Evaluation of Modeling and Simulation Complexity on Studying the Impacts of Electrical Vehicles Fleets in Distribution Systems

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Abstract – Evaluations of possible grid impacts from electric vehicles have been published extensively during the past years. Different parameters and assumptions of simulation models are used in these studies. In this work it is investigated if the evaluations of grid impacts can be affected by simulation parameters and modeling complexity. Possible consequences from varying simulation parameters are analyzed at a worst case scenario and randomly generated charging scenarios. For evaluation of minimal voltages or grid losses, smaller time steps and more sophisticated models lead to more precise results. These findings will be used in upcoming works on real time simulator design, for defining study scenarios and choosing proper simulation models.

Keywords: EV, power distribution system, automatic voltage control

NOMENCLATURE

EV	Electric vehicle
LV	Low Voltage
DSO	Distribution system operator
EMS	Energy management system
HIL	Hardware-in-the-loop
Tr	Time resolution of load profile
Ts	Simulation time step
Tc	Time constant of voltage filter
SOC	State of Charge (0~1)
SOC_0	Initial SOC at the beginning of charging
I_{DC}	Battery DC current
U_{DC}	Battery DC voltage
P_{DC}	Battery charging power, DC side
P_{AC}	Battery charging power, AC side
cos	Power factor of EV charger
C_Ah	Battery capacity in Ah
C_kWh	Battery capacity in kWh
U_{AC}	Voltage at the grid connection point of EV charger (AC, RMS value)

I. INTRODUCTION

A foreseeable future with high penetration of renewable generation and electric mobility challenges the grid planning and operation of power distribution systems. One of the objectives of the project SIEM* is to develop a novel real time EV-fleet simulator for studying potential grid impacts and grid integration strategies of large EV fleets. This simulation platform is not only able to simulate large scale distribution grids, detailed models of EVs and multi-EMS systems in real time, but also provides the HIL capability for adding real EVs and real charging devices to the simulated fleet in laboratory tests. In this study, the developed simulator is used in off-line mode in order to simulate a large number of EV grid integration scenarios with various parameter combinations.

Possible impacts of charging EVs on distribution grids are reported by many studies, such as increase in total power demand [1]-[7], voltage variation [1], [2], [7], [8] and power loss [2], [3], [6], [7]. To avoid conventional grid reinforcement necessities, alternative methods like coordinated and intelligent charging schedule management [1], [2], [7] and local charging control mechanisms [8] are often introduced in order to handle the high degree of uncertainty for charging EVs.

Most of these studies have made model simplifications to a certain degree. For instance, EVs are modeled in [1]-[3] and [6]-[9] as a load of constant power during the charging process. The dependency of charging power on battery SOC is neglected. In [5], an advanced, but still linearly simplified, lithium-ion battery model is developed including two charging phases, i.e. the battery is charged first with constant power, and consecutively with constant voltage. In [4], a lead-acid battery model is implemented in a similar manner.

Another property of charging EVs is the stochastic loading in time and space, which is also a focus in some publications. In [3], it is assumed that a fixed percentage of EVs are charging simultaneously in peak or off-peak hours. Another assumption, EVs come back to home with empty batteries, is made by [2], [3], [7]. The modeling of EV charging pattern is improved in other studies [1], [4]-[6] by statistically modeling EV user behaviors. The type of daily trips, driving length and arrival time are modeled by considering statistical information.

In previous publications, it is often argued that better evaluations would be achieved by extending modeling and simulation complexity, without quantitatively analyzing the impacts of different parameters and settings on the simulation. As the simulation assumptions may strongly affect the results, and further the evaluations, it is desirable to study the modeling and simulation parameters and their possible effects. Understanding their importance contributes to build up research scenarios in solving the integration problem of EVs. In worst case analysis, for instance, oversimplification of a scenario can be avoided.

In this study, two different types of EV model are analyzed to quantify the impact of models complexity on the simulation results. The impact of simulation time step is also investigated. Regarding various assessment

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criteria, significance of different modeling and simulation complexity and assumptions are statistically analyzed. In a following step, a sensitivity analysis on EV charging patterns is carried out. Finally, a local charging controller is implemented in the EV model. The effectiveness of this kind of controllers and their possible impacts on LV grids are evaluated.

