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Impact of Uncontrolled Charging with Mass Deployment of Electric Vehicles on Low Voltage Distribution Networks

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***Abstract*—This study aims to quantify the impact of uncontrolled charging of Electric Vehicles (EVs) on the low voltage distribution networks with increasing EV penetration levels. For this objective, key indicators are developed to show the magnitude, scale and duration of the impact on the distribution network. The disseminated results are based on the case study with actual data from the existing distribution networks. The findings of this paper can serve as a benchmark for determining the potential of smart EV charging algorithms and/or the extent of necessary infrastructural reinforcement that the grid operators must incorporate.**

I. Introduction

Mass deployment of Electric Vehicles (EVs) can have a detrimental effect on the Low Voltage (LV) distribution networks due to the increased peak demand and unpredicted charging behaviour. The increased number of EVs increases the total demand for power and energy, which can lead to an overload of system assets like transformers and lines [1], [2]. With the growing quantity of EV owners, the increased load peak can be much higher than the percentage of increased EV share. That is because the new charging demand of EVs will possibly be added on top of the existing peak demand. The transformer is hence under high risk of increased loading which leads to a decreased lifetime, and overloading which will destroy the transformer eventually [3], [4]. Besides, the high penetration level of EVs can aggravate the system power losses and the voltage deviation, especially at the far end of the lines [5], [6]. It has been found that even with a low level of EV penetration, the furthest nodes already experienced measurable voltage deviations [7]. Grid overloading can be reduced with use of distributed generation such as Photovoltaics (PV) [8]. However, power mismatch arising due to the uncertain nature of these resources can lead to local pockets of network congestion that can be avoided if PV to EV charging is integrated [9], [10].

This paper aims to benchmark the technical challenges associated with increasing electrification needs for electrical vehicle charging.

The main contributions of this paper are the following:

- Develop insight on the possible consequences of mass deployment of EVs under uncontrolled charging in terms of transformer overload, line overload and node voltage deviation.
- Define the key indicators that show the magnitude, scale and duration of the distribution grid impacted as the percentage penetration of EVs increases.
- Determine the trend based on key indicators and quantify the critical EV percentage penetration level where its influence on the studied grid infrastructure needs intervention.

Case studies using actual data from existing distribution grids in the Netherlands are performed to support the findings of this paper.

Fig. 1: Heat map showing the overloaded and under-voltage region in the suburban grid with 80 % EV penetration.

II. System Description and Simulation Scenarios

A. Grid Description

One sub-urban grid and one urban grid were investigated in this study. The main parameters of the simulated grids are shown in Table I. The structure of both grids can be observed in the heat map in Fig. 1 and Fig. 4 respectively. In this study, a level of 15 % PV penetration in suburban grid, and a level of 5 % PV penetration in urban grid with 2.5 kW rated power for each installation is considered in all simulated scenarios. The PV penetration is calculates based on the number of loads in the grid.

TABLE I: Grid parameters.

Grid type	Suburban grid	Urban grid
Number of transformers	3	2
Transformer rating [kVA]	400	400
Average line length [m]	6.97	4.62
Number of loads	806	349
Number of households	772	269
Yearly energy demand [MWh] (2018)	2353.03	1680.22

B. EV Fleet Setup

An average number of 0.9 cars per household for given sub-urban grid, and 0.5 cars per household for given urban grid is considered as a base assumption [11]. Factoring in different EV types is out of the scope for this study and the variation of the market share is unknown for future high EV penetration case. Therefore, parameters of the two EV types considered in this preliminary study are summarised in Table II based on market data from [12]. A rated charging power with three phase, 25 A is selected for it is assumed that the higher charging power is more popular in the future.

TABLE II: Parameters of the chosen EV fleet.

