

# Impact of High Penetration of Electric Vehicles, Heat Pumps and Photovoltaic Generation on Distribution Grids – An Analysis of a German Case

Tao Mu  
RZVN Wehr GmbH  
Düsseldorf, Germany  
mu@rzvn.de

Denis Bekasow  
RZVN Wehr GmbH  
Düsseldorf, Germany  
bekasow@rzvn.de

Piet Hensel  
RZVN Wehr GmbH  
Düsseldorf, Germany  
hensel@rzvn.de

**Abstract**—Electric vehicles (EVs), heat pumps (HPs) and the expansion of decentralized photovoltaic (PV) generation will lead to completely new load situations in power systems and may bring great challenges to electric utilities, especially at the distribution level. The methodology of modelling EVs, HPs and PVs is developed, which enables the generation of locally differentiated load scenarios for the power system simulation. Based on the dynamic load flow calculations, four scenarios are generated and simulated for a medium sized town in Germany. The results show the validation of the modelling methodology and the outlook of the distribution grid.

**Keywords**— *electric vehicle, photovoltaic, heat pump, load profile, distribution grid*

## I. INTRODUCTION

The transition from fossil fuels to electricity in the transportation sector will strongly impact electricity consumption [1]. By 2030, it is estimated that the number of electric vehicles (EVs) in Germany will be up to 7 million, with a market share of 15 percent [2]. Besides EVs 5 to 6 million heat pumps (HPs) are needed to meet the 2030 climate protection target set by the German government [3]. Only electrifying the traffic and building sectors is not sufficient to reach the climate protection target. The additional electricity consumption in the heating and traffic sector must be covered by CO<sub>2</sub>-free energy sources. Solar energy is besides wind power one of the best options to meet future energy demand since it is superior in terms of availability, cost effectiveness, accessibility, capacity, and efficiency compared to other renewable energy sources [4]. EVs, HPs and the further expansion of solar generation, especially PVs, will lead to completely new load situations in power systems. Their high penetration may bring great challenges to electrical utilities especially at the distribution level. In this study different scenarios are generated and analyzed for a medium sized town (population: approx. 40,000) in Germany on the basis of a simulation model, in which charging points, HPs and PVs are distributed in the medium-voltage and low-voltage grids.

The following three sections present at first the methodology employed to model the electric demand of EVs, the electric demand of HPs and the generation of PVs respectively. Section V then illustrates and discusses the results of the four future scenarios, and the paper closes in Section VI with conclusions and an outlook.

## II. MODELLING THE ELECTRIC DEMAND OF EVS

### A. Normal Charging

Due to the uncertain development of the mobility sector and thus numerous random variables, a reliable statement about the future distribution of the charging stations and their charging power is not possible. Hence the integration of the charging stations in the simulation model is carried out according to the so-called *area principle*. Accordingly, all low-voltage electricity consumers are equipped with a virtual charging station (VCS). The power of these charging stations corresponds to the average value of the local charging power in a subgrid, namely a local charging profile (LCP).

The concept of LCP is similar to the standard load profile for household, commercial and industrial consumers [5]. In order to establish the LCPs, the spectrum of charging power in the grid and the number of potential charging stations in the subgrids (e.g., one subgrid is the part of grid supplied by one local substation) are investigated. Then individual charging profiles (ICP) are generated for each potential charging station in each subgrid.

To generate the ICPs the following factors are considered in this study: charging location (at home, at work and in public), charging power, battery capacity, driving profile (path length), power consumption, and arrival time. The associated values are taken from the studies in Germany [6].

While driving profile and power consumption are assumed to be constant values (e.g., 50 km / d and 20 kWh / 100 km), the arrival time and battery capacity are modelled as distribution functions. The battery capacity is represented by the uniform distribution function with the range between 20 kWh and 80 kWh. The arrival time is approximated with a normal distribution for the study. For charging at home the expectation of this distribution is 18:00. For charging at work it is assumed that the highest simultaneity occurs at 09:00.

In addition to the parameter settings, it is assumed that the number of charging stations in the grid corresponds to the number of electric vehicles. This means that one EV is allocated to one charging station.

Based on the parameters and assumptions the ICPs in the grid are calculated. The ICPs within one subgrid are then combined to form a subgrid charging profile (SCP). After that the SCPs are divided by the number of consumers located in the respective subgrid, so that the LCPs are formed, which are then assigned to the VCSs in the respective subgrid.

Fig. 1 summarizes the methodology of Modelling the normal charging loads.

