Probabilistic Analysis of Electric Vehicles' Impact on Transmission and Distribution Networks

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***Abstract*— Distribution utilities are already facing problems due to the integration of distributed generation (DG) and the foreseen large-scale deployment of electric vehicles (EVs) could aggravate the situation even further. Similarly, a large EVs share is a concern for transmission system operators as it may substantially increase the network peak power and power-flow fluctuations. The main aim of this paper is to provide a coherent probabilistic methodology for assessing the impact of EVs integration on distribution and transmission networks, including low-voltage (LV), medium-voltage (MV) and high-voltage (HV) network analysis. The simulations are carried out by means of sequential Monte-Carlo simulations, considering the variability of consumption and generation at distribution level and the probabilistic nature of EV charging, highly dependent on users' habits and required comfort. This approach enables to address the high variability of power flows in power networks and can form the basis for network planning and for the development of measures to reduce system cost due to EVs integration.**

Keywords*— *Electric vehicles integration, probabilistic distribution-networks planning, sequential Monte Carlo simulations, unbalanced power flow

I. Introduction

The high share of distributed generation (DG) has already an impact on distribution and transmission network operation. At transmission level, the variability of power flows is a concern and at distribution level, high voltages are usually the first problem. The foreseen electrification of the transportation sector could aggravate the situation even further [1] – [4]. Namely, electric vehicles (EVs) will considerably increase power flows and their fluctuation. Besides, the coincidence of uncontrolled EV consumption and renewables generation is relatively low [5] and the flexibility of EV charging is limited by users' comfort and their required driving range.

For efficient planning of distribution and transmission networks, and thus for avoiding pricy network reinforcements, a methodology for the evaluation of EV impact on network operation is needed. Such methodology must consider the main characteristics EVs consumption (high variability of charging patterns) and the properties of distribution networks operation, e.g. high variability of load consumption and DG generation, unbalanced power flows and uncertainty of operating conditions in the future (e.g. location of new DG). This approach can aid utilities to gain an insight into the impact of EVs on networks in order to be able to identify the most problematic issues (voltage levels, overloading…) when a large number of EVs is introduced. Without a clear picture on the impact of EVs, their integration may turn out to be pricy due to the required reinforcement of the electricity network infrastructure.

Several papers have already addressed many aspects of EV integration. However, many of them tackle only some of the important factors affecting the influence of EVs. In [6] and [7] the authors studied the important issue of dynamic spatial-temporal features of the energy demand focusing on the charging need when facing human factors in real situations, but did not address the impact on distribution network. A spatial-temporal approach was used also in [8], where the impact of EV integration was studied for a MV urban network. The authors presented the results in a probabilistic manner. LV networks, as a probable bottleneck for EV integration, were not observed. Similarly, LV networks were not modelled in detail in [9] where the IEEE 34-bus test feeder was used. In a recent study [10], the authors proposed a new optimal planning method and also focused on the MV level only. In [11], the authors studied the influence of EV on a residential LV network and analysed network reconfiguration optimisation. However, they did not take into account single-phase connection and unbalance as an important factor. In [12] EVs were used as a mean to improve voltage unbalance in a LV network. The study did not use a stochastic approach to network simulations, which may provide misleading results due to the high variability in LV networks. The high variability in distribution network operation was also not tackled in references [13 - 16], where the authors focus on charging optimisation techniques in order to offer support to LV network operation.

The main aim of this paper is to provide a coherent methodology for assessing the impact of EVs integration on a network, including HV, MV and LV network analysis. In terms of distribution network modelling, unbalanced operation is assumed, allowing for the study of single-phase charging. Load and DG probabilistic load-profiles are obtained from measured data and EV charging-load diagrams are constructed based on start-of-journey and travel-distance statistics. A reference MV and LV distribution network is used for simulations and the actual Slovenian transmission grid is used for transmission level simulations. The obtained results at distribution level are probability functions of transformer loading, feeder loading and network voltages. The results at transmission level are given as an increase in feeders' peak-power and an increase of the loss-of-load expectation (LOLE). The methodology can form the basis for network planning and for the development of measures to reduce system cost due to EVs integration.

