

Using Behavior Simulation to synthesize Electromobility Charging Profiles

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Abstract

In recent years a novel approach for the generation of residential load profiles was developed. It is based on an agent-simulation that models each person in a household as a separate software agent. For a new project this model has now been extended to also include transportation and travel times. This allows generating highly realistic mobility profiles. The model uses measurement data from real electric cars to generate charging profiles. Additionally, availability time profiles are generated, that describe when the car could have been charged. This is relevant in the context of PV system integration since electromobility will be one major driver of future electricity demand.

Keywords: load profiles, electromobility, agent simulation

1. Introduction

In the last years a novel approach for synthesizing load profiles was developed. The approach works by using an agent-based simulation approach that uses a psychological desire model to simulate the behavior of the residents. This approach has many advantages compared to a probabilistic approach especially for simulating single households. The model is implemented as a Windows program, called “LoadProfileGenerator (LPG)” and is freely available for download at (Pflugradt, 2017). The model is explained in detail in (Pflugradt, 2016).

Now the model has been extended to include electromobility. Due to the agent-based simulation the activity and the location for each resident in the household is always known. Based on this, it is possible to keep track of where the car of the residents is, how many kilometers it has driven and when it is available to get charged. This paper describes the extended simulation model, shows some of the performed measurements on the charging of the electric cars and the resulting synthetic load profiles.

2. State of the art

Currently data on electromobility charging profiles is rather sparse. (Wang et al., 2015) studied the energy consumption of vehicles based on driving data from Beijing. (Wolbertus et al., 2018) did large studies on the charging behavior of public charging stations but doesn't show individual charging events.

There are a number of approaches for synthesizing electric vehicle charging profiles, for example (Munkhammar et al., 2015), (García-Villalobos et al., 2014) or (Fischer et al., 2019). They all use a stochastic approach to model the driving behaviour. (Fischer et al., 2019) used statistical data to generate probability distributions over the day for driving events and for the driving distance. Based on those probability distributions they simulate the driving and calculate the state of charge (SOC) for each car. Then they simulate the driving behavior of the cars over the year and decide, depending on the current location of the vehicle, if it can be charged.

The novelty of the approach introduced in this paper is in three areas: First, the model will be publicly available to download for free. Second, the agent-based approach enables the simultaneous generation of load profiles for household electricity, warm water and charging electricity demand. This is very important for correctly modelling the impact of longer absences, such as vacations. Third, because detailed probability profiles are not needed for modelling, it is possible to model for example shift workers or part time employees, which make up a large

percentage of the population and are not represented by the other approaches according to the published literature.

3. Model

The basic simulation works by modelling each resident of the household as an independent agent. This agent then decides based on the currently available activities and the current desires what to do next. For example, if the person comes home from work, the person might have a high desire for both relaxing and food and since food is a higher priority, the person will first eat and then maybe watch TV. This principle is shown in Figure 1.

