Potential of increasing PV self-consumption with a combination of smart grid technology and storage in electric vehicles in the residential sector

A case study in Utrecht, the Netherlands

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Abstract

In this Master thesis a model is presented which was developed to simulate the increase of self-consumption of photovoltaic (PV)-power by storing energy in electric vehicles (EVs) using smart grid technology for a case study in the residential sector. The case study consists of a micro-grid including three PV-installations, an office, internet servers, three to five households and two to five EVs in the area of Lombok in Utrecht, the Netherlands. Four scenarios that differ in the amount of kWp for the PV-installations, the number of households and the number of EVs have been constructed. Three different possible smart grid control algorithms are presented that manage the (dis)charging profile of multiple EVs, either in real-time or using linear optimisation with predictions for PV-power and electricity demand. The control algorithms are simulated for a year for all scenarios using data for PV-power and electricity demand from the Netherlands and are evaluated for PV-power self-consumption and relative demand peak reduction. Furthermore a sensitivity analysis is performed in order to test the results for changes in input data and model structure. Results show that smart storage of electricity in EVs can increase self-consumption with 15% to 35%, reduce energy send to the main grid with 5 to 8 MWh per year and increase relative peak reduction with 55% to 75%, depending on which control algorithm and scenario is chosen. Furthermore, in a comparison of scenarios it is shown that installing additional solar power is not advisable when evaluating for self-consumption, because the simulations show that additional solar power will not be used within the micro-grid. Based on the results it can be concluded that designing an EV-charging control algorithm based on linear programming is the best way to increase self-consumption in this case study, because it scores best on self-consumption and relative peak reduction and is least sensitive for the aspects researched in the sensitivity analysis.

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List of abbreviations and symbols

Abbreviation	**Explanation**
CBS	Centraal Bureau voor de Statistiek
CO_2	Carbon dioxide
CGU	Christelijk Gymnasium Utrecht
DG	Distributed generation
DSM	Demand side management
E	Exa (10^{18})
EC	European Comission
EK	Eerste Kamer der Staten-Generaal
EPA	United States Environmental Protection Agency
EU-25	Member states of the European Union per May 1st 2004
EV	Electric vehicle
GHG	Greenhouse gas
ICE	Internal combustion engine
IEA	International Energy Agency
J	Joule
k	Kilo (10^3)
km	Kilometre
KNMI	Koninklijk Nederlands Meteorologisch Instituut
M	Mega (10^6)
MSc.	Master of Science
P	Peta (10^{15})
PR	Performance ratio
PV	Photovoltaic
RES	Renewable energy resources
RPR	Relative peak reduction
RT	Real-time
RQ	Research question
SC	Self-consumption
toe	Tonne of oil equivalent
V	Volt
W	Watt
Wh	Watt hour
Wp	Watt peak
yr	year

Symbol	**Explanation (unit)**
C_{EV_i}	Battery capacity EV_i (Wh)
$E_{EV_i}(t)$	Energy in battery EV_i (Wh)
$E_{EV_i,min}$	Minimum energy in battery EV_i (Wh)
$E_{EV_i,req}(t)$	Required energy EV_i taking into account the energy needed for the next trip and maximum charging power EV_i (Wh)
$E_{EV_i,trip}(t)$	Energy used by EV_i for trips (Wh)
$\eta_{EV_i,in}$	Charging efficiency EV_i
$\eta_{EV_i,out}$	Discharging efficiency EV_i

$f_{EV_i}(t)$	Priority function EV_i
i	EV index
N_{EV}	Total number of EVs
$P_{EV_i}(t)$	(Dis)charging power EV_i (W)
$P_{EV_i,in}(t)$	Charging power EV_i (W)
$P_{EV_i,in,grid}(t)$	Charging power EV_i drawn from grid (W)
$P_{EV_i,in,max}$	Maximum charging power EV_i (W)
$P_{EV_i,in,PV}(t)$	Charging power EV_i drawn from PV (W)
$P_{EV_i,out}(t)$	Discharging power EV_i (W)
$P_{EV_i,out,max}$	Maximum discharging power EV_i (W)
$P_{grid}(t)$	Power send to/from grid (W)
$P_{grid,tot}(t)$	Total power send to/from grid (W)
$P_{load}(t)$	Load demand (W)
$P_{load,prediction}(t)$	Predicted load demand (W)
$P_{load,real}(t)$	Realised load demand (W)
$P_{load,tot}(t)$	Total load demand including EVs and minus load covered by EVs (W)
$P_{PV}(t)$	PV-power (W)
$P_{PV,max\ profile}(t)$	Profile for maximum daily PV yield (W)
$P_{PV,prediction}(t)$	Predicted PV-power (W)
$P_{PV,real}(t)$	Realised PV-power (W)
RPR(T)	Relative peak reduction for period T
SC(T)	Self consumption for period T
$SOC_{EV_i}(t)$	State of charge battery EV_i
$SOC_{EV_i,min}$	Minimum state of charge battery EV_i
t	Time step number
$t_{EV_i,l}$	Time steps for which EV_i is at the loading station
$t_{EV_i,trip}$	Start time next trip EV_i
T	Time period
$T0$	Starting time step for time period T
$U_{EV_i}(t)$	Urgency value EV_i

1. Introduction

1.1 Background

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 64 EJ in 2010, 18% of total final energy consumption of 360 EJ (IEA, 2012) and is expected to further increase due to growing global population and welfare. Issues related to this development include availability, reliability, 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, 10.8 % for the EU-25 Member States[1] in the period 1999-2004 (Bertoldi and Atanusiu, 2007). It is therefore an important sector for changes in the electricity provision and distribution.

In the Netherlands the residential sector makes up 23% of the final consumption of electricity (IEA, 2013a). Renewable energy sources (RES) such as photovoltaic (PV) or wind energy can contribute to the solution of the mentioned issues. In the Netherlands only 4.33% of total energy use and 2.05% of total electricity use in 2012 originated from RES (CBS, 2013), but the government wants to stimulate RES such that 16% of energy production in 2020 is from RES (Rijksoverheid, 2013).

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. In the Netherlands the final consumption of the transport sector was 11,492 ktoe in 2009 of which 93% was oil products (IEA, 2013b).

Electric vehicles (EVs) are a promising technology for reducing the environmental burden of road transport (Essen et al. 2011). Based on three scenarios varying market uptake Essen et al. (2011) concluded that increased market share of EVs achieve overall passenger car CO_2 emission

[1] European Union Member States per May 1st 2004: Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden and United Kingdom (CBS, 2013)

reductions of between 4% and 9% for the EU in 2030, even when additional future electricity supply is generated from gas and coal.

In the Netherlands there were 10049 EVs and 5174 public or semi-public loading stations in June 2013 (Agentschap NL, 2013). This is just 0.001% of the total car fleet in the Netherlands but an increase of 36% compared to December 2012 and 506% compared to December 2011 is showing market uptake. If this trend continues EVs can contribute substantially to reducing GHG-emissions in the Netherlands, but it also creates another issue because electricity demand will increase even further. Also, the typical loading pattern coincides with that of households, which is highest in the morning and the evening (see figure 1.1), thus it contributes to existing peaks in electricity demand in the residential sector.

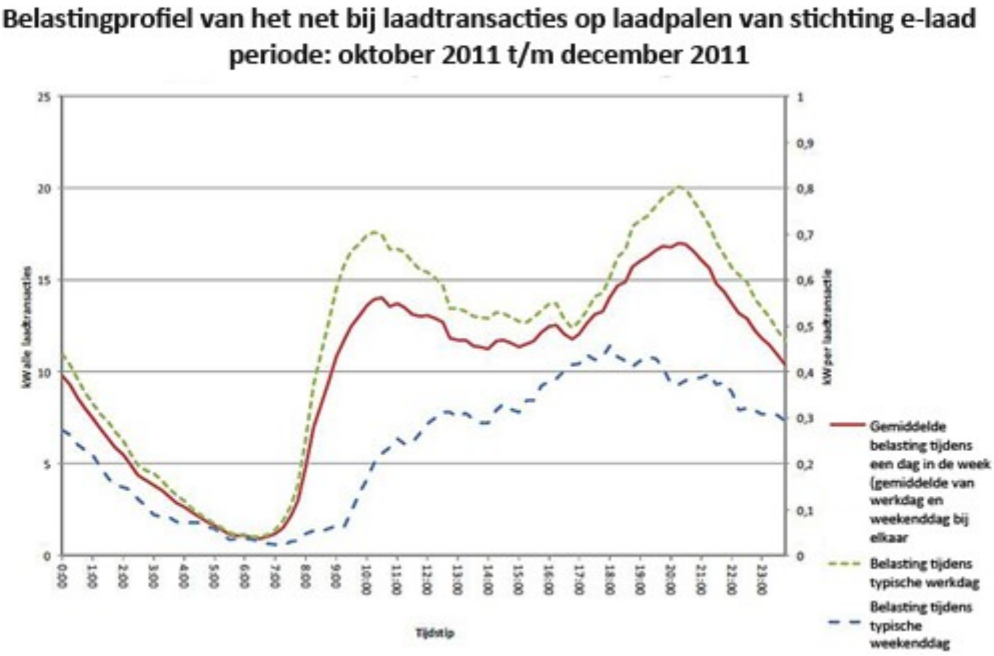


Figure 1.1 Loading profile for electric vehicles. Source: http://www.e-laad.nl/uploads/files/nieuws-2012/Oktober/grafiek2.jpg

PV technology can be part of the solution to problems relating with electricity and transport: there are no emissions of greenhouse gasses during electricity production, and PV technology also fits in a trend towards a more decentralised and independent energy system (Mulder et al., 2010), so called distributed generation (DG). If PV-electricity is used to charge EVs, transport with EVs will cause even less or zero direct GHG emissions.

An important advantage of PV for the residential sector is its scalability; even single households can use this technology. However, the mismatch of

PV production and the load curve 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 is variable on a smaller time scale due to variations in cloud coverage.

Strategies to deal with these issues are for instance demand response (DR) and electricity storage (Castillo-Cagigal et al., 2011a); in their paper DR is defined as shifting load demand in order to achieve a set goal. Optimisation goals are for instance are peak-shifting (flattening load demand curve) or increasing self-consumption (consumption of locally produced electricity behind the meter). This can be done either by consumers themselves, for instance by using certain appliances at optimal times, or using a smart grid; a grid that includes an intelligent control system that can be programmed to perform energy management tasks.

Smart grid technology combines the traditional electricity grid or a micro-grid (a local, low-voltage distribution system) with information and communication technologies in order to add 'intelligence' to the grid (Verbong et al., 2012). The main characteristics of smart grids according to the United States Department of Energy (2009) are that it a) enables informed participation by customers, b) accommodates all generation and storage options, c) enables new products, services and markets, d) provides the power quality for the range of needs, e) optimises asset utilisation and operating efficiently, f) self-heals and g) resists attack.

In a smart grid system a electricity storage can contribute to peak-shifting (see figure 1.2) or, when there is a local PV-installation, increasing self-consumption of PV-power. Disadvantages are that storage is expensive and not environment-friendly (Mulder et al., 2010).

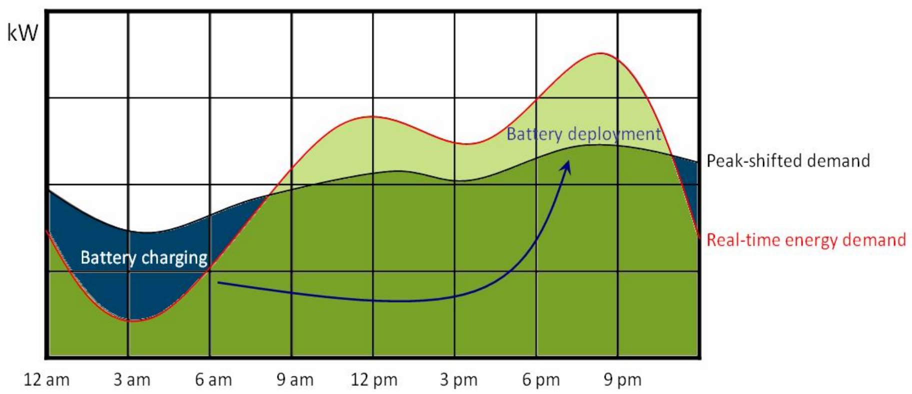


Figure 1.2 Illustration of peak-shifting using energy storage. Source: http://greensmith.us.com/wp-content/uploads/2012/01/Peak-Shifting3.jpg

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. Furthermore, net metering, the current policy regarding selling PV-power in the Netherlands, makes this financially attractive. 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., 2011a). Financial regulations discouraging selling electricity to the grid can reduce the pay back time and therefore attractiveness of PV-installations significantly.

In order to solve these issues options to improve self-consumption must be investigated. Energy could also be stored in EV-batteries. This way EVs can increase self-consumption and contribute to peak-shifting instead of causing extra peaks. Furthermore, by using PV-electricity to power EVs GHG emissions for transportation are reduced.

1.2 Case study: LomboXnet

LomboXnet is an internet company that provides a glass fibre internet connection to about 2500 people in the area of Lombok in Utrecht, the Netherlands. LomboXnet has the ambition to run their activities on locally produced solar power and provides solar powered electricity to several houses in the neighbourhood. Currently there is a micro-grid available that includes three solar panel installations, three houses, two EVs and two EV loading stations which are all connected to LomboXnet's office called the Parkhuis. There are PV-installations placed on the Parkhuis and two nearby schools the Parkschool and the Christelijk Gymnasium Utrecht (CGU). Around the office there are two EVs, a Tesla Model S (from now on referred to as Tesla) and a Nissan Leaf (from now referred to as Leaf), and two EV charging stations, one for the Tesla and one for the Leaf including a public connection. The Leaf can be rented and the Tesla is for private use. A map of Lombok and the mentioned buildings is presented in figure 1.3.

The batteries of the EVs could also be used to store locally produced PV-electricity. In order to make efficient use of the supplied PV-power, the current micro-grid needs to incorporate smart grid technology in order to use the produced electricity, using the EVs as storage. In this research, control algorithms for a smart grid are developed for this project and evaluated using model simulations, contributing to the goal of setting up an efficient decentralised energy system.

Figure 1.3 Map of Lombok with indications of locations of the Parkschool, CGU and the loading station (which is near the Parkhuis) (Van den Berg et al., 2013)

1.3 Previous research

In recent years several researches about options to improve PV self-consumption have been carried out. In a study by Widén et al. (2009) a method to evaluate PV array orientation, demand side management (DSM) and electricity storage for load matching was proposed. Based on high-latitude data it was concluded that storage is the most effective solution for high penetration levels, while DSM is more effective at low overproduction levels. Mulder et al. (2010) have set up calculation rules to dimension storage capacity, based on measurements of seven households in Belgium. Castillo-Cagigal et al. (2011a,b) have modelled and experimented with combinations of storage and active DSM. Their research has shown that this combination can considerably improve self-consumption.

The European Commission Directorate-General For Energy have stated that higher levels of storage are required for grid flexibility and grid stability and smart grids and smart storage are required for developing smart cities, a key energy policy goal (EC, 2013). Verbong et al. (2012) concluded that relevant stakeholders in the Netherlands generally perceive smart grids as a solution to challenges in grid management and sustainable energy supply. It was also concluded that in order to introduce smart grids on a larger scale research should focus more on the domestication of the technology as opposed to the technical and economical aspects of smart grids. Essen et al. (2011) have stated that controlled charging of EVs allows a higher market share of EVs because it prevents local electricity overload. However, in their report they also concluded that the potential of load balancing with EVs seems limited due to the limited total storage capacity of EVs, other more cost-effective storage solutions and concerns regarding effect on battery life.

An important topic for smart grids is how they can help with increasing grid stability in a hybrid RES electricity distribution system; a micro-grid that includes RES but also has a connection to the main grid. Examples of proposed control algorithms with such an optimisation objective are Mohamed and Mohammed (2012), who presented a control algorithm based on fuzzy logic, Sechilariu et al. (2013), who proposed a real-time control system for a micro-grid, Silva et al. (2012), who proposed a Genetic Optimisation method using load and power predictions, Soares et al. (2012), who proposed a new methodology called Signaled Swarm Particle Optimisation, and Tanaka et al. (2011), who used mathematical optimisation to minimise interconnection point power flow fluctuations. In all these papers it was concluded that smart grid technology can significantly improve grid stability and cost of electricity distribution system which includes RES.

Furthermore, several researches on control algorithms for EV charging focusing on grid stability have been carried out. Van den Akker et al. (2012) proposed a greedy strategy for EV charging for a single household to reduce network losses. González Vayá and Andersson (2012) proposed a centralised and decentralised Optimal Power Flow scheme for EV-fleet charging. Khayyam et al. (2012) presented a load controller using fuzzy logic for a vehicle-to-grid system that showed that vehicle electrification could play a role in increasing grid stability. Shuaib et al. (2012) simulated the effect of priority-controlled charging scheme to show that priority based schemes can be used to regulate EV fleet charging.

Smart grids can also be approached from the perspective of households. Guo et al. (2012) proposed a stochastic optimisation method to minimise expected electricity costs of a residential consumer with real-time pricing in a micro-grid consisting of load, RES and electricity storage. They showed that their approach is effective in a real-time system eliminating the need for future knowledge on related stochastic models.

Summarising, recent research on smart grids have a broad scope of applications, focus on different optimisation objectives and use a wide range of mathematical optimisation techniques to design control algorithms. There have been several researches about the use of smart grid and storage to increase PV self-consumption in the residential sector that have shown promising results. Verbong et al. (2012) concluded for the Netherlands specifically that smart grids are seen as a possible solution for power supply issues and the focus should be on implementing the technology in households.

1.4 Problem definition

In figure 1.4 an overview of the current electricity distribution system of LomboXnet is presented. The solar panel installations on the roof of the Parkschool and the Christelijk Gymnasium Utrecht (CGU) provide electricity to the office building of LomboXnet. The power is then divided between the office building, the EV loading station and the houses connected to the local grid. Because it is connected to houses, the load curve is typical for the residential sector; supply and demand do not match well.

If supply is lower than demand, electricity is purchased from the grid. If supply is higher than demand, electricity is sold to the grid. However, for Stedin, the distribution network operator, more DG sources and EVs will mean that new investments in the grid must be made, which is not desirable. It is beneficial for the distribution network operator that LomboXnet's self-consumption increases. Furthermore, if the electricity sold to the grid exceeds 5000 kWh per year, the supplier can buy the electricity for a 'reasonable price' (Elektriciteitswet 1998, article 31c) instead of using net metering. This significantly reduces the payback time of the solar panels. Therefore LomboXnet wants to investigate possibilities to increase self-consumption. However, proposed legislation (EK 33.493 A) changing the 5000 kWh limit to 'unlimited' per January 1st 2014 will most likely be accepted by the Dutch parliament (Simons, 2013).

The goal of this research is to investigate the potential of combining smart grid technology with electricity storage in EVs for increasing self-consumption. This will be done by creating a model of the current micro-grid and simulating the effect on self-consumption of different possible expansions of this grid including smart grid technology.

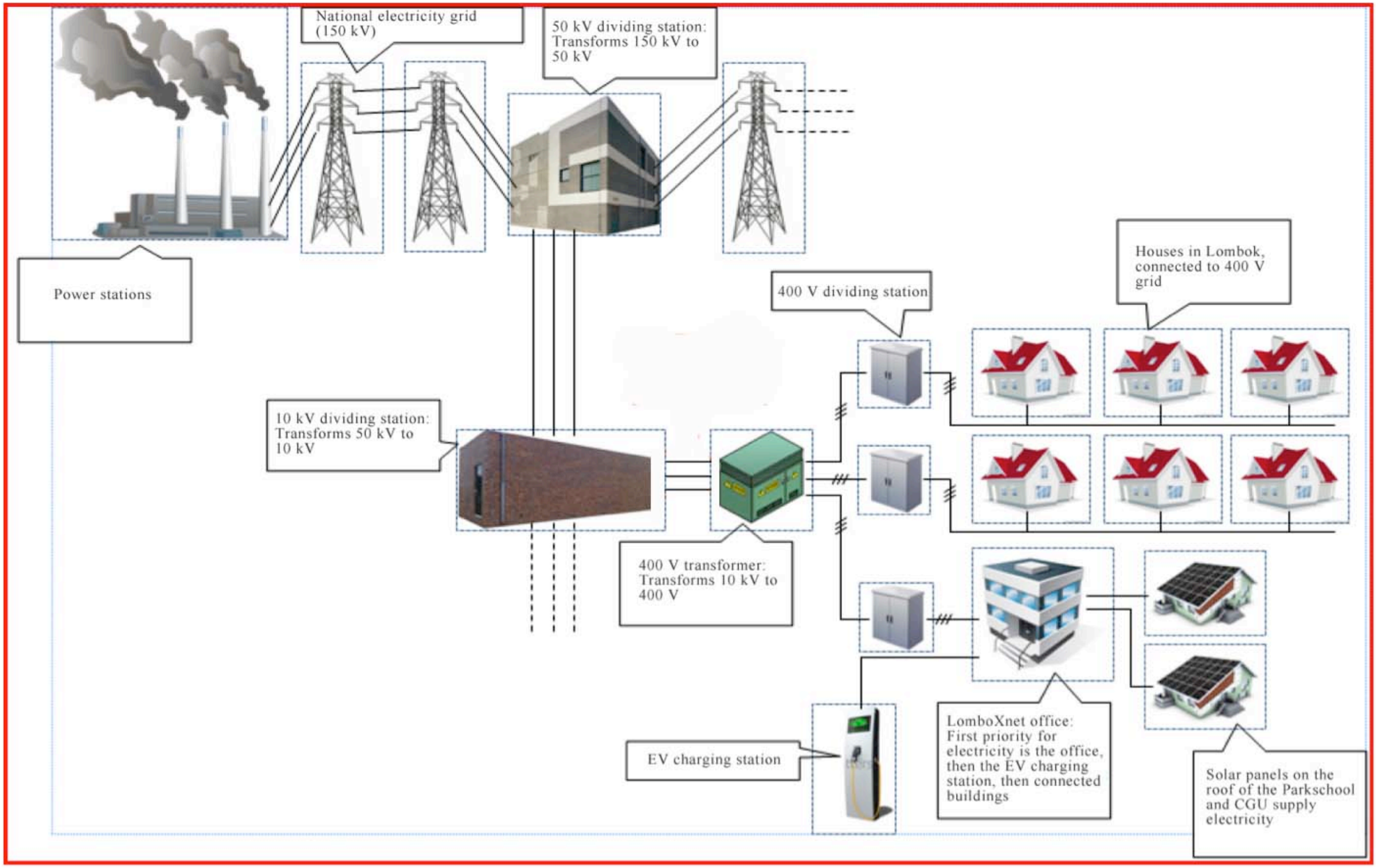


Figure 1.4 Schematic representation of the electricity distribution system nationally and at LomboXnet (Adapted from Van den Berg et al. 2013)

1.5 Research objective and questions

The main research objective is to develop and evaluate algorithms for a smart grid system that can increase self-consumption of PV-power by storing electricity in EVs in the residential sector, in this case LomboXnet, while meeting the demands posed by the use of the EVs. Results from the study can be used for developing strategies to increase use of PV technology in the residential sector. The research objective results in research question RQ1:

RQ1 How and by how much can storage of electricity in EVs in combination with smart grid technology contribute to increasing self-consumption of PV-power for the residential sector in the case of LomboXnet?

In order to answer RQ1 first a baseline situation to compare the effects of the designed system to must be established. This is the current situation at LomboXnet and is investigated with RQ2 t/m RQ5:

RQ2 What are the characteristics of the power supply from the PV-installations?

RQ3 What is the typical load demand curve for the office of LomboXnet?

RQ4 What is the typical load demand curve of the houses connected to the PV-system?

RQ5 What are the technical specifications of the EVs and how will they be used?

When the baseline is established the performance of systems with storage and smart grid technology can be evaluated (RQ6 and RQ7).

RQ6 How and by how much can charging the EVs at LomboXnet using smart grid technology contribute to increasing self-consumption of PV-power?

RQ7 How and by how much can storage of electricity in the EVs at LomboXnet using smart grid technology contribute to increasing self-consumption of PV-power?

1.6 System boundaries

This research focuses on the physical side of energy management in the context of a case study, the research question is dealt with as a mathematical optimisation problem for self-consumption. The research is carried out by data collection and analysis, analysing the electricity distribution in place, writing algorithms for a model and running simulations. Not included are the finances of the project.

Because this is a case study, boundaries are determined by the situation at LomboXnet. The available data for PV, system and technologies are all bound to the case. Results will apply to locations with similar solar insulation and cloud coverage as in the Netherlands.

Effects of smart metering on behavioural changes of participants will not be taken into account. In order to do research for this aspect of demand side management methods such as interviews and surveys must be used, which is not considered within the scope of this research. Also, the goal of the research is to investigate the effect of storing electricity in EVs on self-consumption. Other so-called controllable loads (such as washing machines or refrigerators) are not taken into account.

1.7 Structure of document

In chapter 2 the research method is explained. It includes a definition of the analysis model, the model of the micro-grid at LomboXnet, the method for data collection, the algorithms used to simulate the smart grid control systems, the performance indicators and the method for the sensitivity analysis. In chapter 3 the collected data is presented and analysed and it is explained how the data will be used for the simulations. This chapter contains the answers to RQ2 t/m RQ5. In chapter 4 the results of the simulations are presented. The results include evaluations of the simulations of the algorithms, sensitivity analysis and a comparison and interpretation of the results. The chapter contains the answers to RQ6 and RQ7. Chapter 5 contains the discussion of the results and chapter 6 contains the main conclusions, the answer to the research question and further recommendations.

2. Methodology

2.1 Analysis model

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 and sensitivity analyses. In this case study the micro-grid at LomboXnet is the basis of the model. The basic input is the total electricity demand per time step, the supplied PV-power per time step and the technical specifications and expected use (average trip duration, distance and number of trips per week) of the EVs. The data for load demand of the Parkhuis and PV-power are measured at LomboXnet. The data for household load curves are based on measurements from Liander in 2008 as provided by Claessen who used the dataset for his research (Claessen, 2012).

