Impact of Uncontrolled Electric Vehicle Charging on Unbalanced Suburban Low-Voltage Networks

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***Abstract*—The integration of uncontrolled electric vehicles (EVs) in residential areas introduces new dynamics to the load profile, necessitating a redefinition of the requirements for the distribution network infrastructure. This paper proposes a comprehensive EV modeling and simulation methodology to analyze the impact of uncontrolled EV charging on three-phase low-voltage distribution networks. The distribution system modeling utilizes realistic data, including survey responses, smart meter readings, and statistical datasets collected over several years. This approach is crucial to identifying potential issues in network components and evaluating whether power quality remains within acceptable limits under various EV and photovoltaic (PV) penetration scenarios. The analysis reveals that transformer loading is the most critical parameter affected by EV integration. On the contrary, increasing the PV penetration has a negligible impact on the network's minimum voltage and maximum voltage unbalance factor during uncontrolled EV charging.**

***Index Terms*—electric vehicles, unbalanced operation, Monte-Carlo**

I. Introduction

Climate change is a growing concern for scientists looking for ways to reduce carbon dioxide emissions. The electrification of transportation is a major step towards achieving this goal. In Cyprus, conventional transportation contributes 29% of emissions [1]. Electric Vehicles (EVs) emit little to no carbon dioxide, especially when combined with renewable energy sources. However, the extensive penetration of EVs in residential areas leads to increased power demand and, therefore, infrastructure upgrades [2]. In 2023, global EV sales reached about 40 million units [3], increasing exponentially.

Uncontrollable charging load patterns affect basic load demand and alter traditional load profiles. Although for a small-scale EV integration, the Distribution Network (DN) is not particularly stressed, a large number of EVs could lead to significant undervoltages, overloading of transformers and distribution lines [4] or even high unbalances [5]. Therefore, this imposes the need to develop models and implement studies that examine the limits of modern distribution networks to estimate the hosting capacity of uncontrollable EVs.

The uncertainty regarding the location of the EVs, the varying nominal power and type of their chargers, the time of charging initiation, and the charging duration are crucial factors when conducting such studies. For realistic results, it is essential to model EVs accurately by incorporating all relevant parameters that influence the EV loading profile. The type of network considered (urban, rural, or suburban) shows significant variations for both EV and DN modeling and cannot be considered together. This study focuses on suburban areas, which are characterized by detached and semi-detached households, typically with individual energy systems and the growing adoption of electric vehicles. While urban and rural networks present their own challenges, the decision to focus on suburban distribution networks was made to allow for a more detailed and targeted analysis.

In the literature, several models and methods have been studied to perform such studies. The authors of [6] proposed a comprehensive probabilistic Monte Carlo (MC) analysis of PHEV without correlating the characteristics and location of the power network with the type of EV and the characteristics of the charging infrastructure. A single basic load profile for all consumers and uniform EV charging characteristics are considered in [7], without considering driving patterns, charging types, etc. In [8], a uniform charging request is considered, assuming a symmetric power system. Therefore, the assumptions and omissions in previous models and methodologies may affect the accuracy, reliability, and realism of the findings.

This study presents a MC-based methodology designed to evaluate the impact of EVs on unbalanced suburban LV networks with significant RES penetration. The contributions of the paper are threefold:

- Provide a complete framework to model EV integration.
- The proposed framework integrates PV generation into the impact analysis, offering a comprehensive examination of its impact on the investigated key metrics.
- It delivers specific insights tailored to the DNs in the suburban areas of Cyprus, leveraging the real-world data provided by the DSO.

The remainder of the paper is structured as follows. In Section II, the modeling framework for EVs, PVs, and basic load are described as well as the MC-based analysis method. In Section III, a brief explanation of the case study is given. Then, in Section IV the simulation results are discussed. Finally, conclusions are drawn in Section V.

