sustained net injection at the low-voltage level can raise bus voltages beyond acceptable limits. After voltage transformation, this can result in higher downstream voltages compared to upstream levels, causing power to flow from the distribution system back to the transmission grid. Such reverse power flow (RPF) not only triggers voltage violations but also induces significant intra-day voltage fluctuations. These fluctuations aggravate the thermal burden on transformers and distribution lines, and increase the frequency of tap changer operations. Collectively, these stressors undermine system reliability and highlight that the hosting capacity of low-voltage networks is subject to physical and operational constraints that require careful evaluation.

The underlying cause of RPF lies in short-term imbalances between local generation and demand. Traditional mitigation measures such as energy storages (ESs) are used to shift energy temporally through peak shaving and valley filling. Meanwhile, soft open points (SOPs) can be strategically deployed to interconnect physically separated distribution feeders or distinct networks, enabling real-time power flow control across nodes. However, both types of resources provide only limited flexibility and are constrained by technical and economic factors, including device capacity, degradation rates, and installation costs. To address these limitations, this study introduces data centers (DCs) as an emerging demand resource with strong spatiotemporal flexibility. Their computing workloads can be shifted across time within a day or migrated between network nodes, enabling electric loads to align proactively with periods and locations of surplus photovoltaic generation. This capability allows DCs to reduce net injection at the source and operate in conjunction with ESs and SOPs, making them particularly effective for alleviating RPF in the cross-voltage-level scenarios. By mitigating net injection constraints and reducing voltage violations, DCs help unlock additional DPV hosting capacity, thereby supporting higher levels of photovoltaic integration without compromising network stability.

B. Literature Review and Contritbutions

Recent interest in DCs has been driven by the accelerating digitalization of society. A growing number of literatures has recognized DCs as flexible resources capable of supporting power system operations through spatiotemporal flexibility of electricity demand [1]. By coordinating workload scheduling, enabling temporal shifting and spatial migration of computing workloads, and jointly managing computing, cooling, and storage subsystems, DCs have demonstrated notable capabilities in electric load shifting during peak hours, alleviating local network congestion, and providing ancillary services such as fast frequency regulation and reserve support [2], [3]. A notable advancement is presented in [4], which creatively aligns the

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hierarchical computing architecture of DCs with the multi-voltage structure of modern power systems. By leveraging the spatial mobility of computing workloads, this study facilitates inter-voltage-level load redistribution, thereby enhancing the local absorption of renewable generation. However, the analysis remains confined to spatial migration of electric demand, without examining how such demand reshaping may influence inter-level power flows within the grid. The broader potential of DC flexibility, particularly its ability to actively redirect and regulate power flow directions across voltage levels, remains insufficiently explored along with its implications for multi-level grid coordination.

The maximum hosting capacity of DPVs, defined as the largest installable capacity without violating operational constraints, is often limited by RPF constraints and local absorption difficulties caused by supply-demand mismatches [5]. As DPV penetration increases, RPF, defined as the export of power from low-voltage feeders to higher-voltage systems, becomes more prevalent. Prior studies have shown that such reverse power can lead to over-voltages at low-voltage nodes, shift transformer operating points away from optimal conditions, and even cause protection malfunctions, all of which compromise system stability [6]. To address these risks, recent works have introduced reverse flow constraints[7] and multi-period voltage safeguards [8] into hosting capacity assessments under typical or stochastic scenarios. Others have explored voltage regulation strategies such as on-load tap changers (OLTCs) and inverter-based support to enhance voltage margins and mitigate reverse flow impacts [9]. However, most of these approaches rely on idealized transformer models and neglect non-ideal characteristics such as internal impedance reflection and voltage ratio deviations under high net injection [10]. This limits their ability to accurately define voltage security boundaries or capture the severity of RPFs. Consequently, the flexibility value of DCs tends to be underestimated, while the hosting capacity of DPVs is overestimated, ultimately compromising secure and stable system operation.