The inputs are used to construct scenarios for the electricity demand, PV-power and number of EVs. These scenarios relate to the current situation at LomboXnet and realistic future additions to the micro-grid. The scenarios are the input for simulations of the energy flows in the micro-grid with different control systems for the EVs for different periods of a year; the results of these simulations are loading patterns for the EVs. These are evaluated using performance indicators and sensitivity analyses. The main objectives for the system are increasing self-consumption and peak shaving. The analysis is the basis for conclusions about the potential of the system and further recommendations. An overview of the analysis model is presented in figure 2.1.

2.2 LomboXnet micro-grid model

In figure 2.2 a schematic representation of the model of the micro-grid at LomboXnet is presented. The five main components of the micro-grid are the PV installations, the Parkhuis, uncontrollable load, EVs and loading stations and the connection to the main grid. Red arrows and red cursive text indicates that that component is not (yet) available at LomboXnet at the time of writing, including three EVs; one Leaf and two Ford Focus Electric EVs (from now on referred to as Focus). The extra solar panels CGU are expected in the second quarter of 2014, the extra households, EVs and loading station are expected to be available in January 2014 and discharging of EVs is expected to be operational at the end of the first quarter of 2014.

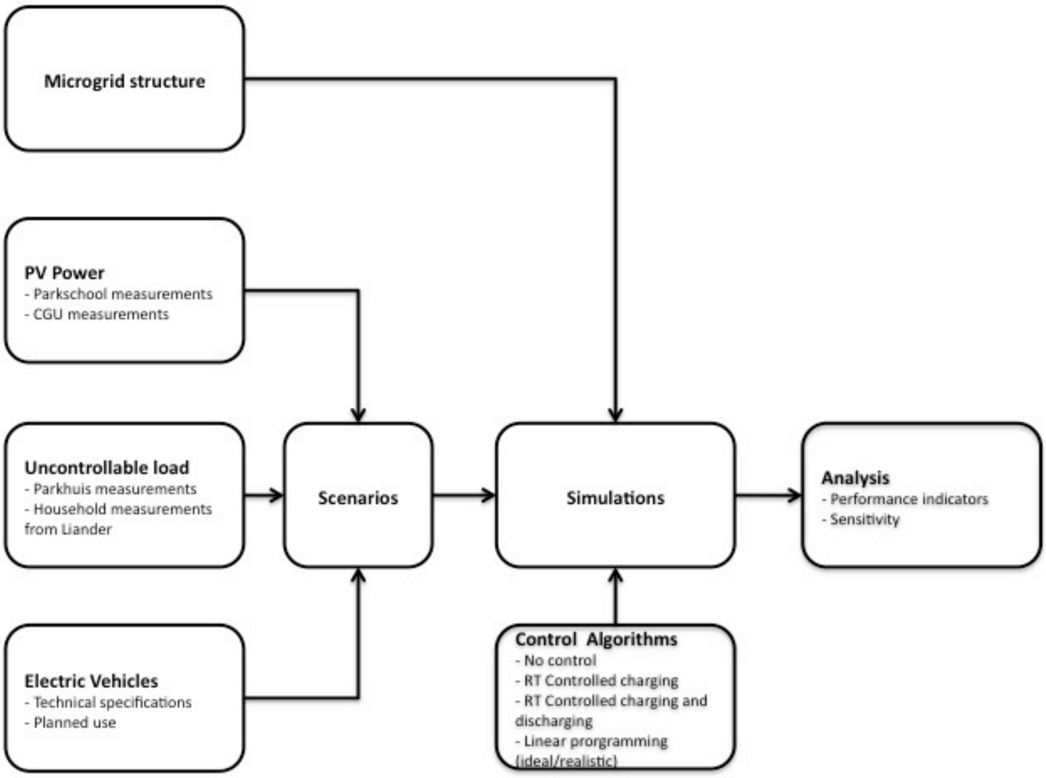


Figure 2.1 Analysis model

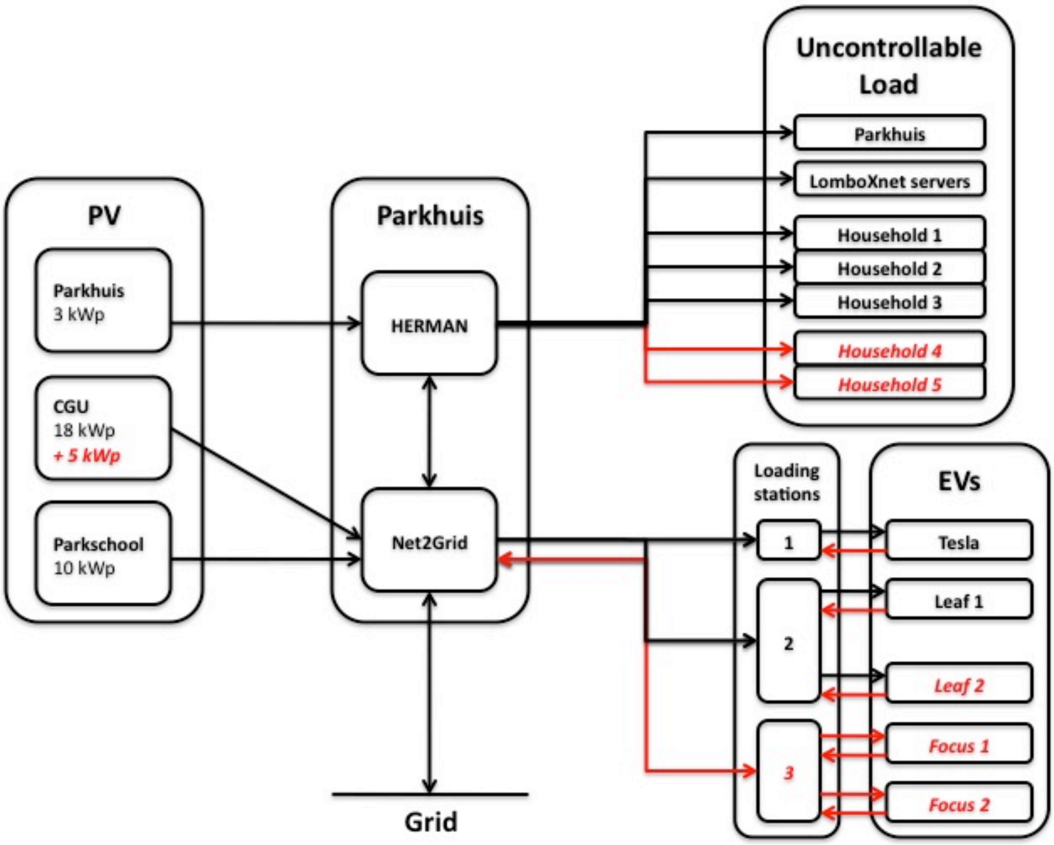


Figure 2.2 Model of micro-grid at LomboXnet. Red and cursive indicates that the component is not yet in place

2.2.1 Parkhuis

The Parkhuis is the centre of the micro-grid where the PV-power is sent to, the power is divided between loads by a device called HERMAN (Herman de zonnestroom verdeler, 2013), the meter Net2Grid (Net2Grid, 2013) and the connection with the main grid is. In the model, the priority where to use PV-power is first the uncontrollable load, then the EVs and then the main grid. The uncontrollable load has priority over the EVs because if one stores electricity in a battery and takes it out later one loses electricity twice with conversion efficiency and a heavier use of the battery will result in a shorter battery lifetime. However, when energy is needed for a planned trip the EV is considered part of the uncontrollable load and has the same priority as the rest of the uncontrollable loads.

2.2.2 PV

There are three PV-installations with a total installed amount of 31 kWp. The locations of the installations are indicated in figure 1.3. PV-power must be used, stored or sold at the same moment it is produced. This can either be by uncontrollable load, EVs or the main grid.

Data for PV-power profiles is directly measured from the installations and can be accessed online. The data is based on measurements after power transformation, so efficiency losses of power transformation are included in the data. The data is available from July 7th 2011 to December 31st 2012 for the installation at the Parkschool and from October 1st to December 31st 2012 for the installation at the CGU.

2.2.3 Uncontrollable load

The uncontrollable load consists of the electricity demand for the Parkhuis, the LomboXnet servers and connected households; for these factors DR is not applied. Currently there are three households connected and in the future this is possibly expanded with two. In reality, the households have their own connection to the main grid. In the model this is not included but load demand is the aggregated total of all uncontrollable loads. This is not a problem since the objective is to increase self-consumption and therefore minimise the excess PV-power which is sold to the grid. The amount of electricity bought from the grid for LomboXnet, which the model calculates for the whole system and not just LomboXnet, is not of particular interest for this research. Also, the households have priority over the EV as explained earlier. In the model of the micro-grid electricity demand must always be met. Electricity is provided either by PV-power, the main grid or electricity extracted from the EVs.

The electricity demand for the Parkhuis including servers was measured from October 29th to November 8th 2012. The data for the electricity demand of the households comes from measurements of 700 houses for a week by Liander in 2008. Furthermore, factors for weekly variations of electricity consumption for a year are used based on measurements of average electricity consumption for a different set of houses taken by Liander in 2007. Based on these measurements a profile for a year is constructed for both the Parkhuis and the households. For the households,. the load profiles are repeated in order to cover a year and multiplied with the factors for weekly variations Because the only the aggregated load demand was measured it is not possible to take the changing of the shape of demand profiles throughout the year into account. This decreases the accuracy of the yearly profile, in the discussion (chapter 5) this is further expanded upon. For the Parkhuis the data was used to construct an electricity demand profile with mean energy use and standard deviation for each hour. In order to construct load profiles for the simulations random values within the standard deviations are used, varying throughout the year with the factors for weekly variations.

2.2.4 EVs and loading stations

The EVs are the controllable load (and supply) and calculating their loading pattern per time step is the main result from the simulations. Since PV and uncontrollable load are fixed, the EVs are the only factor that contribute to increased self-consumption. In the model, the batteries of the EVs can be used to store (and extract) electricity. This is done only if there is excess PV-power (more PV-power than uncontrollable load). However, the EVs are also used to make trips. This means that during trips there is no power exchange with the EV and the micro-grid and that the energy needed for making trips is added to the total electricity demand.

Technical data concerning the EVs is retrieved from manufacturers and the United States Environmental Protection Agency (EPA, 2013). The needed factors for the model are the maximum loading/unloading power, energy use, battery capacity and power transport efficiency. Furthermore, an estimate of how the EVs will be used (average trip duration, distance and number of trips per week) is needed. These factors are used in a function which produces random trip schedules based on the averages.

2.2.5 Scenarios

In order to cover a range of possibilities for LomboXnet different scenarios are constructed. Possible expansions of the current micro-grid are 5 kWp extra PV on the CGU, two extra households, an extra Nissan Leaf and an extra loading station with two Focusses. These factors are combined in four scenarios, presented in table 2.1.

Table 2.1 Overview of characteristics of scenarios

	PV	**Load**	**EV**
Current	Current	Current	Current
Expansion	+ 5 kWP	+ 2 households	+ 3 EVs
Low flexibility	Current	+ 2 households	Current
High flexibility	+ 5 kWp	Current	+ 3 EVs

The scenario "current" represents the situation at LomboXnet as is, the scenario "expansion" includes all possible expansions in the foreseeable future. To name the other two scenarios the term flexibility is used. "Low flexibility" is used to indicate that there is relatively high load demand and low PV-supply, resulting in low excess PV-power and just two EVs to balance demand and supply. "High flexibility" is used to indicate that there is relatively low load demand and high PV-supply, resulting in high excess PV-power and five EVs to balance demand and supply.

2.3 Baseline situation

In the baseline situation no smart grid technology that controls the EV charging patterns is available. It is assumed that when the EVs return from trips they start charging immediately at maximum charging power and only stop when the battery is full. In the baseline situation the EVs only contribute to increasing self-consumption when there is accidental excess PV-power at the time steps of charging.

In this document, the time step numbers are denoted as t and i is defined as the index of the different EVs. In order to determine the loading pattern of the EVs denoted as $P_{EV_i}(t)$, the inputs are maximum charging power and the energy contained in the EV, denoted as $P_{EVi,in,max}$ and $P_{EVi,out,max}$. Furthermore, when an EV is on a trip the energy needed for the trip ($E_{EVi,trip}$) is taken out of the battery. A schematic representation of the system is presented in figure 2.3

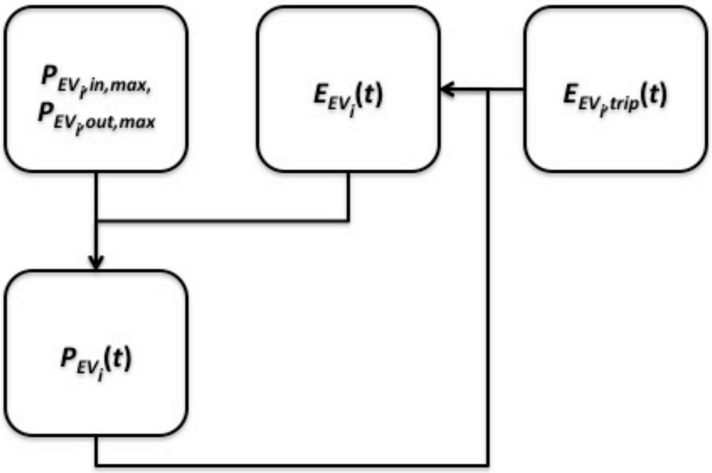


Figure 2.3 Structure of "uncontrolled charging"

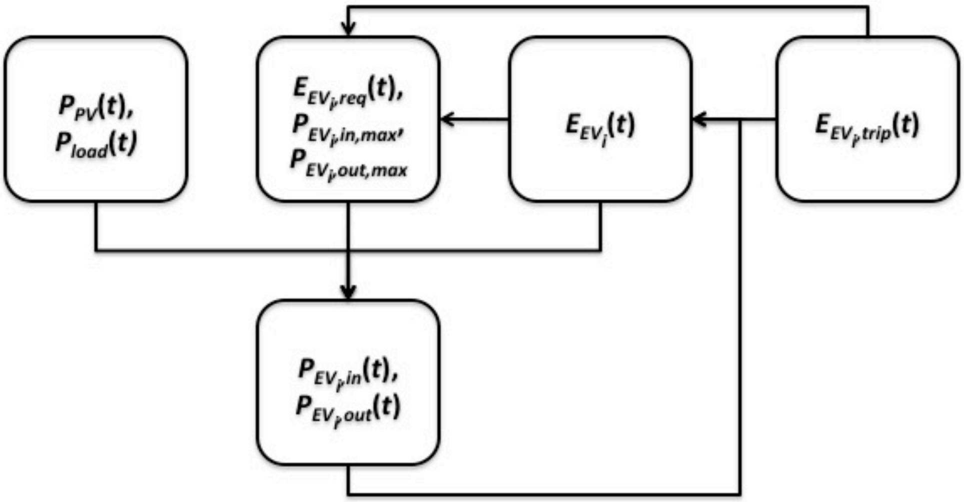
In order to simulate this system a recursive formula is constructed, since $P_{EV_i}(t)$ depends on $P_{EV_i}(t\text{-}1)$. This is because the energy contained in the EVs is the sum of the previously loaded energy (minus the energy needed for trips). In the baseline the loading pattern $P_{EV_i}(t)$ is defined by formula (1):

$$P_{EV_i,in}(t) = \begin{cases} P_{EV_i,in,max} & \text{if} \quad E_{EV_i}(t-1) < C_{EV_i} \text{ and } t \in t_{EV_i,l} \\ 0 & \text{else} \end{cases} \tag{1}$$

With E_{EV_i} the energy in EV_i, C_{EV_i} the battery capacity $P_{EV_i,max}$ the maximum charging power and $t_{EV_i,l}$ the time steps for which the EV is at the loading station (not on a trip).

2.4 Control algorithms

In this section three control algorithms for smart grid technology designed for this research are presented. The main objective of the control systems is to use excess PV-power for charging the EVs in order to increase self-consumption. This is done while meeting electricity demands for EV-trips. The three control algorithms presented are "real-time controlled charging", "controlled charging and discharging" and "linear programming". Although there are considerable differences between these systems, as explained further on in this section, the basic structures are the same (see figure 2.4). In addition to the elements for the baseline PV-power and load demand and the function $E_{EV_i,req}(t)$ that determines the required SOC of EV_i at time step t are used to determine the loading pattern.



2.4.1 Real-time Controlled Charging

Real-time (RT) 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 charging pattern is decided. With this algorithm it is not possible to extract energy from the EV in order to cover electricity demand of the households. If there is more PV-power than electricity demand, the EVs start charging using the excess PV-power until the battery is full or until there is no more excess PV-power. The EV only extracts energy from the grid when there is shortage of PV-power in order to make a trip.

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

$$E_{EV_i req}(t) = \begin{cases} E_{EV_i,trip}\left(t_{EV_i,trip}\right) - \\ \quad P_{EV_i,in,max} \cdot \left(t_{EV_i,trip} - t\right) + E_{EV_i,\min} & \text{if} \quad t \in \left(t_{EV_i,trip} - \dfrac{E_{EV_i,trip}\left(t_{EV_i,trip}\right)}{P_{EV_i,in,max}}, t_{EV_i,trip} \right) \\ E_{EV_i,\min} & \text{else} \end{cases} \tag{2}$$

With $t_{EV_i,trip}$ the time of the next trip, $E_{EV_i,trip}(t_{EV_i,trip})$ the energy required for the next trip, $P_{EV_i,in,max}$ the maximum charging power and $E_{EV_i,min}$ minimum energy in the battery. The 'if' part of equation (2) describes that if a trip is planned, the energy level at the start time of the trips must be the energy needed for the trip. Because the EV has a maximum charging power, the energy level of the time-steps before the start time of the trip also have to be at a certain level, namely the energy required for the trip minus the charging power times the time steps that are left to complete charging. This quantity is added to the minimum energy level of the EV. At all other time steps the required energy in the EV is the minimum energy level of the EV, as the described by the 'else' part of equation (2).

In the case of multiple EVs a priority function f_{EV_i} is needed. First, an urgency value U_{EV_i} is assigned to each vehicle. U_{EV_i} is based on how much time it takes to charge the vehicle to a sufficient energy level for the next trip and the time left in order to achieve this. f_{EV_i} is then calculated as U_{EV_i} proportional to the sum of U_{EV_i} for all vehicles.

$$U_{EV_i}(t) = \left(\frac{t_{EV_i,trip} - t}{t_{EV_i,trip} - t - \left(E_{EV_i,trip}\left(t_{EV_i,trip}\right) - E_{EV_i}(t-1) \right) / P_{EV_i,max}} \right)^k \tag{3}$$

$$f_{EV_i}(t) = \frac{U_{EV_i}(t)}{\sum_i U_{EV_i}(t)} \tag{4}$$

U_{EVi} contains a factor k; in the simulations k = 2 was used so that the effect is increased for EVs that have a high urgency for charging compared to k = 1. However, it was found that the value for k has little effect on the outcome when evaluating system performance for k = 1, 2 or 3, so results apply for all these values for k, although it must be noted that testing the effect of the value k was done late in this research and has not been tested extensively.

The individual loading patterns are now defined by equations (5), (6), (7) and (8).

$$P_{EV_i,in}(t) = P_{EV_i,in,PV}(t) + P_{EV_i,grid}(t) \tag{5}$$

$$P_{EV_i,in,PV}(t) = \begin{cases} f_{EV_i}\eta_{EV_i,in}\left(P_{PV}(t) - P_{load}(t)\right) & \text{if} \quad P_{load}(t) < P_{PV}(t) \\ & \text{and} \quad E_{EV_i}(t-1) < C_{EV_i} \\ & \text{and} \quad t \in t_{EV_i,l} \\ 0 & \text{else} \end{cases} \tag{6}$$

$$P_{EV_i,grid}(t) = \begin{cases} E_{EV_i,req}(t) - E_{EV_i}(t-1) - P_{EV_i,in,PV}(t) & \text{if} \quad E_{EV_i}(t-1) + P_{EV_i,in,PV}(t) < E_{EV_i,req} \\ & \text{and} \quad t \in t_{EV_i,l} \\ 0 & \text{else} \end{cases} \tag{7}$$

$$P_{EV_i,in}(t) \leq P_{EV_i,in,max} \tag{8}$$

Equation (5) describes 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 (6). The EV only extracts energy from the grid when there is shortage of PV-power in order to make a trip, see equation (7). Finally, equation (8) makes sure the total power into the EV cannot exceed the maximum charging power.

2.4.2 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 (9) and (10).

$$P_{EV_i,out}(t) = \begin{cases} \frac{1-f_{EV_i}}{N_{EV_i}-1} \eta^{-1}_{EV_i,out} \left(P_{load}(t) - P_{PV}(t)\right) & \text{if} \quad P_{load}(t) > P_{PV}(t) \\ & \text{and} \quad E_{EV_i}(t-1) < E_{EV_i,req}(t) \\ & \text{and} \quad t \in t_{EV_i,l} \\ 0 & \text{else} \end{cases} \tag{9}$$

$$P_{EV_i,out}(t) \leq P_{EV_i,out,max} \tag{10}$$

With N_{EV_i} the total number of EVs.

2.4.3 Linear Programming

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

With linear programming $\mathbf{c}^{\mathbf{T}}.\mathbf{x}$ (the objective function) is either min- or maximised for $\mathbf{x}$ such that $A.\mathbf{x} \geq \mathbf{b}$ (for minimising) or $A.\mathbf{x} \leq \mathbf{b}$ (for maximising) and $\mathbf{x} \geq 0$. $\mathbf{x}$ is a vector representing the unknown variables to be determined, $\mathbf{c}$ en $\mathbf{b}$ are vectors of known coefficients, A is a matrix of known coefficients and $(.)^{\mathrm{T}}$ is the matrix transpose (Ferguson, 2013).

The problem of the loading pattern can be formulated in such a way that $\mathbf{x}$ represents the loading pattern for each time step t and that $\mathbf{c}^{\mathbf{T}}.\mathbf{x}$ is the amount of electricity stored in the EV. This translates into the following objective function, which is to be maximised:

$$\sum_i \sum_t P_{EV,in,PV}(t) \tag{11}$$

With $P_{EV_i,in,PV}$ the electricity send into the EV. In this section a distinction is made between $P_{EV_i,in}$ and $P_{EV_i,out}$, since optimising for $P_{EV_i,in}$ results in optimising for self-consumption. This is because $P_{EV_i,in}$ is bound to the constraint that only excess PV-power is charged (unless in the case of PV-power shortage) and therefore increases the self-consumption. The target variable $\mathbf{x}$ is bound to constraints, represented by the following formula's:

$$0 \leq P_{EV_i,in}(t) \leq P_{EV_i,in,max}(t), \quad \forall t,i \tag{12}$$

$$0 \leq P_{EV_i,out}(t) \leq P_{EV_i,out,max}(t), \quad \forall t,i \tag{13}$$

$$\sum_{t'=1}^{t} \left(\eta_{EV_i,in} P_{EV_i,in}(t') - \eta_{EV_i,out}^{-1} P_{EV_i,out}(t') \right) \leq C_{EV_i} + E_{EV_i,trip}(t) - E_{EV_i}(0), \quad \forall t,i \tag{14}$$

$$\sum_{t'=1}^{t} \left(\eta_{EV_i,in} P_{EV_i,in}(t') - \eta_{EV_i,out}^{-1} P_{EV_i,out}(t') \right) \geq E_{EV_i,trip}(t) - E_{EV_i}(0), \quad \forall t,i \tag{15}$$

$$\sum_i P_{EV,in,PV}(t) \leq \max\left[P_{PV}(t) - P_{load}(t), 0 \right], \quad \forall t \tag{16}$$

$$\sum_i P_{EV,out}(t) \leq \max\left[P_{load}(t) - P_{PV}(t), 0 \right], \quad \forall t \tag{17}$$

With dummy variable t'. Note that in this case $P_{EV_i,in,max}(t)$ is represented as a function of t, contrary to earlier in this chapter. This is done in order to include that is $P_{EV_i,in,max}$ is essentially zero when an EV is not at the loading station. Also remember that $P_{EV_i,in}(t)$ represents the power drawn from both PV and the main grid, see equation (5).

Constraints (12) and (13) ensure that the maximum (dis)charging power is not exceeded. Constraints (14) and (15) ensure that the energy in the EV does not exceed the battery capacity and is sufficient for trips. Constraints (16) and (17) 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.

In order to show how equations (11) till (17) translate into vectors **c**, **x**, **b** and matrix *A* an example is given for *N* EVs and *T* time steps. The unknown variables are the loading pattern of the EVs at every time step containing $P_{EV_i,in,PV}(t)$, $P_{EV_i,out}(t)$ and $P_{EV_i,in,grid}(t)$, so for every time step *t* three variables are needed for each EV. **x** can now be formulated as follows:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N\cdot 3T-1} \\ x_{N\cdot 3T} \end{bmatrix} \tag{18}$$

with

$$x_{(i-1)3T+t} = P_{EV_i,in,PV}(t), \quad x_{(i-1)3T+T+t} = P_{EV_i,out}(t), \quad x_{(i-1)3T+2T+t} = P_{EV_i,grid}(t) \tag{19}$$

and **x** ≥ 0.