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II. Modeling and Analysis Framework

To evaluate the impact of EV charging profiles on DNs, it is essential to derive individual and aggregate EV load profiles for various operating conditions and time periods. The derivation of individual EV load profiles requires data on the EV's battery capacity (kWh), average power consumption (kWh/km), charger maximum capacity (kW), and the owner's driving behavior (e.g., daily kilometers traveled, departure and arrival times). To assess the overall impact of multiple EVs on the DN, their spatial distribution must be determined, with charging profiles added to the baseline household load. Given the challenges of predicting the techno-economic factors influencing EV adoption, this study assumes uniform probability for EV placement across all households.

Data on driving behavior were collected through a survey conducted in Cyprus to evaluate daily travel habits (see Section II-A). EV characteristics such as battery capacity and power consumption were derived from European EV sales (see Section II-B). Furthermore, the IEC 62196-1 standards, combined with information from the Cyprus DSO on residential building power supply types (single-phase or three-phase), were used to estimate the charging infrastructure for each household (see Section II-C). Rooftop PV generation capacities, based on Cyprus DSO installation data, were assigned to the feeders to incorporate PV contributions (see Section II-F).

A. Driving Pattern

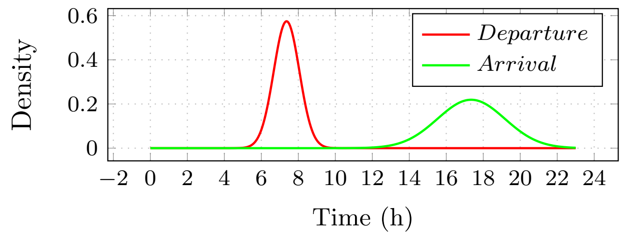
Driving patterns are essential to predict both the charging duration and the charging capacity required by EV owners. This information was gathered through a survey that targeted car owners who rely on private vehicles for their daily commutes. Although survey data was collected from owners of conventional vehicles, it is assumed that driving behavior will remain unchanged when these vehicles are replaced with EVs.

The survey primarily collected the following information: 1) departure times from home and return times for both weekdays and weekends; 2) distances traveled by participants on weekdays and weekends; and 3) Demographic details about the car owner, such as their location and residential setting, which influence the available power supply type (single-phase or three-phase). An evaluation using the Akaike Information Criterion (AIC) identified Student's t distribution as the most suitable model for the arrival and departure time data.

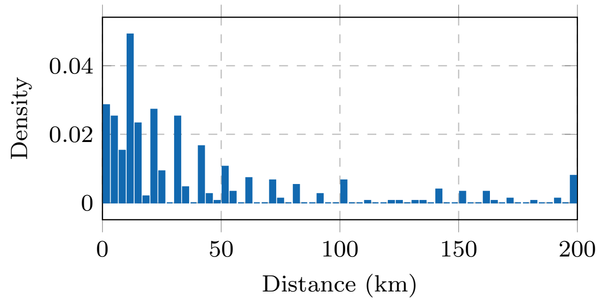
Fig. 1(a) shows the probability distribution function (PDF) for departure and arrival times based on the survey. The highest probability of leaving home is around 07:45 (which was expected due to standard working hours and school programs). The highest probability of returning from work is around 17:30. Fig. 1(b) presents the histogram for the driving distance of people who use their private car on weekdays.

B. Electric Vehicle Type

The type of EV is essential to convert driving patterns into corresponding charging profiles, requiring knowledge of the average energy consumption and battery capacity of vehicles. Since this information is not readily available for the LV networks under study, average sales data at the European level have been used to assign EV types probabilistically to each customer, using a probabilistic mass function [9]. Table I provides the ten most sold EVs in Europe for 2024 [10], along with their technical characteristics relevant to this study [11].



(a) Probability density function of vehicles departure and arrival times on weekdays



(b) Histogram of traveling distance during weekdays

Fig. 1. Survey results on the driving behavior of car owners in Cyprus [2]

TABLE I
Energy consumption and battery capacity of the 10 most popular EV models in Europe for 2024.