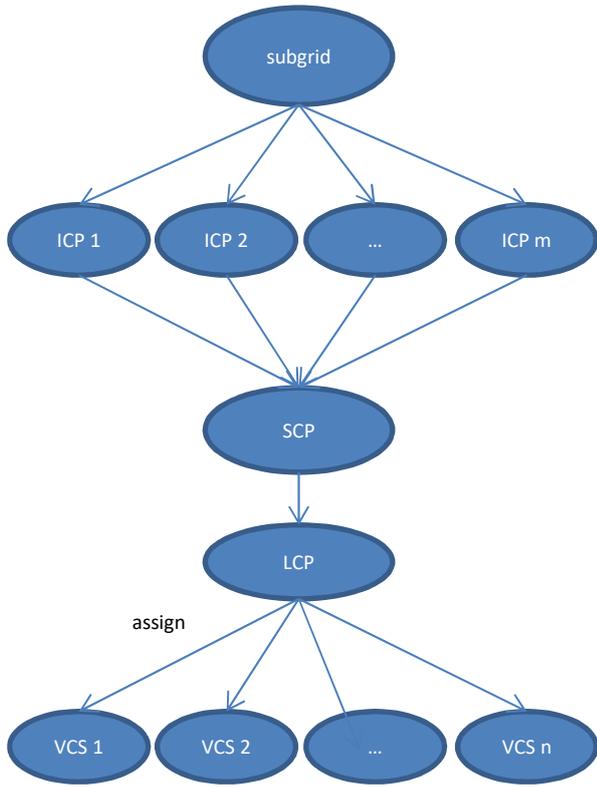


Fig. 1. Modelling of the normal charging loads

The introduced random variables for the arrival time and the battery capacity give rise to various combinations of charging behaviours, which leads to different SCPs and thus LCPs in the same subgrid. Fig. 2 and Fig. 3 illustrate two randomly generated SCPs for one subgrid. They have different simultaneities and peak values. The peak value in Fig. 3 is 51.4 kW more than in Fig. 2.

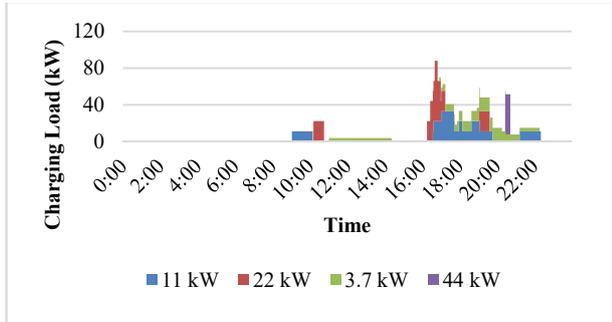


Fig. 2. SCP with low simultaneity

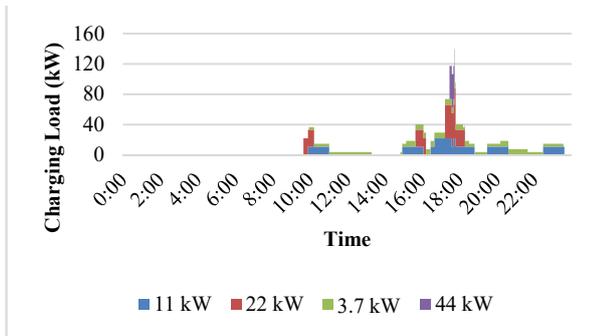


Fig. 3. SCP with high simultaneity

With regard to the worst case, it is necessary to generate LCPs that can represent the extreme charging loads. In order to create the LCPs that can represent the worst case, the algorithm of LCP will be executed as many times as needed. For the heavy load cases, the LCPs with the highest peak value will be selected and then assigned to the VCSs in the respective subgrid. For the light load cases, the LCPs with the lowest peak value will be selected and then assigned to the VCSs in the respective subgrid.

### B. Fast Charging

In contrast to normal charging, the fast charging stations with charging power more than 44 kW are considered separately and explicitly assigned to a connection point in the grid. The allocation of fast charging stations is based on the long-term power system planning of the local utility.

Due to the higher charging power, fast charging stations are not connected directly to the low-voltage distribution system. Instead, they are connected directly to the nearest substation with the specified power. Unlike the normal charging, the fast charging stations receive constant power from the distribution grid. That is to say, they have a charging profile with constant power.

