DESIGN AND IMPLEMENTATION OF LOW-COST ELECTRIC VEHICLES (EVS) SUPERCHARGER: A COMPREHENSIVE REVIEW

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ABSTRACT

This article presents a probabilistic modeling method utilizing smart meter data and an innovative agentbased simulator for electric vehicles (EVs). The aim is to assess the effects of different cost-driven EV charging strategies on the power distribution network (PDN). We investigate the effects of a 40% EV adoption on three parts of Frederiksberg's low voltage distribution network (LVDN), a densely urbanized municipality in Denmark. Our findings indicate that cable and transformer overloading especially pose a challenge. However, the impact of EVs varies significantly between each LVDN area and charging scenario. Across scenarios and LVDNs, the share of cables facing congestion ranges between 5% and 60%. It is also revealed that time-of-use (ToU)-based and single-day cost-minimized charging could be beneficial for LVDNs with moderate EV adoption rates. In contrast, multiple-day optimization will likely lead to severe congestion, as such strategies concentrate demand on a single day that would otherwise be distributed over several days, thus raising concerns about how to prevent it. The broader implications of our research suggest that, despite initial worries primarily centered on congestion due to unregulated charging during peak hours, a transition to cost-based smart charging, propelled by an increasing awareness of time-dependent electricity prices, may lead to a significant rise in charging synchronization, bringing about undesirable consequences for the power distribution network (PDN).

Keywords

Electric vehicle, EV Supercharger, Low Cost, EV Smart Charger

1. INTRODUCTION

The electrification of the transport sector is being driven forward to reduce carbon emissions [1]. As a result, a considerable amount of research has been devoted to tackling the challenges of large-scale EV adoption, including the optimal planning of public charging infrastructure [2] and the integration of EVs into existing PDNs [3]. While the planning of public charging infrastructure is important to meet the charging demand of those without access to home charging, given the large share of households with access to private parking and its inherent convenience, home charging will remain the most important source of EV charging in the future [4].

An important challenge faced by distribution system operators (DSOs) in this respect is the substantial uncertainty regarding the extent of home charging and the resulting consumption from the combined base load and additional EV demand. In contrast to installing public charging infrastructure, where DSOs can plan the required infrastructure (by) virtue of an approval

process), home chargers are typically installed without informing the DSO. This issue is further aggravated by the residential customers' freedom to fully utilize the existing grid connection capacity and contribute to a coincidence factor (CF) that the grid was never built. In the case of Denmark, the grid connection of single-family houses is typically limited to 25 A per phase and thus can easily accommodate 11 kW chargers alongside normal household consumption [5].

Not surprisingly, these challenges have led to great interest in evaluating the potential impact of residential EV charging on PDNs [6–11]. Initial concerns have focused on the coincidence of uncontrolled charging events with peak hours, which has led to extensive research on smart charging strategies aimed at benefiting the PDN [12]. However, the present energy crises and surging electricity prices in Europe have raised awareness of possible savings from the time-dependence of charging costs. This has stimulated the growth of smart charging services, targeted mainly at minimizing charging patterns in which many EVs charge simultaneously and thus cause stress to PDNs. This article is devoted to analyzing various charging strategies on the LVDN of the municipality of Frederiksberg (Denmark), with inspiration from the uncertainty surrounding home charging and the potential effects of the application of cost-based charging. This study builds upon our research on the medium voltage distribution network (MVDN) [6], where the impact of different degrees of charging synchronization was examined.

1.1. Literature Review

In the past years, many studies have been devoted to analyzing the impact of residential EV charging on LVDNs. Given the wide breadth of modeling approaches, we comprehensively analyze the most relevant publications [13–35] in Table 1. The literature is classified concerning (1) the case study, (2) the modeling approach, and (3) the impact analysis methodology.

First, we classify the literature according to the type of LVDN, the geographical area under study, the EV penetration levels, and the charging power at home. Concerning the former, several papers use real LVDN topology data from different end countries [14-16,19-22,24,32]. However, many research papers lack data and use either synthesized or benchmark LVDNs [17,18,23,25–27,33] or only consider certain LVDN components [34,35]. Furthermore, a wide range of geographical areas are investigated in the existing literature. Whereas urban LVDNs are most widely covered in the reviewed publications, rural and suburban LVDNs also receive considerable attention. Other studies include the analysis of campestral [20] or particularly densely populated inner-city areas [22,33]. In addition, previous research varies about the analyzed EV penetration level and charging power, ranging from low charging powers of 1.44 up to 11 kW. Second, concerning the modeling approach, the literature can be distinguished concerning the charging strategy and the base load and EV load modeling methodology. Concerning the former, most studies focus on analyzing the impact of uncontrolled charging [15– 24, 26, 27, 32–35]. Furthermore, several papers address the topic of ToU-based charging [15, 17]. Finally, the impact of a variety of smart charging strategies is investigated. These are predominantly aimed at benefiting the LVDN or simultaneously serving both the EV user and the LVDN. Such strategies include static charge schedules [34], valley-filling [18], peak-shaving [26] and load-flattening [23] methods, transformer- [16] and voltage-dependent charging [15], the maximization of PV self-consumption [27] or cost- and CO2-minimised charging with grid constraints [18,33].

