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A Full AC Time-Series Analysis of Photovoltaic Hosting Capacity in Niger's Grid

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ABSTRACT

The integration of solar photovoltaic (PV) systems into sub-Saharan African distribution grids presents a transformative opportunity to enhance energy access and sustainability. However, accurately quantifying the hosting capacity (HC), the maximum PV power that can be accommodated without violating operational limits, remains a major challenge under variable generation and demand. This paper presents a full alternating current (AC) time-series analysis of PV HC in Niger's River-Zone (RZ) distribution grid using hourly resolution over a full year. The methodology applies α-scanning to determine the maximum admissible PV scaling factor (α_{max}), constrained by voltage and thermal limits. Detailed grid modeling in Pandapower is coupled with dynamic voltage regulation through multi-step capacitor bank control to capture the benefits of reactive power support. Results showed that HC was a highly time-dependent metric, with significant intra- and inter-day variability shaped by PV availability, load patterns, and grid conditions. The voltage remained within regulatory bounds (0.9–1.05 p.u), and all thermal constraints were met, thus validating the control strategy. Daily HC values frequently approached or surpassed the available PV generation potential, suggesting that the network retained additional margin for further PV integration under existing operating conditions. The calculated penetration ratio reached up to 50% with minimal intraday variability, indicating consistent alignment between PV output and load demand throughout daylight hours. This dynamic framework offers critical insights for planning high-renewable penetration in weak grids. It supports informed investment decisions and provides a replicable, data-driven approach for PV integration across emerging economies.

1 | Introduction

The deployment of grid-connected photovoltaic (PV) capacity has expanded rapidly, growing from less than 50 GW in 2010 to over 1 TW by 2024 [1–3]. This rapid integration is transforming distribution networks from passive, one-way feeders into actively managed, bi-directional systems [4]. Although this shift accelerates decarbonization, high PV penetration can induce voltage challenges, reverse power flow, and thermal overloading, particularly in medium-voltage (MV) feeders that were never designed for large-scale distributed generation [5, 6]. Accurately estimating hosting capacity (HC; i.e., the maximum PV power that can be connected without exceeding operational limits) has therefore become a priority for distribution system operators [7].

Much of the early HC assessments often relied on conservative worst-case snapshots, such as peak-irradiance and minimum load [8, 9]. This approach overlooks the temporal variation in PV output and demand; it often yields results that are either overly conservative or internally inconsistent [10, 11]. More recent efforts have introduced time-series simulations [12], probabilistic methods [13], and advanced grid control, including reactive power support and tap-changing transformer [14]. Yet, few open-source studies provide an integrated, high-fidelity framework that combines (1) full alternating current (AC) power-flow fidelity, (2) hourly resolution over extended horizons, and (3) explicit modeling of advanced grid controls, such as on-load tap changers (OLTCs) or multi-step capacitor banks.

As a result, a research gap remains in the need for transparent, reproducible frameworks that evaluate PV HC, while simultaneously capturing grid dynamics relevant to real-world distribution grid networks, especially in a data-constrained context.

This paper addresses the gap by presenting a comprehensive, fully open-source HC assessment for the River Zone (RZ) MV network, implemented entirely in the Pandapower platform [15]. Key improvements include: (1) a high-fidelity AC model incorporating realistic impedances, transformers, shunt devices, and spatially distributed PV plants; (2) hourly measured time series of load and PV for 1 year, preserving simultaneity between production and demand; (3) an α-scanning algorithm that incrementally scales PV injections until the first violation of voltage (upper and lower) or thermal limit, yielding instantaneous HC metrics; (4) dynamic reactive power support via multi-step capacitor banks controlled by hysteretic-based voltage logic, fully integrated into the power flow simulations; and (5) scenario analysis quantifying the marginal HC benefits from OLTC operation and synchronous generator de-commitment.

The framework is entirely reproducible and provides evidence-based insights for guiding distribution system investment decisions, whether through physical reinforcement or advanced control-based intervention.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature on PV HC assessment and control strategies. Section 3 presents the materials and methods. Section 4 provides the simulation results. Section 5 discusses the key findings considering system flexibility, operational constraints, and planning implications. Finally, Section 6 concludes the paper with practical insights.

2 | Literature Review

Recent studies on PV HC commonly use a static worst-case snapshot approach, typically midday peak irradiance paired with minimum demand [10, 16]. While computationally efficient, this method ignored temporal correlations between PV output, load, and grid control actions, leading to conservative and non-generalized estimates.

Follow-up investigations showed that hourly time-series simulations can reveal up to twice the HC potential compared to snapshot analyses [17, 18]. This recognition led to the adoption of quasi-static time-series (QSTS) simulations, where thousands of sequential power-flow calculations were performed at hourly or sub-hourly intervals. Jain et al. [8] demonstrate that QSTS simulations can yield HC estimates that were 60%–200% higher than those obtained from conventional snapshot methods, thereby exposing the significant underestimation inherent in static approaches. While snapshot analyses offer computational simplicity, Jain et al. emphasize their inability to account for the duration and frequency of the voltage and thermal limit violations, which were essential for accurately assessing the grid's ability to integrate additional PV capacity [10].

To account for the inherent uncertainty in PV generation and load demand, more recent studies have adopted probabilistic and Monte Carlo (MC) frameworks to improve the accuracy of HC assessment. For instance, Ayaz et al. demonstrated how scenario generation and reduction schemes based on MC simulation can effectively capture stochastic variations, enabling distribution networks to accommodate higher PV penetration levels without breaching operational limits [19]. Similarly, Han et al. proposed a two-stage optimization framework that integrates heuristic methods with time-series power flow analysis. These methods incorporated PV output variability into HC evaluations, enhancing probabilistic estimations, thereby offering insight for active network management in an unbalanced distribution system [20].

Parallel research has increasingly focused on mitigation strategies to enhance PV HC. OLTC transformers have been shown to increase HC by 20%–50%, while smart inverters employing volt-var or volt-watt droop control contribute an additional 30%–40%, offering reactive power support and improved voltage regulation. Aydin et al. investigated decentralized OLTC control mechanisms that leverage local measurements to dynamically regulate voltage, integrating MC probabilistic assessment to ensure robust operation without extensive remote monitoring [21]. Complementing this, Hamedi et al. explored dynamic expansion planning models that embed smart inverter-based voltage regulation strategies into low-voltage networks. By utilizing reactive power absorption to mitigate voltage rise at the point of common coupling, their approach yielded a stable grid operation under high PV penetration [22].

Despite these advances, few peer-reviewed studies have applied full AC, hourly QSTS to West African distribution networks. Most utilities in the region rely on a deterministic spreadsheet for interconnection studies. Pilot projects in South Africa, Côte d'Ivoire, and Senegal have shown that time-series assessments are feasible even with limited field data by leveraging satellite-derived irradiance, synthetic load libraries, and open-source tools [23–25]. However, a comprehensive benchmark for PV HC has not yet been established for the Nigerien power system.