Model	**Energy Consumption (kWh/100km)**	**Range (km)**	**Sales (%)**
Tesla Model Y	16.4	350	23.7
Tesla Model 3	13.7	420	20.7
MG 4	17.1	360	9.8
VW ID.3	16.4	360	9.6
Audi Q4 e-Tron	18.3	420	7.7
VW ID.4	17.3	445	7.0
VOLVO EX30	17.8	360	6.4
Skoda Enyaq	17.1	450	5.6
BMW iX1	17.0	380	5.1
Renault Megane	15.8	380	4.5
Average consumption:	16.7		

C. EV Charging Characteristics

The IEC 62196-1 standard outlines four different charging modes, from slow AC charging (3.7kW) to quick DC charging (240kW) [12]. Based on data provided by the DSO, in Cyprus suburban areas, 80% of residential buildings are detached houses equipped with a 3-phase power system; therefore, 11kW charging systems are used. The remaining (20%) are considered to have a 3.7 kW (one-phase) charging system.

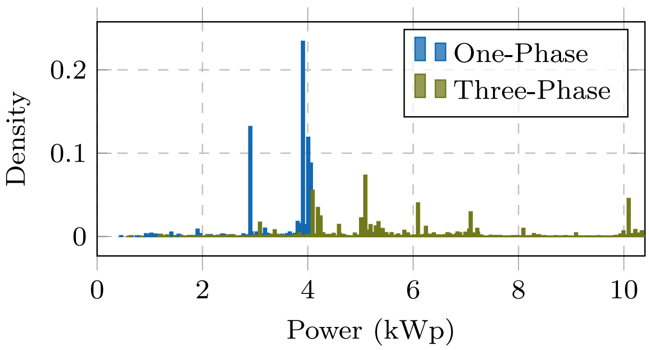


Fig. 2. Statistical distribution of rooftop PV installation capacities for one-phase and three-phase connections

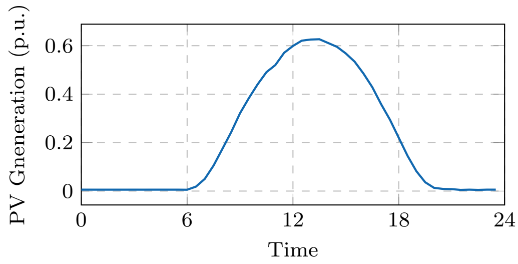


Fig. 3. Daily rooftop PV generation profile in per-unit (p.u.) values, used uniformly across all households.

D. Individual EV Load Profile Calculation

Calculating individual EV charging profiles begins by determining the state of charge (SoC) of each vehicle following its daily trip. Subsequently, the charging time (T_{ch}) of each EV is calculated using (1), which depends on the vehicle's battery level at the time of arrival (SOC), the total energy capacity of the EV (E_{cap}), and the charging rate (ξ_{cha}). The specific characteristics of the charging station utilized for each vehicle are outlined in Section II-C.

$$T_{cha} = \frac{(1 - SOC) \cdot E_{cap}}{\xi_{cha}} \tag{1}$$

Since this study aims to find the worst-case scenario limits for EV integration, a "dumb" charging strategy is considered, in which all EVs are connected for charging within 30 minutes after the return time at full charging power, aiming to recover the energy lost during the last trip.

E. Basic Household Load Profile

To formulate the total household load profile, we need to combine the basic household load profile with the individual EV load profile. Thus, the basic load consumption for 218 residential houses from smart-meter data has been used [13]. Profiles are randomly assigned to each household in the under-study DN using a uniform distribution. The consumption profile of each residential house is configured so that the cumulative consumption is equal to 90% of the average of the three most critical consumption net load values actually measured at the substation. The 90% has been used, considering the remaining 10% of the power consumed in losses.

F. PV Generation Profile

Statistical data of installed rooftop PV capacities were used to define a probability mass function (PMF), shown in Fig. 2. Based on this PMF, the PV capacity at each residential unit was randomly assigned. The maximum power of one-phase and three-phase is 4.16 kWp and 10.4 kWp accordingly, based on the limits set by the DSO. Due to the geographic proximity of the households, we assume that the PV generation profile is identical in per unit system (shown in Fig. 3) but scaled according to the installed PV capacity.