Ref.	Year	LVDN	Case s	tudy					Modeling approach				Impact analysis						
			Area				Penetration (%)	Power (kW)	Strategy	Base	load	EV load		Ap.	Focus	5			
			R	S	U	0	[Step]			Ap.	Data	Ap.	Data		T	С	V	L	0
[13]	2014	BE			X		100	3.3	2, 5	D	SM	D	TS	D	X		X		_
[14]	2015	GB	Х		Х		15, 30, 60		1	Р	SM	Р	EV-t	Р	Х		Х		Х
[15]	2015	EU, NA		Х	X		5-100 [5]	3.84, 4.6	2,3,5	D	S	D	CS	Р		X	Х		Х
[16]	2016	GB					0-100 [10]	3.6	2,6	Р	S	Р	EV-t	Р	Х	X	Х		
[17]	2017	В			X		34, 50, 65	2.6, 3.7	2, 3	Р	S	Р	TS				Х		
[18]	2019	EU B		Х			30, 70		2,4,7,8	D	S	Р	TS		Х		Х	Х	
[19]	2019	DK		Х			25-100 [25]	3.7, 11	2	D	SM	Р	TS, EV-t	Р	Х	Х	Х		
[20]	2019	DE	Х	Х		X	0-150 [12.5]	8	2		S	Р		D	Х	Х	Х		
[21]	2020	Æ			X		up to 100	3.7, 7, 11	2	Р	S	Р	EV-t	Р	Х		Х		
[22]	2020	AT	Х	Х	X		0-80	3.7, 11	2	Р	S	Р	TS		Х	Х	Х		
[23]	2020	GB B	Х	Х	X		100	7	2, 8	Р	SM	Р	TS, EV-t	Р	Х		Х		Х
[24]	2021	CH			X		0-100 [20]	3.7, 11	2	D	SM	Р	TS	Р	Х	X			
[25]	2021	В					0-100 [20]	6.6-11.5	10	D		Р	TS	D	Х		Х		Х
[26]	2021	В					20, 40, 60	1.44, 3, 3.6	1,2,3,8	Р	S	Р	CS	Р			Х		Х
[27]	2021	GB B					5-50 [20]	3.7	2,9	Р	S	Р	TS	Р			Х	Х	Х
[28]	2021						10, 30, 50	3.7	2	D	S	Р	TS	Р	Х		Х	Х	
[29]	2021	<i>B</i> , S	Х	Х	Х		0-100	17.5	2	Р	S	Р	EV-t	D	Х		Х	Х	
[30]	2021	AT					5-100	3.3, 6.6, 11	2, 5	D	SM	Р	TS	D	Х		Х		
[31]	2021	CH AT, NL,	Х	X	Х		15, 24, 33, 100	7–22	2	D		D		Р	Х	Х	Х		
[32]	2022	DE	Х	Х	X		20, 50, 80	3.3-11.5	2	D	S	Р	CS, TS	D	Х	X	Х		
[33]	2022	SE S	Х		X		up to 100	6.9	2, 4	D	SM		GPS	Р	Х	Х	Х		
[34]	2022	NL				X		11	2, 11	D	S	ABS	EV-t	D		Х			
[35]	2022	GB	X	Х	X		0-100 [10]	3	2	D	SM	P	EV-t	D			X	X	
[*]	2023	DK			Х		40	11	2,3,4	Р	SM	ABS	TS	Р	Х	Х	Х		

International Journal on AdHoc Networking Systems (IJANS) Vol. 14, No. 1, January 2024 Table 1: Literature review on the impact of residential EV charging on low voltage distribution

networks, including this paper [*].

Abbreviations: ABS, Agent-Based Simulation; Ap., Approach; C, Cable; CS, Charging Station; EV-*t*, EV trial; L, Losses; NA, North America; O, Other; R, Rural; S, Suburban; SM, Smart meter; T, Transformer; TS, Travel Survey; U, Urban; V, Voltage deviation/unbalance; *B*, Benchmark LVDN; *D*, Deterministic; *P*, Probabilistic; *S*, Synthetic; Country codes follow ISO 3166 [36]. **Charging strategies**: 1, Real charging profiles; 2, Uncontrolled; 3, ToU; 4, Cost-minimization; 5, Voltage-based; 6, Transformer-based; 7, CO2-minimisation; 8, valley filling/load flattening/peak shaving; 9, PV self-consumption maximization; 10, phishing attacks; 11, static charge schedules.

In [29,30,34,35], the results are obtained by one-shot simulation. However, this can lead to biased results, especially for LVDNs, which are often small in scale and thus can encompass significant variation in the location of EVs and the specific charging Behavior. Probabilistic power flow simulations are applied in [14,16,19,23]. These studies can capture the uncertainty of inputs and often provide better estimates of grid bottlenecks. Most studies assess the impact on system voltage in terms of voltage deviations or imbalance and the impact on the transformer or cables. Finally, only a small share of studies considers the impact of EV charging concerning grid losses or other aspects such as harmonic distortion [26].

1.2. Research Gap and Contribution

The literature review revealed several research gaps, which served as an inspiration for this paper. To begin with, access to LVDN data remains an issue. Contrary to a large share of existing documents, this study is based on real data from an urban LVDN of the municipality of Frederiksberg (Denmark).