## III. MODELLING THE ELECTRIC DEMAND OF HPS

The integration of the electric demand of HPS into the simulation model is based on the annual electricity consumption (AEC) and temperature-dependent load profile (TDLP).

### A. Deriving AEC from Annual Heating Demand

It is assumed here, that most of HPS are installed in new or recently renovated buildings. As the heating demands of these buildings are not exactly known, they are estimated from the typical building area and average heat consumption.

$$AHD_i = A_i \times h_a \quad (1)$$

$AHD_i$  is the annual heating demand of consumer  $i$ .  $A_i$  is the typical building area (125 m<sup>2</sup> for a house, 70 m<sup>2</sup> for an apartment).  $h_a$  is the average heat consumption (60 kWh/(m<sup>2</sup>·a) for a house, 50 kWh/(m<sup>2</sup>·a) for an apartment).

The resulting heating demand of the consumer is then converted to AEC using the coefficient of performance (COP).

$$AEC_i = AHD_i / COP \quad (2)$$

In order to simulate the worst case for the electric grid, it is assumed that only air/water HPS with the lower COP of about 2.5 will be installed instead of groundwater HPS with a higher COP.

Considering the different penetration degree of HPS in the subgrids, the AECs are then scaled and integrated into the simulation model for each low-voltage house connection.

$$AECP_i = AEC_i \times s_p \quad (3)$$

$AEC P_i$  is the annual electricity consumption of consumer  $i$  with the penetration degree  $p$ .  $s_p$  is the scale factor, which may be different in subgrids.

### B. TDLP

In order to convert the derived AECs (kWh) to loads (kW), TDLPs are introduced into the simulation model. The standardized TDLPs for HPs are provided by the local utility. Fig. 4 shows the TDLPs of the utility.

For the dynamic load flow calculation, the TDLP with temperature of  $-12\text{ }^\circ\text{C}$  is employed for the heavy load case in this study.

## IV. MODELLING THE GENERATION OF PVS

### A. Investigation of the PV Potential

The evaluation of the future feed-in situation of PVs is carried out based on a PV potential study of the utility. The buildings, which are suitable for the installation of PVs, were identified in the study. According to the building architecture, particularly the roof shape, the potential power of PV was also estimated in that study, which was based on an exact solar cadastre of all buildings.

The PVs and the investigated feed-in potentials are integrated into the simulation model using the specified GIS-ID of the connection points in the distribution grid.

### B. Feed-in Profile of PV

In contrast to the electricity consumption, the power outputs of PVs at a geographically adjacent location are similar. In the region of a local utility, a simultaneity factor of up to 0.9 can be assumed.

The feed-in profile of PV is directly proportional to the rated power and thus does not need to be normalized to an annual energy consumption. As a reference for the respective feed-in profiles, power measurements of large local PV systems are used. In addition to the rated power, other information, such as the tilt and alignment of the measured PV equipment, are also needed to adapt the feed-in profiles of PV systems to different site conditions.

The typical 24-hour feed-in profiles of PV considering the environmental influences are exemplarily illustrated in Fig. 5.

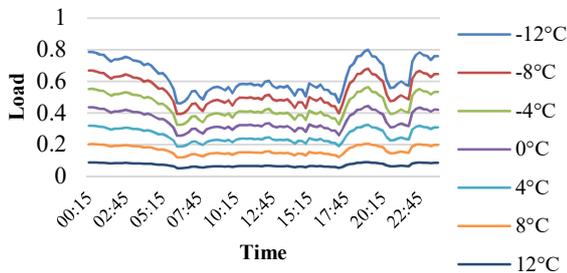


Fig. 4. TDLP of HPs

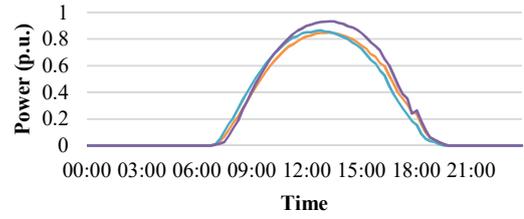


Fig. 5. Typical 24-hour feed-in profiles of PV

TABLE I. AMOUNTS OF THE KEY ELECTRIC COMPONENTS

Electric Component	Amount
HV/MV Substation	3
MV/LV Substation	211
House Connection Point	9,877
Decentralized Generator	230

TABLE II. LOAD AND DECENTRALIZED GENERATION

Loading Case	Power from High Voltage Grid (MW)	Decentralized Generation (MW)	Load (MW)
Heavy Load Case	30.2	1.3	31.5
Light Load Case	14.8	12.0	26.8

## V. RESULTS AND DISCUSSION

The modelling methodology described above is applied in a local electrical utility in Germany to evaluate the impact of high penetration of EVs, HPs and PVs on the distribution grid.

