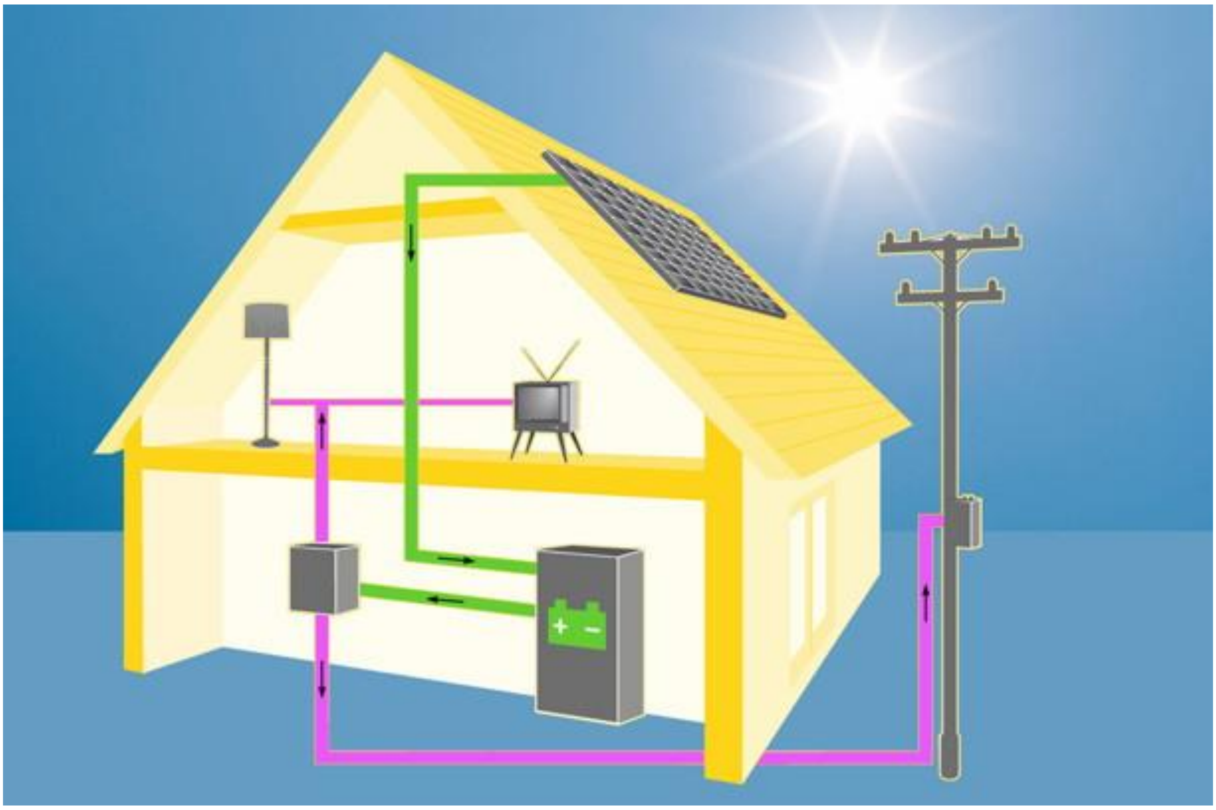
Residential batteries – The ‘missing piece’?

The contribution of battery systems in conjunction with PV systems to the (economic) value for different stakeholders in the Netherlands



Master Thesis Energy Science. Track: Systems analysis
May 2015

Name: Wouter Schram
Student number: 3539822
Address: Thorbeckelaan 8A
3551BR Utrecht
Email: wouterschram@gmail.com
Supervisor: Dr. W.G.J.H.M. van Sark
Second reader: B. Elsinga
Dr. E. Nieuwlaar

Universiteit Utrecht

Abstract

A mismatch exists between supply and demand of PV electricity. While residential solar panels produce electricity during the day, most electricity is used in the evening. The possible abolishment of net metering could make equipping PV systems with a battery attractive. Potentially, this battery could address the supply and demand mismatch and reduce peaks in consumption. In this research, various aspects of residential storage was investigated. First, based on a meta-analysis of existing literature of Lithium-ion batteries and based on experience curves, possible cost developments of Lithium-ion battery systems were determined. The meta-analysis resulted in predictions for 2020 of around 250 €/kWh, while experience curves indicated values of around 150 €/kWh. Using power data (measurements every 10 seconds) and battery simulations, the average optimal storage size for a neighborhood in the Dutch city Amersfoort was determined to be 3.18 kWh. The optimally sized batteries have a large impact on overproduction of PV electricity: more than half of the overproduction was covered by the batteries. The impact on peak shaving and load shifting was limited when the batteries were not controlled, but large when batteries were precharged. The most important factors for consumers determined by a consumer survey were product lifetime and safety.

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1 Introduction

June 16, 2013. The German spot market price for electricity reached a record low of -100 $^{€}/_{MWh}$ between 14:00 and 16:00 o'clock (EEX, 2013). With more renewables in the energy mix, negative prices could also be possible in the Netherlands (Chaves-Ávila, et al., 2012)). Meanwhile, Dutch Minister of Economic Affairs has publicly announced that in his view the net metering policy, allowing PV owners to sell oversupply of electricity to the grid at retail prices, should be abolished (Tweede Kamer, 2013). If PV owners would be treated like energy companies, could this mean that at certain moments they would have to pay money when producing electricity with their solar panels?

1.1.1 Societal background

In recent years, the installed renewable capacity in the Netherlands has slightly increased. However, given the EU 2020 goals it can be expected that the amount of renewable energy in the Dutch energy mix will experience strong growth in the upcoming years: the Netherlands are bound to increase the renewable energy supply from 4,5% in 2013 to 14% in 2020 (CBS (2013), European Parliament (2009)). To enforce this, the Dutch government -along with a broad alliance of energy related organizations- signed the "Energy Agreement on sustainable growth" (SER, 2013). In this agreement, the goal was set to have 6000 MW_e on-shore wind and 2050 MW_e off-shore wind[1] in 2020. No specific goal was set for Photovoltaics (PV), although it was stated that 1 million households and Small and Medium Enterprises should be "substantially" self-sufficient (SER (2013), p. 79). Earlier, in 2011, an alliance of energy companies launched a plan to achieve 4000 MW_e in 2020. Since 2010, the total installed capacity of PV doubled each year, from 88 MW_e in 2010 to 722 MW_e in 2013 (CBS, 2014).

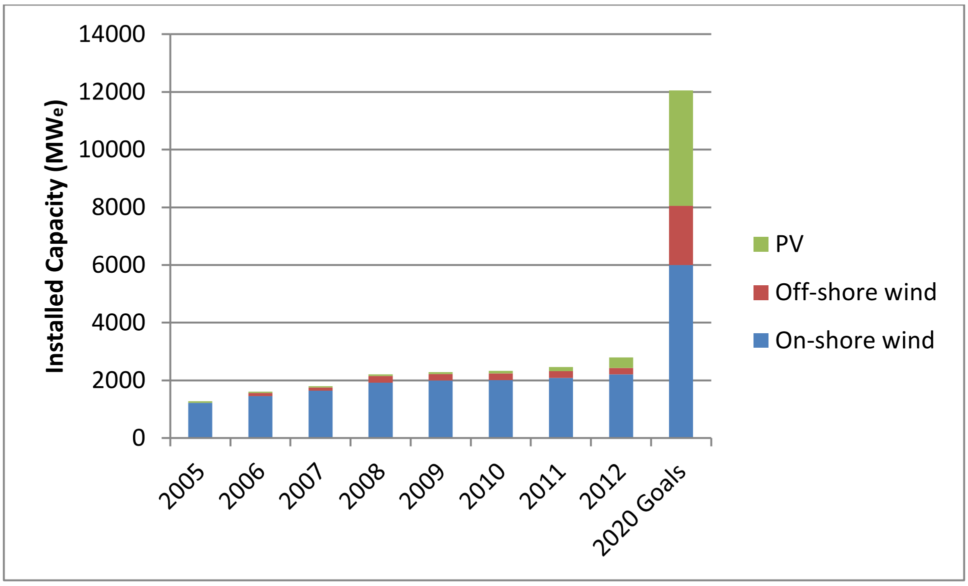

Figure 1, Installed capacity renewable electricity. Sources: for wind energy SER (2013) and for solar KEMA (2011).

Evidently, having more renewables in the energy mix has several advantages. Examples are the decrease of dependence on import and decrease of greenhouse gas emissions. However several challenges arise with the integration of more renewables in the energy mix. Probably most prominently, are the costs: governments often opt for the most cost-efficient implementation of incentives to increase renewables (see e.g. SER (2013)). A second consideration is the flexible and uncontrollable nature of renewable energy sources. Particularly, because a supply and demand mismatch exists between e.g. PV and household electricity demand (see Figure 2). Both challenges form important themes within this research.

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[1] 4450 MW_e off-shore wind in 2023.

Simultaneously, electricity use is expected to increase in the upcoming years. Rooijers et al. (2014) expect an increase in electricity use in all of their scenarios for the Dutch energy supply in 2030. In the business-as-usual scenario they expect an increase of 23%. Causes are, among others, the possible electrification of household heat demand (i.e. heat pumps), and penetration of electric vehicles (EVs) (Rooijers, et al., 2014). Regarding EVs, the Dutch government aims to have 200.000 EVs in 2020, and 1 million in 2025 (Rijksoverheid, 2011). With average use, an EV would increase a household's electricity consumption with 42% (Brouwer et al., 2013).

With an evenly spread increase of electricity load, the peak demand will also increase. This can be even more amplified when heat pumps are used and EVs are charged directly after standard working hours, at the current peak demand. The peak demand forms an important cost variable for the energy system. On the one hand because flexible power plants have to be employed to cover the peak demand. These power plants are characterized by high marginal costs. On the other hand because peak demand determines the peak capacity of the electricity grid and thereby has influence on investment requirements of net operators as well as electricity suppliers. Recent developments in the Dutch electricity market led Distributed System Operator (DSO) Liander to believe large investments in the grid are needed (Kamp, 2014).

A phenomenon that can flatten out the peak of PV electricity production, as well as the household peak demand, is Domestic Energy Storage (DES). For this application, electrochemical storage (or batteries) has received much attention. In contrast to the most common form of grid storage (hydro storage), batteries are applicable for small-scale distributed energy systems. When during the day, a PV household produces more electricity than it uses, currently this electricity is exported back into the grid. Using an integrated PV battery system as an alternative, overproduction of electricity could be stored, and used in the evening when there is no PV electricity production (see Figure 2). This would increase the self-consumption of PV electricity, which has several advantages: for example, reduction of electricity transport and encouragement of consumers to control energy behavior (Castillo-Cagigal, et al., 2011). Furthermore, when there would be 'smart timing' of operation of the batteries, it could contribute to shave the peaks of local production as well as consumption. This implies that integration of ICT solutions can be a valuable addition.

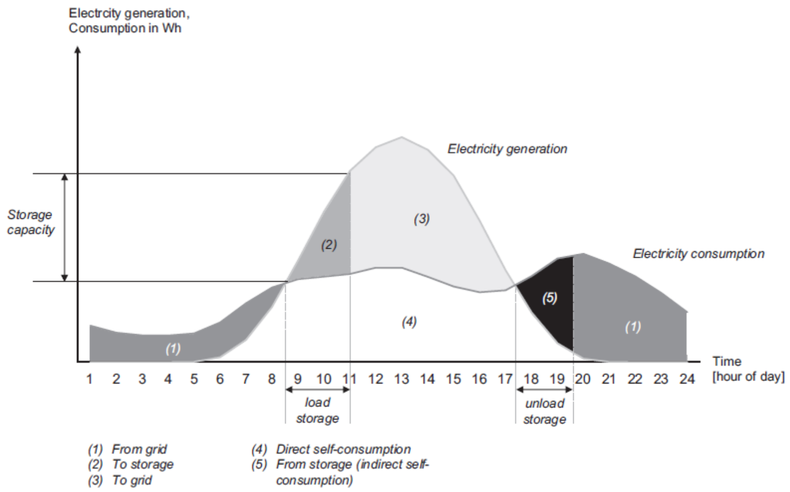


Figure 2, general logic domestic energy storage: part of the supply and demand mismatch is solved by implementing storage. Source: Hoppmann et al. (2014)

1.1.2 Scientific background

Various studies have examined integrated PV-battery systems. Castillo-Cagigal et al. (2011) designed a system with PV, storage and DSM and found that DSM on its own could increase PV self-consumption from 32.7% to 46.8%. For storage to accomplish the same increase, a storage size of 0.2 days of autonomy was needed. In an average Dutch household this would mean a rather small storage size of less than 2 kWh[2]. This shows that although DSM can make a valuable contribution, it cannot be the potential game changer that residential storage is. A second finding was that stored electricity increases non-linearly with increased storage size (Castillo-Cagigal, et al., 2011). This shows that there will be an optimal storage size. Because the exact relationship between storage size and yearly stored electricity is unknown, and will vary per household, this optimal storage size can be difficult to determine. Hoppmann et al. (2014) focused on determining economically optimal sizes of PV and lead-acid storage systems. They found that these systems could, under the right price circumstances, already be profitable in 2013. RMI et al. (2014) went one step further: they investigated the possibilities of a 'utility in a box', i.e. being self-sufficient without connection to the grid. Their proposed system consisted of an integrated PV-battery system supplemented with a small diesel generated. They forecasted grid parity possible already today on Hawaii, and well before 2030 for millions of residents of the states New York and California.

1.1.3 Gap in literature

However, there are some difficulties with applying the research of RMI et al. (2014) to the Dutch situation. For example, their assumptions on costs of solar panels are higher than prices in the Netherlands. On the other hand, the solar irradiation assumed is much higher than in the Netherlands. This makes going completely off-grid much less realistic: enormous PV and battery systems would be needed, or extensive use of micro diesel generators. The first is evidently not optimal from an economic point of view, and the second from an environmental point of view. It may be more interesting to focus on the intermediate step before establishment of completely self-sufficient micro-grids: becoming *more* self-sufficient.