II. EV CHARGING-LOAD DEFINITION

EV charging load plays an important role when assessing the impact of EV integration on network operation [6]. The shape of EV load diagrams depends on the EV itself (battery size, charging power…) and is strongly influenced by user behaviour. The main parameters used for the definition of EV charging load diagrams are the distance travelled within a day, charging start times, charging power, battery capacity and the required battery state-of-charge (SOC). In terms of user behaviour, we assumed that EV usage in the future will not change significantly compared to the nowadays use of conventional vehicles.

The travel distance within a day is an important input parameter as it determines the needed daily energy in order to maintain the required SOC of batteries. Figure 1 shows the diagram of the distribution of the daily travel distance for Denmark [17], which was used for calculations.

The second parameter, which directly affects the shape of the EV load, is the distribution of the beginnings of daily trips. The data set was taken from the same source [17]. The beginnings and the duration of trips help to estimate the time when the vehicle is parked and available for charging.

A. *Reference charging scenarios*

The charging scenarios reflect EV-user behaviour and the daily travel distance. According to the data on the daily trips, we have defined three basic charging scenarios:

- Scenario A (ScA): once per day charging in the afternoon (after work).
- Scenario B (ScA): twice per day charging, in the morning (ScBm) and in the afternoon (ScBa).
- Scenario C (ScC): once per day charging in the lower night tariff.

Scenario A is the most basic case, which assumes that users start charging EVs when they arrive home after work. Charging twice per day in Scenario B is associated with longer daily travel distances, requiring charging at two locations. In Scenario C, the charging time is adapted to the tariff system. Namely, it is reasonable to expect that some users will charge EVs during the lower night-time tariff. The basic data (mean value and standard deviation) of the charging scenarios are given in Table I. Within simulations, the individual EV will follow one of the defined charging scenarios. The length of charging is defined based on the daily travelled distance (consumed energy) and the requirement that all EVs have to be fully charged on the next day in the morning.

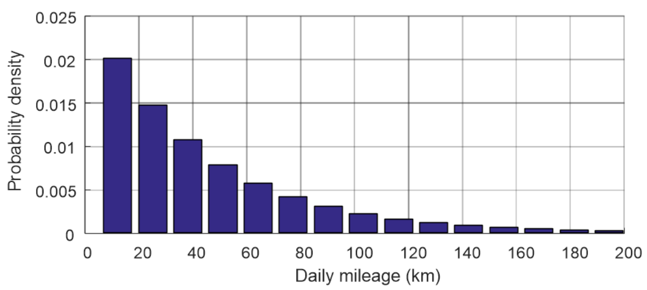

Fig. 1. Probability distribution of daily travel distances [17].

TABLE I. BEGINNING OF CHARGING FOR DIFFERENT CHARGING SCENARIOS.

	Charging scenario	Mean hour	Standard deviation
ScA	Once per day charging in the afternoon	16:00	2 h
ScB	Twice per day charging, in the morning (ScBm) and in the afternoon (ScBa)	10:00 16:00	3 h 2 h
ScC	Once per day charging in the lower night tariff	22:30	0.5 h

TABLE II. DEFINITION OF SIMULATION CASES AS A MIX OF DIFFERENT CHARGING SCENARIOS.

	C1 (mostly afternoon charging)		C2 (mostly night charging)	
Charging point	household	business/public	household	business/public
ScA	50 %	10 %	5 %	5 %
ScBm	/	50 %	/	5 %
ScBa	10 %	/	5 %	/
ScC	40 %	40 %	90 %	90 %
Total	100 %	100 %	100 %	100 %

B. *Mapping the EV charging load to the distribution network*

In order to be able to assess the in influence of EVs on the distribution network, we have to map the EVs load to the network. This means that the EV charging load has to be assigned to specific network nodes. For this purpose, we have defined two distinct types of charging points in the network: a household charging point (at these points EVs are charged according to scenarios ScA, ScBa and ScC) and a business/public charging point (EVs are charged according to scenarios ScA, ScBm and ScC). Based on these assumptions, two simulation cases are defined (C1 and C2), which differ in terms of charging scenarios composition. Table II summarizes these cases.