This paper is outlined as follows. In Section II, specifications and assumptions of the electric grid and EVs are introduced. Two EV models of different complexity are also introduced. Section II also describes simulation related settings and parameters. The simulation results are presented and discussed in Section III. Finally, first performance results for a real time EV fleet simulation are given, followed by an overall conclusion.

II. GRID AND EV MODELS

Simulation and analysis of this study are based on a reference LV grid. EV models, with different complexity, are developed and parameterized using manufacture datasheets of EV and charging equipment. In this section, the models and assumptions are described.

A. Grid Model

A reference LV grid model is selected for this study [9]. The topology of this grid can be found in [1] and the model is implemented in the software package Opal-RT ePHASORsim [16]. Grid equations are solved in the time domain using the RMS method. Some characteristic information of this grid is presented in Table I.

TABLE I. CHARACTERISTICS OF THE REFERENCE LV GRID BASED ON THE SYNTHETIC LOAD PROFILE OF THE CONSIDERED DAY

MV/LV transformer, rated power	400 kVA
Number of feeders	4 (radial)
Number of households	170
Peak loading of transformer	37.5 %
Average loading of transformer	17.1 %
Maximum of voltage deviation	-3.5 %
Mean voltage deviation	-1 %
Grid losses (including transformer loss)	1.1 %

B. Household Consumption Profiles

A set of household consumption profiles is generated with a time resolution of 1 s, based on an algorithm given in [10]. These profiles describe the consumption of 170 households on an arbitrary winter day. For analysis of different simulation time steps, filtered profiles with a time resolution of 10 s, 60 s and 600 s are calculated by applying a simple moving average function. One profile is exemplarily illustrated in Fig. 1.

C. EV Models

A real plug-in electric vehicle (PEV) [11], powered by a Lithium-ion battery is modeled in this study. Its battery pack consists of 88 cells and provides a capacity of 50 Ah (being equivalent to 16.5 kWh at nominal battery voltage of 330 V). In order to evaluate impact of model complexity on simulation results, both a simple and a complex EV model are developed in this work based on measurements and manufacturer data.

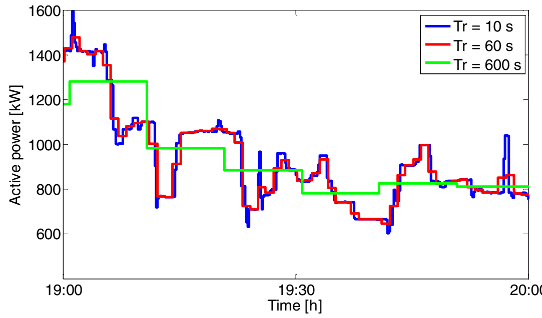


Fig. 1: Load profile (of one household) in different time resolutions.

TABLE II. PARAMETERS OF THE TWO EV MODELS, MOTIVATED BY THE DATASHEETS IN [11]-[13].

	Simple EV model		Complex EV model	
Battery capacity	C_kWh = 16.5 kWh		C_Ah = 50 Ah	
U_{DC}	Constant, 330 V		Variable, max. 362 V	
SOC range	0.1-0.9		0.1-0.9	
EV charging power	Constant		Variable	
Charging controller	No		Yes	
cosφ	1		1	
Charger efficiency	1		< 1	
EV charger type	slow	fast	slow	fast
Rated charging power [kW]	3.7	20	3.7	20

Simple EV model

The simple model draws a constant charging power from the grid, until the battery is full. SOC dependency on battery voltage, battery internal resistance and converter losses are neglected in this model. Accordingly, SOC is defined in the simple model by charged energy with respect to battery capacity C_kWh (Table II).