There also are some limitations to the research of Hoppmann et al. (2014). For example, they used load profiles and hourly solar irradiation data. Evidently, this is less accurate than using sub-hourly PV production and household consumption data, as will be done in this research. PV production is not only dependent on solar irradiation, but also on e.g. ambient temperature. Furthermore, Hoppmann et al. focused on a typical household, with average consumption. Particularly in this case, it is essential to differentiate between households, because storage can be much more attractive for PV owners with much oversupply as compared to PV owners with average oversupply. Lastly, Hoppmann et al. (2014) maximized feed-in tariff at the wholesale price (which is unrealistic in a short-term scenario in the Netherlands, because this would be a big difference from the current net metering scheme). They also assumed no policy differences tax that is included in the current retail price. This is unsure, because a problem with current price schemes is the perceived 'tax evasion' of PV; this could be seen as an over subsidy. The assumption is that storage would receive the same subsidy. To make the results applicable for more policy scenarios, in this research the focus will lie on at which difference between a feed-in tariff and retail electricity prices, residential storage can be attractive.

1.1.4 Research questions

The main question of this research will be:

How would battery systems in conjunction with PV systems contribute to (economic) value for different stakeholders in the Netherlands?

To answer this research question, several sub questions are being investigated:

1. What could be the cost development of residential battery systems?

[2] It should be noted that the research was not done for the Dutch situation, so numbers cannot be transferred one on one.

2. What is the relation between increasing battery size and Net Present Value of storage for different PV households and what would be the optimal storage size for these households?
3. For the optimally sized batteries, what would be (a) the impact on overproduction, (b) the results for various indicators of battery degradation (c) the impact on consumption and production power peaks on neighborhood level and (d) the impact on peak loads on neighborhood level?
4. How would precharging of the optimally sized batteries impact the battery degradation indicators, and the peak shaving and load shifting on neighborhood level?
5. What could be non-financial barriers for consumers?

1.1.5 Scientific relevance

This research will contribute to the scientific literature by being the first research on the value of integrated residential PV battery systems that takes multiple stakeholders into account. Research question one is relevant, because peak reduction could represent additional benefits of residential storage for the energy system. Thereby this question investigates integrated PV battery systems from the point of view of a service operators. Research question 2 till 4 investigate the systems from the economic perspective of a consumer. Research question 5 aims to take the entire system into account.

Research question 5 represents a specific contribution to the scientific literature. Indisputably, there is a behavioral aspect in the supply and demand mismatch. In the Netherlands, early initiatives on providing smart meters were aimed at giving consumers insight in their electricity use. Activities in demand side management (DSM) focus on load shifting of controllable household devises from the peak load hours, for example by giving price incentives (dynamic pricing). At the same time, various researchers report that behavioral factors remain largely neglected in research about smart grids. For example, Geelen et al. (2013) argue that current smart grid approaches focus on technology and economic incentives, while including consumers in product and services development receives less attention. Verbong et al. (2013) see two main perspectives about consumer involvement. The first perspective is that of the 'homo economicus': the consumer that acts based on economic maximization of self-interest. This perspective is covered by research question 4. The second perspective encompasses that emotional incentives are equally important; this perspective is covered by research question 6. It is important to include non-economic factors, to prevent premature lock-in in a non-optimal pathway (Verbong et al., 2013).

2 Methodologies

The research questions stated in the previous chapter require different methods for answering them. Figure 3 shows an overview of how the research questions are translated into research products. Furthermore, it shows the connection between the research questions. Research question 1 serves as input for research question 2-4. Research question 2-4 are strongly connected: the same data source and methodology were used. Furthermore, results of research question 2 served as input for the results of research questions 3 and 4: subsequent simulations were performed based on the optimal sizes determined in research question 2. Research question 5 fills the gap left by the previous research questions, but uses no direct input from these research questions. This chapter describes the methods in detail.

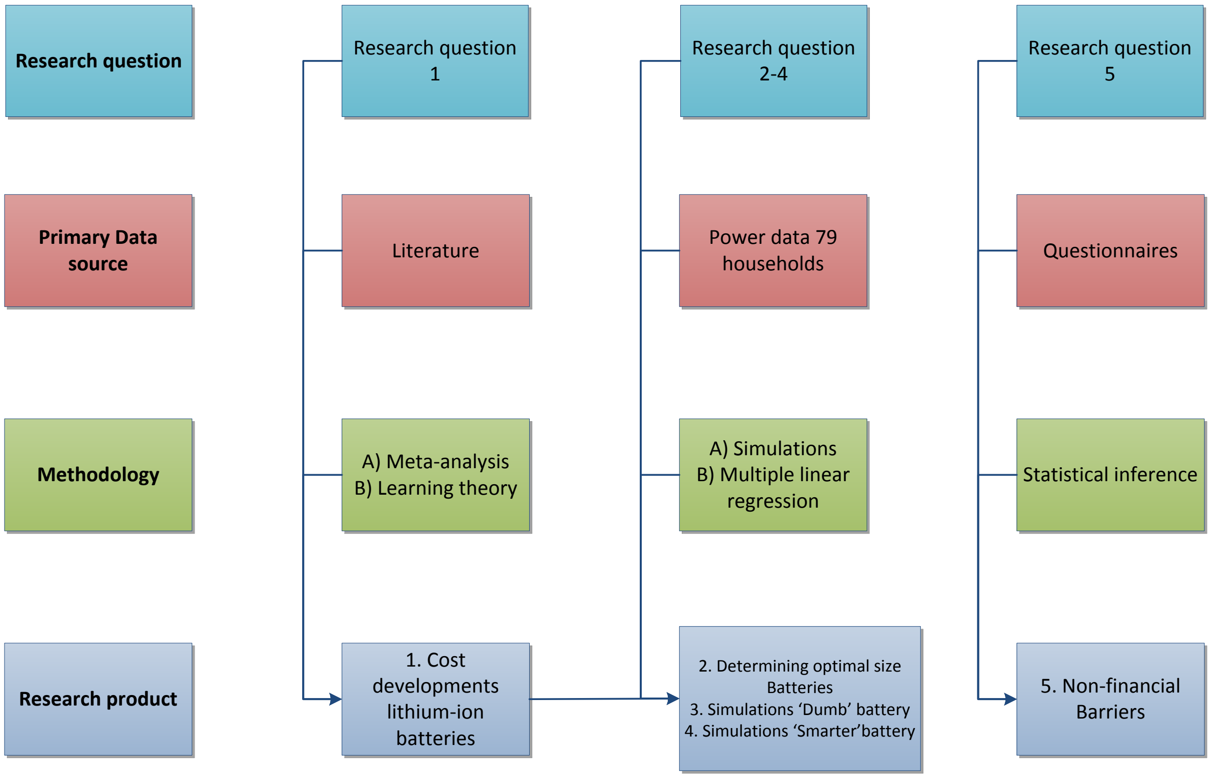


Figure 3, flowchart of this research

2.1 Cost development

6. What could be the cost development of residential battery systems?

This research question involved a very challenging combination: the price development of a residential battery system is extremely important to the attractiveness of a storage system, and at the same time is very unsure. This is due to the fact that residential energy storage is in a very early stage of development.

Therefore, an elaborate research was executed to determine possible price developments. Central to the approach of this research question is data triangulation: different methods were used to construct a comprehensive framework around price developments of electrochemical energy storage. Thereby, this research goes further than many previous studies that incorporated either a meta-analysis (e.g. Stewart (2012)), a bottom-up costs analysis (e.g. McKinsey (2012)), or experience curves (e.g. Matteson & Williams (2015)). In this research, first a meta-analysis was performed on general predictions regarding cost development of electrochemical energy storage. Next, a meta-analysis was performed on learning rates of Lithium-ion Batteries (LiBs). For both meta-analyses, data was collected using search engines Scopus and Google Scholar. Additionally, grey literature was taken into account. Grey literature was critically assessed before incorporated in this research. In general, publications from renowned consultancy companies were taken into account, but individual websites on the matter were not. Snowballing was used to access the ground source of predictions as much as possible; in this way, specific assumptions within literature could be assessed. In the meta-analysis about learning rates, it turned out most studies about learning rates of LiBs were aimed at consumer electronics. Therefore, the next step was to construct a learning curve based on LiB costs in (Plugin Hybrid) Electric Vehicles (PH)EVs.

The time scope for literature taken into account in this research question is 2009-2015. This is a relatively extensive period, taken into account the rapid developments in this area. However, this choice can provide valuable insights regarding trends in predictions of price developments.

Since the use of LiBs in car batteries is relatively recent, this experience curve is based on few data points. However, it does give an indication. For the period 2011-2013, cost data was based on DOE (2014), cumulative production was based on Pillot (2014)[3]. The 2014 cost data was based on Lux Research (2014) and cumulative production on Pontes (2015).

To translate the determined learning rates (LRs) to a future cost, the relatively conservative prediction of Pillot (2014) from Avicenne Energy was used (see Figure 4). In addition to Figure 4, note that Navigant Research (2013) expects 3.8 million EVs in 2020, and US national goals amount to at least six million (PH)EV sales in 2020 (IEA, 2013).

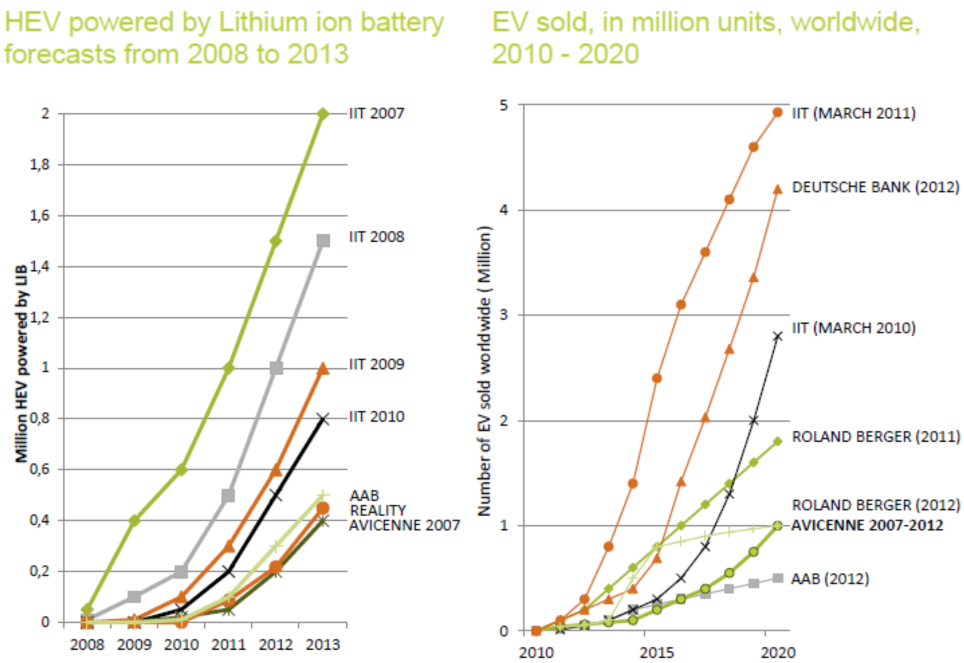


Figure 4, past and future predictions of Avicenne Energy. Source: Pillot (2014)

[3] This data was validated by Bloomberg (2014b).

2.2 Input data

The data needed for research question 2-4 was received from research institute DNV GL. As part of the "Smartgrid: rendement voor iedereen" project, for 100 households the power interaction with the grid was measured every 10 seconds. Note that data concerned net metered power; therefore it was not possible to analyze consumption and production individually. The period of measurement was November 2013 till October 2014.

There were three problems with the quality of the data. Firstly, data from various dates was missing for all households. Data of the entire days 13, 20, 22, 27 and 29 November, 3, 5, 6, 9, 11, 12, 13, 17, 18 and 23 December, 15, 18 and 21 January, 19 and 24 February, 14, 26 and 30 March, 1, 2, 5, 8, 16 and 19 April, 17 May, 23, 25, 28, 30 and 31 July, 8, 20, 26 and 27 August, and 2-31 October were missing. It was assumed that the remaining dates were a representative for a year. This choice was made because otherwise much more additional assumptions had to be incorporated, resulting in equal uncertainty of final results. Sensitivity analysis was performed to see the effect of decreasing or increasing production.

Secondly, data for individual households also often was incomplete. Criterion for leaving a household outside the analysis, was whether more than a month of the (remaining) data was missing. As a result, 21 households were kept outside of the research.

Lastly, extreme outliers could be observed from data (e.g. a 10 kW production peak for a few data points of a household that had few overproduction in the rest of the year). Therefore, when minima or maxima of an individual household were needed, a certain percentile was assumed to be the minimum/maximum of this household.

Of the remaining 79 households, eight households had no solar panels, and an additional seven had a total overproduction of less than 10 kWh[4]. On average, the households with a higher overproduction exported on average 983 kWh to the grid (standard deviation 559). The average consumption from the grid of all 79 households was 2637 kWh (standard deviation 1113).

Table 1 shows the most important input parameters of this research. Since all parameters are under significant uncertainty, sensitivity analyses was performed on the results of research question 2 – 4; minimum and maximum input values for the sensitivity analysis are also shown in
Table 1.