To fill the aforementioned gaps, this study proposes a comprehensive modeling and optimization framework, explicitly incorporating the spatiotemporal flexibility of DCs, for accurately quantifying and enhancing DPV hosting capacity. The main contributions are summarized as follows:

1) Transformer reverse power flow constraints are explicitly modeled. The internal impedance, excitation characteristics, and practical reverse loading limits of distribution transformers are incorporated into hosting capacity assessment. Compared to conventional idealized models, this formulation captures realistic transformer behaviors under reverse flow, providing a more accurate assessment of DPV hosting capacity.

2) An integrated multi-resource optimization framework is developed. Spatial routing capabilities of SOPs, temporal shifting abilities of ESs, and combined spatiotemporal flexibility of DCs are jointly modeled in a unified framework. Explicitly modeling resource interactions and coupling constraints significantly enhances the utilization of network flexibility to increase DPV hosting capacity.

3) The spatiotemporal flexibility of data centers is explicitly quantified. Workload migration constraints, latency tolerances, and redistribution capabilities across spatial nodes are rigorously formulated within the optimization model. Unlike simplified approaches, this model provides a precise quantification of DCs' regulatory capabilities, demonstrating their substantial value in mitigating reverse power flows and improving DPV hosting capacity.

II. PROBLEM DESCRIPTION

To systematically address the limitation of DPV hosting capacity under RPF constraints, this paper proposes an integrated evaluation framework that incorporates the spatiotemporal flexibility of DCs. As illustrated in Fig. 1, the framework aims to enhance DPV hosting capacity by coordinating flexible DC workloads with ESs and SOPs. First, the bidirectional operational behavior of distribution transformers is analyzed, and a quantitative method is developed to characterize their power transfer capability under RPF conditions. Second, a modeling is introduced to capture the spatiotemporal flexibility of DCs, which enables workload scheduling across both time and space. Finally, a hosting capacity evaluation model is constructed by integrating the spatiotemporal flexibility of DCs, in coordination with ESs and SOPs. Their joint operation enables dynamic power balancing, enhances voltage stability, and significantly mitigates RPF events in distribution networks.

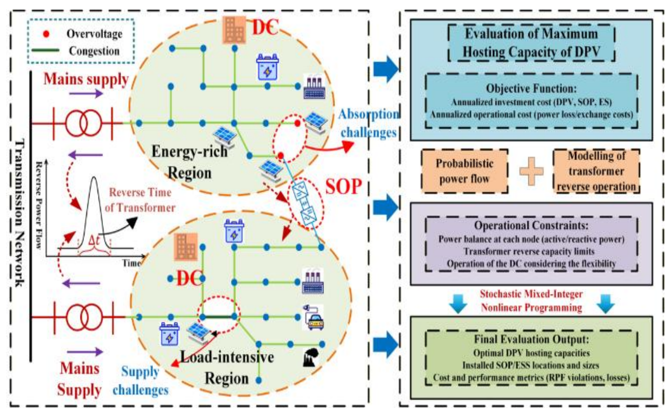

Figure 1. Evaluation framework for determining the maximum hosting capacity of DPVs under RPF constraints

A. *Transformer Modeling with Reverse Power Flow*

In conventional transformer modeling, the primary-to-secondary voltage ratio is typically assumed to be equal to the ideal turns' ratio K, representing a simplified relationship between transmission and distribution voltage levels. However, in practical applications, internal impedance introduces voltage drops that cause deviations from this ideal ratio.

(1) Transformer Voltages under Reverse Power Flow

The transformer's percent impedance $u\%$, typically obtained from factory short-circuit testing, reflects the impact of internal impedance on voltage drop. During step-down operation, with the low-voltage (LV) side shorted, the impedance voltage referred to the high-voltage (HV) side is:

$$u\% = \frac{Z_{T,1}}{Z_{N,1}} = \frac{I_{N,1}(Z_1 + Z_2')}{U_{N,1}} \tag{1}$$

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where $I_{N,1}$ is the rated primary current; $U_{N,1}$ is the rated secondary voltage; $Z_1$and $Z_2'$are the HV side self-impedance and the LV side impedance referred to the HV side, respectively; $Z_{T,1}$ and $Z_{N,1}$ are the total transformer impedance and the total rated impedance referred to the HV side, respectively.