EV	Type I	Type II
Percentage of total EVs	70 %	30 %
Battery size	50 kWh	100 kWh
Average energy Consumption	6 km/kWh	4 km/kWh
Charging Power	17.25 kW (3x25 A)	17.25 kW (3x25 A)

The EVs are evenly distributed throughout the grid. However, the location of charge points are differentiated into Home, Semi-public and Public neighbourhoods. That is because for each location, the EV has its typical charging behaviour e.g. particular pattern of arrival time and charging duration, and it has a significant impact on the grid, in combination with the base-load feature of that location. For the sub-urban grid, 50 % of the chargers are used in the home (residential) neighbourhoods and the rest are equally distributed between semi-public and public neighbourhoods. Similarly, 25 % of the chargers are for residential neighbourhood in urban grid, and the rest of the chargers are equally shared by semi-public and public neighbourhoods. The average charging frequency is assumed to be four times per week for each car, out of which three charging events occur in the weekdays and one in the weekend.

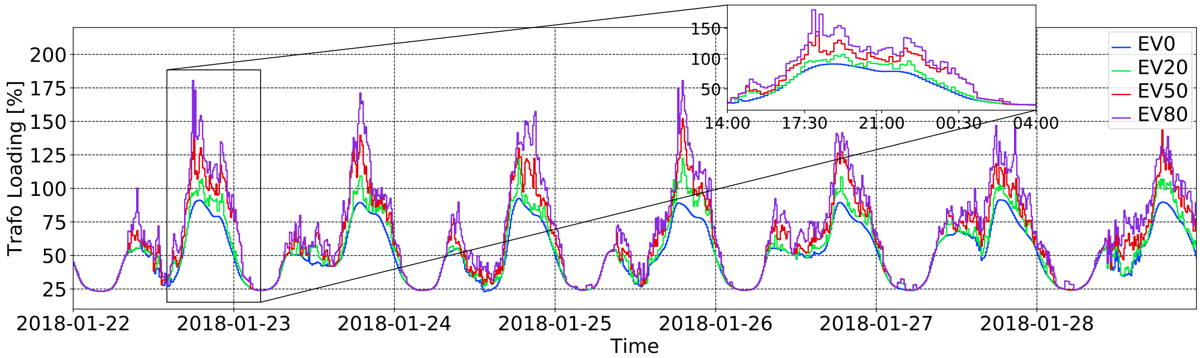
It is assumed that charging is initiated with rated power immediately after the EV arrives at the charge point. The arrival time is selected from its probability distribution obtained from an open data platform [13], [14]. This platform also provides probability distribution of the parking time and the energy demand from real measurement data for different charger types (home, public and semi-public). While these two parameters together govern the charging duration for the given event, the challenge is that probability sampling may not give a physically viable option. For example, if the energy demand selected from the measured distribution is higher than the amount that can be delivered by uncontrolled charging within the corresponding obtained parking time by sampling, this value cannot be preserved in simulations. The challenge is further exacerbated because the arrival SoC of the two EV types signify different chargeable battery capacity for the event. Therefore to represent the grid impact of uncontrolled EV charging, this paper considers the start time and duration of a given event based on the available measured data while avoiding such input inconsistencies that can arise from a random selection of multiple probabilities. However, this choice can cause deviations from the actual probability distribution. A multivariate probability analysis can improve the accuracy of the data if further interdependence information of individual probability is given [15]. Besides, a aggregated consideration of available data can be a interesting research initiative to reduce the uncertainty and complexity in the simulation model [16]. This is out of scope of the present paper.