Table 1, Input parameters

	Min	Base	Max	Based on
Cost battery (€)	100	**200**	300	See chapter 3.1
ΔElectricity price (€)	0,08	**0,16**	0,28	
ΔElectricity price Increase	0%	**1%**	3%	SER (2013)
Discount rate	0,02	**0,04**	0,08	Hoppmann et al. (2014)
$\eta^{round\ trip}$	0,76	**0,81**	0,91	Hoppmann et al. (2014)
Life time (years)	5	**15**	20	Based on Heymans et al. (2014), Tesla Motors (2015a), this research

[4] It was impossible to determine whether these households had a very small PV installation, or these values were due to measurement errors

The cost of the battery is an essential parameter and was extensively investigated in research question 1. The ΔElectricity price (difference between retail electricity price and feedin tariff) is completely dependent on the electricity pricing scheme; as a base, this was estimated to be €0,16. This was estimated to increase with 1% per year, as the Dutch government announced to pay investments in renewable energy from increasing existing energy taxes (SER, 2013). The η^c and η^d were assumed to be equal at 0.9, resulting in a $\eta^{\boldsymbol{round\ trip}}$ of 0.81. This efficiency includes inversion losses. Making an appropriate assumption for lifetime was complex. This is subject of debate regarding Electric Vehicle (EV) batteries, and moreover residential batteries operate under different circumstances than EV batteries. Heymans et al. (2014) estimate that 80% of the capacity of EV batteries is left after eight years. The residential battery that was launched by Tesla has a warranty of 10 years (Tesla Motors, 2015a). The lifetime was assumed to be higher, because also with capacity loss, a battery would still be able cover a large part of the PV overproduction (some elaboration on this can be found in paragraph 3.3.4). Limiting the life time to performance guarantees would therefore underestimate the total possible use of the battery.

One special sensitivity analysis was performed; this sensitivity analysis was not on one of the input parameters, but on the input data: PV electricity production, or more specifically, on the rate of self-sufficiency[5]. Hourly solar irradiation ($E_j^{Irradiation,hour}$) data was obtained from KNMI (2015), and converted to percentages of the total yearly irradiation per 10 seconds *i*:

$$p(E^{Irradiation})_i = \frac{E_j^{Irradiation,hour}}{\sum_j (E_j^{Irradiation,hour}) * 360}$$

For all households *k*, this could be converted to the Extra Production for household *k* with on moment in time *i*:

$$E_{i,k}^{Extra\ Production} = p(E^{Irradiation})_i * E_k^{Yearly\ Net\ Metered\ consumption} * SolarMultiplier$$

Note that since $\sum_i (p(E^{Irradiation})_i)$ = 1, the extra production meets the entire net metered consumption of household *k* if the SolarMultiplier = 1, hence the self-sufficiency would be 100%.

2.3 Determining optimal storage size

2. What is the relation between increasing battery size and Net Present Value of storage for different PV households and what would be the optimal storage size for these households?

Using MATLAB, use of batteries was simulated to determine yields of batteries from various sizes. The specific code can be found in Appendix 7.3.

[5] Self-sufficiency $= \frac{E_{\text{production}}}{E_{Consumption}}$

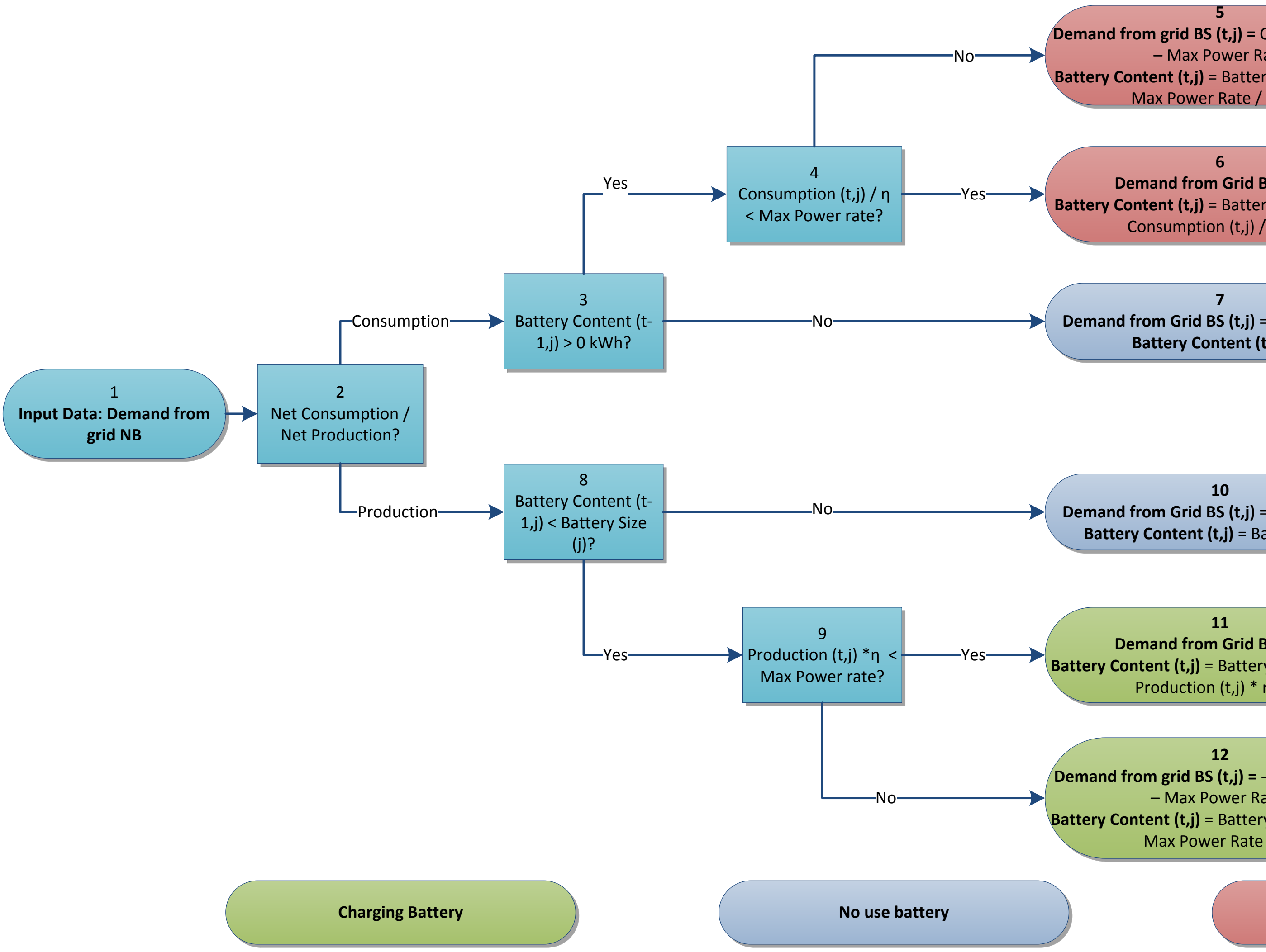


Figure 5 shows an overview of all steps that have to be undertaken by the model, for every household, every 10 seconds, and various storage sizes. Block 2, 3, 4, 8 and 9 represent the decisions that in reality typically would be made by an energy management system. The input data (Block 1) was received from DNV GL (see Paragraph 2.2). Block 5, 6, 7, 10, 11 and 12 represent the consequences on two variables: the input to the battery content of a household, and the (new) demand from the grid of a household. The battery content served as input for the energy management system in the next time step, while the new demand from grid served to construct a new dataset with inclusion of a battery. The output data (block 13) was used to do succeeding calculations; in this research question to determine the Net Present Value (NPV) for different storage sizes.

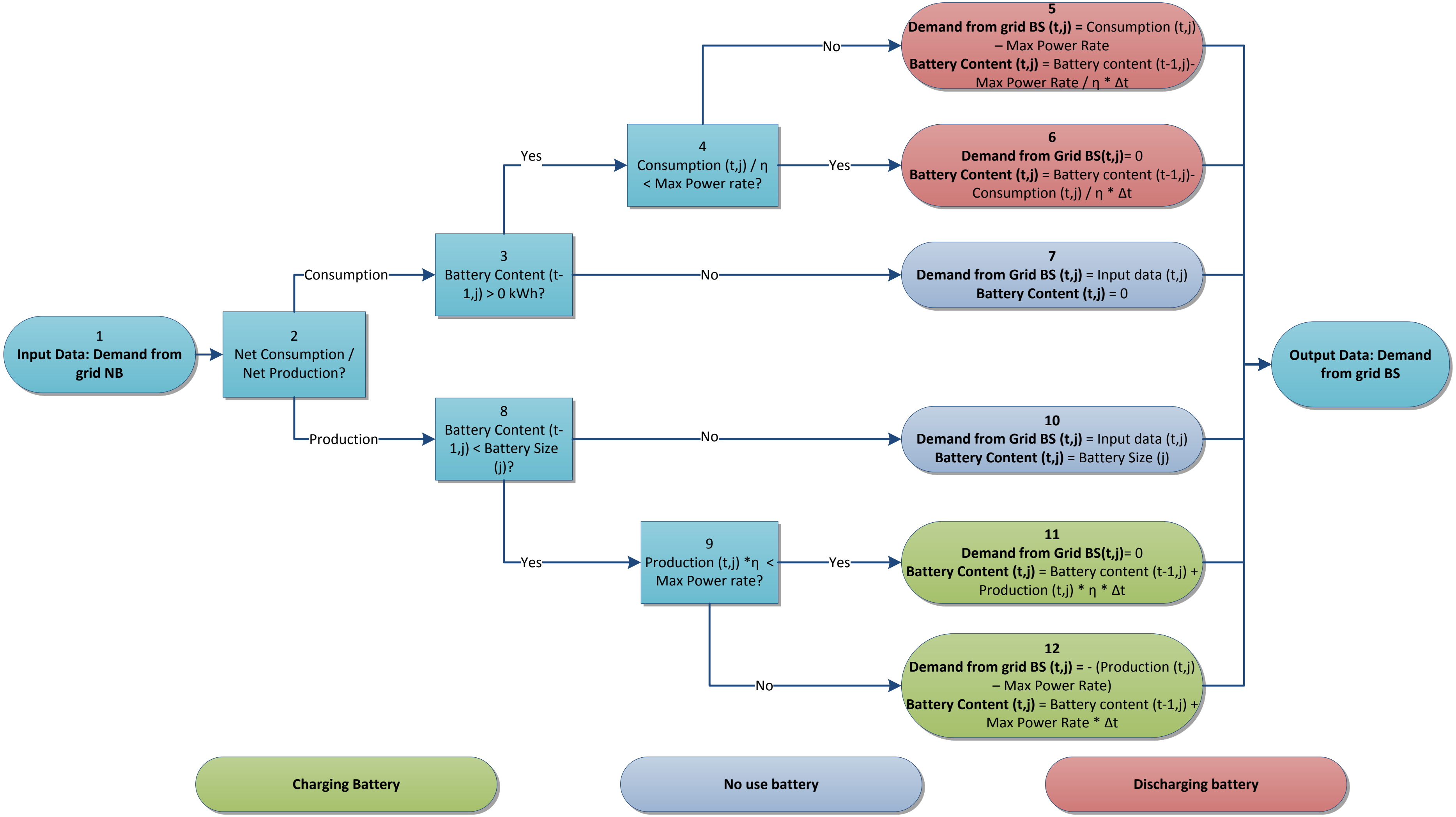


Figure 5, Flow chart of Battery use. BS = battery scenario. In the actual model, there are also feedback loops from block 5, 6, 7, 10, 11 and 12 to blocks 3 and 8.

In this research, the optimal storage size for a household was defined as the storage size with the highest NPV. For each household, we determined the NPV using discounted marginal benefits and costs. The Marginal Benefits encompass the additional benefits if the battery size would be increased by one unit. Similar to Hoppmann et al. (2014), storage sizes were increased at intervals of 0.5 kWh. To determine the MBs, several steps had to be undertaken.

First, it had to be determined whether there was overproduction (Block 2):

If $P^{PV} > P^{Consumption} \rightarrow E^{P} = (P^{PV} - P^{Consumption}) * \Delta t$

With Power (P) expressed in Watt, time (Δt) in seconds and overproduction (E^{P}) in Joule. Next, it has to be determined whether this overproduction can be stored in the battery (i.e. Battery content < Battery Size, Block 8). If the battery is already fully charged, the battery is not used and nothing happens to the input data (Block 10). If a battery is not fully charged, E_{P} can be stored in the battery:

$$E^{P,Battery} = (P^{PV} - P^{Consumption}) * \Delta t * \eta^{c}$$

With η^{c} as the charging efficiency.

This is limited (block 9) by:

$$E^{P,Battery}/_{\Delta t} \leq Power\ rate_{max}$$

All energy that cannot be stored in the battery is exported to the grid ($E_{P,Grid}$). The energy stored in the battery ($E^{P,Battery}$) can be used at a later moment, when there is net consumption. So when Battery content > 0 kWh, Consumption from battery $E^{C,Battery}$ (in Joule) is:

$$E^{C,Battery} = (P^{PV} - P^{Consumption}) * \Delta t * \eta^{d}$$

with η^{d} as the discharging efficiency.

