Modeling Intelligent Energy Systems: Co-Simulation Platform for Validating Flexible-Demand EV Charging Management

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***Abstract*—Energy systems experience a rise in complexity: new technologies, topologies and components, tighter links to other systems like markets and the increased usage of information technology. This leads to challenging questions that can not be answered via traditional methods. The goal of including renewable energy and clean technologies in the grid, however, requires solutions for the resulting complex problems.**

This paper investigates dynamic demand response for intelligent electric vehicle charging as a use-case for detailed hybrid models that cannot be properly handled by traditional tools alone. Universal modeling languages and specialized domain-specific modeling solutions are brought together via standardized co-simulation interfaces to achieve maximal flexibility and minimal implementation efforts.

This combination of previously numerically incompatible modeling paradigms enables a detailed look into the dynamics of hybrid component models while keeping the comfort and the strength of established tools. This coupling of a Modelica-based physical simulation engine, a commercial power system simulation tool and an agent-based discrete event simulator for energy grids results in a novel co-simulation platform. This visionary concept provides the high level of detail, scope, flexibility, scalability and accuracy in simulations needed to analyze and optimize energy systems of the future.

***Index Terms*—Charging management, co-simulation, electric vehicles, flexible-demand, modeling, simulation software.**

List of Used Abbreviations

API Application programming interface.
DG Distributed generation.
DR Demand response.
EV Electric vehicle.
FMI Functional Mock-up Interface.
OCV Open circuit voltage.
PV Photovoltaics.
RTP Real-time pricing.
SOC State of charge.
V2G Vehicle-to-grid.

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I. Introduction

INTELLIGENT energy systems are expected to utilize the demand flexibility to increase the self coverage with the help of renewable and distributed energy generation. Demand side management mechanisms like real-time pricing (RTP) or dynamic physical demand response (DR) [1] will automatically control loads to flatten peak consumption. Renewable and distributed generation impose high fluctuations on small time scales, like minutes down to seconds, with a strong dependency on local geographical situations. RTP based on hourly price signals, is an adequate measure for market-based DR on an energy-based global level. But an hourly lag time between price signals is not capable of reflecting the actual real-time supply/demand situation regarding power flow and voltage situations in the electricity network [2], [3]. Appropriate DR mechanisms for grid operation are interruptible or demand reducing contracts [2], which can take physical constraints (e.g., thermal loading, voltage levels) as well as local market constraints or system constraints into account.

Intelligent controls for these mechanisms have real-time constraints of seconds to minutes, depending on their objectives (e.g., power quality in EN 50160). They use information technology to integrate intrinsically with related domains like emerging energy markets. From the energy market perspective, electric power is seldom taken into account, which is the most important thing from the grid operation perspective. Increasing numbers of distributed actors and control components lead to unprecedented complexity [4]. Feedback loops, autonomous strategies and variable structure dynamics pose severe problems for traditional modeling and simulation approaches [5], [6]. A change of an hourly price signal might have transient effects or cause oscillations and even instabilities on the distribution grid. The automatic change of set points can directly influence the price. Usually reserve and balance requirements based on peak demand forecasts do not take price responsiveness into account [2]. The reactions of a large number of participating players have to be simulated on a much smaller time scale, perhaps even with real-time constraints in order to be able to make profound conclusions.

For representing DR activities, models should be comprehensive, based on physics, interactive and reasonably aggregated

[7]. This makes it absolutely essential that continuous elements, discrete and asynchronous events, stochastic elements and autonomous actors can be seamlessly integrated within a single model. While there are powerful methods, formal languages and tools for each of these categories, it is their combination that is still in its childhood. Probably the currently most mature approach to cover as many aspects of future energy systems within a single simulation environment is the GridLAB-D project [5].

This paper explores the capabilities of combining GridLAB-D with one of the state-of-the-art tools, PowerFactory [8], and with a universal modeling environment, OpenModelica [9], to create a versatile platform for simulating flexible EV charging algorithms for demand response. The main contribution of this work is to show the modeling capabilities provided by a flexible simulation environment composed of a heterogeneous set of simulation tools, to cope with system complexity by *scalability* and *modularity*. Namely, we demonstrate the possibilities and strengths of standardized coupling of a universal modeling approach with highly specialized, domain specific energy simulation tools. The given application—EV charging as flexible demand—is delivered by a real-world research project and it contains all of the four distinct types of sub-models mentioned above.

