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Probabilistic and Time-Series Analysis of the Combined Impact of Electric Vehicles and Photovoltaic Systems on Voltage Profiles in a Real Low-Voltage Distribution Network

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Abstract. The increasing integration of electric vehicles and photovoltaic systems significantly affects voltage conditions in low-voltage distribution networks. This paper presents a probabilistic assessment of their impact on voltage profiles in a real low-voltage feeder. A Monte Carlo-based framework is employed to progressively allocate electric vehicle chargers and photovoltaic systems across network nodes and to quantify the probability of voltage violations under critical operating conditions, including peak load and maximum solar radiation. Based on a predefined probability threshold, representative integration levels are selected for detailed weekly time-series simulations. The results indicate that moderate integration levels remain within acceptable limits, whereas higher deployment of electric vehicles and photovoltaic systems substantially increases the risk of undervoltage and overvoltage, particularly at electrically distant nodes. Furthermore, the temporal distribution of electric vehicle charging is shown to significantly influence voltage performance, with regulated charging strategies mitigating critical voltage deviations. The findings highlight the importance of combining probabilistic and time-series analyses for hosting capacity assessment and provide practical insight into integration limits and operational measures in real low-voltage networks.

Key words. photovoltaic systems, electric vehicles, distribution networks, voltage profiles, Monte Carlo simulation.

1. Introduction

The rapid integration of photovoltaic (PV) systems and electric vehicles (EVs) into low-voltage (LV) distribution networks is significantly transforming their operational characteristics. Traditionally designed for unidirectional power flow, LV networks are increasingly exposed to bidirectional flows, voltage fluctuations, and altered load patterns. These developments require advanced analytical tools to assess the impact of distributed energy resources and flexible demand on network performance. One of the central challenges in this context is the concept of hosting capacity, defined as the maximum level of technology integration that can be accommodated without violating operational constraints. Hosting capacity has been widely investigated in relation to PV systems, and its relevance is expanding to other low-carbon technologies such as EVs and distributed storage [1-3].

Monte Carlo methods are widely applied in hosting capacity assessments to capture uncertainties related to spatial allocation, load variability, and renewable generation. Several studies employ Monte Carlo-based probabilistic power flow simulations to evaluate PV hosting capacity under randomised load and generation conditions [4, 5]. The Monte Carlo approach has also been extended to multi-technology scenarios. For example, probabilistic power flow calculations have been conducted to analyse the combined impact of PV systems, heat pumps and/or EV charging over representative periods throughout a year [1, 2]. In the context of EV integration, Monte Carlo simulations are frequently used to represent the uncertainty of charging behaviour [6, 7].

Historically, LV distribution grids were modelled as passive systems with limited analytical attention. In large-scale studies, LV networks were frequently represented as aggregated loads connected to the secondary side of a transformer, while detailed topology and phase asymmetries were neglected [4, 8-10]. However, with the increasing integration of distributed generation and flexible loads, detailed LV modelling has become essential for accurate voltage assessment.

Although numerous studies address PV integration or EV charging individually, fewer investigations systematically analyse their combined impact in real LV feeders using both probabilistic and time-series approaches within the same modelling framework. There is a need to quantify how spatial allocation and temporal operation jointly influence voltage violations in practical networks. This paper addresses this gap by presenting a probabilistic Monte Carlo assessment of EV and PV integration in a real LV feeder, followed by detailed weekly time-series simulations at representative integration thresholds. The study evaluates voltage behaviour at the electrically most critical node and examines the effect of regulated EV charging on mitigating voltage deviations.

The remainder of the paper is structured as follows. Section 2 describes the case study network and the input datasets used in the analysis. Section 3 presents the simulation methodology, including the Monte Carlo framework and the weekly time-series approach. Section 4 discusses the results of the probabilistic and temporal analyses. Finally, Section 5 summarises the main conclusions and outlines directions for future work.

2. Case study and input data

This section presents the case study network and the input datasets used for the analysis. The description includes the topology and technical characteristics of the selected LV feeder, as well as the load, solar radiation, EV charging, and PV generation profiles applied in the simulations.