III. Simulation Results

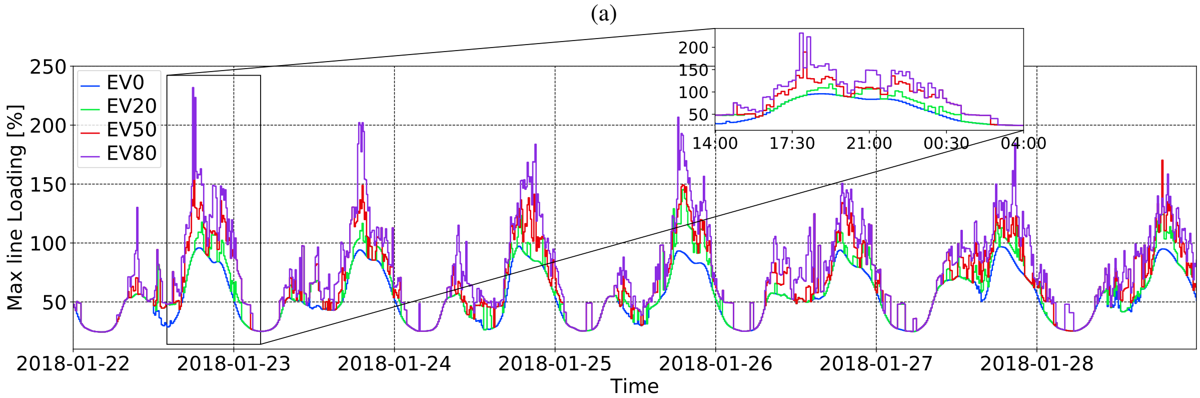
A. Suburban grid

The daily variation in transformer loading for a week (From Monday to Sunday) in winter with a time resolution of 10 minutes is shown in Fig. 2a and the maximum line loading among all lines at a given instance of time is shown in Fig. 2b. The results are for EV penetration levels of 0 % (EV0), 20 % (EV20), 50 % (EV50) and 80 % (EV80). It is conspicuously shown in the graph that the overall loading of both transformer and line rises when the EV penetration level grows. Most of the peak loading caused by EV charging directly adds on top of the peak loading of the basic load (0 % EV) and this tendency is less fierce in the weekend, which related to the prevalent arrival and parking time of the EV fleet during the week. Even though the peak loading reaches incredibly high value, there is still plenty of capacity for charging during the night and this ensures the technical potential for smart charging algorithms.

Aside from the transformer and line loading which varies with time, there are two other aspects that are interesting and considered in this study. First is the percentage length of overloaded lines in the system as EV penetration increases since the cost of line replacement depends on the length and the result is shown in Fig. 3a. What is the size of the influenced area when a grid congestion happens is also interesting. Thus the percentage number of nodes in the system which experience an under-voltage (below 0.9 p.u.) as the EV penetration level increases is plotted in Fig. 3b.



(a)



(b)

Fig. 2: Comparison of the grid loading of suburban grid with different EV penetration levels (a) Peak transformer loading (b) Peak line loading

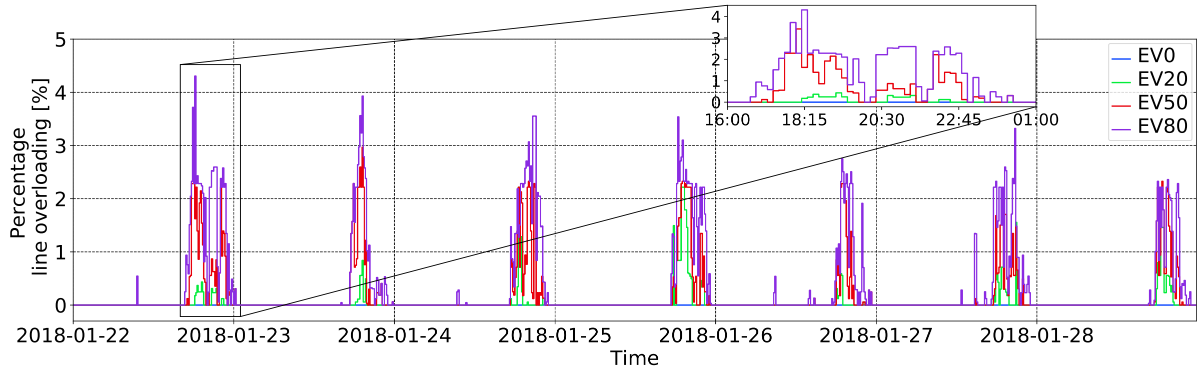
TABLE III: Variation in key indicators of suburban grid performance.