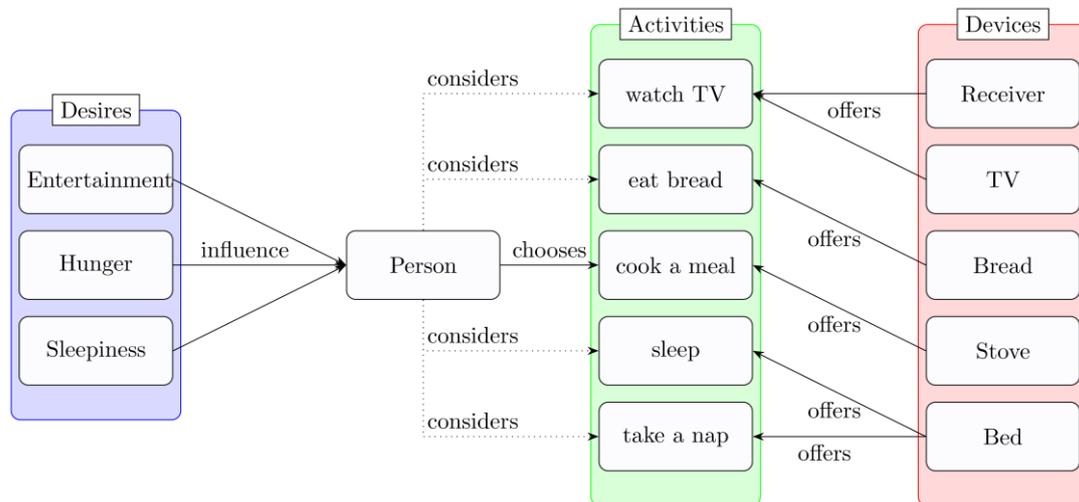


Figure 1: Basic Idea of the LoadProfileGenerator

3.1. Requirements

Due to this approach it is possible to generate realistic activity profiles for each person. From the activity profiles the load profiles can be generated.

The challenge was to extend the existing model to combine different households with different combinations of routes and transportation modes. Some examples of the different options are shown in Figure 2. For example, the same household could either have two cars and live far from any city or have no cars and very short travel distances to all points of interest.

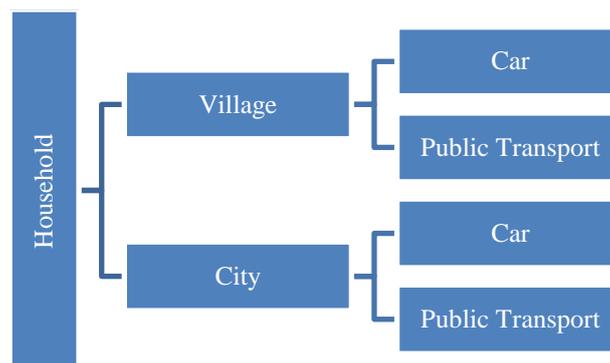


Figure 2: Different transportation scenarios that need to be combined with a household

An additional requirement was that travel routes can be multi-modal. That means one route can require the combination of different transportation devices, as shown in Figure 3. To get from home to work, a person might first have to take the elevator and then the car.

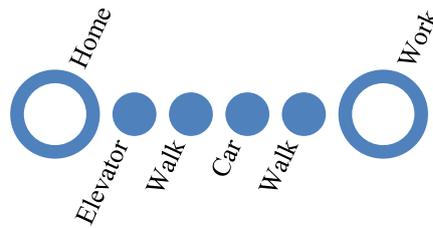


Figure 3: Travel steps for one example travel route

Quite frequently there are different travel options to reach the same goal. For example, a child might take a bus to go shopping, but a mother might take a car. So personal preferences and limitations on the use of transportation devices need to be integrated too.

There are different types of constraints to the transportation devices. Busses, for example, only run at certain times, but are always available, no matter when and by whom they were last used. Cars on the other hand are only available at a single location at a time and if the one person used the car to drive to work, the other person can't use the car at the same time to go shopping. Electric cars can only be charged at certain places and can't be used if the SOC is too low. Different transportation devices can go at different speeds. Electric cars have a state of charge that needs to be tracked.

3.2. Model

For modelling a relational database approach was used. The entities used in the LPG are written in italics in this section to aid in understanding.

The approach chosen for the model was to first define *sites* and *transportation devices*. Then the next step is defining *transportation device categories* for all *transportation devices*. For example, all cars are assigned to the category "car", while the different busses get assigned to the category "bus". This allows switching out internal combustion engine cars for electric cars without changing any of the *travel routes*. Every *transportation device* can consume resources that are logged, which makes it possible to keep track of, for example, the charging status of an electric car.

Then different *locations* in the LPG, such as rooms in a house, are assigned to the *sites*. *Travel routes* are defined between the sites. Each *travel route* has at least one *travel route step*. Each step has a distance and a *transportation device category*. Figure 3 shows an example for a *travel route*.

The travel routes are combined into a *travel route set*. The *travel route set* describes all travel options for a *household*. The LPG makes sure that it is possible to travel from every *location* in a *household* to every other location to avoid problems with people getting stuck in one location. If this rule wasn't enforced, it might be possible to create a situation where a person can travel from home to the office and from the office to the supermarket, but not from the supermarket home. This would theoretically be solvable with a path finding routine, but due to computational constraints it seemed more reasonable to instead enforce the rule that there needs to be a *route* between each *site*.