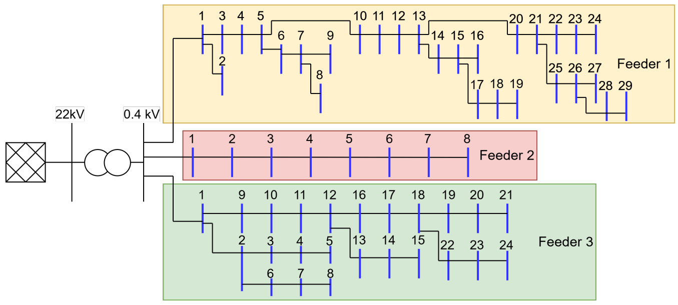


Fig. 4. Single-line diagram of the suburban low-voltage distribution network, comprising three feeders connected to a 22/0.4 kV transformer.

G. Monte Carlo-based Analysis Method

The methodology proposed to analyze the impact of EVs on LV DN is shown in Algorithm 1. A MC-based analysis was implemented, considering 300 iterations of the daily analysis at 30-minute intervals. In each iteration, there are different placements of EVs, PVs, and loads (nodes and phases). Once the MC simulation is complete, the script outputs several performance metrics and data, including transformer and line loading, voltage deviation, and voltage unbalanced factor.

Algorithm 1 MC-based analysis method

Require: Network data, household basic load profile, driving profile PDF, EV type data, EV charging infrastructure, PV generation profile.

for `PV Pen.` $\in \{20\%, 40\%, 60\%\}$ **do**
  for `EV Pen.` $\in \{0\%, 20\%, 40\%, 60\%, 80\%\}$ **do**
    for `i` $\in$ `{0,...,300}` **do** ▷ MC iterations
      • `Randomly assign basic household load profiles`
      • `Basic load modification based on 3-day average substation measurements`
      • `Randomly assign individual EV and PV profiles to the corresponding units`
      • `Run quasi-dynamic simulation`
    end for
  end for
end for
`Present MC analysis results`

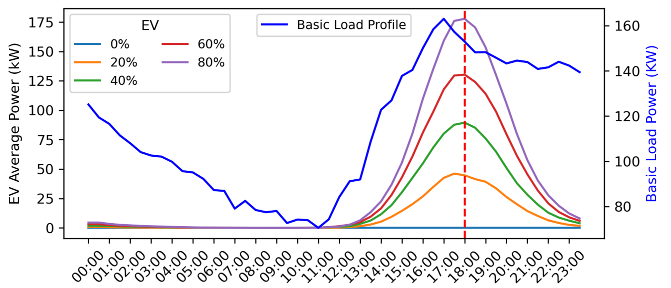


Fig. 5. Daily load profile of the base residential demand (blue curve, right axis) and the average EV charging demand (left axis) under different EV penetration levels (0%–80%).

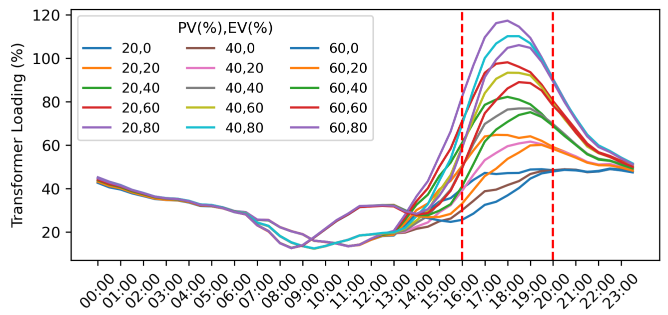


Fig. 6. Average transformer loading profile during a weekday under varying EV and PV penetration levels.

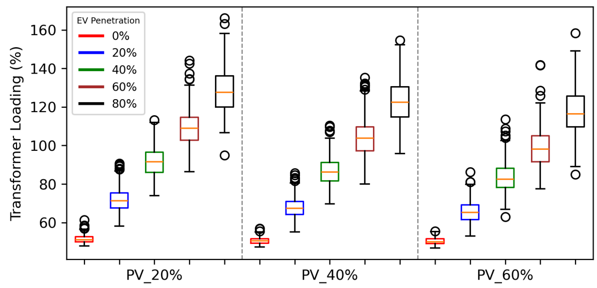


Fig. 7. Statistical distribution of transformer loading under different EV and PV penetration levels.

