Sensitivity Analysis of Electric Vehicle Impact on Low-Voltage Distribution Grids

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***Abstract*—The presented work identifies the dominating influencing factors in electric vehicle (EV) modelling on low-voltage distribution grids to establish guidance for reliable impact assessments of increasing EV penetration. Seven aspects are distinguished with respect to the modelling of the load of EVs that influence the flows and voltages in the grid. For each of these aspects sensitivity analyses are carried out by running power flow simulations in a Monte-Carlo fashion to account for the stochasticity in the model parameters. The impacts are analysed using a variety of metrics including transformer and line loadings. The highest sensitivities are observed for the number of vehicles in the grid, the used charger power rating and the modelling of driving patterns. The grid configuration as well as locally higher EV shares gain significance for line loading assessments. Car modelling and people's charging behaviour play minor roles.**

***Index Terms*—electric vehicle, low-voltage distribution grid, Monte-Carlo simulation, sensitivity analysis**

I. Introduction

To fulfil the commitments of the Paris Agreement 2015 [1] the transportation sector is obliged to drastically reduce its CO_2 emissions. The increased efforts towards electric vehicles (EVs) show a route forward to achieve a decarbonisation. As a consequence, the power grid infrastructure is expected to face increased loading. Private and uncontrolled charging at home, presumably the most common charging method [2], impacts especially low-voltage distribution grids. Not only the additional energy demand poses a challenge, but the peak power increase emerges as the crucial factor for grid planning and risk assessment. Fig. 1 depicts the load duration curve (LDC) of the transformer for the household load in the selected grid. Although the transformer peak loading ($\sim$55%) in the studied grid is well below operational limits, the LDC still demonstrates how rare load cases can substantially increase the required operating range. The effect of EVs on the LDCs and especially on peak loads requires therefore a thorough modelling and analysis to avoid ill-informed decisions that lead to under- or over-dimensioning of the grid components and potentially to higher costs for grid operators.

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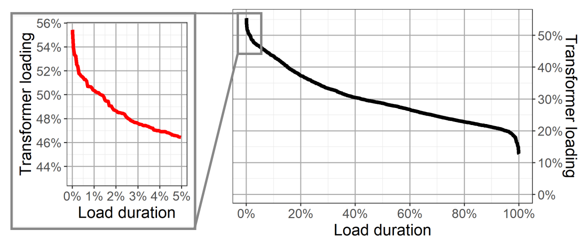

Fig. 1. Transformer load duration curve of household loads in January.

A common approach to evaluate these peak power increases caused by EVs is based on measured or modelled charging load profiles which are added to the existing loads [3], [4]. However, the rapid developments in the EV market question the future applicability of these patterns. A main limitation concerns the up-rise of pure battery EVs in contrast to plug-in hybrid EVs. Moreover, the ever increasing battery capacities and hence EV driving ranges as well as the EV usage habits need to be considered in future assessments. Finally, the emerging higher charger power ratings can substantially change the charging patterns [2].

Successful attempts to model charging profiles often employ a modular approach as reviewed in [5]. They determine the energy and power demand based on travel data, EV specifications, and available charging infrastructure [6]–[12]. Such a modular approach offers the advantage of flexible modelling for future assessments and it allows for stochastic modelling in form of Monte-Carlo simulations [9], [10]. However, the sensitivities of used modelling assumptions, e.g. EV specifications or people's charging behaviour, have not been comprehensively investigated yet. While some studies explore the influences of varying single factors such as penetration levels or charger ratings [11], [12], the presented work integrates seven influencing factors, here referred to as *dimensions*, into a single framework. These *dimensions* split up EV charging into a handful of tangible characteristics, which could be expressed as questions like 'when do people charge' or 'how often do people charge'. By closely investigating each *dimension* and the interaction between them one can obtain a better understanding of their sensitivities with respect to the overall grid load. This allows to break down complex models into the influences they have on the basic charging characteristics. Combining this insight with the sensitivities found in this paper will improve the quality and reliability of EV modelling since overly complex or simplistic models can be identified. Furthermore, this work improves the ability to judge whether assumptions and results may generalise to other environments or not. In this work, the framework incorporates a real-world case in Switzerland by using a residential low-voltage grid model, metered household loads, and a large scale mobility survey. In this set-up, multiple *models*, which integrate regularly used modelling techniques and assumptions, are compared against one another for each *dimension*. The resulting assessment of the *dimension's* relevance may provide guidance for future work on EV integration and system planning.

The remainder of the paper is structured as follows: Section II introduces the modelling of the seven *dimensions*, Sec. III presents the simulation framework and Sec. IV displays the results from which Sec. VI draws the conclusions.