Then a *transportation device set* is defined which combines all the *transportation devices* for the *household*. The LPG again enforces that for every site there are devices for at least one *travel route*.

This model is visualized in Figure 4. By combining all these elements makes it possible to comprehensively model the traveling behavior of the residents in various configurations in a flexible and universal way. The model makes it possible to combine different transportation options with different routes for the same household.

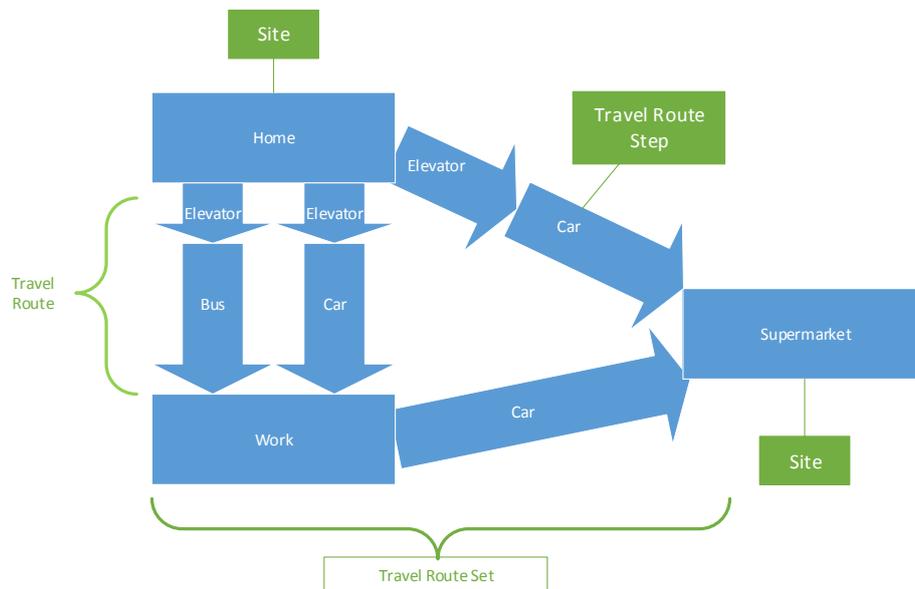


Figure 4: Data Model for the transportation module

3.3. Simulation

During the decision-making process of choosing the next activity, the software agent first checks the available activities and the reachability of each activity. For example, it checks if an electric car is available and sufficiently charged for a two-way trip. Then it picks the activity that satisfies its current desires best.

To model the charging process, the software includes a database of measured high-resolution charging profiles which are then truncated as needed to recharge the battery from the taken trips. For this purpose charging points are defined and if, for example, the car is at home, it will be charged. Intelligent charging control with peak shaving is currently still under development though.

4. Measurements

Of particular interest are the diverse charging profiles of the different cars. Probably largely due to the still early stage of the entire development of electric cars, the charging patterns differ significantly between manufacturers and models. Figure 5 shows an optimal charging behavior.

Other cars show curious aspects such as:

- the poor power stability in the later phase of the charging of the Nissan Leaf, where the power varies by more than 1000 W, see Figure 6. This only happens when charging with 3.7 kW. When charging the same car with 10 kW, no such fluctuations occur.
- The charging behavior for two different Renault Zoe Models are shown in Figure 7 and Figure 9. They show a very strong decrease in charging power as the SOC increases. The behavior improved considerably already though from 2014 to 2017.
- The Renault Zoe has the worst charging profile regarding the production of reactive power, as shown in Figure 8 and Figure 10. It is visible that Renault improved this significantly from the 2014 model to the 2017 model.
- The Citroen C-Zero performs frequent brief measurements that cause power dips for unknown reasons.