Case C1 foresees that 50 % of the users, which are connected to household charging points, will charge after work in the afternoon (according to ScA). Next, 40 % of EVs will be charged during the lower night tariff (according to ScC), and a smaller part (10 %) will be charged according to

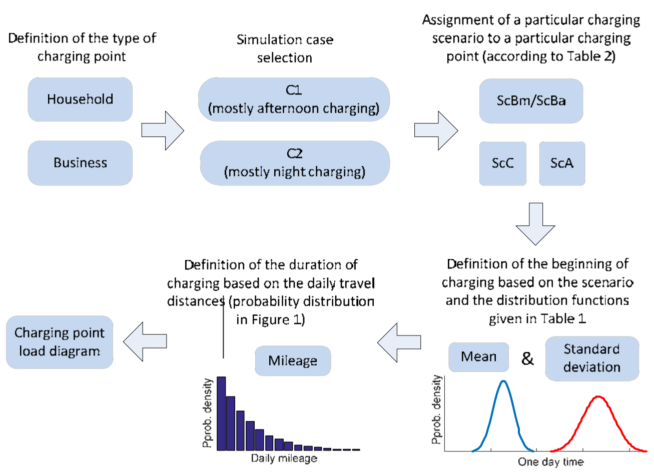

Fig. 2. Flowchart for the definition of a charging point (i.e. network node) load diagram.

scenario ScBa. Business/public charging stations are mostly used in the morning (60 %) and in the evening (40 %). Case C2 assumes that the majority of users (90 %) will charge during the lower night tariff and that the others will be uniformly distributed between ScA and ScBa. Figure 2 shows the flowchart for the definition of a charging point (i.e. network node) load diagram. Based on the type of charging point (household or business), simulations cases (C1 or C2), the distribution of the beginnings of trips and statistical data on daily mileage distribution, the consumption diagram of a particular grid charging point is calculated.

C. Mapping the EV charging load to the transmission network

Mapping of EV charging load to the transmission network depends on the topology of distribution networks and their connections to the transmission network via transformers. In this manner, the mapping is performed indirectly and presents the upgrade of the mapping of EVs to the distribution network. This procedure allocates additional power required for the EV charging among the nodes on the transmission level, i.e. the coupling points between transmission and distribution. The power shares are added to the existing nodal powers, which is followed by the power flow calculation.

III. SIMULATION METHODOLOGY

In this section, the simulation methodology for the distribution and transmission networks is described.

A. Distribution network simulations

The operation of distribution networks, and especially LV networks, is highly variable. Therefore, the Monte Carlo based approach offers a viable option for the analysis of such networks and can be used to describe different phenomena with an expected probability of occurrence [18].

1) Load and DG modelling

For load consumption modelling, measured 15-minute LV-load diagrams were used as a source for sampling. The database consists of thousands of yearly measurements from which probability density functions (PDF) are constructed. Loads are randomly sampled from these distributions. By using real load diagrams, network operation can be represented more accurately than just by using simultaneity factors. The aggregated load diagram varies by the type of user (commercial or household). The loads operate at a constant power factor of cosφ = 0.95. For DG modelling, measured 15-minute PV-generation diagrams were used as a source for sampling. The PDF, which fits best to the input data, is the Weibull distribution, and is chosen by the Bayesian criterion. It has to be noted, that the models of the load and PV have different values of parameters for each 15-minute interval during the day, and change according to weekday and season.

2) Calculation of the number of EVs for each MV/LV substation

For the analysed network, the number of EVs is defined based on the number of households in the network, the average number of EVs per households in the country and the average contribution of households to transformer peak power.

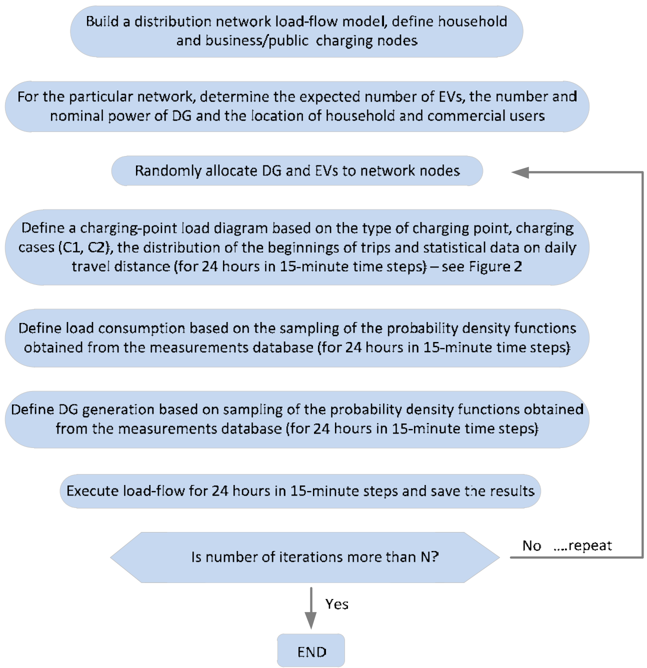

Fig. 3. Flowchart of the sequential Monte-Carlo algorithm basic steps.

