Journal of Power Technologies 100 (1) (2020) 85–91

Impact of uncoordinated electric vehicle charging on the distribution grid

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Abstract

Charging electric vehicles (EVs) represents an extra and increasing load for the power system. And the higher the charging power is, the more likely it is that serious problems will arise. In addition to home charging, in Hungary - the area of interest in this paper - Level 2 chargers in the streets are currently installed with a maximum charging power of 22 kW. Since the local market share of EVs is low at present and expected to remain relatively low in the years to come, it is essential to see where the limits of the low-voltage distribution grid are in terms of taking the extra EV charging load. This paper presents extensive simulation results taking various EV charging characteristics, arrival statistics, household load variation, and other assumptions into consideration to determine how EV charging will affect the low voltage grid. The stochastic simulations were conducted in DIgSILENT Power Factory augmented with a Python code. Simulation results indicate that an already moderately loaded grid is capable of accommodating EVs at a penetration level of approximately 20%, which can be considered a high value.

Keywords: DIgSILENT, electric car, Level-2 charging, stochastic simulation

1 Introduction

With the spread of electric vehicles (EVs) worldwide, system operators are facing a situation when excessive load on distribution grids is likely to cause several power quality issues. By the end of 2018, over 10 000 cars had been registered with electric drives, of which nearly half are fully electric, and further growth is expected due to incentives, for example tax exemptions, cheaper operation and fuel costs [1]; [2].

Since the share of EVs in the current car pool is very small, there are no comprehensive datasets available regarding the impacts of EV charging on the distribution grid, though some surveys have already been made: [3] demonstrates examples from Finland, [4] from Norway, and [5] from the UK. Among the possible impacts we can mention the following [6]: increase in system thermal loading, deterioration of voltage profiles, increase in losses and asymmetry, reduction in transformer lifetime [7], and an increase in harmonic distortion due to the chargers is possible, with possibly greater sensitivity to power system disturbances [8]. Hence there is a need for simulations so as to gain better insight into these possible impacts. However, operators have to face multiple uncertainties: time and space randomness of EV charging [9], different state-of-charge (SOC) values and battery capacities, driver behavior [6], variations in household loading, phase assignment of loads, etc.

Most papers assume that without any kind of charge control, EV batteries start charging as soon as they are plugged in [9] and they investigate different EV penetration levels. [9] investigates the impact of plug-in EV charging on a Chinese distribution grid and finds that a grid in Beijing can accommodate approximately 20-30% EV penetration (meaning that 20-30% of households have EVs) before encountering power quality issues. [10] analyzed the impact on voltage imbalance of a distribution grid in Thailand with various EV penetration levels, and also determined a limit of 20-30% penetration. [11] gave 25% for the UK, whereas [12] calculated that Sweden could handle a larger penetration. In weaker grids, such as in Malaysia the 20% penetration level is also the upper limit [13]. [14] takes realistic arrival profiles and charging characteristics into consideration to compose a stochastic simulation. Many papers conduct Monte-Carlo simulations (see e.g. [3] , [15]), which we also used alongside real-life data for modeling.

The novelty of our approach is that more parameters are taken as random variables and their values are determined based on the features of currently available EV models, real measurements and statistical data (see the modeling assumptions in Section 2) and we used a Hungarian distribution area, which is a representative example of a typical Central European grid. The paper is organized as follows: Section 2 presents the modeling assumptions, Section 3 briefly introduces the algorithm that stochastically scheduled the

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cars and assigned charging power, SOC distribution, etc. to every load. In Section 4, the results obtained are described with the stochastic simulations while Section 5 sets out the main findings and conclusions.

2 Modeling assumptions

To make the simulation realistic, various assumptions were made regarding the grid model, the EVs and the household loads.

2.1 Assumptions regarding the model

The investigated grid is shown on Fig. 1. This is an LV network in rural Hungary with a moderately high loading, see Fig. 2. All simulation results are depicted on boxplot figures, i.e. every time 10 runs were conducted, hence the figures represent a statistical evaluation of the results obtained.