$$\frac{dSOC\_kWh}{dt} = \frac{P_{AC}}{C\_kWh} \tag{1}$$

Complex EV model

As illustrated in Fig. 2, a more detailed EV model consists of a battery and an AC/DC converter. The battery is described as a voltage source and an internal resistance. Both of them are variable depending on the battery SOC, which in turn is defined as the integral of DC current over time with respect to battery capacity:

$$\frac{dSOC\_Ah}{dt} = \frac{I_{DC}}{C\_Ah} \tag{2}$$

Commercial EV chargers are also equipped with a local AC voltage controller. This controller adjusts the charging power based on grid voltage at the EV connection point. Its characteristic curve is described in Fig. 3. The controller is experimentally parameterized as $u_{AC1} = 0.93$ and $u_{AC2} = 0.90$ (p.u.). Optimal parameterization of the controller is out of the scope in this work. Finally, the AC/DC converter is modeled using a polynomial function of converter losses.

$$P_{AC} = \frac{(1-\beta)-\sqrt{(1-\beta)^2-4\gamma\cdot(\alpha+P_{DC})}}{2\gamma} \tag{3}$$

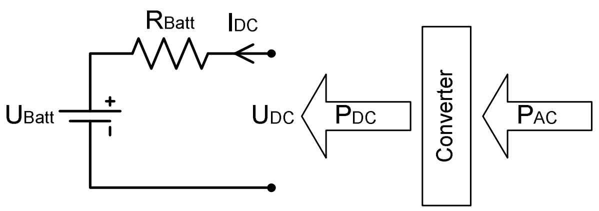


Fig. 2: Schematic diagram of the complex EV model.

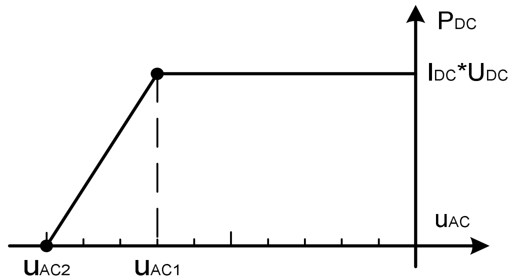


Fig. 3: Characteristics of the AC voltage controller in the complex EV model.

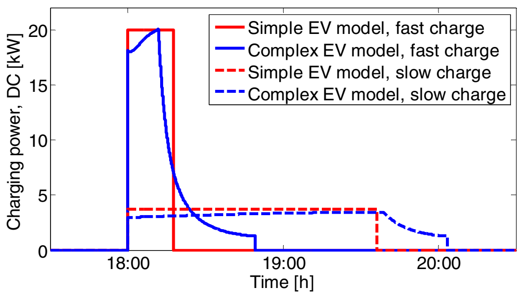


Fig. 4: Typical charging curves of different EV models and charging modes.

The EV power consumption at the AC side can be calculated from its DC power consumption with equation (3). Here, α, β and γ are loss coefficients.

Lastly, the complex model switches from constant DC current to constant DC voltage charging mode when the battery voltage reaches 360 V. This value is motivated by experimental measurements of a fast DC charger by Chalmers University of Technology and HRM Engineering [14].

Slow and fast charging

Both the simple and complex EV model can charge at a maximum DC power of either 3.7 or 20 kW. These values are motivated by commercially available chargers for normal households: an onboard charger [12] requiring a normal single phase outlet, can provide slow charging power of 3.7 kW (measured at AC side). Alternatively, some fast charging stations [13] can provide a maximum charging power of 20 kW (measured at DC side) and requires a three phase power connection. Higher charging rates (e.g. 50 kW or 63 kW, proposed by some prototype and new standards) are out of scope of this work due to the fact that this high charging power requires a special grid connection, which is not state of the art of normal LV households. Typical charging curves of one EV, using the simple and complex model (assuming charging controller is not in operation, due to normal grid voltage conditions), are shown in Fig. 4. In analogy to existing research discussed in Section I, parameters such as EV penetration level and charging times are modeled as random processes. In all study scenarios, a maximum EV penetration and the worst position are applied. These maxima will be defined more specifically in the next subsection.

D. *Definition of Maximum EV Penetration and Worst Charging Position for the Grid*

The maximum hosting capacity of the studied LV grid is defined as a limiting case, during which the maximum aggregated EV charging power equals to 150 % of the MV/LV transformer's rated power. Accordingly, the maximum penetration is then defined as the ratio between the number of EVs and the number of households in the LV grid. An overview for three different charging modes is shown in Table III.