3) Sequential Monte-Carlo algorithm

The simulation methodology is based on the sequential Monte Carlo algorithm, i.e. Monte Carlo simulations using simple random and time-sequential sampling. The statistical variables are sampled at a random day at a particular time (i.e. 15-minute interval in the day). The main statistical variables, used for load-flow calculations, are:

- Daily-travel distances
- Time of the beginning of charging
- Consumers' load and DG generation

The time of beginning of charging is the parameter with the highest uncertainty as it is based on the assumptions of EV users' behaviour.

Figure 3 provides a diagram of the sequential Monte-Carlo algorithm basic steps. One simulation run comprises calculations for a 24-hour period in 15-minute intervals. A sufficient number of Monte-Carlo simulations can be determined by the confidence interval, where 90 % is usually used. This is the interval where the searched parameter lies in with a 90 % probability.

B. Transmission network simulations

In this research, the following calculations are performed in order to assess the impact of EVs on the transmission network:

- Power-flow calculation in order to identify critical transmission lines in terms of possible overloading;
- Calculation of LOLE for assessing the reliability level of the network.

Power-flow calculation is performed by applying the Newton-Raphson method (fast decoupled method) resulting in active and reactive line power flows and nodal voltages. If reactive power and voltages are not observed, the DC method can be used in order to speed-up calculation.

Mathematical formulation of LOLE can be found in [19]. The methodology requires input data regarding power plants: installed power and availability, thus actual data for the Slovenian power plants are considered. In addition, the hourly total load of the transmission network that includes the EV loading is required for the calculation. Therefore, for each simulated scenario the LOLE index is calculated respectively.

The final step prior to the calculation is to scale up the nodal generation and loading according to the long-term load forecast and investment plans for the year of interest. This research does not address the forecasting approach and the expected total system consumption is taken from the national long-term projections. This consumption is proportionally allocated among the system nodes according to the current nodal powers.

IV. Case study

For the case studies, we used the data from Slovenian power networks and measured diagrams of users and DG. For distribution networks, year 2017 was taken as a base case for the comparison of the future scenarios in the year 2030. For the transmission network, the future scenarios results were calculated for the year 2035. In 2017, the influence of EVs on network operation is negligible. The number of EVs for Slovenia in 2030 and 2035 is based on the predictions according to the slow, moderate and fast scenarios. We have assumed the fast growth scenarios, where 180.000 EVs are foreseen in 2030 and 300.000 in 2035. Both, battery EVs and hybrids are considered. The total number of cars was 1,097,000 in the beginning of 2017 and is not expected to rise significantly due the already high number of cars per household, i.e. 1.31. The number of households in Slovenia is approximately 820,000.

For load-flow simulations DIgSILENT PowerFactory was used. For realistic representation of the real network circumstances, some assumptions have been taken into account. In case of twice-per-day charging it is assumed that the EVs will not charge within the same HV/MV substation twice. Two types of distribution systems are modelled, i.e. rural, where the majority of consumption are households, and urban, which supplies also a large share of commercial consumers (buildings). Depending on the type of consumers the shares of household and public/commercial charging points is defined.

The following EV characteristics were used: battery capacity of 24 kWh, average consumption 0.2 kWh/km, charging power 3.6 kW for single-phase and 7 kW for three-phase charging. Unbalance was taken into account (three-phase simulations). According to the relatively short daily-travel distances, a larger battery would not significantly affect the results and a much smaller battery is not expected for battery EVs in the future.