A. Description of the real low-voltage network

A single feeder of an LV distribution network is selected as the case study. The network is supplied by a 250 kVA, 20/0.4 kV Dy5 distribution transformer, which feeds a total of seven LV feeders. The analysed feeder operates as a radial three-phase network and supplies 36 residential consumers, three of which are already equipped with PV systems in operation [11].

For detailed voltage analysis, one representative node was selected. It is located at the end of the feeder and represents the electrically most distant node from the transformer. A total of 13 households are connected upstream of this node, and the cumulative cable length between the transformer and the selected node is 498 m. Due to its electrical distance and the accumulated line impedance, this node is expected to exhibit the most pronounced voltage deviations under both high load and high generation conditions.

In radial LV networks, voltage deviations typically increase with electrical distance from the transformer, making end-of-feeder nodes the most critical locations for both undervoltage and overvoltage phenomena. Therefore, analysing the most distant node provides a conservative estimate of network performance. If voltage limits are respected at this critical point, they are expected to be satisfied at all upstream nodes. This approach significantly reduces computational complexity while preserving the reliability of the assessment.

B. Household load profiles

To enhance the accuracy of the simulations, each consumer is assigned its actual electrical energy consumption profile obtained from the local distribution network operator (DNO) [11]. For households with existing PV systems, the measured power export to the grid is also included in the dataset.

The time-series data were recorded over a one-year period with a 15-minute temporal resolution, corresponding to the highest available measurement granularity. For this study, a representative spring week is selected for detailed analysis. This period reflects realistic operating conditions characterized by moderate demand levels and significant solar generation potential, making it suitable for evaluating the combined impact of EV charging and PV generation.

It should be noted that the use of a single representative week does not capture seasonal variations in load demand and PV generation. Winter conditions may lead to higher loading and increased risk of undervoltage, while summer periods may result in more pronounced overvoltage due to higher PV output. However, the selected spring week represents a balanced operating condition in which both effects may occur simultaneously, making it a suitable basis for assessing the interaction between EV charging and PV generation. Therefore, the presented results should be interpreted as indicative of typical operating conditions rather than absolute worst-case scenarios over the entire year.

Figure 1(a) presents the aggregated load profile of the analysed feeder during the selected week. The time interval corresponding to the maximum aggregated demand is later used to represent the critical operating condition for undervoltage assessment.

As only active power measurements are available for residential consumers, all loads are modelled with a unity power factor. This assumption is consistent with the available data and simplifies the subsequent power flow calculations.

In practice, residential loads may exhibit a power factor slightly below unity due to the presence of inductive appliances. Including reactive power consumption would increase line currents and consequently lead to larger voltage drops along the feeder. Therefore, the unity power factor assumption may result in a slight underestimation of undervoltage severity. However, for LV residential networks, power factors are typically close to unity, and the impact on voltage profiles is generally limited. Moreover, since the same assumption is applied consistently across all analysed scenarios, the comparative results and conclusions regarding hosting capacity remain valid.

C. Solar radiation data

The objective of the analysis is to evaluate voltage conditions under realistic yet technically demanding operating scenarios. Solar radiation data corresponding to the same representative spring week are therefore used to determine PV generation. The meteorological dataset [12] includes global horizontal and diffuse solar radiation with a temporal resolution of 15 minutes, matching the resolution of the load measurements.

Figure 1(b) illustrates the global and diffuse solar radiation profiles for the selected week. Within the selected week, the time interval with the highest recorded global solar radiation is identified to represent the critical condition for overvoltage assessment.

D. Electric vehicle charging profiles

EV charging profiles are based on real measurement data obtained from a residential charging station. Power measurements were conducted with a temporal resolution of 15 minutes, consistent with the resolution of the load and solar radiation datasets used in this study.

The charging station has a nominal power rating of 22 kW, while the connected electric vehicle is limited to a maximum charging power of 11 kW. Two charging modes were identified: a higher-power mode (“fast”) and a lower-power mode (“eco”). In practice, the average charging power during high-power sessions was approximately 8 kW, whereas low-power charging sessions exhibited average values around 4 kW.