II. State of the Art

Electric vehicles are assumed to play an ever more important role in the electric distribution grid. Due to the challenges they pose and the opportunities they offer, there is a large number of studies available that assess their potential impact by the means of simulation. These simulation studies cover a broad field of topics, ranging from evaluations of the impact on the distribution grids, optimal charging algorithms, to traffic based demand models.

A. Traffic Simulation and Routing

In [10], an agent-based traffic demand model [11] is used in micro-simulations to estimate the energy demand over the day. Price signals are sent from the power system simulation to assure that the resulting charging patterns do not violate given grid constraints. Coupling of transportation information for locating and routing to the nearest charging point is proposed in [12], using a model of public transport to include less congested charging points.

B. Energy Demand

A large number of publications deals with the modeling and the estimation of the expected energy demand due to electrification of individual transportation, especially in relation with future penetration scenarios.

Micro-simulation-based activity models are used in transportation research for traffic forecasting. In [13], the resulting trip length distributions are used in combination with generated schedules to predict energy and power demand geographically and over the day.

Especially important is the forecast of the energy demand for scheduling the generation and allocation of energy on the market. This has been done within nationwide or global scopes [13] and on the distribution level (e.g., [14], [15]).

C. Power Electronics

The grid interface is also subject to extensive research. The topics range from on-board and stationary chargers through circuit topologies and wireless charging to the interface specification for controlled charging protocols. An excellent overview of the current status and implementation of battery chargers, charging power levels and infrastructure for plug-in electric vehicles and hybrids is given in [16].

D. Charging Algorithms and Impact on the Grid

The optimization of the charging process is concerned with a variety of objectives:

- Constraints: voltage limits, maximum transmission capacity and battery cycles.
- Grid operation: minimization of losses in the grid, e.g., load-oriented.
- Distributed resources: vehicle-to-grid (V2G) capabilities, e.g., providing peak power.
- Market: price-oriented dynamic tariffs, e.g., customer costs reduction.
- Supply-oriented: integration of renewable energies and mitigation of fluctuations.

The corresponding control algorithms are based on centrally coordinated, decentralized and distributed mechanisms and rely on communicating control and measurement signals. Controlled charging usually relies on dedicated measurements to limit the consumed active power or on utilizing reactive power for voltage control.

In [12], a decentralized architecture is proposed in which every charging point calculates the maximum available charging power based on the demand and power factor of all available customers. Broadband communication and symmetric loads are assumed to simplify and speed up the calculation. The comparison between global and local optimal scheduling of charging and discharging to minimize total costs for the customer is demonstrated in [17]. The corresponding simulations are based on hourly load profiles. Reference [18] deals with the optimization of the charging of an aggregated EV fleet that decreases customer costs while reducing system load impacts. The conclusions are based on accumulated measured load profiles on system level.

In [19], the charging management is based on a dynamic distribution system tariff to avoid congestion in the local distribution system, based on predicted day-ahead planning. Coordinated charging to minimize power losses, based on stochastic programming taking forecast errors of the load profiles into account, can be found in [20]. The impact on voltage levels is analyzed in depth for summer and winter scenarios, but without considering an additional temperature-dependent energy demand for the EV.

Reference [21] describes a hybrid simulator for EV charging applications, [22] combines it with market mechanisms. Reference [23] even analyzes EV charging with stochastic environments.

E. Shortcomings of Commonly Used Models

Models for the analysis of these applications and phenomena are usually based either on universal languages (like Matlab) or implemented explicitly analytic. Often, models of sub-components need to be simplified and it is hard to include expert modules for batteries, vehicle usage or market rules that would expose more sophisticated behavior.

Studies proposing new EV charging algorithms to facilitate load-shifting or prevent congestion usually employ simplifying static models. Typically the charging profiles are determined based on an energy demand derived from tracked driving patterns of normal combustion cars. Realistic demand profiles are replaced by taking only the average energy demand of an electric vehicle into account, see e.g., [24], [25].

Models considering net effects, e.g., overall energy balances, are only valid and suitable when using simulation time steps that are far too coarse to account for critical incidents in the distribution grid. Even though these considerations are essential proof-of-concept studies, many critical questions, regarding for instance grid stability, remain thus untouched on the level of detail needed for real-world applications.

