An Outage Probability Model for Electric Vehicles in Low Voltage Grids

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***Abstract*—The current uptake of electric vehicles (EVs) results in new challenges for the electricity grid. Due to their relatively high power and potentially synchronized demand, existing local grid capacity might become inadequate in the near future. To provide insight into this development, this work proposes an approach to approximate the outage probability in low-voltage (LV) grids due to EV charging. The introduced model can be used as a tool to understand the impact of uncontrolled EV charging in existing and new LV grids. A case study demonstrates this approach with a grid of 40 households: at 35% EV penetration rate the outage probability is approximately once every 50 days.**

***Index Terms*—EV charging, grid congestion, grid planning, home charging, power capacity**

LIST OF SYMBOLS

$p_{\text{start}}(t)$	Probability distribution of the charging session start time
N	Number of EVs in the LV grid
n	Expected number of EVs that charge on a given day
$\bar{n}$	Number of EVs that charge simultaneously
x	Charging regime number
z	Charging regime power level
β_x	Fraction of EVs that charge according to regime x
a_x	Probability of charging an EV on a given day for regime x
$r_{\mathrm{P_z}}$	Charging power ratio for power level z
k_x^z	Expected EVs that charge for regime x with power z
$p_x^z(t)$	Probability of charging an EV for regime x with power z
$s_{\bar{n}}^n$	Probability that at least $\bar{n} \in n$ charge simultaneously
$P_{\text{baseload}}(t)$	Base load power in LV grid [kW]
$P_{\text{limit)}}$	Power limit in LV grid [kW]
$c(t)$	Grid capacity in number of EVs
P_{charging}	Expected average charging power [kW]
p_{outage}	Outage probability for a given day

I. INTRODUCTION

In the current energy transition from fossil fuel to clean and sustainable energy generation with e.g. solar and wind energy, the transport and mobility sector plays a key role. Since EVs allow the use of sustainable generated energy without (directly) emitting carbon dioxide and other greenhouse gasses, they offer more flexibility in energy source compared to fossil fuel based cars. Within the European Union, the Netherlands is one of the front-runners in EV adoption with a 25% market share for EVs in newly sold passenger cars in 2020, only second to Sweden with 32% [1].

This rapid increase of the EV penetration rate causes stress on the electricity grid infrastructure: the power output of a three-phase EV charger is comparable to the average power load of roughly ten households. All passenger cars in the Netherlands together drove around 110 billion kilometers on Dutch roads in 2018 [2]. At an average EV energy consumption of 17.5 kWh per 100 kilometers this results in around 19.3 TWh of additional electrical energy demand. In contrast, the total annual household electricity consumption in the Netherlands is around 22.7 TWh in the year 2018 [3]. Currently used LV grids which were designed years ago based on the then applicable parameters [4] might be unprepared for the loads in the near future. Research [5] shows that uncoordinated EV charging may lead to overloading of grid components. The relatively high peak power of only a few uncoordinated EV chargers on top of the expected base load could result in overloading existing LV grids. In a field test to investigate the impact of future grid scenarios carried out in Lochem, the Netherlands [6], researchers demonstrated this by introducing 20 EVs and other appliances, (e.g. electric ovens) in an LV grid serving 80 households, which led to a short power interruption.

In the literature, EV charging data and behavior is widely discussed. In [7], a data generator that uses parametric models to generate synthetic samples of EV charging sessions based on existing data sets is introduced, while in [8] a so-called trip chain generation based on semi-randomized trips is applied. The organization *ElaadNL* collects and publishes EV charging data in the Netherlands [9]. This gives a reasonable insight in the present-day charging behavior of EVs. The work in [10] introduces a method that calculates the expected grid load of a set of EVs based on group characterization of driving behavior, but does not consider the actual probability that this set of EVs causes an outage. However, if we consider a specific LV grid, there is a probability that the charging behavior may be relatively different to this general behavior. A small deviation of the expected charging behavior may already cause an outage. Also, a 'perfect storm' in which a coincidence of factors that yield a peak can occur. To analyze the impact of this, this paper presents three main contributions:

- A model to calculate the probability that an EV charges at a given time during a given day.