Moreover, detailed microscopic modeling of the EV charging demand still needs to be used in the reviewed grid impact literature. Within this work, we want to bridge this gap by using a novel agent-based simulator, GAIA [37]; that allows us to model EVs' daily natural charging rhythm, referred to throughout this paper as the genuine charging pattern. The technology in the GAIA model is based on a steady-state SoC distribution [38] and a probabilistic decision-to-charge model that uses information-sharing [39] to simulate and analyze different charging strategies. Furthermore, there needs to be more studies that try to capture the combined probabilistic nature of both residential base load and EV load while analyzing the resulting grid impact. In this work, we propose a probabilistic model that can address the variation in residential base load demand based on smart meter data and the uncertainties resulting from the additional demand for EV charging by accounting for home charging availability, charging location, and the decision to trust in space and time.

Last, most papers address the initial concern of grid impacts arising from uncontrolled charging or analyze smart charging strategies considering grid constraints. However, as previously indicated, the recent increase in electricity prices might cause a considerable shift in charging behavior towards cost-based charging strategies already offered by multiple parties in Denmark. While shifting charging to periods of lower prices during the night might benefit the LVDN when EV penetration is common, synchronization effects of many EVs following the same objective could cause new concerns for LVDNs. Recently, there has been an increasing interest in multiple-day cost-minimization, where parties involved with EV charging have developed energy price forecasting tools for such optimization. Thus, we address this research gap within this work and analyze the impact of various cost-based charging strategies.

The subsequent sections of this manuscript are structured as follows:

The paper's methodology is explained in Section 2. The principal discoveries of this research are presented and discussed in Section 3. In conclusion, the paper concludes with the conclusions presented in Section 4.

2. METHODOLOGY

The methodology of this paper is presented in Fig.1 and consists of four steps, to be discussed in more detail in the following. The four large boxes that range from light to dark green highlight the individual steps.



Figure 1: Grid impact analysis methodology. Dark, grey-shaded rhomboids display the input data, and orange-shaded rectangles represent the external parameters. The light grey-shaded hexagon illustrates the input of the GAIA model. White-shaded rectangles represent the results obtained in each step. Purple shapes show the workflow of the Monte Carlo simulation (MCS). (For the reader's understanding of the color references in this figure legend, please consult the online version of the article.) [57]

2.1. Low Voltage Power Distribution Network Modeling

Traditionally, LVDNs have been planned and operated as passive PDNs based on the so-called 'fit-and-forget' premise. Following this approach, the operation was predominantly determined during the planning stage by adequately sizing transformers, conductors, and other equipment according to a power demand forecast assuming a certain CF, resulting in little need for monitoring and control [40]. As a result, DSOs typically do not have readily available electrical models of their LVDN, and open data is limited to Geographic Information Systems (GIS) for asset management purposes [41]. But when dispersed energy resources like electric vehicles (EVs) become more widely used, a more active LVDN will inevitably emerge. Thus, a significant task is to model LVDNs in order to analyze the time and magnitude of probable charging peaks [42].

Within this work, we analyze three parts of Frederiksberg's urban LVDN, labeled LV1, LV2, and LV3. Data on the network topology is collected from the DSO Radius, a partner in the FUSE

project [43]. The data, extracted from Radius' GIS system, encompasses information on the location and characteristics of its transformers, cable cabinets, and respective underground cables.

	LV1	LV2	LV3
Rated apparent power (kVA)	630	500	
Derated apparent power (kVA)	525.0	416.7	
Rated voltage (kV)		10.5/0.42	
Relative short-circuit voltage (%)	4.14	5.4	
Real part of rel. short-circuit voltage (%)	0.75	1.06	
Iron losses (kW)	0.717	0.697	
Angle shift (°)		30	

Table2: Overview of transformer parameters for each LVDN. [57]

The GIS data is converted into a suitable electrical model using the package Panda Power [44] in Python. We focus our analysis on the MV/LV transformer and the underground cables connecting the transformer and cable cabinets. The household connections, i.e., underground lines connecting the LVDN customer with the cable cabinet, need to be modeled due to a lack of data.

2.1.1. Modelling of the Transformer and Cable Cabinets

Each LVDN (Un=0.4 kV) is connected to the MVDN (Un=10 kV) through a typical Danish distribution transformer with a 10.5/0.42 kV nominal ratio. The nominal capacities of the MV/LV transformers vary between 500 and 630 kVA. To account for the impact of likely phase imbalances within the LVDNs, we assume a slightly unbalanced system of 40%, 30%, and 30% phase loading and reduce the nominal capacity by using a dating factor of 0.83. An overview of the transformer characteristics and parameters is provided in Table 2.

The connection to the MVDN is modeled as the slack bus with the voltage angle set to 0° . The voltage is set to 1.05 p.u. to align with the common practice of the DSO to operate the system at a slightly higher voltage level to ensure that voltage variations are within acceptable limits. As indicated in the GIS data, the cable cabinets are modeled through buses at their respective locations.

