TAMING UNCERTAINTY IN DISTRIBUTION GRID PLANNING – A SCENARIO-BASED METHODOLOGY FOR THE ANALYSIS OF THE IMPACT OF ELECTRIC VEHICLES

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ABSTRACT

The grid planning uncertainty related to the impacts of electric mobility on low voltage distribution grids can be decomposed into four dimensions: first, the often still opaque knowledge of today's state of the grid; second, the speed of EV market penetration; third, the evolution of EV load patterns; fourth, the spatial distribution of EVs.
This paper presents a methodology based on Monte Carlo simulations that can be used to reduce uncertainty and quantify the chance of overloading of specific lines or the likelihood of voltage violations on given buses. The output can be used to justify grid planning decisions. It has been found that the rated power of car chargers and the width of the time window in which most cars return home (time coincidence) have a significant influence on the outcomes. The methodology is applied to a case study of a residential low voltage grid located in central Switzerland.

INTRODUCTION

Distribution grid operators have designed power grids for decades with the principle of "fit and forget". The paradigm worked well, until in recent times the rise in distributed generation and the electrification of mobility and space heating started dropping new, considerable burdens on the shoulder of an aging infrastructure.
The mantra for operators, as always, is to react to ensure grid adequacy, reliability and safety. *Keep the lights on*, no matter what. The substantial issue is that the incoming wave of electrification carries substantial unknowns with it, casting a veil of opacity that hinders long term planning.

Pervasive uncertainty

Following the wave of photovoltaic expansion, plug-in electric vehicles (PEVs) are now a prominent emerging technology in residential electrification. The speed of adoption depends on a tangled web of relationships between technology, costs, policies and social dynamics. The uncertainty on the actual impact on a low voltage grid can be decomposed into four dimensions:

Uncertainty on the status of the grid, or "reality gap": low voltage distribution grids are only now becoming (slowly) more monitored. There is often a "reality gap" between what the grid planner believes is the state of the grid and, for better or worse, the actual state of the grid.

Uncertainty on adoption speed: it is unclear how fast PEVs will spread. Sudden technology breakthroughs or aggressive policies may radically change the picture with relatively short notice.

Uncertainty on load patterns: the load profile of a PEV depends on the rated power and the mode of usage, which in turn depends on an ecosystem of stochastic factors like house location, workplace location, energy cost, mobility preferences, personal lifestyle, external charging management schemes like aggregators or coordination solutions on neighborhood or parking scale. There is intrinsic uncertainty on how each of these factors will evolve in the near future and, therefore, how load patterns will develop.

Uncertainty on geographical distribution of new units: on the small scale of residential distribution grids, neighbourhood effects[1] can create a cascade adoption of PEVs, with consequent emergence of local hot-spots.

Such pervasive uncertainty can be daunting, pushing grid planners towards preventive overinvestments, *wait-and-see* strategies, or resort to the use of forecasts of technology adoption to target and schedule countermeasures. The last option, while instilling confidence, may turn out to have undesired repercussions in case of errors.

Fragility to forecasting errors

Forecasts provide predictions that can be used to work out decisions and design adaptation or mitigation plans. As remarked by Taleb in [1], *the forecast translates into a decision, and, accordingly, the uncertainty attached to the forecast is endogenous to the decision itself.*
The comforting nature of forecasts may induce an excessive confidence in planning decisions, introducing fragility into the system. Focusing the attention on the predicted scenarios might lead to a neglection of other possibilities [2]. For these reasons, we propose to move towards adaptive grid planning approaches that account for uncertainty without depending on long-term forecasts.

Non-predictive grid planning

Ironically, long-term forecasts of technology adoption tend to change at a fast pace. Models of electric consumption of new appliances are frequently revised as technology evolves. Both are far from being consistent across researchers or providers. On the other hand,

[1] More affluent neighborhoods change first, and the (purchasing) choices of an individual tend to affect the choices of neighbors.

investments in grid infrastructure are meant to be future-proof, with depreciation periods of 30-40 years. It is therefore desirable to adopt planning methods and processes that are able to account for such variability in models and forecasts and that can estimate the likelihood of a given outcome, such as the need for a transformer replacement, in a stable fashion. Such non-predictive approaches should highlight which outcomes are intrinsically uncertain, because of, for instance, large sensitivity to specific model parameters.