Particularly by using dynamic models for the battery system different aspects can be investigated, like stability of control loops, impact of varying environmental parameters (e.g., temperature), different charging power requirements, voltage-dependent charging duration, road conditions or height profiles. Static profiles of the battery's state of charge cannot provide this flexibility.

III. Simulation Platform Prototype

The immense work that lies behind rich and validated component libraries of domain-specific tools makes a re-implementation in another specific language practically unfeasible. Additionally, the need to investigate new phenomena and applications power systems makes it vital to be capable of integrating such tools within modern flexible modeling environments. This is especially true when testing and validating flexible-demand management systems by means of simulation, since such systems typically consist of complex components comprising various technologies from many different domains. Even more, they are also (directly or indirectly) influenced by other, non-technology-related factors, like consumer behavior, traffic or weather.

The goal of this work is the implementation of a prototype platform specifically designed for the dynamic, interacting simulation of flexible-demand EV charging management systems. The following aspects were considered as guidelines to achieve this objective:

- *Interoperability*: To profit from existing domain-specific solutions a simulation platform needs to facilitate the synchronous deployment of different tools.
- *Modularity*: A modular design is essential in order to guarantee flexibility, preferably by means of object-oriented methods.
- *Scalability*: Detailed models and use-cases potentially comprise a high amount of components and computational effort. By means of co-simulation, models can be separated and distributed over multiple computation nodes.

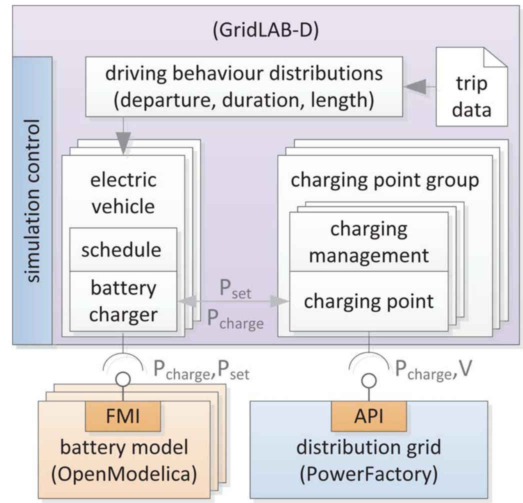

Fig. 1. Simulation environment: schematic view of the simulated components and their interfaces.

- *Usability*: A simulation environment has to provide the utilities to allow the proper modeling and analysis of applications, including an adequate modeling language, data logging and visualization tools.

To this end, GridLAB-D was adapted to fit the specified requirements and was coupled with OpenModelica and PowerFactory (see Fig. 1). The coupling of GridLAB-D and OpenModelica demonstrates the seamless interplay of continuous (equation-based) elements with discrete (event-based) elements within a co-simulation environment, based on the standardized interface specification FMI (Functional Mock-up Interface) [26]. The coupling of GridLAB-D with PowerFactory demonstrates the advantages gained from using a domain-specific utility within a general co-simulation environment.

A. GridLAB-D

GridLAB-D [5] is an open-source simulation and analysis framework for power distribution systems. Its core is a discrete event-based simulator together with a set of modeling and analysis tools.

Within the scope of this work, GridLAB-D is responsible for the simulation of the electric vehicles, the charging process together with the charging management and the simulation control. Each component of the simulated system is represented by a dedicated object in GridLAB-D. Conceptually, these objects are concurrently executing entities that are by themselves responsible to update their internal state according to the global simulation time. The simulator looks for changes in the states of the objects (discrete events) and enables the synchronized interaction between them. The object tells when the next change of its state will happen, respectively when it wants to be updated the next time. Due to this mechanism the time steps between the events are typically not equidistant, but adapt according to the model's dynamics. If any update occurs, all objects will be synchronized at the actual simulation time.

GridLAB-D 's modeling language is used for defining models and allows to generate a hierarchical population of objects by nesting them. An example of a typical resulting structure for the EV models used in this work can be seen in Fig. 1.

B. OpenModelica

OpenModelica [9] is a general-purpose multi-physics simulation environment that comes with a large standard library of components from various domains, e.g., electrical, thermal, mechanical or control-oriented elements. It is based on the Modelica language which was initiated as a specification language for describing differential algebraic equation-based models, allowing model exchange among various modeling tools and different working groups [27].