Indicators	0 % EV	20 % EV	50 % EV	80 % EV	Impact
Peak Transformer Loading [$P_{\text{ol,xmer}}$,%]	92.58	124.13	152.04	180.57	Magnitude
Peak Line Loading [$P_{\text{line,max}}$, %]	97.29	145.40	189.35	231.85	Magnitude
Lowest Node Voltage [$V_{\text{node, min}}$, p.u.]	0.90	0.86	0.83	0.76	Magnitude
Maximum percentage length of overloaded lines [$l_{\text{ol,line}}$, %]	0	2.22	3.42	4.31	Scale
Maximum percentage of under-voltage nodes [$N_{\text{uv,node}}$, %]	0	21.66	23.27	29.85	Scale
Percentage time of transformer overload [$t_{\text{ol,xmer}}$, %]	0	3.97	13.79	19.74	Duration
The ratio of energy delivered when transformer overload [$r^{\text{xmer}}_{\text{E-ov}}$, %]	0	7.66	25.71	36.05	-
Average transformer loading [$P_{\text{av,xmer}}$, %]	52.72	56.68	63.42	70.36	Utilisation

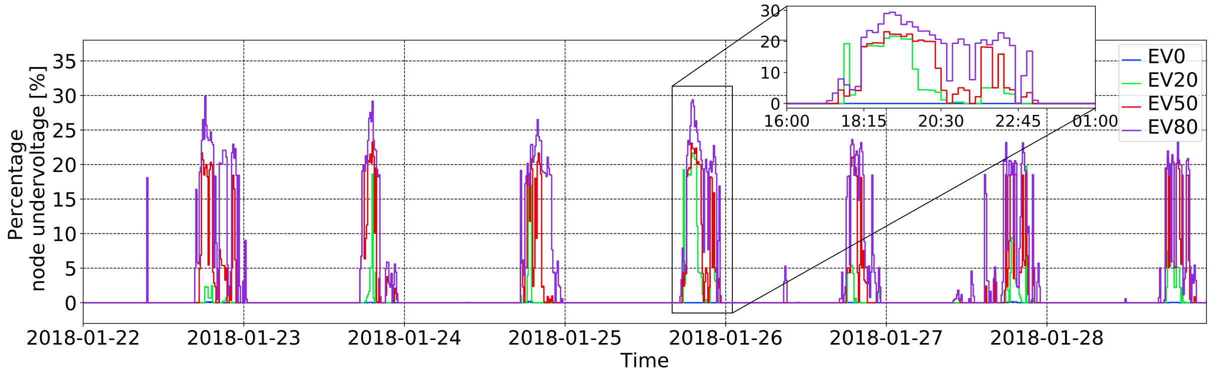
From two loading curves in Fig. 2, it can be observed that both transformer and line loading shares similar trend versus the time. Comparably, the congestion scale in suburban grid which is reflected in the percentage length of line overloading and node undervoltage percentage also presents a similar trend versus time, as exhibited in Fig. 3.

The heat map of suburban grid in Fig. 1 can connect the above findings together easily. This heat map is a snapshot of the grid under its maximum loading moment when both the maximum line loading and the transformer loading reaches their peak value. In this simulated sub-urban grid heat map, the overloaded transformers, lines and undervoltage regions with 80 % EV penetration level are depicted in red and blue separately. The location of the overloaded transformer is highlighted in the circle and the following study on the transformer is focused on this overloaded transformer. Most of the area in the grid shows different degrees of voltage drop and loading increase and there is a significant big area experiences heavy congestion at the lower left corner of the heat map. Based on the heat map we can see that the overloaded transformer is upstream from the maximum overloaded line and an undervoltage area presents further downstream. The most congested components are interconnected and interactive with each other, leading to the identical trend in Fig. 2 and Fig. 3.

While the EV chargers are assumed to be evenly distributed across the grid, a more clustered charging scenario can lead to localised, but more significant overloads. On the other hand,



(a) Percentage length of overloaded lines in the system as EV penetration increases.



(b) Percentage number of nodes in the system with under-voltage as EV penetration increases.

