Simulation of electric vehicles daily charging in a low-voltage network to reduce grid reinforcement needs

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***Abstract*—The growing fleet of electric vehicles (EVs) in the low-voltage (LV) networks is an essential concern for the Distribution System Operator as it represents a significant increase in consumption thus potentially leading to costly grid expansions to prevent congestion. However, grid expansion can be postponed or even avoided if 'smart' solutions like load shifting are put in place. In this paper, we propose a methodology which simulates the EV daily trip- and charging profile with the consequent power flows in the electrical network. The smart-charging algorithm enables shifting the EV charging load in case of detected congestion. The algorithm is tested in an LV grid of a mountainous region in Slovenia. The algorithm is run for a typical week, with a 15-min resolution, with a Monte Carlo simulation performed to study the worst-case scenario. Finally, we analyse the results on the robustness of the grid and the benefits of the studied smart-charging algorithm.**

Keywords—Congestion management, Coordinated charging, EV charging, Grid reinforcement, Load shifting

I. INTRODUCTION

The current global challenge is the energy transition, which necessitates the drastic reduction of greenhouse gas emissions and the rapid electrification of essential industries. In 2018, the transport sector was responsible for 8.2 Gt CO_2 emissions, or 24 % of direct CO_2 emissions from fossil fuel combustion [1]. Passenger road vehicles are responsible for 3.6 Gt CO_2 of this total.

In this regard, the European Union set the goal of replacing a portion of the current combustion engine fleet with electric vehicles (EVs). In 2020, they announced a goal of 30 million EVs in the European fleet by 2030 [2]. In the same vein, Slovenia aims for ambitious objectives for the electrification of its transportation sector. In its last report on the development of the transport sector [3], the Slovenian government proposed that only cars emitting less than 50 gCO_2/km will be sold on the market, i.e., given the current state of technology, only electric and hybrid vehicles will be manufactured. The Slovene government estimates that up to 20 % of its vehicle fleet, or approximately 200,000 vehicles, will be electric by 2030.

These measures could help alleviate the impact of our mobility on the global climate, however, the introduction of new electrical loads into the electrical network must be carefully analysed to ensure grid reliability and security of supply, and thus prevent grid congestions [4]. Indeed, if the uptake of EVs is strong and the grid is too weak, the simultaneous charging of EVs could become unsustainable and require excessively expensive grid reinforcement.

While the scope of this analysis is bounded to the study of EV uptake, the necessity for the Distribution System Operators (DSOs) to upgrade their grid for the future technological and social transformations is part of a broader context. It features the general trends toward more locally produced energy from renewable energy sources (RES), the democratisation of electricity, and the widespread deployment of advanced metering infrastructure.

The document's structure is as follows: Section II examines the state of the art of simulation of EV charging and its effect on the electrical network, as well as the techniques for EV load shifting. Section III describes the method proposed in this paper and the architecture of the algorithms. The application of this method to a low-voltage (LV) network in Slovenia is described in Section IV, while the results are presented in Section V. The concluding remarks comprise the final section of the paper.

II. LITERATURE REVIEW

The research is based on three research questions, namely: What are the best practices for predicting EV charging profiles? How does the charging of electric vehicles affect the electrical network? How can the adverse effects be avoided and mitigated?

A. Predicting EV charging profile

The EV charging load depends on several factors, such as the user's driving and travel habits. This renders the charging load for a single EV user stochastic [5]. In order to implement this stochasticity and eliminate the random error from the forecasts, Monte Carlo simulations are widely used in the literature [6], [7], [8], [9], [10].

The authors in [7] and [8] used trip chains based on the Mark chain model to predict where, when and for how long an EV drives every day, with probabilities varying by day and hour. In contrast, [10] proposes three distinct stochastic methods which use separate independent variables to define the daily EV trip. It was demonstrated that the iterative method with dependency between the three variables produced the most accurate forecasts, particularly during peak hours.

Departure time, travelled distance, and arrival time are required variables for EV charging profile forecasting, but other variables can be valuable as well. For the creation of a trip chain, driving time and the parking duration are essential [8]. The definition of destinations is also important. In most cases, three destinations are defined: home, work, and the third destination which can encompass remaining activities such as shopping, leisure activity, or meal. Alternatively, if

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statistical data on travel patterns are sufficient [8], each of these activities can be analysed separately.

Distributions for characteristic variables are typically normal, or in the case of multipeak distributions, Gaussian mixture models and copula functions can be used [8], [10].