3 | Materials and Methods

3.1 | Network Description

This study focuses on the RZ subsystem of Niger's national power grid, encompassing both transmission and MV distribution systems operated by the National Electric Company (NIGELEC). The modeled network captures the complete regional backbone, the main conventional generation facilities, the interconnection with Nigeria, and the local distribution feeders near newly commissioned PV installations. The network architecture is based on the FICHNER single line diagram (Figure 1), updated to reflect the commissioning of major generation assets, including the Gorou Banda (GB) diesel power plant with five units of 20 MW, the Goudel thermal plant with a total capacity of 89 MW, and the newly integrated 30 MW PV

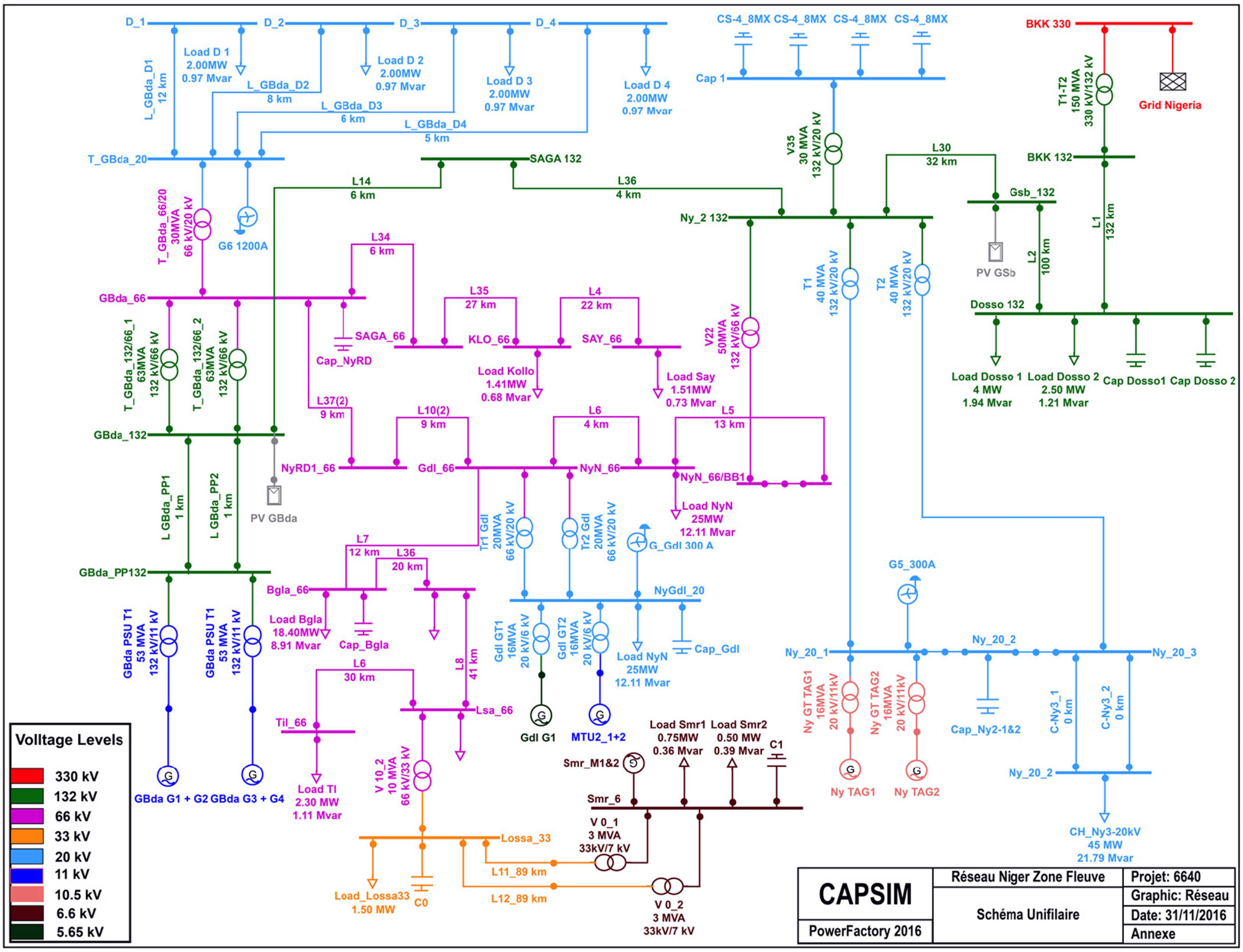

FIGURE 1 | Single-line diagram of the RZ power system.

plant at GB [26]. The simulation model was implemented using the Pandapower [15] platform and incorporates detailed electrical parameters and their configurations from utility planning documents. The network operates across four voltage levels (20, 33, 66, and 132 kV) and integrates critical elements to ensure system reliability, flexibility, and redundancy.

To reflect near-term planning scenarios, planned infrastructure upgrades were incorporated. These scenarios include the (1) construction of a 132 kV double-circuit line for evacuating power from the Kandaji Hydroelectric Station; (2) reinforcement of the Niamey North substation to improve operational reliability; (3) voltage uprating of Goudel-Niamey North line from 66 to 132 kV; and (4) replacement of aging transformers at Niamey II to improve thermal performance and reduce network losses.

3.2 | Time-Series Load and PV Data

The HC simulations rely on hourly profiles of both load demand and PV generation over an entire year (8760 h), covering the full 2024 period. This annual dataset captures seasonal and diurnal variations in both solar resource availability and electricity consumption, thereby providing a comprehensive representation of the operational dynamics of the Nigerien power system. The analysis encompasses both dry and rainy seasons, reflecting distinct climatic influences on PV production and cooling-driven demand patterns.

Load profiles were provided by NIGELEC and were generated from a combination of smart meter records, substation SCADA logs, and synthetic modeling where direct measurement was unavailable. The data were normalized and spatially mapped to feeder buses using smart meter identifiers. Preprocessing steps include spline-based interpolation for missing values and anomaly filtering based on standard deviation thresholds.

Further, PV generation profiles were developed from two sources: (1) for existing PV installations, profiles were based on measured output data supplied by NIGELEC, scaled to the installed capacity and smoothed to account for inverter ramp-rate limitations and (2) for projected PV scenarios, profiles were generated using satellite-derived irradiance data from photovoltaic geographical information system (PVGIS) calibrated against measured production from a local reference plant. All time series were constructed with hourly resolution and synchronized time indices to preserve simultaneity between load demand and PV production. No temporal smoothing was applied beyond inverter response constraints, ensuring that short-term fluctuations and ramp events were retained in the

QSTS simulation. This approach supports realistic evaluation of voltage and thermal limits over extended operational horizons.

3.3 | Methods

To ensure a structured and reproducible approach, the approach was organized into four sequential phases, as illustrated in Figure 2. Phase 1 involves data acquisition and preprocessing, including the collection of load and PV profiles from NIGELEC and PVGIS, as well as grid topology from FICHTER plan, data cleaning, and synchronization of hourly time series. Phase 2 consists of AC network modeling using Pandapower, integrating key components, such as OLTC and multi-step capacitor banks. In Phase 3, α-scanning algorithm was applied to systematically scale PV injections and identify hourly HC limits, while testing mitigation scenarios including OLTC action, capacitor switching, and synchronous generator deactivation. Finally, Phase 4 focused on indicators and visualization of results via time series, histograms, boxplots, and stacked bars for comparison.