It should be noted that the charging behaviour of EV users can vary significantly depending on driving patterns, arrival times, and user preferences. The use of data from a single charging station therefore represents a simplification of real-world variability. However, the selected dataset captures typical residential charging characteristics, including variability in charging power and duration. The adopted charging profiles were developed and analysed in detail in a previous paper by the authors [13].

E. Photovoltaic generation profiles

PV systems to be integrated into the network are modelled to simulate electrical energy generation based on the solar radiation data described in Section 2.C. The recorded global and diffuse radiation values are used to determine the available solar input during the selected representative week.

For each household, PV generation is calculated individually, considering the specific installation parameters, including roof orientation, tilt angle, and available roof surface area. The installed capacity of each potential PV system is defined accordingly. The resulting output power at each time step is proportional to solar radiation and the installed capacity of the respective system.

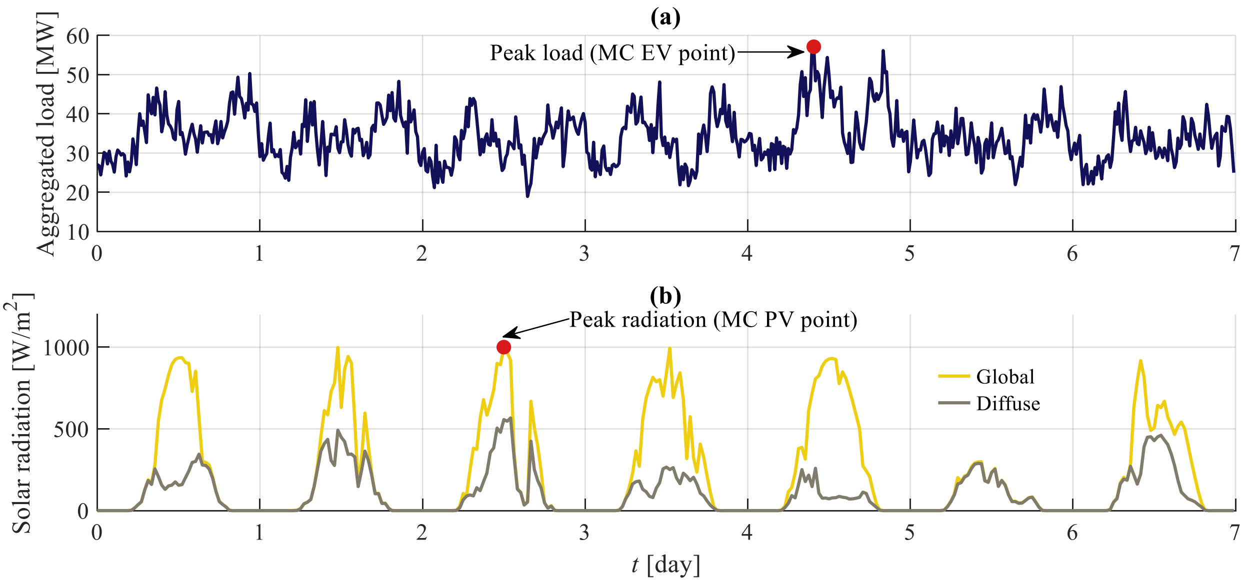

Fig. 1. (a) Aggregated feeder load profile and (b) global and diffuse solar radiation during the representative week.

3. Simulation methodology

This section describes the simulation framework used to evaluate voltage conditions under increasing integration of EV and PV systems. All power flow calculations were performed using MATLAB/Simulink.

Two complementary approaches are employed. First, a Monte Carlo-based probabilistic framework is used to assess the likelihood of voltage violations under randomly allocated EV and PV installations. Second, a deterministic weekly time-series simulation is conducted to evaluate voltage behaviour over the entire representative week. The methodology for both approaches is detailed in the following subsections.