- A framework that approximates the probability that the joint behavior of set of EVs causes an overloading in the low-voltage part of the distribution grid based on its joint energy demand and charging behavior.
- A case study that demonstrates the model in a typical Dutch sub-urban residential area.

In Section II, we characterize EV charging patterns and power demand of a set of EVs. Then, in Section III, we describe the probability model and analyze the time-dependent grid capacity that is available for EV charging. Finally, for each moment we combine the charging demand and grid capacity to calculate the probability that the EV charging demand exceeds the available grid capacity and thus may cause an outage. Section IV gives a case study within a neighborhood of 40 households. Lastly, Section V concludes the paper.

II. EV Charging demand

To model the EV charging demand, we model the probability that a single EV is in the state of charging in Section II-A. In Section II-B we model the joint charging demand of a set of EVs wherein not all EVs follow the same charging behavior. Section II-C investigates the probability that a subset of these EVs charge simultaneously.

A. EV charging probability

We consider each EV charging event in the system as an independent event with a given probability distribution and call this a "charging session". To this end, we introduce a probability distribution for the start time of the charging sessions $p_{\text{start}}(t)$ at any time interval t based on historic data. We express the fixed duration of charging sessions by the number of time intervals, denoted by d. To calculate the probability that an EV is charging in a time interval t, we use the probability that a charging session has started and is still active. This leads to the probability $p(t)$ that an EV charges at time t, given that an EV charges on a certain day with a duration d:

$$p(t) = \sum_{\tau=0}^{d-1} p_{\text{start}}(t-\tau). \tag{1}$$

B. EV charging regimes

In the following we analyze the joint charging demand of a set of N EVs wherein not all EVs follow the same charging behavior. To achieve this, we model discretized charging regimes based on the daily EV energy demand. Typically, not every EV charges every day [11] and the charging frequency is negatively correlated with the battery size [12]. We therefore assume a negative correlation between the charging volume in kWh and the charging frequency, i.e., if EVs do not charge frequently they charge more energy when they do charge. Furthermore, we assume that each individual EV follows one of the given charging regimes: either the EV charges every day a certain amount of energy, every two days twice that amount of energy up to charging x times that amount of energy every x days. We model the charging of each of the given EVs according to one charging regime x only. For the EVs charging according to regime x, we assume that the probability that an EV charges on a given day is $\alpha_x = \frac{1}{x}$. We furthermore assume that the charging regimes are distributed according to the fraction of EV users that show the behavior of that particular charging regime. We denote this charging regime distribution by β_x. The probability of an outage depends significantly on the charging power levels used by the EVs that charge. Therefore we integrate power levels in the model for each power level $z \in Z$ using a charging power ratio r_{P_z} that defines the fraction of EVs that charge with a power level z. Note here that the model can handle an arbitrary number of charging power levels, but that we use the same charging power ratios throughout the whole day. The expected number of EVs that charge on a given day according to a given charging regime $x \in X$ at power level $z \in Z$ is denoted by k_x^z and given by:

$$k_x^z = \lfloor N \times \beta_x \times \alpha_x \times r_{P_z} \rceil, \tag{2}$$

for all $x \in X$ and for all $z \in Z$. Based on this, the expected total number of EVs that charge on a given day is the sum of all k_x^z, denoted by n. As for the following derivations n needs to be an integer and n needs to be equal to the sum of k_x^z, we already round k_x^z to the nearest integer in (2).

$$n = \sum_{x \in X} \sum_{z \in Z} k_x^z. \tag{3}$$

For each charging regime, the EV charging probability $p_x^z(t)$ is calculated using (1) with the corresponding values for the given regime.