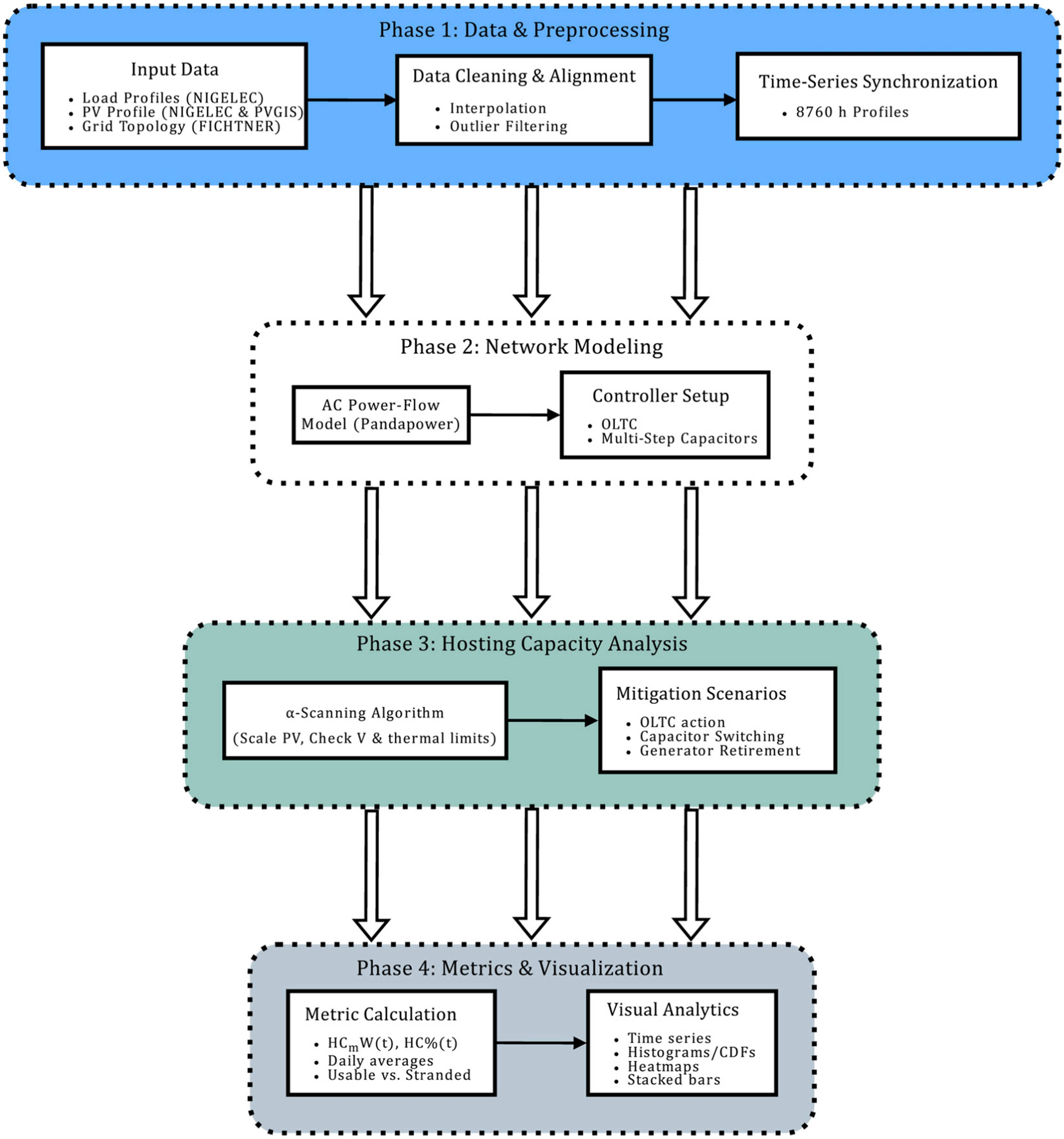

FIGURE 2 | Methodological framework for PV HC assessment.

3.3.1 | Network Modeling Framework

The RZ MV distribution system is modelled with full AC power flow fidelity. Power balance at each bus i is governed by the standard complex nodal equations.

$$P_i + jQ_i = \sum_{j \in N} V_i V_j (G_{ij} - jB_{ij}) e^{j(\theta_i - \theta_j)}. \tag{1}$$

Equation (1) ensures Kirchhoff's current law in its complex form and conserves both active (P) and reactive power (Q) at every node [27, 28]. This equation provides the physical basis for all subsequent HC calculations.

3.3.2 | Time-Series Boundary Conditions

Hourly profiles, as seen in Equation (2), for load $P_{\text{load},i}(t)$ and base PV generation $P_{\text{pv},j}(t)$ were assigned via ConstControl object for all $t \in \{1, ..., 744\}$.

$$P_{\text{load},i}(t), P_{\text{pv},j}(t) \; \forall \; t \in \{1, ..., 8760\}. \tag{2}$$

This time-indexed representation preserves simultaneity between PV output peaks and load throughs, which is essential for assessing voltage rise and other temporal effects.

3.3.3 | α-Scanning Algorithm for Instantaneous HC

To quantify the HC at each time step, a uniform PV scaling factor α was defined. Later, $\alpha_{\max}(t)$ was determined, which satisfies all operational constraints [29], presented in Equation (3).

$$P_{\text{pv},t}^{\text{inj}}(t, \alpha) = \alpha.\, P_{\text{pv},j}(t). \tag{3}$$

The search space for α spanned from 0 to 2 in increments of 0.05. For each hour t, HC is defined as the largest α that does not violate both voltages, $V\,\text{min} \leq V_i(t) \leq V\,\text{max}$, and thermal loading, Loading $(t) \leq 100\%$, limits.

This approach yielded an hourly-resolved, constraint-based HC metric.

3.3.4 | Reactive Power Support Via Multi-Step Capacitors

Voltage regulation is modelled through a dynamic capacitor bank control. Each shunt, Equation (4), comprises m identical steps of Q_{base} Mvar. They are activated by hysteretic control logic as presented in Equation (5).

$$Q_{\text{sh}}(t) = \text{step}(t).\, Q_{\text{base}}, \quad \text{step}(t) \in \{0, 1, ..., m\}. \tag{4}$$

$$\begin{cases} \text{step}(t) + 1 & \text{if } V_i(t) < V_{\text{set}} - \varepsilon \\ \text{step}(t) - 1 & \text{if } V_i(t) < V_{\text{set}} + \varepsilon, \\ \text{step}(t) \text{ otherwise} \end{cases} \tag{5}$$

where ε is the voltage tolerance band (deadband) that determines the switching threshold of the capacitor bank controller.

This control emulates automated capacitor switching in MV networks, enabling local voltage support without requiring operator intervention.