When operating in RPF, current flows from the LV to HV side, and the LV winding becomes the primary. The impedance voltage referred to the LV side becomes:

$$u'\% = \frac{Z_{T,2}}{Z_{N,2}} = \frac{I_{N,2}(Z_1' + Z_2)}{U_{N,2}} = \frac{K^2 I_{N,1}(\frac{Z_1}{K^2} + Z_2)}{U_{N,1}} \tag{2}$$

where $I_{N,2}$ and $U_{N,2}$ are the rated secondary current and rated secondary voltage; Z_1' and Z_2 are the HV side impedance referred to the LV side and the LV side self-impedance; $Z_{T,2}$ and $Z_{N,2}$ are the total transformer impedance and total rated impedance referred to the LV side, respectively.

Since percent impedance is a physical property, it remains constant across forward and reverse modes:

$$u'\% = u\% \tag{3}$$

Accordingly, the voltage relationships under each mode are:

$$KU_2 = U_1(1-u\%) \tag{4}$$

$$U_2' = KU_1'(1-u\%) \tag{5}$$

where U_1 and U_2 are the HV and LV side voltages in step-down operation, and U_1' and U_2' are the LV and HV side voltages in reverse (step-up) operation, respectively.

(2) Transformer Capability under Reverse Power Flow

As discussed above, when a step-down transformer operates in step-up (RPF) mode, the internal impedance drop occurs on the low-voltage winding, which elevates the LV side voltage. The resulting magnetic distortion increases iron and copper losses, accelerates thermal aging, and ultimately shortens transformer lifespan, thereby limiting its allowable reverse loading capacity. Consequently, industry standards define a reverse loading coefficient ε (where $0 < \varepsilon < 1$), stipulating that the reverse loading should not exceed ε.

$$S_{ren} \le \varepsilon S_N \tag{6}$$

where S_N is the rated transformer capacity and S_{ren} is the transformer's RPF transfer capability.

B. Data Center Modelling Considering Spatiotemporal Flexibility

This section introduces a unified modeling framework to quantitatively characterize the spatiotemporal flexibility of DCs, explicitly integrating heterogeneous IT workloads with the operational adaptability of infrastructure-level systems. Each component is modeled with high temporal resolution and constrained by operational flexibility limits that reflect practical system capabilities.

$$\begin{Bmatrix} P_{DC}(P_{d,t}^{IT}, P_{d,t}^{co}, P^{fix}) \\ s.t.\ \ g(M_{d,t,st}, \lambda_{d,t}^{sen,tra}, \lambda_{d,t}^{tol,deal}, O_{d,t}^{in}) \end{Bmatrix} \tag{7}$$

where $P_{DC}(\cdot)$ denotes the total power consumption function of DC d at the time t. Specifically, $P_{d,t}^{IT}$ represents the IT power consumption, while $P_{d,t}^{co}$ and P^{fix} denote the auxiliary power consumption components, such as cooling and power conditioning systems. The function $g(\cdot)$ encapsulates the operational constraints of the DC. $M_{d,t,st}$ indicates the number of active servers of type st in operation. $\lambda_{d,t}^{sen,tra}$ refers to the volume of delay-sensitive workloads migrated from other nodes for processing, and $\lambda_{d,t}^{tol,deal}$ denotes the volume of delay-tolerant workloads that has already been processed. $O_{d,t}^{in}$ represents indoor temperature of the DC.