II. Modelling Framework

The modelling framework follows a bottom-up approach, as depicted in Fig. 2. First, the charging load of individual cars over time is generated by determining the charging demand from *driving patterns* and the *type of EV*. People's *charging behaviour* and the used *charger type* then govern the resulting load of individual vehicles in the examined grid. The *penetration level* and *EV placement* specify how many cars are used as well as their connection points in the grid. The total EV load is added on top of the base load, i.e. the metered household loads in the area, and then added to the grid in a radial or meshed *configuration*.

In Sec. II-A the underlying data sources are introduced, while Sec. II-B to II-H provide details for each *dimension*. Table I gives an overview over all *models*.

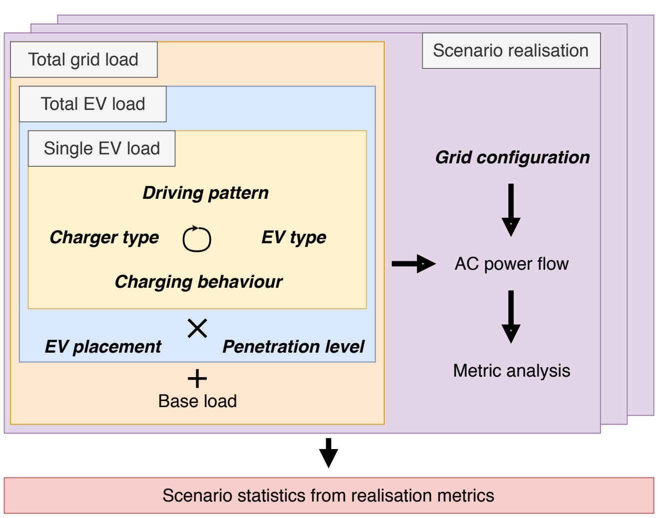

Fig. 2. Modelling framework used to assess the impact of EVs on distribution grids, all *dimensions* marked in bold.

TABLE I
Overview over EV modelling dimensions and models.

Dimension	**Default model**	**Additional models**
Driving patterns	MZMV sampling	independent GMM (A1) joint GMM (A2) availability based (A3)
EV type	sales based average	sales based sampling (B1)
Charging behaviour	Gaussian threshold	uniform threshold (C1) always charging (C2)
Charger type	0% 11kW	25% 11kW (D1) 50% 11kW (D2) 100% 11kW (D3)
Penetration level	20%	40% (E1) 60% (E2) 80% (E3)
EV placement	even	mildly clustered (F1) strongly clustered (F2)
Grid configuration	radial	meshed (G1)

A. Available data

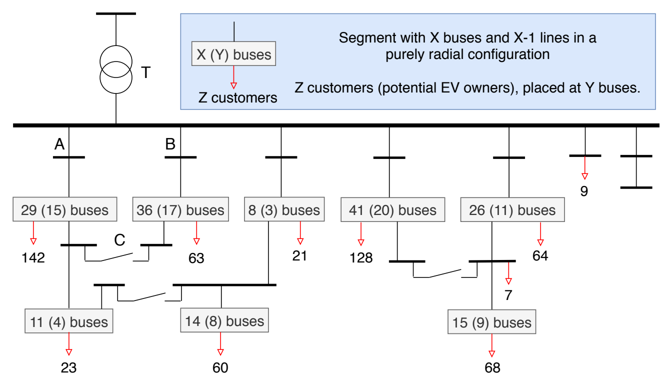

Fig. 3. Low voltage grid with customer location.

For the study, a low-voltage distribution grid operated by IWB, the distribution system operator of the City of Basel, was chosen. Fig. 3 shows its main topological characteristics. The transformer rated at 630 kVA connects the 400V level to the higher voltage level (11kV). According to the geographical information system (GIS) of the grid model, the 196-bus system hosts in total 585 households at 89 connection points which are eligible as EV connection points in this study. In general, the main strand lines are rated at about 350A and the household connections at 140A. In addition, a smart meter data set with 15-minute resolution for the considered grid is used as base load. Since the measured base load reaches its highest values in January the work focuses on this month only. Fig. 1 shows the LDC of the base load.

The outcome of the 2015 Swiss national travel survey 'Mikrozensus Mobilität und Verkehr' (MZMV) [13] forms the basis for the driving pattern modelling. The data set consists of about 40'000 1-day travel surveys, 20'000 of which contain information about car movements. The data set is processed to yield a table of round trips that start and end at home. Stops during a round trip, e.g. for shopping, are possible but are not included in the modelling. Between two round trips the car is per definition at home. Each trip is associated with a departure time, an arrival time, a travel distance and the day of the week on which it occurred. While each weekday is treated separately, seasonal variations as well as geographic properties are not considered since further splits of the data set would weaken the representativity of the results. As the survey is primarily based on combustion cars, it has to be assumed that the mobility behaviour does not change with the switch to EVs until similar surveys with sufficient EVs exist.