EV charging predictions and observable data show clear charging peaks: if private and public charging procedures are considered, a morning work charging and afternoon home charging can be observed [7]. If only private charging is assumed, the charging peak occurs from late afternoon to 1 am, with a relatively wide spread of the arrival time [6], [10]. Uncertainty is much higher during peak periods and is exacerbated by the inclusion of higher charging powers [7], [10].

B. *Effects of EV charging on the network loading*

Four different aspects of the grid can be analysed when performing an impact assessment of EV penetration in the distribution system: the voltage stability, the power quality, the peak load and the transformer performance [11], [12]. Our study primarily focuses on the peak load aspect. Researchers in [13] tested a set of 12,700 plug-in and hybrid slow-charge EVs and showed that a maximum of 10% of EVs can be safely integrated into the grid without the use of a control strategy. Scientists in [14] analysed a fleet of similar EVs with a charging power of 6.6 kW and connected to an extensive network of 12,000 nodes comprised of several low voltage networks connected to distribution transformers. They demonstrated that even with low EV penetration, the transformer was experiencing load surge. In addition, it was demonstrated that a high penetration rate (70 %) reached as much as 131 % of the transformer's nominal maximum load. Literature also shows that the impact of EVs is not necessarily proportional to the penetration rate increase, in terms of transformer load [14] or power quality indexes evolution, such as SAIFI [15].

C. *Algorithms for smart charging*

As demonstrated above, failing to implement a control strategy for EV charging immediately places a strain on the distribution networks, and the greater the adoption of EVs, the greater the burden. Two common approaches tackle this issue: decentralised and centralised scheduling [5], [16].

1) *Decentralised scheduling*

Decentralised scheduling involves economic incentives, such as lower electricity costs during off-peak hours, which can persuade EV owners to delay their charging time. These types of incentives, which are static tariffs, can result in two distinct outcomes. Authors in [14] demonstrated that charging EVs between 5 pm and 1 am was more beneficial to the grid than charging every EV owner upon their return home. Alternatively, such an incentive may significantly increase the peak load during certain early evening hours, as observed in [17]. The methodology of decentralised scheduling introduces gradient projection technique [18], non-cooperative game strategy solutions [19], multi-stage optimization or multi-agent methods [5]. The peak load can be reduced while using coupled multi-agent methods, particularly in wintertime [16]. In general, the decentralised approaches aim to minimise the individual EV owner costs for charging, thus filling the valley periods [19], [20], [21], and this is their main benefit. However, grid-level issues cannot be addressed simultaneously [16]. And optimal solutions for a decentralised approach required high-resolution knowledge of the grid and EV status, necessitating a huge amount of data and communication that is, in most cases, not feasible [5].

2) *Centralised scheduling*

Centralised scheduling involves one central operator determining the charging time for each EV in a fleet. Required information includes charging times, charging rates and grid capacity. The main advantage of centralized scheduling is the guarantee of power reliability and quality. Combining EV charging schedules with RES production or vehicle-to-grid (V2G) mechanisms can be very promising [16]. However, the optimisation burden increases as the number of EVS on the grid increases. In case of excessive EV penetration, this can become computationally expensive very quickly [5]. Last but not least, [5] recommended a hybrid approach combining both centralised and decentralised control strategies. The recommended system is a two-level system, with the first level being centralised and the second level being decentralised.

III. METHOD

Our analysis aims to demonstrate the possibility and benefits of shifting the charging of EVs from congested to uncongested periods without compromising the local network while maximising the utility of the EV owners. As shown in Figure 1, a four-step method was followed for achieving this objective.