Fig. 3: Comparison of the congestion scale of Suburban grid

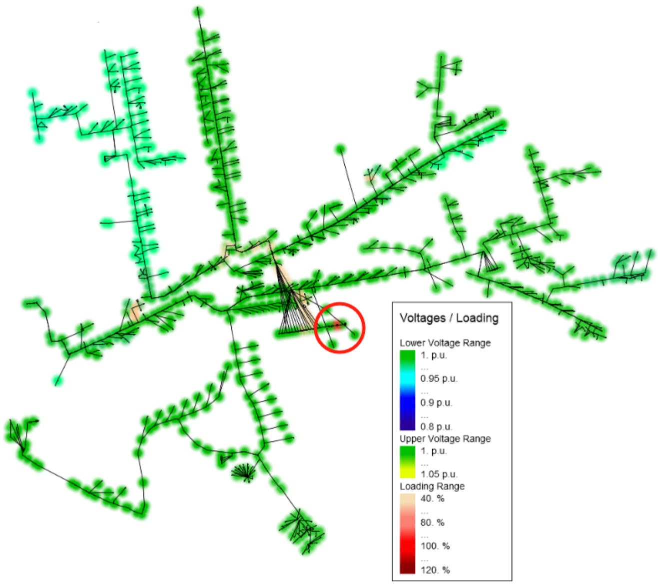


Fig. 4: Heat map showing the under-voltage region in the urban grid with 80 % EV penetration.

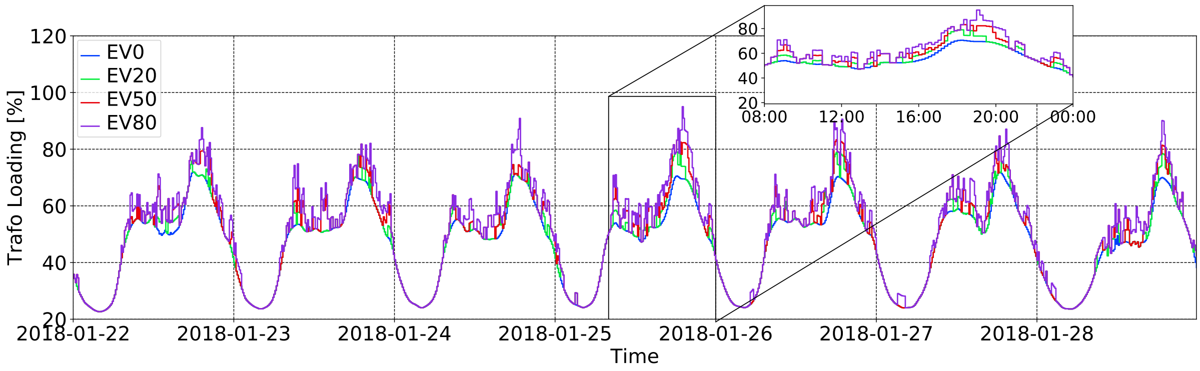
in the evenly distributed scenario, the area of the affected grid when the line overload occurs can be more significant. In order to quantify the influence of uncontrolled EV charging, further representative index are investigated. The magnitude, the scale, the duration and the quantity of grid impact as EV penetration level increases based on eight selected key indicators are summarised in Table III.

The variation in the indicators $P_{\text{ol,xmer}}$, $P_{\text{line,max}}$, $V_{\text{node,min}}$, $l_{\text{ol,line}}$ and $N_{\text{uv,node}}$ (refer Table III for definition) are compared for the two grids in Section IV. $t_{\text{ol,xmer}}$ is important because duration of overload can suggest how much flexibility in energy demand from EV charging is necessary in terms of time. The parameter $r^{\text{xmer}}_{\text{E-ov}}$ as the ratio of the energy delivered when the transformer is overloaded ($E^{\text{xmer}}_{\text{ov}}$) and the overall energy delivered by this transformer ($E^{\text{xmer}}_{\text{total}}$), as given by (1)