3.3.5 | HC Metrics

To assess the network's ability to accommodate PV generation under varying operating conditions, this study computes several key indicators derived from the hourly values of the PV scaling factor, $\alpha_{\max}(t)$. This factor represents the maximum multiplier of baseline PV injections that can be safely integrated onto the grid without violating voltage or thermal constraints.

Therefore, the first metric, instantaneous HC, is expressed in megawatts (MW) and is calculated by Equation (6) as the product of $\alpha_{\max}(t)$ and the total baseline PV injection at each hour.

$$\text{HC}_{\text{MW}}(t) = \alpha_{\max}(t).\, \sum_j P_{\text{pv},j}(t). \tag{6}$$

This metric represents the maximum amount of PV power (MW) that can be safely injected into the system at a time, considering both network voltage limits and equipment thermal ratings [30, 31].

In addition, Equation (7) helps to compute a penetration ratio by normalizing the HC with respect to the total system load. This dimensionless metric allowed the evaluation of the relative PV hosting potential of the grid under varying demand levels.

$$\text{HC}_{\%}(t) = \frac{\text{HC}_{\text{MW}}(t)}{\sum_i P_{\text{load},i}(t)} \times 100\%. \tag{7}$$

A high penetration ratio indicates the network's ability to accommodate significant PV capacity relative to its demand, which is particularly relevant for planning autonomous or highly renewable systems [32].

Finally, Equation (8) estimates the daily mean HC, which provides a smoothed indicator of PV integration potential.

$$\overline{\text{HC}}_{\text{daily}} = \frac{1}{24} \sum_{h=1}^{24} \text{HC}_{\text{MW}}(d, h). \tag{8}$$

This metric helps identify typical system behavior, filter out short-term variability, and inform decision-making in grid reinforcement planning and investment prioritization [9].

Collectively, these indicators provide both temporal and normalized insights into the network's flexibility in integrating PV under both current conditions and simulated reinforcement scenarios.

3.3.6 | Mitigation Scenarios and Reinforcement Strategies

Three reinforcement scenarios were simulated to assess their impact on HC: (1) OLTC regulation, modelled as a $\pm 10\%$ dynamic voltage swing at the slack bus; (2) reactive power compensation, enabled via the control logic in Equations (4) and (5), and (3) generator retirement, representing the deactivation of synchronous machines under high-renewable penetration scenarios.

The resultant HC is decomposed as follows [33]: Equation (9) estimates the total HC, while Equation (10) calculates the unusable portion.

$$\text{HC}_{\text{total}} = \text{HC}_{\text{installed}} + \text{HC}_{\text{remaining}} + \text{HC}_{\text{OLTC}}. \tag{9}$$

$$HC_{unusabe} = \sum_j P_{pv,j} - HC_{total}. \quad (10)$$

This structure identifies both usable and stranded PV potential, supporting cost-benefit analysis of infrastructure upgrades.

4 | Results

In order to distinguish between the intrinsic HC of the grid and the effects induced by operational interventions, the results are structured around two complementary scenarios. The first scenario represents a baseline case, in which PV integration is evaluated under current grid conditions without active voltage support. The second scenario considers a mitigation case, in which dynamic control of capacitor banks is deployed to ensure reactive power regulation. This scenario-based framework allows for a systematic comparison between the inherent hosting limits of the grid and the extent to which targeted voltage control strategies can increase allowable PV penetration, thus providing a transparent basis for impact assessment.

4.1 | Base Case Scenario: HC Without Active Voltage Control

The baseline scenario reflects the current operational configuration of the grid, in which PV generation is gradually increased using the α-scanning methodology, without the support of any dedicated voltage regulation mechanisms. This scenario serves as a reference for assessing the intrinsic capacity of the grid under current load conditions and taking into account the existing characteristics of the grid.

4.1.1 | Voltage Behavior Under Base Case Conditions

Figure 3 illustrates the voltage distribution recorded across all buses during the α-scanning process. The results reveal a broad dispersion of voltage magnitudes, with a significant share of values falling below the lower regulatory threshold of 0.9 p.u. These undervoltage conditions are particularly pronounced during periods of elevated demand, when reactive power reserves within the network are limited. Such behavior indicates that voltage constraints emerge as the primary limiting factor for additional PV integration in the absence of active control.

The occurrence of deep voltage depressions further suggests that the network operates close to its voltage stability margins under base case conditions. As PV injections increase, the lack of coordinated reactive power support exacerbates voltage sensitivity, thereby reducing the system's ability to accommodate additional distributed generation without violating operational limits.

4.1.2 | HC Under Base Case Conditions

The corresponding α-scanning results are presented in Figure 4, which depicts the admissible PV scaling factor over the simulation horizon. The α_{max} values remain relatively constrained, reflecting the early activation of voltage violations as PV penetration increases. The stepwise progression of the curve highlights the nonlinear relationship between incremental PV injection and network feasibility, whereby modest increases in generation can abruptly trigger unacceptable operating states.

Importantly, these early violations substantially limit the number of time steps during which PV generation can be accommodated. As a result, the network can host admissible PV injection for fewer than 500 PV-active hours over the year, indicating that voltage instability emerges rapidly under baseline operating conditions. This restricted temporal hosting window reveals a fundamental weakness of the grid in its uncontrolled state, as voltage constraints prevent sustained utilization of available solar resources even when thermal margins remain largely unexploited.

These findings demonstrate that, under base case conditions, the network's HC is primarily governed by voltage stability rather than thermal constraints. This structural limitation highlights the need for implementing targeted voltage regulation measures to enhance system robustness. In particular, active voltage support mechanisms are expected to mitigate early constraint activation, stabilize voltage profiles, and thereby extend the number of hours during which PV injection can be accommodated, motivating the evaluation of mitigation strategies in the subsequent scenario.

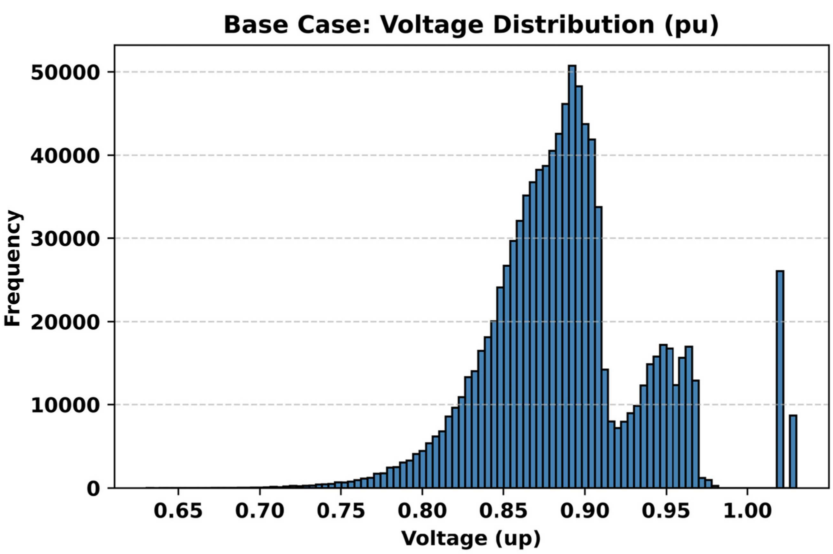

FIGURE 3 | Voltage distribution under base case conditions.

