Increasing Self-consumption of Photovoltaic Electricity by Storing Energy in Electric Vehicle using Smart Grid Technology in the Residential Sector

A Model for Simulating Different Smart Grid Programs

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Keywords: Smart Grid, Photovoltaic Electricity, Self-consumption, Electric Vehicle, Energy Storage.

Abstract: In this paper a model has been developed which intends to simulate the increase of self-consumption of photovoltaic (PV)-power by storing energy in electric vehicle (EV) using smart grid technology in the residential sector. Three different possible smart grid control algorithms for a micro-grid consisting of solar panels, a household and an EV are presented that manage the (dis-)charging profile of an EV, either in real-time or using linear optimization using predictions for PV-power and electricity demand. The different control algorithms are simulated for a year using data for PV-power and electricity demand from the Netherlands and one specific EV. Preliminary results of the model are presented, showing that all control algorithms could significantly increase self-consumption and reduce peaks in electricity demand from the main grid. Although the difference in performance of the control algorithms for self-consumption is marginal, we find that linear optimization works better than the real-time algorithms for peak reduction.

1 INTRODUCTION

The worldwide increase of electricity demand poses major challenges in the energy sector. Since 1971, the final consumption of electricity has increased four-fold to 60 PJ in 2010 (IEA, 2012) and is expected to further increase due to growing global population and welfare. Issues related to this development include availability, cost and environmental issues such as global warming and depletion of resources. While the industrial sector has the highest demand for electricity, demand in the residential sector shows the highest increase in Europe (Bertoldi and Atanusiu, 2008) and is therefore an important sector for changes in electricity provision and distribution.

Another important sector contributing to global warming is the transport sector. Globally the contributions of the transport sector to greenhouse gas (GHG)-emissions amounted to nearly 20% in 2009 (Hoen et al., 2009). According to the European Federation for Transport and Environment (2011) CO_2 emissions from the European transport sector have increased by 29% since 1990.

Electric vehicles (EVs) are a promising technology for reducing the environmental burden of road transport (Essen, et al. 2011). If EV sales increase it can be beneficial for reducing GHG-emissions, but it also creates another issue; electricity demand will increase even further. Also, the typical charging pattern of EVs without a control system coincides roughly with that of households (E-laad, 2012), which is high in the morning and the evening and low in the afternoon; it thus contributes to existing peaks in electricity demand in the residential sector.

PV technology can be part of the solution to problems relating with electricity and transport, since there are no emissions of greenhouse gasses during electricity production. If PV electricity is used to power EV's, transport with EV will cause even less or zero GHG emissions. An important advantage of PV for the residential sector is its scalability; even single households can use this technology.

However, the mismatched production and load curve for PV for domestic use poses a challenge. PV installations produce most electricity around noon, when solar insulation is high, while electricity demand is usually low then. In addition, solar power supply may be variable due to variations in cloud coverage.

J. van der Kam M. and G. J. H. M. van Sark W..
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DOI: 10.5220/0004763000140020
In *Proceedings of the 3rd International Conference on Smart Grids and Green IT Systems* (SMARTGREENS-2014), pages 14-20
ISBN: 978-989-758-025-3

Strategies to deal with these issues are for instance demand response (DR) and electricity storage (Castillo-Cagigal et al., 2011): in their paper DR is defined as shifting load demand in order to optimize electricity demand. Optimization goals are for instance peak-shifting (flattening load demand curve) or increasing self consumption (consumption of locally produced electricity behind the meter) .

Smart grid technology combines the traditional electricity grid or microgrid (a local, low-voltage distritibution system) with information and communication technologies in order to add 'intelligence' to the grid (Verbong et al., 2012). DR is an essential aspect of smart grids, and is achieved by turning appliances on and off within a certain timeframe.