$\mathbf{c}^\mathbf{T}.\mathbf{x}$ must equal the objective function, see equation (11), so **c** is formulated as follows:

$$\mathbf{c} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{N\cdot 3T-1} \\ c_{N\cdot 3T} \end{bmatrix} \tag{20}$$

with

$$c_{(i-1)3T+t}=1,\quad c_{(i-1)3T+T+t}=0,\quad c_{(i-1)3T+2T+t}=0 \tag{21}$$

Vector **b** represents all the constraints, see equations (12) till (17). There are 4 constraints per EV per time step, equations (12) till (15), plus two per time step for the total system, equations (16) and (17), so **b** is formulated as follows:

$$\mathbf{b}=\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{(4N+2)T-1} \\ b_{(4N+2)T} \end{bmatrix} \tag{20}$$

with

$$\begin{aligned}
b_{(4N+2)(t-1)+4(i-1)+1} &= P_{EV_i,in,max}(t),\\
b_{(4N+2)(t-1)+4(i-1)+2} &= P_{EV_i,out,max}(t),\\
b_{(4N+2)(t-1)+4(i-1)+3} &= C_{EV_i}+E_{EV_i,trip}(t)-E_{EV_i}(0),\\
b_{(4N+2)(t-1)+4(i-1)+4} &= E_{EV_i,trip}(t)-E_{EV_i}(0),\\
b_{(4N+2)(t-1)+4N+1} &= \max\left[P_{PV}(t)-P_{load}(t),0\right],\\
b_{(4N+2)(t-1)+4N+2} &= \max\left[P_{load}(t)-P_{PV}(t),0\right]
\end{aligned} \tag{22}$$

Finally, matrix A is formulated to ensure that every component of $A.\mathbf{x}$ corresponds to the correct component of **b**:

$$A=\begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{bmatrix} \tag{23}$$

with

$$A_1=\left[a_{mn}\right]_{mn}=\begin{cases} 1 \quad \text{if} & m=(4N+2)(t-1)+4(i-1)+1 \\ & \text{and} \quad n=(i-1)3T+t \text{ or } n=(i-1)3T+2T+t \quad ,\forall t,i \\ 0 \quad \text{else} & \end{cases} \tag{24}$$

$$A_2 = \left[a_{mn}\right]_{mn} = \begin{cases} 1 & \text{if} \quad m = (4N+2)(t-1)+4(i-1)+2 \\ & \text{and} \quad n = (i-1)3T+T+t \\ 0 & \text{else} \end{cases} \quad ,\forall t,i$$

$$A_3 = \left[a_{mn}\right]_{mn} = \begin{cases} \eta_{EV_i,in} & \text{if} \quad m = (4N+2)(t-1)+4(i-3)+3 \\ & \text{and} \quad n = (i-1)3T+t' \text{ or } n = (i-1)3T+2T+t' \\ -\eta_{EV_i,out}^{-1} & \text{if} \quad m = (4N+2)(t-1)+4(i-3)+3 \\ & \text{and} \quad n = (i-1)3T+T+t' \\ 0 & \text{else} \end{cases} \quad ,\forall t,i,\forall t' \le t$$

$$A_4 = \left[a_{mn}\right]_{mn} = \begin{cases} -\eta_{EV_i,in} & \text{if} \quad m = (4N+2)(t-1)+4(i-3)+4 \\ & \text{and} \quad n = (i-1)3T+t' \text{ or } n = (i-1)3T+2T+t' \\ \eta_{EV_i,out}^{-1} & \text{if} \quad m = (4N+2)(t-1)+4(i-3)+4 \\ & \text{and} \quad n = (i-1)3T+T+t' \\ 0 & \text{else} \end{cases} \quad ,\forall t,i,\forall t' \le t$$

(24) cont.

$$A_5 = \left[a_{mn}\right]_{mn} = \begin{cases} 1 & \text{if} \quad m = (4N+2)(t-1)+4N+1 \\ & \text{and} \quad n = (i'-1)3T+t \\ 0 & \text{else} \end{cases} \quad ,\forall t,i'$$

$$A_6 = \left[a_{mn}\right]_{mn} = \begin{cases} 1 & \text{if} \quad m = (4N+2)(t-1)+4N+2 \\ & \text{and} \quad n = (i'-1)3T+T+t \\ 0 & \text{else} \end{cases} \quad ,\forall t,i'$$

With indices *m* and *n* and dummy variables *t′* and *i′*. The problem now becomes:

$$\max\left\{\mathbf{c}^{\mathrm{T}}\mathbf{x} \mid A\mathbf{x} \le \mathbf{b} \wedge \mathbf{x} \ge 0\right\} \tag{25}$$

The main advantage of linear programming is that it gives the optimal charging pattern for the EVs. However, contrary to the real-time programs linear programming is based on <u>perfect</u> 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, several assumptions have been made; load demand prediction is based on realised load demand from the previous day (excluding some exceptions, explained further on in this section), no technological learning takes place in predicting load demand and predictions of PV-power have an uncertainty of σ for each time step. In this thesis, this method is called "Linear Programming (Realistic)" contrary to "Linear Programming (Ideal)", which assumes the ideal case of perfect information.

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 per household. Because of this predictions for Saturdays will be based on data for Sundays and predictions for Mondays will be based on data for Tuesdays. This results in the following equations:

For Tuesdays, Wednesdays, Thursdays, Fridays and Sundays:

$$P_{load,prediction}(t) = P_{load,real}(t - 24\mathrm{h}) \tag{26}$$

For Mondays and Saturdays:

$$P_{load,prediction}(t) = P_{load,real}(t + 24\mathrm{h}) \tag{27}$$

The input for PV is based on PV-power predictions. It is assumed that prediction deviates from the real value with standard deviation σ, as follows:

$$P_{PV,prediction}(t) = P_{PV,real}(t) \pm \sigma \tag{28}$$

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

Finally, because of time constraints only 24 hour simulations are executed. It is estimated that one simulation has order n^2 time-complexity, with n the number of variables. Simulations for longer time periods therefore require a much longer calculation time, which was not feasible for the time available for this research. This is a problem for modelling linear programming because if there is only one trip in a day the control algorithms will only tell the EV to charge and not to discharge in the evening and night in order to be able to charge excess PV-power the next day. For this reason the original objective function is adapted, see equation (29).

$$\sum_i \sum_t k\left(P_{EV_i,in,PV}(t) + P_{EV_i,out,PV}(t)\right) - \sum_t P_{EV_i,grid}(t) \tag{29}$$

With k a scaling factor in order to determine the relative importance of the first two factors compared to the third. Using k = 100 it was found that the control algorithm works approximately as if equation (11) was used for a simulation longer than 24 hours. This means that equation (21) is adapted, see equation (30):

$$c_{(i-1)3T+t} = 100, \quad c_{(i-1)3T+T+t} = 100, \quad c_{(i-1)3T+2T+t} = -1 \tag{30}$$

2.6 Performance indicators

The research question can be dealt with as an optimisation problem and quantitative results for increased self-consumption can be given. Self-consumption is defined is the relative amount of PV-power for period T used by the households and the EVs. Because this indicator is relative (SC(T)∈[0,1]) it is easy to compare different situations. It is defined in formula (31).

$$\mathrm{SC}(T) = \sum_{t=T0}^{T} \frac{\min\left[P_{PV}(t), P_{load}(t) + \sum_i P_{EV_i}(t)\right]}{P_{PV}(t)} \tag{31}$$

With T the period that is evaluated, $T0$ the start time of period T.

Another important indicator is the amount of energy sold to the grid for period T. This indicator gives an absolute measure of self-consumption. It is defined in equation (32).

$$P_{grid,in}(T) = \sum_{t=T0}^{T} \max\left[P_{PV}(t) - P_{load}(t) - \sum_i P_{EV_i}(t), 0\right] \tag{32}$$

With T the period that is evaluated, $T0$ the start time of period T.

A third indicator, relative peak reduction for period T (RPR(T)) is also used for evaluation. RPR compares the deviation of the average of the load demand for the main grid $P_{grid,tot}(t)$, defined in equation (33), with a control algorithm ($P_{grid,tot,control}(t)$) to "Uncontrolled charging" ($P_{grid,tot,no\ control}(t)$) and is defined in equation (34).

$$P_{grid,tot}(t) = P_{load}(t) - P_{PV}(t) + \sum_i P_{EV_i}(t) \tag{33}$$

$$\mathrm{RPR}(T) = 1 - \frac{\sum_{t=T0}^{T} \left| P_{grid,tot,control}(t) - \overline{P_{grid,tot,control}(t)} \right|}{\sum_{t=T0}^{T} \left| P_{grid,tot,no\,control}(t) - \overline{P_{grid,tot,no\,control}(t)} \right|} \tag{34}$$

So for example, an RPR-score of 0 indicates no relative peak reduction compared to "uncontrolled charging", a RPR-score of 1 means load demand is totally flat for that day and a negative RPR-score would mean that there are more peaks compared to "uncontrolled charging". RPR is mainly of interest for the net manager, because electricity supply at peak times has to be bought from peak load power plants, which is more expensive than electricity from base load power plants.

2.7 Sensitivity analysis

The proposed model is based on several assumptions and has many different inputs. It is not always clear how these effect each other and the quantitative results needed for answering the research question. For this reason a sensitivity analysis of the model is performed in order to test the results on changes in inputs and assumptions. Because it is not possible to provide an analytical sensitivity analysis due to the complex nature of the model, the sensitivity analysis will be performed by running simulations with varying input factors. By comparing the results from these simulations the sensitivity of the model for the varied factors can be quantified.

Ideally, the sensitivity analysis would be executed by varying all input factors and all possible combinations of input factors for all possible values of these factors. However, due to the limited time available for this research choices about which factors to use have been made, based on assumptions on which factors are most relevant. Part of these factors are covered by random functions each simulation, the difference in input factors for the four scenarios, some of these factors will be varied explicitly for the sensitivity analysis.

Each simulation is based on several random functions. These functions represent factors that will vary from day to day. The variation of these factors is part of the main results. Random functions are used for:

- Selected 24-hour PV-profile
- Variation in load demand Parkhuis
- Selected households for load demand profile
- Factors related to EV-trips (is there a trip that day, start time, end time, distance)

- E_{EV_i} at time step t = 0

The scenarios are based on possible expansions of the micro-grid at LomboXnet. The impact of these factors is clear when the results of the scenarios are compared. The factors varied in the scenarios are:

- Installed kWp PV-installations
- Number of households connected to the micro-grid
- Number of EVs

Furthermore other factors assumed important for the results are tested in the sensitivity analysis. Because of time constraints for the research only the sensitivity of the scenarios "current" and "expansion" for these factors is tested. These scenarios are deemed most interesting for the sensitivity analysis because "current" represents the system at LomboXnet as is and "expansion" covers all possible expansions in the foreseeable future. The factors include:

- Yearly average electricity demand households
- Trips per week for the Tesla and the Leafs
- EV-types
- E_{EV_i} at time step t = 0
- Quality of PV-power prediction $P_{PV,prediction}$ (variation of σ with a maximum yield per day)

For the quality of PV-power prediction σ, see equation (28), is varied. While it is possible for P_{PV} to be zero, there is a maximum PV-yield per time step. In order to take this into account, for each month a profile of maximum PV-power $P_{PV,max,profile}$ is created. This is done by fitting the function defined in equation (35) to the maximum yield found in the datasets for each month.

$$P_{PV,max,profile}(t) = a \cdot e^{-b^2(t-t_{max})^2} \tag{35}$$

After fitting values for a (maximum yield), b (spread) and t_{max} (time step of maximum PV-power) $P_{PV,max,profile}$ for each month is defined. In the sensitivity analysis $P_{PV}(t)$ can never exceed $P_{PV,max,profile}(t)$, no matter how big σ is.

Furthermore, the sensitivity of the results for the battery capacity of the EVs will be tested. In the model the batteries can always be charged at maximum charging power, but in reality charging will be much slower when the state of charge of a certain battery approaches SOC = 1. This mechanism can not be included in the way the linear programming algorithm is set up, because it would alter the constraints **b** for each variation of **x**. For a fair comparison of control algorithms it was therefore chosen not to include this effect in all simulation. But to get an idea of how much this effects the outcome simulations will be run where the battery capacity is 90% of its origin value.

3. Input data

3.1 PV

The data for PV-power per hour is provided by LomboXnet. The PV-power is measured after conversion, i.e., it is the AC power, and any losses from the transformer are thus included. The data of the PV-installations at the Parkschool is available from July 6th 2011 to December 31st 2012 and shown in figure 3.1. The data of the PV-installations of the CGU is available from October 1st 2012 to December 31st 2012 and is shown in figure 3.2. In order to get a more clear view of the yearly variation the total amount of produced PV-power per week is shown in figure 3.3 for both installations.

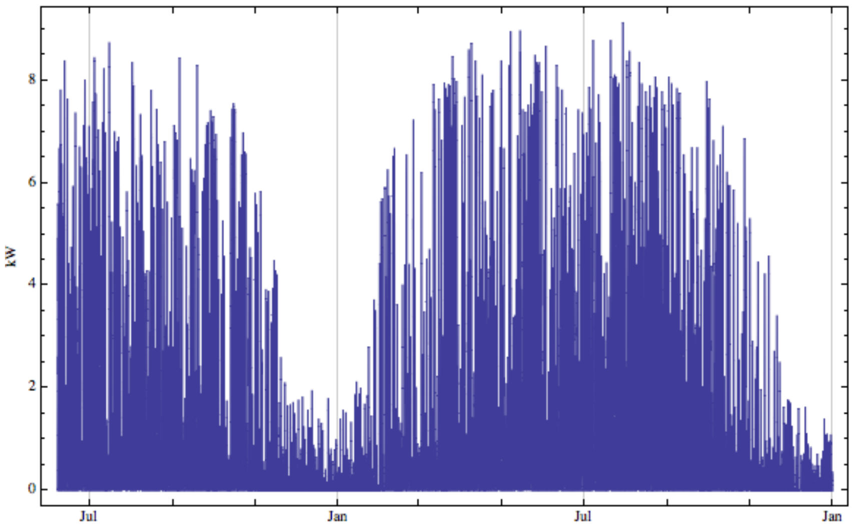


Figure 3.1 Hourly PV-power data for the Parkschool from July 6th 2011 to December 31st 2012

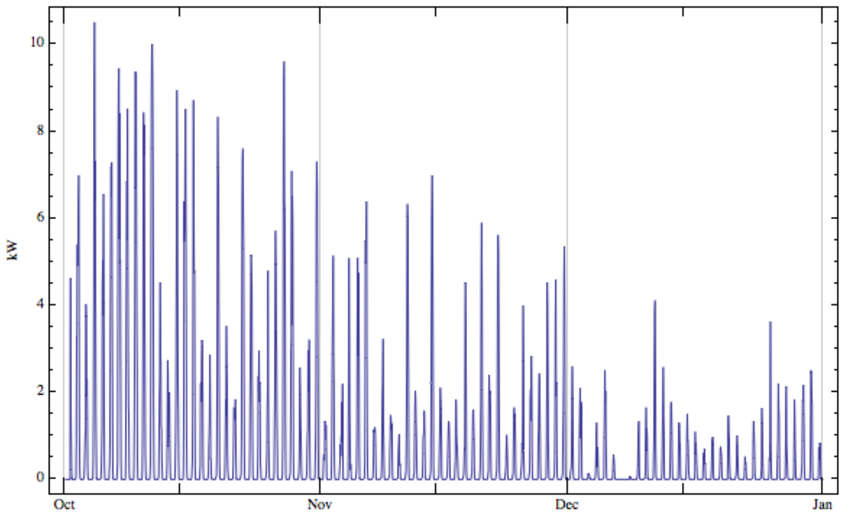


Figure 3.2 Hourly PV-power data for the CGU from October 1st 2012 to December 31st 2012

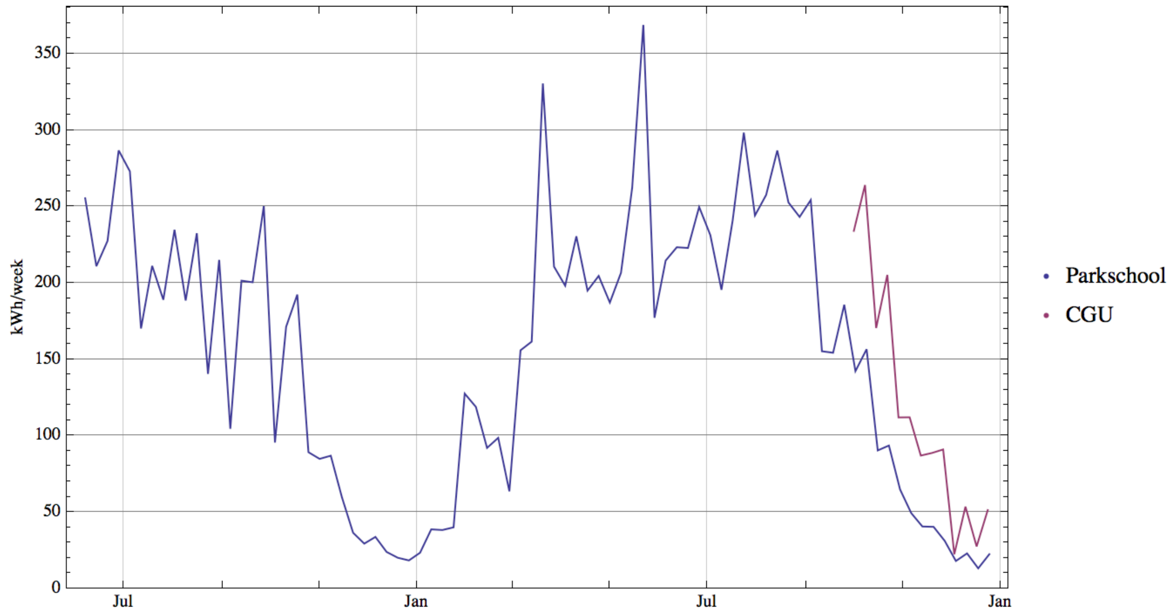


Figure 3.3 PV-power per week for the Parkschool and CGU

For the Parkschool installation the performance ratio (PR) is calculated. The performance ratio is defined in equation (36) (SMA, 2013).

$$PR = \frac{\text{actual reading of plant output}}{\text{irradiation value} \times \text{plant area} \times \text{module efficiency}} \tag{36}$$

With an actual reading of plant output of 8226.82 kWh, an irradiation value of 989 kWh/m^2 for 2012 (KNMI, 2013), 40 panels and panel area of 40 * 1.6 m^2 and a module efficiency of 15.4% (Suntech, 2013) this results in a performance ratio of 0.85.

Reliable data for the installation at the Parkhuis is not available, but this will be simulated by taking data from the other installations and normalising this data to a nominal power of 3 kWp. This will be the same for the extra 5 kWp for the high PV-scenario and the periods of the year for which there is no data from the CGU available. In figure 3.4 a scatter plot of the PV-power of the CGU and the Parkschool is given for the period for which data from both installations is available. In order to find the ratio of the power supply of the two installations, two linear function fits were made for the data between 11:00 and 15:00 in order to exclude extreme values of the mornings and evenings. First a function was fitted of the form $f(x) = a\ x$ for all data between 11:00 and 15:00, it is found that $a \approx 1.52$. Because from the scatter plot it seems that the ratio is different for lower values of P_{PV} than for higher values a second fit was made which consists of different linear functions for the lower and higher values of P_{PV}.

For the second fit it is found that $a \approx 2.26$ for the lower part and $a \approx 1.10$ for the higher part, meaning that the CGU installations performs relatively better when solar insulation low than when is high solar insulation. For the simulations the ratio of the nominal power 18 MWp (for CGU) / 10 MWp (for Parkschool) = 1.8 was used for scaling the PV-power. The fitting of the functions was done after the final simulations were performed.

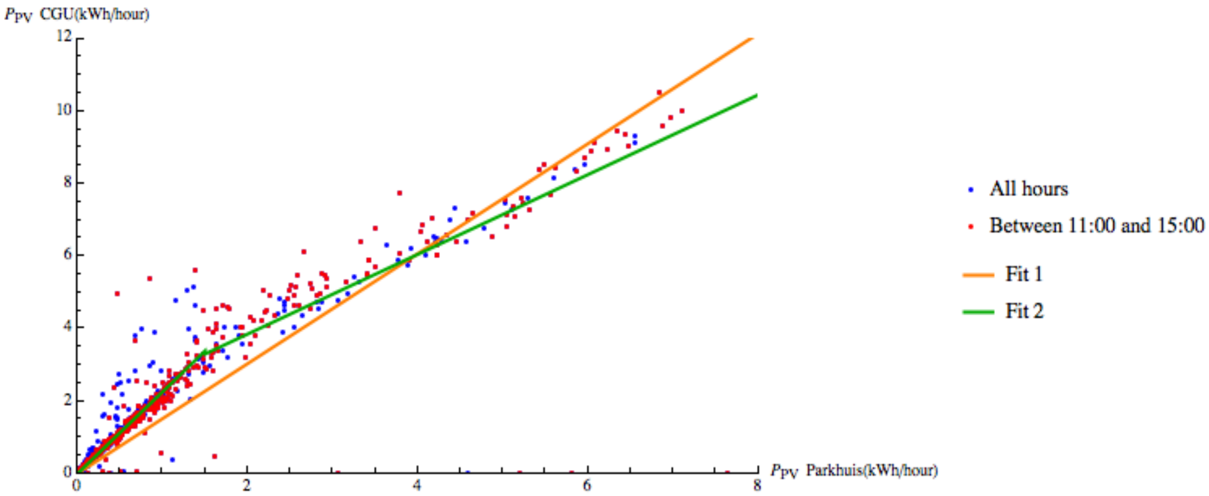


Figure 3.4. Scatter plot of PV-power of the CGU and the Parkschool for the period for which data from both installations is available including two fitted functions

3.2 Load demand

3.2.1 Households

Load demand data for the households is based on week-long measurements with time intervals of 15 minutes from Liander taken in February 2008 of a neighbourhood with approximately 700 houses, from which 400 were randomly selected. The data is provided by Claessen who used it for his MSc. Thesis *Smart Grid Control* (Claessen, 2012). He in turn has received it from the Technical University of Twente. A randomly selected example of the data provided to me for a week for three houses is shown in figure 3.5.

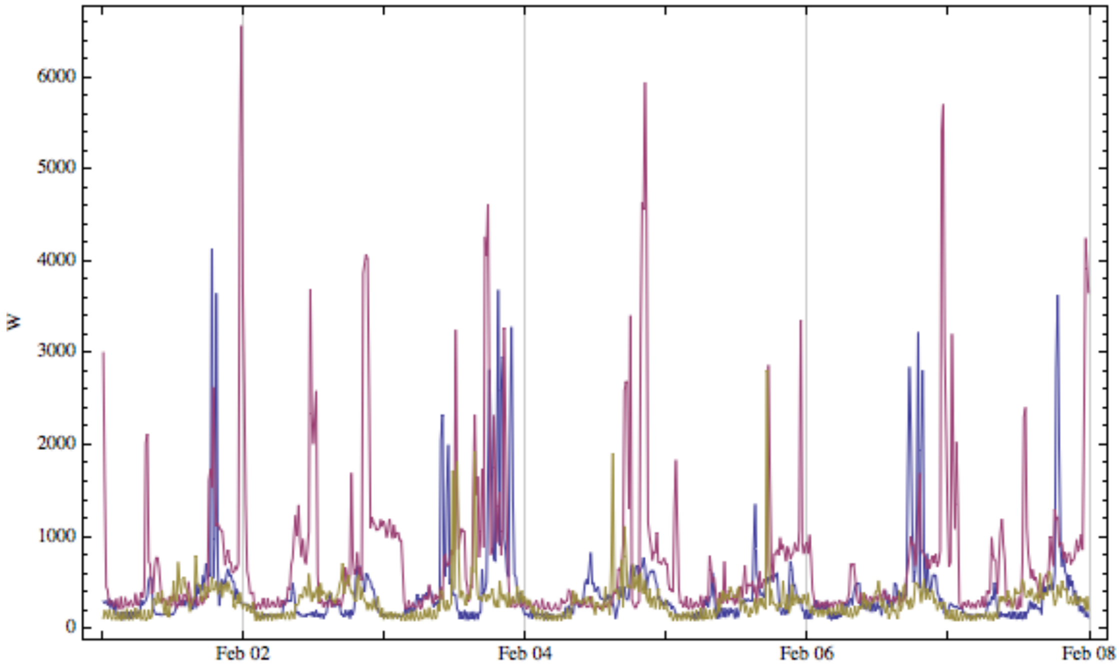


Figure 3.5 Load demand data for a week for three households

The week-long data is repeated 52 times to cover a year for each household. However, in order to account for yearly variation in demand the original data is multiplied by a different factor for each week, based on measurements of average consumption for a different set of houses taken by Liander in 2007. The factors for each week were extracted from the year-long data is provided to me and shown in figure 3.6.

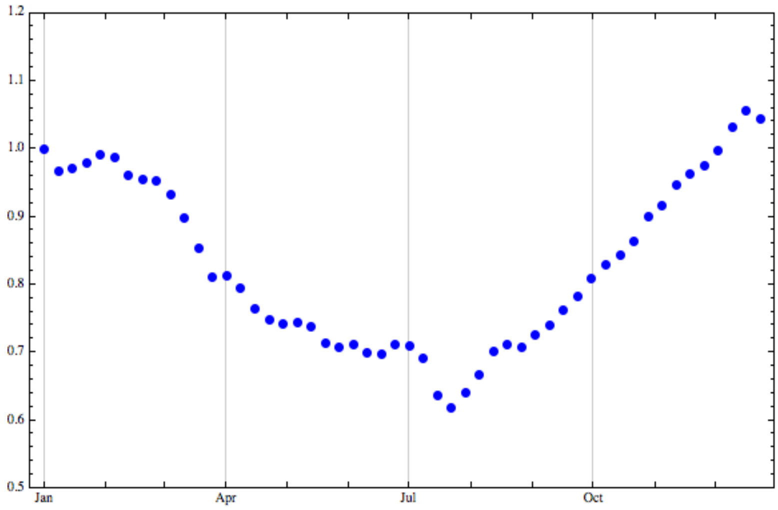


Figure 3.6 Weekly energy use compared to the first week of January

The original data was adapted to make it applicable for the year 2050, the year at which the research of (Claessen, 2012) is aimed. The data was multiplied with a scaling factor assuming an annual growth of electricity consumption of 0.5%. This research is aimed at the near future, so the data, which was already multiplied by this scaling factor, is multiplied with 1.005^{-26} to make it applicable for 2014.