2.1.2. Modelling of Underground Distribution Cables

The LVDN cables are underground cables, of which the majorities are composed of different cable segments with often other parameters. Thus, each cable segment is modeled in cable muffs that connect individual and different cable segments. While the GIS data determines the location of the cables, the electrical parameters for each line are unknown. The GIS data only contains information about the phase material, the cross-section area, and the number of conductors, as shown in Table 6 found in Appendix A.1. Therefore, we derive the electrical parameters for each cable segment from the NKT product catalog [45] by selecting the relevant cable type that reflects the unique combinations of the characteristics of the cable mentioned above. As a common practice in Denmark, LVDN cables possess four conductors, including the neutral phase. As indicated in Table 6, lines either keep four conductors with equal conductor and unbiased cross-section or three conductors and a separate neutral with often smaller cross-section. This work considers the electrical parameters defined by the conductor characteristics since our analysis is based on a balanced power flow. Cross-sections range from 50 to 240 mm2, and the phase material varies between copper (Cu) and aluminum (Al). The maximum current capacity from the cable catalog is calibrated to average Danish conditions. This work does not account for potential local hotspots caused by proximity to heat pipes or narrow road sections. Assuming an

average ambient soil temperature of 15 \circ C and a thermal resistance of 1 K m/W with cables directly laid in the ground, the maximum current carrying capacity is multiplied with a correction factor of 1.43 and 1.05, respectively [45]. Furthermore, a reduction factor of 0.6 accounts for the mutual influence of several circuits laid directly in the ground with a free distance between cables of one cable diameter. Last, as already applied during the modeling of transformers, we set the derating factor of the nominal capacity of the cables to 0.83 to account for the overloading effect of potential phase imbalances.

	LV1	LV2	LV3
Number of cable cabinets	32	41	45
Number of cable muffs	10	43 3	38
Number of cables	44	87	89
Total cable length (km)	1.65	2.58	2.98
Number of apartments (Na ⁱ)	155	203	413
Number of single-family houses (N _h ⁱ)	58	100	149

Table 3: Characteristics of each LVDN in Frederiksberg. [57]

2.1.3. Low Voltage Distribution Network Characteristics

The final topology of the three modeled LVDNs is illustrated in Fig. 2. As can be seen, the LVDNs differ in size and do not exhibit the typical radial layout usually found in LVDNs. Rather, they are operated as weakly meshed LVDNs even in normal operation. Thus, compared to conventional radial LVDNs, most customers can be supplied through multiple pathways, allowing demand to be distributed across different components and thus reducing the loading on individual assets [42]. Furthermore, compared to the rest of Frederiksberg, the selected LVDNs are islanded grids not fed by multiple transformers. Thus, even though not fully representative of the overall LVDN, the chosen areas provide a good case study to assess the worst-case impact of EVs on Frederiksberg's LVDN. An overview of the traits of the three LVDNs may be seen in Table 3.

2.2. Base Load Modeling

Following the modeling of the LVDN topology, the residential base load demand must be determined. The base load modeling approach can be separated into three steps, namely:

- 1. The Estimation of the number of residential customers,
- 2. The modeling of the base load based on smart meter data and
- 3. The calibration of the base load to match the measured transformer load.

Each step is discussed in more detail in the following.

2.2.1. Estimation of Residential Customers

The given LVDNs supply two types of residential customers: single-family houses and apartments. However, the exact number of residential customers within each LVDN is still being determined. As a result, we follow a stepwise approach that enables us to identify the total number and location of single-family houses and apartments within each LVDN.

First, we use the GIS data on the household cable connections, as illustrated by the green lines in Fig. 2, to select all cable cabinets and cable muffs that connect LVDN customers. Second, we use GIS data, Open Street, and Map [46] to identify and match dwelling addresses with

previously selected cable cabinets and muffs. Third, we leverage data from the Danish Address Register [47] to estimate the number of residential customers living in single-family houses (i.e., only one registered address) or apartments (i.e., multiple registered addresses) for each selected address. A summary of the number of residential customers who live in apartments and single-family houses for each of the three LVDNs is presented in the last two columns of Table 3.



a. Network topology of LV1



b. Network topology of LV2



c. Network topology of LV3

Figure 2: Network topology of the three LVDNs. Red star illustrates transformers; cable cabinets and muffs are shown by blue rectangles and purple dots, respectively. The modeled cables are indicated by orange lines, while the un-modeled household connections are shown in green. Grey lines depict the road network; buildings are outlined with grey shapes. (The reader is directed to the online version of this article for an interpretation of the color references in this figure legend.) [57]

As can be seen, the total number of customers increases from LV1 to LV3. The share of single-family houses ranges from 26%–33%, which is considerably higher than the share of roughly 3% for the entire Frederiksberg [48]. Thus, the selected areas do not fully represent the dwelling structure in the rest of Frederiksberg. However, the chosen LVDNs represent a good case study for analyzing the potential worst-case impact of EVs due to the higher share of households with home charging opportunities.



Figure 3 Comparison of the measured and sampled base load for weekdays in January. Results for LV1– LV3 are shown in 20-min resolution from left to right. Orange lines illustrate the estimated transformer loading for 2020. The initial and calibrated sampled base loads, based on 1000 simulations, are

characterized by purple and green box-whisker plots, respectively. (The reader is directed to the online version of this article for an interpretation of the color references in this figure legend.) [57]

2.2.2. Residential Base Load Modeling

To model the base load consumption, we use a large smart meter data set encompassing electricity consumption measurements in hourly resolution covering January in the period 2019–2022. The profiles originate from different anonymized locations within the service area of the DSO Radius. For each year, the raw data contains a minimum of 2269 and 2378 and a maximum of 2484 and 2493 records of individual apartments and single-family houses without electrical heating. The data is subjected to several post-processing steps to eliminate erroneous inputs and ensure proper formatting. The processing involves (1) the removal of incomplete and faulty data, (2) the up-sampling of the hourly measurements to 5 min resolution using linear interpolation, and (3) the generation of 24-hour load profiles, starting at noon on a given day. For each residential customer, a 24-hour load profile is randomly sampled and attributed to the respective bus, dependent on the type of dwelling (i.e., apartment or single-family household). As a result, the base load demand is stochastic and will differ between simulation runs.