C. Simultaneously charging EVs

To estimate the expected number of simultaneously charging EVs in a time interval t, we consider charging sessions as independent events with a probability given by the EV charging probability distribution for the different charging regimes $p_x^z(t)$. Based on this, the probability that exactly $\bar{n}$ out of the set of n EVs charge simultaneously in a time interval follows a binomial distribution. We assume that the EVs are distributed based on the expected numbers used in (2). This leads to the following approximation:

$$s_{\bar{n}}^n(t) = \sum_{\hat{n}=\bar{n}}^{n} \binom{n}{\hat{n}} \prod_{x \in X} \prod_{z \in Z} \Big(p_x^z(t)\Big)^{\left(\hat{n}\frac{k_x^z}{n}\right)} \Big(1 - p_x^z(t)\Big)^{\left((n-\hat{n})\frac{k_x^z}{n}\right)}. \tag{4}$$

This applies for all $x \in X$ and for all $z \in Z$, where $s_{\bar{n}}^n(t)$ approximates the probability that at least $\bar{n}$ out of n EVs charge. Note that every charging regime x has its own given EV charging probability distribution $p_x^z(t)$, with k_x^z charging EVs following that given distribution. Since we use time dependent probabilities $p_x^z(t)$, we find the probability of simultaneously charging at least $\bar{n}$ EVs for every time interval t.

III. Model description

A. Grid capacity

In the model, the available grid capacity for EV charging is given by the capacity limit of the feeder cable P_{limit} minus the base load power P_{baseload} which is already present in the feeder. We aim to express the available grid capacity by the number of EVs that can simultaneously charge, so we divide the grid capacity in kW by the expected average charging power P_{charging}. We denote the number of EVs that can charge simultaneously by the grid capacity c:

$$c(t) = \left\lfloor \frac{P_{\text{limit}}(t) - P_{\text{baseload}}(t)}{P_{\text{charging}}} \right\rfloor. \tag{5}$$

The expected average charging power P_{charging} is based on the ratio between the different power levels, defined by the power ratio r_{P_z}:

$$P_{\text{charging}} = P_1 \cdot r_{P_1} + P_2 \cdot r_{P_2} \cdots + P_u \cdot r_{P_u}. \tag{6}$$

B. Outage probability

In any time interval t, any set with at least $\bar{n}$ EVs might charge simultaneously. When $\bar{n}(t)$ exceeds the total capacity $c(t)$ in any time interval t, overloading occurs. Overloading grid components in an LV grid for a relatively short time does not directly lead to critical failure, as is shown in [6], therefore it is important to choose the length of intervals t sufficiently long. However, overloading grid components more frequently, even for shorter time spans, increases the wear of those components and thus increases the probability of a critical failure. Therefore, whenever such an overloading occurs in the model, we assume this causes a critical failure in the power grid infrastructure and thus results in a power interruption, a so-called outage. We are interested in the probability that such an outage occurs. For an outage in a time period t we need to know that there has not been such an outage in the previous time periods. Otherwise the system would not have 'reached' time period t. This means that in our model we assume that an outage can happen only once a day and that an overloaded grid is restored before the beginning of a new day. This means we only need to determine the probability of the first outage. This depends on the available capacity c(t) thus we can use (4) to determine the probability that an outage happens, which is $s^n_{c(t)+1}(t)$. The probability that an outage does not happen is $\left(1 - s^n_{c(t)+1}(t)\right)$. The probability that the number of charging EVs exceeds the available capacity $c(t)$ (causing an outage) in any time interval t during a full day we denote by p_{outage}:

$$p_{\text{outage}} = \sum_{t \in T} \left(\prod_{t=0}^{t-1} (1 - s^n_{c(t)+1}(t)) \right) s^n_{c(t)+1}(t). \tag{7}$$

Note that the model relies on the assumption that the distribution of charging regimes in the set of EVs charging on a day n is the same as in the set of EVs charging simultaneously $\bar{n}$. Also, the model does not consider special events that might change the charging behavior, such as major sport events. Usually, the combined capacity of the multiple LV feeders connected to one transformer exceeds the capacity of the transformer itself, thus an overloading of the transformer might occur prior to overloading an individual feeder cable. Furthermore, an overload in one single phase may have a higher probability due to unbalance in grid loading, as is shown in [6]. These factors all may result in an underestimation of the expected outages in the model.