The yearly electricity demand for the households in the provided dataset range from 754.863 to 15669 kWh per year and is shown in figure 3.7. In the case of LomboXnet, only three to five houses are connected to the micro-grid. It is therefore not expected that there will be a large variation in the electricity demand from households. Because of this only houses are selected which have an electricity demand within 30% of the average for Lombok, which is 3680 kWh (Van den Berg et al., 2012), which leaves 143 households from which three to five are randomly selected for each simulation. The effects of a larger or smaller load demand will be investigated through the outcome of the scenarios, sensitivity analysis and different months.

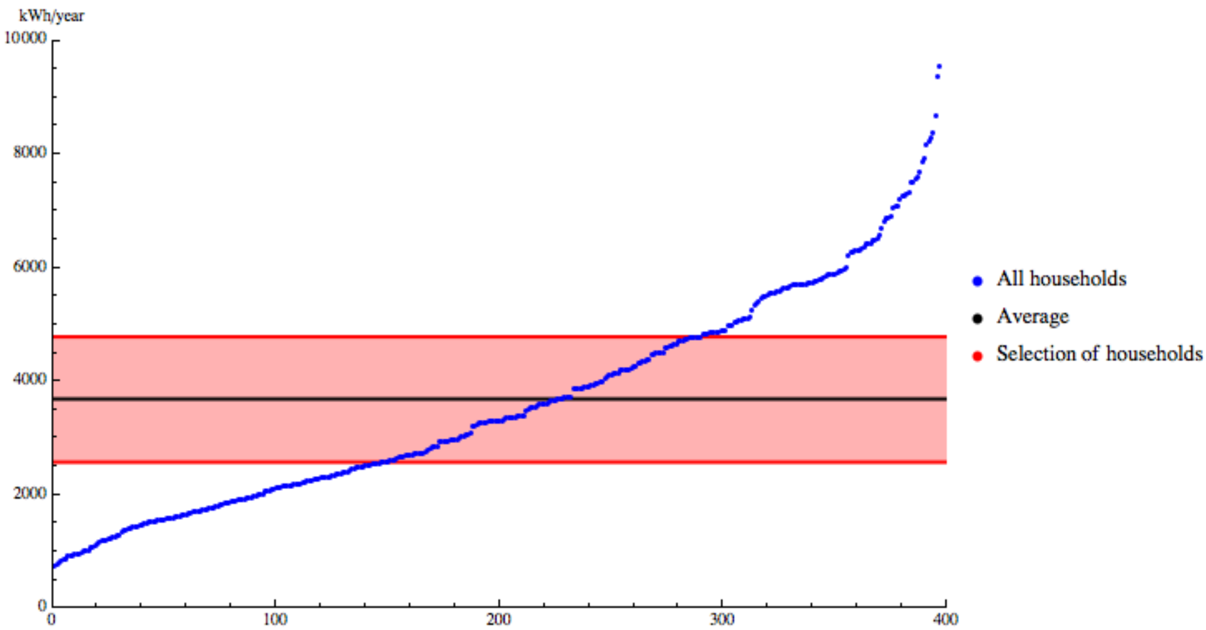


Figure 3.7 Total load in for all households, the average and the used selection of houses

3.2.2 Parkhuis and servers

The data on which the electricity demand of the Parkhuis is based is provided by LomboXnet. From October 29th to November 8th 2012 the net electricity use, demand minus PV-power production, was measured. In order to get insight into the energy demand of the Parkhuis, PV-data for each hour was extracted from the original data. The result is shown in figure 3.8.

The servers are constantly using about 2.3 kW, which should be the minimum demand for Parkhuis. Since the graph shows that the demand falls below this value often and is sometimes even negative, it is clear that the applied method does not work perfectly. Therefore the choice is made to use the data to establish a profile for the simulations in order to create a more realistic demand curve.

The method by which this is done is first to assume a constant minimum demand of 2.3 kWh for the servers. Then the profile of the Parkhuis is established by taking the average and deviation for each hour excluding the minimum and maximum, see figure 3.9. In the final simulations, the demand for each hour is varied within the limits of the deviation, so a realistic demand curve can be simulated.

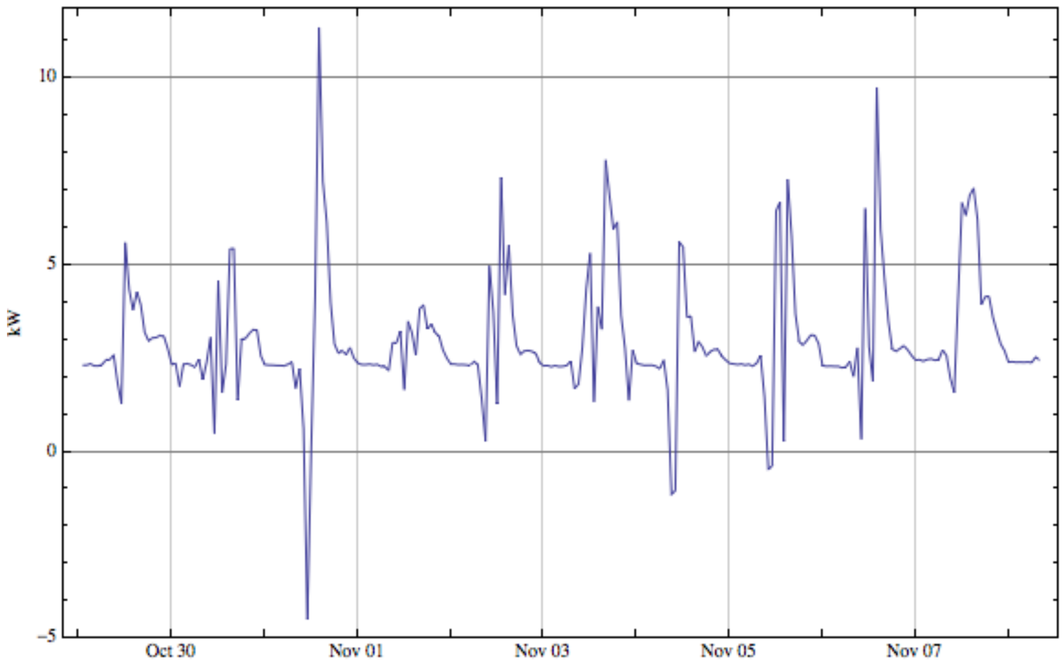


Figure 3.8 Load demand for the Parkhuis for October 29th to November 8th 2012

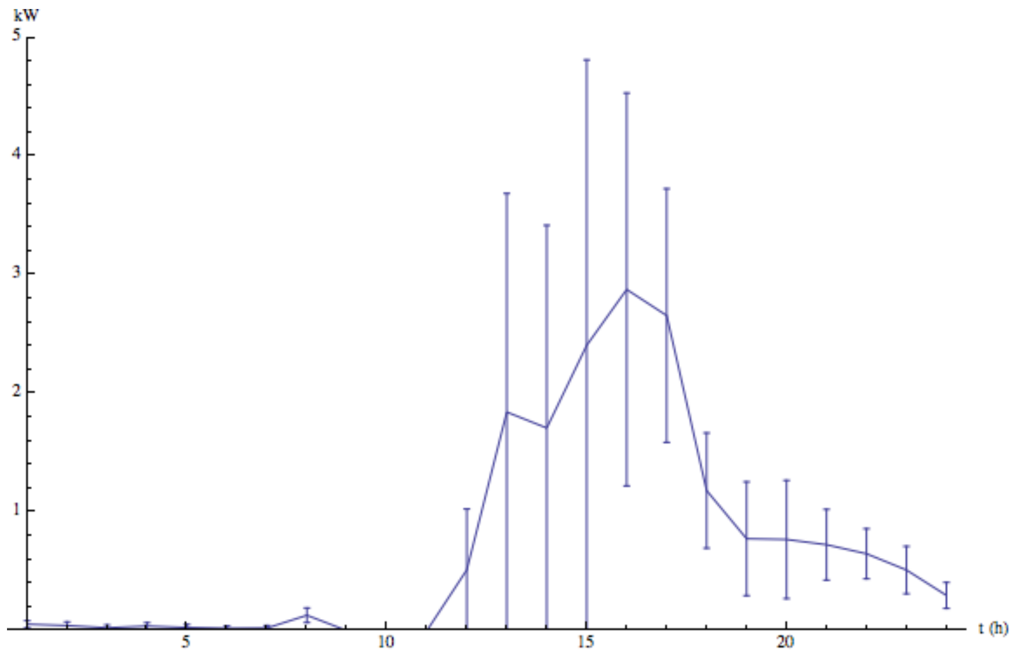


Figure 3.9 Generated load demand profile for the Parkhuis minus servers including deviations

3.3 EVs

The technical specifications for the EVs were retrieved from the respective manufacturers and the United States Environmental Protection Agency. In case of a lack of data a reasonable assumption is made. Only the technical specifications which are relevant to the micro-grid model are included. In table 3.1. an overview of the input data is presented. An interesting observation is that the relevant technical aspects for the Nissan Leaf and the Ford Focus are very similar to each other, especially when compared to the Tesla.

Furthermore an estimation of the use of the EVs must be made. This was done based on the ideas on EV-use from Robin Berg at LomboXnet. The result is presented in table 3.2. The Tesla is for private use and the Nissan Leaf(s) are rental cars. Both cars are estimated to make about three trips per week which will last between 3-6 hours and will be between 20 km and full range. The third loading station is not yet in place, but if it is there it will be used by at least one Ford Focus Electric which is used for commuting. This is why trip per week, trips times and minimum trip distance are longer for the Focus then for the Tesla and Leafs. It is not yet known what second car would use the third loading station, here it is assumed that it will be a second Ford Focus with the same characteristics.

Table 3.1 Relevant technical specifications for simulated EVs

Tesla Model S (2013, 85 kWh)				
Source	*Tesla*[2]	*EPA*[2]	*Assumption*	*Used in model*
C_{Bat} **(kWh)**	85	85		**85**
$P_{max,in}$ **(kW)**	11/22			**22**[3]
$P_{max,out}$ **(kW)**			11/22[4]	**22**[3]
Combined P_{cons} **(kWh/km)**		0.236[5]		**0.236**
Range **(km)**		426	288[6]	**288**
η_{in}			81%	**81%**
η_{out}			81%	**81%**
SOC_{min}			20%	**20%**
Nissan Leaf (2011/12 model)				
Source	*Nissan*[2]	*EPA*[2]	*Assumption*	*Used in model*
C_{Bat} **(kWh)**	24	24		**24**
$P_{max,in}$ **(kW)**	3.3/6.6			**6.6**[3]
$P_{max,out}$ **(kW)**			3.3/6.6[4]	**6.6**[3]
Combined P_{cons} **(kWh/km)**	0.173	0.211[5]		**0.211**
Range **(km)**	175	117	91[6]	**91**
η_{in}		81%		**81%**
η_{out}		81%		**81%**
SOC_{min}			20%	**20%**
Ford Focus Electric (Third generation)				
Source	*Ford*[2]	*EPA*[2]	*Assumption*	*Used in model*
C_{Bat} **(kWh)**	23	23		**23**
$P_{max,in}$ **(kW)**	6.6			**6.6**[3]
$P_{max,out}$ **(kW)**			6.6[4]	**6.6**[3]
Combined P_{cons} **(kWh/km)**		0.199[5]		**0.199**
Range **(km)**		122	92[6]	**92**
η_{in}			81%	**81%**
η_{out}			81%	**81%**
SOC_{min}			20%	**20%**

[2] Sources: Tesla Model S: www.teslamotors.com, Nissan Leaf: www.nissan.nl/Leaf, Ford Focus: www.ford.nl/Focus, EPA: www.fueleconomy.gov

[3] It is assumed that the fast charging option is available.

[4] It is assumed that discharging is as fast as charging.

[5] Based on 55% city and 45% highway driving. The EPA values are considered more reliable than the manufacturer values so these are the values that are used in the model.

[6] The assumed range is much lower than the rated EPA-estimated range, because it is calculated with the combined P_{con} (city and highway) and the EPA-estimated range assumes the minimum P_{cons} and a minimum SOC of 10%. In the model this is not of particular interest, the only interesting aspect is the SOC at the start and return of a trip. This is why it is not considered a problem.

Table 3.2 EV use

Car	Trips per week (average)	Trip duration (h)	Trip times of day (h)	Trip distance (range) (km)
Tesla	3	Between 3 and 6	Between 9:00 and 19:00	20-288
Leaf 1	3	Between 3 and 6	Between 9:00 and 19:00	20-91
Leaf 2	3	Between 3 and 6	Between 9:00 and 19:00	20-91
Focus 1	5	Between 6 and 10	Between 8:00 and 19:00	60-92
Focus 2	5	Between 6 and 10	Between 8:00 and 19:00	60-92

3.4 Scenarios

Based on the input data the following scenarios (see table 3.3) are constructed.

Table 3.3 Input data for the scenarios

		Current	Expansion	Low flexibility	High flexibility
Installed PV-power (kWp)	*Parkhuis*	3	3	3	3
	Parkschool	10	10	10	10
	CGU	18	23	18	23
	Total	**31**	**36**	**31**	**36**
Average electricity demand per year (MWh)	*Parkhuis*	6.3	6.3	6.3	6.3
	Servers	20	20	20	20
	Households	11	18	18	11
	Total	**37.3**	**44.3**	**44.3**	**37.3**
Total battery capacity EVs (kWh)	*Tesla*	85	85	85	85
	Leaf	24	48	24	48
	Focus	0	46	0	46
	Total	**109**	**179**	**109**	**179**

Each scenario is evaluated for every month of the year and based on the results they can be compared on the performance indicators for a year. In the case of the scenarios "current" and "low flexibility", both including 2 EVs, the simulations will have a time steps of 15 minutes. For input data of PV-power and load demand from the Parkhuis an interpolation function will be used in order to convert the data from a resolution of 1 hour to 15 minutes. In the case of the scenarios "expansion" and "high flexibility", both including 5 EVs, the simulations will have time steps of 1 hour because of time considerations; it is estimated that one simulation has order n^2 time-complexity, with n the number of variables. The input data for household demand will therefore be averaged for an hour.

3.5 Sensitivity analysis

In the sensitivity analysis the factors yearly average electricity demand households, trips per week for the Tesla and the Leafs, EV-type and energy in EV battery at the start time of a simulation are varied. For each factor, three scenarios are investigated, with "medium" or "normal" being the value that is used for the main simulations. The scenarios and associated values are presented in table 3.4.

Table 3.4 Input data for the sensitivity analysis

Yearly average electricity demand households	**Scenario**	**Lower**	**Medium**	**High**
	kWh/yr	2680 ± 30%	3680 ± 30%	4680 ± 30%
Trips per week for the Tesla and the Leafs	**Scenario**	**Less**	**Medium**	**More**
	Trips per week	1	3	6
EV-type for "current"[6]	**Scenario**	**Normal**	**All Tesla**	**All Leaf**
	EVs	1 Tesla, 1 Leaf	2 Tesla	2 Leaf
EV-type for "expansion"[7]	**Scenario**	**Normal**	**All Tesla**	**All Leaf**
	EVs	1 Tesla, 2 Leaf, 2 Focus	5 Tesla	5 Leaf
Energy in EV battery at start time simulation	**Scenario**	**Normal**	**Empty**	**Full**
	$E_{EVi}(0)$	Random	$=E_{EVi,req}(1)$	$=C_{EVi}$

Using the PV-datasets, for each month equation (35) was fitted for the variables a, b and t_{max}, resulting in a maximum PV-power profile for each month. The results are presented in figure 3.10. In the main simulations σ is 10%, in the sensitivity analysis σ is varied between 0 and 50%.

[7] It is assumed that EV-trips can make use of the total battery capacity of the EV, meaning that in the scenario "All Tesla" maximum and mean trip distance will increase and in the scenario "All Leaf" maximum and mean trip distance will decrease compared to scenario "normal"

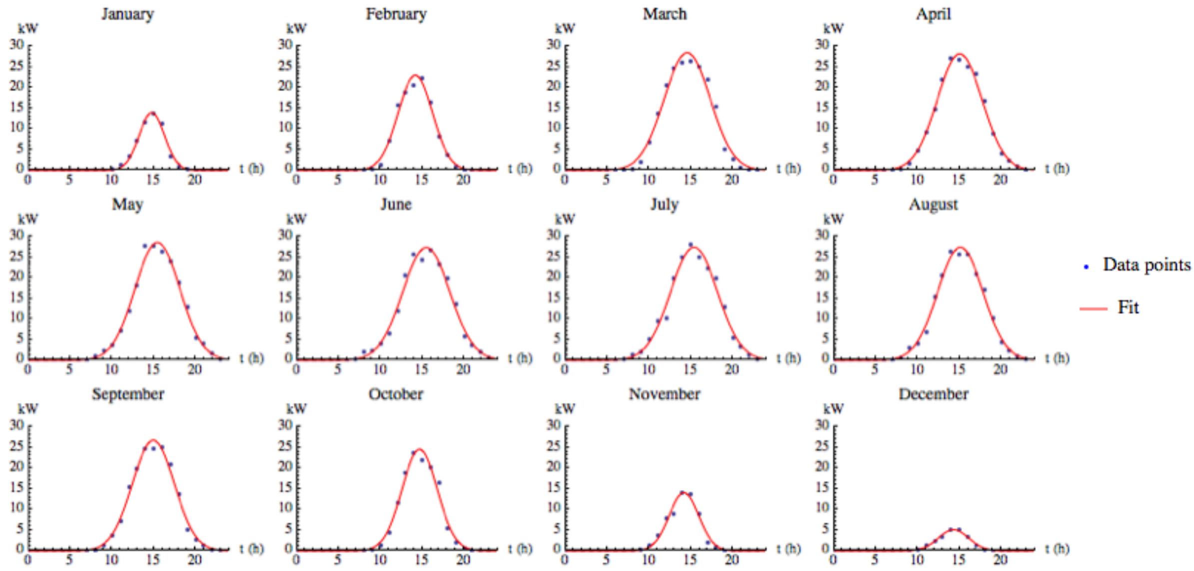


Figure 3.10 Established $P_{PV,max,profile}$ for each month

4. Results

In this chapter the results from the simulations are presented and analysed. In section 4.1 the results for each separate scenario are presented. In section 4.2 the results of the sensitivity analysis are presented. Finally, in section 4.3 the results of the performance indicators and sensitivity analysis for all scenarios are compared. This comparison gives insight into the operation of the control systems under different conditions and conclusions for which control algorithms are preferred can be derived from these results.

4.1 Scenarios

In this section the results for each scenario are presented. Each consists of two parts.

In the first part the PV, load, and EV-charging profiles for one particular day are shown. These examples are based on the same PV-profile, EV-trips and load profiles (for the scenarios "expansion" and "high flexibility" two more households are included). The examples show a day in July, which means high PV yield and low household load, because then the effects of the control systems are more clear then in a winter situation. In the examples all the EVs take a trip in order to show the effects of the control systems, in the complete year-long simulations this will occur only 18% (for "current" and "low flexibility") and 4% (for "expansion" and "high flexibility") of the time. In all the examples the EV-batteries are half full at t=0, except in the case of "uncontrolled charging", since the batteries are fully charged in the previous night.

In the second part of the sections on the scenarios the results of the total simulations are shown. The results are evaluated for the performance indicators as defined in section 2.6 for each month and for the total year. Conclusion on system performance of each control algorithm for each scenario is based on the results for these indicators. All results per month per control algorithm are based on 60 24 hour-simulations for each scenario, 60 instead of 30 in order to improve the statistical basis of the results, which means yearly results are based on 720 simulations for each scenario.

4.1.1 Current

In figure 4.1 the example simulations for the scenario "current" are presented. The different effects of the control simulations can be explained with the help of these pictures.

In the case of “uncontrolled charging”, the EVs arrive at the loading station after a trip and start charging until they are full, in this case it means that they start charging in the late afternoon (Tesla) and evening (Leaf).

In the case of “RT controlled charging”, the Tesla starts loading at 10:00 because it needs the energy for a trip, while the Leaf starts loading at 11:00 because at that time there is excess PV and the energy is not needed earlier. Both EVs also charge when coming back from the trip, since there is a small amount of excess PV.

In the case of “RT controlled charging and discharging” both EVs start discharging because there is no PV to cover load demand. For the Tesla this means that it will have to charge at maximum power longer than in the previous case in order to have sufficient energy available for the trip. The trip with the Leaf is later that day, so because energy was discharged in the night more energy can be stored during the afternoon, which results in higher self-consumption of PV-power when compared to the previous case (see later). In the evening the energy available in the EVs is discharged to cover load demand.

In the case of “linear programming (ideal)” both EVs charge much less in the morning than in the previous case, because the system takes into account the planned trips. The total amount of discharged power is just enough to have the storage amount available to cover maximum self-consumption in the morning. In the evening the energy available in the EVs is discharged to cover load demand. Note that the realistic case of “linear programming” does not deviate much from the ideal case, although the load curve is less flat.

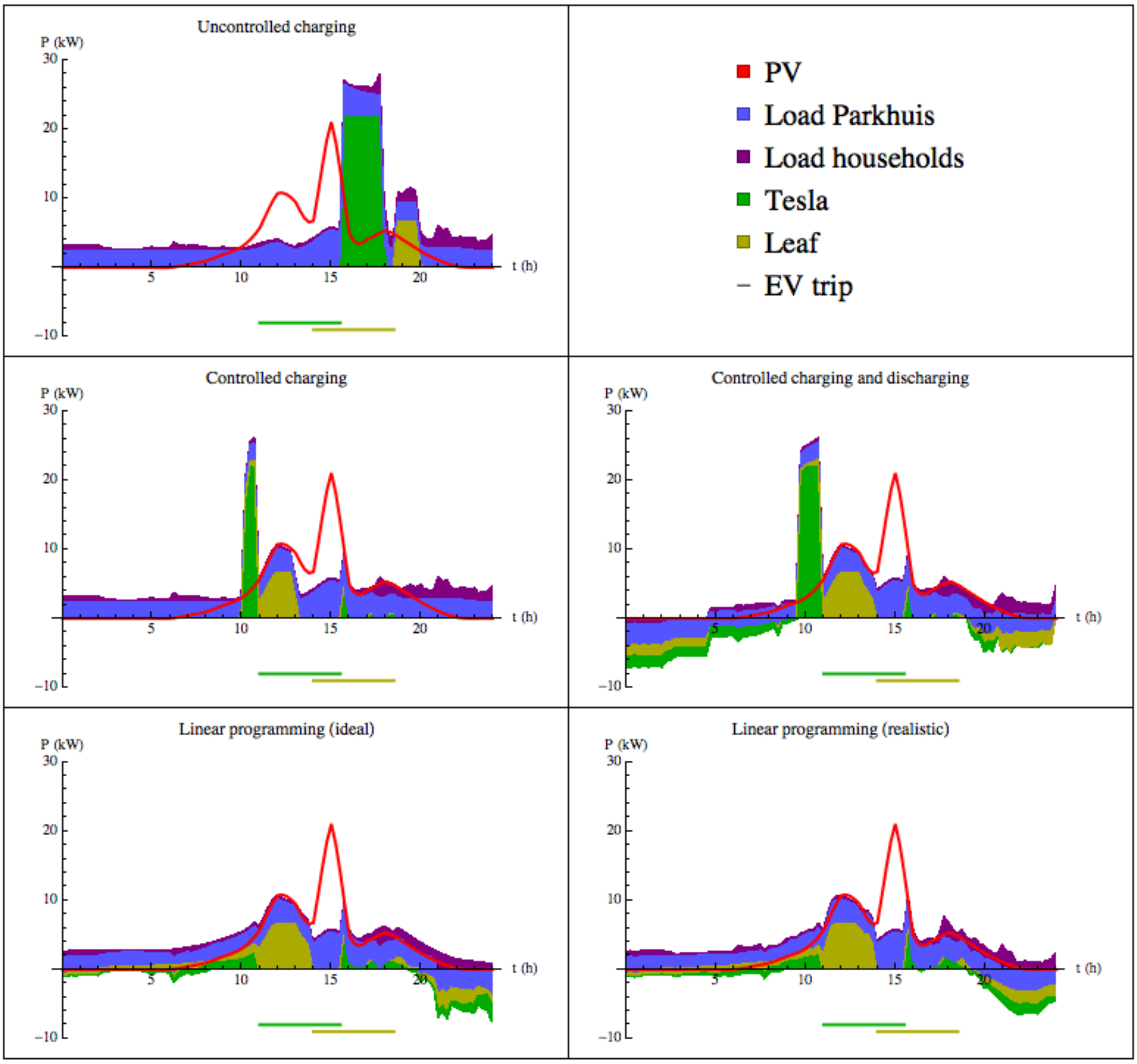


Figure 4.1 Example of a 24 hour-simulation for each control system in the scenario "current". The top of the colored area shows the total load demand, if the colored region is under the x-axis it means the batteries are discharging. The lines indicate the times the EVs are on a trip, with a color corresponding to the color presented in the legend

In figure 4.2 the results of the simulations evaluated for the performance indicators per month and for the total year are presented. It can be seen that all proposed control systems contribute significantly to self-consumption and reduce the energy send to the grid. Although the difference between the baselines and the control systems for self-consumption is small or non-existent for months with little PV-power (especially December), the difference between the performances of the control systems during the other months is relatively small.

As expected the “linear programming (ideal)” algorithm performs best in all cases. However, the difference on self-consumption and energy send to the grid between “linear programming (realistic)” and “RT controlled charging and discharging” are small. The difference between these control algorithms is more clear when looked at peak reduction, in which “linear programming (realistic)” performs better than “RT controlled charging and discharging”.

Furthermore, it is interesting to note that in months with low PV and high load (January, February, October, November and December) “RT controlled charging” performs better on peak reduction than “RT controlled charging and discharging”, while in the rest of the months it is the other way around. The explanation for this is that when there is little excess PV-power the EV will discharge a lot of energy so that it needs to charge much more energy for a trip than if it had not discharged, while if there is plenty excess PV-power the EV will have charged enough PV-power for a trip and can send energy to the other loads which flattens total load demand.