In contrast to a block-diagram approach (e.g., Simulink), it relies on universal acausal modeling concepts (e.g., energy conservation laws in physical domains). This approach has led to considerable progress in the simulation of heterogeneous systems, i.e., systems comprising elements from different simulation domains [28].

In order to incorporate Modelica models into the presented framework, well-established modern standards for co-simulation are employed. OpenModelica provides the ability to export stand-alone components according to the standardized interface specification FMI for Model Exchange [26], the foundation for a new trend of co-simulation-based applications [29]–[31]. These self-contained components are used to accomplish the coupling to GridLAB-D. This is done by deploying a dedicated FMI wrapper developed for the synchronous interaction between these continuous equation-based components and the discrete event-based simulation environment provided by GridLAB-D.

C. PowerFactory

DIgSILENT PowerFactory, a specialized and well-established power system simulation and analysis tool, is used to represent the electric grid and the supply side. It provides various dynamic models and controls which can be scripted to analyze e.g., frequency demand response [8] and has built-in interfaces to make use of other applications, like Matlab/Simulink, OPC server/client access or via external dynamic-link libraries. It supports offline and time-synchronized real-time simulation for validating control algorithms or connecting to real process data [32].

In addition, an interface for coupling other applications with PowerFactory is available. Within the scope of this work, a dedicated C++ API wrapper has been developed on top of this interface, which is used to parametrize and steer simulations in PowerFactory as well as to access the corresponding results.

IV. Electric Vehicle and Infrastructure Model

The simulation components for modeling electric vehicles, vehicle usage, charging station infrastructure and demand-side management have been implemented in GridLAB-D, while the vehicle batteries and the electric grid were implemented in OpenModelica and PowerFactory, respectively (see Fig. 1). The employment of such domain-specific and well established state of the art tools provides an adaptable design that can be elaborated for more sophisticated applications.

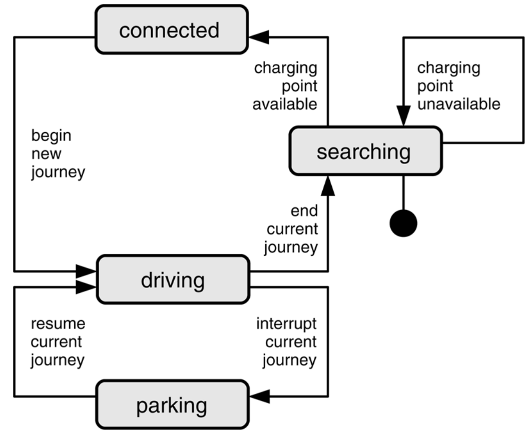

Fig. 2. Schematic view of the possible states and transitions of the electric vehicle model.

A. Electric Vehicles

Electric vehicles are modeled as finite state machines, with the states corresponding to the possible operating modes:

- *Connected*: The electric vehicle is connected to a charging point and the battery is being charged. It stays in that state even if the battery is fully loaded and stopped charging.
- *Driving*: The vehicle consumes energy from the battery for locomotion, air condition and other appliances, based on average values.
- *Parking*: The vehicle does not consume energy for locomotion but is not connected to a charging point. It might however consume energy for air condition and other appliances.
- *Searching*: The vehicle is searching for an available charging point. If the designated charging point is not available, the electric vehicle remains in this state, otherwise it starts charging immediately.

Fig. 2 shows a schematic view of the states and the allowed transitions in the electric vehicle model. The behavior of the states can be easily modified to account for different models of energy consumption due to route selection, traffic conditions, air conditioning or other appliance usage.

B. Vehicle Schedule

The actual sequence of state transitions of a vehicle model during a simulation run is determined by a vehicle's *schedule*. This schedule represents the behavior of the driver and can in principle be arbitrarily complex in order to model realistic scenarios, including for instance active consumer participation via specific charging requirements.