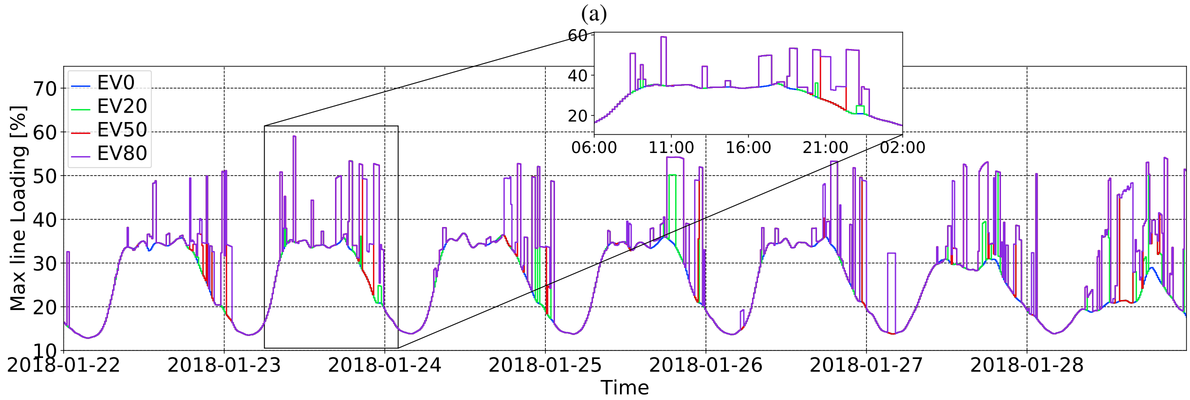
$$r^{\text{xmer}}_{\text{E-ov}} = \frac{E^{\text{xmer}}_{\text{ov}}}{E^{\text{xmer}}_{\text{total}}} \tag{1}$$

Further investigation is needed to derive insight on grid congestion as a consequence of combined effect of magnitude and duration of overload. Similarly, $P_{\text{av,xmer}}$ can indicate the utilization of installed infrastructure and it can be seen that the variation in this parameter is more gradual than peak ($P_{\text{ol,mer}}$). The method of obtain indicators $t_{\text{ol,xmer}}$, $r^{\text{xmer}}_{\text{E-ov}}$ and $P_{\text{av,xmer}}$ is applicable for line overloading analysis as well.

The findings of this study are important because the nature of the grid impact will govern the type of necessary intervention. For example, indicators showing a high magnitude, low duration grid impact may necessitate a different smart charging



(a)



(b)

Fig. 5: Comparison of the grid loading of urban grid with different EV penetration levels (a) Peak transformer loading (b) Peak line loading

method than one with low magnitude, high duration overloading. The geographical scale and utilisation factor can provide insight into the potential of smart charging as compared to conventional infrastructure reinforcement solution.

B. Urban grid

Similar analysis were applied on the urban grid. The heat map of the simulated 80 % EV penetration level scenario at the moment of its maximum line loading reaches the peak are shown in Fig. 4 and the most heavy loaded transformer is highlighted in the circle. The following analysis on the transformer focus on this heavy loaded transformer. The loading of the focused transformer and the maximum line loading among all lines is shown in Fig. 5. The transformer loading and maximum line loading of urban grid shows a dissimilar trend with each other, which suggests these two loading behaviour are not highly co-related. This is supported by the heat map of urban grid in Fig. 4 that the transformer, the max loaded line and the voltage drop area are not directly connected.

Since there is no overloading situation happening in urban grid, the overloading scale analysis is then omitted. The rest of the key indicators are inspected together with suburban grid in the next section.

IV. Comparison of Key Indicator Trends Between Suburban and Urban Grid

This section describes the trend in the defined key indicators as a function of EV penetration and discusses the possible reasoning behind these variations. Fig. 6 shows that the variation in the maximum transformer and line loading ($P_{\text{ol,xmer}}$ and $P_{\text{line,max}}$, respectively) as a function of EV penetration (N_{ev},%) for sub-urban and urban grids respectively.