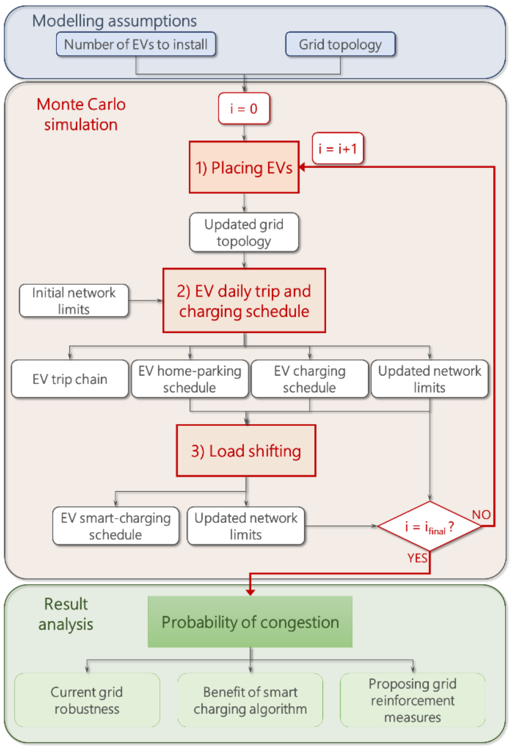

Figure 1: Methodology followed in the study

1. **Placing the EVs** – An algorithm defines the location of new EVs in the grid based on a priority list considering the individual household distance from the transformer, power connection type, and other distributed energy resources owned by the consumer.
2. **Simulating the daily trip and charging time** of each EV.
3. **Shifting the charging schedule** – in case of congestion occurring in the feeder or transformer, the charging of an EV

is shifted to another timeslot during which the EV is stilled parked at home.

4. **Estimating the robustness of the network** – after performing a Monte Carlo simulation of the first three steps, the probability of congestion for each feeder of the network and transformer is calculated. The final goal is to propose a feeder upgrade measure or transformer replacement.

This study aims to provide credible worst-case scenarios to the DSO, therefore the simulation is run multiple times for several iterations and at different EV penetration rates – i.e., Monte Carlo simulation.

Before demonstrating the setup, data has been collected to establish the system assumptions. Each algorithm's underlying assumptions are listed in the following sections.

A. Placing EVs

The first algorithm aims at placing a defined number of EVs in the grid. The EVs could be placed randomly but this could significantly affect the results. To simulate as realistic future scenarios as possible, the priority rules are created based on basic topology information:

- the presence of other flexible assets inside the household (PV, heat pump or battery),
- the connection type (single-phase or three-phase),
- the distance from the load to the medium voltage (MV) to low voltage (LV) transformer.

EVs require a high charging power in comparison to the usual household consumption on the low voltage (around 1 or 2 kW at peak times). In this study, the modification of the agreement between the DSO and the end-user for the connection power is not considered. Therefore, households connected with three-phase could be more likely to own an EV than single-phase connected households. It is also foreseen that households which currently own a battery and/or a PV unit could be more likely to adopt new technologies such as EVs. Finally, households located far from the transformer stations are more likely to create high deviations of voltage and thus generate problems in the grid [16] and are therefore also favoured.

Further assumptions include the fact the charging stations are private and are dedicated to a single EV so households cannot own multiple EVs. In addition, to analyse the worst-case scenario of EV charging, it is assumed that EVs only charge at home and nowhere else during their trip.

The first algorithm therefore only requires two inputs: the initial grid topology and the number of EVs to place. The output of the function is an updated grid topology with a list of households that own an EV and its charging station.

B. Simulating the daily trip and charging time of an EV

The second algorithm aims to define the daily trip of an EV to define the consumption of the car and the time needed to fully charge for the following day. For this, a set of assumptions is needed:

a. The car starts and ends its trip at *Home*. No trip is allowed from *Home* after 8 pm.

b. Two other destinations are possible: *Work* or *Other*. The *Other* category includes a variety of activities, such as leisure, going to a restaurant, or picking up children. *Work* can be reached only once per day, no later than noon, and for 8 hours. The parking time in *Other* is randomly selected, with a maximum of 2.5 hours.

c. The distance between the three destinations follows a gamma distribution based on statistical data [22].

d. The time of the first departure follows a lognormal distribution and is based on literature [8], [23].

e. The car is supposed to drive at an average speed of 60 km/h.

f. The average consumption of the car is set to 195 Wh/km, reflecting the consumption of current EVs on the market [24].

g. The EV's battery usable is randomly selected between 40 and 85 kW.

h. The EV's charging is assumed to require only active power. Moreover, the charging power ($P_{charging}$) depends on the loads' contracted power ($P_{contracted}$):

   - For single-phase households: $P_{charging} = min\,(7.4\ kW, P_{contracted} - 1\ kW)$
   - For three-phase with contracted power $\geqslant 23$ kW: $P_{charging} = 22\ kW$
   - For three-phase with contracted power <23kW: $P_{charging} = min\,(11\ kW, P_{contracted} - 1\ kW)$

The algorithm was run separately for each EV. The three outcomes are a daily trip chain for each car, a schedule for parking (and being plugged in) at home, and a charging schedule. The departure time for a particular EV is assumed to be the same every day for a given iteration. The time resolution is 15 minutes, so the daily schedules consist of 96 timeslots.