B. Driving pattern

The driving pattern models people's car usage. The first model is *MZMV sampling*, which directly uses trips from the MZMV data set by concatenating them into a month-long time series. In contrast, the following three models rely on a parametric description that aims at resembling the nature of the MZMV data set. Such models can be used if no travel survey is available. The *independent GMM* model fits a Gaussian mixture model (GMM) to the probability density functions (PDF) of the departure time in the MZMV data set and another one to the arrival time. The *joint GMM* model approximates the joint PDF of the two time variables. In contrast, the *availability-based* model uses the share of cars at home, i.e. the car availability. The share varies during the day and from its rate of change transition probabilities between being and not being at home are calculated. Based on the transition probabilities car trips are sampled. Fig. 4 illustrates for all four models the resulting PDFs of the arrival time as well as the availability during the day. For the latter three parametric models a logarithmic normal distribution determines the driving distance for each trip. All models, including the fitted parameters, are described in detail in [14].

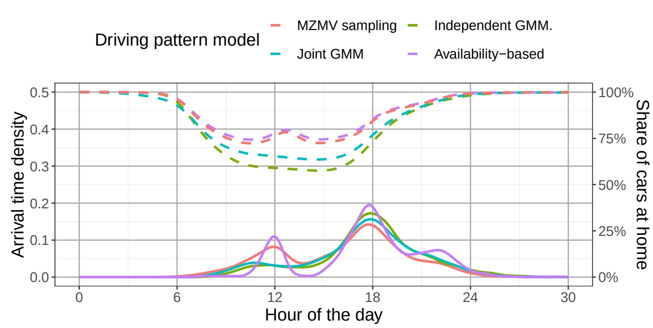

Fig. 4. Availability curve (dashed) and arrival time distribution (solid) of driving pattern models on Mondays.

C. Electric vehicle type

The EV characteristics of interest are the car's battery capacity and the energy consumption per kilometre. Two approaches are tested: 1) modelling a diverse fleet with different vehicle classes [6], [11], [12] or 2) assuming a single average vehicle using the sales-based average. Table II shows a compilation of the most sold EV models in Europe in 2018 which forms the basis for the analysis [15], [16]. At a later stage, increases in battery capacity by 25% and 50% as well as consumption variations of $\pm 10\%$ are considered.

TABLE II
ENERGY CONSUMPTION AND BATTERY CAPACITIES OF THE 10 MOST SOLD EVS IN EUROPE IN 2018 [15], [16]

Model	Consumption [kWh/100km]	Battery capacity [kWh]	Sales [-]
Nissan Leaf	16.5	40	40609
Renault Zoe	15.7	41	38538
BMW i3	16.4	42.2	24432
VW e-Golf	16.8	35.8	21252
Tesla Model S[1]	18.4	100	16682
Tesla Model X[1]	21.4	100	12694
Hyundai IONIQ	14.4	30.5	9605
Smart fortwo	15.9	17.6	8688
Kia Soul EV	17.1	33	6641
Jaguar i-Pace	22.3	90	6319
Fleet average	16.9	49.4	-

D. Charging behaviour

While driving patterns define the times a car is available for charging, the charging behaviour defines below which threshold of state of charge (SOC) people start to charge. A SOC of 0% represents a fully depleted and 100% a fully charged battery. The first of three models follows the analysis in [17] by approximating people's personal threshold by a Gaussian distribution $\mathcal{N}(45\%, 19\%)$ truncated between $[10\%, 100\%]$. As a second model, a uniform threshold distribution between $[10\%, 100\%]$ is tested. In the *always charging* model everybody starts to charge as soon as the SOC drops below 100%, i.e. people charge after every drive. Regardless of the model, the charging process is assumed to commence upon arrival without delay to avoid complexity. The analysis of the survey "My Electric Avenue" [18] indicates that about 65% of EV owners charge within 15 minutes upon arrival.

E. Charger type

Two charger types with power ratings of 3.7kW and 11kW are considered for home charging. While the power ratings themselves are known, their share of installation is subject to the sensitivity analysis. Starting with only 3.7kW chargers, i.e. 0% 11kW chargers, being installed, the share of 11kW stations is increased to 25%, 50% and ultimately to 100%. For all chargers active power factor correction, hence a power factor of unity, is assumed [19].

F. Penetration level

The number of EVs in the grid is expressed by four penetration levels which are defined as the share of households that own an EV. Starting from the load case with no EVs, penetration levels of 20%, 40%, 60% and 80% are tested.

[1]All models in 100kWh configuration for simplicity and in light of overall increasing battery capacities.