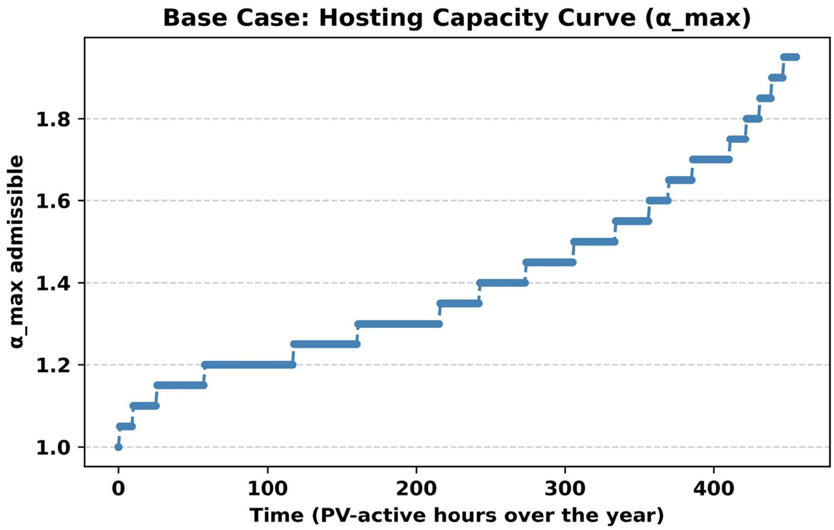

FIGURE 4 | Instantaneous HC curve based on α-scanning under Base case conditions.

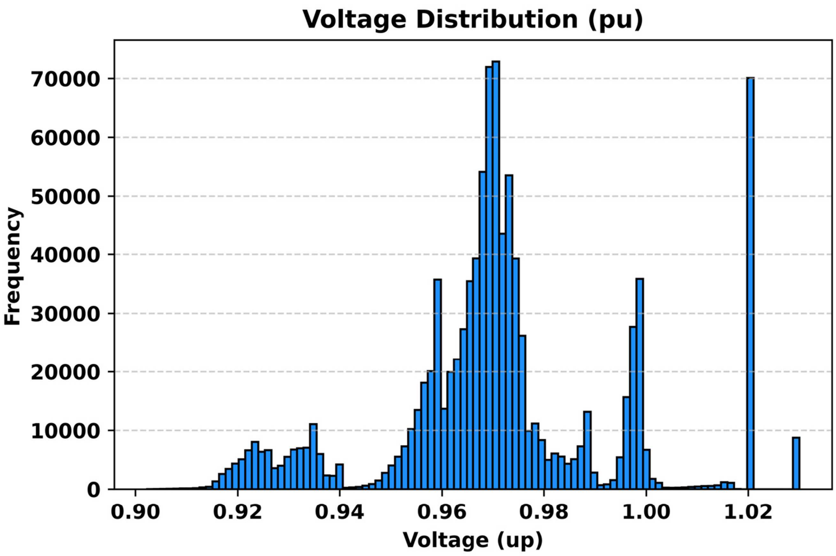

FIGURE 5 | Voltage distribution across all buses during the α_max determination.

4.2 | Mitigation Case: HC With Dynamic Capacitor Bank Control

In the mitigation scenario, multi-step capacitor banks governed by hysteretic voltage control logic are activated to provide localized reactive power support. The purpose of this scenario is not to modify the underlying HC assessment procedure, but rather to quantify how targeted voltage regulation influences the admissible level of PV n integration. By maintaining the same α-scanning framework as in the base case, the incremental impact of the control strategy can be evaluated consistently and transparently.

4.2.1 | Voltage Behavior Under Capacitor Control

Figure 5 presents the voltage distribution observed across all buses and time steps during the HC determination with active capacitor control. Compared to the base case, voltage magnitudes are markedly more concentrated, with values predominantly clustered between 0.94 and 1.00 p.u and a clear peak around 0.97 p.u. Importantly, all voltages remain within the regulatory limits prescribed by the Nigerien grid code. The reduced dispersion and absence of severe undervoltage events demonstrate the effectiveness of reactive power injection from the capacitor banks in stabilizing voltage profiles under varying load and PV conditions. This behavior confirms that the mitigation strategy directly addresses the dominant constraint identified in the base case, namely voltage instability, and establishes a more robust operating envelope for PV integration.

4.2.2 | HC Enhancement Under Mitigation

The α-scanning results obtained under the mitigation scenario are presented in Figure 6. Compared to the base case, the admissible PV scaling factor (α_{max}) exhibits a substantially enlarged feasible domain across the simulation horizon, with higher PV penetration levels tolerated before any operational constraint is reached. This behavior indicates that improved voltage regulation directly translates into enhanced HC.

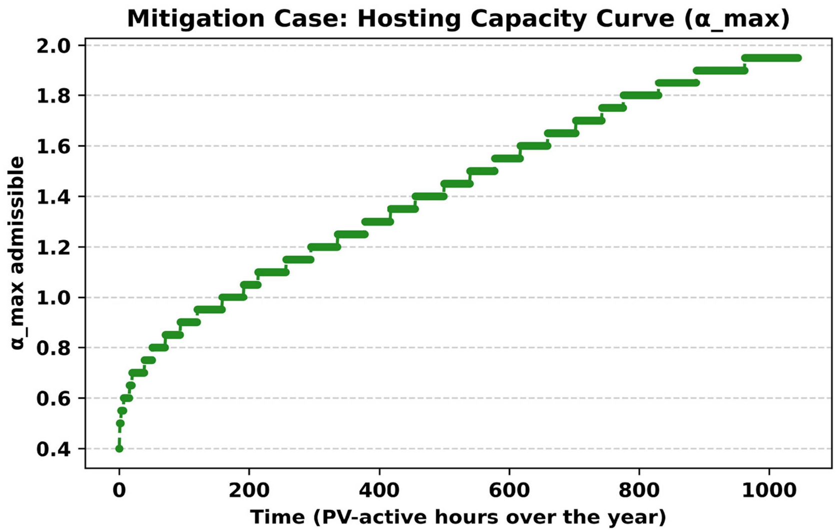

FIGURE 6 | Instantaneous HC curve based on α-scanning.

A notable outcome of the mitigation strategy is the pronounced extension of the temporal window during which PV injection remains admissible. Under uncontrolled conditions, the network accommodated PV generation for fewer than 500 PV-active hours over the year, reflecting early voltage-limit violations. With the activation of multi-step capacitor bank control, this duration increases to more than 1000 h, corresponding to an improvement of over 150% in the number of hours during which PV integration is technically feasible. This increase demonstrates the effectiveness of reactive power support in stabilizing voltage profiles and preventing premature constraint activation.