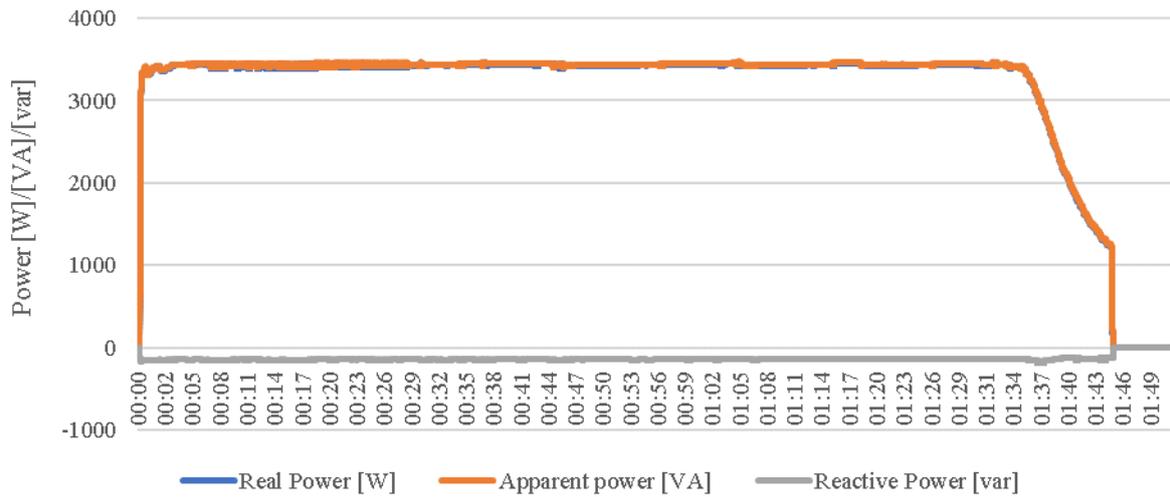


Figure 5: Charging measurement for an Opel Ampere from 2013

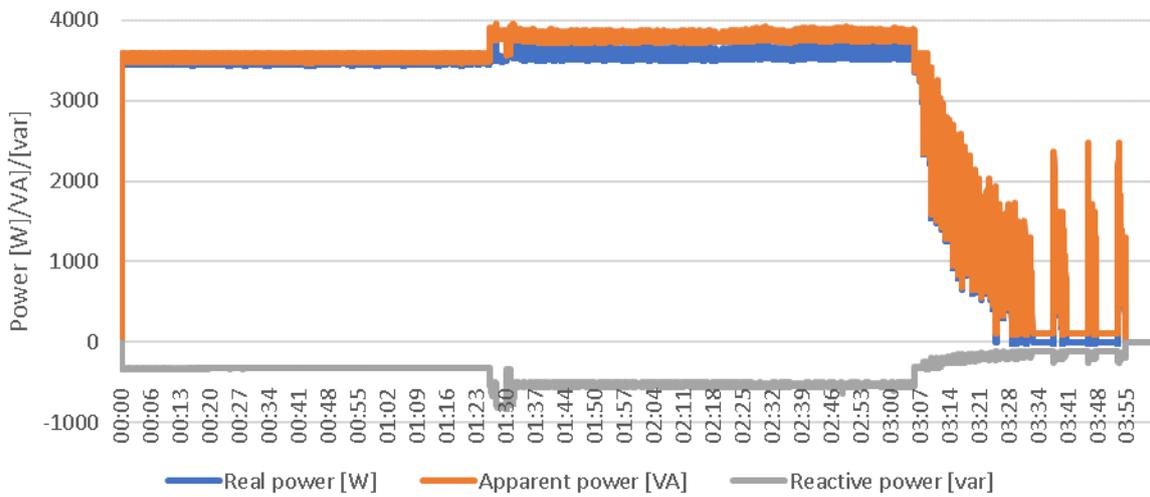


Figure 6: Charging behavior of a Nissan Leaf from 2015

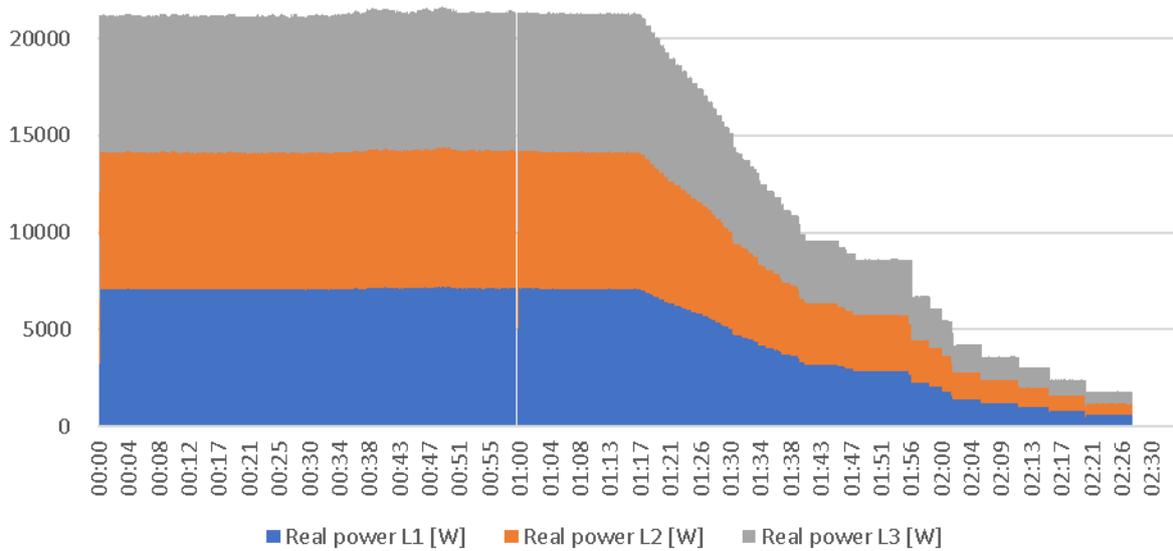


Figure 7: Charging behavior for a Renault Zoe from 2017 that uses three phases

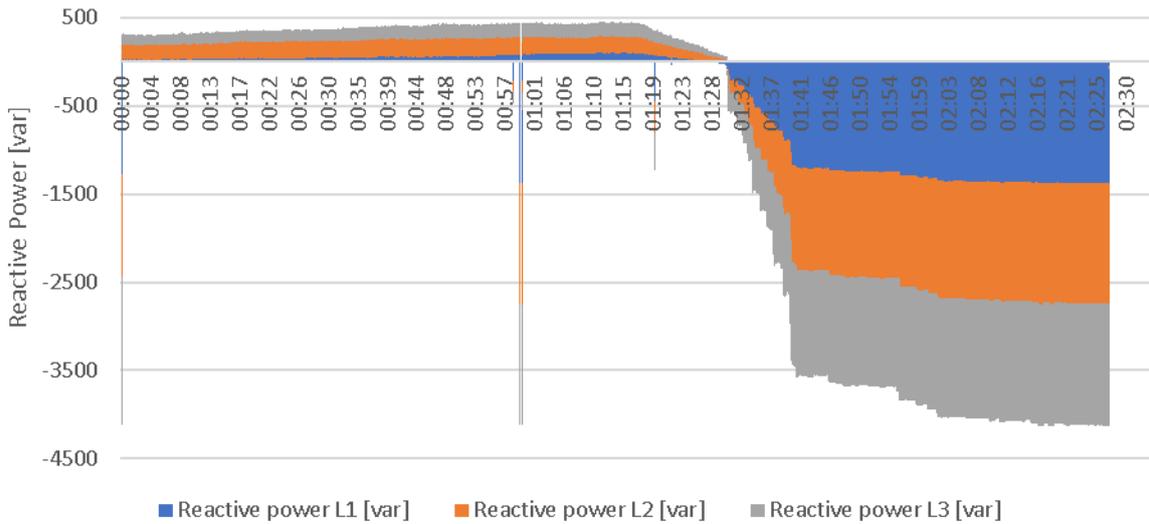


Figure 8: Reactive Power of the charging process for a Renault Zoe from 2017

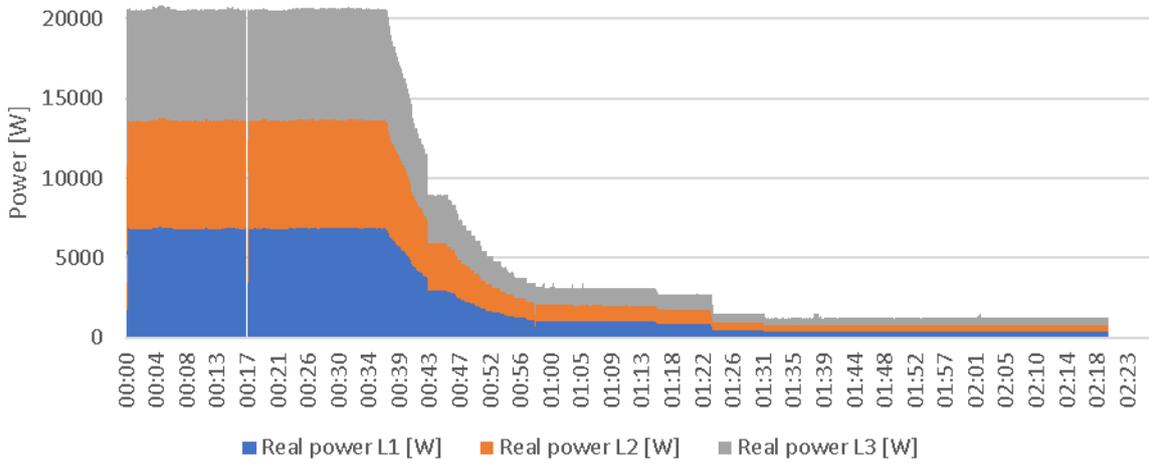


Figure 9 : Real power from the charging process of a Renault Zoe from 2014