The main power grid can be used as virtual storage for electricity. When supply is higher than demand, electricity can be fed back and sold to the grid and vice versa. This is an interesting option, because in that case an expensive battery is not needed. However, with increasing numbers of PV-installations this strategy can become problematic, because of the increased power transport over the electricity grid. This will cause the need for more investments in the grid in order to prevent overloads. In response to this threat, several countries in Europe have started implementing policies to stimulate self-consumption (Castillo-Cagigal et al., 2011).

PV electricity could also be stored in EV batteries. This way EVs can help increase self-consumption. Furthermore, by using PV electricity to power EVs GHG emissions for personal transportation are reduced.

In this paper the potential of combining smart grid technology with electricity storage in EVs for increasing self-consumption in the residential sector is investigated. This is done by creating a model of a microgrid containing a household, solar panels and an EV and simulating the effect on self-consumption of PV-power of the system using smart grid technology. The baseline for the potential is the absence of a smart grid and is called "Uncontrolled Charging". The strategies investigated are "Real-time Controlled Charging", "Real-time Controlled Charging and Discharging", and "Linear Programming".

In section 2 the methodology is presented: it includes the structure of the microgrid (2.1), the proposed smart grid systems (2.2) and evaluation method (2.3). In section 3 the first simulation results are presented, analyzed and compared. Section 4 concludes the paper.

2 METHODOLOGY

The potential of increasing self-consumption by storing PV energy in EVs is investigated by performing computer simulations and evaluating the results on performance indicators for self-consumption and peak-reduction.

The basic input for the model is the total electricity demand of households per time-step, the supplied PV power per time-step and the technical specifications and planned use (average trip duration, distance and number of trips per week) of the EVs. Based on these inputs the electricity distribution for each time-step *t* is decided.

2.1 Micro-grid Model

The micro-grid contains a PV-installation, a household with electricity demand, an EV and a connection to the main grid; all elements are connected. The PV-power and household electricity demand are considered uncontrollable, Demand Side Management is not taken into account here, while the EV loading pattern is partly controllable and partly uncontrollable (when energy is needed for trips).

2.1.1 PV and Electricity Demand

The PV-installation provides electricity to the microgrid. Data for PV-power profiles per time-step is provided by Robin Berg from the company LomboXnet. The dataset relates to a PV-installation of 10 kWp in Utrecht, the Netherlands and is available at hourly time resolution from July 6th 2011 to December 31st 2012. For this paper it is assumed that the simulated household has 8 panels of 250 Wp available, which leads to an estimated annual yield of 1700 kWh assuming an annual yield of 850 kWh/kWp, typical for the Netherlands.

The household has a certain electricity demand profile that must be met at all times. Data for household electricity demand is provided by Felix Claessen and is based on measurements by Liander (Claessen, 2012). The dataset relates to 400 households in the Netherlands and is available per 15 minutes for a week in February 2008. The weekly data is repeated for a year multiplied by a factor per week based on measurements from Liander in 2007. In this research only the households are selected that use 3500 ± 20% kWh per year.

2.1.2 Electric Vehicle

The battery of the EV is used as storage for excess PV-power and energy can be extracted from it when there is shortage of PV-power. The EV is also used to make trips; energy needed to make trips is considered inelastic demand and must be met at all times. When an EV is on a trip it is not available to exchange energy with the micro-grid. It is assumed that on average three trips per week are made with the EV, lasting between 4 and 8 hours, taking place between 8:00 and 22:00 and using between 20% and 80% of the battery capacity.

Without a smart grid program, the EV, if connected, will always charge until its full. This strategie is called "Uncontrolled Charging" and is represented by equation (1).

$$\text{If } E_{EV}(t-1) < C_{EV} \wedge t \in t_l \rightarrow P_{EV,in}(t) = P_{EV,in,max} \quad (1)$$

With $E_{EV}(t)$ the energy contained in EV-battery, C_{EV} the battery capacity, t_l the time-steps for which the EV is at the loading station, $P_{EV,in}(t)$ the EV charging power and $P_{EV,in,max}(t)$ the maximum EV charging power.

One EV is simulated, with technical specifications based on Tesla Model S (Tesla, 2013). The technical specifications are presented in table 1.