Leveraging Monte Carlo Simulations

In the context of grid planning, the aim is to decouple the action from the forecasts of technology adoption and follow a more general scenario-based attitude. In fact, even a perfect forecast on the penetration rate of a technology in a certain year would address only one of the four dimensions of the uncertainty. The actual impact on the grid would still depend on the spatial distribution of the new units, the individual load patterns, i.e. functions of the rated power of the chargers, habits of the users, etc., and the uncertainty on the current utilization level of the grid.
Monte Carlo simulations are collections of random experiments designed to explore a space of possible realizations. Each random experiment tests a peculiar variation of parameters. Collectively, this set of experiments provides a rich picture, which allows to estimate the likelihood of some outcomes, conditional to the input parameters. Several scenarios with different modelling parameters can be tested to explore sensitivities, tipping points, critical conditions, potential bottlenecks, but most importantly, to identify invariant quantities, establish which outcomes are intrinsically uncertain, which have a higher confidence, and which actions can be conducted or avoided as an ideal future strategy.

METHODOLOGY

This paper presents a methodology for non-predictive analysis of the impact of electric vehicles on distribution grids based on Monte Carlo scenario analysis. For illustration purposes, the methodology is applied to a real low-voltage residential electricity grid in Switzerland.

Initial setup

The study area is a low-voltage grid of a residential area in central Switzerland (Figure 1). The grid consists of 298 buses, of which 198 are connection points, and 553 residential customers. The maximum peak load is 650 kW. A "status-quo scenario" is built by populating the grid with load profiles of 15-minutes timesteps, spanning one year, from July 2016 to July 2017, to create an accurate depiction of today's state of the grid. Profiles for unmetered customers are generated using time-inhomogeneous Markov Chain Models built on real profiles of customers of comparable annual consumption, based on [3]. The individual synthetic profiles are adjusted such that the aggregated load matches the metered load at the transformer. A deterministic power flow is then run to compute line loading and voltage levels. Quasi-dynamic power flow simulations are carried out using the planning platform *Adaptricity.Sim*. Such arrangement provides the baseline for further expansions scenarios of PEV.

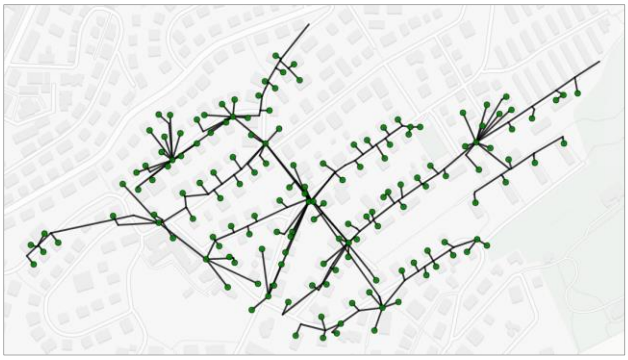

Figure 1 – Low voltage residential test grid.

Framing the problem

The uncertainty related to future scenarios of electric mobility is explored and address with Monte Carlo simulations that span an exploration space designed to highlight relevant sensitivity. PEV units are added on top of the status-quo scenario. To prevent model overfitting, PEVs are modelled in a way that aim at preserving both representativeness and simplicity, the details are discussed in section *Modelling Decisions*. Three models of PEV are tested and compared in three scenarios, i.e. *Model A*, *Model B*, *Model C*. The models' differences are summarized in Table 1 and formalized in detail in Table 2.

Table 1 – Key features of the three PEV scenarios

Scenario	Characteristic features
Model A (harsh)	High charging power (11kW) High commuting coincidence
Model B (medium)	High charging power (11kW) Mild commuting coincidence
Model C (mild)	Low charging power (3.7 kW) Mild commuting coincidence

Definitions

Some definitions are given to facilitate further discussion:
PEV penetration rate: ratio in percent between the number of PEVs and the number of metered customers.

Monte Carlo Variation (MC-Variation): Simulation of 1-year, with a given set of stochastic model parameters, a given penetration of PEVs and a given geographical allocation of the units on the grid.

Monte Carlo Scenario (MC-Scenario): A collection of several MC-Variations, with common modelling assumptions.

Violated line: line with ampacity exceeded at least once, within a MC-Variation.

Violated bus: bus with voltage exiting the range 0.9-1.1 p.u. at least once, within a MC-Variation.