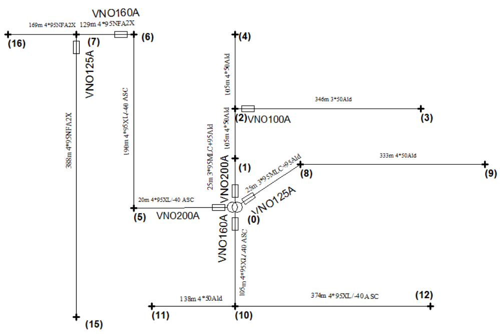

Figure 1: The investigated LV grid

Household loads are single-phase loads and are evenly distributed along the lines, which means that if there are 2 loads on a 25 m long line, they are 8.33 m apart from each other (and from the ends of the line, respectively). The phase distribution is also even, but randomly assigned. This means that asymmetry is kept low in the model grid.

MV/LV transformers in Hungary have no-load tap changers: ±2 taps, with 2.5% voltage change of each tap. The transformer nominal power is 400 kVA with short-circuit voltage $u_k = 4.22\%$ and 5.9 kW copper loss.

Line data is given on Fig. 1, with the following electric parameters (Table 1).

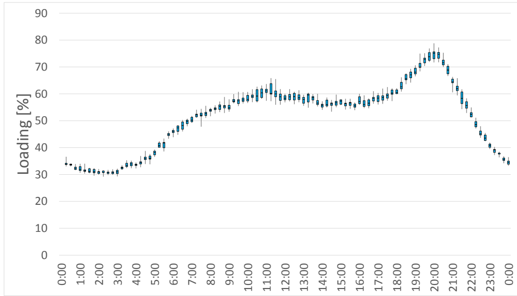

Figure 2: Loading of the MV/LV transformer without EVs

Table 1: Positive sequence electric parameters of the line types

Type	R1 [/km]	X1 [/km]	Rated current [kA]
Ald	0.72	0.06982	0.14
MLC95	0.32	0.07541	0.21
NFAX2	0.32	0.07541	0.24
XL40	0.311	0.159	0.22

2.2 Assumptions regarding the household loads

Household load profiles are assigned randomly from a pool of 500 loads of which Fig. 3 shows 5 profiles as an example. The power factor of the household loads was taken to be 0.85 to which a random variable for each load with Gaussian distribution with 0 mean and 0.05 standard deviation was added (power factor larger than 1 was naturally not allowed).

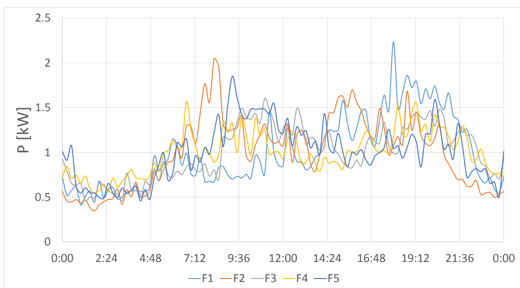

Figure 3: Household load profiles (example)

2.3 Assumptions regarding electric cars and chargers

Even though it was assumed that the chargers are not going to be home chargers, one can still suppose that the local inhabitants will use them in most of the cases. There are 142 households in the analyzed grid, and investigations for 10%, 20%, 50% and 100% penetration of electric cars were simulated, which means 15, 28, 71 and 142 cars, respectively.

All chargers are taken to be 22 kW Level 2 chargers with cos φ = 1, but not all of the cars are capable of charging with this power at the time of writing of the paper. Based on car manufacturers' data, we determined two scenarios:

- one in which 1% of the cars have a charging capability of 22 kW, 4% of them have 11 kW, 10% of them have 7.2 kW and 85% of them 3 kW;
- while in the other scenario these numbers are 2%, 10%, 20% and 68%, respectively.

Cars arrive to chargers according to the density function depicted on Fig. 4. This distribution is in good accordance with measurements done in Norway on a fleet of EVs [4] and the very detailed analysis done by [16].