### A. Characteristic Data of the Distribution Grid

The utility supplies electricity to a medium sized town (the population is about 40,000) in Germany. The amounts of the key electric components are listed in Table I.

In order to model the load cases (heavy and light load), two characteristic days are selected. Table II shows the selected load cases with the load and generation values.

### B. Definition of the Scenarios

The operation condition of the distribution grid depends on the development speed of EVs, HPs and PVs in the distribution system. According to the progress report from the German National Platform for Electric Mobility, by 2025 a market share of between 4 and 6.5 percent is expected. By 2030, it is estimated that the number of EVs will be between 4.2 and 7 million, with a market share of 10 - 15 percent [2]. Respectively, two scenarios are defined for the utility, namely the market shares of 6% and 15%. In this study one more ambitious scenario, a market share of 45%, is also simulated and analysed (see Table III).

The scenarios differ not only with respect to the market share of EVs but also with respect to the distribution of the charging power. In scenario 1, which represents the short-term development of EVs, there is a relatively high share of 3.7 kW charging points. Scenario 2 and 3, however, consist mainly of 11 and 22 kW charging points (see Table III).

TABLE III. SCENARIOS

Scenario	Basic load	Market share of EVs (%)	Charging power	Charging period	REP of HP (%)	REP of PV (%)
1	Heavy Load	6	3.7 kW (73.7%) 11 kW (21.5%) 22 kW (3.5%) 44 kW (1.3%)	every day	7	0
2	Heavy Load	15	3.7 kW (29.4%) 11 kW (36.9%) 22 kW (27.4%) 44 kW (6.3%)	every day	16	0
3	Heavy Load	45	3.7 kW (29.4%) 11 kW (36.9%) 22 kW (27.4%) 44 kW (6.3%)	every three days	16	0
4	Light Load	0	-	-	0	100

The charging loads depend not only on the market share of EVs but also on the charging behaviour. For scenario 1 and 2, it is assumed that all the EVs charge every day, resulting in a relatively high simultaneity. In scenario 3, the more realistic case, it is modelled that EVs charge every three days

In order to observe the worst case, the charging loads are integrated into the simulation model on a heavy-load day. In addition, the generation of PVs is not considered in these heavy-load scenarios. For HPs two realization extents of potential (REP) are analysed, namely 7% and 16%.

100% of the PV potential in the area of the utility is assumed to be realized in the fourth scenario. EVs and HPs are not included in this scenario, because they counter the impacts of PVs on the distribution grid [7]. For the purpose of the observation of the voltage increase the potential PVs are modelled on a light load day.

### C. Result Comparison between Scenario 1 and 2

The assessment of the penetration of EVs and HPs is based on a dynamic load flow calculation for the heavy load day. The load curves of the two simulated scenarios are illustrated in Fig.6 and Fig.7: The maximum loads are increased in the two scenarios by 26.4% and 74.3% respectively. This result may appear counterintuitive at first, as it implies almost constant charging simultaneities for scenario 1 and 2. Actually, the simultaneity factor of 0.33 in scenario 2 is much lower than the respective factor of 0.62 in the first scenario. The proportional increase in the grid load results from the increase of the average charging power (6.4 kW vs. 13.9 kW), the number of fast charging stations (7 vs. 17) and the load of HPs (1.6 MVA vs. 4.0 MVA).