The exploration space

For each MC-Variation, units are allocated at random to metered customers, with equal probabilities. Clustering and neighbourhood adoption dynamics are not modelled. The parameters of each unit are sampled independently, following the distributions of Table 2. Penetration rates span from 10% to 60%, in incremental steps of 10 percentage points. A total of 180 simulations of 1-year are carried out, split equally across the three scenarios.

Metrics of interest

The focus of the simulations is on line overloading and voltage violations. In order to summarize the results of the several MC-Variations in a tractable fashion, aggregated metrics are used, such as the total length of overloaded lines and the total number of buses with violations.

Modelling Decisions

In this paper, a simplifying assumption is that all PEVs are charged only at home. Each PEV has a battery capacity of C [kWh], an energy utilization (while driving) of E [kWh/km] and a charging power at home of P [kW]. Each PEV carries out one trip every day of D [km], re-enters at home at an arrival time AT [clock time] and starts charging immediately, with perfect efficiency, until the battery is fully loaded. All parameters except the charging rated power P vary stochastically within the PEV population (Table 2). The battery capacity C and the energy utilization E are constant within one MC-Variation and are randomly sampled. Conversely, arrival time AT and driving distance D are sampled independently for each day and each PEV. Different commuting habits are modelled by imposing that different PEVs have different mean arrival times AT_{μ} and different mean driving distances D_{π}, with different variances.

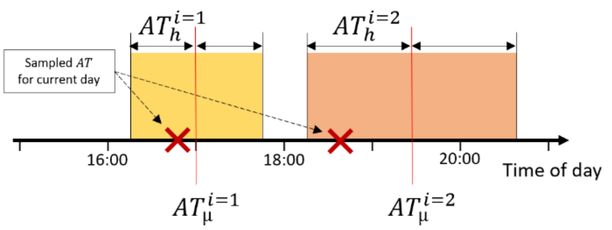

Figure 2 – Example of assignment of arrival time for two PEVs.

More formally, within one MC-variation, the i-th PEV is assigned a mean arrival time AT_{μ}^{i} and a half-amplitude AT_{h}^{i}. Each day, the arrival time AT^{i} of the i-th PEV is sampled with uniform distribution from the interval $\left[AT_{\mu}^{i} - AT_{h}^{i}, AT_{\mu}^{i} + AT_{h}^{i}\right]$, see Figure 2. An analogous assignment of parameters is carried out for the driving distance D. The probability distributions adopted for D_{μ}, D_{s}, AT_{μ}, AT_{s} are reported in Table 2.

Table 2 – Parameters of PEV models

Parameter	Symbol	Probability Distrib.	Distribution Parameters
Battery capacity	C	Uniform	min = 15 kWh max = 90 kWh
Charging power	P	Fixed	**11 kW (Model A)** **11 kW (Model B)** **3.7 kW (Model C)**
Energy utilization	E	Uniform	min = 0.165 kWh/km max = 0.24 kWh/km
Arrival time (mean)	AT_{μ}	Truncated normal	min = 14:00 μ = 18:00 **σ = 1 hours (Model A)** **σ = 2 hour (Model B)** **σ = 2 hours (Model C)** max = 21:00
Arrival time (half-amplitude)	AT_{h}	Truncated normal	min = 30 minutes μ = 1 hour σ = 1 hour max = 3 hours
Driving distance (mean)	D_{μ}	Truncated normal	min = 10 km μ = 30 km σ = 20 km max = 100 km
Driving distance (half-amplitude)	D_{h}	Truncated Normal	min = 5 km μ = 10 km σ = 10 km max = 30 km

For the sake of clarity, Figure 3 reports an example of the distribution of the aggregated PEV load in one of the modelled scenarios. The quantile plot features the aggregated PEV load summarized over all MC-Variations for 50% penetration rates of *Model A "harsh"*, and all days of simulation.

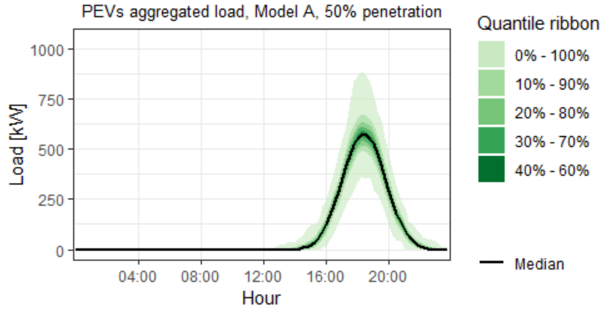

Figure 3 - Aggregated PEV load, Model A, 50% penetration rate

RESULTS AND DISCUSSION

The three PEV models (Model A "harsh", Model B "medium", Model C "mild"), differ only in the rated power of car chargers and the degree of "coincidence of commuting", modelled by the standard deviation of the mean arrival time AT_{μ} within the PEV population (Table 1, Table 2). Nevertheless, there are striking differences between the outcomes of the three scenarios, indicating significant model sensitivities to input parameters.