A. Definition of integration levels

The integration level is defined as the number of households equipped with additional EV charging stations or PV systems within the analysed feeder of 36 residential consumers. For EV, the integration process starts from the baseline case with no EV chargers installed and increases progressively by adding one EV charging unit at a time to randomly selected households. For PV systems, the baseline case includes the three existing PV installations mentioned in Section 2.A. The integration level is then increased by successively adding one additional PV system per step to households not yet equipped with PV generation.

B. Monte Carlo simulation framework

A Monte Carlo approach is applied to account for the stochastic spatial allocation of EV chargers and PV systems within the feeder. For each integration level, the required number of devices is randomly assigned to eligible households, and a quasi steady-state simulation is performed under the selected critical operating condition (peak load for EV integration and maximum solar radiation for PV integration), see Figure 1.

For each case, 30 iterations are carried out using different random allocations. Voltage magnitude is evaluated at the selected node, representing the most critical location in the feeder. A voltage violation is recorded if the voltage exceeds the prescribed limits.

The probability of voltage violations is calculated as the ratio of violating cases to the total number of iterations. Based on this probability curve, the integration level corresponding to a 30 % violation probability is identified and used as the reference configuration for subsequent weekly time-series simulations.

C. Weekly time-series analysis

Following the probabilistic assessment, a deterministic weekly time-series simulation is performed to analyse voltage behaviour over the entire representative week. The simulations are carried out with a 15-minute temporal resolution, consistent with the load and solar radiation datasets. For each time step, a quasi steady-state simulation is performed, and the voltage magnitude at the selected node is evaluated.

The weekly analysis includes multiple scenarios: a baseline case without additional EV chargers or PV systems, an EV-only integration scenario, a PV-only integration scenario, and combined EV-PV integration scenario. The number of installed devices in each case is selected based on the probabilistic threshold identified in the Monte Carlo analysis.

D. Voltage evaluation criteria

Voltage magnitude is evaluated with respect to the statutory limits defined for LV networks. The nominal phase-to-neutral voltage is 230 V, and the allowable operating range is ±10 % of the nominal value.

In the Monte Carlo analysis, a violation is recorded for a given iteration if the voltage magnitude at the selected node exceeds the prescribed limits. In the weekly time-series analysis, violations are evaluated at each 15-minute time step, allowing both the occurrence and duration of voltage deviations to be assessed.

4. Results

A. Monte Carlo simulation results

The results of the Monte Carlo analysis are presented in Figure 2, which illustrates the probability of voltage violations at the selected node as a function of the integration level for EV chargers and PV systems.

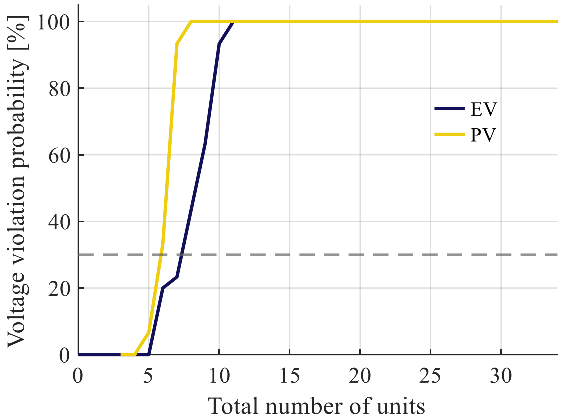

Fig. 2. Probability of voltage violations at the selected node as a function of the total number of installed units.

For EV integration, the probability of undervoltage increases progressively with the number of installed charging units. At lower integration levels, voltage deviations remain within the prescribed limits for most spatial allocations. However, beyond a certain number of EV installations, the probability of violations rises more rapidly, reflecting the cumulative impact of increased loading at electrically distant locations. In contrast, PV integration primarily leads to overvoltage conditions during periods of high solar radiation. The probability curve for PV systems exhibits a similar increasing trend with the number of installed systems.

The stochastic allocation of devices results in a non-linear increase in violation probability, highlighting the sensitivity of the feeder to the spatial placement of distributed technologies. This confirms that voltage performance cannot be assessed solely based on the total number of installed units, but must also consider their location within the network.