For a particular penetration level, the charging position of EVs is not yet specified. In order to determine the critical charging positions for the grid, 10.000 combinations are randomly generated. During this process, each EV is considered to be changed with maximum rated power (3.7 or 20 kW). By analyzing the voltage minima in each simulation, a "worst charging positioning" for each of the 3 charging modes is determined. These positions correspond to the lowest voltages in Fig. 5. The calculated minima voltage is often much lower than the allowed limit in practice. However, this study is not focused on the minimal value but the deviation of these values with different modeling parameters. It is thus used as the reference for the further analysis.

TABLE III. MAX. EV PENETRATION FOR DIFFERENT CHARGING MODES

Index	Charging mode	Description	Max. EV penetration
F	Fast charging	All EVs	17 %
M	Mixed charging	50 % EVs at fast charging; 50 % EVs at slow charging	29 %
S	Slow charging	All EVs	95 %

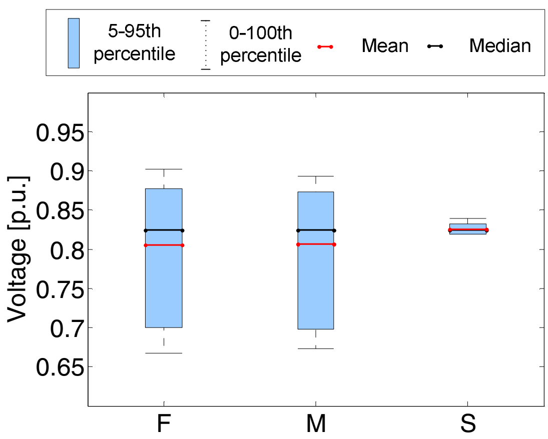


Fig. 5: Distribution of grid voltage minima by variation of EV charging positions with maximum EV penetration.

E. *User Profile and Charging Pattern*

It is hereby assumed that all EVs charge once per day; EV owners come back at home in the evening and charge their vehicles overnight until the next trip. Charging patterns are thus defined by an arrival time (t_0) and SOC_0, which stands for the amount of energy still stored in the battery at the beginning of a charging process. The EVs are continuously charged, until a maximum SOC (0.9) is reached.

Using the maximum penetration level and the worst grid positions, study scenarios are defined as follows. In a "worst case", it is assumed that the EVs start charging simultaneously at 18:30 and the SOC_0 of batteries is at the minimum level (0.2). In a "sensitivity study", considering the uncertainty of user behavior, t_0 and SOC_0 are randomly generated from probability distribution functions. The arrival time of EVs is generated based on a normal distribution (99 % percentile lies between 17:00 and 20:00); the initial SOCs are uniformly distributed between 0.2 and 0.8.

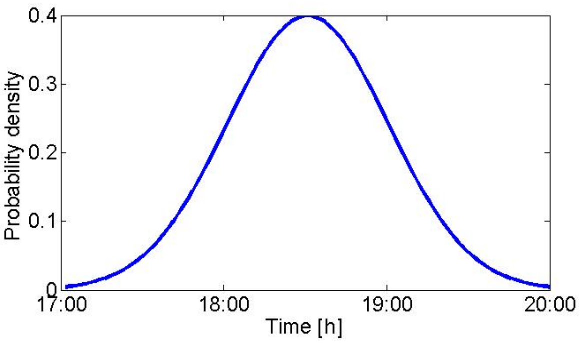


Fig. 6: Probability density of EVs arrival time.

F. *Parameters of Numerical Solver*

In many existing EV models, such as the works listed in Section I, simulation time steps of 15 minutes or 1 hour are often used. This may be sufficient for analyzing seasonal power demand or grid losses. However, according to the power quality standard EN 50160, DSOs should guarantee the supply voltage within a range of ±10 % around the nominal value based on the measurement value during a 10 minute interval [15]. Therefore, it is reasonable to set the simulation step below 10 minutes in order to have a sufficiently detailed representation of grid voltage. In this study, time steps of 10 s, 60 s and 600 s are applied. Since this study concentrates on the evaluation of grid impacts caused by EVs, thus a fixed time range from 17:00 to 23:00 is used in all simulations.