A. *Representative distribution network model*

A representative distribution network was built based on data from distribution network operators. The main aim of the representative grid is to represent adequately different distribution networks. The representative grid covers the area of one HV/MV substation. At the MV level, two feeders are modelled in detail, i.e. an urban feeder and a rural feeder. An equivalent load models the rest of the substation load and generation. At each of the two modelled feeders, one LV network is modelled in full detail, i.e. one urban LV network connected to the urban MV feeder and one rural LV network connected to the rural MV feeder. MV/LV transformers and equivalent loads represent all other LV networks. Each network type has its own characteristics. For example, in the rural area, the feeders are longer and the load density is lower as opposed to the urban grid, where shorter feeders with higher load density are used.

1) Simulated network description – MV network

The representative MV network represents an urban and a rural feeder, taking into account the typical properties of these two types of distribution networks in Slovenia. A 31.5 MVA, 110/20 kV transformer supplies the HV/MV substation. A peak loading of 20 MVA occurs in January. The control of the on-load tap changer (OLTC) is classic, based on the secondary voltage, where the reference voltage is set to 1.03 (±0.01) p.u. The feeder parameters used for the MV network are given in Table III, where the nominal voltage U_n, the nominal (max) current I_n, series resistance r, series reactance x and susceptance b are given. The length of the rural feeder is 15 km, which represents a relatively long feeder. At the beginning, there are five 400 kVA transformers, followed by eight 250 kVA transformers and two 160 kVA transformers at the end of feeder. The length of the urban feeder is 7 km, where all MV/LV transformers are 400 kVA. The rural feeder supplies mainly households and the urban feeder supplies a mix of commercial (30% of all consumption) and household consumers.

The maximal voltage drop that occurs on the MV rural feeder is round 2.7 % and the power consumption is 3 MVA (29 % of maximum line loading), which represent a realistic voltage drop and loading. Maximal voltage drop on the MV urban feeder is 0.4 % and the power consumption is 1.8 MVA (16 % loading). The equivalent MV load is also sampled from the measurements database and has a peak power consumption of 10.5 MVA.

2) Simulated network description – LV networks

Two LV networks were modelled in detail, one urban and one rural. Both networks present a representative model with realistic consumption, voltage drops and length of lines as in actual networks in Slovenia. The rural LV network supplies 70 consumers through a 20/0.4 kV 160 kVA transformer with a peak consumption of 120 kVA. The network consists of four overhead lines. Maximal voltage drop is 7 % (10 % is allowed in Slovenia). The main lines have a cross-section of 70 mm2 (total length 3 km), while laterals are 35 mm2 (total length 2 km) or 16 mm2 (total length 1.5 km).

TABLE III. MV-NETWORK FEEDER PARAMETERS.

Rural feeder	**Urban feeder**
Al/Fe 70/12	NA2XS(F)2Y 1x150RM
length= 15 km	length= 7 km
U_n = 20 kV	U_n = 12/20 kV
I_n = 290 A	I_n = 309 A
r = 0.413 Ω/km	r = 0.210 Ω/km
x = 0.362 Ω/km	x = 0.122 Ω/km
	b = 79.796 S/km

TABLE IV. LV NETWORK LINE PARAMETERS.

Rural LV network			Urban LV network
X00/0-A 70 (NFA2X)	X00/0-A 35 (NFA2X)	X00/0-A 4x16 (NFA2X)	PP 00-A 4x70 (NAYY)
U_n = 0.6/1 kV	U_n = 0.6/1 kV	U_n = 0.6/1 kV	U_n = 0.6/1 kV
I_n = 223 A	I_n = 142 A	I_n = 91 A	I_n =175A
r = 0.496 Ω/km	r = 0.972 Ω/km	r = 2.139 Ω/km	r = 0.444 Ω/km
x = 0.100 Ω/km	x = 0.100 Ω/km	x = 0.100 Ω/km	x = 0.0754 Ω/km
			b = 254.5 S/km

The urban LV network has a 400 kVA MV/LV transformer and a peak power consumption of 220 kVA (approx. 50 % of the transformer loading). There are five main lines and the maximal voltage drop is around 6 %. The lines are shorter, around 400 m altogether. The line parameters are given in Table IV.

B. *Transmission network model*

Modelling of the transmission network is a much easier task compared to the modelling of the distribution network due to lower complexity of the transmission network. Conventional power plants and industrial loads are modelled as nodal powers, injected at appropriate locations in the network, and MV/LV generation and loading are allocated through the network according to the topology. Transmission network encompasses HV levels at 110 kV, 220 kV and 400 kV. The transmission network is not represented by some typical equivalents as in the case of distribution, but parameters of actual lines and transformers at HV level are taken into account when applying modelling suitable for power flow calculations.

