INTEGRATION OF ELECTRIC VEHICLES IN THE DISTRIBUTION GRID PLANNING PROCESS BY EXTENDING A MULTI AGENT ENVIRONMENT

Jan KAYS  
TU Dortmund University – Germany  
jan.kays@tu-dortmund.de

André SEACK  
TU Dortmund University – Germany  
andre.seack@tu-dortmund.de

Johannes ROLINK  
EWE - Germany  
johannes.rolink@ewe.de

Christian REHTANZ  
TU Dortmund University – Germany  
christian.rehtanz@tu-dortmund.de

ABSTRACT
With electric vehicles becoming a more attractive alternative to combustion vehicles, they appear as new volatile loads in the low voltage distribution grids. Until now, they are at the best only considered rudimentarily in the planning process.

This paper presents the modelling of electric vehicles as agents in a multi-agent simulation environment for planning purposes. Integrating a model of mobility behaviour, the developed agent allows for the realistic consideration of electric vehicles in the planning process, including interactions with other network users. The resulting system is demonstrated within a test grid.

INTRODUCTION
Recent studies demonstrate that the necessary distribution grid extension in the following years is mainly driven by renewable energy generation units. However, not only feed-in units but also new loads with a high rated power are installed in the system. One of these new load types are electric vehicles (EV), whose amount is supposed to increase over the next years. Since the low voltage grids are not designed for a high simultaneity of loads, EV may generate unacceptable thermal overloading or voltage violations in the grid [1]. Besides at charging stations, EV are assumed to be charged at home in residential areas. With a rated charging power of several kW, the requested power is higher than the typical domestic loads that are assumed in low-voltage grid planning. This has an impact on grid extension strategies [2]. Although the amount of renewable power units increases in the distribution grids and EV are becoming a more attractive option for customers, these new participants are only considered rudimentarily in the planning process.

Research shows, that extensions can be avoided, if charging is controlled by the operator [3]. The concept of smart charging, using the battery storage systems for providing system services, is analysed in [4] and [5]. Even with distribution functions for the charging behaviour the impact on the grid is high [6].

A detailed analysis of the electric vehicles’ charging probabilities in detail [7][8][9]. The target in [10] is the derivation of standard load profiles for EV. An agent-based transportation model for human behaviour is set up in [11] in order to receive the resulting behaviour of EV. In this system, negotiations with aggregated groups of vehicles are done to optimise the system. Additionally, the balancing of volatile renewable infeed is sought. But besides the exemplary analysis of their impact on the grid, EV and their mobility behaviour are not yet considered adequately in the planning of distribution grids.

In this paper, a time-series based distribution grid simulation environment is therefore extended to consider the impact of EV on the grid directly in the distribution grid planning process. Since conventional planning methods are not able to take into account intelligent interactions between different users, a new approach is necessary to determine their influence on loading situations in the grids. Dimensioning a distribution network area only based on the results of classical extreme scenarios with additional EV may provoke inefficient network constructions due to unnecessary oversizing. However, describing and modelling different actors with specific behaviours becomes very difficult if their interactions should also be taken into account.

Facing these challenges, but also the opportunities of a more accurate system modelling, a simulation system based on a multi-agent environment is developed, generating detailed time series of asset loadings, generation and load behaviour. Within this simulation environment, every network participant, like a domestic load or a photovoltaic generator, is represented by an agent of its own.

This paper starts with a description of the existing multi-agent system, illustrating the proceeding of the simulation. Afterwards, the modelling of electric vehicles as agents within this simulation environment is explained, including the assumed mobility behaviour. The resulting influence of EV in the distribution grid is demonstrated and evaluated in a low voltage test case scenario.

SIMULATION WITHIN A MULTI-AGENT SYSTEM
The basic structure of the simulation environment is a multi-agent system (MAS). Agent-based systems
feature modular construction of intelligent and autonomous entities, called agents, that live and interact in a simulation environment. The concept facilitates the modelling of real systems with complex interactions, due to the system’s decomposition in agents. Besides the enhanced accuracy of the system due to the detailed modelling with agents, the flexibility of MAS in changing the size and elements is one of the main advantages [12]. This section describes the developed system and the agents for household loads and photovoltaic generators, representing distributed generation.

The existing system

The principle structure of the simulation system, which is being developed at the TU Dortmund University, was already published in [13] and is shown in Fig. 1. For a given time interval, the simulation system determines the situation in the grid for every time step of the interval.