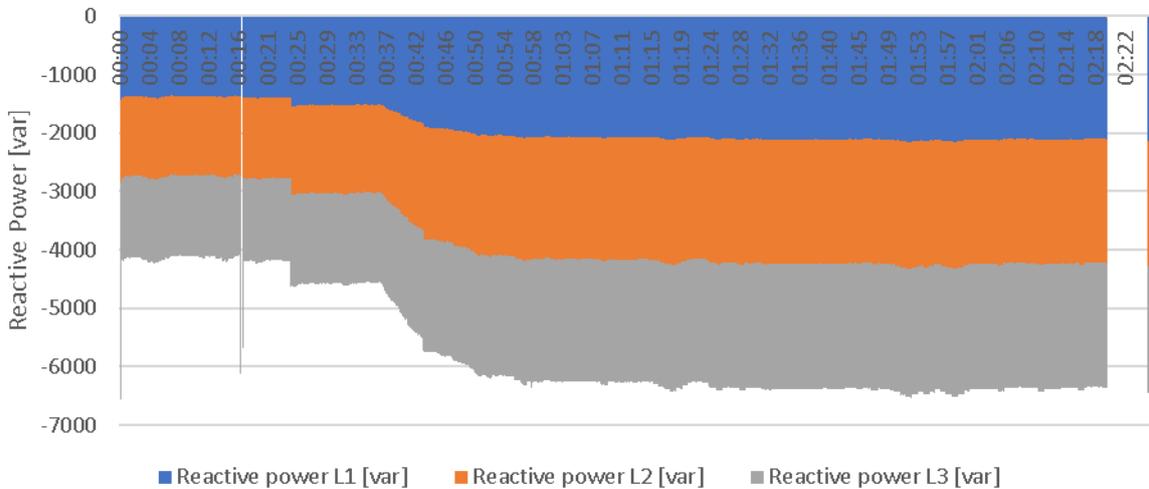


Figure 10: Reactive power from the charging process of a Renault Zoe from 2014

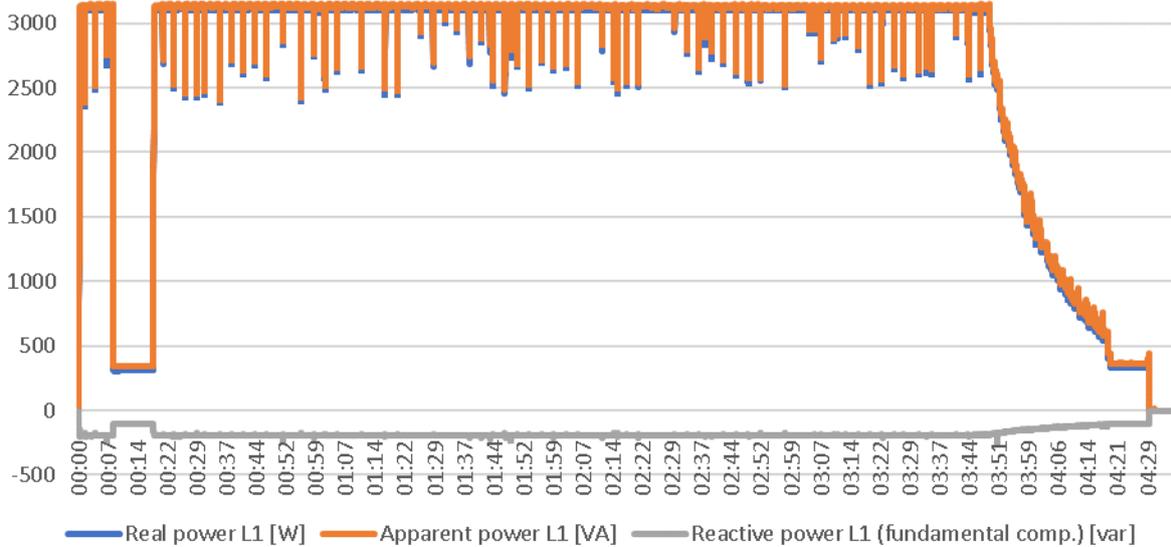


Figure 11: Charging behavior of a Citroen C-Zero from 2016

5. Results

Due to the increasing sector coupling, the interaction between PV-Systems, electric cars and battery systems become increasingly relevant. In many cases, smart grid algorithms are not validated with good availability and demand profiles of electric cars though. This research provides an