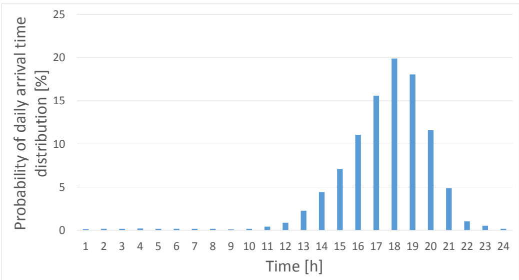

Figure 4: Distribution of EV arrival times [17]

Table 2 shows the currently available EVs' battery capacity (the data was taken from car manufacturers' datasheets). Based on these data the cars in the simulation had the following battery capacity: 24, 28, 30, 40, 50 and 60 kWh, all with the same probability. The chosen values represent a larger loading scenario, since cars with larger battery capacity have to be charged longer.

Besides the battery capacity an important piece of information is the state of charge (SOC) of the battery when arriving to charge and also when leaving the charging stations. Fig. 5 and Fig. 6 show these data, respectively.

Even though charging with Level 2 chargers results in a nonlinear curve regarding SOC changes (see Fig. 7), in this research it is considered as linear (this approximation is in good accordance with real charging characteristics up to 90-92% of SOC).

Charging time was thus calculated as follows:

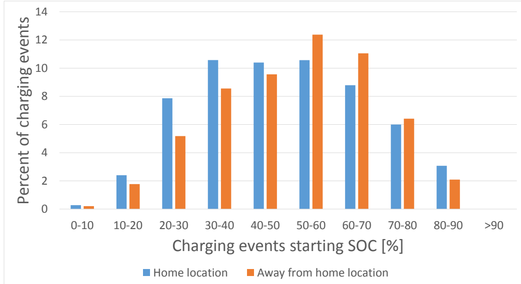

Figure 5: Battery SOC at the beginning of charging events [18]

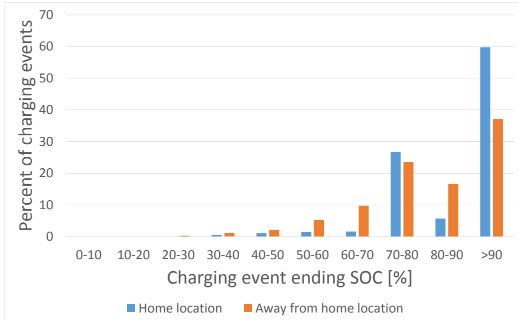

Figure 6: Battery SOC at the end of charging events [18]

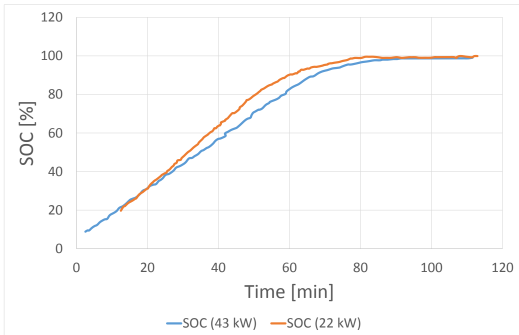

Figure 7: Battery SOC change during charging of a Renault Zoe [19]

$$T = \frac{SOC_{end} - SOC_{start}}{S_{charger}} \cdot C_{battery}$$

where: SOC_{end} – the SOC at the end of a charging event, SOC_{start} – SOC at the beginning of a charging event, $S_{charger}$ – nominal apparent power of the charger, $C_{battery}$ – battery capacity in kWh. With 22 kW charging power, the charging time is in the range of 45–90 minutes, which correlates well with the results obtained from [20] with similar parameters.

Table 2: Battery capacity of plug-in hybrid and pure electric EVs

Pure EV		Plug-in hybrid	
Type	**Battery capacity [kWh]**	**Type**	**Battery capacity [kWh]**
Audi e-Tron	95	Audi A3 e-Tron	8.8
BMW i3	22–33	Audi Q7 e-Tron	17
Opel Ampera	60	BMW i8	7
Peugeot iOn	16	BMW X5	9
Fiat 500e	24	Chevrolet Volt	16–18
Ford Focus	33,5	Hyundai Ioniq	8.9
Hyundai Kona	39.2–64	Kia Niro	8.9
Hyundai Ioniq	28	Mitshubishi Outlander	12
Kia Soul	27	Toyota Prius III	4.4
Kia Niro	39.2–64	Toyota Prius IV	8.8
Nissan Leaf II	24–60	VW Golf GTE	8.8
Mitshubishi MiEV	16		
Renault Fluence	22		
Renault Zoe	41		
Tesla S	60–100		
Tesla X	60–100		
VW Golf-e	24–36		

2.4 Assumptions regarding electric cars and chargers

Since the charging power of cars is currently low, it is expected that many chargers are required to fulfill the charging needs.