Quantile plots are used to summarize the results of the three PEV MC-Scenarios (Figure 4, Figure 5, Figure 6). The total length of overloaded lines and the total number of violated buses are used as assessment metric. Each

colour band, or *ribbon*, covers one decile of outcomes. Ribbons are plotted against the PEV penetration rate.
In this case study, for *Model A* (Figure 4) the tipping point for line overloading is at 30% penetration rate, while it moves to 40% penetration for *Model B* (Figure 5), and to around 60% for *Model C*. In other words, in this case twice as many electric vehicles can be accommodated without significant countermeasures, if future scenarios converged towards *Model C* instead of *Model A*. Similarly, in the case of a penetration rate of 50%, the median scenario of *Model A* has ca. 650m of overloaded lines, while the median of *Model B* is ca. 350m and the median of *Model C* is zero.

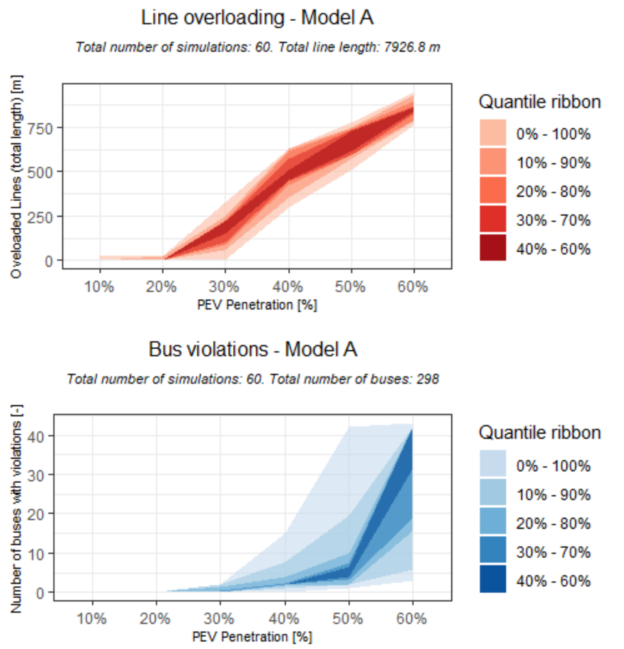

Figure 4 – Results of MC-scenario with PEV model A "harsh".

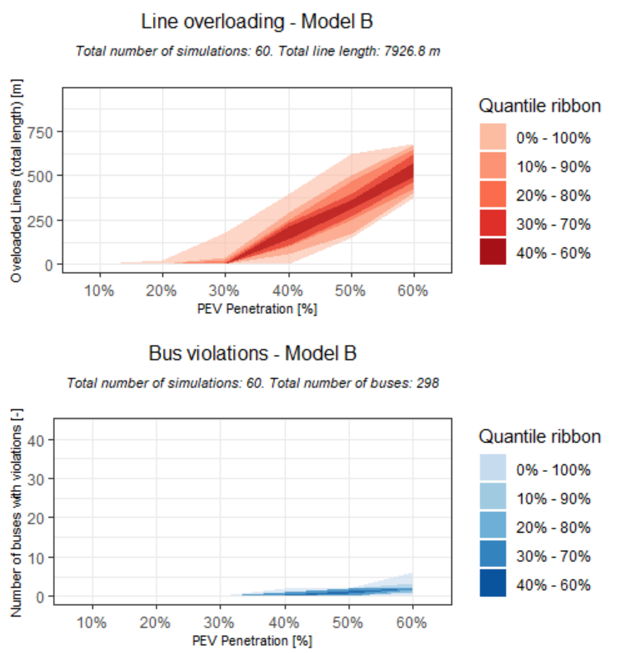

Figure 5 – Results of MC-scenario with PEV model B "medium".

Similar considerations apply for tipping points of voltage violations. The number of buses with voltage violations grows rapidly with *Model A*, which features higher installed capacities and coincidence effect. Effects are less relevant in *Model B*, to the point that the scenario *Model C* features zero voltage violations even in the worst case.