Simulation model

As illustrated in Fig. 7, the grid and EV model are separately arranged in two subsystems. In each simulation time step, node voltages are determined first by the grid model. Charging current of EVs is then calculated in the EV model based on the present node voltage and the actual SOC. For EV models without local AC voltage controllers, this simulation model is stable.

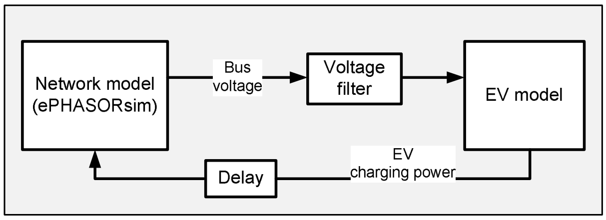


Fig. 7: Schematic diagram of simulation model

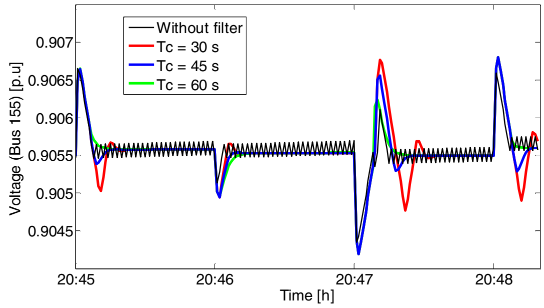


Fig. 8: Dynamic response of voltage with different filter parameter settings

Voltage control in the complex EV model

Due to the presence of voltage based charging control in the complex EV model, simulation results show small oscillations when the voltage is near the controller's tolerance boundaries. To mitigate this oscillation, which is introduced through the non-simultaneity of solving the grid model and solving of the EV model, a first-order filter is implemented within the simulation loop (Fig. 7). Besides, the simulation only provides results every 60 s, although a smaller simulation time step of 1 s is applied in solving the model, so that the simulation has sufficient time to converge. This method is also utilized by other commercial simulation software, like PowerFactory, where an internal loop is applied at each time step in dynamic simulations.

The transfer function of the implemented filter is described as:

$$G(s) = \frac{1}{\frac{T_c}{T_s}s+1} \tag{4}$$

By tuning filter parameters, system response is investigated. First outcomes are shown in Fig. 8. It can be seen that a filter with time constant of 45 s helps the system reaching a steady state within 60 s. It also stabilizes the result between two output steps. At the beginning of a load profile update, on the other hand, a voltage overshoot can occur (Fig. 8). A filter time constant of 45 s produces a moderate overshoot. Thus, this combination of filter parameter and simulation time step is chosen in following simulations. Because of the model characteristics and the large filter time constant, the EV model with voltage controller is only used in the simulation time step of 60 s (model is solved with time-step of 1 s).

III. RESULTS AND DISCUSSION

Results from a series of EV fleet simulations will be discussed. First, the dependence of simulation results on numerical solver parameters is evaluated. Next, the particular choice of EV model (simple or complex) is evaluated. Finally, the real-time computation of a large EV fleet is performed.

A. *Impact of Numerical Solver Parameters*

The first evaluation is carried out on the “worst case” scenario in which all EVs arrive simultaneously at 18:30 and the SOC of their batteries is at value 0.2. The temporal distributions of node voltage, transformer loading and total charging demand between 17:00 and 23:00 are shown in Fig. 9. According to the grid code [15], maximum voltage deviation should not be higher than 10 % in 95 % of the time. It also should never be lower than 0.85 p.u. of the nominal voltage. Thus, the voltage deviation is evaluated by observing the 95th and the 100th percentile of voltage statistics. Besides, the complex EV model is not implemented in the step-size of 10 s. In this time range, a more detailed battery model is required.

Results with both simple and complex EV models have shown the same tendency in all three charging modes, i.e. smaller time steps lead to larger voltage deviations, which can be considered as more accurate. Therefore, for evaluation of voltage, simulations with smaller time step should be adopted, if suitable models are available. Besides, the total voltage distribution resulting from complex EV models is smaller than the one in which simple EV models were used. As expected, the power consumption (e.g. 3.7 or 20 kW) varied in modes F, M and S has a higher impact on the voltage minima and thus requires a more careful consideration when modeling EVs.