Intuitively it can be expected that overload magnitude is directly proportional to EV penetration level due to increase in number of EVs connected during peak hours. The following are some interesting insights that can be derived from the results

- The main observation is that unlike suburban grid, where the impact of increase in EV penetration leads to significant overloads, this is not the case with urban grid, even with highest considered EV penetration ($N_{\text{ev}} = 80\,\%$). The first reasoning is that the suburban grid has a very high base-load that both its transformer and the maximum line loading almost reach 100 % even with none EV connected to the grid. Another reason is the number of urban households (269) is less than the suburban case (772). The assumption on average number of cars per household is much lower for urban (0.5) as compared to suburban (0.9). As a consequence, the actual connected

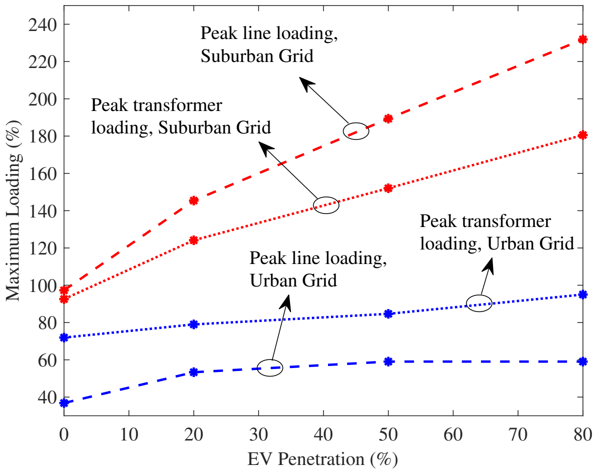


Fig. 6: Transformer and line loading trend as a function of EV penetration for Sub-urban and Urban grid.

EVs as a function of penetration level is lower for the urban grid, leading to a correspondingly lower EV charging power demand. Furthermore, the number of EVs in the grid was estimated based on the car statics where the car mobility is not included. Which means the data can only reflect the location of car ownership but not the actual location where the car frequently parks.

- The maximum line overloading is relatively more severe than the maximum transformer loading for sub-urban grid. This trend is not observed for urban grid, where peak line loading is lower and flattens with higher EV penetration. From the heat map of these two grids we can see the maximum line loading of suburban grid mainly aggregated in the main lines but in urban grid the maximum line loading appears locally to a greater degree. Two hypotheses are proposed based on the observation. If the absolute number of EV is greater than certain threshold, the loading of the main lines (which is the accumulated loading of all their sub-branch lines) will surpass the regional line loading, and then the feature of regional line loading will be less distinct. Besides, the grid congestion tendency might be grid specific that different grid characteristics alters the magnitude and the allocation of the grid loading.
- The slope of the plot-lines ($\frac{\Delta P_{\text{ol,xmer}}}{\Delta N_{\text{ev}}}$ and $\frac{\Delta P_{\text{line,max}}}{\Delta N_{\text{ev}}}$, respectively) can be reduced by means of smart charging for achieving power demand flexibility. Thereby, $\frac{\Delta P_{\text{ol,xmer}}}{\Delta N_{\text{ev}}}$ and $\frac{\Delta P_{\text{line,max}}}{\Delta N_{\text{ev}}}$ as a function of EV penetration can be used to benchmark the performance potential of the smart charging algorithm for the given operating scenario. More data point is needed to attain a more accurate trend and the slope.

Furthermore, Fig. 7 shows the minimal node voltage trend as a function of EV penetration for both suburban and urban grids. The voltage line in both grids present a linear trend.