Figure 6 – Results of MC-scenario with PEV model C "mild".

Strategies to cope with sensitivities

It is worth noticing that up to a penetration rate of 20%, in all scenarios the impact is limited. Most distribution grids have some margin to accommodate extra load. This means that, in general, the grid planner does not have to blindly rely on models but can harvest data from early adopters to tune and fit models to the specific features of each specific area, reduce uncertainty, take action, and keep iterating. The ability to extract value out of data becomes a tool to plan in a robust manner without overinvesting.
A complementary measure is to resort to smart charging strategies to coordinate the behavior and narrow it down to a spectrum of desired charging patterns.

Geographical visualization of likely outcomes

Even with equal modelling choices and penetration rates, the set of lines with overload can change significantly depending on the geographical allocation of the units. The real future allocation is not known ex ante, and several configurations with substantially different outcomes may be equally likely. To extract actionable information, attention can be focused on the outcomes with the highest confidence, i.e. outcomes that are invariant throughout all MC-variations.
For example, Figure 7 summarizes the results of all MC-variations adopting PEV *Model A* and a penetration rate of 50%. Green elements are the ones that never

experience violations. On the other hand, red elements are violated in 100% of simulations. Orange elements are violated in at least one MC-variation.

Figure 7 – Example of traffic light geographical visualization. Here: Model A, 50% penetration rate.

Table 3 – Color codes of Figure 6

Color	MC-variations with violations [%]
GREEN	0%
ORANGE	0% < *x* < 100%
RED	100%

Such visualization of the impact for a given penetration level relies on the fundamental assumption that the model used is representative. As stated before, this can be achieved by leveraging information harvested on early adopters and/or applying control strategies to steer the behaviour of the PEV population. Under this assumption, the Monte Carlo approach provides a comprehensive framework to plan countermeasures or, whenever uncertainty persists (the "orange" cases), to justify an upgrade in metering infrastructure to obtain the double benefit of reducing uncertainty from the *reality gap* and improving models.

CONCLUSIONS

Monte Carlo simulations can span an exploration space and provide a quantitative estimation of the likelihood of certain outcomes, conditionally to a given input set of assumptions. Nevertheless, it is difficult to justify *a priori* that a certain set of assumption is more representative or likely than another. In other words, the likelihood of a given set of assumptions about future scenarios is undefined (Figure 8).

In order to use the presented methodology, it becomes therefore paramount for grid planners to extend the data gathering infrastructure, i.e. grid sensors in both the medium and low-voltage grid level, and use the thus acquired knowledge to constantly update grid models that can represent the space of possibilities of the near future. Monte Carlo simulations can then be used iteratively, i.e. over a sequence of planning cycles, to discriminate each time between high- and low-uncertainty events. In case of large uncertainty, it may be more effective, if feasible, to postpone investment decisions, set financial resources aside, gather more data and then act quickly.

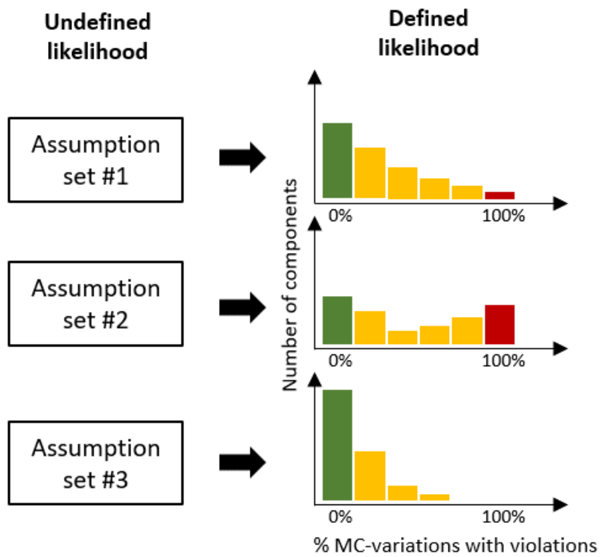

Figure 8 – Exemplification of the dependence on assumptions

Monte Carlo scenarios can be flexibly defined depending on the knowledge about the situation at hand. Thus, the local situation can be reflected without over-simplifying generalizations.

The Monte Carlo approach requires few input data and reduces the number of necessary assumptions. Moreover, the dependence on external expert knowledge decreases because of lower prediction requirements for planning.

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