2.2.3. Calibration of Base Load

While the LVDNs mainly supply residential customers, many non-residential loads, such as small shops or businesses, exist. However, the location and electricity demand of these non-residential customers are still being determined, and common consumption, such as street lighting, shared areas in apartment complexes, etc., is also not considered due to a lack of data. To address the mismatch between sampled and measured base load, we use linear least squares regression to calibrate the residential demand profiles to the average transformer loading, as described in more detail in Appendix A.2.

2.3. EV Load Modeling

The modeling of the EV charging demand is structured into three main steps, namely:

- 1. The EV ownership modeling,
- 2. The Simulation of home charging events, and

2.3.1. EV Ownership Modeling

The number and location of EVs within each LVDN significantly affect the potential grid impact. Given that both factors are characterized by a large degree of uncertainty, we use a stepwise probabilistic approach to determine residential EV ownership.

To begin with, we estimate the number of cars for each residential customer according to the type of dwelling, where we define single-family houses as detached and terraced, linked, or semi-detached houses and apartments as multi-dwelling houses or blocks of flats. With no representative data available that indicates the car ownership for Frederiksberg concerning the type of dwelling, we apply iterative proportional fitting (IPF) [49] to account for the differences in car ownership between dwelling types [50] and between Frederiksberg and the national level [51]. We make use of the Python package IPFN to fit the car ownership per dwelling type as calculated from the Danish National Travel Survey (DNTS) [52] to the distribution of dwelling type (i.e., roughly 3% single-family and 97% apartment) [48] and the distribution of car ownership within Frederiksberg (approximately 61.9%, 33.6%, 4.0%, and 0.5% of families own no, one, two, or more than two cars) [51]. The distributions calculated from the DNTS and for Denmark. For each apartment and single-family house, we sample the car ownership of the specific customers from the IPF distributions while considering a maximum number of three cars per household.

Subsequently, we obtain the number and location of EVs dependent on the previously determined number and location of cars. We align our analysis with Frederiksberg's EV strategy [53], which aims to reach 40% of pure EVs by 2030.

2.3.2. Simulation of Residential Charging Events

The simulation of the charging demand is a complex task that we address using a purpose-built agent-based simulator [37]. This simulator combines precise and reliable trip diaries collected through the DNTS [52] with fine-grain origin-destination traffic flow data to generate detailed synthetic trip diaries for the simulation agents. The agents then track the consumption of their EVs and select when and where to charge based on a comprehensive representation of the public and private charging infrastructure.



Figure 4: Comparison of car ownership for apartments (left) and single-family houses (right). The distribution for Denmark [51] and Frederiksberg, according to the DNTS [52], and after orange, purple, and green coolers indicate IPF. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The choice of charging is based on a discrete choice model that considers the present SoC and the remaining trip diary requirements while accounting for detours, waiting time, and parking restrictions. The initialization of agents and the decision to search for a charging option are based on the models for steady-state SoC distributions and the decision to charge introduced in [38]. The simulator monitors the entire charging infrastructure, handles the queue process when required, and also simulates the charging events, taking into account the specifications of the vehicles and charging stations. Advanced features include information sharing in the public charging domain [39] to reduce waiting time. This indirectly influences the private charging demand, as the two systems are complementary.

For each EV within the LVDN, we sample an agent for the given day in our simulation to infer the opportunity for home charging, the decision to charge, the charging location, and other relevant parameters such as the energy demand or the arrival and departure times at home. Agents living in detached or terraced houses are allocated to EVs in single-family dwellings, while agents residing in blocks of flats, student residences, or other types of dwellings are attributed to EVs in apartments.

Next, by analyzing the sampled agents' home parking conditions, we determine the opportunity for home charging. For those agents with reliable access to parking at their premises (i.e., in the carport or the front yard) or next to the property (i.e., reserved, always, or normally space parking), we infer that home charging will be available. Furthermore, we define good workplace parking conditions as having a permanent parking space provided by the employer and free parking, defined as always or normally available, to allow agents with such parking conditions to opt to cover their charging demand at work.

Subsequently, the decision to charge and the charging location are determined by analyzing the charging logs of the simulation day. If the charging logs do not encompass a charging event of the respective agent, the agent did not charge on the given day, and as a result, no home charging event is attributed to the EV. On the contrary, recorded capturing events for the given population are further analyzed according to the trip purpose to distinguish between home, workplace, and public charging events. While the latter two are accounted for in the agent-based simulation, they are not simulated in the LVDNs directly. However, they are modeled indirectly because such charging events reduce the use of private home charging.



Figure 5: Overview of the Simulation Framework. The simulation day is shaded in dark grey. The corresponding window in which charging can take place for each agent is illustrated in green. The power flow simulation period is shown in orange. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) [57]

Last, the steady-state energy demand $\delta\epsilon$ of each EV and the arrival, stop-of-charging, and departure times are extracted from the charging logs. The charging logs lie within the window of charging opportunity, which encompasses duration longer than 24 hours, i.e., the time between

the arrival at home on the preceding day of the trip diary and the departure on the next day. Thus, as illustrated in Fig. 5, the start of charging could precede the simulation day. It could also fall outside our 24-hour power flow simulation period, which starts at noon, to cover the evening peak load periods and fully explore the long window of cheaper electricity prices during the night. However, our analysis of the GAIA results shows that EV demand is equivalent throughout the week, excluding special days. Hence, we can shift the charging demand preceding our power flow simulation period by 24 hours to the same time window on the next day.