![Diagram of the agent-based simulation system](image)

After an initialisation phase, the fundamental procedure during one time step is always identical and described in the following (the numbers refer to the numbered arrows in Fig. 1):

1. The time agent informs the other agents that a new time step begins.
2. The weather agents get their local weather from a database and provide it to their subscribers (load and photovoltaic agents), while the node agents pass the time information to their own subscribers (directly connected loads and photovoltaic generators at the node). The market agent sends the current market price to its subscribers.
3. The load and photovoltaic agents calculate their power consumption or feed-in for the given input data. Both types send their results to their node agents and to the market agent.
4. The node agents forward the aggregated power of the local consumption and feed-in to the grid agent.
5. The grid agent performs a power flow calculation to determine the loading of grid assets and nodal voltage profiles. The results are stored in a database for further analysis. Subsequently, the time agent is updated that the calculations of this time step are finished.

The resulting time series of all relevant variables and parameters are stored in a database for post-processing and analysis after the simulation. In contrast to conventional network planning scenarios, this knowledge facilitates the decision if network extensions are needed or if alternative solutions like limiting the renewable feed-in might be cost efficient.

Modelling the household loads

Based on the research of [14] and [15] the frequency of occurring power consumption of households within (quarter-) hourly time intervals is describable with probability distribution functions. The analysis of available smart-meter measurements shows that generalized extreme value distribution functions are most suitable to model the probability of occurrence of domestic power consumption. Therefore, the load agents implement a stochastic behaviour on the basis of individual distribution functions for every time step. Additionally, the loads are susceptible individually by changing energy prices or the outdoor temperature.

Modelling distributed generation

With photovoltaic units being the most common distributed generation in low voltage grids, the focus is on their agent-based representation. The photovoltaic agent implements the detailed model that is described and validated in [16]. The assumed necessary parameters take into account that every photovoltaic unit has different installation conditions. The required local weather is determined with the triangulation method, which is presented in [17].

MODELLING ELECTRIC VEHICLES AS AGENTS

Being primary low voltage loads with high power demand, EV should be considered in the distribution grid planning process. Besides charging, their battery storage may also be used as an intelligent storage system. If EV react sensitive to market prices and interact with other grid users, a complex model is necessary to describe them realistically.

This section describes the development of an agent for EV, embedded in the MAS simulation environment and implementing mobility behaviour. The agent’s development is leaned on the recommendations in [18].

The mobility behaviour

A comprehensive analysis of the mobility behaviour is done in [8] and briefly introduced in the following. There, a probabilistic model of the behaviour of EV is
derived and used in this paper. Based on a traffic study, the most important states of EV during the day are determined. These are “at home”, “at work” and “elsewhere” in combination with possible transitions between them (see Fig. 2).

The model is based on a non-homogeneous semi-Markov-process, allowing for regarding time dependencies in the calculated transition probabilities. These transition probabilities $P_{ij}(\tau)$ indicate the probability of changing from state $i$ to state $j$ assuming state $i$ is occupied in time interval $\tau$. Additionally, the model indicates the sojourn time of the states, which is necessary to identify the available charging time. The probabilistic calculation of the driven distances between the states determines the reduced capacity of the EV. The determination of these three variables is explained in detail in [8]. In this paper, only the residential charging is considered, thus state 1 is important to derive the availability of an EV.

Defining input and output parameters

The results from the mobility model of [8] are given in quarter hourly resolutions in matrix $P$ for the transition probabilities, matrix $W$ for the driven distances probabilities and matrix $F$ for the sojourn time probabilities. Besides them, some static input parameters are necessary for a realistic simulation of EV (Table 1). Some internal parameters change during the simulation and are listed in Table 2.

Table 1 Static input parameters for the agent

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variable</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery capacity</td>
<td>$E_{EV}$</td>
<td>kWh</td>
</tr>
<tr>
<td>Rated charging power</td>
<td>$P_{N, EV}$</td>
<td>kW</td>
</tr>
<tr>
<td>Energy consumption</td>
<td>$E_{EV, spec}$</td>
<td>kW/km</td>
</tr>
<tr>
<td>Minimum State of Charge</td>
<td>$SoC_{min}$</td>
<td>%</td>
</tr>
<tr>
<td>Power factor</td>
<td>$cos(\phi)$</td>
<td>-</td>
</tr>
<tr>
<td>Grid node of EV owner</td>
<td>Node ($)</td>
<td>-</td>
</tr>
</tbody>
</table>

Some input data of the simulation environment is required for the calculations of any EV-Agent in every time step. Besides the local power consumption $P_{load}(t)$ and the local photovoltaic feed-in $P_{PV}(t)$, the market price for energy $p(t)$ is relevant for the agent’s decisions.

Based on all these parameters, the EV agent is able to determine its behaviour, finally resulting in an active ($P_{out}(t)$) and reactive power ($Q_{out}(t)$) balance.