With $E_{EV,min}$ the minimum energy in EV-battery, $P_{EV,out,max}(t)$ the maximum EV discharging power and $\eta_{EV,in}$ and $\eta_{EV,out}$ ^{the} (dis-)charging efficiency.

Table 1: Technical specifications of simulated EV.

C_{EV} (kWh)	85
$E_{EV,min}$	20% C_{EV}
Energy consumption (kWh/km)	0.2
Typical range (km)	340
$P_{EV,in,max}$ and $P_{EV,out,max}$ (kW)	22
$\eta_{EV,in}$ and $\eta_{EV,out}$	80%

2.2 Smart Grid Programs

In this section several control algorithms for electricity distribution within the micro-grid are proposed. All control algorithms require trips to be planned in advance. The minimum amount of energy in the battery is 20% allowing for short emergency trips.

2.2.1 Real-time Controlled Charging

"Real-time controlled charging" uses the difference between P_{PV} and P_{load} for every time-step t. Based on the energy content of the EV the loading pattern is decided. In this algorithm, it is not possible to extract energy from the EV in order to cover electricity demand of the households.

First $E_{EV,req}$, the minimum amount of energy in the EV taking into account energy needed for trips and maximum charging power, is defined in equation (2).

$$\text{If } t \in \left(t - \frac{E_{EV,trip}}{P_{EV,in,max}}, t_{trip}\right) \rightarrow E_{EV,req} = E_{EV,trip} - P_{EV,in,max} \cdot (t_{trip} - t) + E_{EV,min} \quad (2)$$
$$\text{If } t \notin \left(t - \frac{E_{EV,trip}}{P_{EV,in,max}}, t_{trip}\right) \rightarrow E_{EV,req} = E_{EV,min}$$

With $E_{EV,trip}$ the total energy used for the trip and t_{trip} the start-time of the trip.

The loading pattern is then defined by equations (3), (4), (5) and (6).

$$P_{EV,in}(t) = P_{EV,in,PV}(t) + P_{EV,in,grid}(t) \quad (3)$$

$$\text{If } P_{load}(t) < P_{PV}(t) \wedge E_{EV}(t-1) < C_{EV} \wedge t \in t_l \rightarrow P_{EV,in,PV}(t) = \eta_{EV,in}(P_{PV}(t) - P_{load}(t)) \quad (4)$$

$$\text{If } E_{EV}(t-1) + P_{EV,in,PV}(t) < E_{EV,req}(t) \wedge t \in t_l \rightarrow P_{EV,grid}(t) = E_{EV,req}(t) - E_{EV}(t-1) - P_{EV,in,PV}(t) \quad (5)$$

$$P_{EV,in}(t) \leq P_{EV,in,max} \quad (6)$$

With $P_{EV,in,PV}(t)$ the PV-power used for charging the EV, $P_{EV,in,grid}(t)$ the power from the main grid used for charging the EV, $P_{PV}(t)$ the available PV-power and $P_{load}(t)$ the total load demand of the household.

Equation (3) denotes that the EV is charged with power from the PV-installations and from the grid. If there is more PV-power than electricity demand, the EV starts to charge until it is full or until there is no more excess PV-power, see equation (4). The EV only extracts energy from the grid when there is shortage of PV-power in order to make a trip, see equation (5). Finally, equation (6) makes sure the total power into the EV cannot exceed the maximum charging power.

2.2.2 Real-time Controlled Charging and Discharging

This program uses the same equations as "real-time controlled charging", but is also able to extract energy from the EV in order to cover electricity demand of households. The additional equations are presented in (7) and (8).

$$\text{If } P_{load}(t) > P_{PV}(t) \wedge E_{EV}(t-1) > E_{EV,req}(t) \wedge t \in t_l \rightarrow P_{EV,out}(t) = \eta_{EV,out}^{-1}\left(P_{load}(t) - P_{PV}(t)\right) \quad (7)$$

$$P_{EV,out}(t) \le P_{EV,out,max} \quad (8)$$

2.2.3 Linear Programming

Increasing self-consumption of PV-power by controlling the loading pattern of an EV can be described as a linear optimization problem and solved by using linear programming. Linear programming is a method to solve constrained optimization problems. Constrained optimization is a technique used often in research on smart grids. Recent examples are Guo et al. (2012), Silva et al. (2012), Tanaka et al. (2011), González Vayá and Andersson (2012).