G. Electric vehicle placement

The placement of EVs may become critical if many cars are charged within a neighbourhood connected by the same line to the transformer. Therefore, an evenly spread placement, where each household's probability of owning an EV is equal across the grid, is compared with two levels of EV clustering. While the mild clustering results in some local hotspots, the strong clustering places all EVs directly next to each other.

H. Power grid configuration

Three circuit breakers in the grid (like element C in Fig. 3) can be switched to change between a radial and a meshed grid configuration which are both used by the grid operator.

III. Simulation

This section treats the combination of *dimensions* with the respective *models* and the metrics employed for the analysis of the power flow results. In the following, a *scenario* is referred to as the selection of a single *model* for each *dimension*. For each *dimension* a *default model* is selected as indicated in Table I. Starting from a *reference scenario*, which is based purely on *default models*, the variation of a single *dimension* at the time provides a first indication for the *dimensions'* impacts. Subsequently, *scenarios* with multiple variations are simulated. All variations are stated explicitly alongside figures, for all other dimensions the default models apply.

To incorporate the stochastic nature of some *models*, each *scenario* is simulated 400 times with random samples of the selected *models*. For each of these 400 *scenario realisations* a time-series power flow computation with a 15 minute resolution is performed with MATPOWER [20]. The results of each *realisation* are then evaluated with respect to a set of metrics. This Monte-Carlo style approach is performed for each *scenario* separately and yields the basis for the sensitivity analysis in which the metrics of the *realisations* are displayed. Since the simulation of a single *scenario* requires about five hours on a standard machine, multiple *scenarios* were simulated in parallel on a 36-core machine with 479 GB RAM.

The primary metrics of interest are the relative changes in the loading of the transformer and lines. Therefore, relative LDC changes for each *scenario realisation* are computed at selected percentiles of the LDC according to

$$\text{relative LDC change} = \frac{\text{LDC}_{\text{with EVs}} - \text{LDC}_{\text{without EVs}}}{\text{LDC}_{\text{without EVs}}}. \quad (1)$$

Besides, the aggregated charging load over time is evaluated.

IV. Results

Fig. 5 depicts the results of the simulations varying a single dimension with respect to the default case to enhance the intuition of each dimension's impact. The abbreviation used for the varied *models* can be found in Table I. The relative transformer peak load increase is indicated on the left y-axis while the absolute values are plotted on the right one. The dashed line marks the transformer peak load (55.4%) with no EVs added. The Box-Whisker-Plots (1,5 IQR) represent the distribution of the 400 *scenario realisations*. This first analysis suggests that, not surprisingly, variations in the penetration level and the charger type clearly cause the biggest impact, further investigated in Section IV-A.

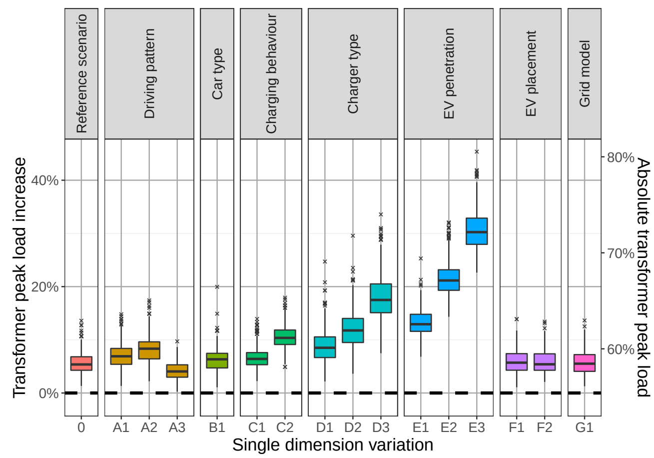

Fig. 5. Impact of single dimension variations on the transformer peak load, values relative to the scenario without EVs (dashed line) on the left y-axis and in absolute terms on the right y-axis, see Table I for abbreviations.

A. Penetration level and charger type

Several combinations of these two dimensions are simulated to investigate their interaction. The resulting transformer peak load increases are shown in Fig. 6. In a first analysis it appears that the transformer peak load increases proportionally to the penetration level, i.e. to the number of EVs, hence suggesting the lack of a correlation between the two dimensions.

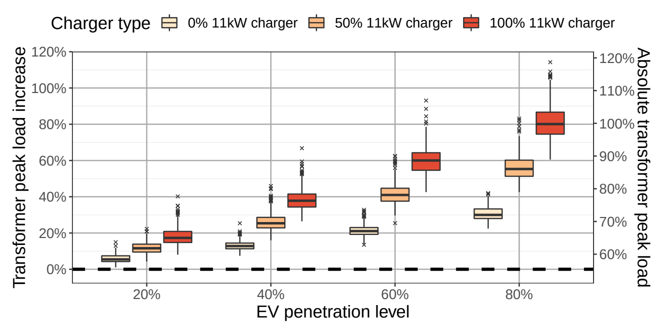

Fig. 6. Penetration and charger type scenarios.