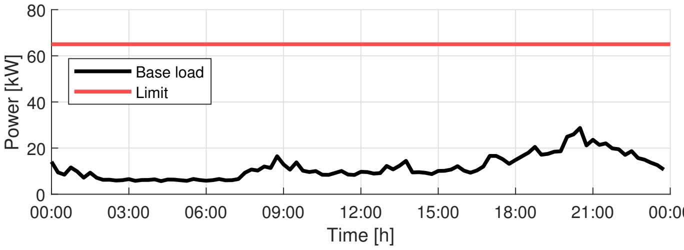

Fig. 1: The base load pattern of the residential area and the maximum power limit of the corresponding feeder.

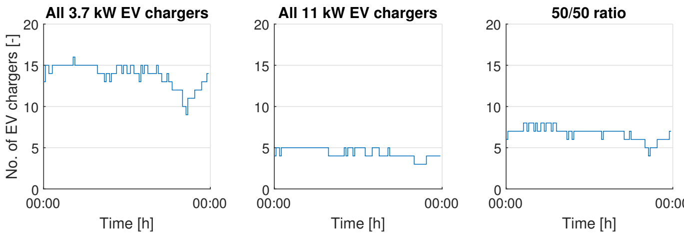

Fig. 2: Available capacity $c(t)$ for charging EVs.

IV. Case Study

To demonstrate the model, we use a case study for a residential area with 40 households. Section IV-A presents the set-up, Section IV-B presents the general results and in Section IV-C discusses a parameter sweep over two variables.

A. Set-up

We assume that all home and public charging stations in the residential area are connected to the same feeder and also follow the same plug-in time probability distribution. Fig. 1 shows in black P_{baseload}, the base load pattern of the residential area. This base load is simulated with *DEMKit* [13] for a variety of household types. The power limit of the corresponding feeder, $P_{\text{limit}} = 65$ kW, is shown in red in Fig. 1. This value is based on local variables such as the LV cable specifications and transformer capacity. We assume that the area between the limit and the base load is available for charging EVs.

For this case study, we consider three different scenarios: 1) all EVs charge at $z = 3.7$ kW, 2) all EVs charge at $z = 11$ kW and 3) a 50/50 ratio of both charging power levels. The available capacity $c(t)$ for EV charging for each of the three scenarios is shown in Fig. 2. We choose to use five charging regimes. The plug-in time probability distribution p_{start} is a combination of private and public charging plug-in time probability distributions with 15-minute intervals imported from the *ElaadNL* open database [9] and is shown in Fig. 3. The charging regimes are based on an average driving distance of 38 km per day, the average driving distance of a Dutch passenger car [2]. The EV efficiency is set at 0.175 kWh per km. This results in an energy demand per EV per day, which together with the charging power results in a charging session

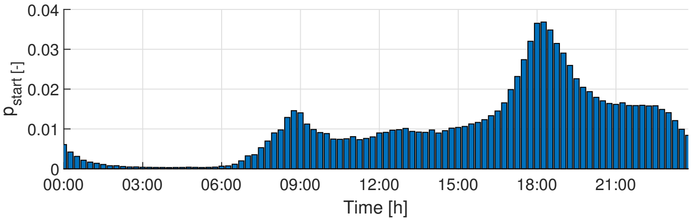

Fig. 3: The plug-in time probability distribution [9].

duration expressed by d. The combination of p_{start} and d results in the EV charging probability $p_x^z(t)$ for every charging regime x and charging power level z. Five charging regimes at two power levels (3.7 and 11 kW) yield effectively ten EV charging regimes, as shown in Fig. 4. The charging regime distribution β_x is set at 0.55 for x = 1, 0.15 for x = 2 and 0.10 for x = 3, 4 and 5.