Importantly, constraint violations under the mitigation scenario remain well defined and occur only at higher α values, confirming that the observed gains in HC are achieved without compromising system security. Rather than masking underlying structural limitations, the voltage control strategy addresses the dominant constraint identified in the base case, thereby expanding the feasible operating region. These results highlight the critical role of targeted voltage regulation in unlocking latent hosting potential and enabling sustained PV integration over a significantly larger portion of the year.

4.2.3 | Thermal Loading Assessment Across Scenarios

Thermal loading of lines and transformers was monitored for both scenarios throughout the HC assessment (Figure 7). Across the full simulation period, loading levels remained predominantly below critical thresholds, with no persistent or systematic overloads observed.

These results indicate that thermal constraints do not constitute the primary limitation for PV integration in the studied network. Instead, voltage stability emerges as the dominant bottleneck. The mitigation strategy indirectly contributes to smoother power flow distribution by stabilizing voltage profiles, thereby reducing the likelihood of localized stress concentration on network assets.

4.2.4 | Temporal Evolution of HC and PV Potential

Figure 8 presents the annual evolution of daily PV potential and HC, supplemented by a 7-day moving average comparison. Both PV potential and HC exhibit clear seasonal patterns; however, HC remains consistently high throughout the year, reflecting strong grid flexibility supported by the capacitor-based voltage regulation scheme. Daily HC values frequently approach or exceed the available PV potential, indicating that the network maintains additional operational margin for further PV integration under the existing configuration.

The 7-day mean curves in Panel (c) show that HC generally follows the seasonal trend of PV availability while remaining above it during extended periods, highlighting unused hosting capability. These results confirm that HC is time-dependent and is shaped jointly by load levels, voltage conditions, and reactive power support. This analysis demonstrates that the system can reliably accommodate substantial PV penetration without violating technical limits, and that the current control strategy ensures stable PV-load alignment throughout daylight hours.

4.2.5 | Temporal and Intra-Day Variability of PV Hosting Penetration Ratio

Figure 9 illustrates the evolution of the daily mean PV hosting penetration ratio throughout the year, accompanied by a 7-day moving average that helps mitigate short-term variability. The penetration ratio remains predominantly within the 35%–55% range across most of the year, indicating that a substantial share of daily electricity demand can be supplied by admissible PV injections under α_{max} conditions. Although short-term fluctuations are evident, the smoothed trajectory reveals extended periods during which penetration levels remain consistently above 45%. This behavior reflects a sustained alignment between HC and load demand under varying operating conditions. Toward the end of the year, a gradual reduction in penetration is observed, consistent with seasonal changes that affect both PV availability and demand profiles. Overall, the annual trend confirms that the network can support moderate to high PV contributions over long time horizons, while maintaining compliance with voltage and thermal constraints.

Complementary insight is provided by Figure 10, which summarizes the monthly distribution of the penetration ratio and highlights seasonal patterns in hosting performance. Median

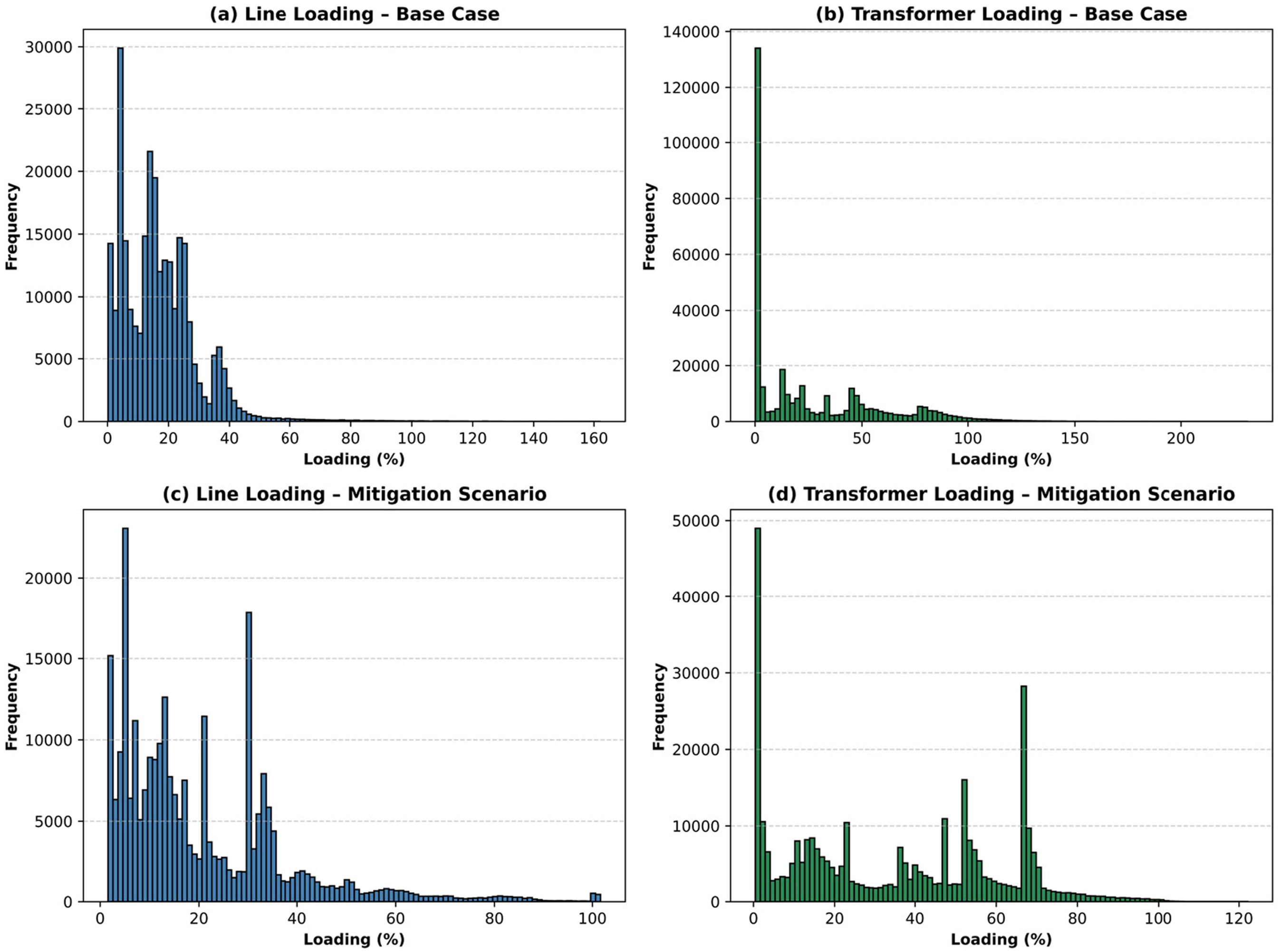

FIGURE 7 | Distribution of line and transformer loading rates across scenarios.

values remain high from March through November, typically ranging between 45% and 55%, underscoring the network's ability to sustain elevated PV penetration during most of the year. During these months, the interquartile ranges are relatively narrow, indicating stable intra-day behavior and limited sensitivity to short-term variations in PV output or load demand. In contrast, January, February, and December exhibit lower medians and broader spreads, reflecting more variable operating conditions during periods of reduced solar resource availability. While isolated outliers appear in several months, they represent infrequent operating states and do not alter the overall distribution. Taken together, the monthly statistics demonstrate that the network maintains robust hosting performance across seasons, while capturing the influence of seasonal PV load interactions on the system's hosting flexibility.