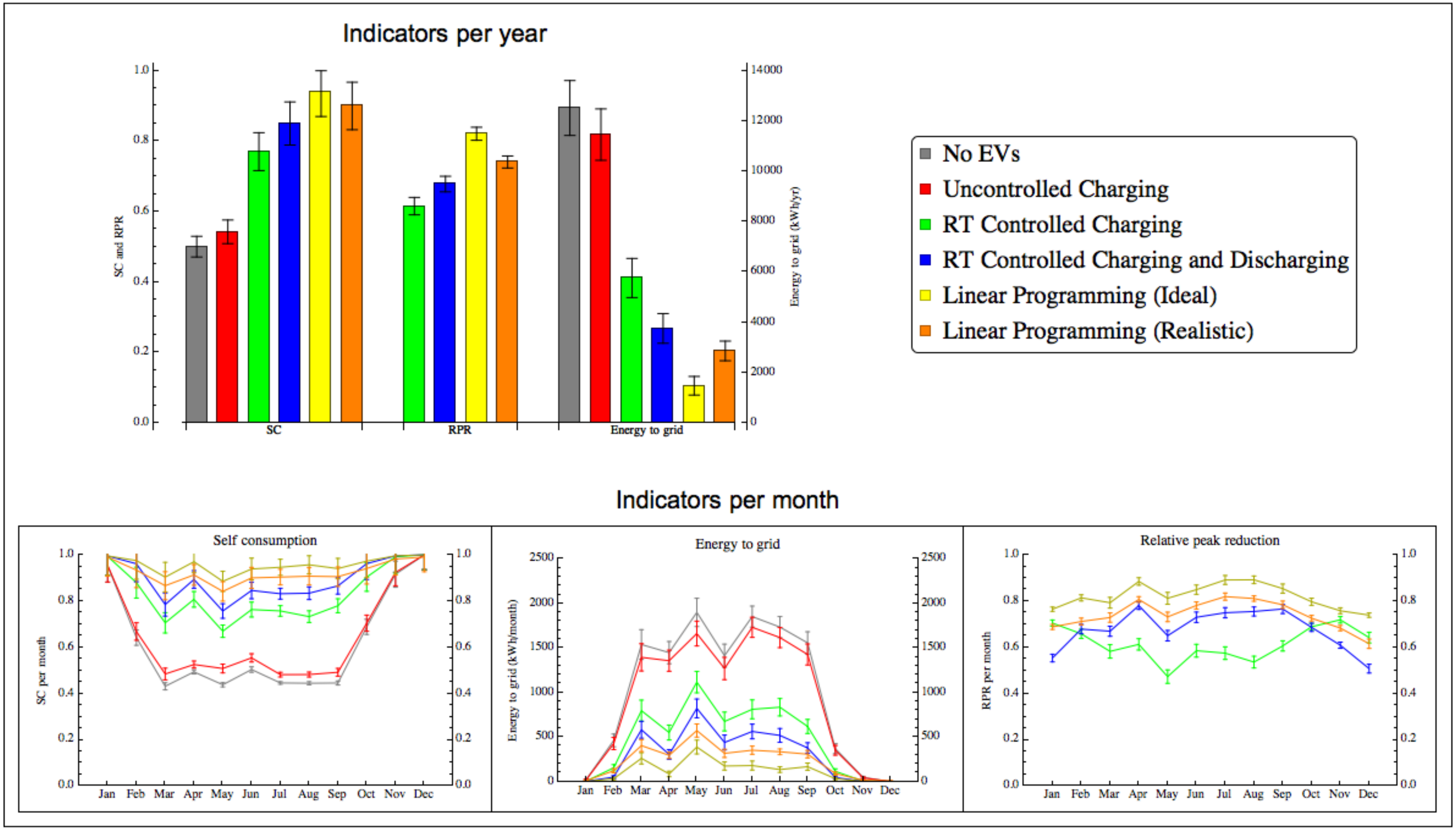


Figure 4.2 Results evaluated for performance indicators of the scenario "current"

4.1.2 Expansion

In figure 4.3 the example simulations for the scenario "expansion" are presented. The figures will not be discussed as extensively as in the previous section, because the effects are similar. However, the effects in the load pattern are bigger, because more EVs are used. An interesting aspect to note is that in both cases of "linear programming" both Focus EVs are minimally (dis)charged.

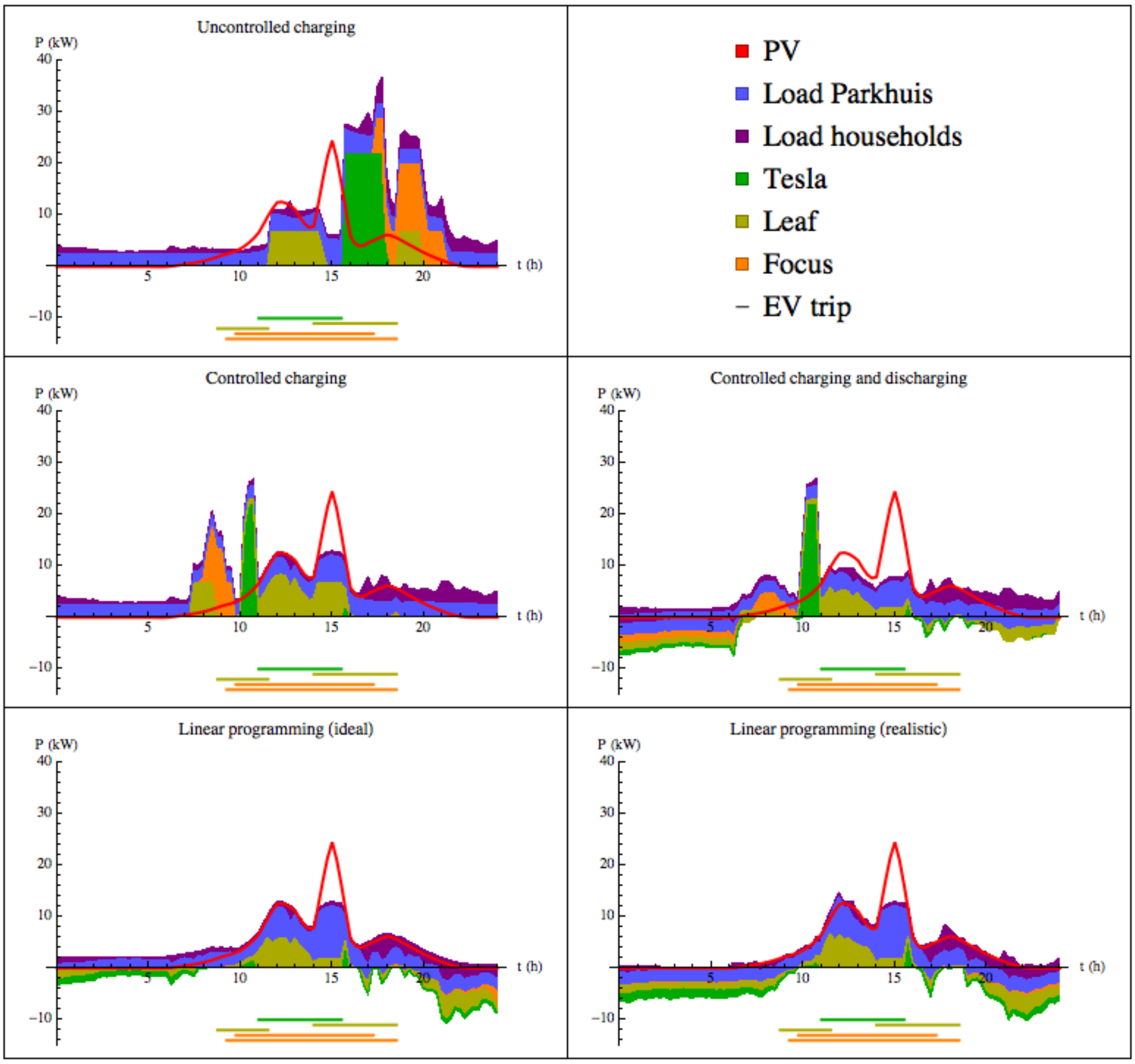


Figure 4.3 Example of a 24 hour-simulation for each control system in the scenario "expansion". The top of the colored area shows the total load demand, if the colored region is under the x-axis it means the batteries are discharging. The lines indicate the times the EVs are on a trip, with a color corresponding to the color presented in the legend

In figure 4.4 the results of the simulations evaluated for the performance indicators per month and for the total year are presented. These results will not be discussed as extensively as in the previous section since the effects are similar, but note that the variation per month on self-consumption is more significant here than in the previous section. Furthermore, "linear programming (realistic)" performs bad on self-consumption in months January, November and December, but because PV-power is low in that months, the effect is limited on a yearly basis.

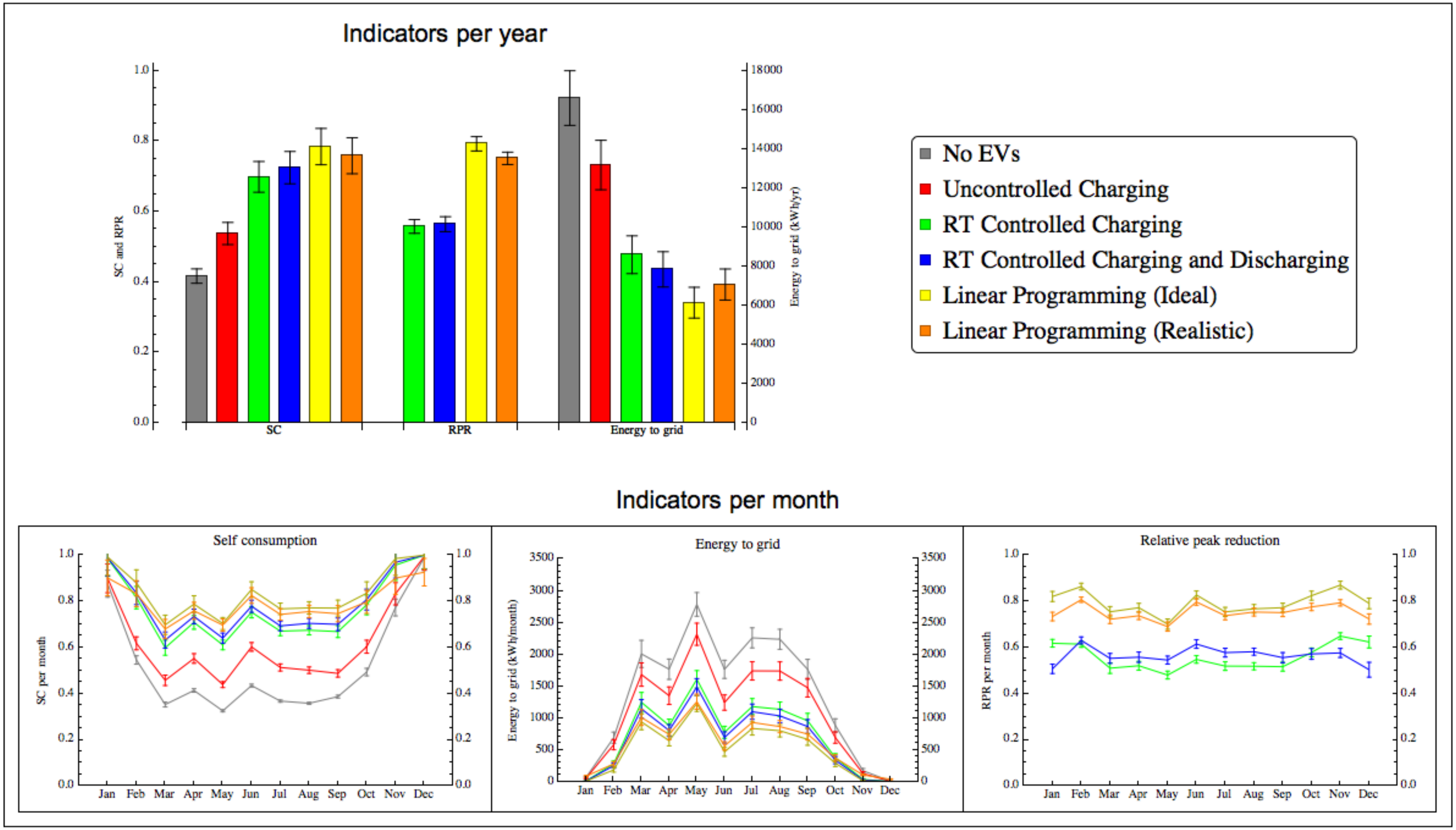


Figure 4.4 Results evaluated for performance indicators of the scenario "expansion"

4.1.3 Low flexibility

In figure 4.5 the example simulations for the scenario "low flexibility" are presented. The results are similar as with the scenario "current", but in this scenario there is less excess PV-power to charge or store.

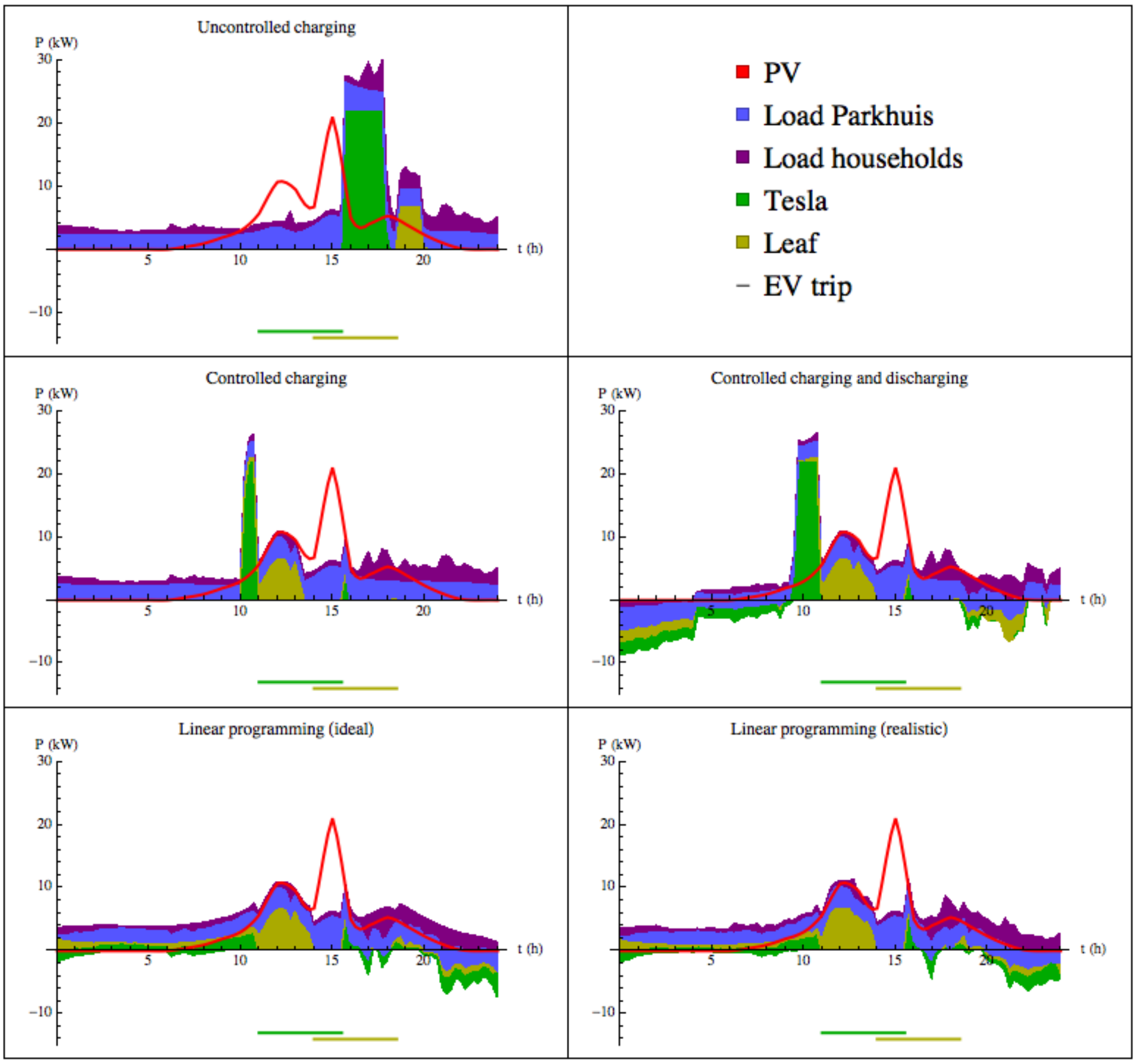


Figure 4.5 Example of a 24 hour-simulation for each control system in the scenario "low flexibility". The top of the colored area shows the total load demand, if the colored region is under the x-axis it means the batteries are discharging. The lines indicate the times the EVs are on a trip, with a color corresponding to the color presented in the legend

In figure 4.6 the results of the simulations evaluated for the performance indicators per month and for the total year are presented.

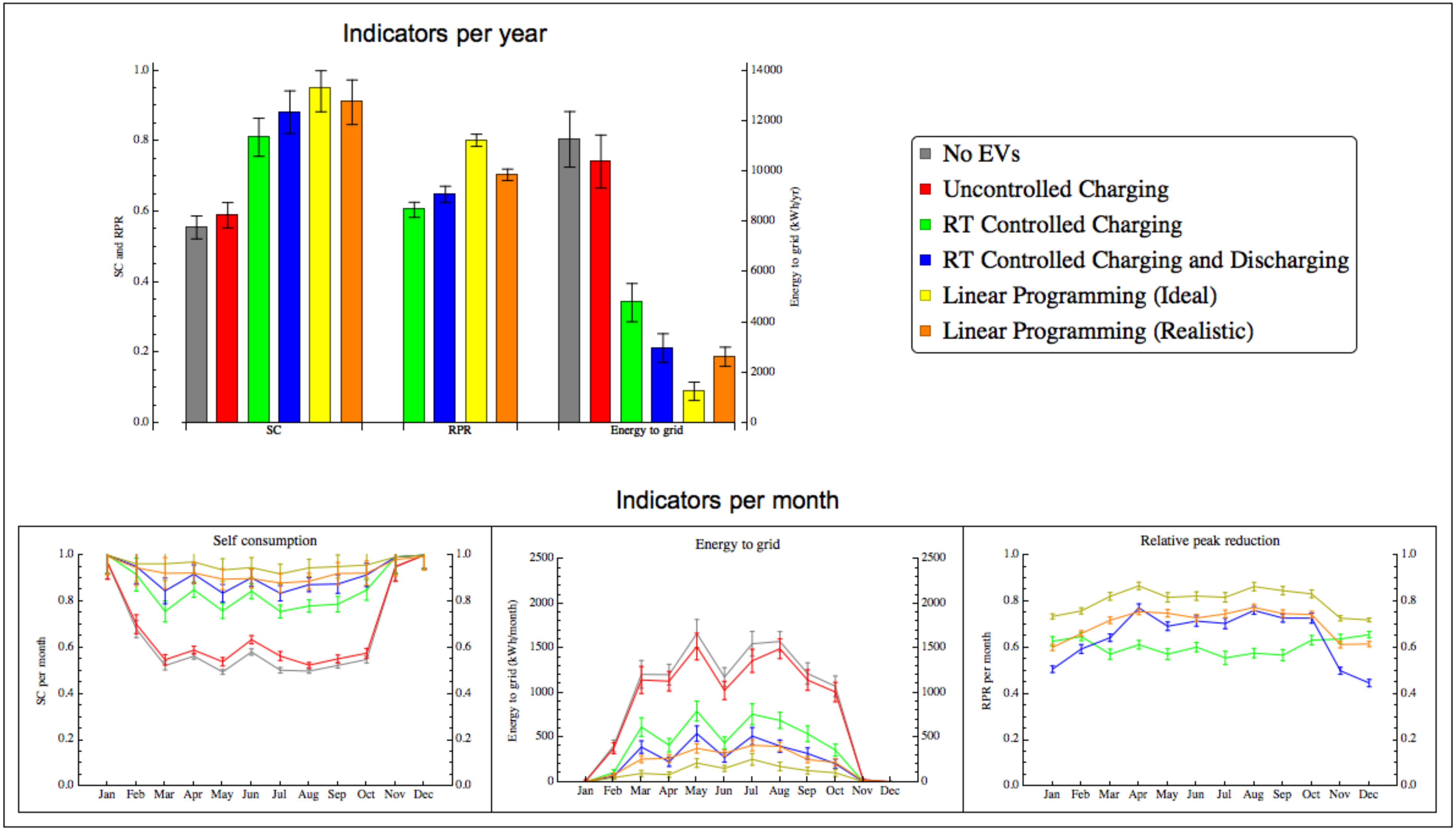


Figure 4.6 Results evaluated for performance indicators of the scenario "low flexibility"

4.1.4 High flexibility

In figure 4.7 the example simulations for the scenario "high flexibility" are presented. The results are similar as with the scenario "expansion", but in this scenario there is more excess PV-power to charge or store.

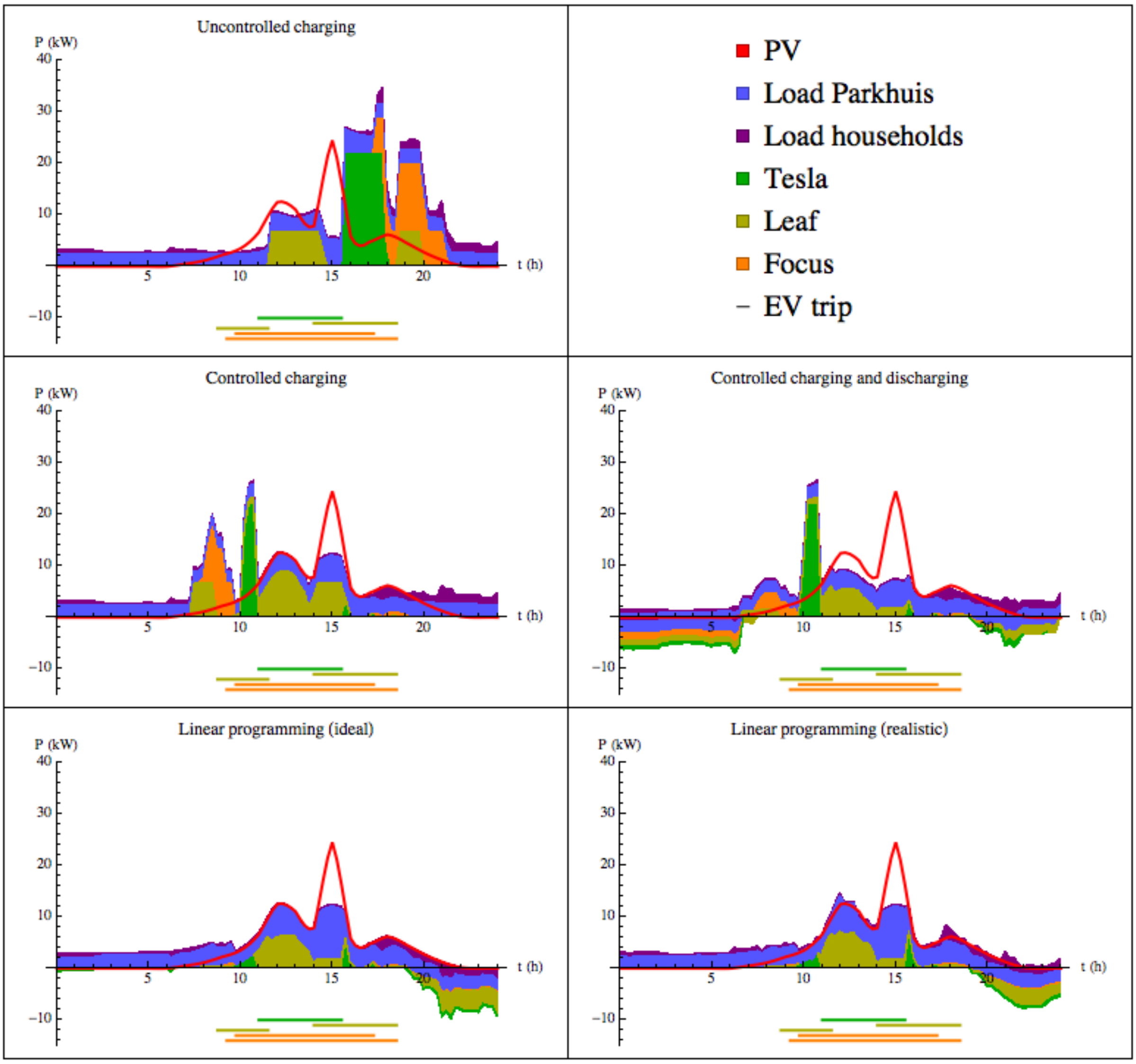


Figure 4.7 Example of a 24 hour-simulation for each control system in the scenario "high flexibility". The top of the colored area shows the total load demand, if the colored region is under the x-axis it means the batteries are discharging. The lines indicate the times the EVs are on a trip, with a color corresponding to the color presented in the legend

In figure 4.8 the results of the simulations evaluated for the performance indicators per month and for the total year are presented.

