SYNTHESIZING ELECTROMOBILITY CHARGING PROFILES

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ABSTRACT

Electromobility will be a major driver of future electricity demand and will have a significant impact on the load profile. In the last years, a load profile generator for residential load profiles was developed that uses a novel approach of modeling the residents as independent software agents, thus enabling the detailed modeling of the behavior of the residents. It is freely available and has been downloaded thousands of time.

The load profile generator has now been extended to include electromobility. This is helpful both for research and for system planning of charging stations. This paper introduces the model, measurements from the charging of different electric cars and some simulation results.

INTRODUCTION

Electromobility will be one of the main drivers for future energy demand. For the planning of charging stations, development of smart grid algorithms or grid planning purposes, charging profiles are needed. Frequently no measurement data is available, so synthesizing profiles is the only option.

In the last years, a novel approach for synthesizing high-resolution residential load profiles has been developed and implemented in a Windows program called "LoadProfileGenerator" (LPG). This approach models the people in the household as independent desire-driven software agents. This approach has many advantages compared to a probabilistic approach, especially for simulating cases that are more difficult to model with standard probabilistic approaches, such as shift workers, families or students. The software is freely available for download at [1] and the model is explained in detail in [2]. Now the model has been extended to include electromobility. This paper introduces the model extension and shows some of the results.

STATE OF THE ART

Every week there are new headlines about the rapid spread of electric vehicles (EV). The impact on the low voltage grids of high adoption rates of EV is still not fully researched though.

There are various papers analyzing the impact of EV on the load. For example [3] analyzed the electric consumption of EVs for Beijing. Other studies investigate influencing factors for the connection times, such as [4].

A number of papers have introduced different models for synthesizing charging profiles, for example [5–7]. Those all use a stochastic approach to describe the plug-in behavior, which works very well for larger populations but is not ideal to produce profiles for individual households with the highest possible realism as possible.

Compared to the existing approaches, the model introduced here has several important additional features that improve the results. First, due to the full and detailed behavior simulation with a time resolution of 1 minute, a detailed list of activities of the residents can be generated. These activities include things like days off work around holidays, staying home from work due to illness, vacations and much more. It is also rather easy to model things like irregular shopping for food or behavior-dependent activities such as running the dishwasher depending on how many dirty dishes were generated recently. Of particular relevance is the ability to model shift workers, which have substantially different load profiles compared to office workers, since millions of people in Germany alone are working in shifts.

METHOD

The LPG is based on a psychological behavior model [8]. It models the residents as independent, desire-driven software agents. The basic idea of this is shown in Figure 1. The central element is the person. The person has multiple desires that influence their behavior. Then in the household different devices offer different activities to the person. The person then calculates the utility of each activity, defined as having the minimum deviation in each desire from the target value and chooses the best one.

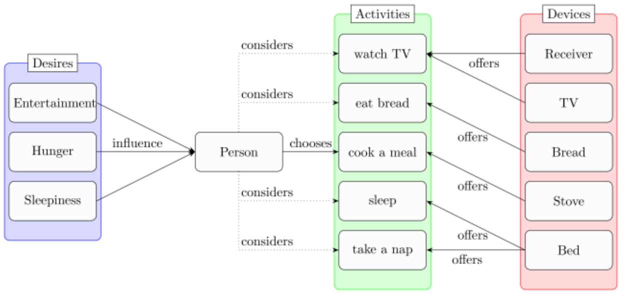

Figure 1: The basic idea behind the LPG

Requirements

The model has now been extended to include mobility in general. The challenge was to extend the model in a way that it is possible to combine different households, transportation devices and travel routes in a very flexible way. For example, it should be possible to place an office worker household either in a city and have them use public transport or place the same household with the same behavior patterns in a small village and have them drive to work every day, as shown in Figure 2.

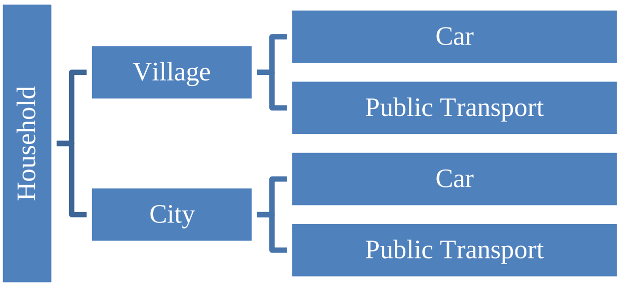

Figure 2: Combining households with different transport options and different routes

Additionally, it was required to model the entire transportation process, for example taking the elevator, walking to the car, driving, then walking again and finally arriving at work. This is important because that way the individual parts of the journey can be modelled in detail and the elevator electricity use can be included in the house electricity consumption.