2.3.3. EV Charging Scenarios

Having discussed EV ownership and residential charging event modeling, we will now focus on our five scenarios, consisting of our baseline (S0) and four EV charging scenarios (S1-S4). The charging scenarios will determine the charging time and the number of events. For each charging scenario, we consider the charging power to be 11 kW, regardless of the EV's SoC and type of residential customer. In the following, we discuss the modeling of the selected scenarios in more detail. (S0) No EV charging: The baseline for evaluating the impact of the four EV charging scenarios is determined by assessing the state of the three LVDNs with no EVs present. (S1) Uncontrolled charging: Our first EV charging scenario models uncontrolled charging as modeled by GAIA, where no management is imposed on the charging process. All EVs that need to be set on the given day start charging upon plug-in and continue charging until their charging demand δε is met. (S2) ToU tariff-based charging: Our second charging scenario models the behavior of minimizing setting costs by postponing the start of charging to periods of lower ToU tariffs. No dynamic management is applied; thus, the EV charging continues until its initial charging demand $\delta \varepsilon$ is met. Upon arrival at home, the EV users determine the required charging time to fulfill their demand. They select the first continuous charging interval that minimizes the tariff costs while considering the departure time. EV users can schedule the start of charging in halfhour intervals and are assumed to charge their EV at the lowest prices as early as possible while making ideal decisions. Charging is modeled according to Radius' domestic ToU winter tariff [54], which is based on the new Danish tariff model 3.0 [55] and came into effect in January 2023. The tariff costs at the time of writing, denominated in Danish krone (DKK), are

illustrated in Figure 6. It is seen, the tariff consists of a low load period (00:00–06:00), two high load periods (06:00–17:00 & 21:00–00:00), and one peak load period (17:00–21:00). Peak load periods are priced roughly nine times higher than low load periods, which introduce a strong incentive for EV users to shift their charging away from those periods.



Figure 6: Price elements of S2-S4 (1 DKK 0.13 e). The ToU tariff (January 2023) is shown in purple. The electricity spot market price and combined price signal for Wednesday, 13-01-2021, 12:00 to Thursday, 14-01-2021, 11:55 and Wednesday, 12-01-2022, 12:00 to Thursday, 13-01-2022, 11:55 are illustrated by orange and green, solid and dashed lines, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) [57]

While the tariff costs are regularly adjusted based on the forecasted level of electricity prices, the tariff scale factors of 1/3, 1, and 3 for low, high, and peak load periods will remain unchanged until the tariff model is revised.

Fig. 6 illustrates the electricity spot market price and combined price signal. When comparing the spot market prices for 2021 and 2022, the difference between high and low electricity prices over 24 hours has increased significantly due to the energy crises. However, when looking at the combined price signal, it becomes obvious that both price signals follow a similar pattern due to the influence of the ToU tariff. Thus, the charging behavior derived from the optimization is expected to be the same. Nonetheless, we selected the electricity price 2021 for our simulation, as current electricity prices should eventually converge to the historical trend. It is important to stress that our simulation of cost-minimized charging is to be seen as an example of charging behavior based on the current situation. ToU tariffs and market designs might change, and large-scale EV penetration could potentially impact spot market prices, which is not considered. Furthermore, spot market prices vary daily and thus influence the charging behavior, even though the general pattern of lower prices during the night is expected to be the same. For the paper, we assume that EV users will also be able to exploit price variations in the future with similar price patterns as of today.

The above minimization problem was solved in Promo [56]. This optimization problem is plagued with equivalent degenerate solutions when the minimum cost function is constant for periods longer than the required charging time. To break the degeneracy between configurations with equal cost, we introduce a small penalty that grows linearly for each time step within one hour, with a value of 10-7 DKK/kWh for each optimization step. By design, when the price is equivalent within one hour, this penalty forces charging to begin as early as possible.

(S4) Synchronized cost-minimized charging: While the previous charging scenario mimics charging based on day-ahead electricity spot-market prices and assumes no influence on the natural charging patterns of EV users, multiple-day price forecasts might influence the charging pattern of EV users. Hence, it could cause charging synchronization challenges on days with hours of exceptionally low electricity prices. Such synchronization effects could also be caused by other reasons, such as public holidays, where everyone would want to charge their EV on the preceding day for an upcoming long-distance trip. To assess the impact of such events, we force all EVs to set on the same day rather than following their natural behavior. It is important to note that the steady-state SoC distribution still determines the initial SoC level, and this decision only anticipates the charging event. Hence, the majority of the EVs that are forced to charge will require a smaller amount of energy than what could be expected based on the vehicle's battery capacity.

Consequently, S4 is not a worst-case scenario but rather a lower bound for the potential impact of massive synchronization of charging demand. Estimates for the worst-case scenarios depend on many external factors, ranging from environmental conditions such as temperature, which affects the vehicle's range; wind and precipitation, which can strongly impact electricity cost; and social events and holidays. Due to the complex interplay of such external factors, we opt to proceed with the proposed lower bound for the worst-case scenario rather than attempt to simulate a particular system.