A reasonable yet simple schedule has been implemented for the purpose of this paper to serve as a proof of concept. Whenever a vehicle is not connected to a charging point, it defines journeys with the help of sequential states called *outbound trip*, *parking* and *return trip*. The vehicles are driving when either an outbound trip state or a return trip state is active, and they are parking otherwise. Since the driving process itself is not subject to the investigation, it is assumed that when on a journey, a third of its complete duration is spent for the outbound trip, for parking and for the return trip, respectively. The total traveled

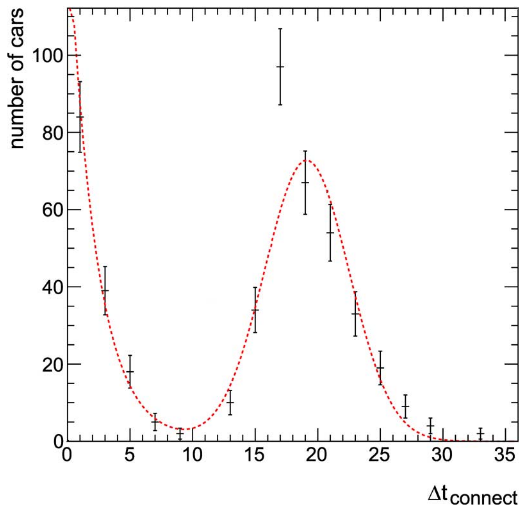

Fig. 3. Example for fitting the distribution of $\Delta t_{\mathrm{connect}}$ (red dashed line) from car rental data. The data points show the distribution of the time that cars remain unrented after they were returned to the rental station between 4 p.m. and 5 p.m. In the proposed EV simulation scenario this corresponds to the distribution of the time that the electric vehicles stay connected to a charging point (see Section V).

distance of a journey is split equally among the outbound trip and the return trip. Note that it was assumed, that charging is not possible during the journey.

During simulation, periods of charging and journeys are alternating according to a Markov chain. Their respective durations are drawn from statistical distributions, that depend on the time of day and/or the travelled distances. The according distributions have been extracted by fitting available real-world car rental data (see Section V) with simplifying models, e.g., exponential or Gaussian distributions. Fig. 3 shows an example where the time span $\Delta t_{\mathrm{connect}}$, for which vehicles stay connected to a charging point if they arrive (and possibly start charging) between 4 p.m. and 5 p.m., is fitted from car rental data with a combination of an exponential and a Gaussian distribution.

The schedules are also responsible for choosing a new charging point after every trip. In the current implementation this is done randomly within a group (representing a location). In case no charging point is available, a vehicle's status is changed to *searching* for a predefined amount of time.

C. Vehicle Battery

The electric vehicles' batteries are modeled as physical entities. Within the scope of this work, OpenModelica models are used for the simulation of the charging and discharging of batteries [33]. For that purpose the professional Electric Energy Storage (EES) library [34] was employed, which implements components for describing the dynamic behavior of batteries. The utilized battery model is composed of n_s serially connected cells with an ohmic impedance R and capacity C. Depending on the model complexity, self discharge, the internal linear dynamic impedance and aging (state of health) are considered. Given the consumed power $P(t)$ of the battery, the model describes the discharge rate Q (or charge rate if $Q > 0$) and the state of charge SOC. Using a look-up table of well-known material dependent measurements (e.g., lithium ion polymer), the open circuit voltage OCV and the total voltage $V(t)$ are computed.

D. Battery Charger

The battery charger is implemented in GridLAB-D and works according to an SOC-dependent charging strategy. It reduces the charging power linearly towards zero when the SOC is above a certain threshold to completely charge the battery, coarsely mimicking a CCCV (constant current, constant voltage) charging behavior. Hence, the actual SOC directly influences the charging time and charging power needed.

E. Charging Point Infrastructure

The electric vehicles are able to connect their batteries to charging points. The power output used for charging can be adjusted by the battery itself (SOC-dependant charging profile) or the charging management system (flexible-demand management). Typically, several charging points are combined to a charging point group, which is directly connected (as an independent node) to the common electric distribution grid. In the current implementation the charging point groups are very generic and hold for instance no geographical information.

F. Electric Distribution Grid

A simple medium voltage network with three medium/low voltage transformers has been modelled. Typical cable specifications and line lengths between 3 to 10 km have been used for the medium voltage grid. Each of the three low voltage networks consists of one household load, a load representing the charging point and a photovoltaic system (PV). Cable lengths of 50 to 150 m and rather small cross-sections have been used to ease the investigation of the voltage line drop caused by charging and household loads.

For investigating the dynamics of demand response algorithms like the charging control of EV, it is important to have a realistic simulation setup. Especially the dynamics of the loads influence the controller performance. For investigating the impact of single phase charging (and PV generation) it is necessary to have a 3-phase/4-line model for unbalanced power flow. Synthetic profiles would be insufficient, since the power consumption on the household level is stochastic.