Another requirement was that persons need to be both realistic and flexible in the transportation devices they use. For example, children would not use the car, but adults could. But only use it if a car is actually available. If no car is available, because it is used by another person, they should automatically switch to using the bus.

Model

This section describes the model. The entity names used in the program are in cursive to help in understanding.

The first thing to be defined are the *transportation devices*. Every *transportation device* has a *transportation device category*, a speed, and if applicable, a charging load type, a total range, and maximum charging power. The *transportation device category* determines, if a device is limited to a single location or not. For example, a car is location limited: It can only be used by a single person at a single location at a time. A bus on the other hand can always be used, no matter who else is currently using it or where it was used last.

Every household can have a different set *of transportation devices* available. For example, household A might have a bicycle, a fast car and their feet. Household B might have two slow cars, their feet and access to a bus. These combinations are defined in a *transportation device set.*

Every set can be combined with every *household* to test for example the impact on the entire load profile of the *household* if the people need more time to get to work due to slower transport.

The next entity are the *sites.* In the LPG every activity is assigned to a *location*, such as kitchen, living room or office. All the locations are assigned to *sites*, such as “home”, “work” or “supermarket”. *Sites* can have charging stations that offer charging with certain load types, such as electricity or gasoline.

Between the *sites travel routes* are defined. *Every travel route* consists of one or more steps, a distance and a *travel device category*. One example of such a *travel route* is shown in Figure 3. It is visible that *travel routes* can encompass multiple different devices on the same route, such as elevators, feet, cars or even busses.

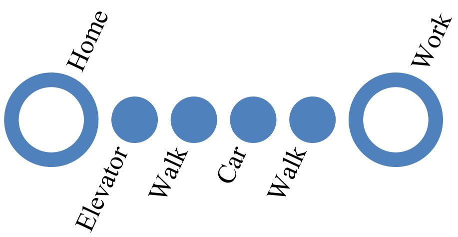

Figure 3: Example of a travel route

To make it easier to vary the *travel routes* across different households, *travel routes* can be combined into a *travel route set*. Every *travel route set* can then be combined with every *household* and every *transportation device set* to evaluate all possible combinations. One requirement is though that there needs to be a *travel route* between every *site*. Indirect routes such as site C only being reachable from Site A by first traveling to site B are not supported.

Simulation

Using the agent simulation and the transportation devices, realistic movement profiles can be generated. Thus, the simulation knows for every time step where the car is, what the current SOC is and where it is going to go next. Based on those it is possible to generate charging profiles. The next step will be using charging profiles based on measured charging profiles from different electric cars and adjusting them as needed. This is planned for the next version.

MEASUREMENTS

Different electric cars use different charging strategies. Modeling charging as simple rectangle profiles can introduce a significant error. To evaluate the differences between cars, a measurement project was started where 10 different electric cars where charged and the charging was recorded with a time resolution of 1 Hz. This section will show selected examples of the different charging profiles. One example of such a charging profile is shown in Figure 1 and Figure 2. The chart shows that this car uses a large amount of reactive power and modeling this behavior with a simple rectangular profile would introduce large errors.

In the charts below it is visible for example that Renault made significant progress in optimizing the charging process in the years from 2014 to 2017 (Figure 4 vs. Figure 5). Figure 6 shows that for example the Zoe has very high reactive power demands of up to 6300 var.

Figure 7 shows that the Nissan Leaf towards the end of the charging process does some balance charging where it waits a few minutes and then tries to top up the battery three times to maximize the range. Tesla has a very smooth charging curve, but towards the end they tend to simply switch off single phases (Figure 8)