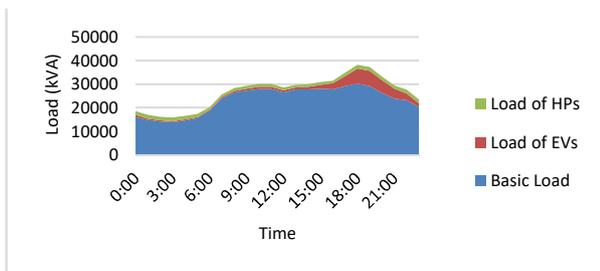


Fig. 6. Load curve of scenario 1

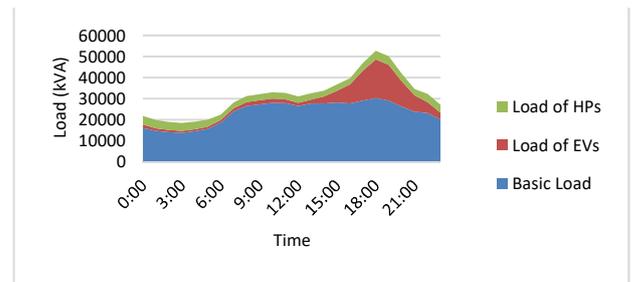


Fig. 7. Load curve of scenario 2

TABLE IV. OPERATION LIMIT VIOLATION OF SCENARIO 1 AND 2

Element with operation limit violation	Scenario 1	Scenario 2
Nodes with voltage < 0.9 p.u.	75 (0.4%)	999 (6%)
Power Lines with load > 100%	6 (0.23 km)	181 (3.1 km)
Transformers with load > 100%	0 (0%)	17 (12%)

Due to the additional load from EVs and HPs, low voltage and overload occur. The violations of operation limits in scenario 1 and 2 are listed in Table IV.

In scenario 1, there are only two subgrids, in which the voltage limit is violated. From 17:00, the voltage drops below 0.9 p.u. for several hours in both subgrids. In scenario 2, there are voltage maintenance problems in the entire low-voltage grid: 6% of the nodes in the low-voltage grid are subjected to a limit violation (voltage below 0.9 p.u.). Most of the low voltages occur in the evening between 17:00 and 21:00 (see Fig. 8). This is because most of EVs are charged in the evening.

There were no area-wide overloads of lines in the two scenarios. In the scenario 2, a total of 181 line sections with a total length of 3.1 km are identified to be overloaded in the low-voltage grid. In the subgrid "Gymnasium" a 114 m long NKBA 4x40 cable has a load of over 300% for a short time. Most of the overloads take place in the evening (see Fig. 9).

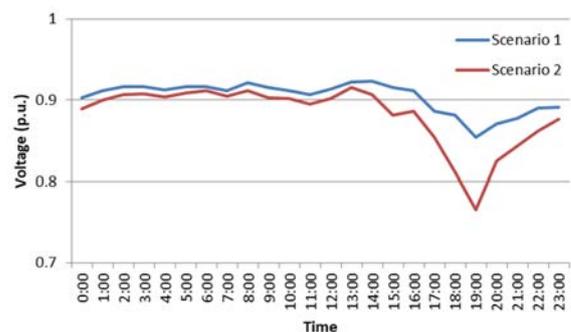


Fig. 8. Minimum voltage in the low-voltage grid

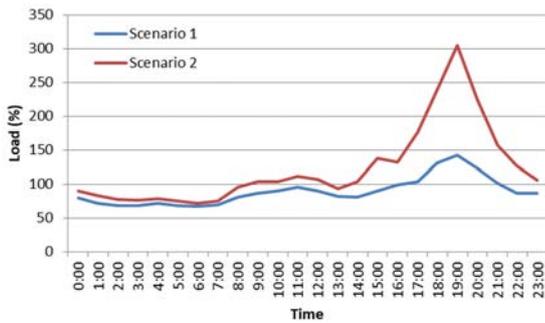


Fig. 9. Maximum load of power lines in the low-voltage grid

In contrast to the scenario 1, transformer overload was identified for 17 local substations in the scenario 2. The maximum load (177%) occurs at a 630 kVA transformer in the substation "Gymnasium". The average transformer utilization increased from 33% to 50% in the scenario 2.

#### D. Result Comparison between Scenario 2 and 3

The load of distribution system depends on the charging period of EVs. In scenario 2 it is assumed that all the EVs are charged every day. This is an extreme situation, which could happen before holidays. Scenario 3 is more practical, assuming that all the EVs are charged every three days. With the same charging power and charging start time (see Table V), the LCPs are comparable in the scenario 2 and 3, although there are three times of EVs in the scenario 3. The LCPs of one subgrid is depicted in Fig. 10.

From Fig. 10, we can see that the peak charging loads of the two LCPs are almost identical (0.469 kW for scenario 2 and 0.478 kW for scenario 3). However, the time span of peak load is considerably broader in the scenario 3 than in the scenario 2. Therefore, the results of low voltage and overload in the scenario 3 are similar to the scenario 2, but the durations are longer.