LOLE calculation does not require any network modelling, since only the generation adequacy is observed when the reliability of supply is assessed by the definition provided in [19]. Some further extensions of LOLE calculation that allow also for inclusion of network adequacy are available in [19]. However, these approaches were not applied in this research since network loading and identification of potential critical lines in terms of possible occurrence of overloading were assessed by means of standard power-flow calculation, as explained in the previous paragraph.

As explained in Section III.B, the total power production and consumption have to be modified according to the long-term national plans that incorporate all investments into new production units on the transmission level and the long-term load forecast for the year of interest. It is important to note that production at the distribution level is recognized as a lower consumption on the transmission level meaning that also the national long-term development plan for the distribution network is very important for this research. The analysis is focused on the year 2035 with noticeable share of EVs in transportation.

V. Simulation Results

Simulation results are show separately for the distribution and the transmission network.

A. *Distribution network results*

Simulation results show the influence of EVs on distribution network operation for the year 2030. The conditions in 2017 are taken as the base case and a consumption growth of 1.5 % per year was taken into account. The results show the values with a 90 % probability, which are usually used when using Monte Carlo simulations [18]. This means that 10 % of the worst results is omitted.

1) *HV/MV transformer loading*

The impact of EVs on the transformer for both simulation cases for 2030 (C1, C2) is shown in Figure 4. The results show that a 14 % peak increase can be attributed to load growth and, depending on the case, up to 13 % to EVs. The afternoon charging (C1) has the highest peak because at that time the traditional consumption is also high.

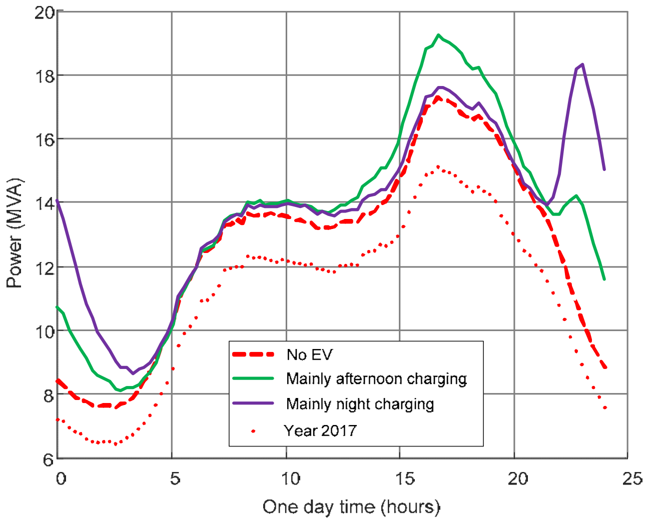

Fig. 4. Power-flow through the HV/MV transformer in 2030 for fast EV growth and different simulation cases (3.6 kW charging power).

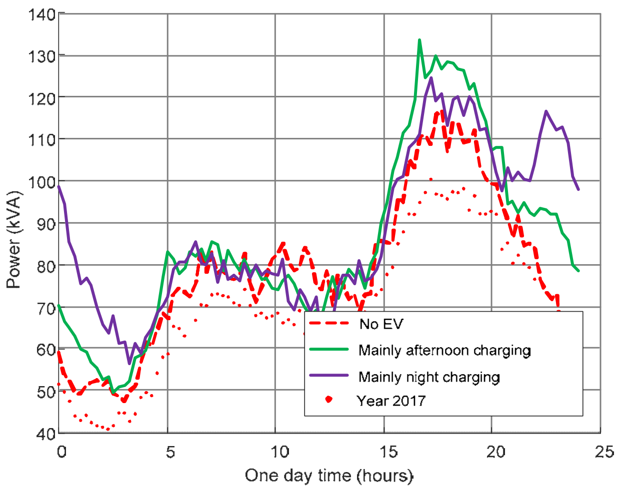

Fig. 5. Power-flow through the 160 kVA MV/LV transformer in 2030, supplying a rural network, fast EV growth and different simulation cases (3.6 kW charging power).