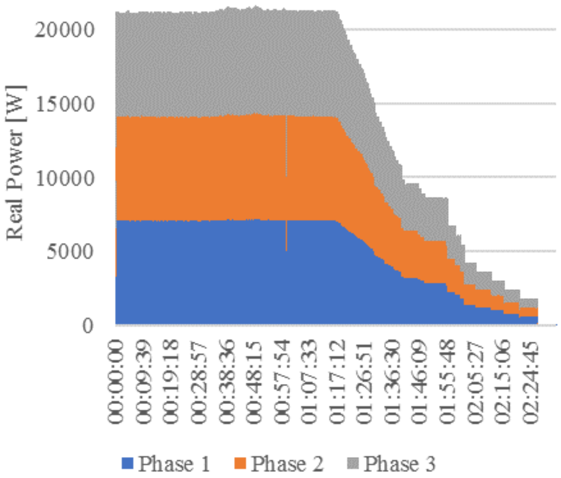

Figure 4: Charging profile of a Renault Zoe (2017)

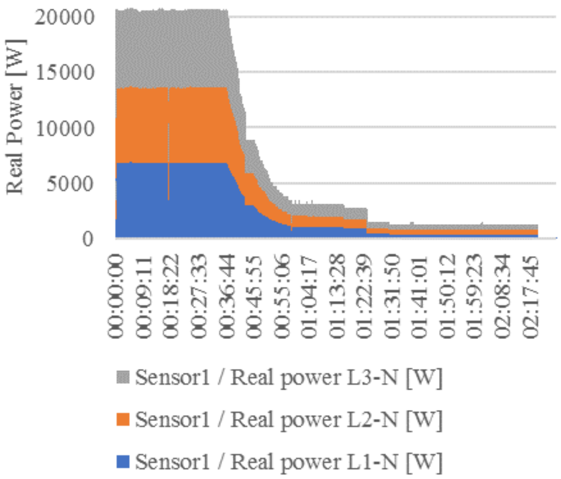

Figure 5: Charging profile of a Renault Zoe (2014)

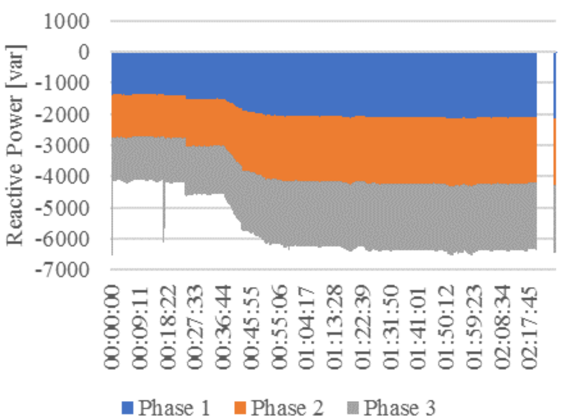

Figure 6: Reactive power while charging a Renault Zoe (2014)

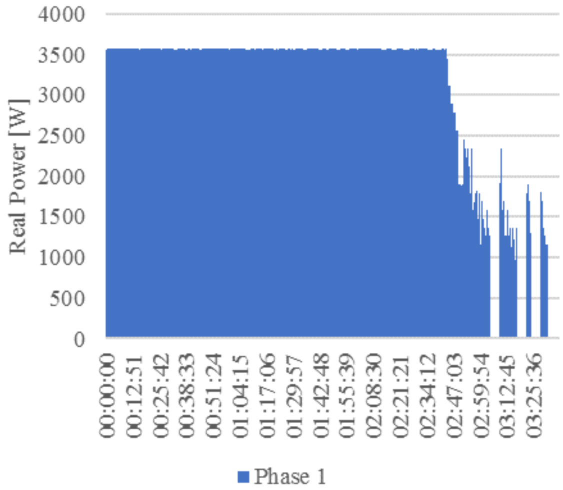

Figure 7: Charging profile for a Nissan Leaf (2015)

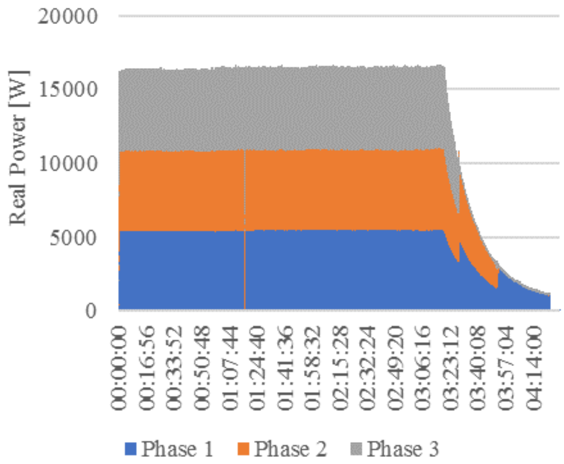

Figure 8: Charging Profile of a Tesla X to 100%

SIMULATION RESULTS

This section shows some of the simulation results, both of the behavior simulation, and the average yearly electricity profile. Due to limited space, only examples from single person households will be shown. All examples use the simplest charging strategy: the user plugs in the car as soon as he/she gets home.