Again, this is limited by the Max Power rate[6]:

$$E^{C,Battery}/_{\Delta t} \leq Power\ rate^{max}/_{\eta^{d}}$$

Block 5 and 6 represent the consumption from a battery and thereby are closely related to the benefits of storage. The yearly energy covered by a battery ($E^{C\ total,Battery}$) for household *j* can be calculated by summing all consumption from the batteries over time period *i* of 10 seconds, corrected by a factor $\frac{365}{297}$ due to the missing data (see Paragraph 2.2):

$$E_{j}^{C\ total,Battery} = \sum_{i}^{2566080} E_{i,j}^{C\ total,Battery} * \frac{365}{297}$$

[6] Max Power rate is defined as the maximum output from the battery

One should note that the flow chart of

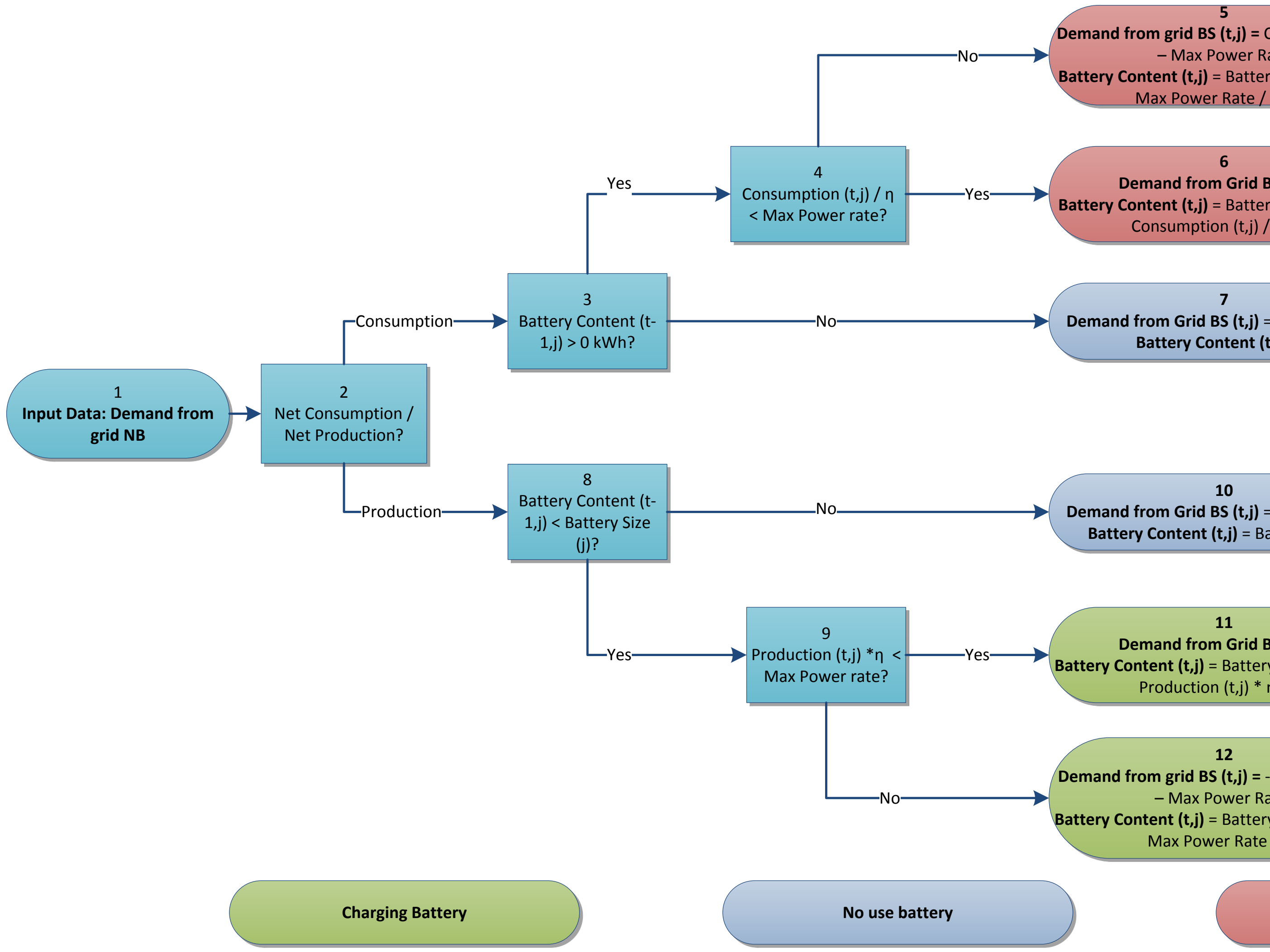


Figure 5 represents the simulation of the battery and subsequent effects on interaction with the grid. When the battery is correctly simulated, the yield also can be simply calculated comparing the situation without battery and the situation with the simulated battery on yearly export to the grid:

$$E_j^{C\ total,Battery} = \left(E_j^{P,Grid}(No\ battery) - E_j^{P,Grid}(Battery)\right) * \eta^d * \eta^c * \frac{365}{297}$$

Subsequently, the financial benefits of the battery B_{batt} (in €) can determined by the product of $E_j^{C\ total,Battery}$ in kWh and the $\Delta\ Electricity\ price$ $(^{€}/_{kWh})$[7]:

$$B_j^{Batt} = E_j^{C\ total,Battery} * \Delta\ Electricity\ price$$

With
$\Delta\ Electricity\ price$ = Retail electricity price – Feed-in tariff

Now the Marginal Benefits can be determined:
$$B_{s,j}^{M} = B_{s,j}^{Batt} - B_{s-0.5,j}^{Batt}$$

[77] Note that with net metering policy in place, the retail electricity price and the feed-in tariff are by definition equal, so $\Delta\ Electricity\ price$ = 0 → $B_{batt} = 0$.

Since batteries are modular, Marginal Costs were assumed to be constant. This is in line with the dominant qualification regarding storage costs. In reality, larger batteries will be somewhat cheaper per kWh.

NPV per household
Using the above we thus define NPV per household based on battery size:

$$NPV_{s,j} = NPV_{s-0.5,j} + \frac{\sum_{t=0}^{Lt}\left(B_{s,j}^{M} * (1+Y_i)^t/(1+dr)^t\right)}{(1+dr)^t} - C^M$$

With
s = Battery size (in kWh)
B^M = additional benefits after increasing battery size to size *s*
C^M = additional costs after increasing battery size to size *s*

Optimal storage size
Economic theory dictates that the optimal investment decision can be found where the marginal costs MC equal the marginal benefits MB:

$$C^M = B^M \rightarrow \frac{dC}{dS_{\mathrm{batt}}} = \frac{dB}{dS_{\mathrm{batt}}}$$

If the B^M are discounted, this point will coincide with the maximum value of the NPV analysis that was explained previously.

2.4 Simulation with optimally sized batteries

3. For the optimally sized batteries, what would be (a) the impact on overproduction, (b) the results for various indicators of battery degradation (c) the impact on consumption and production power peaks on neighborhood level and (d) the impact on peak loads on neighborhood level?

For this research question, the data was used as described in paragraph 2.2, and the model as illustrated as in

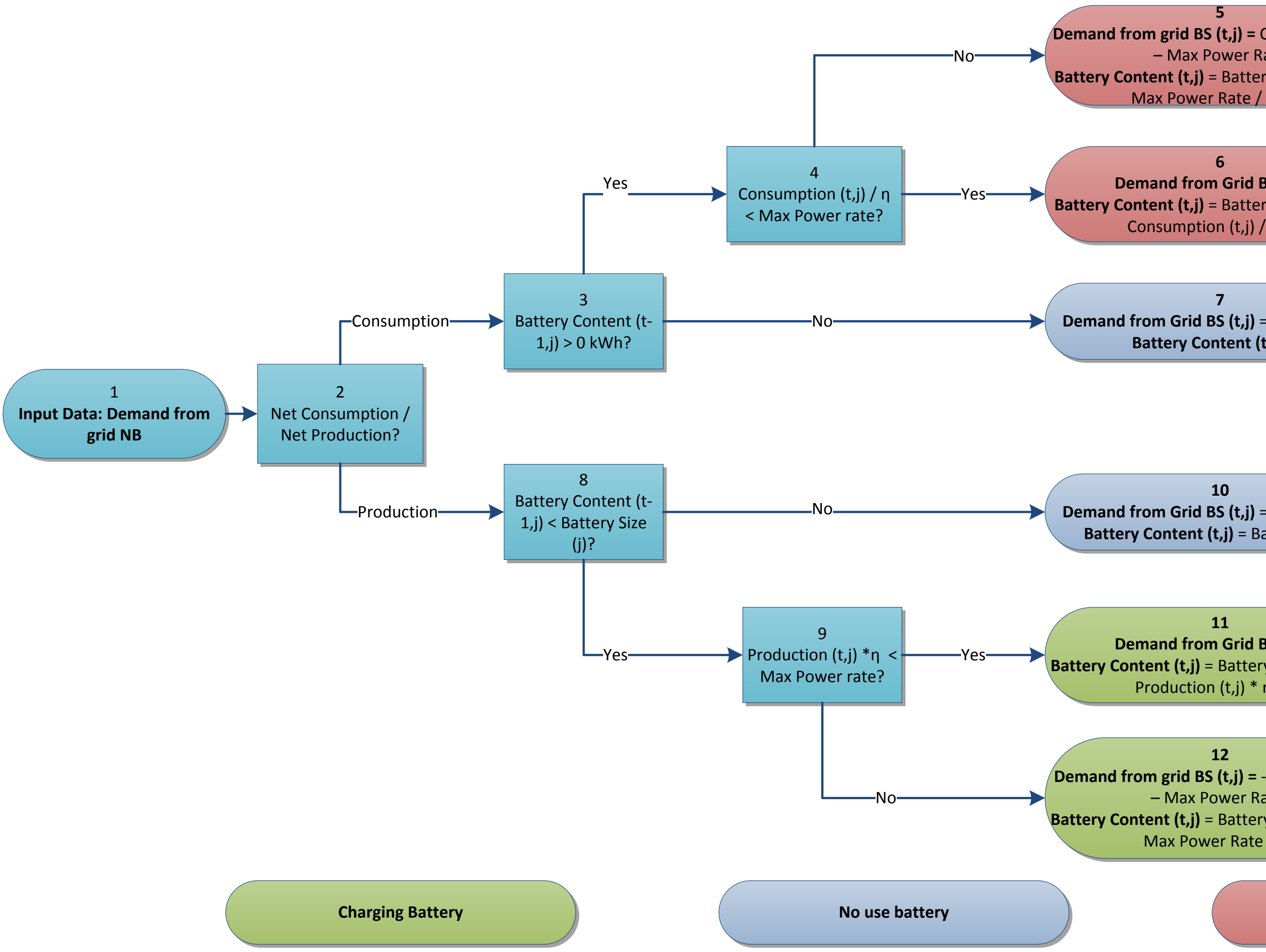


Figure 5.

2.4.1 Overproduction

Self-consumption of PV electricity is increasingly becoming a central issue around PV. Self-consumption is the part of the total energy produced by the solar system (E_{PV}, in kWh) that is directly consumed (E_{direct}, in kWh) by the same prosumer. This can be increased by storage in a battery, leading to the following definition of self-consumption (similar to the definition of Castillo-Cagigal et al. (2011)):

$$SC^{total} = \frac{E^{direct} + E^{C\ total,Battery}}{E_{\text{PV}}}$$

However, since the data obtained for this research were net metered data, self-consumption per household could not be obtained: it is impossible to determine the isolated production and consumption data. However, we do know the *overproduction*. Overproduction is the direct opposite of self-consumption:

$$E_j^{P,Grid} = 1 - SC.$$

In other words, overproduction is the part of E_{PV} that is exported to the grid. One could say that from a system's perspective overproduction is actually the most relevant part of E_{PV}; this is the part that is put on the grid and can cause problems with intermittency. Note that without a battery, $E_j^{P,Grid} = E_j^P$:

all overproduction is exported to the grid. Evidently, implementing batteries would reduce the $E_j^{P,Grid}$: part of the overproduction is now exported to a battery ($E_j^{P,Battery}$).

The impact on overproduction (in %) can be determined by:

$$Impact\ on\ Overproduction = \frac{\left(E_j^{P,Grid}(Battery) - E_j^{P,Grid}(No\ battery)\right)}{E_j^{P,Grid}(No\ battery)} * \eta_d * \eta_c$$

Note that there is actually a larger impact on overproduction, however this impact is partly due to charging and discharging efficiency losses. Therefore, we multiply with these efficiencies.

2.4.2 Battery degradation indicators

The prediction of battery degradation and factors influencing it is still not fully understood (Barré, et al., 2013). In this research, three indicators for battery degradation were examined: average Depth of Discharge (DOD), average State of Charge (SOC) and total energy throughput. Note that the DOD is a less important factor for Lithium-ion batteries than for e.g. lead-acid batteries (Peterson, et al., 2010). Thereby it is mainly of interest if one would opt for a different battery than the Lithium-ion battery. Still, relationships between DOD and battery degradation are also found for the LiB (Barré et al. (2013), Hoke et al. (2011)). The DOD for each day *i* and each household *j* was determined by

$$\mathrm{DOD}_{i,j} = SOC(max)_{i,j} - SOC(start\ of\ day)_{i,j}$$

Defined this way, the multiple charge and discharge cycles during one day are not taken into account. Therefore, the total energy throughput for household *j* was also calculated:

$$Total\ energy\ throughput = E_j^{C\ total,Battery} + E_j^{P\ total,Battery}$$

This indicator is possibly the most important indicator for battery degradation (Peterson, et al., 2010). Lastly, the average SOC is taken into account. Battery degradation increases when batteries operate under a high SOC (Fu, et al., 2014).

2.4.3 Peak shaving

As can be seen in the flow chart, the model produces a net data set of demand from the grid for each household. To determine the neighborhood peaks, the cumulative demand from the grid (in kW) at point in time *i* was determined by summing over all households *j*:

$$Total\ Demand\ from\ grid_i = \sum_{j}^{79} Demand\ from\ grid_{i,j}$$

The consumption and production peaks are then found by taking respectively the maximum and minimum of the total demand for every day. Again, the situation without batteries and with optimally sized batteries were be compared, to determine the peak shaving that can be attributed to the batteries.

2.4.4 Load shifting

Lastly, the peak loads were found by summing the total demand over a period of four hours. This was based on CE Delft & Kema (2012), see Figure 6. The two-hour peak load of day *k* was determined by:

$$Four\ Hour\ peak\ load_k = \sum_{i=TimingPeak-360}^{Timing\ Peak+1080} Total\ Demand\ from\ grid_i * 10$$

As can be seen in Figure 6 and was observed by the data, summing from one hour before the peak till three hours after the peak resulted in a higher peak load than when was summed from two hours before and after. The four hour peak load of the neighborhood will be compared for the situation with and without batteries.