B. Result

Fig. 5 shows the results for the case study. For every possible EV penetration rate, the outage probability and the expected days between outages are shown for the three scenarios. This indicates that a higher charging power increases the probability of an outage: a shorter charging time does not make up for the higher power level in terms of the outage risk. There is a difference between 3.7 and 11 kW charging: with only 3.7 kW charging, the outage probability is once every 500 days at 50% penetration rate. However, the probability of an outage using only 11 kW charging is already much larger at only 17.5% EV penetration rate: once every 50 days. We also studied the case wherein there is a 50/50 split between 3.7 and 11 kW charging, for which we obtained the probability of an outage every 50 days at approximately 35% EV penetration rate.

C. Parameter sweeps

For the 50/50 scenario, we perform a parameter sweep over the mean driving distance, which was previously set at 38 km per day. Fig. 6 shows the sweep from 10 to 80 km with steps of 10 km. A larger driving distance results in longer charging time and thus the probability of an outage increases. Fig. 6 at around 30% EV penetration rate shows a cut-off point from which the probability of an outage starts to rise due to the influence of longer charging sessions caused by larger driving distances. This shows that the daily EV energy demand significantly influences the results. Fig. 7 shows the results for another parameter sweep over the LV feeder limit of 40 to 85 kW in steps of 5 kW. The results show that a relatively small increase in feeder power limit extends the number of vehicles that can charge on this LV feeder without creating outages.

V. Conclusion

This paper presented a model that approximates the probability of simultaneously charging sets of EVs based on EV charging session information such as energy demand and plug-in time. The probability for a single EV to charge is used to characterize the joint behavior of a set of EVs, e.g., in a residential area. With this information, we approximate the probability that certain numbers of EVs charge simultaneously at a given time, possibly exceeding the available capacity and thus causing an outage on an LV feeder. The multiple charging regime modeling method that is introduced combines a plug-in time distribution, discretized energy demands and discretized charging power levels in a single model to calculate the probability of an outage due to EV charging in various scenarios. The case study shows that reducing the charging power in general significantly reduces the risk on outages at higher EV penetration rates. The parameter sweep over the LV feeder limit in the case study shows that a slight increase of the LV feeder limit reduces the probability of outages significantly.

Future work involves three-phase load flow modeling to create the opportunity to look at phase-balancing of EV chargers. This issue together with several mentioned assumptions might make the presented model too optimistic in terms of expected outages at different EV penetration rates: in practice, outages could happen earlier than is presented here.

Acknowledgment

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References

[1] The International Council of Clean Transportation, "On the electrification path: Europe's progress towards clean transportation," Available at https://theicct.org/publications/electrification-path-europe-mar2021 (Accessed: 12-04-2021).

[2] CBS, "OViN," Available at https://www.cbs.nl/nl-nl/maatwerk/2019/22/totaal-afgelegde-kilometers-op-nederlands-grondgebied (Accessed 12-04-2021).

[3] 'CBS', "Energieverbruik van particuliere huishoudens," Available at https://www.cbs.nl/nl-nl/achtergrond/2018/14/energieverbruik-van-particuliere-huishoudens (Accessed 12-04-2021).

[4] P. van Oirsouw, *Netten voor distributie van elektriciteit*. Phase to Phase, (ISBN = 9789081798303), 2011.

[5] A. R. Abul'Wafa, A. El'Garably, and W. A. F. Mohamed, "Impacts of uncoordinated and coordinated integration of electric vehicles on distribution systems performance," in *2017 Nineteenth International Middle East Power Systems Conference (MEPCON)*, 2017, pp. 337–364.