The integration level corresponding to a 30 % probability of voltage violations is indicated in Figure 2 and adopted as the critical threshold for further analysis. The 30 % threshold corresponds to 8 EV chargers and 6 PV systems. The respective numbers of installed units at this probability level are selected as representative configurations for the subsequent weekly time-series simulations. This approach ensures that the detailed temporal analysis focuses on scenarios that are probabilistically relevant and close to the operational limits of the feeder.

To address the adequacy of the number of Monte Carlo simulations, a convergence analysis was performed for the selected integration levels (8 EV chargers and 6 PV systems). The results are presented in Figure 3, where the probability of voltage violations is shown as a function of the number of evaluated scenarios.

The results indicate that the Monte Carlo estimate converges rapidly, with the probability stabilizing after approximately 30-50 scenarios for both EV and PV cases. The final estimates obtained with 100 scenarios exhibit only minor variations, confirming that the statistical uncertainty is sufficiently low. This demonstrates that the use of 30 scenarios in the initial analysis provides a reasonable approximation of the violation probability, while higher sample sizes further improve robustness without significantly altering the results.

Therefore, the convergence analysis validates the use of a limited number of Monte Carlo iterations for the assessment of voltage violations, while confirming that the selected integration levels remain close to the defined 30 % threshold.

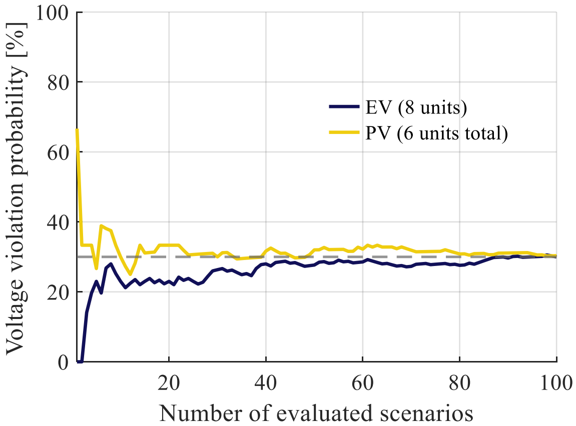

Fig. 3. Convergence of voltage violation probability at the selected node as a function of the number of evaluated scenarios for the selected number of EV and PV units.

B. Weekly voltage behaviour

Figure 4 presents the weekly voltage profiles at the selected node for the different integration scenarios. In Figure 4(a), the baseline case is compared with EV-only and PV-only integration at the Monte Carlo threshold levels. In the EV-only scenario, charging is assumed to occur during typical evening hours, when residential demand is already elevated. Consequently, pronounced voltage drops are observed during these periods, particularly between approximately 17:00 and 23:00. The voltage frequently approaches the lower statutory limit, reflecting the cumulative impact of coincident residential load and EV charging at the electrically most distant node.

In contrast, the PV-only scenario results in elevated voltage levels during daytime hours, with noticeable peaks around midday corresponding to maximum solar radiation. These overvoltage tendencies occur during periods of reduced residential demand, emphasizing the reverse power flow effect associated with distributed generation.

Figure 4(b) illustrates the combined EV and PV scenario with regulated (time-shifted) charging. In this case, EV charging hours are redistributed to reduce simultaneous loading during peak demand periods. As a result, the severe evening voltage drops observed in the EV-only case are mitigated. Furthermore, partial overlap between EV charging and daytime PV generation contributes to a more balanced voltage profile. The combined effect reduces extreme deviations and improves overall voltage stability. These results demonstrate that, beyond the integration level itself, the temporal distribution of EV charging plays a critical role in determining voltage performance in LV networks.