By scaling these values by the EV penetration (the number of cars) the additional power demand per car is calculated. The upper plot in Fig. 7 depicts this re-scaling. At first, it again appears as if the two *dimensions* influence the results independently of each other. However, when analysing only the added EV load (lower plot in Fig. 7) a different picture emerges. Firstly, an aggregation effect occurs, meaning that with an increasing number of EVs the average load per car decreases since a superposition of the peak load of all EVs, i.e. simultaneous charging of all EVs, becomes statistically less likely. Secondly, the deviation between the two plots differs depending on the charger type. Two effects are at play. On the one hand, higher charger loads cause not only higher peak EV loads (equivalent to the EV load per car) but also shift the peak more towards the base load peak around 6 o'clock, hence EV and base load peak coincide more. On the other hand, the penetration level increase itself causes a mere scaling of the EV load including the mentioned aggregation effect without shifting the timing. However, the peak of the total load (sum of base and EV load) is affected in timing which counters the aggregation effect. Fig. 9 shows an exemplary case of the base and EV load against time. The plot is discussed in detail in Sec. IV-C related to the driving pattern results.

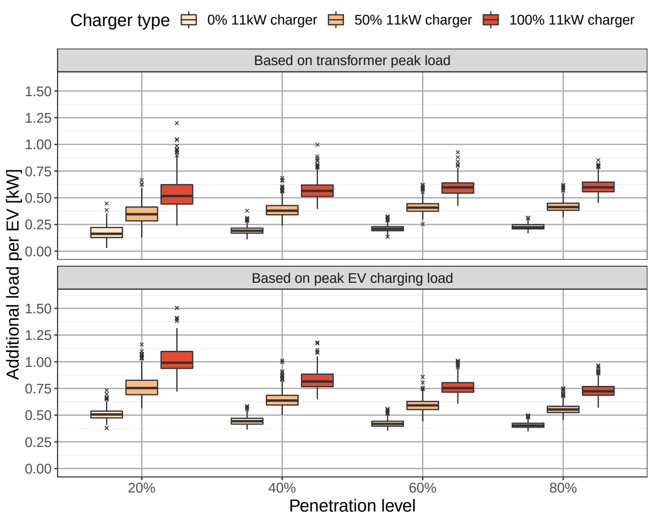

Fig. 7. Additional peak load normalised by the number of cars.

B. Charging behaviour

When comparing different charging behaviours, the case of people charging after every trip creates a significantly higher peak load increase than the other two models as shown in Fig. 8. In addition, covering the daily average energy use (MZMV average driving distance $\sim$30km, average energy consumption from II-C $\sim$0.17kWh/km) with a 11kW charger requires around half an hour of charging. The longer charging time of slower chargers leads to more overlapping of people's charging periods. The resulting higher coincidence factor causes the relatively strong impact of the *always charging* scenario for slow chargers; its peak load increase amounts to nearly double the one of the other two charging behaviours. For higher charger power ratings the peak load increase is more similar across the three behaviours. The *Gaussian* and *uniform threshold* models show no major difference amongst each other. People charge in both cases every other or third day, hence less often but over a longer period. This leads to lower coincidence factors than for the *always charging* model. The slightly higher increase seen for the uniform distribution is explained by a bit more frequent charging and thereby higher coincidence factors.

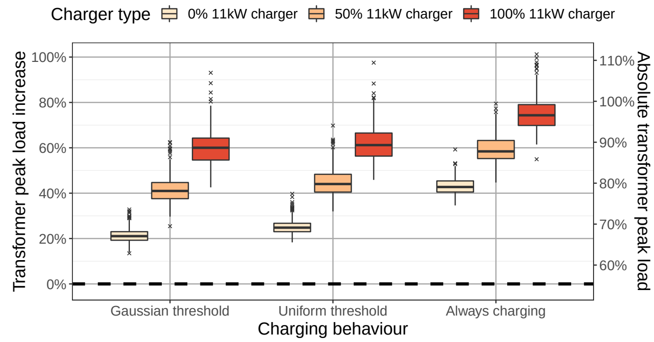

Fig. 8. Charging behaviour impact for 60% EV penetration.

C. Driving patterns

Since the driving patterns and more specifically people's arrival times govern the charging period, a comparison between the distribution of EV charging load on Mondays and Saturdays illustrates the sensitivity with respect to driving patterns well. On both days the number of trips (including no trips) per person is very similar but the arrival time distributions differ notably. This leads to a wider spread charging period on Saturday and lower peak loads, especially for higher charging powers as depicted in Fig. 9.