The variables used in the linear program are $P_{EV,in,PV}(t)$, $P_{EV,grid}(t)$, $P_{EV,out}(t)$, for every time-step t. In order to maximize self-consumption, the PV-power used to charge the EV is maximized. This results in the following problem:

$$\max \sum_{t} P_{EV,in,PV}(t) \quad (9)$$

subject to the following constraints:

$$P_{EV,in,PV}(t) + P_{EV,in,grid}(t) \le P_{EV,in,max}, \quad t \in t_l \quad (10)$$

$$P_{EV,out}(t) \le P_{EV,out,max}, \quad t \in t_l \quad (11)$$

$$\sum_{t'=1}^{t} \eta_{EV,in}\left(P_{EV,in,PV}(t') + P_{EV,in,grid}(t')\right) - \sum_{t'=1}^{t} \eta_{EV,out}^{-1} P_{EV,out}(t') \ge E_{EV,req}(t) + E_{EV,trip}(t) - E_{EV}(0), \quad t \in t_l \quad (12)$$

$$\sum_{t'=1}^{t} \eta_{EV,in}\left(P_{EV,in,PV}(t') + P_{EV,in,grid}(t')\right) - \sum_{t'=1}^{t} \eta_{EV,out}^{-1} P_{EV,out}(t') \le C_{EV}(t) + E_{EV,trip}(t) - E_{EV}(0), \quad t \in t_l \quad (13)$$

$$P_{EV,in,PV}(t) \le P_{PV}(t) - P_{load}(t), \quad t \in t_l \quad (14)$$

$$P_{EV_i,out} \le P_{load}(t) - P_{PV}(t), \quad t \in t_l \quad (15)$$

With dummy variable t'. Constraints (10) and (11) ensure that the maximum (dis-)charging power is not exceeded. Constraints (12) and (13) ensure that the energy in the EV is sufficient for trips and does not exceed the battery capacity. Constraints (14) and (15) ensure that not more energy is (dis-)charged then there is excess or shortage of PV-power (when there is not enough PV-power for trips energy is extracted from the grid). Furthermore, all variables are non-negative.

Contrary to the real-time programs linear programming is based on perfect information; all the constraints are known for all time-steps t. However, PV-supply and electricity demand are not known exactly in advance. In order to provide realistic prediction of how effective this program would be in reality, some assumptions have been made. In this paper, the method is called "realistic linear programming".

It is assumed that the calculations are made at midnight and are based on the load pattern from the previous day. An exception is made for weekends, since weekend load demand differs significantly from weekdays. However, the data is only available for a week. Because of this predictions for Saturdays will be based on data for Sundays and vice-versa. The input for PV is based on PV-power predictions. It is assumed that prediction deviates from the real value with a standard deviation σ of 10%. This results in the following equations:

$$P_{load,prediction}(t) = P_{load,real}(t - 24\text{h}) \quad (16)$$

$$P_{PV,prediction}(t) = P_{PV,real}(t) \pm 10\% \quad (17)$$

The linear program is then executed with the predicted values, while it is evaluated with the real values.