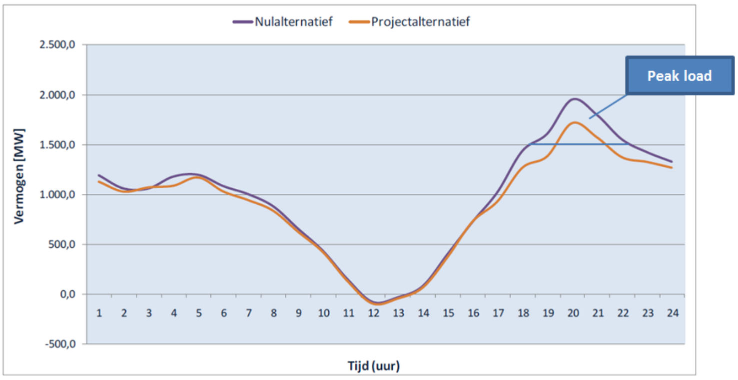


Figure 6, electricity demand in residential areas. Source: CE Delft & Kema (2012), adjusted version

2.5 Simulation precharged battery

4. How would precharging of the optimally sized batteries impact the battery degradation indicators, and the peak shaving and load shifting on neighborhood level?

For this research question, the data was used as described in paragraph 2.2, and the model as illustrated as in

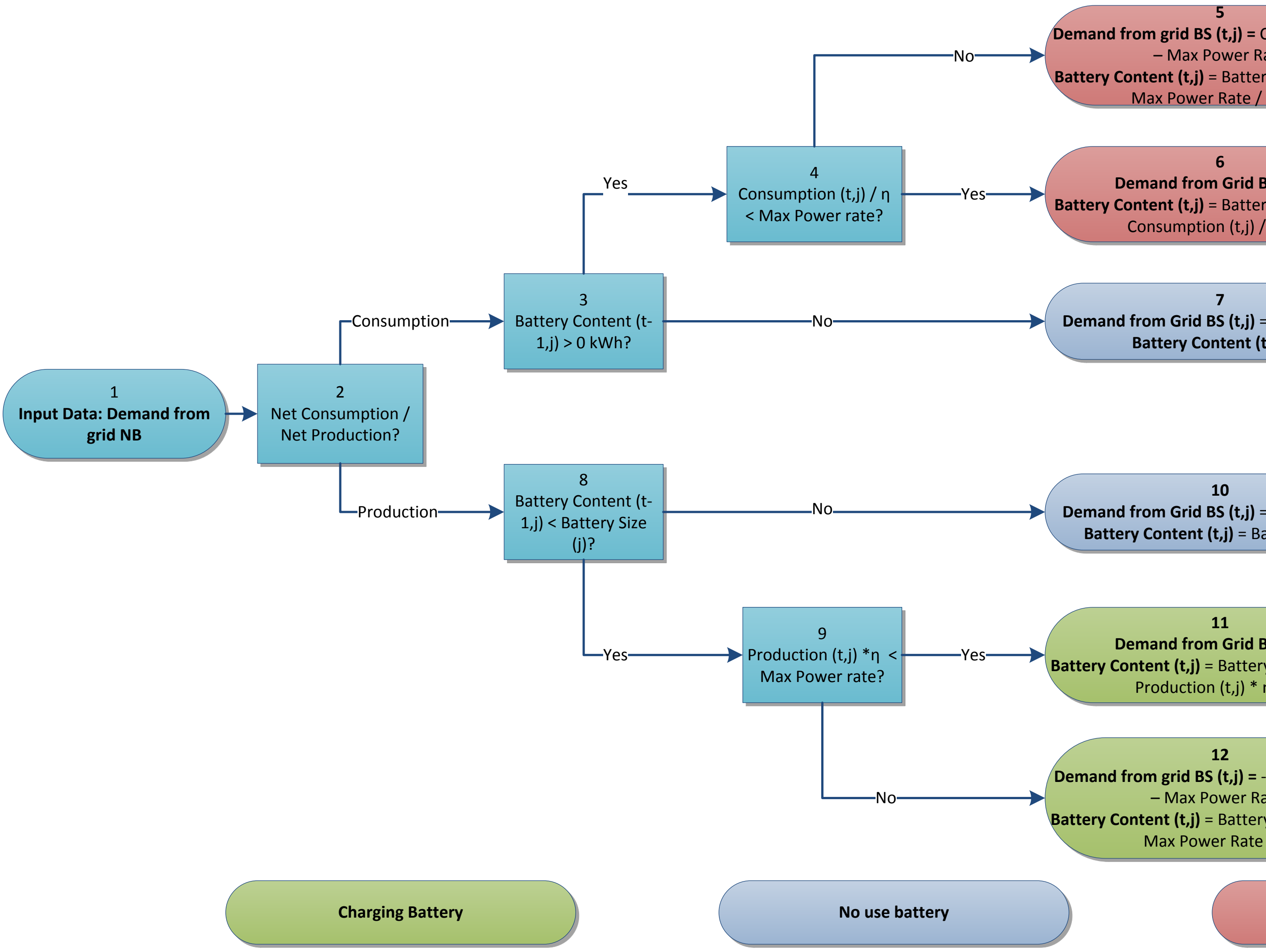


Figure 5.

First, it has to be established when peaks in demand occur. The charging program has to ensure that at these moments, the battery will be used to cover (part of) the load. So when there is not enough oversupply from the PV system, the batteries could, to some extent, be charged using electricity from the grid. Precharging needed for household *j* on day *k* is determined by:

$$Precharging_{j,k} = Evening\ Demand_{j,k} - Battery\ Content_{j,peak}$$

Evidently, the precharging is limited by the battery size of the household: $Precharging_{j,k} \leq Battery\ size_j$.

Hence, the maximum amount of precharge needed is determined by the evening demand of a household. To minimize the … of $E_{P,Battery}$ by electricity from the grid, the battery content at the initial peak is subtracted from the evening demand. In a smart grid application, the energy management system should communicate all this information to a central information system. This information could for example be based on consumer input, indicators of electricity use pattern during the day, etc. Determining suitable indicators falls outside the scope of this research; for this research, perfect information was assumed. The precharging is equally spread over the hours 10 – 17.

Compared to the flow chart in

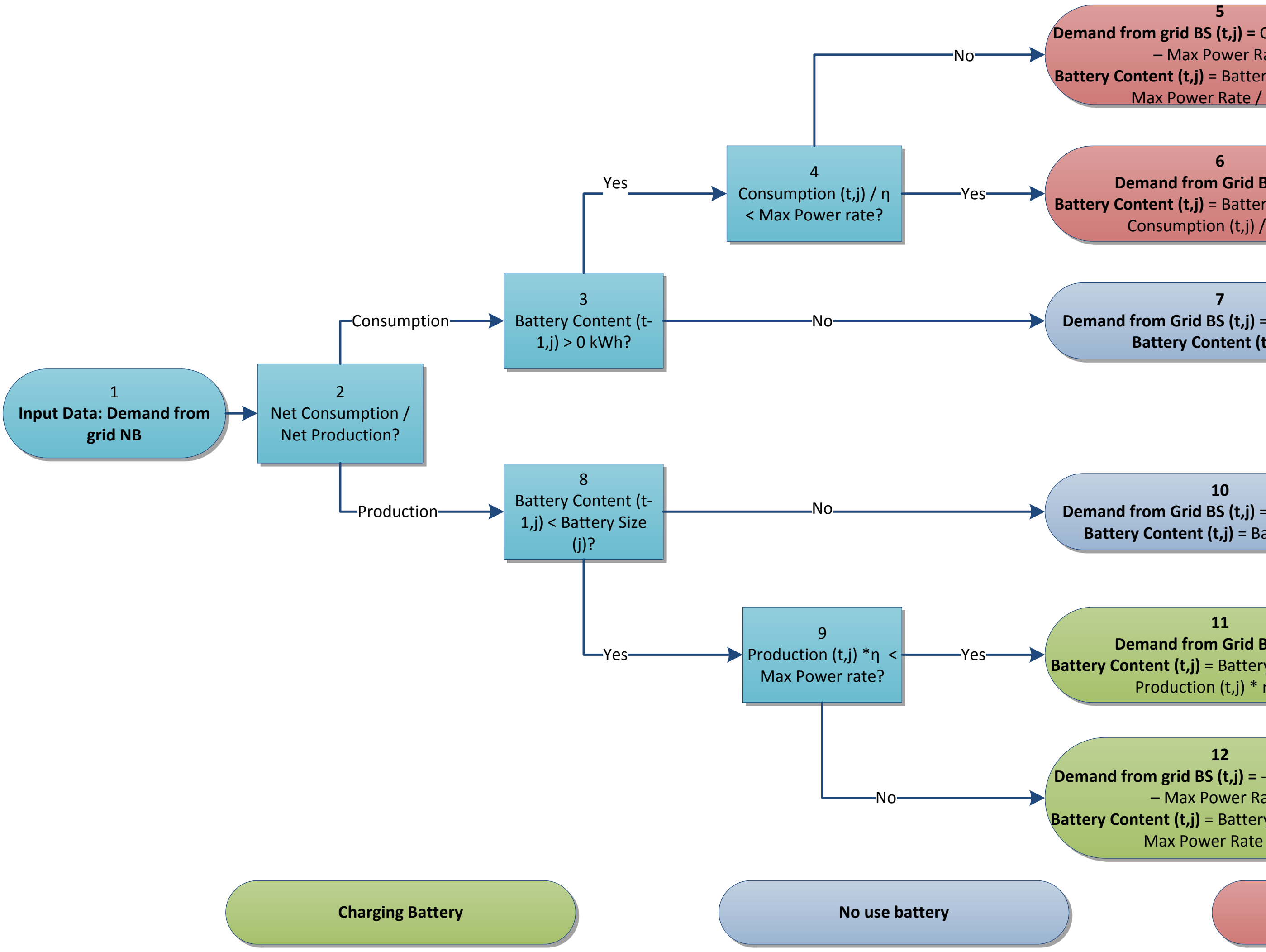


Figure 5, the new power $Input\ Data$ for every household j and every point in time i = $Demand\ from\ grid\ NB_{i,j} + Precharging_{i,j}$. Subsequently, the model will be run again with the optimally sized batteries, but now including precharging. The system including precharging will be compared to the system without battery use and the system with non-controlled batteries.

2.6 Social acceptance

5. What could be non-financial barriers for consumers?

Apart from the economics and grid integration, social acceptance can be a challenge for more deployment of renewables. The NIMBY (not-in-my-back-yard) effect is a well-known example.

To determine the non-financial barriers, a survey was performed[8] on 168 respondents: 112 PV owners, 53 non-PV owners and 3 unknown. Respondents were recruited via social media, visitors of a PV website, and the network of a PhD student from Utrecht University.

The following characteristics form the dependent variables:

- Product lifetime

[8] This survey was constructed and conducted as part of the course “Consultancy Project” (GEO4-2519). However, (statistical) data analysis was largely absent in that project, so will be performed as part of this thesis.

- Safety
- Noise level
- Grid independence
- Environmental impact
- User friendliness
- Structural change (Renovation requirements)
- Maintenance friendliness
- Space use

These characteristics were based on literature research and interviews with the stakeholder of the Consultancy Project, which was GDF Suez. The characteristics were examined regarding the perceived *importance* and *concerns* of the respondents. Regarding importance, each respondent was asked to rate each characteristics on a five-point scale ranging from “very unimportant” to “very important”. Regarding the concerns, each respondent was asked to make a top three. The question asked was:

> *“If you think about energy storage in your residence, from which of the characteristics do you expect most problems? Make a top three, with ‘1’ being the characteristic with the most problems, followed by ‘2’ and ‘3’.”*

Concerns are different from importance, because a respondent can consider some characteristics very important, but simultaneously does not consider those characteristics a potential problem or challenge for DES. Therefore concerns may relate more to potential barriers, while importance relate more to preferred design of the product. Note that these concerns do not necessarily correspond with actual problems with DES; the perception of the respondent is central.

Within subjects: Comparing characteristics (all respondents)

On all results, statistical inference was performed. Because data on dependent variables is ordinal, non-parametric tests were used. It was first established whether an overall statistical difference exists between the characteristics, using Friedman ANOVA test. When statistical differences existed, Wilcoxon Signed-Rank Test was used to determine which characteristics differed. The conservative method of Bonferroni was used to correct for multiple comparisons. This means the required level for statistical significance is:

$$p = \frac{\alpha}{\left({}^{n(n-1)}/_{2}\right)}$$

Where:
α = standard significance level
n = number of variables = 9

This results in required significance levels of p = 0,00139 for $\alpha = 0{,}05$ and p = 0,000278 for $\alpha = 0{,}01$

Also, effect sizes were determined, using (after Corder & Foreman (2009), p. 39):

$$\text{Effect size} = \frac{|z|}{\sqrt{n}}$$

Where:
z = test statistic
n = number of matched pairs = 38

Between subjects: Comparing PV owners and non-PV owners on characteristics

Furthermore, two groups were compared: PV owners and non-PV owners. These two groups represent different target groups for batteries. Regarding PV owners, their system would be retrofitted with a storage system, while non-PV owners represent the target group of a new integrated PV battery system. Specific policies will determine for which group residential batteries will be more attractive (e.g. abolishment of net metering also for current systems, or only for future systems). Because the future policies are unknown, both groups have to be taken into account separately. The groups were compared regarding the importance they attach to and concerns they have about the different characteristics, using the Mann-Whitney U-test.

3 Results

3.1 Cost developments lithium-ion batteries

3.1.1 Cost developments based on meta-analysis

Figure 7 shows an overview of all literature found on prediction of battery storage costs. All costs found in literature are converted to 2015€. Some additional information about the studies can be found in Table 3.