[6] G. Hoogsteen, A. Molderink, G. Smit, J. Hurink, B. Kootstra, and F. Schuring, "Charging electric vehicles, baking pizzas, and melting a fuse in Lochem," *CIRED: Open Access Proceedings Journal*, vol. 2017, no. 1, pp. 1629–1633, October 2017.

[7] M. Lahariya, D. Benoit, and C. Develder, "Synthetic data generator for electric vehicle charging sessions: Modeling and evaluation using real-world data," *Energies*, vol. 13, p. 4211, August 2020.

[8] K. Walz, D. Contreras, K. Rudion, and P. Wiest, "Modelling of workplace electric vehicle charging profiles based on trip chain generation," in *2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 2020, pp. 459–463.

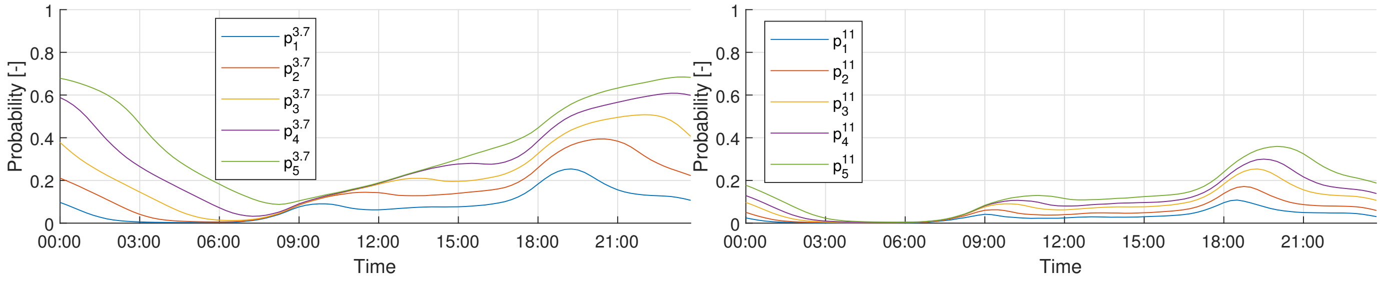
[9] ElaadNL, "Open database," Available at https://platform.elaad.io/analyses/ElaadNL_opendata.php (Accessed 12-04-2021).

[10] L. Calearo, A. Thingvad, K. Suzuki, and M. Marinelli, "Grid loading due to ev charging profiles based on pseudo-real driving pattern and user behavior," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 3, pp. 683–694, 2019.

[11] A. Hoekstra and N. Refa, "Characteristics of Dutch EV drivers," Jan. 2017, 30th International Electric Vehicle Symposium and Exhibition, EVS 2017, EVS 2017 ; Conference date: 09-10-2017 - 11-10-2017. [Online]. Available: http://www.messe-stuttgart.de/en/evs30

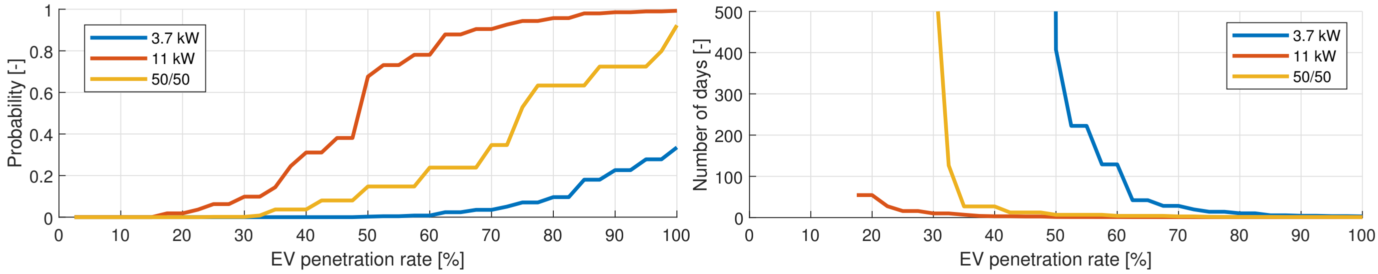
[12] J. Quirós-Tortós, L. F. Ochoa, and B. Lees, "A statistical analysis of EV charging behavior in the UK," in *2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM)*, October 2015, pp. 445–449.