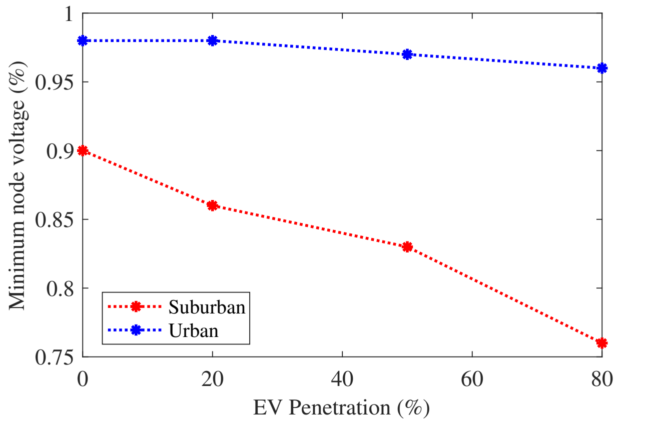


Fig. 7: Minimum node voltage trend as a function of EV penetration

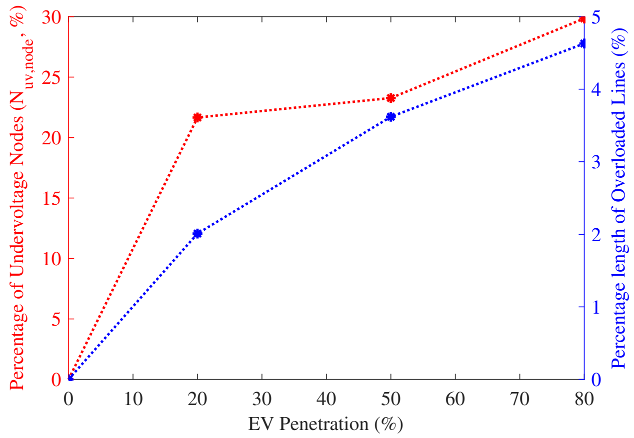


Fig. 8: Scale of grid impact as EV penetration increases in the Sub-urban grid.

suburban grid has a way worse voltage problem than the urban grid as expected which is again related with the absolute number of EVs that are connected to the grid.

$N_{\text{uv,node}}$ and $l_{\text{ol,line}}$ indicate the scale of grid impact with uncontrolled EV charging in the sub-urban grid. Fig. 8 shows the $N_{\text{uv,node}}$ and $l_{\text{ol,line}}$ as a function of N_{ev} for the suburban grid. These parameters are not shown for urban grid because even high EV penetration did not cause overload in the system. Note that the indicators are plotted on double y-axis with different limits. It can be observed that $N_{\text{uv,node}}$ is relatively higher than $l_{\text{ol,line}}$, suggesting that the challenge of under-voltage is more significant in percentage terms. Further, the curves tend to flatten with increasing EV penetration, indicating that the impact is located at certain critical regions in the considered grid. This is particularly more plausible because a uniform distribution of connected EVs is considered in the study.

However as highlighted before, more simulated data-points are necessary for further analysis to make a more conclusive suggestion on the observed tendencies. Furthermore, it is important to consider that the observed loading patterns are grid specific which can change with operating scenarios such as topology, base-load, daily work-place migration from suburban to urban grids and a more clustered EV distribution.

V. Conclusions and Future Work

In this paper, the impact of uncontrolled EV charging is investigated with two actual distribution grids in the Netherlands. Different EV penetration levels are simulated based on available measured field data and the obtained results support the intuitive understanding that the variations in transformer/line overloading and node under-voltage increase with higher penetration. Specifically, it was found that the impact of uncontrolled EV charging is relatively higher in sub-urban as compared to the urban grid for the given scenarios.

Key indicators are defined to understand the impact on the studied grids and some interesting insights are derived based on their trends as a function of EV penetration. For example, the curves for percentage under-voltage nodes and overloaded branches in the network tend to flatten with increasing number of EVs suggesting that the impact locates at specific grid regions. It is recommended that further analysis with more simulated data-points can provide deeper understanding of the underlying tendencies.

The main conclusion is that the key indicators defined in this paper and the corresponding trends shown for uncontrolled EV charging can be useful to benchmark the grid impact in terms of magnitude, scale and duration. Reducing the slope of these parameters as a function of EV penetration can be applied to evaluate the effectiveness of developed smart charging algorithms in reducing the footprint of increasing transportation electrification on the existing distribution network.

There are several things can be considered for further research. More EV penetration levels can be added for simulation. How the grid impacts varies with the increasing absolute number of EVs instead of relative EV penetration levels can be examined. Simulation with same settings can be tested on different grid types. How grid characteristics affect the grid performances with uncontrolled charging can be explored via control variable method. The EV mobility should also be covered in future study in order to improve the accuracy of actual connected number of EVs.

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