III. Case Study Description and Analysis Metrics

A. Distribution Network System Model

The proposed methodology is tested on a realistic three-phase LV DN in a suburban area, based on data from the Cyprus DSO. The network comprises a substation equipped with an 11/0.4 kV, 315 kVA delta-wye (Δ-Y) transformer. Three radial feeders extend from the substation, with a total of 61 nodes, as depicted in Fig. 4. Each feeder serves 30 residential customers who are randomly assigned to nodes (max. three per node) in each iteration, with the exception of Feeder 2, which includes 24 customers due to the feeder scale. Therefore, a total of 84 customers are considered. For network modeling, the open-source Pandapower power-flow solver has been used [14]. It is important to mention that only the weekdays of July are simulated, as this period is considered the most stressful due to high cooling demands, which can lead to transformer overloading and undervoltage issues.

B. Analysis Metrics

1) Transformer and Line Loading Metric: The maximum transformer loading (TL) and line loading (LL) are calculated using (2), expressed as a percentage of the single-phase nominal apparent power $S_{1\phi\text{-nominal}}$. Among the three phases S_a, S_b, and S_c, the percentage loading of the most loaded phase is determined. For line loading, the analysis identifies the line that is the most loaded from the total number of lines.

$$\text{Max Loading } (\%) = \frac{\max\{S_a, S_b, S_c\}}{S_{1\phi\text{-nominal}}} \cdot 100 \qquad (2)$$

2) Voltage Deviation and Unbalance Metric: The voltage deviation metric is defined as the minimum average voltage of the most affected node at each time interval and iteration. To evaluate voltage imbalance within the DN, the voltage unbalance factor (VUF) is calculated according to IEC 61000-2. This metric is critical for identifying significant voltage deviations and determining whether power quality remains within acceptable limits under varying operating patterns.

IV. Results and Discussions

A. Transformer Loading

Figure 5 illustrates the average load profiles for EV charging and the basic network load. Based on the driving patterns derived from the questionnaire, the majority of EV charging occurs during high-demand hours, contributing to an increase in peak consumption. As further depicted in Fig. 6, increasing EV penetration significantly impacts transformer loading, particularly between 15:00 and 20:00. With higher PV penetration, a slight reduction in maximum transformer loading is observed. However, after 18:00 (when the PV contribution ceases) and before 10:00 (when EV charging demand is low), the integration of PV has no discernible impact on transformer loading, as evidenced by overlapping profile lines.

At high EV penetration levels, the EV demand alone becomes comparable to the base residential load, effectively doubling the total network demand during peak hours. A detailed sensitivity analysis, presented in Fig. 7, and summarized in Table II, quantifies these effects. Specifically, for every 20% increase in EV penetration, the maximum transformer loading rises by approximately 25%, assuming a constant level of PV.

B. Line Loading

The results of the impact analysis on line loading are presented in Fig. 8, and their summary in Table II. For every 20% increase in penetration of EVs, the maximum line loading increases by around 10-13% with constant integration of PVs. However, for every 20% increase in PV penetration, the maximum line loading is reduced by approximately 1- 3%. In all scenarios, there are no instances of overloading any lines within the network. The most heavily loaded lines are those that connect the transformer's low-voltage side to the feeders.

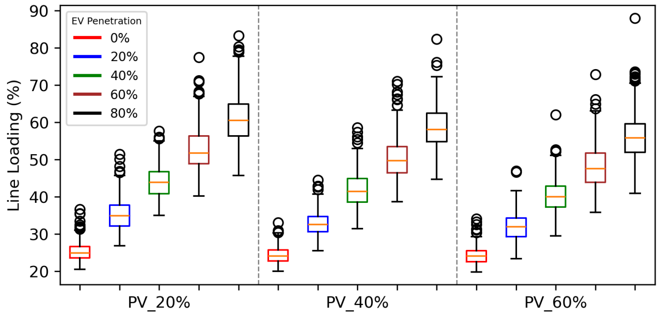


Fig. 8. Statistical distribution of line loading under different EV and PV penetration levels, showing the sensitivity of lines stress to both technologies.