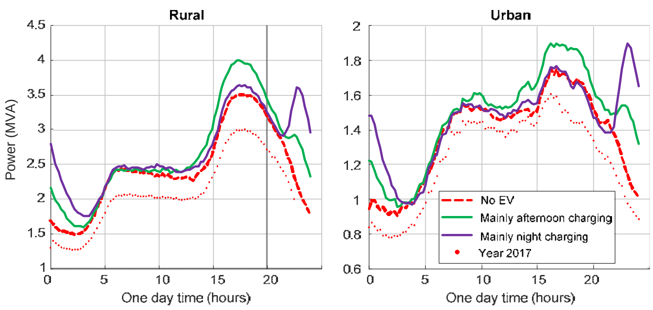

Fig. 6. Power-flow of urban and rural feeders in 2030 for fast EV growth and different simulation cases (3.6 kW charging power).

2) MV/LV transformers loading

The peak loading of MV/LV transformers in 2017 was around 60 % of their nominal power (see Figure 5). Due to a stochastic nature of household consumers, the power flow exhibits some variability. In the case of higher number of EVs in the network, the peak of the rural 160 kVA transformer rises from around 100 kVA to 130 kVA (i.e. for 30 %). The peak power of the urban 400 kVA transformer rises for 14 %.

3) MV and LV feeders loading

The power flow of the MV urban and rural feeders is shown in Figure 6, where the differences of the two types of network can be also seen. More consumers of the commercial type are connected to the urban feeder, resulting in higher consumption during working hours. On the urban feeder, there is a higher peak due to EV charging around 4:00 pm (case C1) or around 11:00 pm (case C2). On the rural feeder, there is a more distinctive EV peak in the afternoon.

The results suggest that EVs will not substantially affect MV feeders loading, which is also due to the usually low loading of feeders in distribution networks because of conservative planning in the past. In comparison to MV feeders, the loading of LV feeders due to EVs is much higher. The loading will increase up to 16 % due to load increase and up to 50-67 % due to the impact of EVs. This suggests that LV networks are the most susceptible to EV integration. The main reason for higher loading is a simultaneous charging of EVs on the same LV feeder. Namely, in a rural network only a couple of EVs charging at the same time and on the same LV feeder can significantly increase the power flow.

4) Voltage profiles

Voltage drops on MV urban feeders are small in comparison to rural feeders, especially due to their larger cross-section and shorter length. In majority of cases, the voltage drops on urban feeders are up to 1 % and on rural feeders up to 4 %. We can conclude that voltage profile is not critical in this part of distribution network.

In LV networks, the influence of single-phase connection of loads and EVs is significant. Figure 7 shows the LV profile in the rural network where all EVs are allocated randomly between phases and are charging with 3.6 kW (single-phase). Different colours present node voltages at different feeders. Even a small number of EVs charging on the same phase results in a relatively high asymmetry, which has an influence on loads and network losses. On LV feeders, the maximal voltage drop increases to 4.9 % due to the increased loading in 2030. However, single-phase EV charging results in much worse conditions, as the voltage drops can be more than 10 %, which is not acceptable for the majority of utilities. For comparison, Figure 8 shows the same situation as Figure 7, with the exception that EVs are charged through a three-phase connection with a power of 7 kW. The difference is significant, i.e. the voltage drops are less pronounced.

B. Transmission network results

The performed analysis is focused on the year 2035. The results are presented for:

- an initial case with a referential operating state for the year 2035 without EVs present,

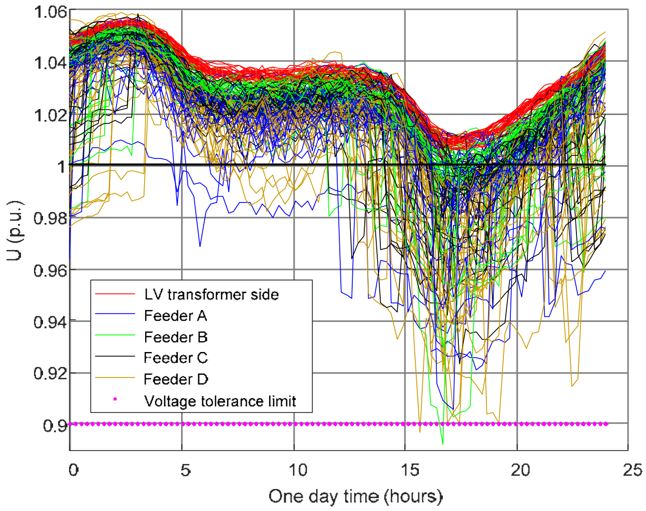

Fig. 7. Voltage profile in rural LV network in 2030, for the case of single-phase charging (3.6 kW charging power), fast EV growth and simulation case C1.