2.3 Evaluation

All programs are simulated for each month of the year. Based on the simulations the potential of increasing self-consumption (SC) is calculated. Self-consumption is defined as the relative amount of PV-power for period T, with starting point T0, used by either the households or the EV, see equation (18).

$$\text{SC}(T) = \sum_{t=T0}^{T} \frac{\min\left[P_{PV}(t), P_{load}(t) + P_{EV}(t)\right]}{P_{PV}(t)} \quad (18)$$

A second indicator, relative peak reduction (RPR) is also used for evaluation. RPR compares the deviation from the average of the load demand for the main grid $P_{grid,tot}(t)$, defined in equation (19), with a control algorithm, denoted as $P_{grid,tot,control}(t)$, to "uncontrolled charging", denoted as $P_{grid,tot,no\ control}(t)$, and is defined in equation (20):

$$P_{grid,tot}(t) = P_{load}(t) + P_{EV}(t) - P_{PV}(t) \tag{19}$$

$$\mathrm{RPR}(T) = \frac{\sum_{t=T0}^{T} \left| P_{grid,tot,control}(t) - \overline{P_{grid,tot,control}(t)} \right|}{\sum_{t=T0}^{T} \left| P_{grid,tot,no\,control}(t) - \overline{P_{grid,tot,no\,control}(t)} \right|} \tag{20}$$

So for example, an RPR-score of 1 indicates no relative peak reduction compared to “uncontrolled charging”, a RPR-score of 0 means load demand is totally flat for that day and a RPR-score above 1 would mean that there are higher peaks compared to “uncontrolled charging”.

3 RESULTS

In this section, the first results from simulations are shown. The results are based on 20 simulations per month for each smart grid program. In figure 1, examples of individual runs for each program are given. They are based on the same load and PV profile and EV-trip.

In the case of “uncontrolled charging”, the EV arrives home in the evening and starts charging when there is no PV-power available. In the cases of “Controlled charging” and “Controlled charging and discharging” the EV only loads in times of excess PV-power, but there is still a large peak in the charging profile, since the EV needs to load much