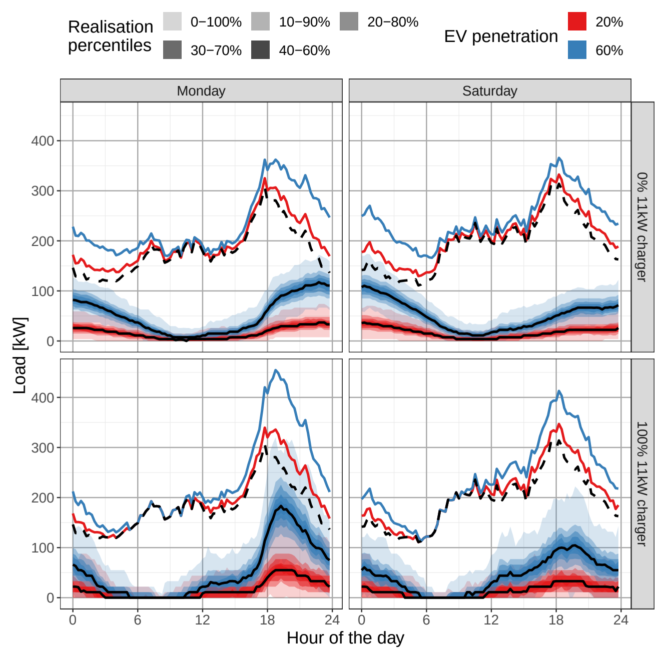

Fig. 9. Distribution of realisations of EV load (coloured areas) including their median (solid black line), the base load (dashed line) and the resulting median of the total load (solid coloured lines) during a day.

With this example in mind, it becomes apparent why the modelling of driving patterns needs special attention. The proposed GMMs match the peak load metric obtained with the *MZMV sampling* model within small margins, illustrated in Fig. 10. Revisiting the availability curves of both models in Fig. 4, the *joint GMM* model comes closer to the *MZMV* *sampling* model and hence more cars are available around noon. However, the sharp increase around the evening is captured better by the *independent GMM* model. The model choice is therefore a trade-off and is dependent on the timing of the critical base load. The availability-based model even further pronounces the arrivals at noon at the cost of the accuracy of the evening arrival times. Overall, a carefully chosen model yields satisfactory results.

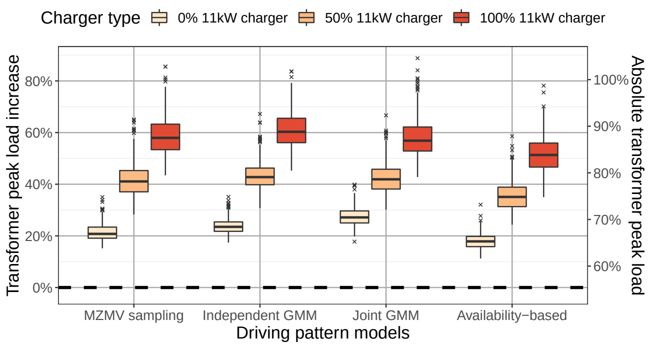

Fig. 10. Impact of driving pattern modelling on the transformer peak load for a 60% EV penetration.

D. Electric vehicle type

The car type modelling influences the battery discharge and hence the charging frequency and duration of each individual EV. However, Fig. 11 shows that the model differences between a diverse EV fleet and a single average car barely influence the EV loads and the transformer peak load metric. Increases in battery capacity and variations of the EV's energy consumption yield notable differences, especially for higher charging power. Generally speaking, with larger batteries and lower consumption people charge less often and hence the coincidence factor decreases (this effect would also be seen if the average travel distance decreased). Consequently, this observation gives reason to use a single average car model to represent a diverse fleet. Furthermore, it underlines that driving patterns and charging behaviour already create diversity among individual EVs such that the diversity of EV types becomes irrelevant.

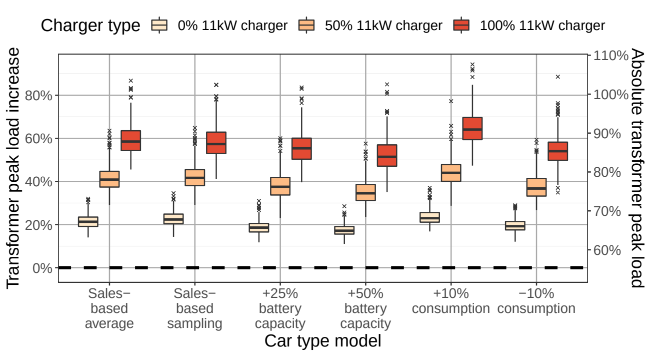

Fig. 11. Impact of the car type modelling on the transformer peak load for a 60% EV penetration.