As shown in Fig. 9 (b) and (c), the simulation time step has slight impacts on the statistics of transformer loading and total charging load. The model complexity, however, makes a larger difference, especially when EVs are in the slow charging mode. A survey on grid losses is presented in Table IV. Considering all three charging modes, simulations at time step of 60 s and 10 s result in similar losses, while the simulation with time steps of 600 s leads to a lower value. Modeling complexity can also significantly affect the losses. This finding is important for setting up long-term simulations, which in current practice often oversimplified by large simulation step and simple models.

TABLE IV. GRID LOSSES ON THE WORST CASE SCENARIO WITH DIFFERENT PARAMETER COMBINATIONS

Charging mode	Ts [s]	Simple EV model	Complex EV model
Fast charging	600	6.47 %	6.19 %
	60	8.18 %	6.95 %
	10	8.16 %	-
Mixed charging	600	5.67 %	5.45 %
	60	6.63 %	5.89 %
	10	6.70 %	-
Slow charging	600	9.15 %	8.53 %
	60	9.52 %	8.72 %
	10	9.55 %	-

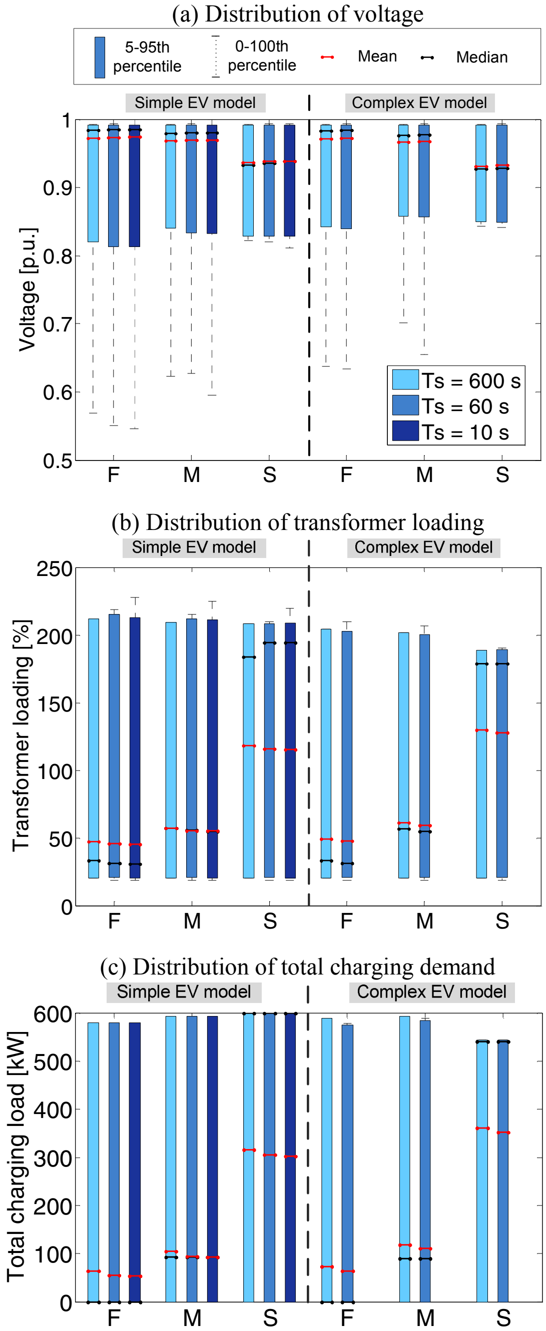


Fig. 9: Statistical summary of simulation results on the worst case scenario. F, M, and S: Fast, mixed and slow charging mode, resp.

In summary, for studying voltage profiles and grid losses, application of a complex EV model and simulation time step of 60 s can be recommended. Concerning transformer loading and the charging demand, influence of simulation settings is uncritical. The simulation time step affects more strongly the extremes rather than the mean or median of the results. Additionally, the specification of EVs and EV charger can also largely affect the assessment of voltage, especially when voltage minima are under study.