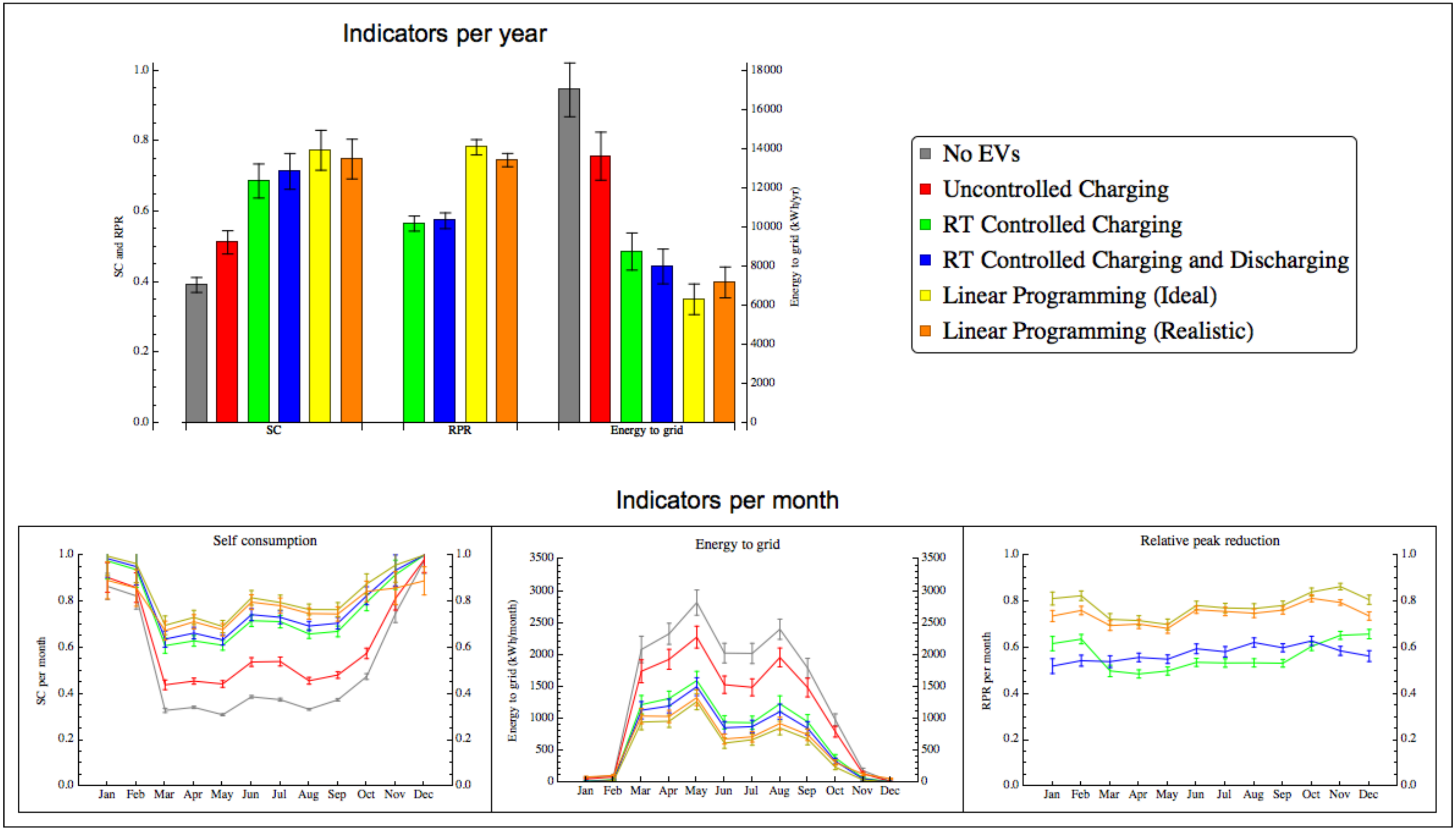


Figure 4.8 Results evaluated for performance indicators of the scenario “high flexibility”

4.2 Sensitivity analysis

In this section the results from the sensitivity analysis are discussed. In section 2.7 a distinction was made between factors affecting the results included in each 24 hour-simulation, the difference between scenarios and factors only tested in the sensitivity analysis. Here, only the latter are discussed. Results for the extreme scenarios for yearly average electricity demand households, trips per week, EV-type, energy in EV-batteries at start time simulations and EV-battery capacity are based on 120 simulations while results for the medium scenarios are based on 620 simulations. This was done because of time-constraints for this research. This difference must be taken into account when interpreting the results.

In figure 4.9 results for the sensitivity analysis on yearly average electricity demand households are presented. Based on the graphs, it can be concluded that the yearly average electricity demand only has a slight effect on the outcome, especially for the scenario "current". The largest difference can be seen for "uncontrolled charging", this can be explained that in the absence of a smart charging system the EV charging profiles are not dependent on P_{load}, and a higher household load automatically leads to increased self-consumption. However, when looking at the results for energy to grid for the scenario "expansion", it seems the lower scenario performs better the medium scenario.

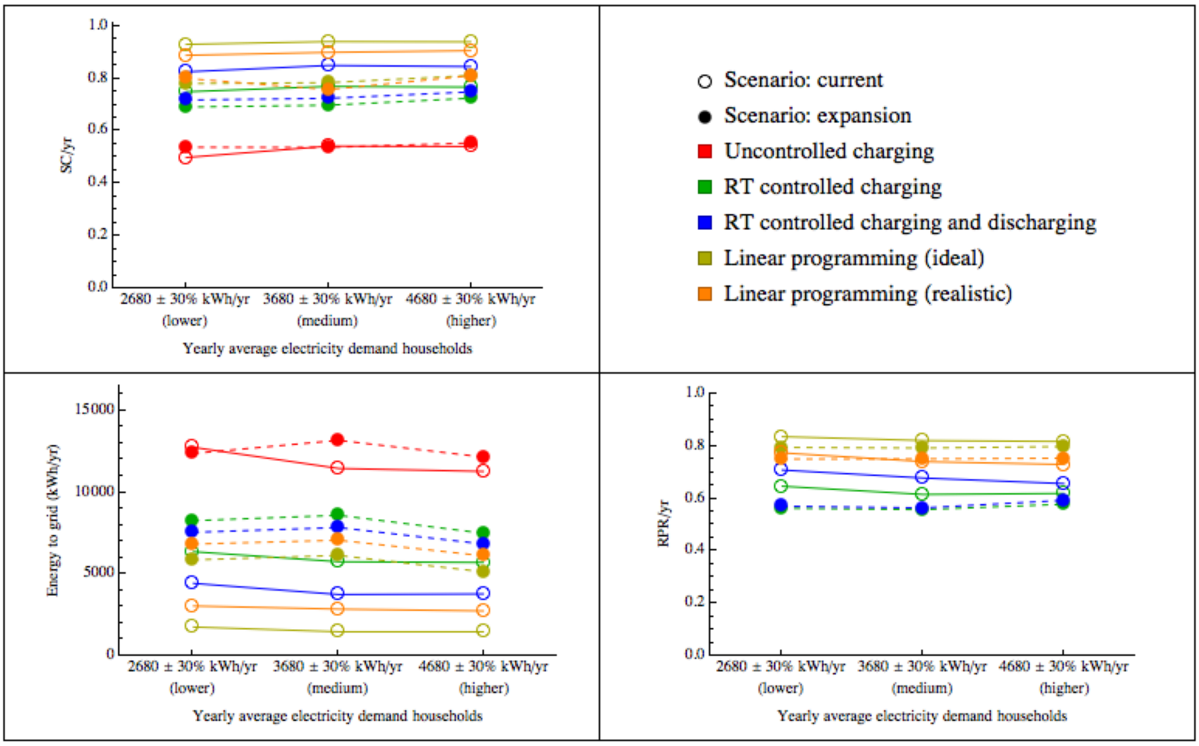


Figure 4.9 Results for sensitivity analysis on yearly average electricity demand households

This is because in the simulations for the lower scenario total PV-yield was lower than in the other scenarios, this can happen because of the lower number of simulations. This is reflected in the results for SC (which is a relative indicator), because here the difference between the scenarios is small. For RPR there is no significant difference between the scenarios. The small effect of yearly average electricity demand households is probably due to the relatively small portion household demand takes up of P_{load} when compared to load demand of the Parkhuis and servers. Also, load demand is highest when PV-power supply is low.

In figure 4.10 results for the sensitivity analysis on trips per week are presented. Based on the graphs, it can be concluded that trips per week has a significant effect on the outcome. For "uncontrolled charging" more trips per week have a positive effect on SC. This is to be expected because with more trips per week EVs will charge more often also during periods with excess PV-power. For all control algorithms in the scenario "current" more trips per week have a negative effect on SC and RPR. This result indicates that the balancing function of the EVs have a greater effect on SC than the energy needed for trips. For the scenario "expansion" less trips per week has results in more energy to grid, but this is due to more total PV-yield in the simulations for less trips than for normal amount of trips (see results for SC). However, while for more trips the effect is the same as for the scenario "current" the difference between less and normal trips is small, meaning that the balancing function and energy needed for trips outweigh each other for these two scenarios.

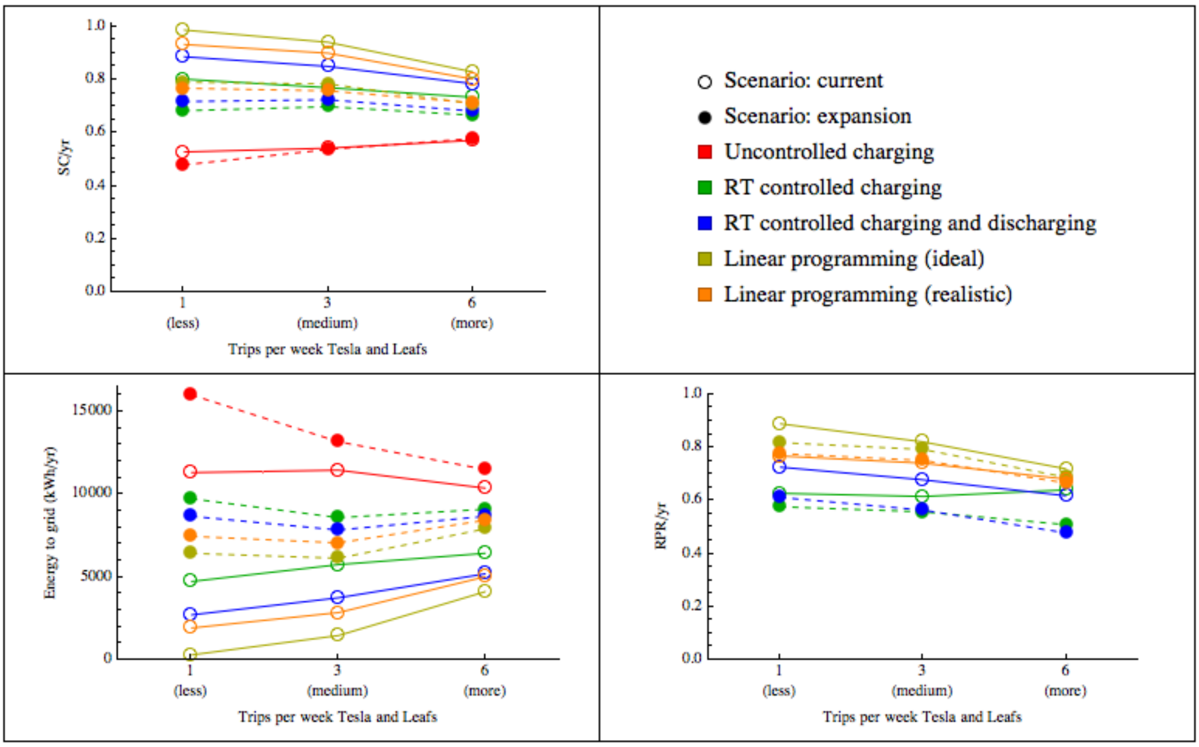


Figure 4.10 Results for sensitivity analysis on trips per week

In figure 4.11 results for the sensitivity analysis on EV-type are presented. The results show that having only Teslas available can have a significant positive effect on SC, especially in the scenario “expansion”, while having only Leafs has a significant negative result on SC, especially in the scenario “current”. This is as expected, because the Tesla has a large range than the Leaf, so it uses more energy for trips than the Leaf. At the same time the Tesla has a much larger battery capacity than the Leaf, so when it is not on a trip it has a greater balancing potential than the Leaf.

In the scenario “expansion” there are more EVs available than in the scenario “current”. Furthermore, the extra EVs in the normal scenario “expansion” are a Leaf and two Focusses, which have a comparable battery capacity as the Leaf. In the normal scenario “current” the relative amount of Teslas is greater than in the normal scenario “expansion”. This is why the effect of “all Tesla” is greater in the scenario “expansion” and the effect of “all Leaf” is smaller. Another interesting aspect is that the difference between the EV-type scenarios is smaller for the linear programming algorithms than for the RT algorithms. You could say that using a mathematical optimisation control algorithm instead of a RT control algorithm decreases the need for including cars with bigger battery capacities in the micro-grid. Furthermore, RPR is not significantly effected by EV-type.

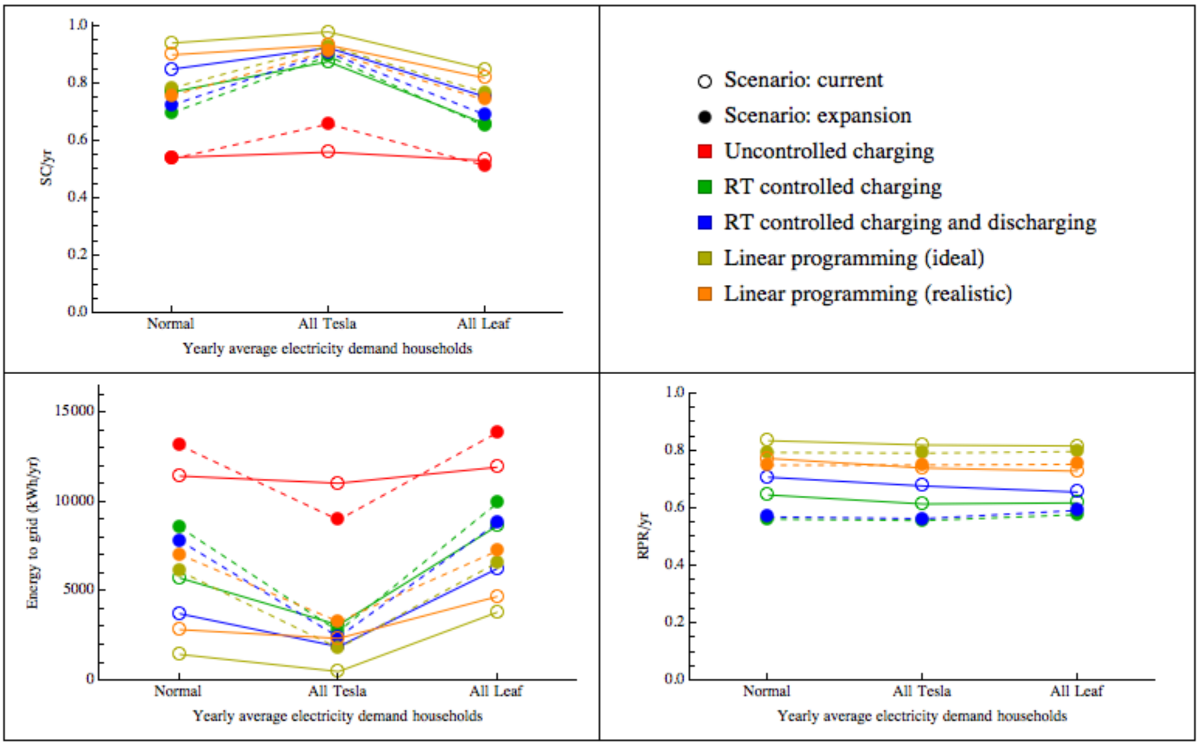


Figure 4.11 Results for sensitivity analysis on EV-type

The results of the sensitivity analysis for the energy in the EV-batteries at time step t = 0 are presented in figure 4.12 for the scenario "current" and 4.13 for the scenario "expansion". Only results for SC are shown, the results per month for the main simulations can be found in figure 4.2. The graphs show that especially the outcomes for RT control algorithms are sensitive to starting energy. In summer months, EV-batteries are more likely to be relatively full around midnight, due to high excess PV-power. In the case of "RT controlled charging" this means that self-consumption in summer months is over-estimated in the main simulations. If the EVs can also discharge the batteries will not be completely full because they will discharge energy in the evenings to cover load demand. The extreme scenario of the battery being completely full at midnight will therefore not occur. But is still is possible that the results for "RT controlled charging and discharging" are over-estimated in the main results, especially in the scenario "expansion", although to a lesser extent than if discharging is not available. For the linear programming control algorithms over-estimation of results is small.

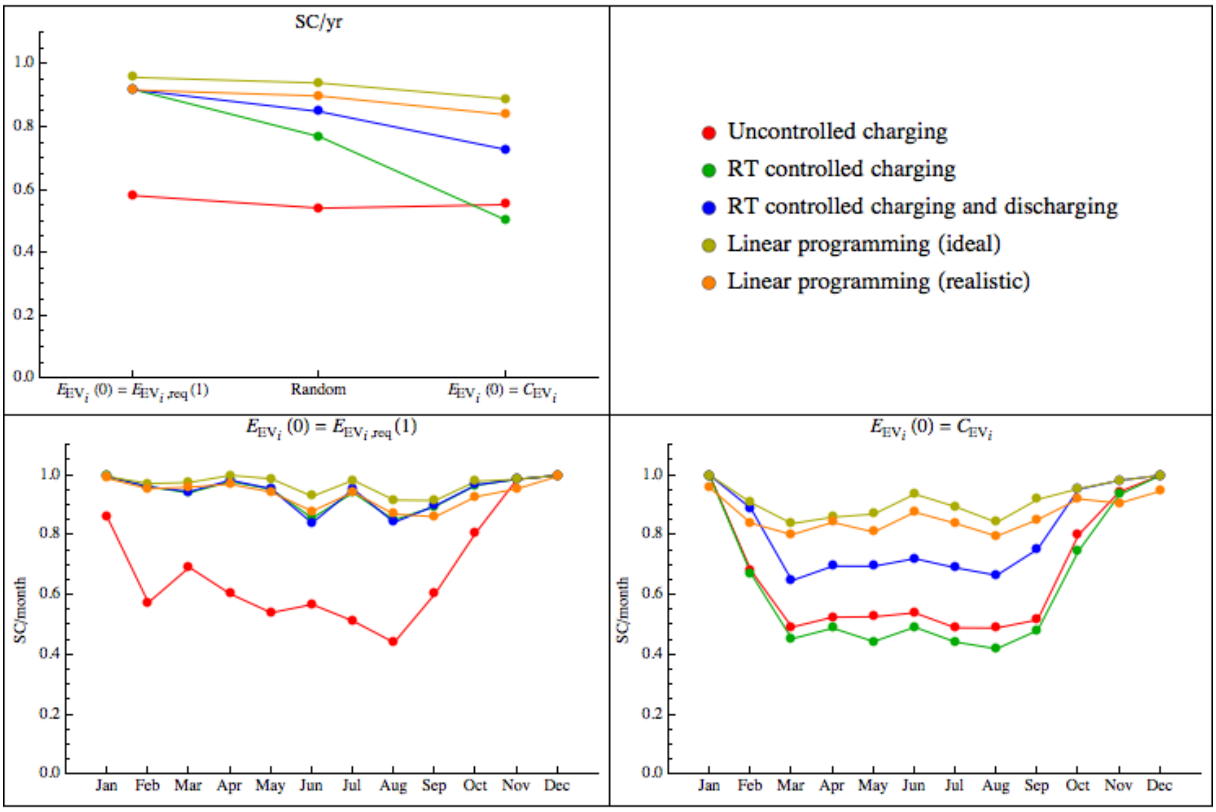


Figure 4.12 Results for sensitivity analysis on energy in EV-batteries at start time simulations for the scenario "current"

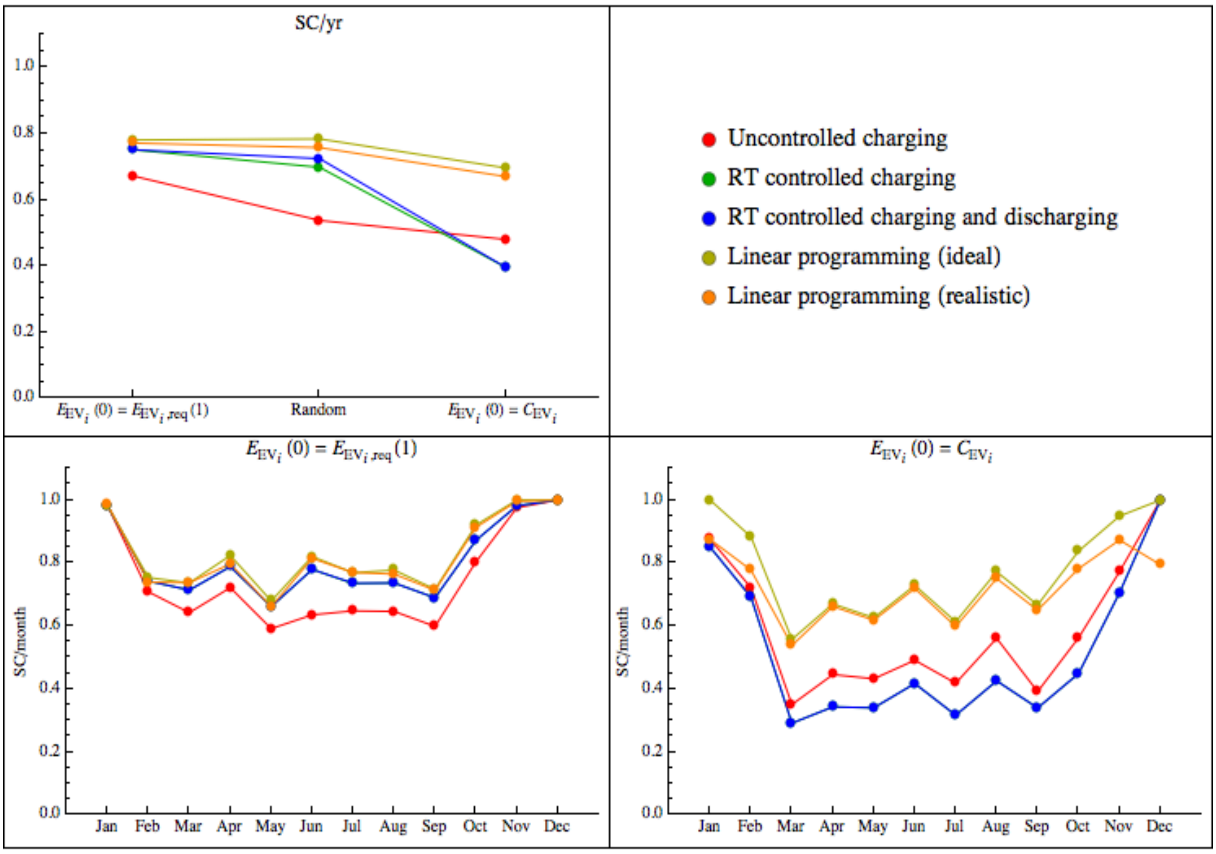


Figure 4.13 Results for sensitivity analysis on energy in EV-batteries at start time simulations for the scenario "expansion"

In order to quantify the amount of over-estimation of the effect of the RT control algorithms the simulations for a month are executed. This way the energy in the EV-batteries at the starting time only have to be determined for the first day of the month, so the random function has a much smaller effect on the outcome. Results for SC of the 24 hour-simulations and the month simulations for the scenarios "current" and "expansion" are presented in figure 4.14. Based on the results it is concluded that the largest effect on SC is for "RT controlled charging"; -15% in the scenario "current" and -4% in the scenario "expansion". For the control algorithm "RT controlled charging and discharging" the effect is -6% for the scenario "current" and +1% for the scenario "expansion". Overall it is concluded that especially the results for SC of "RT controlled charging" in the scenario "current" are significantly over-estimated, while for the other cases the effect is limited.

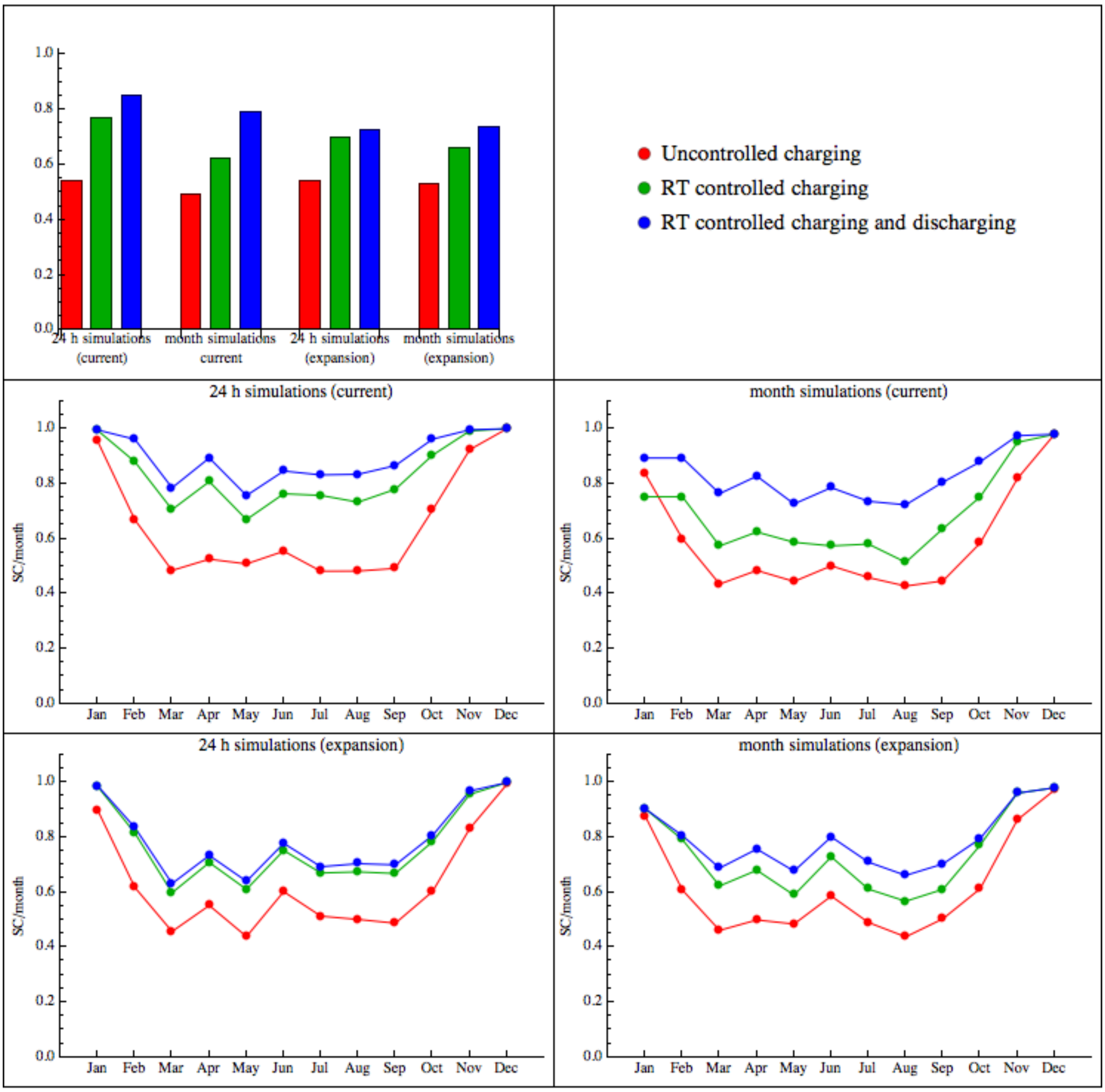


Figure 4.14 SC of 24 hour-simulation compared for the month simulations for the baseline and RT control algorithms for the scenarios "current" and "expansion"

In figure 4.15 results for the sensitivity analysis on quality of PV-power prediction are presented. As expected, increased σ has a negative effect on the results. Results show that the effect increases as σ increases. This is interesting because it shows that if σ is within an acceptable (for instance σ < 20%) investments in increasing quality PV-power prediction has only a slight effect and can be considered unnecessary. Furthermore, variation of σ has a large effect for the scenario "current" than for the scenario "expansion".