Figure 9 shows the carpet plot of the activities of a simulated office worker. It is visible that this person does not use an alarm clock but has a very regular lifestyle with two vacations over the year. Figure 10 shows the average yearly electricity profile. Figure 11 shows the average yearly profile if the person has a distance to work of 5km and uses an EV that gets charged with 10 kW at home. Figure 12 shows the same, but with a distance to work of 30km, which works out to 60km for a round trip. Average daily distance for workdays in Switzerland is about 50km. Figure 13 shows the electricity profile for the same case, but the charging power is limited to 3kW. The charging then extends significantly further into the night.

Figure 14 shows the averaged electricity profile for a shift worker, who also has to commute 30 km to work and who is working in three shifts. It is visible that this working pattern does not generate the huge evening peak.

This short study shows that there will be a very strong need intelligent charging control as soon as a larger number of EVs are in use. The electricity consumption of average commutes will significantly change the load profile. And the charging times of office workers are not very well suited to charging with photovoltaic energy. This means that by offering charging stations at company parking spaces, utility companies have the potential to directly sell cheap photovoltaic electricity without any need for buffering.

Table 1 shows the yearly energy consumption of the different cases for comparison.

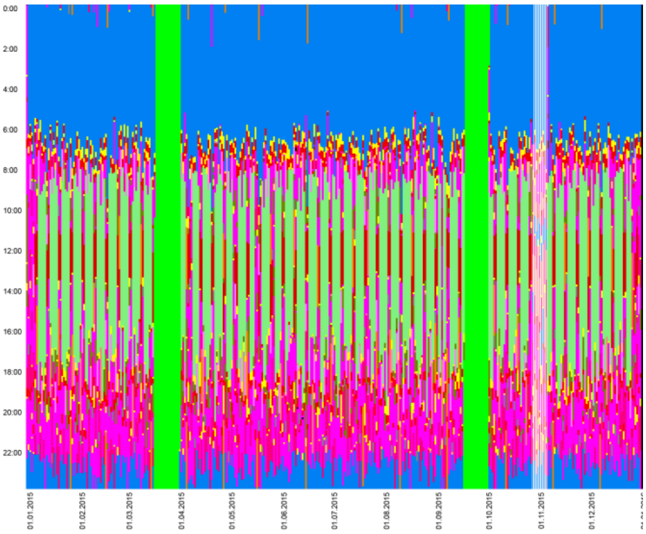

Figure 9: Carpet plot of the activities of the office worker without EV. Blue is sleep, light green is work, bright green areas are vacations, white is illness, yellow is hygiene and purple is leisure time, such as TV, internet or food.

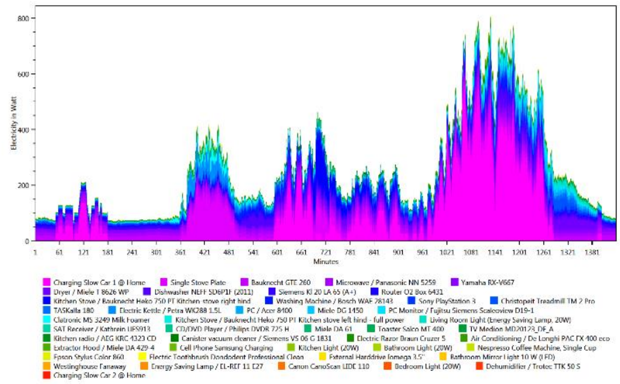

Figure 10: Averaged yearly electricity load profile without any electric vehicle

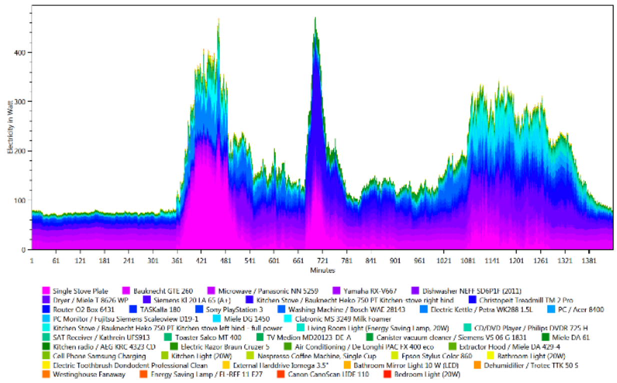

Figure 11: Averaged yearly electricity profile with a driving distance of 5 km to work