The charging points are modeled as 3-phase loads connected to a bus, with the load representing the demand of a household. The actual active (and reactive) power can be set from the co-simulation environment and represents the charging power of the battery.

Load profiles are taken from a detailed measurement campaign that monitored the active and reactive power for every phase and every second of almost every single device and the total household for a period of 2 weeks in summer and winter. About 30 profiles have been measured and the data has been averaged for various periods, like 1, 5 and 15 minutes in addition to the one second root-mean-square profiles [35].

Distributed generation, like from the PV system, is modeled also as a 3-phase negative load, and is represented by measurement profiles. Alternatively, it could also be modeled using

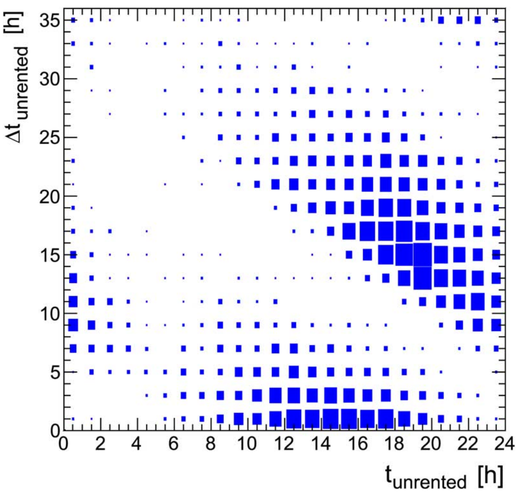

Fig. 4. Example of extracted car rental data. The data shows the duration $\Delta t_{\mathrm{unrented}}$ between two rentals, in dependence on the time of day t_{unrented} at which the vehicle had been returned by the customer.

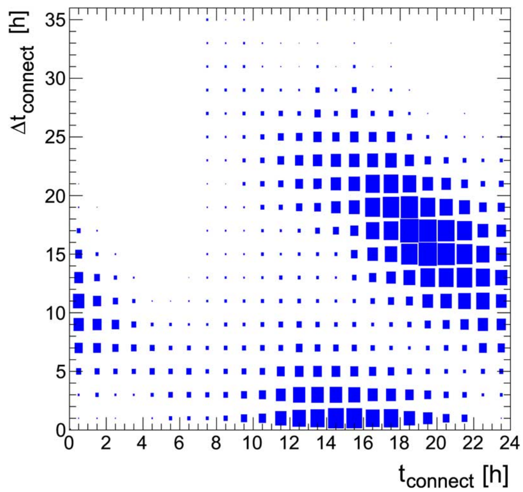

Fig. 5. Resulting distribution depicting the simulated user behavior. Shown is the time $\Delta t_{\mathrm{connect}}$ for which electric vehicles are connected to a charging point, in dependence on the time of day t_{connect} at which the vehicle had arrived and connected to the charging point.

an dynamic interacting weather-dependent model in OpenModelica.

G. Charging Management

The charging management system implements the EV charging algorithm. It has access to the state of the electric distribution grid, i.e., voltage levels at the charging points, and can take actions in case of overloads or voltages above or below allowed limits, i.e., regulate the active power consumption of the charging points.

An algorithm controlling the set points of the charging points, i.e., the maximum allowed power output of each individual charging point, has been implemented as a proof of concept for a charging management. The algorithm reduces the set point of a charging point by the step ΔP in case of under voltage and increases it stepwise if the voltage limits are not violated

$$P_{i,\mathrm{set}}(t_{k+1}) = \begin{cases} \min\left(P_{i,\mathrm{set}}(t_k) + \Delta P, P_{i,\mathrm{max}}\right) & U_i > U_{\mathrm{max}} \\ \max\left(P_{i,\mathrm{set}}(t_k) - \Delta P, 0\right) & U_i < U_{\mathrm{max}} \end{cases}$$
$$\forall t, \forall i:\ 0 \leq P_{i,\mathrm{charge}}(t) \leq P_{i,\mathrm{set}}(t)$$

The next cycle time t_{k+1} of the controller is issued to the simulation control to announce an update of the simulation. During periods of increased model dynamics the increment in time can be reduced to enhance the accuracy of the simulation.