[13] G. Hoogsteen, "A cyber-physical systems perspective on decentralized energy management," Ph.D. dissertation, University of Twente, ISBN = 9789036544320, December 2017.



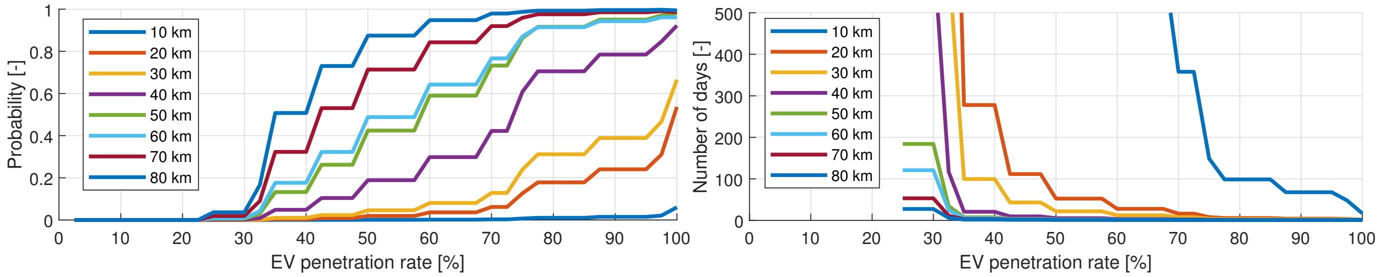
(a) 3.7 kW (b) 11 kW

Fig. 4: The EV charging probability distributions p_x^z for the charging power levels z = 3.7 (a) and z = 11 kW (b) for the five different charging regimes x.



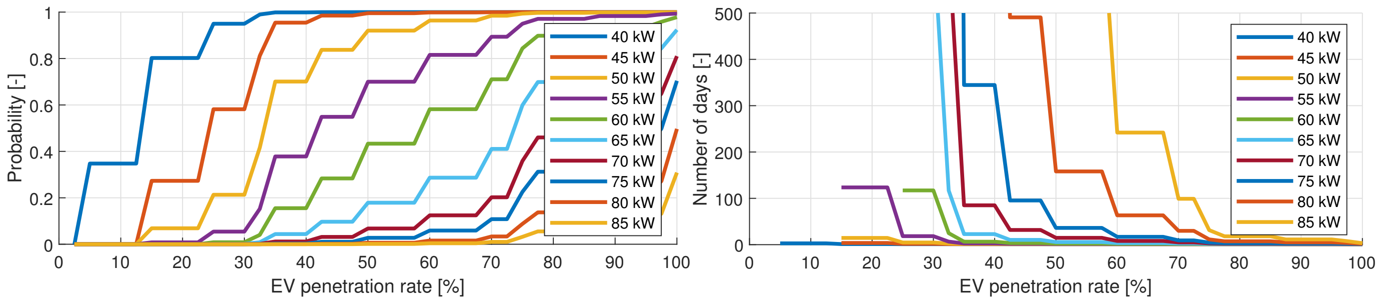
(a) Probability of an outage (b) Number of days before an expected outage

Fig. 5: Case study results for the probability of an outage (a) and expected number of days before an outage happens (b) against EV penetration rate.



(a) Probability of an outage (b) Number of days before an expected outage

Fig. 6: The probability of an outage (a) and expected number of days before an outage happens (b) against EV penetration rate for a parameter sweep over the mean driving distance in km.



(a) Probability of an outage (b) Number of days before an expected outage

Fig. 7: The probability of an outage (a) and expected number of days before an outage happens (b) against EV penetration rate for a parameter sweep over the LV feeder limit in kW.