E. Grid configuration

Up to this point the analysis focused on the transformer peak load. The grid configuration as well as the placement of EVs in the grid do not affect the total load (except for losses) nor the transformer-based metric. However, the peak load changes strongly for lines A and B in Fig. 3 when switching from the radial to the meshed configuration. The latter creates a levelling effect such that the previously higher loaded line A sees lower peak line loading at the expense of a higher peak load for line B, as shown in Fig. 12. Not only for this case but the grid overall, the meshed configuration provides a beneficial line loading situation. Even very high penetration levels of 80% can be accommodated without major peak load increases when considering the power line ratings for the meshed grid. As mentioned before, the transformer peak load still increases substantially under such a scenario. This emphasises the importance of assessing the affected grid elements separately and identifying the critically loaded ones.

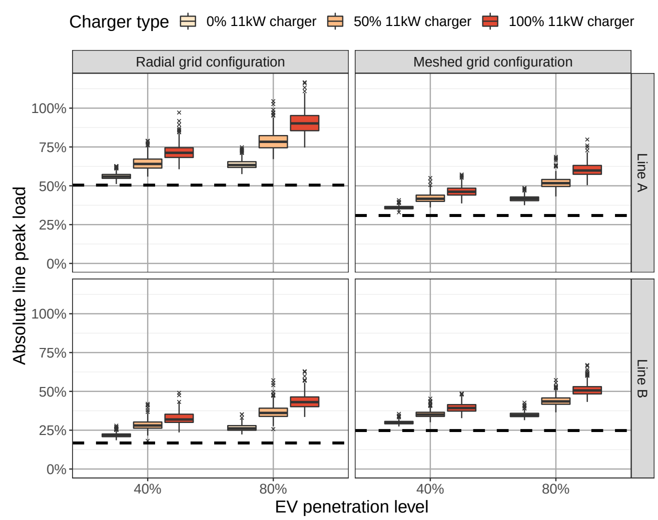

Fig. 12. Impact of the grid configuration on peak loading for lines A and B.

F. EV placement

Peculiar aspects of this dimension require an adjustment of the plotting functions. Fig. 13 compares the evenly distributed placement with a mild and an extreme clustering for lines A and B. Due to the clusters either being located at a branch or not, the realisations yield a non-normal distribution, illustrated as dots for single *realisations*. Line B experiences substantial peak load increases for the *realisations* when it happens to host an EV cluster, but low impact in the other situations. The global penetration level increases primarily the likelihood of higher loads and secondarily the peak itself for clustered scenarios. The clustering can hence be seen as a locally higher penetration level. Since line A hosts more customers, it is exposed to higher base loads. Therefore, the relative impact of clustering is less extreme than for Line B. Moreover, aggregation effects come into play causing lower peak load increases for line A.

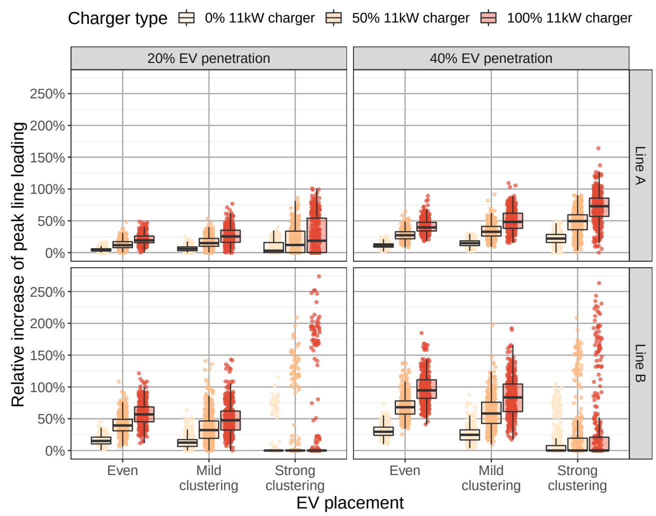

Fig. 13. Impact of clustered EV placement on peak line loading for lines A and B using single realisations (dots) and their summary (boxplots). Y-axis according to (1) for peak loads.

G. Load duration curves

The primary focus of the study lies on the peak load, nevertheless a brief analysis of other points on the LDC provides further valuable insights. Fig. 14 shows that the absolute transformer load quickly decreases when considering non-peak hours. This means that for grids with EVs still only a small number of hours determines the power rating requirements if no smart charging is employed. Furthermore, the spread of the results reduces drastically for non-peak hours which increases their trustworthiness. This observation holds throughout the scenarios and also for line loadings. EV impact analyses should therefore also consider non-peak load hours to provide backing for peak load assessments governed by extreme cases with large uncertainties.