Table 2 Changing internal parameters of the agent

<table>
<thead>
<tr>
<th>Parameter Variable</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charging power</td>
<td>$P_{EV}(t)$</td>
</tr>
<tr>
<td>State of charge</td>
<td>$SoC_{EV}(t)$</td>
</tr>
<tr>
<td>Charging level (SoC absolute)</td>
<td>$E_{EV, SoC}(t)$</td>
</tr>
<tr>
<td>Available capacity</td>
<td>$E_{EV, cap}(t)$</td>
</tr>
</tbody>
</table>

Targets of the EV agent

Implementing the most probable behaviour of EV and their owners, the EV agent has one main target. With the owner always requiring a certain degree of mobility, the EV is charged whenever Eq. (1) holds.

$$SoC_{EV}(t) \leq SoC_{min} \quad (1)$$

In all remaining cases, the EV agent targets for optimising the economic welfare or ecologic balance of the charging procedure. If the EV owner operates a distributed generation unit, especially a photovoltaic unit, he may aim to maximise his own consumption, which is possible with EV. Therefore, the EV agent checks, if the difference between nodal generation and consumption is positive (Eq. (2)). Then, the EV is charged until this condition is no longer true or the EV is completely charged. Using this local-produced electric energy, the local grid utilisation is reduced.

$$P_{EV}(t) - P_{load}(t) \geq 0 \rightarrow P_{EV}(t) > 0 \quad (2)$$

Additionally, if the cars are able to react on volatile customer prices for electrical energy, sensitivity to the price is conceivable. So, when Eq. (1) is false but the price for consuming energy is lower than a predefined price limit $p_{min}$, the EV charges anyway and reduces charging costs. Equation (3) describes this behaviour.

$$p(t) \leq p_{min} \rightarrow P_{EV}(t) > 0 \quad (3)$$

The targets defined by Eq. (2) and (3) are facultative and future oriented but describe optional reasoning of the EV agent during the simulation.

Embedding the agent into the MAS

For the implementation of the targets, the EV agents are embedded into the existing MAS-simulation environment. The direct connection to the node agent facilitates the integration.
Implemented behaviour

The structure of the implemented algorithm and the logical reasoning of the EV agent are depicted in Fig. 3. The reasoning is based on the described targets. In the end of every time step, the internal data is updated and the calculated power consumption is written into a result database as well as sent to the node agent.

SIMULATION

For the demonstration of the simulation system an exemplary low voltage grid is used, which is depicted in Fig. 4. It consists of a local substation with four low voltage feeders (F1 – F4), having a typical topology for rural areas in Germany. At each of the feeders F1 – F3 32 households are connected to the grid. The distances between the households vary between 18 and 32 m. Feeder F4 powers a less densely build residential area with only 20 households and longer distances between them (30 – 54 m). At some of the nodes, photovoltaic generators are installed with rated installed capacity of 10 kW. The lines of the feeders F1, F2 and F4 are overhead lines with a diameter of 70 mm² or 95 mm². Feeder F3 is a cable with 150 mm². The transformer has a rated capacity of 400 kVA and the voltage at the medium voltage bus bar is set to 1 pu.

In this test case, the impact of EV is analysed within a simulation period of two weeks during summer with a chronological resolution of one hour. In the basic scenario the present-day situation without EV is simulated. The EV scenario assumes that 10% of all households own an EV, thus 12 EV in this grid, each one has a rated charging power of 3.7 kW or 11 kW. With the simulated time series, the resulting loading situation with additional EV is determinable. These time series are sorted by order to build duration curves, facilitating the frequency of occurrence analysis and the derivation of recommendations for network reinforcements.

The local transformer loading is depicted in Fig. 5, showing a significant increase of the maximum loading with the EV connected to the grid.

Not only the loading of lines and transformers is higher, but changes in the resulting nodal voltages are visible. The resulting duration curve for the marked nodes in Figure 4 is shown in Figure 6. Especially for weak feeder lines, the charging of EV has a significant impact on the voltage profile. It even violates the boundary of 0.9 pu in some time steps. On the basis of the simulated time series, the frequency of these violations and the resulting operation reserve in every time step is made available.
CONCLUSION

The presented extension of the multi-agent simulation environment with an agent model of electric vehicles allows for their consideration in the distribution grid planning process. Taking into account the mobility behaviour of the EV owner, a realistic modelling of the cars is possible. The generated time-series in the chosen test grid demonstrate that a high penetration rate (10% of all households) influences the thermal loading and nodal voltages significantly, especially in weak feeders. The multi-agent simulation environment allows for the consideration of different and interdependent influencing parameters on single participants in the system.

In future work, the reaction on the market price will be transformed to an active market price influence, if larger groups are considered or the market price is varied locally.

REFERENCES


1 The participation of Johannes Rolink has been during the time when he worked at the TU Dortmund University.