B. *Sensitivity Analysis on EV Charging Patterns*

In order to evaluate the impact of the uncertainty of EV behaviors on simulation results, a sensitivity analysis using randomly generated EV charging patterns (described in section II-E) is implemented. At each charging mode (F, M, S), 100 statistical realizations are simulated with a particular EV model. For EVs with a fast charger, the battery SOC increases over 0.2 within 600 s, which may lead to overcharge in some scenarios. Therefore, the following evaluations are limited on a simulation time step of 60 s.

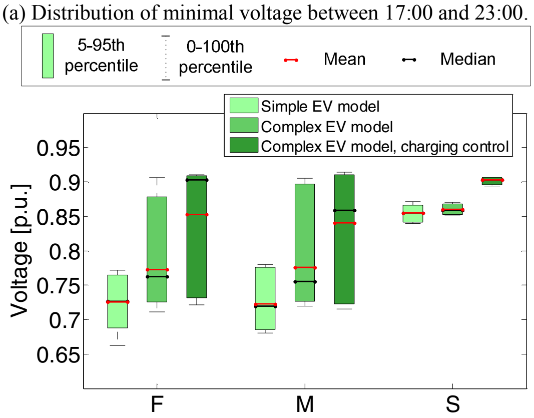
Fig. 10(a), distributions of the recorded minimal voltage over 100 statistical realizations, and 10 (b), distributions of the 95th lowest voltage percentile, are analyzed in first step. Following conclusions are found:

1. Considering results of the worst case (Fig. 9(a)) and of the sensitivity analysis, minimal voltage values are markedly different than the predefined worst case. However, the difference by lower bound of 95th voltage percentile is less significant. Considering the bandwidth of both minima and lower bound of 95th percentile of voltage, voltage profile is very sensitive to charging pattern (especially F and M).
2. In general, the simple EV model produces results of lower voltage. The voltage minima are less sensitive to patterns then applying complex models. In contrary, the simple EV model leads to a larger span width of the 95th voltage percentile.
3. The voltage controller, combined with the complex EV model, can generally contribute to support the grid voltage. Results show that the voltage median rises in both observations (Fig. 10(a, b)). Also, the lower boundaries of the 95th voltage percentile are improved. However, due to the input delay of the controller and its internally limited current gradient, the extreme value, the lower bounds of voltage minima in Fig. 10(a), is not improved by this type of controller.
4. Additionally, through the comparison of Fig. 5 and Fig. 10(a), it can be concluded that the EV charging position and the charging pattern have similar significance on grid voltage (for both minimum and bandwidth).

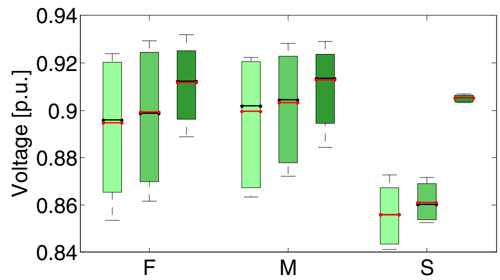
Fig. 10(c, d, e) show statistics obtained over all time steps and the 100 stochastic realizations of each charging mode. Overloading of transformer (> 100 %) is not often reached in both fast and mixed charging mode, although the hosting capacity is defined as 50 % higher than the transformer's rated power. Besides, peak values of EVs' charging demand are also significantly reduced than those in the worst case. Grid losses are also largely reduced, comparing Fig. 10(e) to losses of the worst case in Fig. 9. By analyzing the median and the range of losses, it can be found that grid loss is more correlated with charging pattern than with the model complexity.

Thus, modeling of temporal charging patterns is extremely important for determining "realistic" worst case considering the loading and total load. Further, both spatial and temporal features of charging pattern have remarkable impacts on studying voltage profile. Model complexity and the charging controller have no significant impact on these results.

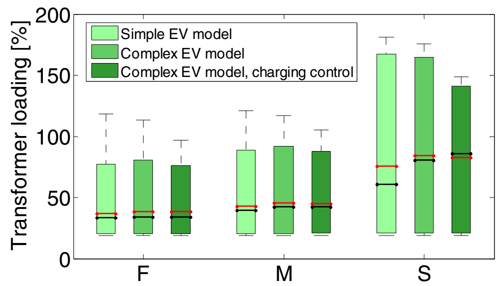
(a) Distribution of minimal voltage between 17:00 and 23:00.