All studies predict a decline in costs of energy storage. On average, the studies predict a decrease from 624 €/kWh in 2010 to 363 €/kWh in 2015, 254 €/kWh in 2020 and 171 €/kWh in 2030. The differences between studies are large. Note that most studies give cost ranges; often these ranges do overlap. Remarkably, studies agree more on the long-term future than on the present and short-term future. One possible explanation is that many studies, implicitly or explicitly, take policy goals as a base for their prediction. The US Department of Energy stated a goal of 150 $/kWh in 2030. From there, studies may adjust their prediction accordingly to their specific research; a process known in the Psychology field as anchoring. On the other hand, strong political commitment has an influence on the trajectory of the cost reduction; such a goal may serve as a self-fulfilling prophecy. The large spread on the short term may be due to the large spread in prices in this early stage of development. The starting costs have a larger influence on the cost prediction in the short term, than in the long term (Gerssen-Gondelach & Faaij, 2012).

Investigating the literature more in detail, an important notion can be made. Over the course of the years, especially after 2011, the predictions of storage cost have become more optimistic (see Table 2). Evidently, the negative trend is statistically not significant due to the limited number of data points (Pearson's r = -0,336 one-tailed p = 0,073). However, the hypothesis is further confirmed when looking at individual studies: several (corporate) authors published a more optimistic update of their earlier predictions.

Table 2, 2020 battery cost prediction per publication year. Sources: see Table 3

Publication year study	Average 2020 prediction (2015€/kWh)
2009	293
2010	269
2011	308
2012	260
2013	255
2014	210

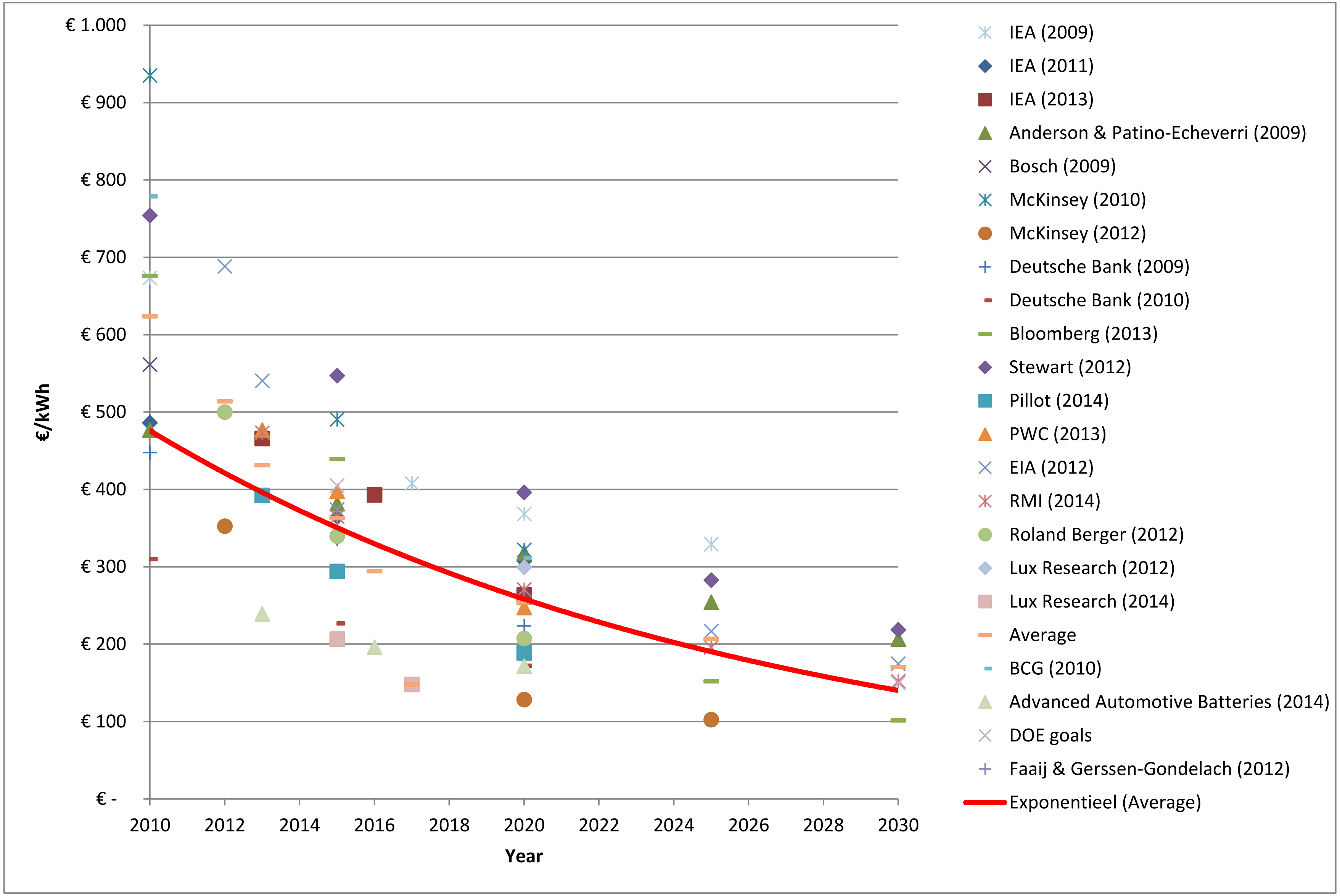


Figure 7, overview of different price projections for Lithium-ion batteries.

Table 3, additional information of studies used in Table 3

Source	Comment
IEA (2009a)	Based on projected LiB cost of a 150 km range EV. Expectations conceded a range of 470-620 $/kWh on the short term (2015-2020) and 350-530 $/kWh on the long term (2020 and beyond). Specific years were not given, because the IEA reckoned the price development depended on the unsure development in production in the upcoming years. For this research, 2017 was chosen as the year for the short term prediction, and 2025 for the long term prediction
IEA (2011)	Based on eyeballing of figure with target cost range and expected cost range. Range in 2010: 400-800 $/kWh, 2020: 300-470 $/kWh
IEA (2013)	Based on statement: "According to the U.S. Department of Energy (U.S. DOE), battery costs based on development efforts have gone […] to USD 485/kWh of usable energy at the end of 2012. These cost gains may take 3-4 years to be realized by industry, but the numbers give an indication as to what is possible in the near term." (IEA, 2013, p: 17). IEA take a 9.5% CAPR, so it was assumed that the costs would be 485 $/kWh in 2016 and decreased annually with 9.5% until 2020. Further assumptions: production of 100 000 batteries per year and profit margins excluded
Anderson (2009)	Data points of baseline scenario are illustrated in Figure 7. This scenario is based on a 4% CAPR. Rationale for this CAPR is the decreased CAPR of LiB for consumer electronics (9.9% for period 1998-2005, but 5.4% for period 2002-2005). Values for optimistic values in 2015, 2020 and 2030 are 350, 300 and 250 $/kWh, respectively. This scenario is based on bottom-up cost improvements. Values for pessimistic scenarios are 775, 750 and 775 $/kWh for 2015, 2020 and 2030 - an increase due to possible instability in South-America, where many Lithium reserves are located.
Bosch (2009)	Battery capacity of 20 kWh. Predictions for 2020: 500/350/250 in €/kWh (Market potential low/base/high respectively)
McKinsey (2010)	2010 costs is average of data provided by participating companies (range: 375-1500 €/kWh). 2015 (range: 275-750 €/kWh) and 2020 (range: 230-450 €/kWh) projections are based on proprietary data and include improvements in production engineering, future economies of scale, and mutual learning between different battery applications (HEV, PHEV and BEV). Participating companies were mainly oil and gas companies, car manufacturers and Electrolyser companies
McKinsey (2012)	Based on bottom-up "should-cost" model. Numbers are prices. Data from interviews with experts from automotive and battery industry, academia, and governments.
Deutsche Bank (2009)	Based on discussions with companies from automotive and battery industry. 25 kWh pack, 30% gross margin
Deutsche Bank (2010)	Update from earlier predictions, because prices fell down faster than expected (from 650 $/kWh in 2009 to 450 $/kWh in the end of 2010). Predictions based on 7.5% CAGR price reductions, driven by fierce competition. Based on discussions with industry experts and car makers
Bloomberg (2013)	Data in Figure 7 based on eyeballing learning curve published by Bloomberg (2013). However, data points shown in the same figure (based on collected prices) indicate lower prices than the learning curve.
Stewart (2012)	Meta-analysis of 16 studies performed in period 2000-2011

Pillot (2014)	Pack cost for EV at production of >100 000 packs/year. Based on Lithium-nickel-manganese-cobalt technology and Lithium-manganese spinel technology, which have similar cost as LFP (BCG, 2010). Not specified whether the numbers are prices or costs – presumably prices, because in more detailed figures margin and warranty are included.
PWC (2013)	Based on interviews with component manufacturers, battery suppliers and industry experts. Application is not specified for the battery cost. Presumably concern PHEV batteries which is the main subject of the report – standalone batteries are cheaper
DOE (2012)	Average of Reference scenario & High technology scenario. High technology scenario is based on a technological breakthrough that enables reaching the DOE storage price goals, reference scenario is a business-as-usual scenario. Ranges for 2015, 2020 and 2030: 405-675 2010$/kWh, 260-520 $/kWh, 150-350 $/kWh respectively. Concerning prices; margins unknown.
RMI (2014)	Meta-analysis based on (extrapolation of) studies of Navigant, DOE and Bloomberg. 2012$
Roland Berger (2012)	Costs of complete battery systems, based on value chain analysis.
Lux Research (2012)	Based on analysis cost structure Lithium-ion battery and potential cost innovations
Lux Research (2014)	Evaluation of Tesla's Gigafactory. Costs of Tesla batteries. Alleged current Tesla battery costs are 274 $/kWh, resulting in 196 $/kWh with claimed 30% cost reduction in 2017-2020.
BCG (2010)	Bottom-up analysis component costs. Interviews with different players in supply chain EV battery and academic experts. Margin: 13%. Range: 360-440 2009$/kWh. Cost analysis is aimed at the Lithium-nickel-cobalt-aluminum battery. The Lithium-iron phosphate battery is cheaper and more suitable for standalone storage
Anderman (2013)	2013 and 2016 data point are costs of Tesla battery at production volume 25000/year and 50000/year and is including pack components, but excluding pack integration and gross margin. 2020 data point are costs of EV market batteries in general (including pack integration) where I assumed a gross margin of 21% (which was mentioned earlier in the report about a different batteries)[9]
Gerssen-Gondelach & Faaij (2012)	Based on learning curves (LR = 17% and LR = 9%). Start values either 800 2010$/kWh or 1200 $/kWh. Range 2020: 200-600 $/kWh. Range 2025: 200-300 $/kWh

For example, Lux Research published two critical reports on LiBs. In the first report, they estimate the costs of storage to be 396 $/kWh in 2020, concluding that it was unlikely for (Plugin-Hybrid) Electric Vehicles (PH(EV)s) to reach mass market (Lux Research, 2012). Their second study around LiBs emphasized the likely overcapacity of the Gigafactory Tesla and battery manufacturer Panasonic. Lux Research estimates the cost reduction for a Tesla Model 3 to be $ 2800; not be enough to produce a low-cost EV (Lux Research, 2014). This cost reduction was based on the analysis that the cost for Tesla were 274 $/kWh at that time (2014). The 30% battery cost reduction that Tesla's CEO Elon Musk foresees with his Gigafactory, would lead to a battery price of 196 $/kWh in 2017 (Lux Research, 2014). Hence, Lux Research indicates that their estimation for battery costs in 2020 was already well surpassed by Tesla as early as 2014, two years after the initial study.

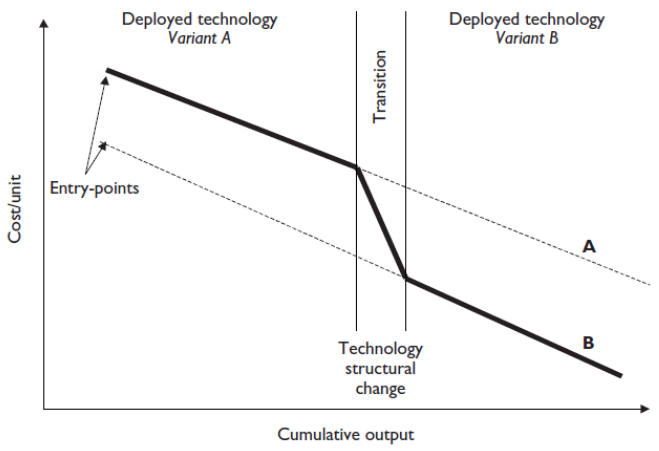
[9] Data report not fully accessible

A second example of a negatively adjusted prediction, are the studies of Deutsche Bank. According to them, already in the first study the “aggressive outlook put [Deutsche Bank] well out of consensus. And yet, in retrospect, it has proven to be not quite aggressive enough” (Deutsche Bank, 2010, p: 19). Deutsche Bank observed a steep decline in battery prices in one year, forcing them to update their initial forecast from 650 $/kWh in 2010 and 325 $/kWh in 2020 to 450 $/kWh in 2010 and 250 $/kWh in 2020. This is also a striking example of the uncertainty in short term prices stressed before: the 2009 prediction for 2010 was almost 50% higher than the actual price in 2010, while using the same sources (see Deutsche Bank, 2009, p:1 and Deutsche Bank, 2010, p:1).

Furthermore, the IEA adjusted their forecast positively in their series of publications. In 2009, IEA expected the LiB price for a 150 km range EV to become around 440 $/kWh in “2020 and beyond” (IEA, 2009a, p: 148). The forecast for 2020 became 380 $/kWh in their 2011 study, 325 $/kWh in their 2013 study to 300 $/kWh in their 2014 study.

Possibly the most remarkable adjustment came from McKinsey. In their 2010 study, they provided a range of 230-450 €/kWh as prediction for the 2020 battery cost. Two years later, they predicted a cost of 128 €/kWh; almost twice as low as the *lower bound* of their initial range.