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Figure 7: Load modeling results for each LVDN. While the baseload is black, the three plots ordered from the left illustrate the EV load for S1, S2, and S3 in green, orange, and purple. Results for S4 are displayed in red on the right due to the considerably larger magnitude of the EV load. Shaded areas with different intensities indicate the 0%–100% (lighter), 5%–95% (medium), and 25%–75% (darker) percentiles. Colored dashed lines depict the 95% percentile for the aggregated loads. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) [57]

3. RESULT

Having discussed the methodology of this work, we now present the results, which we structure as follows. First, we dive into the load modeling results for both the base- and EV load. Subsequently, we analyze the conditions of the LVDNs with no EVs present. Last, we present the main findings of our work, the grid impact for each charging scenario.

3.1. Load Modeling Results

To begin with, we focus on the load modeling results, which serve as an input to the power flow simulations. The total power load variation along the day in each grid is shown in Fig. 7. Several observations stand out. First, it can be seen that the EV load exhibits more volatility than the base load due to the large variation introduced by the multistep sampling approach, as discussed in Sections 2.3.1 and 2.3.2. A summary of the sampling results for each step is presented in Table 8 of Appendix B.2. Second, the EV load in each grid is rising with the number of residential customers, and a comparable increase in the base load accompanies it. Third, the risk of secondary peaks triggered by cost-based charging is visible but will depend on the specific LVDN and charging pattern. In Table 4, we compare the peak load of S2–S4 to S0 and S1, respectively, and present the probability of introducing a new peak based on our 1000 simulations. While for S2 and S3 the likelihood of causing a further rise is highest for LV2 and LV3 when compared to S0, the probability of secondary peaks induced by S2 and S3 being higher than the peak of S1 is small, thus offering a solution with a potentially smaller impact on the grid. On the contrary, S4 triggers a peak load increase in all simulations with a significant magnitude, as shown in Fig. 7. Those results, therefore, provide a first indication of the risks posed by synchronized cost-minimized charging, which could potentially yield massive secondary peaks by altering the natural charging patterns of EV users.

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	LV1			LV2		LV3			
	S2	S 3	S 4	S2	S 3	S 4	S2	S 3	S 4
S 0	16	8.2	100	52	36	100	53	32	100
S 1	0.3	0.1	100	1.4	0.5	100	0.9	0.2	100

 Table4 :Likelihood (%) of peak load increase in each LVDN for S2–S4 with respect to the peak load in S0 or S1, respectively. [57]

The discrepancy in peak load originates from the difference in the CF and base load levels in each charging scenario. The CF of charging, defined as the ratio of EVs charging at a given time to the total number of EVs, is illustrated in Fig. 8. While uncontrolled charging yields the lowest CF for each scenario with medians below 5%, S2 and S3 slightly increase the CF due to synchronization of setting during the nighttime. While the median of the peak period lies slightly above 10%, the CF can rise to 30% on rare occasions for LV1. In S4, we changed the charging pattern that forces all EVs to charge on the same day. Thus, the CF increases drastically, with a maximum median of more than 50%. In the following, if not indicated otherwise, results for LV1, LV2, and LV3 will be illustrated in green, orange, and purple, respectively.

3.2. No EV Charging (S0)

Next, we present the findings of our grid analysis with no additional EV load. The simulation results set the benchmark against which we will compare all results observed in charging scenarios S1–S4. Below, we discuss the findings for the transformer and cable loading and the voltage drop.



Figure 8 Coincidence factor of charging, defined as the percentage of EVs charging at a given time relative to the total EV population throughout 24 h. For each hour, the distribution of CFs in each LVDN is illustrated. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) [57]

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Figure 9: Transformer loading for each LVDN and scenario, where S0–S4 is ordered from the left to the right. Horizontal red lines indicate the dated nominal load (solid) and N-1 redundancy limit (dashed). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) [57]

3.2.1. Transformer Loading

First, we analyze the transformer loading, which provides a good indication of the utilization of the grid. For our analysis, we concentrate on congestion (>100% loading) and the DSO's operational limit of 66% to ensure N-1 security. While exceeding the critical operating load would not necessarily directly result in reinforcements, repeated violations would prompt Radius to investigate measures to reduce the demand, such as re-routing or reinforcing promptly to ensure sustainable operation under the failure of one grid component.

The transformer's load throughout the simulation period is shown in Fig. 9. As seen in the left plot, the initial transformer loading conditions for each LVDN are distinct, caused by the interplay of the number of customers and the transformer's nominal power. LV1 not only has the lowest number of customers but also exhibits the highest transformer rating of 630 kVA and thus consistently operates below 40% loading. LV2 and LV3, on the other hand, possess the highest number of customers and equally rated transformers of 500 kVA. LV2 occasionally exceeds the 66% threshold during the evening peak in outlier events, i.e., with a likelihood of less than 1%, as indicated in Table 5. LV3 shows the highest relative transformer load, where peak loading regularly exceeds the operational threshold of 66% for at least one hour. The transformer peak load of LV3 lies in the range of roughly 70%–90%.

Consequently, as the EV penetration rate increases, LV1 is likely to be the most resilient grid, while LV3 is the most susceptible to congestion. The charging strategies will determine the magnitude of potential reinforcements for LV3. LV2, on the other hand, is a prime example of a well-utilized transformer to date but might also require transformer upgrades with increasing EV adoption to comply with the DSO's N-1 strategy.