This algorithm could be implemented as a distributed controller, operating locally hosted in the charging point, or centrally and communicating the necessary measurement and control signals with the battery charger.

However, more sophisticated approaches, including for instance also reactive power control, consumer participation or congestion costs, could be very well implemented and investigated in this simulation framework. The algorithm can be implemented in GridLAB-D or outside and connected to the simulation environment via the standardized FMI interface.

V. Vehicle Driving Behavior

For the sake of reflecting a realistic driving behavior, the implementation of the vehicle schedule was based on information extracted from the data of 6 locations for the year 2011 of a commercial car rental provider, including approximately 7700 rides. Even though this data includes itself no information about electric vehicle usage (all the vehicles have ordinary combustion engines), it allows to extract the characteristic user behavior, e.g., distributions of departure times, trip durations or vehicle types. Fig. 4 shows one of the extracted data sets that has then been used for the simulations.

This data allows to construct a realistic driving behavior model for a fleet of electric vehicles. For this, it is assumed that the theoretical time available for charging an electric vehicle corresponds to the periods in which the real-world vehicles were not rented. This is consistent with scenarios with a low penetration of charging points, but where users depend on dedicated infrastructure (similar to gas stations). For alternative scenarios, the driving patterns of the electric vehicles can be changed by using different distributions of departure times, trip durations, etc., based on other appropriate traffic patterns (e.g., of commuters).

In contrast to using the exact travelling data directly as static input, this stochastic approach is highly scalable, both with respect to the number of cars as well as the length of the simulated time interval.

VI. Results

A. User Behavior

Fig. 5 shows for a typical simulation run the histogram of the time a vehicle stays connected to a charging point $\Delta t_{\mathrm{connect}}$ in dependence on the time-of-day the vehicle was connected t_{connect}. This distribution is the outcome of the dynamic scheduling of charging periods and journeys, as described in Section IV-B. When the simulated driving behavior based on the statistical distributions is compared with the corresponding real car-rental data of recorded journeys in Fig. 4, one can see that this simplified approach reproduces the characteristics

TABLE I
BATTERY SPECIFICATIONS

single cell capacity	1500 As
number of cells per battery	100
energy demand when driving	20 kWh/100 km
maximum charging power	11 kW

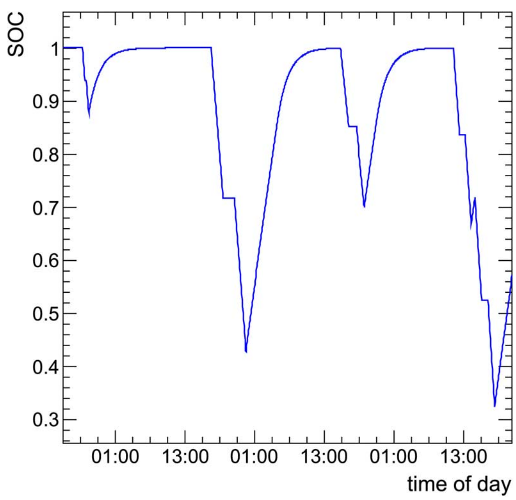

Fig. 6. Example simulation of a battery's SOC over a period of several days.

of a real-world scenario very well. Other characteristics, like duration of trips or driven distances, are also well reproduced.

B. Battery Operation

Table I gives an overview of the specifications relevant for the simulation of battery operation. Fig. 6 shows a typical evolution of a battery's SOC. Several periods of discharging due to traveling can be seen, each according to a dynamically scheduled trip. Also the effect of the SOC depending battery charger is visible.

As a result of the discrete event simulation, the length of the time step between two subsequent simulation steps depends on the actual events taking place. Fig. 7 demonstrates the non-uniform sequence of simulation steps due to the need for control caused by voltage violations. Obviously, the level of detail and accuracy of our dynamic interacting approach is superior to static simulations. Compared to approaches using fixed time steps this method is overall also superior with respect to performance.