In figure 4.16 results for the sensitivity analysis for EV-battery capacity are shown. The graph show the relative decrease of SC when compared to normal simulations. This sensitivity analysis is meant to estimate the order of magnitude of the absence of the change in maximum EV-charging power when the battery is nearly full. The results show that this is in the range of 0.1% to 3% and that for the control algorithms it is around 1.5%.

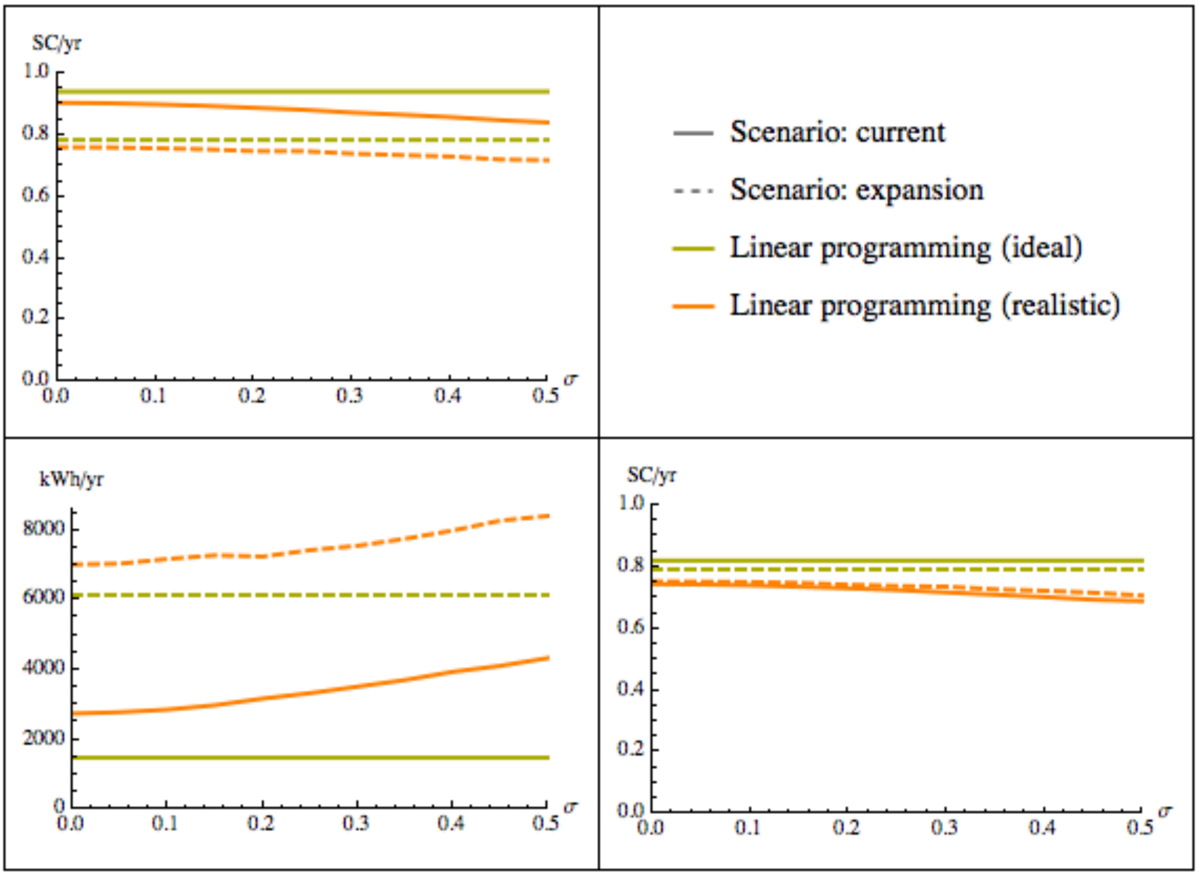


Figure 4.15 Results for sensitivity analysis on quality PV-power prediction

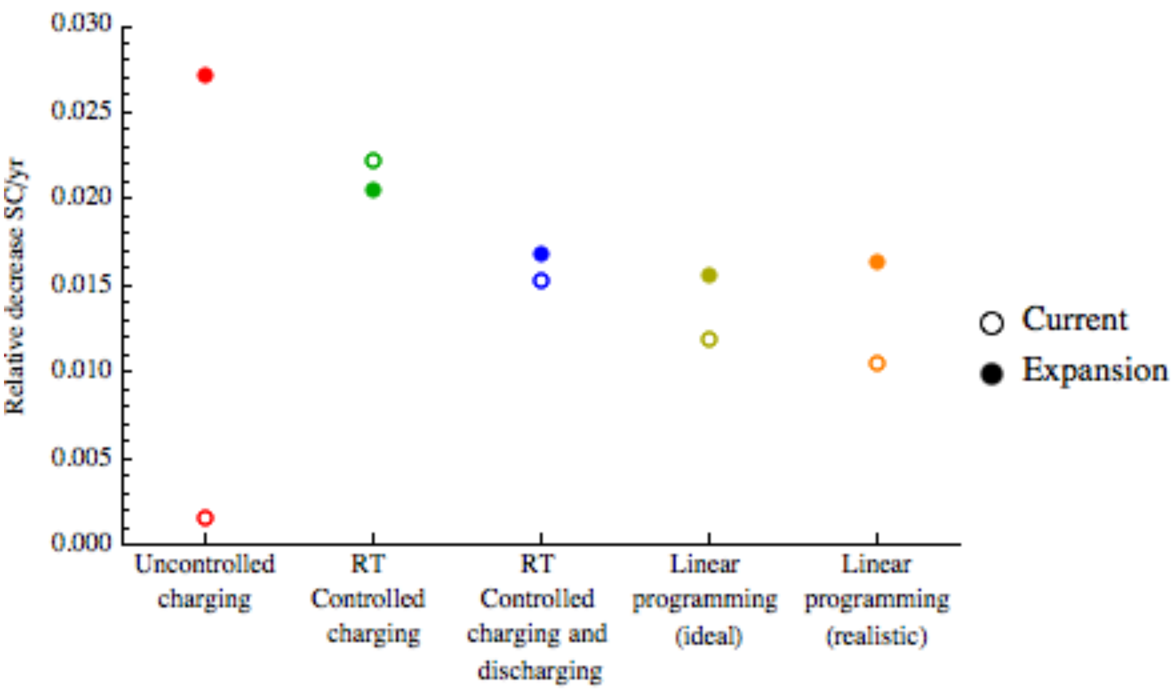


Figure 4.16 Results for sensitivity analysis on EV battery capacity

4.3 Comparison and interpretation

In figure 4.17 results for a year for all scenarios are presented. Based on these graphs conclusions on the working of the control algorithms and the scenarios can de drawn. First the results for control algorithms will be compared and interpreted and then the scenarios. The results of the sensitivity analysis on energy in EV-batteries at start time simulations and EV-battery capacity are included in the standard deviations of the results[8].

4.3.1 Control algorithms

First of all it can be seen that all have a positive effect of 25% to 55% on SC compared to "uncontrolled charging" and the control algorithms with the possibility of discharging EVs to cover load score 3% to 25% better than "RT controlled charging". "Linear programming (ideal)" is the optimal solution, but when looking at the realistic version the difference between linear programming and a RT control algorithm is small. The results for SC are also reflected in the indicator energy to grid, which gives an absolute measure for self-consumption.

Furthermore, all control algorithms score positive on RPR, between 56% and 82%. The difference between "RT controlled charging and discharging" and "linear programming (realistic)" is more clear on RPR than on SC; the former scores between 5% and 20% worse than the latter.

4.3.2 Scenarios

When comparing the scenarios, one of the first things to notice is that the difference of "current" versus "low flexibility" and "expansion" versus "high flexibility" is small. The only difference between these scenarios are the number of households included in the micro-grid (see table 2.1), so based on these results it can be concluded that household load demand is too small a portion of total load demand to make a big impact on the results. Also, load demand is highest when PV-power supply is low. In the sensitivity analysis of yearly average electricity demand households, the same conclusion was drawn.

There is a large difference when comparing "current" and "low flexibility" versus "expansion" and "high flexibility". The first two score better on all indicators than the latter two, leading to the conclusion that the extra electricity demand and balancing capacity of the EVs cannot consume and balance all the 5 kWp extra installed PV-power. This means that without further expansions of the micro-grid

[8] The section on sensitivity analysis for these factors only contained results for SC. Calculations were also performed for the other indicators and are included in the standard deviations.

at LomboXnet an investment in extra PV-installations is not necessary and when the goal is increasing SC it is a bad decision.

Overall the results are promising. It is shown that storage of PV-electricity in EVs can significantly increase PV-power self-consumption while meeting demands posed by EV use, reducing the need for a separate battery. As a side-effect, load demand is flattened during a day, which is beneficial for the grid manager.

However, some results from the sensitivity analysis show that the effects might be over-estimated. The most important factor is the energy in the batteries at the start of the simulations. In the main simulations this factor was determined by a random function. This might lead to over-estimation especially for the RT control algorithms during summer months, even more if EV-discharging is not available. The largeness of this effect has been estimated by performing month-long simulations for the RT control algorithms and has been included in the standard deviations of the results. Furthermore, an estimation was given for the reduced SC because of the absence of the change in maximum EV-charging power when the battery is nearly full, which is around 1.5% for the control algorithms.

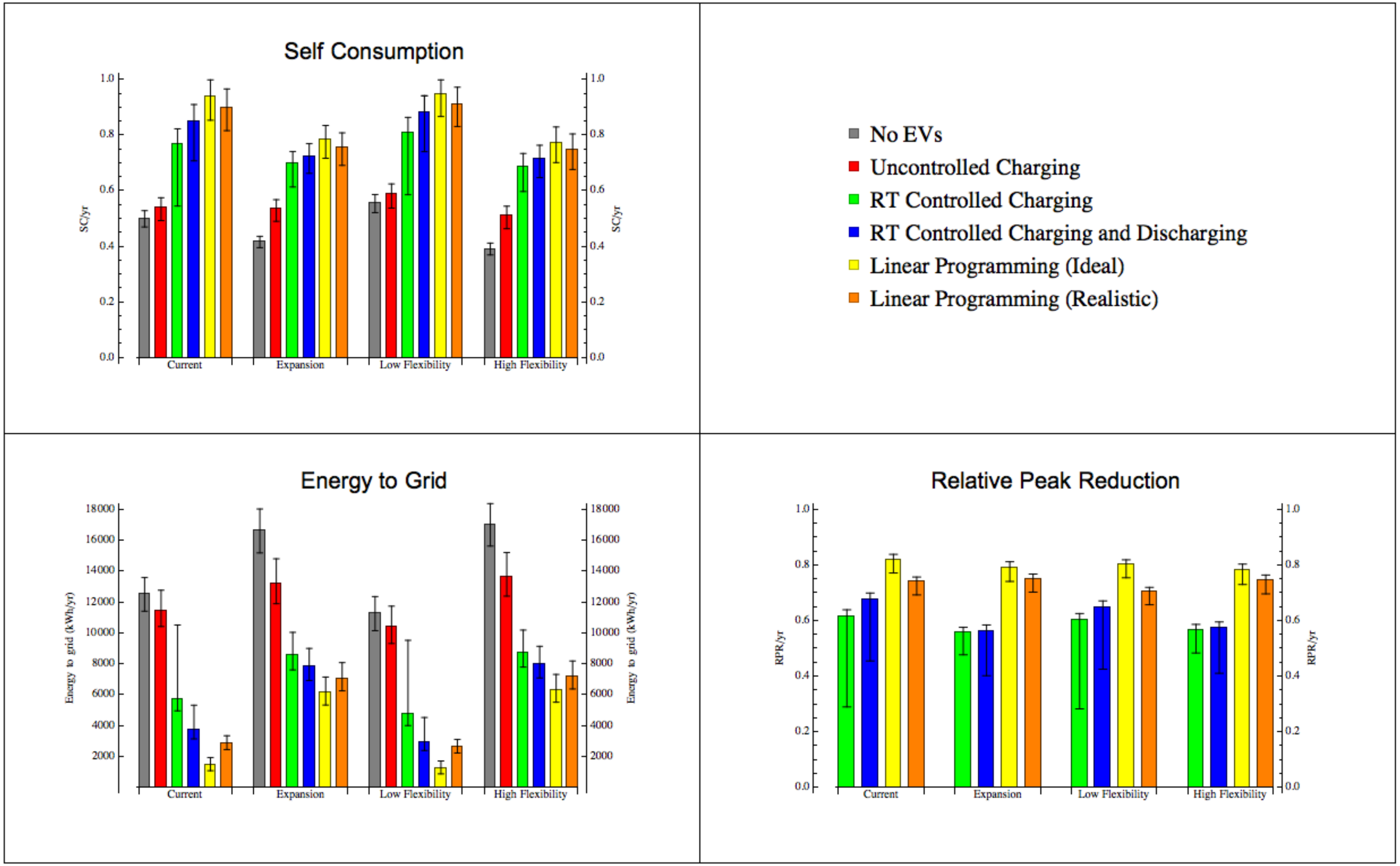


Figure 4.17 Results evaluated for performance indicators for a year of all scenarios

5. Discussion

The results presented in the previous chapter are based on a number of assumptions and data sets that effect the quality of the results. In this chapter the most important ones related to model structure, input data and the simulations will be discussed. Furthermore, uncertain factors that will become important when actually implicating a smart grid system at LomboXnet will be expanded upon.

5.1 Model structure

EV charging power

In the model the batteries can always be charged at maximum charging power, but in reality charging will be much slower when a battery is almost full. Because this aspect could not be included in the current form of linear programming it has not been taken into account. This model can be improved by using another mathematical optimisation method which can incorporate this effect. An estimation of the effect has been given, which showed that SC decreases with around 1.5% for all control algorithms.

Low Voltage transport losses

Energy losses due to transport through the micro-grid were not taken into account in the model. In a research similar to this research Claessen (2012) concluded that transport losses in a micro-grid are significant. This model could be improved by including transport losses.

5.2 Input data

PV

In the simulations, PV data for the Parkschool from July 6th 2011 to December 31st 2012 was used and PV data for the CGU from October 1st 2012 to December 31st 2012. In the months January until September only upscaled data from the Parkschool was used for the PV-profiles. For this, the ratio 18 MWp/10 MWp was used, while determination of the ratio using linear fitting showed that this ratio might not be representative of the real situation. However, because the fitting was done after the simulation period, this was not taken into account. For future simulations it is advisable to first further research the ratio between the performance of the two systems. Because results are given for a whole year, it must be taken into account that the sample base is relatively small, respectively one and a half year and three months. Furthermore, interpolation was used in the simulations with time steps of 15 minutes. In reality, PV-power will show more variation at that time resolution, it is not clear how much that will effect the results.

Electricity demand households

The profile for electricity demand of households is based on a dataset of 400 households from 2008 and measurements for a week factor in 2007. Both measurements were taken at different locations at different times, so it is not known how closely they resemble a typical load demand pattern in Lombok. Also the dataset contains information on aggregated load demand for one week in February, which means that scaling the dataset for a year might not necessarily reflect how electricity demand changes throughout a year. Outcomes of the model may be improved by using data measured in Lombok itself, but this was not available at the time of writing. Furthermore electricity demand for a longer time period then a week, preferably for a whole year, can improve the results. However, the sensitivity analysis showed that demand for households has a very limited effect on the outcomes of the model, so this factor is not very important for the results.

EV technical specifications

The input for the technical specifications for each EVs is based on two sources (manufacturer and EPA) and assumptions (see table 3.1). The two sources sometimes contradict each other. The EPA is considered a neutral source and is therefore deemed more reliable, but factors such as range and power-consumption depend to a large extend on the user. Best would be to use personal data from the person driving the EV for these factors, but this was not available. The used numbers should be considered an estimation. Furthermore, since there was no information on discharging power available it is assumed that the EV can discharge as fast as it can charge. If this value turns out to be lower, the effect of control algorithms that include discharging will be decreased, with as minimum the results of "RT controlled charging".

EV use

The characteristics of EV use for all EVs are based on thoughts and estimations by Robin Berg from LomboXnet. It could turn out that the use of EVs is different than expected. The sensitivity analysis on trips per week showed that EV-use does effect the outcomes of the model significantly. In the sensitivity analysis two extreme scenarios, 1 and 6 trips per week, were simulated. The resulting range for the indicators gives a good idea on what the maximum effect of different EV use than expected could be.

5.3 Simulations

Time steps

Because of time considerations the scenarios "expansion" and "high flexibility" were simulated with time steps of one hour as opposed to 15 minutes. In the graphs for individual runs (figures 4.1, 4.3, 4.5 and 4.7) it can be seen that changes in charging patterns do occur within a 15 minute resolution. A one hour resolution might affect the quality of the results, but it is not clear how much. Faster calculation methods or computers can solve this problem.

Objective function of linear programming

Because longer than 24 hour-simulations of the linear programming control algorithms could not be executed in the time-frame of this research the objective function of linear programming was adapted in order to simulate the behaviour of the original objective function. In the experience of the author the adapted objective function performed as it should, but it is not possible to perform this test for all simulations. However, based on the performed tests it is estimated that this aspect does not affect the results significantly.

Energy in EVs at start of simulations

The energy in the EVs at time step t=0 is determined by a random function. The sensitivity analysis showed that this might lead to over-estimation of the results, especially for the RT control algorithms during summer months, even more if EV-discharging is not available. An estimation of this effect has been given by running month-long simulations for the RT control algorithms. It was shown that the effect is largest for "RT controlled charging" in the scenario current (-15% for SC) and this effect should be taken into account. The model can be improved by making yearlong simulations available, which will only require the starting energy of the first day of the year.

Sensitivity analysis

Ideally the sensitivity analysis would cover the variation of every factor within reasonable limits and every combination of factors. For this research this was not possible due to time constraints. The selected factors are considered most interesting by the author, but it is not clear for every factor how much impact variation would have on the results. Furthermore, the sensitivity analysis is based on 120 24 hour-simulations for each scenario, which is small when it gives results for a year. Results can be improved by performing a more extensive sensitivity analysis.

5.4 Practical implementation

In this thesis, a model is proposed in order to quantify the potential of increasing PV self-consumption in the case of LomboXnet. LomboXnet aims at implementing such a system in the near future, therefore it is interesting to consider some points that are relevant when transferring the model to reality

Hardware

LomboXnet already has a smart meter available and also PV-power is directly measured. However, for the proposed control algorithms it would be necessary to install smart meters at every household connected to the micro-grid. Furthermore a device needs to be installed to which all the data (Parkhuis, households, PV and EVs) is send and that can control the electricity distribution based on a selected control algorithm. For real-time control algorithms the data must be send to this device in real-time, while the linear programming algorithm only needs the data when calculating the electricity distribution (for instance at 24:00) in order to make predictions.

PV-power forecasting

For the linear programming control algorithm PV-power forecasting for the next day must be made available. The forecasting should include the predicted PV-yield for every time step for all PV-installations. In order to provide optimal predictions the performance of the PV under different external conditions can be further investigated, but the sensitivity analysis showed that above a certain threshold the quality of PV-power predictions only has a limited impact on system performance.

EV-trip planning

For all proposed control algorithms it is necessary to plan all EV-trips at least one day in advance and enter them into the system. It might be unreasonable to expect that effort from everyone involved in the project. An alternative could be to have the SOC of EV-batteries always be a certain value, but this would reduce to potential of increasing self-consumption. In this research a minimum SOC of 20% is assumed, allowing for a short-distance emergency trip.

Demand side management

It is possible that in the houses connected to the micro-grid a demand side management system is installed. This way household load demand would shift more towards times when PV-power is available and increase self-consumption. If this is the case the potential of further increasing self-consumption by storing electricity in EVs will be reduced.

6. Conclusion and recommendations

In this thesis, a theoretical model is proposed in order to quantify the potential of increasing PV self-consumption with a combination of smart grid technology and electricity storage in EVs in the case of LomboXnet. For this model three control algorithms are developed: "RT controlled charging", "RT controlled charging and discharging" and "linear programming". Four scenarios are constructed, based on the current system in place at LomboXnet and possible future expansions. The effect of the control algorithms is simulated for all scenarios and evaluated on self-consumption, energy send to the main grid and relative peak reduction. The results are compared to a baseline, in which no control algorithm is available. The results show that smart storage of electricity in EVs can increase self-consumption with 15% to 35%, energy send to the main grid with 5 to 8 MWh per year and relative peak reduction with 55% to 75%, depending on which control algorithm and scenario is chosen. Furthermore, a comparison of scenarios showed that extra installed kWp solar power is not advisable when evaluating for self-consumption.

Based on the results it can be concluded that designing an EV-charging control algorithm based on linear programming is the best way to increase self-consumption for LomboXnet. Although such a design would be more complex than RT algorithms, because it is based on predictions and needs a longer calculation time, the linear programming algorithms perform best in the simulations and even more importantly in the sensitivity analysis. The RT control algorithms score almost as good as the linear programming algorithm for SC, but score significantly worse for RPR and turn out to be very sensitive to uncertainties and assumptions in the model, especially for the scenarios with only two EVs available. However, if a less complex smart grid system is more desirable the RT control algorithms also contribute significantly to SC, especially if discharging is available.

The developed model is based on several assumptions and uncertainties that affect the quality of the results. Some assumptions in the model, such as EV-charging efficiency and energy in EV-batteries at the start of a simulation, were left out on purpose in order to give a fair comparison of control algorithms. However, the sensitivity analysis showed that the RT algorithms are more sensitive to these factors than the linear programming algorithm. If, based on the results presented in this thesis, a choice is made for which option is most interesting for LomboXnet further research could focus on developing a more precise model for that specific control algorithm. Furthermore, datasets can be improved if more data is available, this is especially important for datasets related to load demand of households, since they are based on households in a different area in different years. Measuring load demand in Lombok could improve the quality of the results. Finally, with more research time and a more efficient simulating environment more simulations with more time steps can be executed, giving a better statistical base for the results. Also, combining the theoretical model with field tests could give a good idea on how the system functions in a real-life environment.

Recommendations

Based on this research the following recommendations are made for LomboXnet:

- Significant increase of self consumption using the EVs is possible, this project deserves further pursuit.
- Sophisticated mathematical optimisation as proposed in this paper works better than the proposed real-time control algorithms and is the more interesting option for a final design.
- Quality of PV-power predictions do not have a big impact on system performance above threshold of about 20% and should therefore not be the primary focus of the final system design.
- Although the potential of increasing self consumption with the proposed real-time control algorithms is significantly lower, they are still an interesting option if a less complex control system is desired, since self consumption can still be improved.
- Installing extra solar panels is not needed from the perspective of increasing self consumption, unless more demand is added to the micro-grid.
- Since planning of EV-trips is essential in the proposed control algorithms, a survey under future participants on their willingness to plan trips in advance is desirable.
- If further research is desired, choosing between the proposed options makes it easier to focus on a particular algorithm and develop a more in-depth model.