III. Evaluation of Maximum Hosting Capacity of Distributed Photovoltaics

A. Modelling of Maximum Hosting Capacity of DPV

To facilitate an economic assessment of the proposed planning model, this study formulates an annualized investment cost function that accounts for the capital expenditures associated with SOPs, DPVs, and ESs. The formulation considers the respective service lifetimes and discount rate to convert one-time capital investments into equivalent annual costs. Specifically, the investment cost of each resource is expressed as a function of its unit capital cost and the installed capacity.

$$\begin{cases} \min\ \Theta_{plan}(\Theta_{inv}) \\ s.t.\ n(c(\bullet), S(\bullet),) \le 0 \end{cases} \tag{8}$$

where $\Theta_{plan}(\cdot)$ denotes the function of equipment investment. Θ_{inv} denotes the cost of the equipment to be planned. The function $n(\cdot)$ encapsulates the investment constraints of the equipment including DPVs, ESs and SOPs. $c(\cdot)$ and $S(\cdot)$ denote the unit capacity cost and installed capacity of DPVs, ESs and SOPs.

To comprehensively assess the operational economics of distribution networks, this study incorporates both annual power loss costs and electricity exchange costs with the upstream grid. The former is computed based on nodal power injections and associated system losses, while the latter accounts for the net cost of electricity purchase or sale, depending on the direction of power flow under varying distributed photovoltaic (DPV) generation and load conditions.

$$\begin{cases} \min \Theta_{oper}(\Theta_{loss}, \Theta_{\text{int}}) \\ s.t.\ \ o(P_{i,t}, P_{ij}^{sop,L}, P_{n,t}^{\text{int}}, P_{d,t}^{IT}, P_{d,t}^{co}, P_{ch,t}^{es}, P_{dis,t}^{es}) \le 0 \end{cases} \tag{9}$$

where $\Theta_{oper}(\cdot)$ denotes the function of system operation costs. Θ_{loss} denotes the annual cost of distribution losses. Θ_{int} denotes annual purchase–sale interaction cost. The function $o(\cdot)$ encapsulates the operational constraints of the equipment including DPVs, ESs and SOPs. $P_{n,t}^{int}$ denotes the interchange power between distribution network nand the transmission grid (positive for purchase, negative for sale). $P_{ch,t}^{es}$ and $P_{dis,t}^{es}$ denote

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the charging and discharging of the ES. $P_{ij}^{sop.L}$ denotes the loss of the SOP installed between nodes i and j.

B. Solution Algorithm

The planning model is formulated as a constrained optimization problem that minimizes the total system cost, as outlined in (10). In this formulation, Ξ, and Ψ represent the set of 0-1 variables, and the set of continuous variables, respectively. **m** and **p** represent all the 0-1 variables and continuous variables in the model.

$$\underset{\mathrm{m}\in\Xi,\mathrm{p}\in\Psi}{Min} \quad \Theta = \Theta_{plan} + \Theta_{oper} \tag{10}$$

Subject to (1)-(6), (7), (8), and (9).

Finally, the optimization problem (10) is a Stochastic Mixed-Integer Nonlinear Programming (SMINLP) that can be solved by the Gurobi solver. The solution algorithm is shown in **Algorithm 1**.

Algorithm 1: Coordinated DPV Hosting Capacity Evaluation under RPF Constraints

Initialization:

1. Set network topology and parameters of all resources;
2. Set PV uncertainty parameters (mean μ, standard deviation σ, confidence level η).

Main Loop:

1. **Initialize planning variables and parameters.**
2. **Generate stochastic PV output scenarios using Beta distribution**
   Derive shape parameters Beta (α, β) based on statistical data;
   Generate a scenario set $\{P_{pv}^{s}\}_{s=1}^{S}$ reflecting stochastic outputs.
3. **Apply Point Estimation Method (PEM) to scenario aggregation:**
   Compute power injections P_s based on sampled DPV outputs;
   Assign weights w_s using central moment matching;
   Aggregate stochastic effect into deterministic equivalent.
4. **For each resource in the model (DPV, SOP, ESS, DC):**
   Encode investment variables (binary, continuous);
   Formulate AC power flow or linearized model;
   Include DC operational model:
   Include SOP/ES model;
   Include transformer impedance drop under forward-reverse flow.
5. **Construct objective function:**
   Annualized investment cost (DPV, SOP, ES);
   Annualized operational cost (power loss/exchange costs).
6. **Add constraints:**
   Power balance at each node; Transformer reverse capacity limits;
   Node voltage limits under all scenarios.
7. **Solve SMINLP using business solver.**