5 | Discussions

This study provides an expanded, year-round evaluation of PV HC in a weakly meshed sub-Saharan distribution grid using a full AC, α-scanning time-series approach. The scenario-based results confirm that HC is a fundamentally dynamic attribute of the network, driven by the interplay between solar intermittency, seasonal load variability, and voltage-thermal operating constraints. In the base case scenario, the instantaneous HC curve based on α-scanning factor is intrinsically limited by voltage stability, particularly during periods of high load and reduced reactive power availability. This behavior aligns with a growing body of literature demonstrating that hosting limits cannot be reliably captured through static snapshot analyses, as temporal correlations between PV output, load behavior, and network conditions generate highly nonlinear system responses [10, 17].

The mitigation scenario further demonstrates that the integration of multi-step capacitor banks can substantially enhance the admissible HC beyond the intrinsic limits identified in the base case. The hysteretic control of these capacitors enabled sustained compliance with voltage limits across the full annual horizon, even during periods of elevated solar injection. These findings are consistent with earlier studies highlighting the effectiveness of decentralized reactive power support in mitigating voltage rise and improving PV hosting potential in distribution networks [34, 35]. Importantly, the simulations reveal that capacitor-based voltage regulation not only stabilizes voltage magnitudes but also contributes to smoother power flow distribution, with line and transformer loadings remaining well below thermal limits throughout most of the year. This observation supports prior evidence that coordinated voltage support can alleviate localized stress and extend asset utilization without immediate physical reinforcements [36, 37].

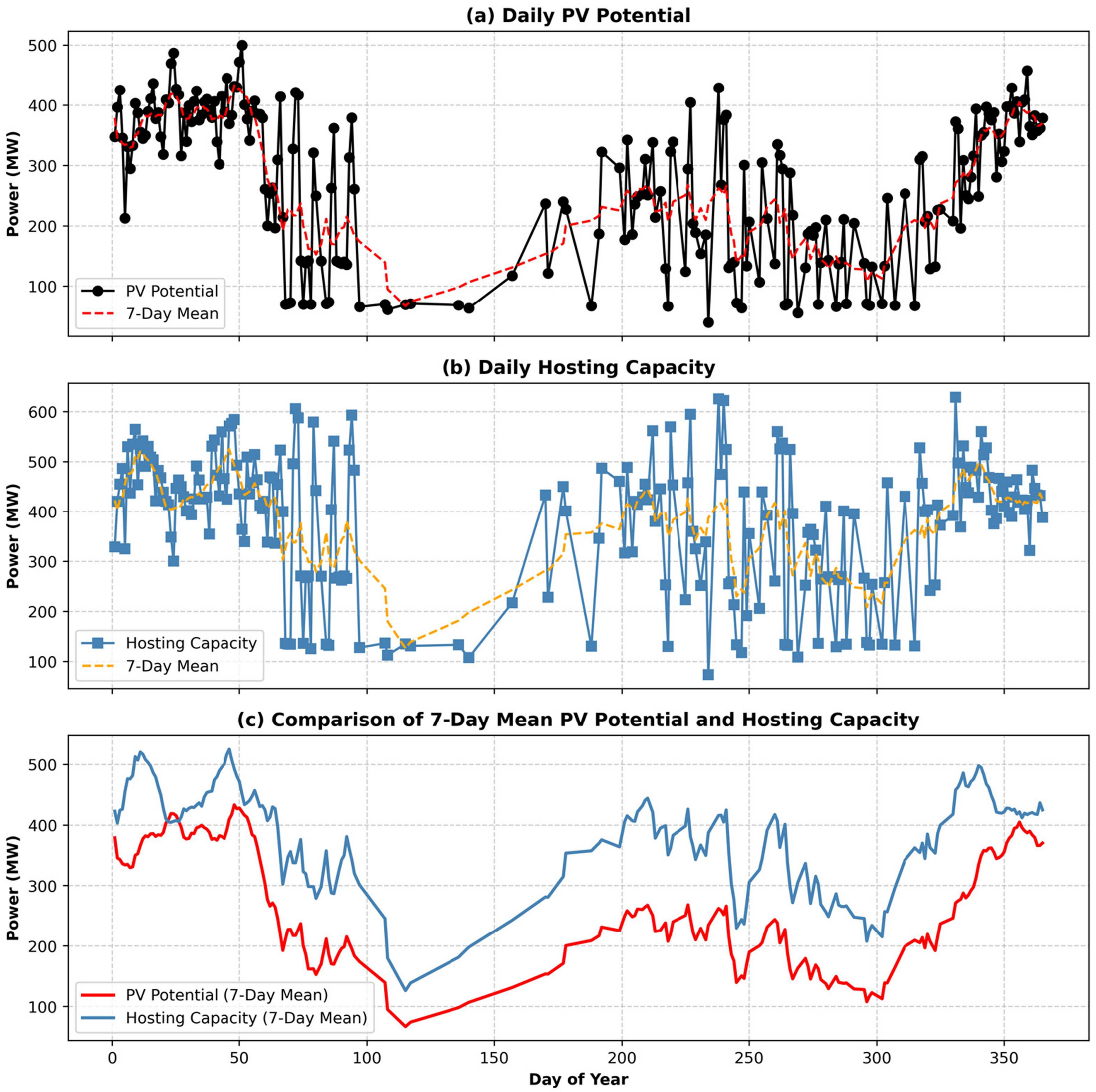

FIGURE 8 | Temporal evolution of daily PV potential and corresponding HC.

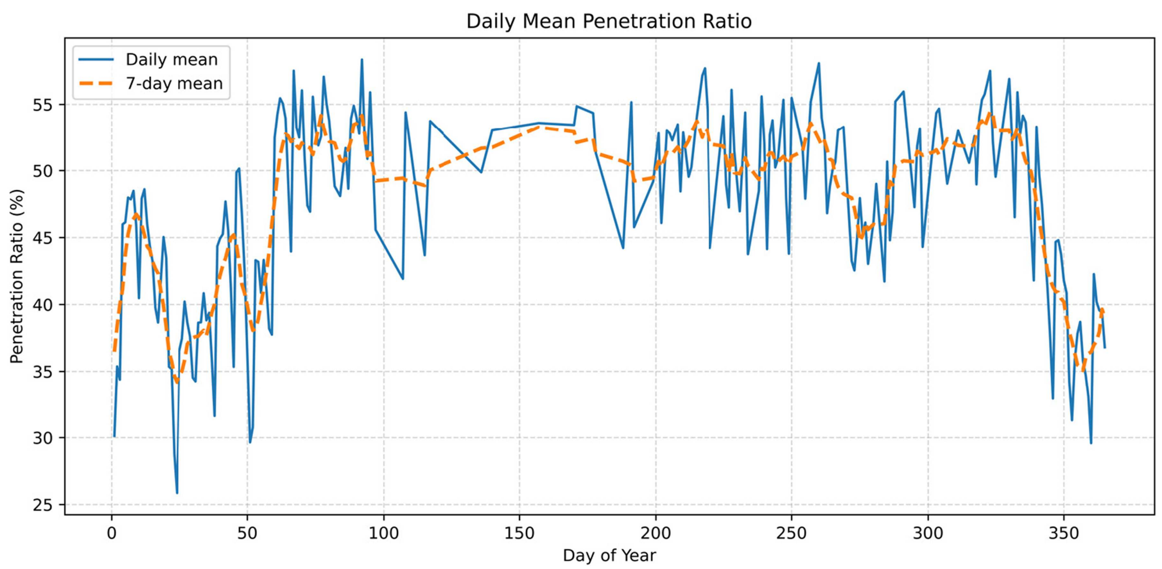

FIGURE 9 | Daily evolution of the PV hosting penetration ratio.