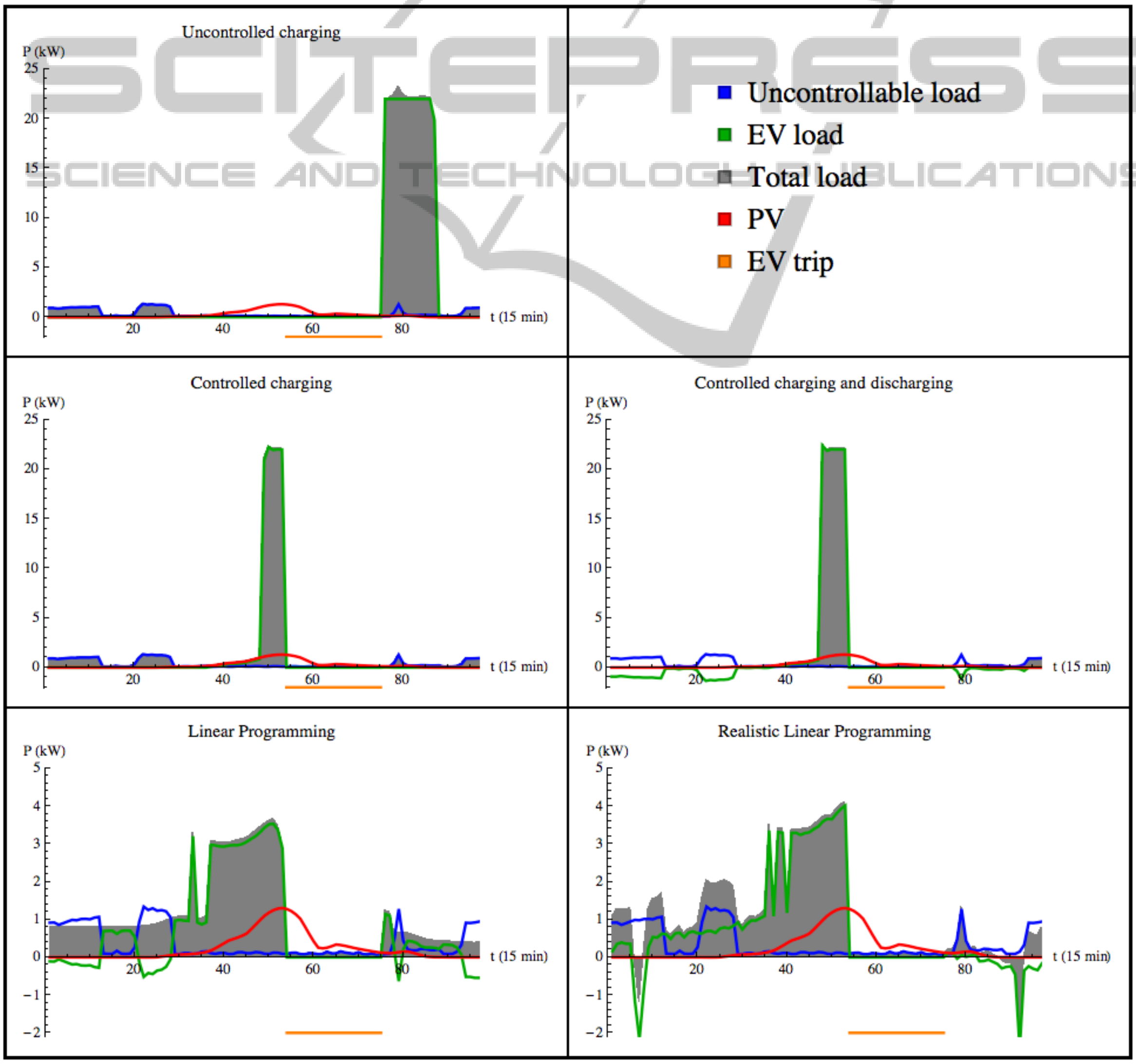

Figure 1: Results of an individual full day run for each control algorithm. The orange bar shows the period during which the EV is being used for a trip.

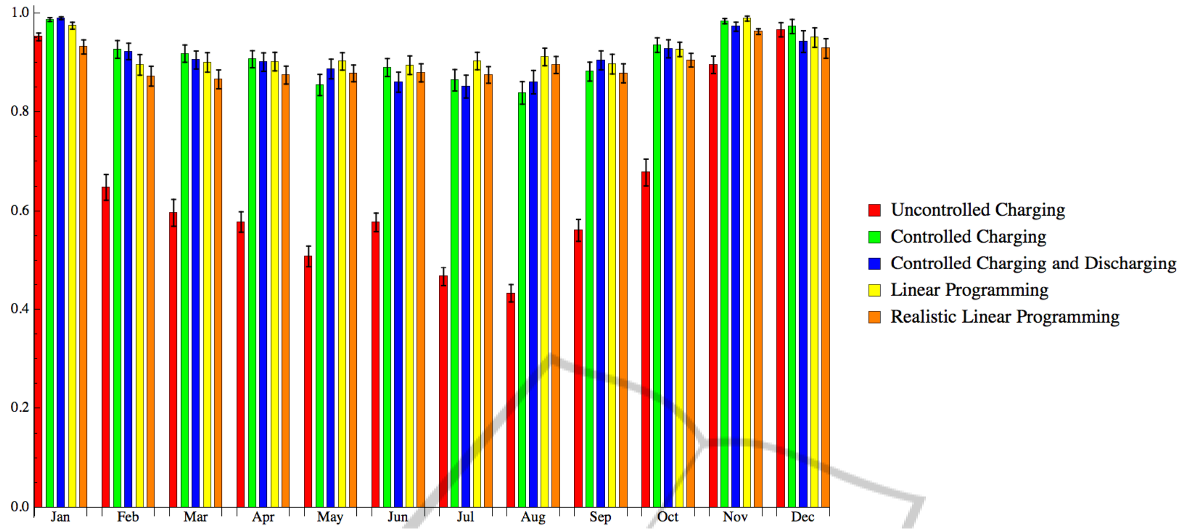

Figure 2: Mean self-consumption and standard deviation of 100 simulations of each control algorithm for each month.