TABLE V. PARAMETER OF CHARGING PROFILE

Parameter	Distribution function	Value
Start time of charging	Normal distribution	Expectation: 18:00 (charging at home) 9:00 (charging at work)
Driving profile	Constant	50 km/d
Power consumption	Constant	25 kWh/100 km
Battery capacity	Uniform distribution	20 – 40 kWh 60 – 80 kWh
Charging power	Random choice	3.7 kW (29.4%) 11 kW (36.9%) 22 kW (27.4%) 44 kW (6.3%)

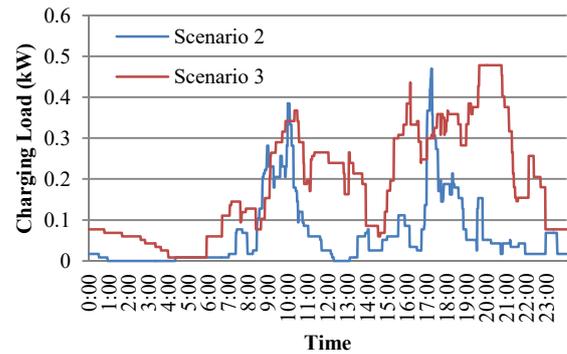


Fig. 10. LCP of one subgrid in scenario 2 and 3

#### E. Results of Scenario 4

A total of 1,488 potential buildings for PVs are identified. More than half of them (54%) have the potential generation power between 5 and 6 kWp. The total power, which could be generated by the potential PVs, is 8.8 MWp. Compared to the current decentralized generation the feed-in power would be increased by 73%.

All node voltages (medium and low voltage) are within the voltage limits ( $\pm 10\%$ ). The highest voltage occurs with 1.08 p.u. in the low-voltage grid. The high penetration of PV shows a relatively small influence on the load of power lines. On the most lines, the loads decrease. The total length of the overloaded cables is about 335 m, which are all in one subgrid. This result confirms experiences from other studies that the installation of PV in densely populated urban areas (in contrast to rural areas with low electricity consumption and relatively weak grids) usually does not lead to critical grid states.

## VI. CONCLUSION AND OUTLOOK

Based on the simulation model of the distribution system, the methodology of modelling EVs, HPs and PVs is developed, which enables the generation of locally differentiated load scenarios. Taking into account the penetration degree and the distribution of EVs, HPs and PVs, four scenarios are generated and simulated. The maximum load increases by 26.4% and 74.3% in the scenario 1 and 2 respectively. With full expansion of PV, the feed-in power of decentralized generation increases by 73%. As the proportion of EVs and HPs rose, the risk of low voltage increases. Since a significantly higher market share of EVs is expected in the medium to long term, without necessary measures such as grid enforcement, generation scheduling and demand side management, area-wide voltage problem will occur in the low voltage distribution grid. In contrast to the voltage maintenance, there will be no area-wide overloads of power lines and transformers. The evaluation of the low load case shows that a high penetration of PV in the low-voltage grid will not lead to overvoltage. Further expansion of PVs is therefore not a problem for the utility.

Based on this study the measures against low voltage and overload will be investigated in the future. Especially, a quantitative analysis of the potential of load management will be conducted in order to avoid the expensive grid enforcement.

## REFERENCES

- [1] D. Fischer, A. Harbrecht, A. Surmann and R. McKenna, "Electric vehicles' impacts on residential electric local profiles - A stochastic modelling approach considering socio-economic, behavioural and spatial factors," *Applied Energy*, vol. 233-234, pp. 644-658, 2019.
- [2] German National Platform for Electric Mobility, "Progress Report 2018 – Market ramp-up phase," Berlin, May 2018.
- [3] Fraunhofer IWES/IBP, "Heat transition 2030: Key technologies for reaching the intermediate and long-term climate targets in the building sector," Study commissioned by Agora Energiewende, February 2017.
- [4] E. Kabir, P. Kumar, S. Kumar, A. A. Adelodun and K. Kim, "Solar energy: Potential and future prospects," *Renewable and Sustainable Energy Reviews*, vol. 82, Part 1, pp. 894-900, 2018.
- [5] H. Meier, C. Fünfgeld, T. Adam and B. Schieferdecker, "Representative VDEW load profiles," Frankfurt (Main), 1999.
- [6] C. Nobis and T. Kuhnimhof, "Mobility in Germany – MiD results report," Study by infas, DLR, IVT and infas 360 on behalf of the Federal Minister of Transport and Digital Infrastructure (FE-Nr. 70.904/15), Bonn, Berlin, February 2019.
- [7] P. Denholm, M. Kuss and R. M. Margolis, "Co-benefits of large scale plug-in hybrid electric vehicle and solar PV deployment," *Journal of Power Sources*, vol. 236, pp. 350-356, 2013.