Comparing the McKinsey studies can provide a hypothesis for an explanation of this trend. In the first research, mainly incumbents were taken into account (see list of participating companies Appendix). A well-known thesis in innovation theory is that more radical innovation does not come from incumbents. The incumbents’ key strengths over time can become their key rigidities, unable to reinvent themselves. In this case, this could be translated in a pessimistic view of the opportunities of radically new ways of driving. In their second study, McKinsey took a completely different approach: they based their cost prediction not on the statements of incumbents, but on a bottom-up “should-cost” model. In this way, they found out battery costs could be far lower than expected by the incumbents. More specifically, the traditional players could be surprised by the rapid development of the LiB technology. Table 2 shows that 2011 serves as the turnaround year for the trend in battery cost predictions; this is also the year that the LiB started to be used on a larger scale in car batteries. This can be theoretically supported by looking at the ‘Technology structural change’ adopted from IEA (2000) shown in Figure 8.



The heavy line is the expected behaviour of the experience curve during a shift of technology from variant A to variant B.

Figure 8, Technology Structural change. Source: IEA (2000)

Making definite statements about an explanation of the developments in decreasing cost predictions falls outside the scope of this research. Evidently, many alternative explanations can be given.

However, there are very strong arguments that this trend is not a coincidence, and therefore it will be taken into account in the remainder of this research.

3.1.2 Cost developments based on experience curves

A second well-known method to monitor cost progress of a technology is the use of experience curves.

3.1.2.1 Critical assessment literature learning rates Lithium-ion battery

Several studies have been performed to establish the learning rate (LR) of the Lithium-ion battery (LiB) technology. These studies were all aimed at the LiB in consumer products. Mayer et al. (2012) compared a one-factor experience curve with a two-factor experience curve. In this research the focus lies on the one-factor experience curve, because it is questionable whether it is possible to forecast separate research, development and demonstration (RD&D) expenditures (Junginger et al., 2010). Using price and cumulative production data for the period 1991 – 2005, Mayer et al. (2012) found a LR of 14%[10] for LiB in consumer products. Matteson & Williams (2015) find a significantly higher LR of 22% for almost the same period (1993 – 2005). Figure 11 shows they have equal price data: the data difference between data points is a constant factor 1.21, which is due to different base year for the US Dollar (Matteson & Williams use 2005$, Mayer et al. do not specify the year). However, the cumulative production differs between the studies (see Figure 12): Matteson & Williams use structurally higher cumulative production data. This is due to the fact that Matteson & Williams look at all LiBs, while Mayer et al. only look at high energy LiBs, which excludes high power batteries as used in many hybrid and plugin electric vehicles. This makes the difference in LR between the studies even more peculiar: with higher cumulative production and similar prices, the LR of Matteson & Williams should be *lower* than the LR of Mayer et al. Therefore, using the data provided in both articles, I reassessed both LRs (See Appendix A). It turned out that the LR provided by Matteson & Williams was roughly correct[11], however the LR corresponding to the data of Mayer et al. should be 18.4%. Ironically, the R^2 in this reassessment is similar to the R^2 of their two-factor analysis[12], which they deemed superior (Mayer et al, 2012). This is still lower than Matteson & Williams, which is due to a relatively much lower first data point of Mayer et al. (15 MWh against 100 MWh), which makes the number of doublings in the data of Mayer et al. higher than that in the data of Matteson & Williams. The (adjusted) experience curves can be found in Figure 9 and Figure 10.

[10] The two-factor experience curve had a somewhat higher R^2: 0.957 instead of 0.910. The LR for the general experience effect was found to be 8% and the LR for the R&D-based LR was 27%.

[11] In this research, a LR of 21.4% was found, which can be explained by a transformation bias since Microsoft Excel spreadsheet software was used here.

[12] R^2 should be 0.955 and not the 0.910 that reported in Mayer et al. (2012) reported. This is almost equal to the R^2 of the two-factor analysis of 0.957.

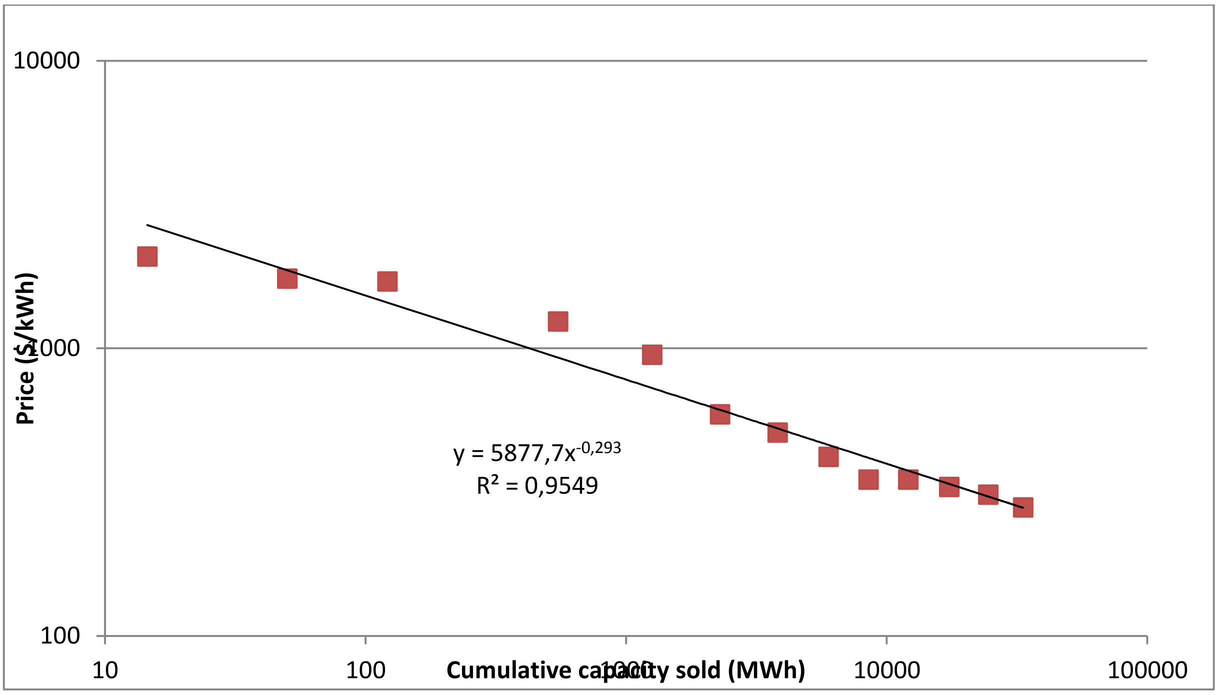


Figure 9, adjusted experience curve based on data Mayer et al. (2012). LR = 1 – $2^{-0,293}$ = 18.4%

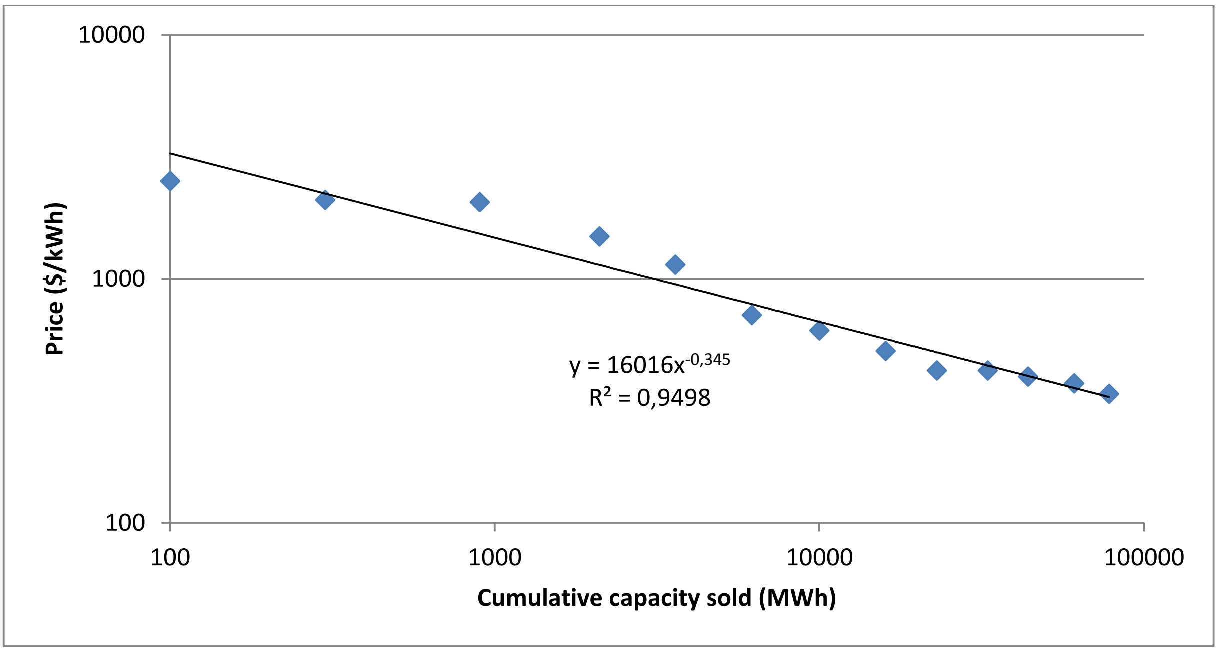


Figure 10, Experience curve based on data Matteson & Williams (2015). LR = 1 – $2^{-0,345}$ = 21.4%

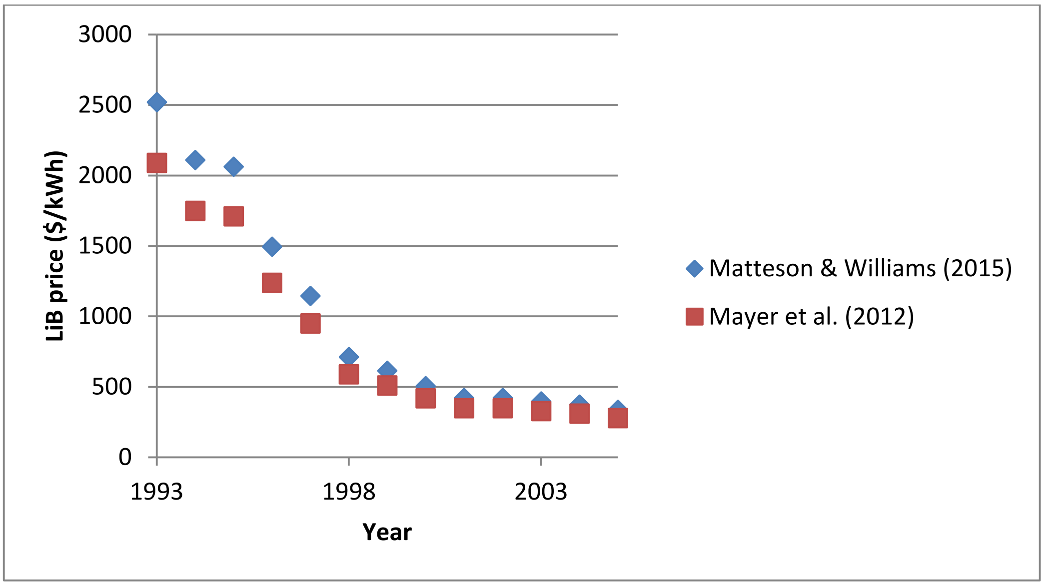


Figure 11, comparison price data Matteson & Williams (2015) and Mayer et al. (2012)

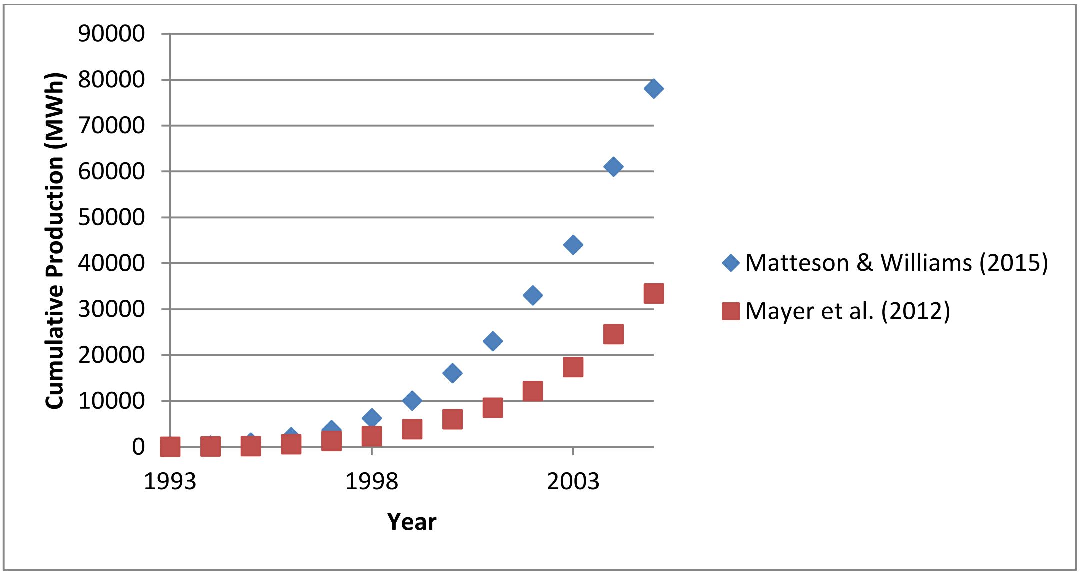


Figure 12, Comparison between Matteson & Williams (2015) and Mayer et al. (2012) regarding cumulative production LiB

However, the article of Matteson & Williams (2015) is not without mistakes either. Next to their own LR, they incorporated a LR adapted from IEA (2013). There was a misunderstanding of scientific discourse between IEA (2013) and Matteson & Williams (2015). From IEA (2013, p: 17): "For potential costs in 2020, Figure 16 looks at the projected compound annual growth of the learning rate, which describes the reduction in cost of batteries through economies of scale. IEA estimates a learning rate of 9.5%, which compares with Deutsche Bank's more conservative 7.5%, albeit at a lower starting cost point. As a point of comparison, laptop batteries developed at a rate of 15% in the 1997-2012 period". The IEA (2013) uses the term learning rate incorrectly here, according to the general definition (see e.g. Junginger et al., 2010). The 9.5% they mention is a Compound Annual Growth Rate (CAGR), which they also mention. This can be derived from the fact that they refer to the 7.5% of the Deutsch Bank, which is also a CAGR (see paragraph 3.1.1 and Deutsche Bank (2010)). Moreover, the IEA did publish a LR in an earlier publication (IEA, 2009b). Based on the number of shipments of small-scale LiBs and the price per cell, an experience curve was constructed resulting in a LR of 30%. Presumably, this experience curve is somewhat less accurate than the learning curves of Matteson & Williams (2015) and the adjusted learning curve of Mayer et al., for several reasons. Most importantly, fewer data points are used. Furthermore, they chose to look at number of shipments, while the other studies looked at physical data. This is suboptimal, because cells can vary in size, which can have an effect on the learning.