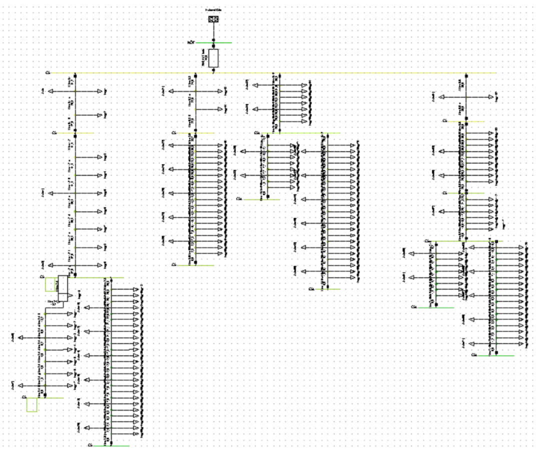

Figure 8: Grid model in DIgSILENT

38 chargers (roughly 25% of the number of all households) were placed in the grid (see Fig. 8, the load symbols pointing left are the chargers, while the load symbols pointing right are the household loads). Chargers are modeled as 3-phase loads.

3 Simulation algorithm

The simulation was performed by a Python script in 15 minute resolution. At every time step, the number of arriving cars is determined (it can be 0, too) and a charging time and charging power is assigned to these cars, which are random variables and are drawn randomly according to the rules presented in Section 2.3. The algorithm also checks whether there are any chargers available and if yes, assigns the car to this charger. This charger is then considered occupied for the pre-determined charging duration. The algorithm does not take spatiality into consideration, i.e. the first available charger in the list of chargers is always taken.

If there are no chargers available, the cars have to wait. It was presumed that the customers are infinitely patient, i.e. they wait until a charger is disengaged, so balking was not modeled.

Simulations with a varying pool size of cars were conducted: 15, 28, 71 and 142 cars. Due to space limitations, here only the results obtained with 28 and 71 cars are described. Simulations with different number of chargers were also carried out, but not included in this paper explicitly.

The algorithm was run 10 times for all configurations. Each of these runs differed from the others, because the arrival times, the starting and ending SOC values, the battery capacity, etc. were changed according to the distributions presented in Sections 2.2 and 2.3. This means that the simulation can be treated as stochastic, and it follows from this that the evaluation of the results is based on boxplot diagrams.

4 Simulation results

As Fig. 2 indicated, the loading of the grid before the chargers were installed was moderate. Fig. 9 shows that the voltage also stays in the accepted region.

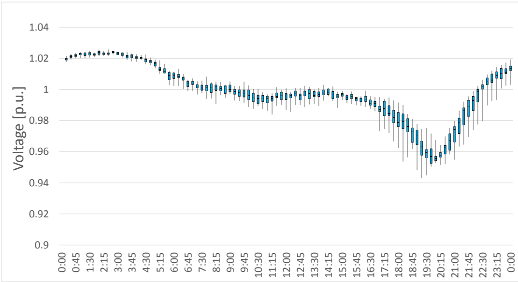

Figure 9: Lowest voltage point in the investigated grid

4.1 28 cars, first battery capacity data

In the first investigated case there are 28 cars, and the first scenario regarding car charging capability is considered. Fig. 10 shows the voltages at the lowest voltage node (which is the furthest node from the MV/LV transformer) and Fig. 11 depicts the transformer loading.

It can be seen that even though there are no limit violations (according to low voltage limits defined in EN 50160, it is $U_{nominal}$ +8%/-7%) in Hungary, transformer loading is very close to 100%.