By inputting the initial network power limit for each period of the day, the algorithm can render an updated calculation of the network available capacity, as expressed in Equation (1) for the MV/LV transformer and in Equation (2) for feeders.

$$P_{available\ ,EV} = P_{Limit} - \sum_{i=1}^{N_{EV}} P_{Charging\ ,i} \tag{1}$$

$$P_{available\ ,f,EV} = P_{Limit\ ,f} - \sum_{i=1}^{N_{EV\ ,f}} P_{Charging\ ,i} \tag{2}$$

With $P_{available,EV}$ and, $P_{available,EV,f}$ the updated available capacity in the transformer and in the feeder *f* respectively, P_{Limit} and $P_{Limit,f}$ the initial capacity limit of the transformer and of the feeder *f* respectively, $P_{charging,i}$ the charging power of the i^{th} EV. N_{EV} and $N_{EV,f}$ are the total number of EVs connected to the whole network and feeder *f* respectively.

C. Shifting the EV charging schedule

In case of congestion, i.e., if $P_{available,EV}$ and/or $P_{available,EV,f}$ is lower than the operational limit (as defined by the DSO), the third algorithm enables load shifting of the EV charging. In the current configuration of the algorithm, priority is given to EVs that are close to being fully charged. In the context of a local market in which EVs compete if network capacities are limited, nearly full EVs are supposedly willing to pay a premium to complete their charge.

The algorithm works as follows: For each timeslot *t*, if there is congestion under feeder *f*, connected and charging EVs under feeder *f* are considered. A Mixed Integer Programming algorithm (MIP) determines which EVs should be shifted to maximise the total state of charge of the entire EV fleet. If the network's available capacity at *t+x* allows it, charging for all selected EVs parked at home and not charging will be shifted to a different timeslot *t+x*.

The algorithm produces a new charging profile for each EV, called smart-charging, and an updated calculation of the network limits, as expressed in Equation (3) for the transformer and Equation (4) for the feeders:

$$P_{available,smart\ EV} = P_{available,EV} \pm \sum_{i=1}^{N_{EV,shift}} P_{Charging,i} \quad (3)$$

$$P_{available,f,smart\ EV} = P_{available,f,EV} \pm \sum_{i=1}^{N_{EV,shift,f}} P_{Charging,i} \quad (4)$$

With $P_{available,smart\ EV}$ and $P_{available,f,smart\ EV}$ the updated available capacity in the transformer and in feeder *f* respectively after load shifting, $N_{EV,shift}$ and $N_{EV,shift,f}$ are the number of shifted EVs connected to the network and to feeder *f* respectively.

IV. Application to a Real Case Study

The methodology presented in the section above was applied to an LV network in Slovenia. The network is representative of a rural and mountainous area. The network is relatively weak and is subject to several outages every year due to the extreme climate conditions and the high demand peaks from the farms connected to the grid. The part of the village under study comprises one MV/LV substation and the 155 loads connected to it. The network is a 13-feeder system configurated in a traditional radial manner. The network currently includes 9 private EV chargers located in 3 different feeders. These chargers were installed in 2021, it is not yet possible to analyse data regarding the charging patterns of EV drivers. The homes where these EV chargers are installed are already connected to three phases. These homes already have PV systems with a capacity of approximately 10 kWp.

The data collected also includes historical power data for more than 3 years at the connection point of each household, as well as at the transformer level. This length of time permits to define reasonable average power profiles for the network. For this study, the capacity limits of each feeder have been calculated for a typical winter week. The operational limit for the feeders has been set to 5 kW, while it was set to 20 kW for the MV/LV transformer. Figure 2 shows a typical Monday load for the transformer and three of the feeders: The feeders I02 and I06 which have the highest cumulated demand, and the feeder I172 which has the second-highest peak demand. The net demand under the feeder I172 is below 0 kW during daytime as several PV systems are connected to this feeder.

A sensitivity analysis on the EV penetration rate was performed with a resolution of 5 %. As the current rate of EV chargers is around 6.4 %, the analysis is conducted from 6.4 % to 100 % penetration rates. For each rate, the three algorithms are run using a Monte Carlo simulation, with 100 iterations.