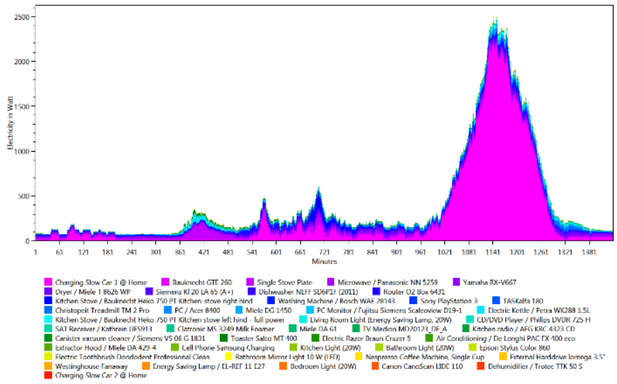

Figure 12: Averaged yearly electricity profile with a driving distance of 30 km to work and 10 kW charging power

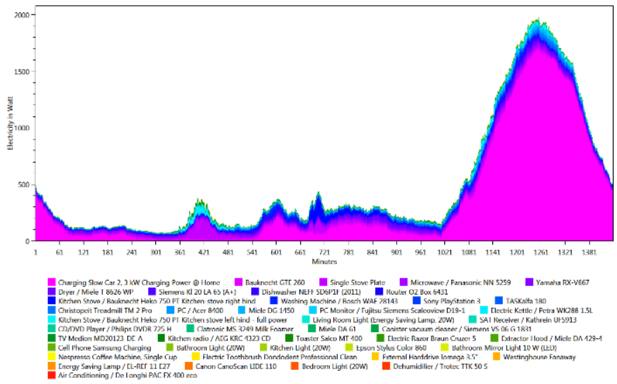

Figure 13: Averaged yearly electricity profile with a driving distance of 30 km to work and 3 kW charging power

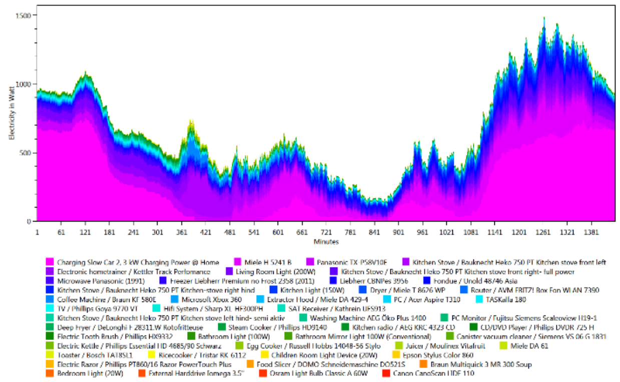

Figure 14: Averaged yearly electricity profile for a shift worker with a driving distance of 30 km to work and 10 kW charging power

Table 1: Comparison of the energy consumptions for different configurations

Type of Household	Figure	Total Yearly Electricity Use [kWh]	Electromobility Energy Use [kWh]
Office Worker without electric car	Figure 10	1533	0
Office worker, EV, 5km to Work	Figure 11	2217	732
Office Worker, EV, 30 km to Work, 10 kW	Figure 12	3654	2261
Office Worker, EV, 30km to work, 3 kW	Figure 13	4382	2998
Shift worker	Figure 14	5983	2370

CONCLUSION

The results show that:

- For modeling EV charging, it is recommended to use measurement data, since real charging behavior diverges significantly from a single rectangle profile.
- There are large differences in the charging behavior of different cars.
- The behavior of the user of the electric car and their work times strongly influence the charging profile.
- For office workers who charge at home, it is very difficult to achieve a high percentage of PV self-consumption with electric cars, since they are mostly not home when there is solar energy available.
- Offering workplace EV charging might become a very interesting business case for utility companies in areas with high PV penetration because it provides an easily controllable, reliable and large energy sink to sell PV electricity with a good profit while at the same time saving them the cost of reinforcing the residential grid areas.

The introduced model makes it possible to easily model different kinds of behavior, mobility patterns and transportation devices to generate input data for analyzing current and future energy systems. The load profile generator is freely available and has proven to be very helpful for other researchers looking for input data for their models.

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