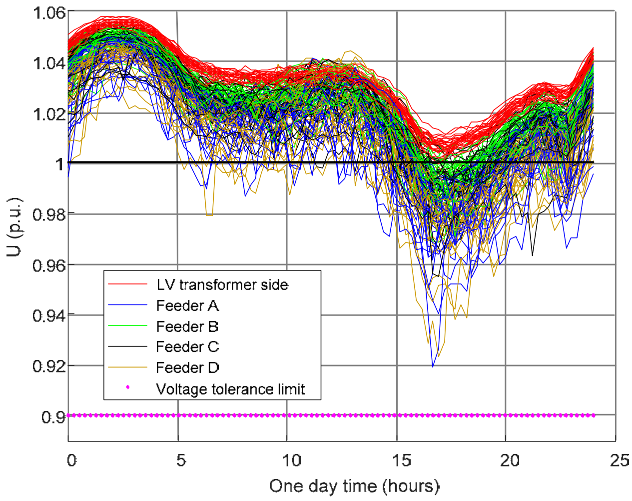

Fig. 8. Voltage profile in rural LV network in 2030, for the case of three-phase charging (7 kW charging power), fast EV growth and simulation case C1.

- cases C1 and C2 presented in Table II and
- an additional case (C3) that presumes controlled charging of EVs by applying peak shaving. This scenario is interesting since the total consumption in peak hours can managed by an appropriate EV charging strategy resulting in a lower loading of the network.

All scenarios consider long-term investment plans for generation units and transmission lines plus long-term load forecast for the year 2035. In addition, two specific time slots are observed:

- **TS1** – a moment of the yearly peak load for the whole system occurring in winter, in our case at 6 p.m. on Dec. 12, and
- **TS2** – a moment with the peak load of EV charging usually observed during the night, in our case at midnight on Dec. 12.

Table V summarizes the results, where the average line loadings for all scenarios for both time slots are given in p.u.

in order to present the average increase of system loading caused by EV charging. As shown, in TS1 the system loading is generally not increased, since in all scenarios EVs are mostly charged before (C1, C3) or after (C2) the time slot TS1 (6 p.m.). Different results are obtained for time slot TS2, especially for scenario C2, with noticeable increase of the system loading (2.22 p.u.). In this case, EVs are charged at the same time during the night, which heavily loads the system.

Table VI presents LOLE in h/year and p.u. Index LOLE reaches high values already in the initial scenario without EVs. This is the result of the fact that the national investment plan does not adequately follow the needs. The system is not self-sufficient and the missing energy is imported. With EVs, LOLE index is increasing and the most critical scenario is again scenario C2.

The results show that the adequate EV charging strategy and charging control systems will be required in order to protect the transmission network from overloading and to obtain reliable supply of consumers.

TABLE V. AVERAGE LINE LOADINGS IN 2035.

Scenarios for 2035	P_{ij} (p.u.) TS1	P_{ij} (p.u.) TS2
Initial scenario	1.00	1.00
C1	1.01	1.52
C2	1.00	2.22
C3	1.00	1.52

TABLE VI. LOLE IN 2035.

Scenarios for 2035	LOLE (h/year)	LOLE (p.u.)
Initial scenario	355.92	1.00
C1	563.14	1.58
C2	655.12	1.84
C3	547.40	1.54

VI. CONCLUSIONS

The results show that first problems due to EV integration can be expected in LV networks, especially in rural LV networks, and will be associated with overloading of transformers as well as with high voltage drops. Even though the transmission network is less sensitive to the EV charging compared to distribution networks, substantial increase in line loading is expected. The results suggest that some actions in terms of controlled charging will be required in order to integrate a larger share of EVs and to avoid costly network reinforcements at the same time. These actions should result in more dispersed beginnings of charging and consequently lower power peaks. The proposed approach allows also for the analysis of advanced charging schemes and can be a useful tool in terms of network planning.

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