3.2.2. Cable Loading

Turning our attention to the cables, we summaries the performance under base load conditions. The DSO does not monitor cord loading but relies on fuses installed at the transformer interface to detect faults and prevent excessive overload events. Given the large variety of cable types, overloading will most likely occur without tripping fuses for cables located farther from the transformer, which tends to have a lower current-carrying capacity. With the unknown fuse limits, we define overloading as cable loading above 100%. While cables can withstand overload situations dependent on a wide range of external factors, it will accelerate the aging of wires.

The distribution of peak loading is shown in Figure 10. The results for the baseline scenario S0 (upper left plot) indicate that most cables possess a significant amount of spare.



Figure 10: Cable peak loading for each LVDN in S0 (upper left), S1 (upper central), S2 (lower left), S3 (more down main), and S4 (right). For illustrative purposes, we only display the highest-loaded cables, i.e., cables 36–89 for S1–S3 and 26–89 for S4. Solid red lines indicate the overload threshold. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) [57]

Table 5: Probability of transformer pt (%) and cable overloading pc (%) in each LVDN and charging scenario. For transformers, both congestion ($L \ge 100$) and violations of the N-1 operational limit ($L \ge 66$) are evaluated. Results are presented for two durations Δ , t (min) and a fraction of cables fc, with Ni representing the total number of wires in LVi. [57]

		$p_t(L)$	≥ 100)	$p_t (L \ge 66)$		$p_c (L \ge$	2 100)		
	Δt	5	60	5	60	5		60	
	f_c					$1/N_i$	1/10	$1/N_i$	1/10
LV1	S 0					0.2			
	S 1					59.5		31.6	
	S 2					5.7		0.9	
	S 3					3.3		0.8	
	S 4	0.9		90.2	35.3	100	83.6	98.3	35.1
LV2	S 0			0.8	0.1	98.7		95.6	
	S 1			90.1	69.2	100	71.2	99.9	37.4
	S2			24.4	4.2	99.5	15.9	97.5	3.7
	S 3			15.1	3.7	99.5	11.8	97.1	3.7
	S 4	100	99.7	100	100	100	100	100	100
LV3	S 0			100	100	100		100	
	S 1	59.7	24.4	100	100	100	1.9	100	
	S2	5	0.2	100	100	100	0.1	100	
	S 3	2.1	0.1	100	100	100		100	
	S 4	100	100	100	100	100	100	100	100

4. CONCLUSION

This paper analyses the impact of residential EV charging on three parts of the urban LVDN of Frederiksberg (Denmark). The research employs a probabilistic approach incorporating smart meter data and a novel agent-based EV simulator (GAIA). The study models the fluctuations in base load and projected residential EV charging demand when 40% of vehicles are electric. To

address the current energy crisis and the increasing concern over fluctuating electricity prices, we propose three cost-based charging methods (S2-S4) and compare their effect on the LVDN to a scenario with no EVs (S0) and one with uncontrolled charging (S1). For each LVDN and charging system, we perform 1000 power flow simulations at a 5-minute resolution for 24 hours on a typical weekday. We also analyze the implications for transformers, cables, and bus voltages.

Likely due to the meshed nature of the grids, the results show that cable and transformer overloading is the primary concern. Still, the expected impact varies greatly between each LVDN. This underlines the importance of performing detailed case studies and monitoring LVDNs. While LV1 seems highly resilient about the upcoming EV adoption, LV2, and LV3, in particular, might require significant reinforcements in the near future. However, the need for such measures is highly dependent on the future charging behavior of EV users. Implementing ToU-based charging can reduce congestion in LV2 and LV3 compared to uncontrolled EV charging. However, the effect of cost-based smart charging will depend on its design. Adopting a cost-based charging strategy that aligns with the natural charging pattern of EV users can further minimize the impact on the LVDN in the short term. It may delay the need for infrastructure upgrades. On the contrary, cost-based smart charging that disrupts the natural charging patterns of EVs, particularly when utilizing multi-day optimization combined with periods of exceptionally low electricity prices, greatly increases the likelihood of significant congestion within the LVDN. Such a shift in charging behavior would lead to a pronounced increase in investment costs, raising questions on how to prevent it.

The findings presented in this paper lay the foundation for future research targeting the following three areas. First, our scenarios depict cases where all EV users adhere to the same charging strategy and level of control and should be viewed as exemplary upper and lower bounds. In practice, the observed behaviors will be a mixture of the scenarios outlined in this paper. Thus, the grid impact is expected to lie within the boundaries of our charging scenarios. Therefore, given the significant impact of S4, future studies should examine the composition of charging strategies and discuss the probability of widespread implementation of multi-day optimizations and the possibility of coordinated charging events. Second, future work should address the uncertainties associated with charging at apartments. While our study assumes the same charging behaviors for all EV users and infers home charging based on the parking conditions, the conditions for different dwelling types may vary. Thus, a more detailed modeling of the charging behaviors at apartment complexes is needed. Future research should consider the uncertainties related to the installation of charging equipment, the possibility of smart charging, and the constraints concerning load sharing to fully understand the impact of home charging at such locations. Lastly, future work should also explore practical, short-term solutions for EV flexibility to mitigate potential congestion and focus on developing appropriate mechanisms to avoid events of extreme synchronization.

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