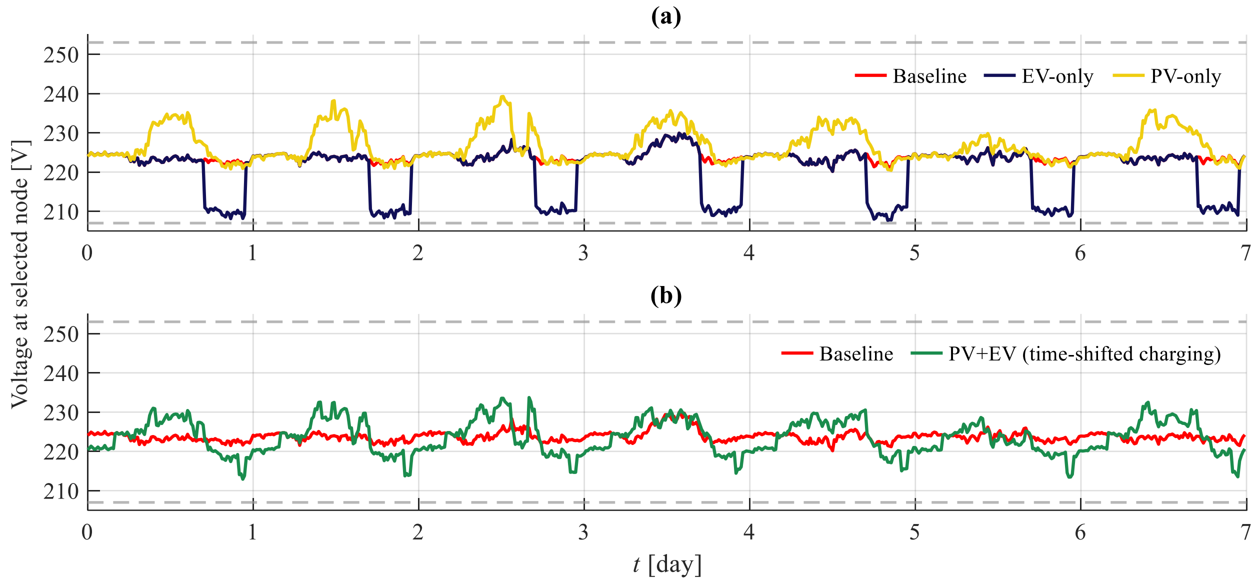

Fig. 4. Weekly voltage profile at selected node. (a) Baseline, EV-only and PV-only scenarios. (b) Baseline and PV+EV with time-shifted charging.

5. Conclusion

This paper presented a probabilistic and time-series assessment of voltage behaviour in a real LV distribution feeder under increasing integration of EV and PV systems. A Monte Carlo framework was used to evaluate the probability of voltage violations as a function of the number and spatial allocation of installed devices. Based on a 30 % probability threshold, representative integration levels were selected for detailed weekly simulations.

The results indicate that EV integration primarily increases the risk of undervoltage during evening charging hours due to coincident residential demand, whereas PV integration leads to overvoltage conditions during periods of high solar radiation. The probabilistic analysis highlights the strong influence of spatial allocation on voltage performance, confirming that total installed capacity alone does not fully determine network impact.

Weekly time-series simulations demonstrate that temporal characteristics play a crucial role in voltage behaviour. Regulated or time-shifted EV charging significantly mitigates voltage drops compared to uncontrolled evening charging. Moreover, partial temporal overlap between EV demand and PV generation can contribute to a more balanced voltage profile.

The applied methodology combines probabilistic Monte Carlo analysis with deterministic time-series simulations, providing complementary insights into network behaviour. The Monte Carlo approach enables the assessment of hosting capacity under uncertain spatial allocation of devices and captures the stochastic nature of network conditions but does not account for temporal correlations. In contrast, time-series simulations provide detailed insight into the temporal evolution of voltage conditions and allow the evaluation of specific operating strategies, such as controlled EV charging, although their results depend on the selected scenarios and input profiles.

This combined approach therefore provides a structured and balanced framework for assessing hosting capacity in real LV networks, enabling both statistical generalization and detailed temporal analysis. The analysis is limited to a single feeder and evaluation at the most electrically distant node. Future work may extend the methodology to multi-node assessment and include additional control strategies or voltage regulation devices.

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