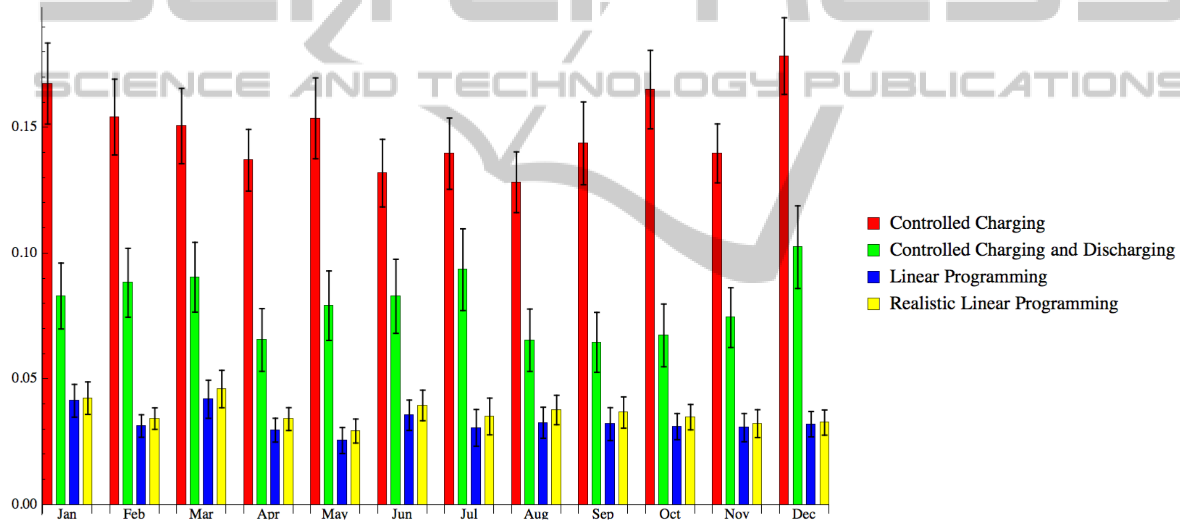

Figure 3: Mean peak reduction and standard deviation of 100 simulations of each control algorithm for each month.

more than there is PV-power available. Note that the latter total load is very small outside the peak.

For both programs using linear optimization the peaks in energy use are much smaller than for the other programs, since the EV never charges at full power, but at 20-25%. Because the requirements for the trip are still exactly planned in the realistic case, there are no problems for EV-use. However, it does not perform as well as the idealistic case, since electricity is fed back to the grid when it could by used to cover load demand.

In figure 2, results from 100 24 hour simulations per month for each program evaluated for self-consumption are shown. It can be seen that even though all systems perform much better than a system without a smart grid, it is difficult to tell which system performs best for self-consumption. The differences between the programs are large when compared for peak reduction (figure 3), showing that “linear programming” flattens the load demand for the main grid significantly better than the real-time algorithms.

4 CONCLUSIONS

In this paper several control algorithms for increasing self-consumption of PV-power in the residential sector, using smart grid technology and electricity storage in an EV, were proposed. The first simulations show that all proposed systems could significantly increase self-consumption. Though the systems have distinctive characteristics for the resulting EV charging profile, it is unclear which system performs best based on the proposed indicator for self-consumption. In order to investigate this issue, more simulations must be carried out.

However, when evaluated on peak reduction, the differences are much more clear. “Linear programming” is superior to the real-time algorithms for peak reduction.

As a follow-up of this paper, an extensive sensitivity analysis will be performed for the following parameters: (a) amount of solar panels (kWp), (b) average yearly household electricity use, (c) technical specifications of the EV, (d) EV trips, and (e) the standard deviation in PV-power predictions. Nevertheless, based on our preliminary results, it is shown that a microgrid using smart grid technology and electricity storage in an EV could significantly increase self-consumption of PV-power in the residential sector.

ACKNOWLEDGEMENTS

The authors would like to thank Robin Berg and Floris Bruning from LomboXnet for providing the data used for the PV- installations and Felix Claessen for providing the electricity demand data for households.

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