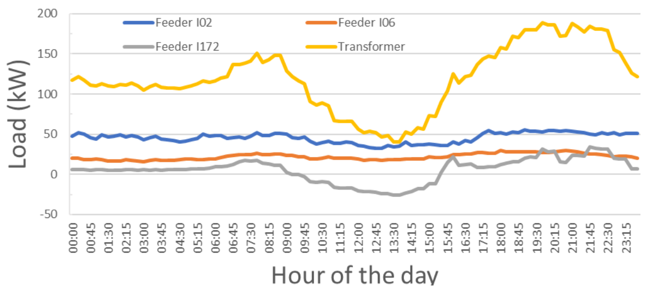

Figure 2: Average load profiles in different feeders for a typical Monday in the winter period

V. Results

A. Tendency to congestion

Simulations revealed that even with 100 % penetration of EVs, the only feeders that could get congested are I02 and I06 (Figure 3), which carry the most loads. For feeder I02, congestion occurs at 40 % EV penetration in the grid, and the likelihood of congestion exceeds 50 % at 55 % EV penetration. The feeder I06 is much less inclined to congestions as they never occurred with EV penetration rates lower than 70 %. However, between 75-100 % EV penetration rates, the likelihood of congestion is very low, as it has occurred no more than 11 % of the time. At the transformer level, the congestion tendency follows a similar pattern as feeder I02, with congestion appearing from 40% of EV-equipped network loads. It quickly reaches 100% change in congestion when at least 70% of the loads are equipped with EVs.

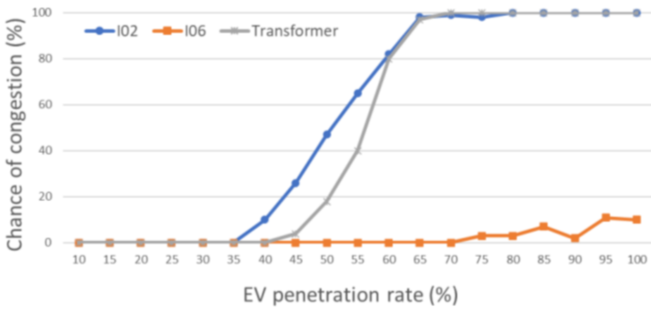

Figure 3: Congestion occurrence in feeders I02, I06 and transformer for each EV penetration rate

This first observation demonstrates that, for the majority of the grid, an adoption rate of electrical vehicles lower than 40% would not cause network issues.

B. Charging profiles

Figure 4 shows the simultaneity of EV charging. The profiles clearly demonstrate that EVs are more likely to be plugged in and charging at the end of the working day: in the afternoon with a high plateau starting around 5 pm for weekdays and 1 pm for weekends, and with a significant number of EVs charging until midnight. For all penetration rates, the maximum number of EVs charging simultaneously occurs between 9 pm and 10 pm, when nearly a third and a quarter of the EV fleet is charging on weekdays and weekends, respectively. Figure 4 also shows that the proportion between the penetration rate and the number of EV charging is quite consistent throughout the day, although the distinction becomes less evident during nighttime and early morning when fewer cars are charging. It is also apparent that the number of EVs charging on weekends is lower because cars are not moving for the entire day.

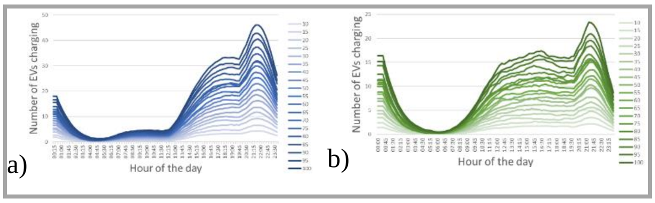

Figure 4: Simultaneity of uncontrolled charging for each penetration rate. a) during weekdays, b) during the weekend

As previously observed in Figure 3, when congestion occurs in two of the weak feeders or the transformer, EV charging is shifted to periods when the feeder has sufficient capacity and the vehicle remains parked at home. When congestions occur at the transformer level, EVs from any feeder can be shifted. In the worst cases, the total number of EVs shifted during the day is 35 on weekdays and 28 on weekends (100 % penetration rate) which is relatively high compared to the size of the EV fleet (23% and 18% respectively).

C. *Load impact*

The impact of EV charging on the transformer loading was also analysed. Figure 5 presents the average available capacity for one day of simulation based on 100 iterations of all loads (Wednesday). Above a certain EV penetration, congestions always appear between 5 pm and 11 pm.