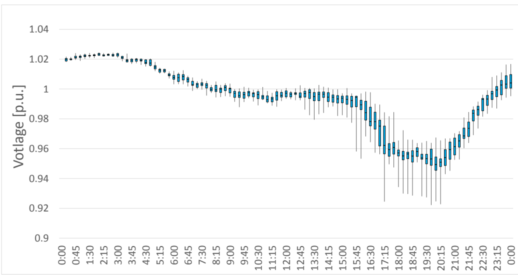

Figure 10: Lowest voltage point in the investigated grid

4.2 71 cars, first battery capacity data

The next case deals with 71 cars, which represents 50% EV penetration in the investigated LV network. Fig. 12 shows the voltage of the lowest voltage

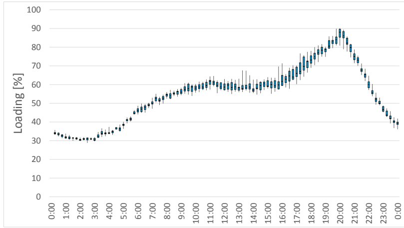

Figure 11: Transformer loading

node: it can be seen that at this penetration level the voltage is outside of the permitted region. Similarly, the transformer is overloaded, see Fig. 13 (lines also get overloaded, but this paper does not contain any diagram depicting that issue). In this case there are even cars that have to wait, because there are too few chargers to fulfill charging needs (Fig. 14).

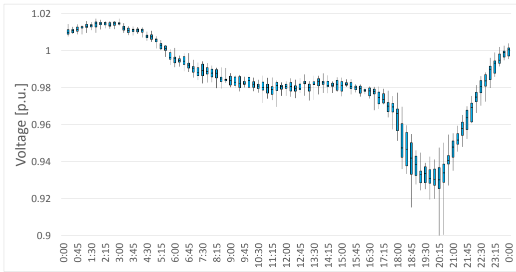

Figure 12: Lowest voltage point in the investigated grid

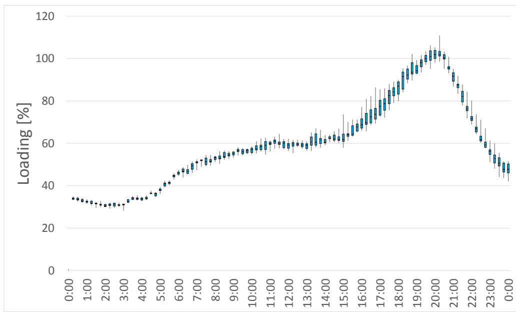

Figure 13: Transformer loading

The results obtained for the second battery capacity dataset were very similar: for 28 cars there was no overloading, the voltage was not out of the limits, but for 71 cars every observed parameter was outside of the permitted limits and cars also had to wait.

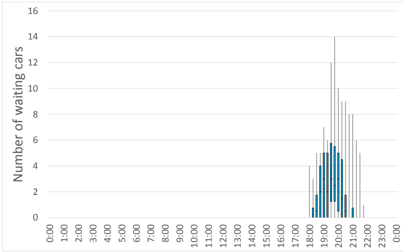

Figure 14: Number of waiting cars

5 Conclusions

The aim of our paper was to create a practical data-based simulation model to study the impact of electric vehicle charging on a low voltage distribution grid. Since multiple uncertain parameters were taken into consideration, a stochastic simulation was conducted. Compared with previous research results and data from industrial stakeholders, the authors suggest that the DSOs should use stochastic calculation methods to acquire data that describe the possible scenarios in a sophisticated manner. In addition to using appropriate technology to integrate e-mobility effectively into the grid, the methods that DSOs use could greatly enhance cost-effectiveness and security of supply. The results obtained demonstrate that at low penetration levels of EVs (up to 20 .. 30%) the current Hungarian distribution grid is capable of accommodating the extra load caused by the charging of electric cars without any kind of modification. For higher penetration levels though, a solution has to be found to alleviate the charging impacts. Controlled charging seems to have huge potential, as do other demand side management and energy storage solutions. Further research is needed to compare different methods in bulk e-mobility integration, which also factors in distributed generation.

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