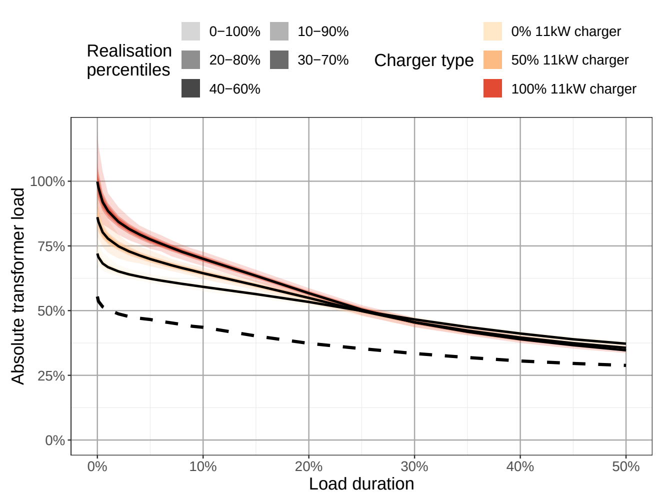

Fig. 14. LDC of absolute transformer loads for an 80% EV penetration as a distribution of realisations (coloured areas and solid line as median) and the base LDC (dashed line).

V. Discussion

This work investigated the impact of EV expansion in a specific urban environment and models with mostly limited complexity. Nevertheless, the presented results provide guidance for other set-ups and more sophisticated modelling approaches. For the generalisation of the results, the essential question to ask is how the change of set-up or model can be interpreted within the given framework. If, for example, EV owners use to charge at work, they will cover only a fraction, e.g. 75%, of their daily energy demand at home, hence at the grid area of interest. Instead of introducing a new *dimension* to incorporate charging at work, one can resemble the effect by reducing the energy consumption per kilometre accordingly, in this example by 25%, and hence the daily energy demand which needs to be covered at home. The provided sensitivity analysis will then give an indication on the impact that charging at work most likely has on the grid. The possibility to estimate effects of such additional aspects of EV charging by expressing them in terms of the proposed *dimensions* highlights the flexibility of this work. Another example is to consider a rural, less-densely-populated area with a different grid infrastructure. As long as the transformer is the critical component, the overall picture would remain similar to the shown results; however, when individual line loading becomes important the applicability of the provided observations becomes limited. Analysing the effect of differing national driving patterns serves as a third illustration of how the presented results can generalise. By analysing how the arrival time distributions and travel distances vary across different countries, first conclusions on the EV impact can be drawn. Since national travel surveys are readily available such a first analysis requires no additional simulations. Lastly, the framework offers the opportunity to study the effects of complex models even before simulating a single power flow. Investigating, for example, how agent-based traffic modelling compares to a simple GMM in terms of the arrival time distribution, can lead to conclusions such as: The models yield a very similar arrival time distribution hence either models could be used, potentially favouring the simpler one; or the models show significant differences which would justify to test both models. Such a comparison not only improves the understanding of the applied models but exposes the use of overly-complex or too simplistic ones. Although a number of simulations is inevitable for each set-up and model choice in order to quantify the EV impact, the framework and results shown, clearly indicate which aspects of EV modelling should be considered first in order to keep the computational burden as low as possible. This ultimately will lead to more effective resource allocation as well as more reliable results.

VI. Conclusion

In light of the previous analyses, the first step in EV modelling is to determine whether the transformer or certain power lines are the critical grid elements. If the transformer is the limiting component, penetration level and charger types are the dominating *dimensions*. If a line is at risk, the grid configuration strongly influences the picture and very clustered EV placement can cause a further load increase.

Driving patterns constitute a major influencing factor on the results. Careful modelling, as for the presented models, can resemble the results obtained with the original driving pattern data set within satisfactory margins, especially when focusing on the arrival time distribution. EV characteristics and charging behaviour reveal a low sensitivity, unless they significantly impact people's charging frequency and hence the coincidence factor of EVs.

The peak EV charging load and its timing with respect to the base load peak mainly determine the impact assessment results. Since charging power, penetration level and driving patterns are the governing factors associated with modelling uncertainty, these dimensions should be subject to parameter variations in any work that aims at assessing the impact of EVs reliably. Further off-peak load analyses can add value for lifetime and risk assessments due to higher confidence.

The analysis of how other set-ups and models affect each *dimension* of this framework presents the opportunity to generalise the shown results. These insights not only improve the understanding of model assumptions but also allow for more reliable impact assessments. With the future introduction of control strategies additional *dimensions* occur, e.g. the control strategy type and how many people apply it. While the *dimensions'* impact on the effectiveness to shift and reduce peak EV loads remains to be determined, controlled charging is expected to be a promising way forward for grid operators to foster EV integration into the grid.

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