easy and convenient method to generate realistic and highly detailed profiles, which include details such as vacations, sickness, rotating shift workers and many more details.

Figure 12 and Figure 13 show two different examples of charging availability profiles. Figure 12 shows the profile of a simplified single office worker with a very regular lifestyle, a single trip in the evening each week to the fitness studio and a shopping trip each Saturday. Also visible are the vacations around Christmas/New Year and the summer vacation. As charging algorithm, a simple “plug in as soon as home” is used. A daily distance of about 50 km and a charging power of 3.7 kW is assumed. The diagram shows that the charging is mostly done in the early afternoon and the car would be available for V2G-applications most of the night.

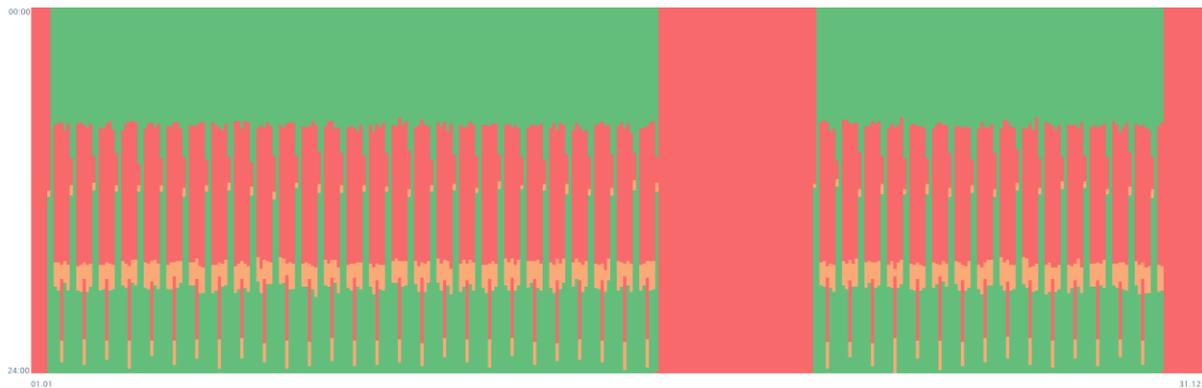


Figure 12: Charging state of the car of a simplified office worker profile. Red is defined as “away from home”, orange means “the car is charging”, and green means “the car is available for charging but the battery is full”.