References

Agentschap NL (2013), Cijfers elektrisch vervoer, retrieved 14-7-2013 from www.agentschapnl.nl/onderwerp/cijfers-elektrisch-rijden

Van den Akker, M., Blok, H., Budd, C., Eggermont, R., Guterman, A., Lahaye, D., Lansink Rotgerink, J., Myerscough, K. W., Prins, C., Tromper, T., Wadman, W. (2012), A case study in future challenges in electricity grid infrastructure, Delft

Van den Berg, M., Van Zevenbergen, B., Schuch, W., Kersten, G. (2013), Onderzoeksrapport; Project: toepassing van smart grid in de wijk Lombok, Hogeschool Utrecht

Bertoldi, P., Atanasiu, B., (2007), Electricity consumption and efficiency trends in the enlarged European Union; Status Report 2006 , Institute for Environment and Sustainability

Castillo-Cagigal, M., Caamaño-Martín, E., Matallans, E., Masa-Bote, D., Gutiérrez, A., Monasterio-Huelin, F., Jiménez-Leube, J. (2011a), PV self-consumption optimisation with storage and Active DSM, for the residential sector, *Solar Energy*, Vol. 85, pp 2338-2348

Castillo-Cagigal, M., Gutiérrez, A., Monasterio-Huelin, F., Caamaño-Martín, E,. Masa, D.,Jiménez-Leube, J. (2011b), A semi-distributed electric demand-side management system with PV generation for self-consumption enhancement, *Energy Conversion and Management,* Vol. 52, pp 2659-2666

Centraal Bureau voor de Statistiek (2011), Hernieuwbare energie; energieverbruik en vermeden verbruik fossiele energie, retrieved 14-7-2013 from statline.cbs.nl/StatWeb/publication/?DM=SLNL&PA=7516

Centraal Bureau voor de Statistiek (2013), Begrippen, retrieved 1-12-2013 from http://www.cbs.nl/nl-NL/menu/methoden/begrippen/default.htm?conceptid=2981

Chen, B., Wu, Y., Tsai, H., (2013), Design and analysis of power management strategy for range extended electric vehicle using dynamic programming, *Applied Energy*, awaiting publication

Claessen, F. N. (2012), Smart grid control; An analysis of control systems within a Dutch residential microgrid incorporating decentralised renewable energy resources, MSc. Thesis, Universiteit Utrecht

European Commission, Directorate-General For Energy (2013), The future role and challenges of Energy Storage, retrieved 8-3-2013 from http://ec.europa.eu/energy/infrastructure/doc/energy-storage/2013/energy_storage.pdf

Elektriciteitswet 1998, article 31c, retrieved 6-3-2013 from http://wetten.overheid.nl/BWBR0009755/geldigheidsdatum_06-03-2013

Eerste Kamer der Staten-Generaal (2013), EK 33.492, Wijziging van de Elektriciteitswet 1998, de Gaswet en de Warmtewet (wijzigingen samenhangend met het energierapport 2011), retrieved 1-12-2013 from http://www.eerstekamer.nl/behandeling/20130611/gewijzigd_voorstel_van_wet/f=/vjafk667e5za.pdf

Simons, W. (2013), UPDATE: Onbeperkt salderen per 1 januari 2014, retrieved 1-12-2013 from http://www.energieoverheid.nl/2013/11/19/update-onbeperkt-salderen-per-1-januari-2014/

Essen, H. van, and Kampman, B., (2011), Impacts of Electric Vehicles – Summary report, Delft: CE Delft, 2011

European Federation for Transport and Environment (2011), How clean are Europe's cars? An analysis of carmaker progress towards EU CO_2 targets in 2010, Brussels: [s.n.], 2011

Ferguson, T.S., (2013), Linear Programming; A Concise Introduction, retrieved 7-12-2012 from http://www.math.ucla.edu/~tom/LP.pdf

Ford (2013), Ford Focus Electric, retrieved 15-8-2103 from http://www.ford.nl/Personenautos/Focus/FocusElectric

González Vayá, M., Andersson, G., (2012), Centralized and decentralized approaches to smart charging of plug-in vehicles, *IEEE*

Guo, Y., Pan, M., Fang, Y., (2012), Optimal power management of residential customers in the smart gird, *IEEE Transactions on Parallel and Distributed Systems,* Vol. 23, No. 9

Herman de zonnestroom verdeler (2013), home website, retrieved 1-12-2013 from http://www.zonnestroomverdeler.nl

Hoen A. (2009), CO_2 emission reduction in transport: Confronting medium-term and long-term options for achieving climate targets in the Netherlands, The Hague, Environmental Assessment Agency, 2009

International Energy Agency (2012), Key World Energy Statistics, retrieved 27-2-2013 from http://www.iea.org/publications/freepublications/publication/kwes.pdf

International Energy Agency (2013a), Electricity/Heat in Netherlands in 2009, retrieved 14-7-2013 from http://www.iea.org/stats/balancetable.asp?COUNTRY_CODE=NL

International Energy Agency (2013b), 2009 Energy Balance in Netherlands in 2009, retrieved 27-2-2013 from http://www.iea.org/stats/electricitydata.asp?COUNTRY_CODE=NL

Khayyam, H., Ranjbarzadeh, H., Marano, V., (2012), Intelligent control of vehicle to grid power, review, *Journal of Power Sources,* Vol 201, pp 1-9

Koninklijk Nederlands Meteorologisch Instituut (2013), Date Centre, retrieved 7-12-2013 from https://data.knmi.nl/

Mulder, G., De Ridder, F., Six, D. (2010), Electricity storage for grid-connected household dwellings with PV panels, *Solar Energy,* Vol. 84, pp 1284-1293

Net2Grid (2013), home website, retrieved 1-12-2013 from https://www.net2grid.com

Nissan (2013), Nissan Leaf e-brochure, retrieved 6-3-2013 from http://www.nissan.nl/NL/nl/vehicle/electric-vehicles/leaf.html

Rijksoverheid (2013), Meer duurzame energie in de toekomst, retrieved 14-7-2012 from www.rijksoverheid.nl/onderwerpen/duurzame-energie/meer-duurzame-energie-in-de-toekomst

Sechilariu, M., Wang, B., Locment, F., (2013), Building-integrated microgrid: Advanced local energy management for forthcoming smart power grid communication, *Energy and Buildings*, Vol. 57, pp 236-243

Shuaib, K., Zhang, L., Gaouda, A., Abdel-Hafez, M., (2012), A PEV Charging Service Model for Smart Grids, *Energies*, Vol. 5, pp 4665-4682

Silva, M., Morais, H., Vale, Z., (2012), An integrated approach for distributed energy resource short-term scheduling in smart grids considering realistic power system simulation, *Energy Conversion and Management*, Vol. 64, pp 273-288

SMA Solar Technology AG (2013), Performance ratio, retrieved 7-12-2013 from http://files.sma.de/dl/7680/Perfratio-UEN100810.pdf

Soares, J., Silva, M., Sousa, T., Vale, Z., Morais, H. (2012), Distributed energy resource short-term scheduling using Signaled Particle Swarm Optimisation, *Energy*, Vol 42., pp 466-476

Suntech (2013), STP255-20/Wd, STP250-20/Wd, STP245-20/Wd, retrieved 7-12-2013 from http://www.redasolar.nl/bestanden/documenten/Suntech/STP_Wd_poly_245-255_156-60_FS35_EN.pdf

Tanaka, K., Yoza, A., Ogimi, K., Yona, A., Snjyu, T., Funabashi, T., Kim, C., (2012), Optimal operation of DC smart house system by controllable loads based on smart grid topology, *Renewable Energy*, Vol. 39, pp 132-139

Tesla Motors (2013), Tesla Model S, retrieved 6-3-2013 from http://www.teslamotors.com

United States Environmental Protection Agency (2013), www.fueleconomy.gov, retrieved 23-8-2013 from http://www.fueleconomy.gov

United States Department of Energy (2009), Smart Grid System Report, retrieved 14-7-2012 from http://energy.gov/sites/prod/files/2009%20Smart%20Grid%20System%20Report.pdf

Verbong, G.P.J., Beemsterboer, S., Sengers, F., (2012), Smart grids of smart users? Involving users in developing a low carbon electricity economy, *Energy Policy,* Vol 52., pp 117-125

Widén, J., Wäckelgård, E., Lund, P.D., (2009), Options for improving the load matching capability of distributed photovoltaics: Methodology and application to high-latitude data, *Solar Energy*, Vol. 83, pp 1953-1966

Appendix

A. Mathematica code for one 24 hour simulation with time steps of 15 minutes

Inputs

```
pPVTempPS;(* data PV Parkschool *)
pPVTempCGU;(* data PV CGU *)
pvf;(* PV factor *)
pLoadTempPH;(* data load Parkhuis *)
pLoadTempHH;(* data load households *)
nHh;(* number of households *)
wf;(* week factors for load households *)
nEV;(* number of EVs *)
month; (* month for simulation *)
pEVMaxI;(* Max EV charging power *)
pEVMaxO;(* Max EV discharging power *)
pEVCons;(* EV consuming power *)
cEV;(* EV battery capacity *)
socEVMin;(* EV minimum SOC *)
ηInEV;(* EV charging efficiency *)
ηOutEV;(* EV discharging efficiency *)
maxTrDis;(* EV maximum trip distance *)
minTrDis;(* EV minimum trip distance *)
trPW;(* EV trips per week *)
trST;(* EV trip earliest start time *)
trET;(* EV trip latest end time *)
maxTrDur; (* EV trip maximum duration *)
minTrDur;(* EV trip minimum duration *)
```

Simulation (per 15 minutes)

```
simq[pPVTempPS_, pPVTempCGU_, pvf_, pLoadTempPH_, pLoadTempHH_, nHh_, wf_, nEV_, month_, pEVMaxI_,
  pEVMaxO_, pEVCons_, cEV_, socEVMin_, ηInEV_, ηOutEV_, maxTrDis_, minTrDis_, trPW_, trST_, trET_,
  maxTrDur_, minTrDur_] :=
 Module[{year, day, startDatePPVPH, startDatePPVCGU, yearPS, pPVTemp, pLoadTempPH2, pLoadTempPH3,
   pLoadPH, pLoadPH2, pLoadTempHH1, pLoadTempHH2, pLoadTempHH3, pLoadHH, pLoadHH2, pPV, pPV2, pLoad,
   EVTrips, EVOnOff, eEVReq, eEVTrip, eEVTrip2, NextTr, pEVMaxIn, pEVMaxOut, eEV0, eEVucf, pEVucf,
   pEVuc, eEVuc, uEVcc, fEVcc, eEVccf, pEVccf, pEVGridccf, pEVcc, eEVcc, uEVccd, fEVccd, eEVccdf,
   pToEVccdf, pEVGridccdf, pFrEVccdf, pEVccd, eEVccd, cons, nc, a, b, c, sol, pEVlp, eEVlp},
  (* DATES *)
  day = RandomInteger[{1, (AbsoluteTime[{2012, month + 1}] - AbsoluteTime[{2012, month}])/(3600 * 24)}]; year = 2012;
  startDatePPVPH = AbsoluteTime[{2011, 6, 7, 0}]; startDatePPVCGU = AbsoluteTime[{2012, 10, 1, 0}];
  yearPS = If[month > 6 || month == 6 && day > 6, RandomChoice[{2011, 2012}], 2012];

  (* PV DATA *)
  pPVTemp =
   If[month ≥ 10,
    ListInterpolation[
     (pvf - 1.8)/4 Take[pPVTempPS, {1/3600 (AbsoluteTime[{yearPS, month, day}] - startDatePPVPH) + 1,
         1/3600 (AbsoluteTime[{yearPS, month, day + 1}] - startDatePPVPH) + 1}] +
      (pvf - 1.3)/(4 * 1.8) Take[pPVTempPS, {1/3600 (AbsoluteTime[{year, month, day}] - startDatePPVPH) + 1,
         1/3600 (AbsoluteTime[{year, month, day + 1}] - startDatePPVPH) + 1}]],
    ListInterpolation[
     pvf/4 Take[pPVTempPS, {1/3600 (AbsoluteTime[{yearPS, month, day}] - startDatePPVPH) + 1,
        1/3600 (AbsoluteTime[{yearPS, month, day + 1}] - startDatePPVPH) + 1}]]];
  pPV = Table[pPVTemp[t], {t, , 25, 1/4}];

  (* LOAD DATA *)
  (* Parkhuis *)
  pLoadTempPH2 =
   ListInterpolation[
    1/4 Table[pLoadTempPH[[Mod[x, 24, 1], 1]] + RandomReal[{-1, 1}] pLoadTempPH[[Mod[x, 24, 1], 2]], {x, 25}]];
  pLoadPH = wf[[Ceiling[AbsoluteTime[{1900, month, day + 1}] / (3600 * 24 * 7)]]]
```

```
  (Table[pLoadTempPH2[t] - 2.3/4, {t, 1, 25, 1/4}]) + 2.3/4;

(* Households *)
pLoadTempHH1 = Table[RandomChoice[pLoadTempHH], {x, nHh}];
pLoadTempHH2 = Table[Take[pLoadTempHH1[[x]], {4 * 24 (Mod[day - 1, 7, 0]) + 1, 4 * 24 (Mod[day - 1, 7, 0] + 1) + 1}],
  {x, nHh}];
pLoadHH = wf[[Ceiling[AbsoluteTime[{1900, month, day + 1}] / (3600 * 24 * 7)]]] Total[pLoadTempHH2];

(* for evaluation linear programming (realistic) *)
pLoadTempHH3 =
 Table[Take[pLoadTempHH1[[x]],
   {4 * 24 (Mod[day - 1 - If[DayName[{2008, month, day - 1}] == Saturday || DayName[{2008, month, day - 1}] == Monday,
          1, -1], 7, 0]) + 1,
    4 * 24
      (Mod[day - 1 - If[DayName[{2008, month, day - 1}] == Saturday || DayName[{2008, month, day - 1}] == Monday, 1, -1],
        7, 0] + 1) + 1}], {x, nHh}];
pLoadHH2 = wf[[Ceiling[AbsoluteTime[{1900, month, day + 1}] / (3600 * 24 * 7)]]] Total[pLoadTempHH3];

pLoad = pLoadPH + pLoadHH;

(* EV trips *)
EVTrips =
 Table[If[Random[] ≤ trPW[[i]]/7,
   {1, Part[Table[{t, Min[t + RandomInteger[{4 minTrDur[[i]], 4 maxTrDur[[i]]}], 4 trET[[i]]]},
      {t, 4 trST[[i]], 4 trET[[i]] - 4 minTrDur[[i]] + 4}],
     RandomInteger[{1, 4 trET[[i]] - 4 minTrDur[[i]] - 4 trST[[i]] + 1}]],
    RandomInteger[{minTrDis[[i]], maxTrDis[[i]]}]}, {0, {0, 0}, 0}], {i, nEV}, {x, 3}];

EVOnOff[t_, i_] := If[EVTrips[[i, Ceiling[t/(4 * 24)], 1]] == 1,
  If[EVTrips[[i, Ceiling[t/(4 * 24)], 2, 1]] ≤ Mod[t, 4 * 24] < EVTrips[[i, Ceiling[t/(4 * 24)], 2, 2]], 0, 1], 1];
eEVTrip[t_, i_] :=
 Total[Table[If[EVTrips[[i, Ceiling[x/(4 × 24)], 1]] == 1 && Mod[x, 4 × 24] == EVTrips[[i, Ceiling[x/(4 × 24)], 2, 1]],
    EVTrips[[i, Ceiling[x/(4 × 24)], 3]] * pEVCons[[i]], 0], {x, t}]];
eEVTrip2 = Table[If[EVTrips[[i, Ceiling[t/(4 × 24)], 1]] == 1 && Mod[t, 4 × 24] == EVTrips[[i, Ceiling[t/(4 × 24)], 2, 1]],
   EVTrips[[i, Ceiling[t/(4 × 24)], 3]] * pEVCons[[i]], 0], {i, nEV}, {t, 1, 297}];
NextTr = Table[Module[{n}, For[n = t, eEVTrip2[[i, n]] == 0 && n < 97 , n++]; {n - t, eEVTrip2[[i, n]]}],
  {i, nEV}, {t, 97}];
eEVReq[t_, i_] :=
 Max[If[EVTrips[[i, Ceiling[1/(4 × 24) (t + Max[EVTrips[[i, Ceiling[t/(4 × 24)], 2, 1]] - Mod[t, 4 × 24], 0])], 1]] == 1 &&
     Mod[t + (EVTrips[[i, Ceiling[t/(4 × 24)], 2, 1]] - Mod[t, 4 × 24]), 4 × 24] == EVTrips[[i, Ceiling[t/(4 × 24)], 2, 1]] &&
     0 ≤ EVTrips[[i, Ceiling[t/(4 × 24)], 2, 1]] - Mod[t, 4 × 24],
    pEVCons[[i]] EVTrips[[i, Ceiling[t/(4 × 24)], 3]] -
     (EVTrips[[i, Ceiling[t/(4 × 24)], 2, 1]] - Mod[t, 4 × 24]) pEVMaxI[[i]], 0], 0] + socEVMin[[i]] cEV[[i]];
pEVMaxIn[t_, i_] := EVOnOff[t, i] pEVMaxI[[i]];
pEVMaxOut[t_, i_] := EVOnOff[t, i] pEVMaxO[[i]];
eEV0 = Table[RandomReal[{1.1 eEVReq[1, i], cEV[[i]]}], {i, nEV}];

(* UNCONTROLLED CHARGING *)
(* energy *)
eEVucf[0, i_] := eEV0[[i]];
eEVucf[t_, i_] := eEVucf[t, i] = eEVucf[t - 1, i] + ηInEV[[i]] pEVucf[t, i];
(* power flow *)
pEVucf[t_, i_] := If[eEVucf[t - 1, i] + ηInEV[[i]] pEVMaxIn[t, i] ≤ cEV[[i]] + eEVTrip[t, i],
  pEVMaxIn[t, i], If[eEVucf[t - 1, i] < cEV[[i]] + eEVTrip[t, i],
   (ηInEV[[i]])^-1 ( cEV[[i]] + eEVTrip[t, i] - eEVucf[t - 1, i]), 0]];
(* calculation *)
pEVuc = Table[pEVucf[t, i], {i, 1, nEV}, {t, 97}];
eEVuc = Table[eEVucf[t, i] - eEVTrip[t, i], {i, nEV}, {t, 97}];

(* CONTROLLED CHARGING *)
(* priority function *)
uEVcc[t_, i_] := Which[EVOnOff[t, i] == 0, 0, eEVccf[t - 1, i] == cEV[[i]], 0, True,
  (NextTr[[i, t, 1]] / Max[NextTr[[i, t, 1]] - Max[NextTr[[i, t, 2]] - eEVccf[t - 1, i], 0] / pEVMaxI[[i]], 10^-9])^2];
fEVcc[t_, i_] := uEVcc[t, i] / Max[Total[Table[uEVcc[t, n], {n, 1, nEV}]], nEV 10^-9];
```

```
(* energy in EV *)
eEVccf[0, i_] := eEV0[[i]];
eEVccf[t_, i_] := eEVccf[t, i] = eEVccf[t - 1, i] + pEVccf[t, i] + pEVGridccf[t, i];
(* power flow *)
pEVccf[t_, i_] := Max[If[pPV[[t]] > pLoad[[t]],
   If[eEVccf[t - 1, i] + ηInEV[[i]] Min[fEVcc[t, i] (pPV[[t]] - pLoad[[t]]), pEVMaxIn[t, i]] ≤
     cEV[[i]] + eEVTrip[t, i], Min[fEVcc[t, i] (pPV[[t]] - pLoad[[t]]), pEVMaxIn[t, i]],
    If[eEVccf[t - 1, i] < cEV[[i]] + eEVTrip[t, i], ( cEV[[i]] + eEVTrip[t, i] - eEVccf[t - 1, i]), 0]], 0], 0];
pEVGridccf[t_, i_] := If[eEVccf[t - 1, i] + pEVccf[t, i] < eEVReq[t + 1, i] + eEVTrip[t, i],
  (eEVReq[t + 1, i] + eEVTrip[t, i] - eEVccf[t - 1, i] - pEVccf[t, i]), 0];
(* calculation *)
pEVcc = Table[pEVccf[t, i] + pEVGridccf[t, i], {i, nEV}, {t, 97}];
eEVcc = Table[eEVccf[t, i] - eEVTrip[t, i], {i, nEV}, {t, 97}];

(* CONTROLLED CHARGING AND DISCHARGING *)
(* priority function *)
uEVccd[t_, i_] := Which[EVOnOff[t, i] == 0, 0, eEVccdf[t - 1, i] == cEV[[i]], 0, True,
  (NextTr[[i, t, 1]] / Max[NextTr[[i, t, 1]] - Max[NextTr[[i, t, 2]] - eEVccdf[t - 1, i], 0] / pEVMaxI[[i]], 10^-9])^2];
fEVccd[t_, i_] := uEVccd[t, i] / Max[Total[Table[uEVccd[t, n], {n, nEV}]], nEV 10^-9];
(* energy in EV *)
eEVccdf[0, i_] := eEV0[[i]];
eEVccdf[t_, i_] := eEVccdf[t, i] = eEVccdf[t - 1, i] + pToEVccdf[t, i] - pFrEVccdf[t, i] + pEVGridccdf[t, i];
(* power flow *)
pToEVccdf[t_, i_] := Max[If[pPV[[t]] > pLoad[[t]],
   If[eEVccdf[t - 1, i] + ηInEV[[i]] Min[fEVccd[t, i] (pPV[[t]] - pLoad[[t]]), pEVMaxIn[t, i]] ≤
     cEV[[i]] + eEVTrip[t, i], Min[fEVccd[t, i] (pPV[[t]] - pLoad[[t]]), pEVMaxIn[t, i]],
    If[eEVccdf[t - 1, i] < cEV[[i]] + eEVTrip[t, i], ( cEV[[i]] + eEVTrip[t, i] - eEVccdf[t - 1, i]), 0]], 0], 0];
pEVGridccdf[t_, i_] := If[eEVccdf[t - 1, i] + pToEVccdf[t, i] - pFrEVccdf[t, i] < eEVReq[t + 1, i] + eEVTrip[t, i],
  (eEVReq[t + 1, i] + eEVTrip[t, i] - eEVccdf[t - 1, i] - pToEVccdf[t, i] + pFrEVccdf[t, i]), 0];
pFrEVccdf[t_, i_] :=
 Max[If[pPV[[t]] < pLoad[[t]],
   If[eEVccdf[t - 1, i] - (ηOutEV[[i]])^-1 Min[(1 - fEVccd[t, i])/(nEV - 1) (pLoad[[t]] - pPV[[t]]), pEVMaxOut[t, i]] ≥
     eEVReq[t, i] + eEVTrip[t, i], Min[(1 - fEVccd[t, i])/(nEV - 1) (pLoad[[t]] - pPV[[t]]), pEVMaxOut[t, i]],
    If[eEVccdf[t - 1, i] > eEVReq[t, i] + eEVTrip[t, i],
     (ηOutEV[[i]])^-1 ( eEVReq[t, i] + eEVTrip[t, i] - eEVccdf[t - 1, i]), 0]], 0], 0];
(* calculation *)
pEVccd = Table[pToEVccdf[t, i] - pFrEVccdf[t, i] + pEVGridccdf[t, i], {i, nEV}, {t, 97}];
eEVccd = Table[eEVccdf[t, i] - eEVTrip[t, i], {i, nEV}, {t, 97}];

(* LINEAR PROGRAMMING *)
(* constraints *)
(* LINEAR PROGRAMMING *)
(* constraints *)
cons[t_] :=
 Flatten[
  {Table[{pEVMaxIn[t, i], pEVMaxOut[t, i], cEV[[i]] + eEVTrip[t - 1, i] - eEV0[[i]],
     - (eEVTrip[t - 1, i] - eEV0[[i]])}, {i, 1, nEV}], pPV[[t]] - pLoad[[t]], pLoad[[t]] - pPV[[t]]}];
nc = Length[cons[1]];
(* linear program *)
c[n_] := Flatten[Table[Which[x ≤ n, -100, n < x ≤ 2 n, -100, 2 n < x ≤ 3 n, 1], {i, 1, nEV}, {x, 1, 3 n}]];
a[n_] := Transpose[Table[Apply[Which, Flatten[{Table[{
        x == 1 + (i - 1) 4 + nc (t - 1 - (3 i - 3) n) && (3 i - 3) n < t ≤ (3 i - 2) n, 1,
        x == 2 + (i - 1) 4 + nc (t - 1 - (3 i - 2) n) && (3 i - 2) n < t ≤ (3 i - 1) n, 1,
        x == 1 + (i - 1) 4 + nc (t - 1 - (3 i - 1) n) && (3 i - 1) n < t ≤ (3 i) n, 1,
        Mod[x, nc] == 3 + (i - 1) 4 && x > nc (t - 1 - (3 i - 3) n) && (3 i - 3) n < t ≤ (3 i - 2) n, ηInEV[[i]],
        Mod[x, nc] == 4 + (i - 1) 4 && x > nc (t - 1 - (3 i - 3) n) && (3 i - 3) n < t ≤ (3 i - 2) n, -ηInEV[[i]],
        Mod[x, nc] == 3 + (i - 1) 4 && x > nc (t - 1 - (3 i - 2) n) && (3 i - 2) n < t ≤ (3 i - 1) n, -(ηOutEV[[i]])^-1,
        Mod[x, nc] == 4 + (i - 1) 4 && x > nc (t - 1 - (3 i - 2) n) && (3 i - 2) n < t ≤ (3 i - 1) n, (ηOutEV[[i]])^-1,
        Mod[x, nc] == 3 + (i - 1) 4 && x > nc (t - 1 - (3 i - 1) n) && (3 i - 1) n < t ≤ (3 i) n, ηInEV[[i]],
        Mod[x, nc] == 4 + (i - 1) 4 && x > nc (t - 1 - (3 i - 1) n) && (3 i - 1) n < t ≤ (3 i) n, -ηInEV[[i]],
        x == 4 nEV + 1 + nc (t - 1 - (3 i - 3) n) && (3 i - 3) n < t ≤ (3 i - 2) n, 1,
        x == 4 nEV + 2 + nc (t - 1 - (3 i - 2) n) && (3 i - 2) n < t ≤ (3 i - 1) n, 1},
       {i, 1, nEV}], True, 0}]], {t, 1, 3 nEV n}, {x, 1, nc n}]];
b[n_] := Flatten[Table[cons[t], {t, 1, n}]];
(* calculation *)
sol = LinearProgramming[c[97], a[97], b[97]];
pEVlp = Table[Table[sol[[t + (3 i - 3) 97]] - sol[[t + (3 i - 2) 97]] + sol[[t + (3 i - 1) 97]], {t, 97}], {i, nEV}];
eEVlp =
 Table[
  Table[
   Total[Take[Table[ηInEV[[i]] sol[[x + ((3 i - 3)) 97]], {x, 97}] +
       Table[ηInEV[[i]] sol[[x + ((3 i - 1)) 97]], {x, 97}] - Table[(ηOutEV[[i]])^-1 sol[[x + (3 i - 2) 97]], {x, 97}],
      t]] - eEVTrip[t, i], {t, 97}] + eEV0[[i]], {i, nEV}];
{pPV, pLoadPH, pLoadHH, pLoadHH2, pEVuc, eEVuc, pEVcc, eEVcc, pEVccd, eEVccd, pEVlp, eEVlp}]
```