C. Flexible-Demand Management

Fig. 8 shows the dynamic response of a controller to a voltage drop caused by recharging a battery. The controller is reducing the voltage drop by decreasing the allowed charging power, see Fig. 9. This happens every control cycle until the allowed voltage limits are not violated any more. By starting every charging cycle with the maximum allowed power consumption, this algorithm would create a transient under voltage, which avoided the need for a smarter charging algorithm (e.g., including a ramp-up of the charging power). Sudden load steps

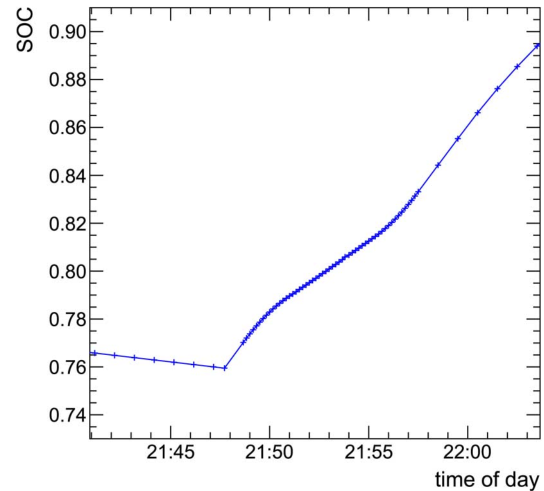

Fig. 7. Example charging process demonstrating the refinement of simulation steps during control actions.

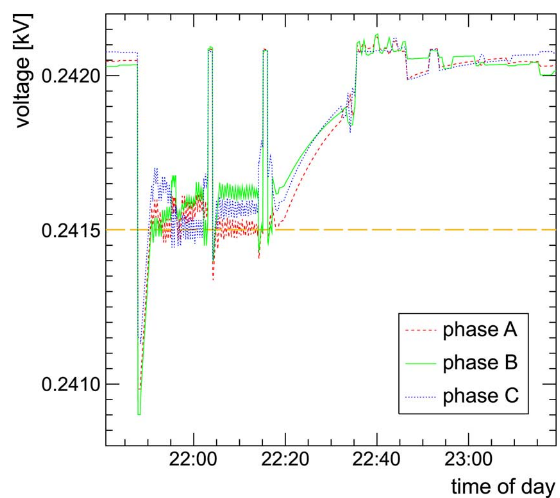

Fig. 8. Voltages during charging process with charging management (11 kW).

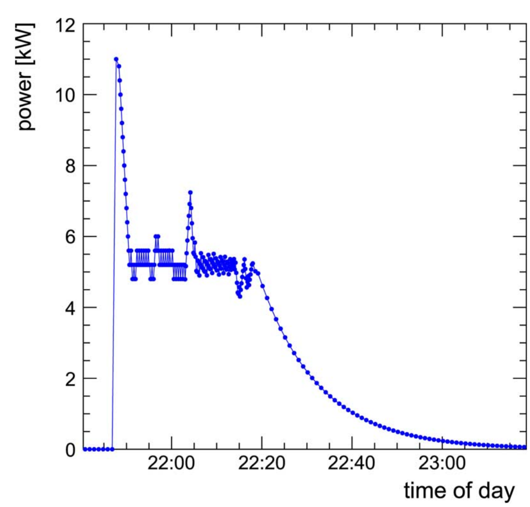

Fig. 9. Active power during charging process with charging management (11 kW). Sum of all three phases.

visible in Fig. 8 during charging are due to the dynamics of the simulated households.

VII. Conclusions and Outlook

This work presents a prototype simulation platform for testing flexible-demand management concepts in the context of electric vehicle charging. To enable the precise investigation of dynamic phenomena its design comprises a general-purpose discrete event-based simulator at the core that keeps track of a model's dynamic evolution. This is enhanced with domain-specific modeling tools to simulate the state of continuous time-based components. Due to the deployment of an object-oriented abstract EV model this approach is highly extensible, facilitating the adaptation to the demands of any given application.

The prototype implementation was realized by adapting GridLAB-D as the core, and coupling it with PowerFactory and OpenModelica. It demonstrates the applicability of the concept for testing flexible-demand charging algorithms and the possibilities given by tool coupling. Compared to conventional static approaches, this facilitates dynamic simulations that shift the level of detail from coarse net balances to elaborate studies of sub-system behavior, like controller stability or oscillations with other charging points.

The implemented prototype of the simulation platform is capable of emulating authentic user behavior based on real-world car-rental data, uses a realistic battery model provided by a professional modeling library and performs reliable electric distribution grid calculations with a validated simulation tool. Due to its modular design it allows to include more complex sub-components in a convenient way. For instance, vehicle schedules including geographical, meteorological and traffic data or V2G management algorithms can be integrated.

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