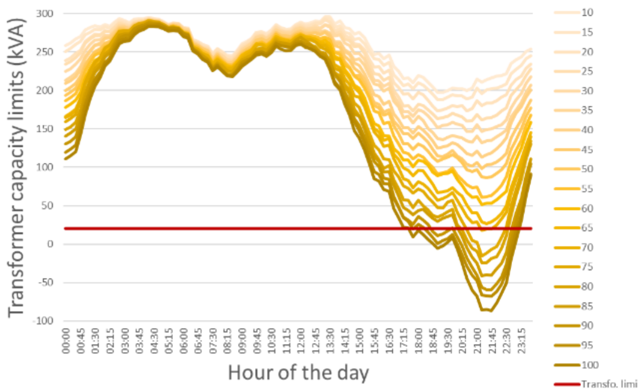

Figure 5: Average transformer capacity available for each EV penetration rate, without controlled charging

Table I reveals that the peak power is 188.01 kW for the baseline scenario with no new EVs in the network, while it reaches 486.75 kW when simulating a complete fleet of EVs without controlled charging, which is 1.2 times the feeder technical limit.

In addition, the ratio between the peak demand and the average demand is calculated following Equation (5).

$$PAR = \frac{max_{t\in T}(P_t)}{\frac{\sum_{t=1}^{T} P_t}{T}} \quad (5)$$

PAR denotes the Peak-to-Average Ratio, P_t the demand power at feeder level (in kW) at instant time t and T the number of observations.

In the absence of a controlling system, there is a relatively constant increase in this ratio as the penetration rate rises. This indicates that the greater the EV penetration, not only does it add demand to the baseline power profile, but it also increases the power disparity between peak hours and off-peak hours, necessitating that the network is able to sustain high loads for brief periods. In contrast, when a smart charging control is implemented, the peak demand naturally does not exceed the feeder limit reduced by the operational limit. As the number of EVs increases, the peak-to-average ratio also increases at a similar rate. However, as the percentage of EVs increases above a certain threshold (approximately 50 %), the ratio decreases as average demand increases but peak power remains stable.

Table I: Peak demand and Peak-to-average ratio (PAR) for each EV penetration rate in the transformer

EV penetration rate (%)	**Peak demand (kW)**		**PAR**	
	Uncontrolled	***Smart***	***Uncontrolled***	***Smart***
6.40	188.01	188.01	1.44	1.44
10	202.47	210.40	1.42	1.48
15	212.27	222.81	1.44	1.51
20	226.96	238.05	1.47	1.55
25	240.00	251.58	1.50	1.57
30	253.61	259.88	1.53	1.57
35	267.90	275.99	1.56	1.61
40	286.88	286.22	1.61	1.61
45	301.97	308.28	1.64	1.67
50	313.68	320.10	1.66	1.68
55	339.11	325.26	1.73	1.66
60	348.24	335.50	1.72	1.66
65	373.34	341.62	1.79	1.64
70	381.65	349.81	1.78	1.64
75	415.50	374.10	1.89	1.69
80	424.43	372.96	1.87	1.65
85	441.26	377.02	1.90	1.62
90	459.10	376.82	1.92	1.57
95	467.76	376.53	1.92	1.54
100	486.75	375.35	1.95	1.50

VI. CONCLUSION

This paper examined and discussed the impact of charging privately owned electric vehicles on the low-voltage network. The methodology consists of three algorithms, with the first algorithm placing EVs in different households that make up the LV network, based on the connection type the houses, the second algorithm simulating a daily trip for each EV and a charging schedule, and the third algorithm shifting the charging periods to uncongested periods, considering the conditions of each feeder and transformer. The simulation system was implemented on a rural LV network in Slovenia that is prone to outages because of its isolation and cable length.

The results show that the two most populated feeders are the only ones to be subject to congestions, even when all houses in the network have an EV charger. With an EV penetration rate of 40 percent or more, one of them is especially susceptible to congestion. Approximately a third of the EV fleet is observed to be charging between 5 pm and midnight on weekdays, resulting in a heavy network load between those hours. During the weekend, however, the number of EVs charging is lower, and charging sessions occur between 1 pm and midnight. The smart-charging scheduling process proved effective for ensuring the network's safe operation in terms of congestion management, with rescheduling impossibility occurring only on rare occasions. This ensures a very high level of EV user satisfaction, as the EVs will always be fully or nearly full charged upon departure from the residence. Smart-charging scheduling thus enables a deferral of grid reinforcement, which is crucial for DSOs seeking to reduce their costs. Finally, the results have shown that smart-charging scheduling allows EVs to be charged outside off-peak hours, thus equalising the power profile, leading to more optimized utilization of the grid.

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