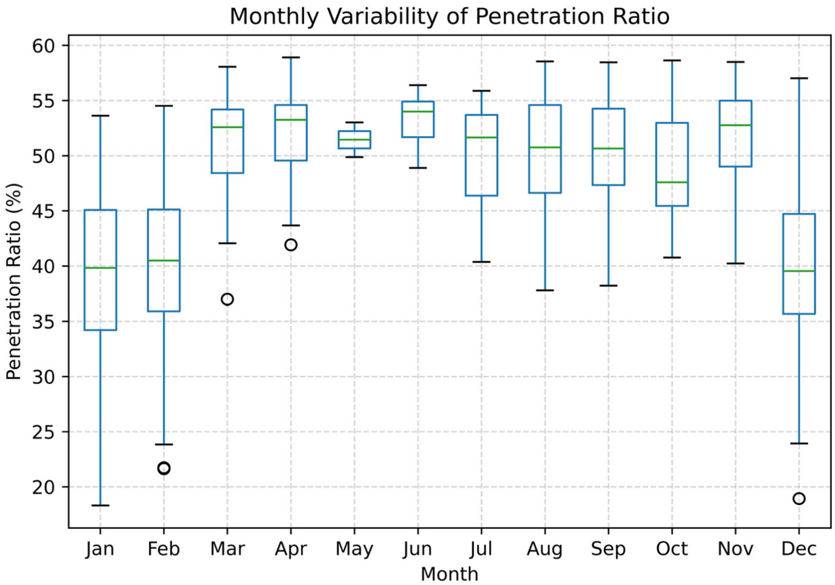

FIGURE 10 | Monthly variability of the PV hosting penetration ratio.

A critical insight emerging is the asymmetric relationship between PV availability and HC under voltage-controlled operation. During several periods, particularly in shoulder-season months, the HC exceeded the available PV potential, indicating latent grid flexibility that remains inaccessible in the uncontrolled base case. This observation corroborates findings by Fatima et al. [38], who reported that hosting limits are often governed more by grid structure and control capability than by solar resource availability alone. Conversely, certain high-irradiance periods exhibited constrained HC despite favorable PV conditions, reflecting localized voltage sensitivities and temporal misalignments between generation and demand. These contrasting behaviors emphasize the importance of identifying not only average hosting limits but also specific operating conditions under which structural constraints become binding.

The penetration ratio analysis further enriches this interpretation by linking HC to system demand coverage. Daily penetration ratios frequently reached values between 40% and 55%, with stable 7-day moving averages indicating persistent alignment between admissible PV injection and load demand over much of the year. This temporal stability reflects the effectiveness of voltage regulation in maintaining operational margins and supports previous studies showing that reactive power coordination reduces reverse power flow stress and limits curtailment requirements [39, 40]. Nonetheless, seasonal reductions in penetration ratio during periods of lower solar availability reveal inherent limitations of PV-dominated systems and reinforce the need for complementary flexibility resources, such as energy storage or demand-side management, as emphasized in recent probabilistic HC studies [19, 20].

Despite its methodological rigor, this study also highlights broader gaps in HC research, particularly within African power systems. While probabilistic and high-fidelity HC methodologies are increasingly documented in the literature, their application remains limited in regions characterized by data scarcity and constrained planning tools. The present full-year, control-aware analysis contributes a rare benchmark for the Nigerien grid, addressing the documented absence of comprehensive HC studies for West African networks [25, 41]. Nevertheless, further advances will require the integration of multi-year climatic variability, probabilistic uncertainty treatment, and evolving regulatory considerations to fully capture long-term system resilience.

Overall, the findings confirm that HC is not an intrinsic, static property of the network, but an emergent and time-dependent outcome shaped by seasonal resource patterns, grid operating conditions, and the effectiveness of voltage regulation strategies. By clearly separating intrinsic hosting limits from mitigation-induced enhancements, this study provides actionable insights for utilities seeking to scale solar PV integration without premature investment in costly reinforcements. The results reinforce the importance of adopting dynamic, data-driven HC methodologies grounded in verifiable power system physics to support Africa's energy transition, while balancing reliability, affordability, and sustainability.

6 | Conclusion

This study demonstrates the critical importance of adopting a time-resolved, α-scanning-based framework for evaluating PV HC capacity in MV distribution systems. The analysis reveals the fundamentally non-static and highly variable nature of HC. Unlike conventional snapshot-based approaches, the proposed methodology captures the coupled influence of PV generation variability, load dynamics, voltage constraints, and thermal operating limits across a wide range of operating conditions. The results show that HC frequently approaches or exceeds available PV generation, indicating latent grid flexibility, while also identifying specific periods of reduced admissibility associated with localized voltage sensitivity and structural constraints.

Across the annual horizon, voltage magnitudes remained within regulatory limits under the mitigation scenario, confirming the technical effectiveness of localized reactive power support. In parallel, the loading profiles of lines and transformers exhibited substantial thermal headroom, with no sustained congestion observed, indicating that existing infrastructure, when supported by appropriate voltage regulation can accommodate higher levels of PV integration without compromising network security. The penetration ratio analysis, evaluated on a daily and seasonal basis, further provides operationally meaningful indicators of the system's ability to supply demand with PV generation, reinforcing the grid's readiness for sustained distributed solar deployment.

Collectively, these findings underscore the need for utilities and planners to move beyond static capacity estimates toward dynamic, scenario-based HC frameworks that explicitly account for temporal variability and control interactions. Such an approach is essential not only for maximizing renewable energy integration but also for deferring costly grid reinforcements through more effective utilization of existing assets, particularly in resource-constrained power systems.

Author Contributions

Hamza Abarchi Halarou: conceptualization, data curation, formal analysis, methodology, software, visualization, writing – original draft. **Yacouba Moumouni:** supervision, validation, writing – review and editing. **Bonkaney Abdou Latif:** methodology, software, writing – review and editing. **Abdoulaye Moussa Falmata:** writing – review and editing. **Amadou Oumarou Fati:** writing – review and editing. **Madougou Saidou:** resources, supervision, validation.

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Data Availability Statement

All Datasets generated and analyzed in this study are available upon reasonable request, except for the hourly input-load data.

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