Output:

1. Optimal DPV hosting capacities; Installed SOP/ESS locations and sizes; Cost and performance metrics (RPF violations, losses)

IV. Case Studies

To validate the proposed model, two modified IEEE-33 bus distribution systems (DSs) are adopted. Four representative daily profiles are selected to capture seasonal variations in DPV generation and load demand. Each system operates at 12.66 kV and is connected to a 110 kV upstream grid at Bus 1. Candidate locations include 7 DPVs and 7 ESSs per system, with SOPs pre-installed at Bus 12 and Bus 25, respectively, as illustrated in Fig. 2. PV output uncertainty is modeled using a Beta distribution with shape parameters $\alpha = 2.06$ and $\beta = 2.5$. To examine RPF-induced voltage violations, both end-node and mid-feeder buses are selected for DPV siting. Additionally, DCs are incorporated as flexible loads, with computing workloads and thermal parameters configured based on [4]. Server operating frequencies and migration limits are considered to emulate spatiotemporal flexibility.

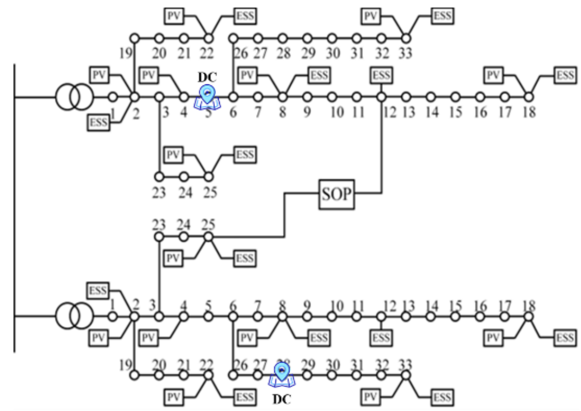

Figure 2. Improving the IEEE-33 node distribution system

A. Results for spatiotemporal flexibility of DCs

To evaluate the contribution of DC flexibility, three configurations are examined across four season-representative days: S1 (SOP+ES+DC), S2 (SOP+ES), and S3 (no flexible resources). Figure 3 summarizes the advantages brought by the spatiotemporal flexibility of DCs. Quantitative results reveal that incorporating DC flexibility in S1 leads to a significant enhancement in the maximum allowable distributed photovoltaic (DPV) hosting capacity, with an 8.51% increase compared to S2. Furthermore, the presence of flexible DC loads results in a 45.53% reduction in the total energy associated with reverse power flow (RPF) events and a 63.16% reduction in the total duration of such events (from 57 to 21 hours across the studied periods). These findings demonstrate that DC flexibility serves as an effective non-wire alternative (NWA) for alleviating local grid stress and enhancing solar absorption.

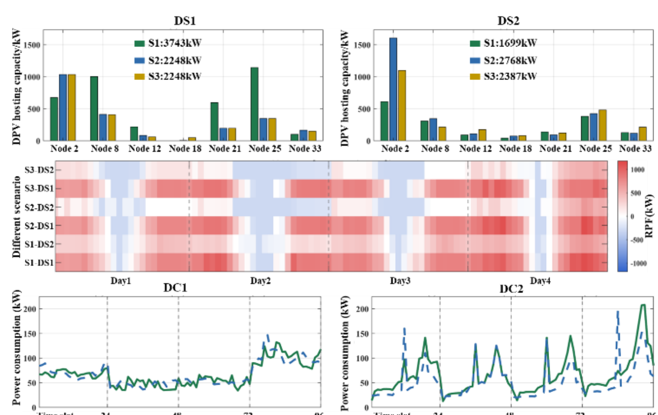

Figure 3. Coordinated flexibility from DCs: hosting capacity gains and reverse power flow mitigation