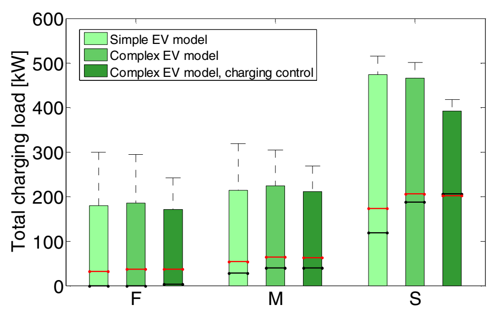
(b) Distribution of the lower bound 95th voltage percentile measured between 17:00 and 23:00.



(c) Distribution of transformer loading.



(d) Distribution of total charging demand of EVs.



(e) Distribution of grid losses.

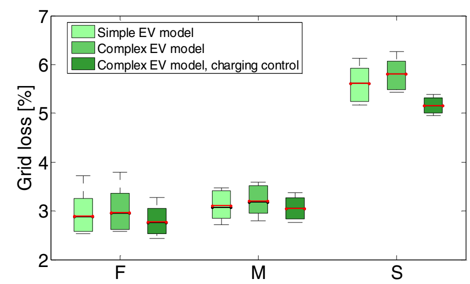


Fig. 10: Results of sensitivity analysis on charging pattern F, M and S: Fast, mixed and slow charging mode, respectively.

C. Real Time Modeling of a Large Grid and EV Fleet

In addition to the studies on grid impacts of EVs, the simulation models can also be utilized in real time mode. This function will be used in further development and tests of management strategies for EV fleet and distribution systems applying complex EV models. The real time performance of the simulator has been tested using a synthetic grid models and large EV fleets. Test results are summarized in Table V. It can be seen that this simulator is capable to simulate grids with about 15000 nodes (three phase) and 2500 EVs in real time.

TABLE V. OVERVIEW SIMULATION PERFORMANCE

Number of nodes	Number of EV	Ts [ms]	Average CPU loading
8976	500	20	29.97 %
14841	2452	200	28.03 %

IV. CONCLUSION

In this study, simple and complex EV models are developed for comparison. Simulations using different models and parameters are carried out in a reference grid. Based on a worst case study and a sensitivity study, the impacts of different parameters on simulation results are analyzed. Their significance considering evaluation aspects is discussed.

For the evaluation of maximum voltage deviations, smaller time steps and sophisticated models should be adopted. Although detailed modeling generally lead to precise results, a combination of complex model and simulation time step of 60 s is recommended for studying grid losses. For studying of transformer loading and total charging load, selection of time step and model complexity has no significant effect. Based on the sensitivity analysis, it is obvious that the worst case of charging pattern causes an overestimation of the EVs' impacts. In order to have a realistic assessment of EVs' charging, a detailed modeling of users' behavior and the charging schedule is meaningful.

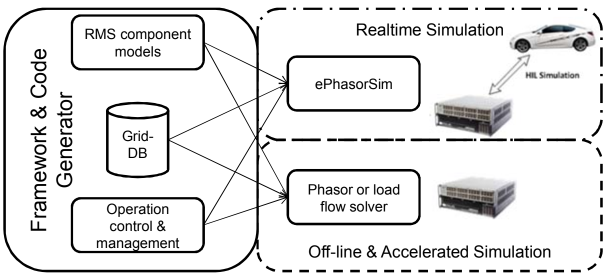


Fig. 11: Sketch of the SIEM system design.

Investigation is limited to one reference LV grid in this study. The finding should be extended by studying its validity for other grid topology and voltage level. Also parameters considering type of EVs and EV chargers can also be evaluated in a broader range in further studies. The derived recommendations and further steps will be applied in the simulation setup of the SIEM project for the on-going research to analyze and optimize EV fleet behavior regarding possible grid impact. Moreover, this simulation will be augmented with a real hardware EV charging system into a HIL platform, presented in Figure 11. This will provide flexibility for software simulation, hardware testing and fast validation of models considering EVs and their charging pattern.

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