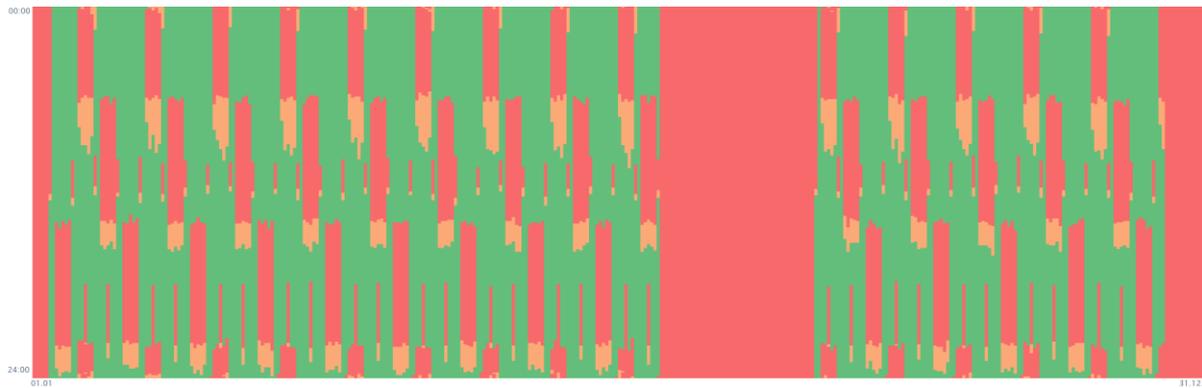


Figure 13: Charging state of the car of a simplified three shift worker profile. Red means away from home, orange means that the car is charging, and green means the car is available for charging but the battery is full.

Figure 13 shows the charging availability for a simplified single shift worker. The same parameters as before were used. It is visible that here the car is also mostly at home and available for V2G-services for example. The averaged yearly charging profiles for both cases are shown in Figure 14. It is visible that the charging behavior varies strongly between the two cars and the charging times of the shift worker match much better with a photovoltaic charging profile.

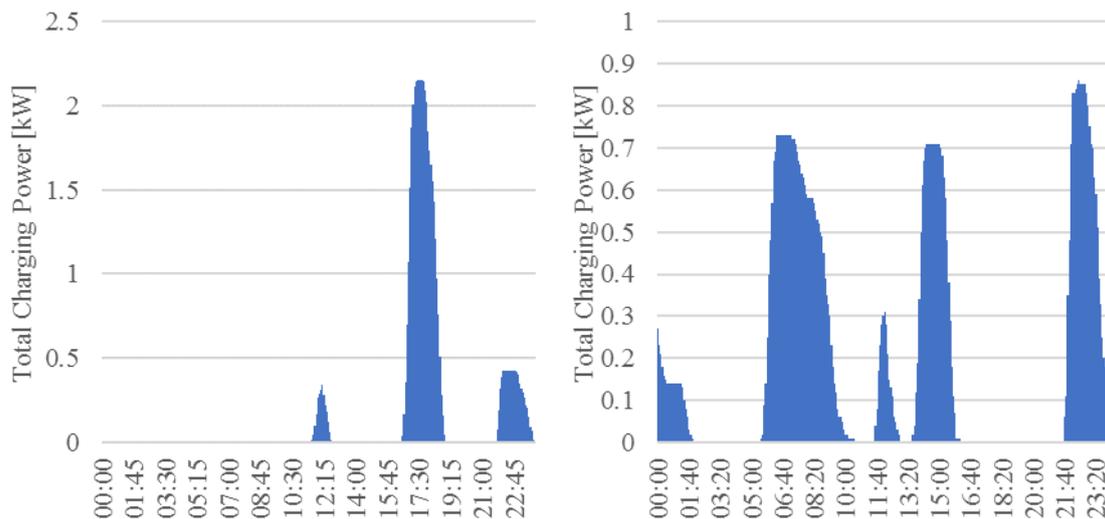


Figure 14: Averaged charging profiles of the two cases for one year. On the left the office worker is shown and on the right the shift worker.

One important conclusion is that the availability of the car für charging depends very strongly on the lifestyle of the car owner. In general, the car of employees tends to be at home around 70-80% of the time, but especially for office workers, the car is rarely home at the time when the most photovoltaic energy is available, which makes charging from the residential PV-System very difficult. For shift workers, the situation is much better. Thus, for minimizing buffer energy storage needs, workplace charging is essential to any future energy system with high PV and high electromobility penetration.

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