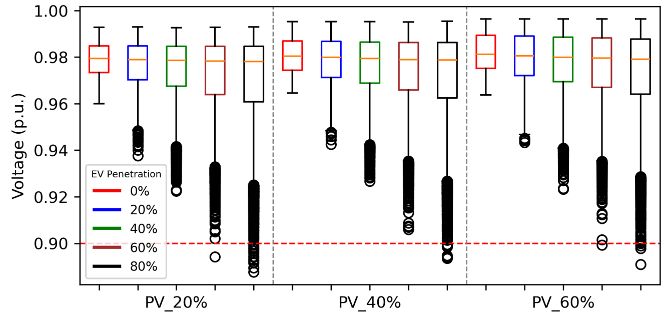


Fig. 9. Minimum voltage deviation across the network under varying EV and PV penetration levels.

TABLE II
SUMMARY OF IMPACT ANALYSIS RESULTS

Test Case (PV-EV)	**TL (Maximum)**	**LL (Maximum)**	**VUF (Maximum)**	**V_{avg} (Minimum)**
20%-0%	57%	31%	1.5%	0.96 p.u
20%-20%	87%	46%	1.7%	0.95 p.u
20%-40%	112%	55%	1.8%	0.94 p.u
20%-60%	131%	67%	2.0%	0.93 p.u
20%-80%	158%	78%	2.1%	0.93 p.u
40%-0%	55%	30%	1.5%	0.97 p.u
40%-20%	81%	41%	1.6%	0.95 p.u
40%-40%	104%	53%	1.8%	0.94 p.u
40%-60%	128%	63%	1.9%	0.94 p.u
40%-80%	152%	72%	2.1%	0.93 p.u
60%-0%	55%	29%	1.5%	0.96 p.u
60%-20%	80%	42%	1.6%	0.95 p.u
60%-40%	103%	51%	1.8%	0.94 p.u
60%-60%	122%	63%	1.9%	0.94 p.u
60%-80%	149%	71%	2.1%	0.93 p.u

C. Voltage Deviation and Voltage Unbalance Factor

The average voltage decreases as EV penetration increases, with a reduction of approximately 0.01 p.u. for every 20% rise in EV adoption. According to the Cyprus DSO, the lower voltage limit is set at 0.9 p.u. Consequently, as illustrated in Fig. 9, voltage limit violations are evident in scenarios with 60% and 80% penetration of EV. It is important to note that PV penetration has a negligible impact on minimum voltage levels within the network. This is mainly attributed to the fact that the lowest voltage levels occur during periods of limited PV generation, underscoring that high-demand intervals remain challenging for voltage regulation, regardless of overall PV integration.

Similarly, the maximum VUF exhibits a marginal increase of 0.2% for every 20% rise in EV penetration. However, it remains unaffected by the level of PV penetration for the same reason, as maximum VUF typically coincides with periods of minimal PV generation. These observations are substantiated by the data presented in Table II.

V. CONCLUSIONS

This paper introduces a modeling technique for EVs and PVs, with an impact analysis methodology, to assess the effects of uncontrolled charging of EVs on DNs. The methodology incorporates the stochastic nature of driving patterns to replicate real-world scenarios closely. The findings indicate that increasing EV adoption is likely to result in challenges such as transformer overloading. Due to peak generation of PVs and peak charging timings of EVs, the integration of photovoltaic energy has minimal impact on performance metrics.

Future work will extend the proposed framework to encompass both urban and rural areas, focusing on diverse charging infrastructures and varying network characteristics. Furthermore, the integration of electrified heating and cooling systems, such as heat pumps, along with storage systems and their distinct operational schemes in coordination with electric vehicles will be explored. These enhancements aim to refine the methodology, enabling more realistic analyses and offering alternative solutions to mitigate challenges in future networks.

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