The observed improvements are primarily driven by the spatiotemporal flexibility of DCs. Temporally, computing workloads can be dynamically scheduled to align with PV generation peaks, which typically occur around midday, thereby reducing net power injection during high-irradiance periods. Spatially, the redistribution of workloads across different nodes enables targeted absorption of locally abundant PV generation, alleviating overvoltage risks and minimizing curtailment. This dual-dimension mechanism fosters coordination between DC management and grid-side flexible assets, enhancing the overall resilience of the distribution network.

B. *Results for different locations of DCs*

To quantitatively assess the influence of spatial siting decisions on grid-interactive data centers, a comparative evaluation was conducted across six node combinations. This analysis aimed to identify optimal siting locations that maximize DPV hosting capacity while minimizing adverse RPF impacts. The results reveal that deploying data centers at nodes 12 and 25, which are each situated at the boundary of distinct load-intensive areas, achieves the most favorable outcomes. Compared to the benchmark combination (nodes 5 and 28), the 12/25 combination increases the DPV hosting capacity by 15.5%, reduces the total RPF electricity by 15.7%, and decreases RPF occurrence frequency by 41.2%.

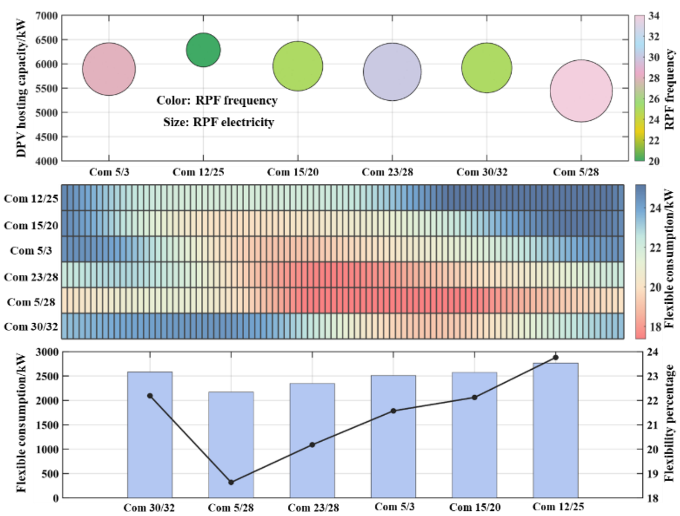

Figure 4. Multi-dimensional evaluation of DC sitting scenarios

In conclusion, the 12/25 siting combination provides superior performance because both nodes maintain electrically neutral voltage conditions arising from their positions between upstream generation corridors and downstream load clusters. This locational characteristic enables the data centers to absorb surplus photovoltaic output during high-irradiance periods while simultaneously buffering load fluctuations, thereby delivering effective spatiotemporal flexibility to the grid. Additionally, this combination leverages the capabilities of SOPs located at the same nodes, facilitating real-time power exchange and voltage regulation across feeders. Overall, the results indicate that the siting of DCs can activate latent flexibility within distribution networks, increase DPV hosting capacity.

V. Conclusion

This research proposes a coordinated framework for evaluating the DPV hosting capacity in low-voltage distribution networks under RPF constraints. By jointly modeling SOPs, ESs, and DCs as flexible resources, the model dynamically reallocates spatiotemporal power imbalances induced by high DPV penetration. Our analysis reveals that incorporating realistic transformer reverse capacity constraints is essential to accurately capture voltage violations caused by RPF. Simulation results show that the proposed strategy significantly enhances hosting capacity and operational resilience. In particular, the participation of DCs reduces the total electricity and frequency of RPF by 45.53% and 63.16%, respectively, and increases DPV hosting capacity by 8.51%. Furthermore, appropriate siting of DCs significantly enhances grid-side flexibility and unlocks greater hosting potential for DPVs.

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During the preparation of this work the authors used ChatGPT4o to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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