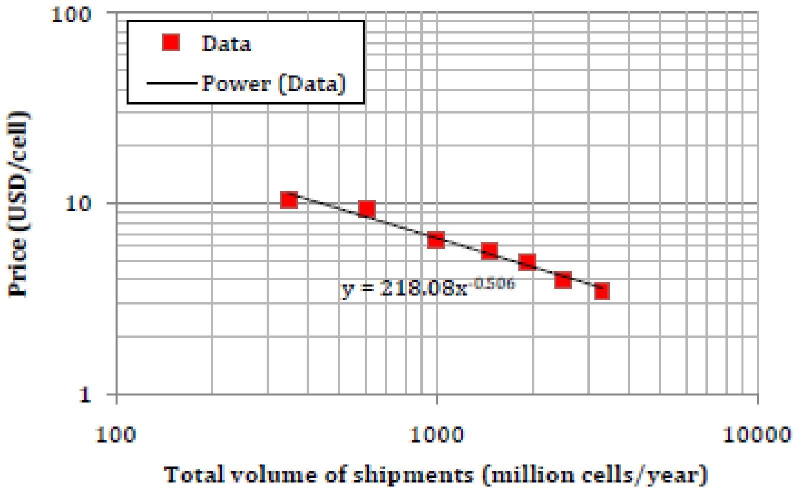


Figure 13, Experience curve small-scale Lithium-ion batteries. Source: IEA (2009b)

Lastly, a study on the PR of consumer LiBs is reported by Shinoda et al. (2011). This study reports a LR of 30%. However, no details are given on data acquisition. Since the cumulative production in the experience curve of Shinoda et al. is lower than both Mayer et al. and Matteson & Williams, it could be that this research only looked at the Japan market – which is the focus of the article. This would be in violation of technological learning theory, which urges to look at global markets (e.g. van Sark (2010a)).

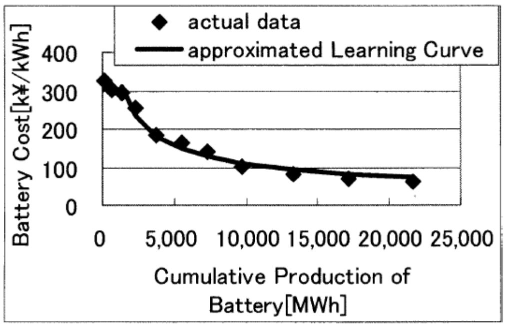


Figure 14, Experience curve lithium-ion batteries. Source: Shinoda et al. (2011)

3.1.2.2 Experience curve on (Plugin-Hybrid) Electric Vehicles

The previously mentioned studies about LiBs were all based on LiBs in consumer electronics. The studies made the assumption that the results can be translated to batteries for (PH)EVs. To validate this assumption, an experience curve for LiBs in (PH)EVs was constructed (see Figure 15). The resulting LR was 23.2% with a R^2 of 0.8973.

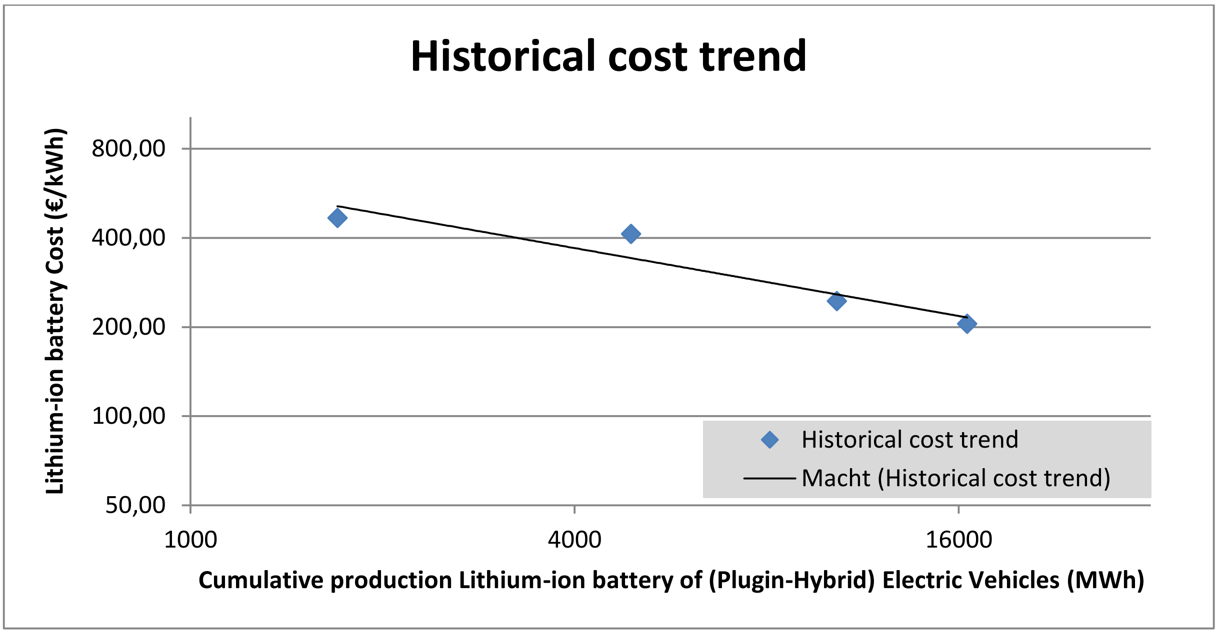


Figure 15, Experience curve Lithium-ion battery technology for PH(EV)s. Sources: DOE (2014), Pillot (2014) Lux Research (2014), Pontes (2015)

The data was validated eyeballing an experience curve provided by Bloomberg (2014a). In Figure 16, it can be observed that according to Bloomberg, the price of EV LiB fell 22.5% with every doubling. This is comparable with our results presented in Figure 12..

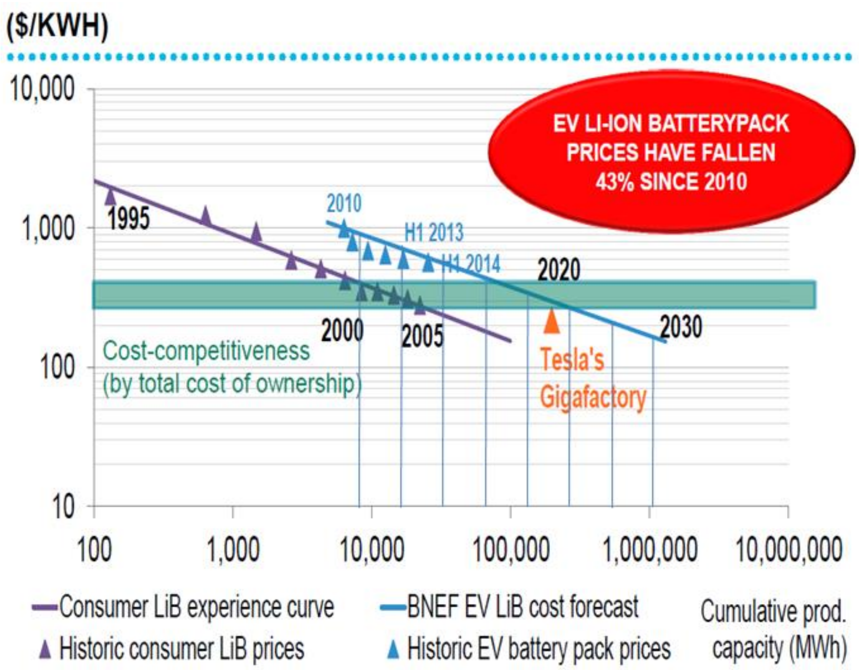


Figure 16, adjusted experience curve Bloomberg (2014a). Blue vertical lines indicate a doubling, starting from 8000 MWh

To translate the determined LRs to a future cost, the relatively conservative prediction on battery demand for EVs of Pillot (2014) from Avicenne Energy was used (see Figure 4, Figure 17).

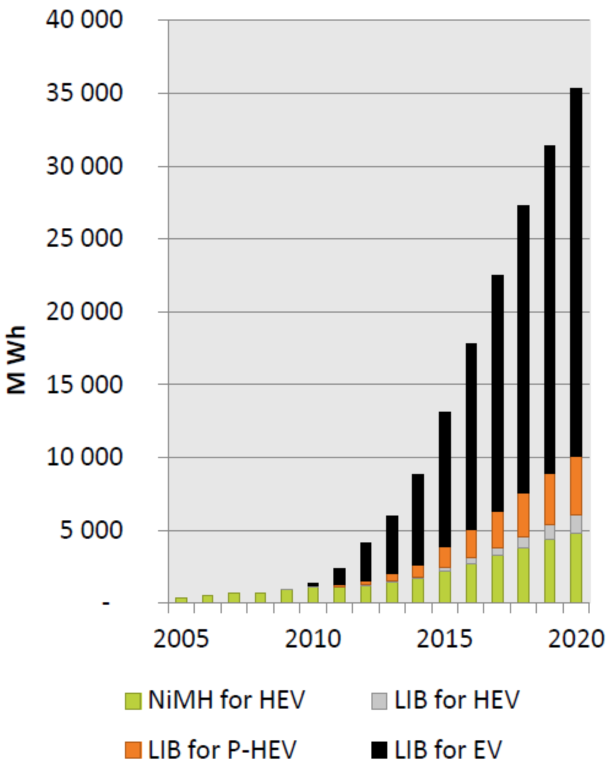
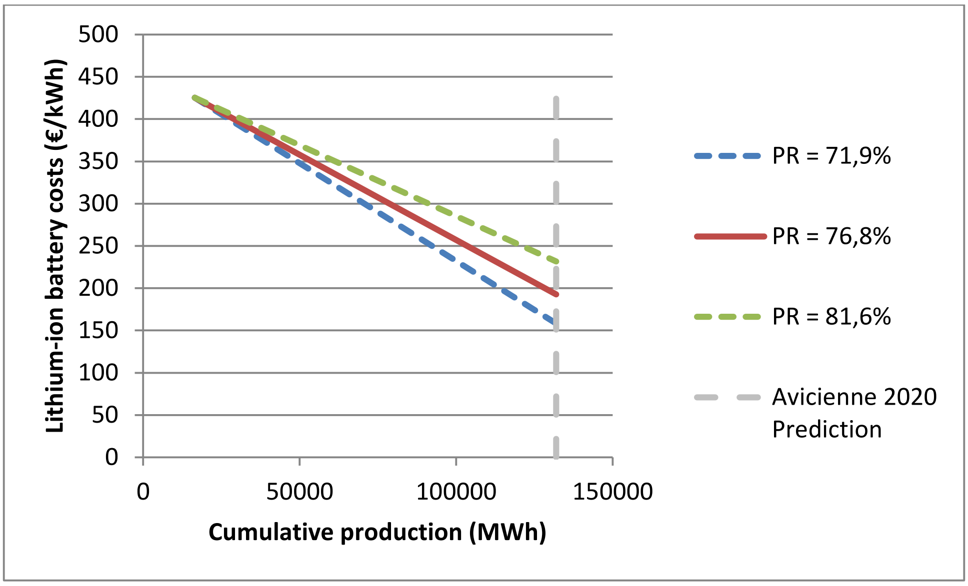


Figure 17, projection battery demand for electric vehicles. Note: only Lithium-ion batteries for PHEVs and EVs were taken into account in this research. Source: Pillot (2014)

Table 4 shows an overview of the found LRs and the resulting 2020 price based on Pillot (2014). Note that when using the 2014 LiB cost of 205 €/kWh provided by Lux Research (2014) as starting point, all LRs result in a 2020 cost prediction that lie below the *lowest* 2020 prediction found in literature: 128,26 €/kWh (McKinsey, 2012). Using Bloomberg's battery price index of 2014 (425 €/kWh), 2020 prices would become 150-250 €/kWh. Still, these prices lie within the lower bound of literature *cost* predictions.

Table 4, Overview learning rates and resulting 2020 LiB cost predictions based on projection Pillot (2014).

Source	LR	Resulting 2020 cost based on Lux, 2014 (€/kWh)	Resulting 2020 price based on Bloomberg, 2014 (€/kWh)
Matteson & Williams (2015)	22%	97	202
Mayer et al. (2012)	18,4%	112	231
IEA (2009b)	30%	70	146
Shinoda et al. (2011)	30%	70	146
Bloomberg (2014a)	22,5%	96	198
This research	23,2%	93	193



The battery price index used by Bloomberg encompasses a *middle of the pack* price. This seems also the case for the studies found in literature. For example, many studies give ranges even for the prices at the time of these studies. An argument could also be made to incorporate the lowest prices of ranges, instead of the average price: the Best Available Technology production cost (Sark, et al., 2010b).

There are several indications for the fact that the current prices are lower than the price index of Bloomberg. Next to Lux Research (2014), there are several other sources that claim a comparable price. For example, the difference between a Tesla with a 85 kWh battery capacity and one with a 60 kWh battery capacity, excluding taxes, is € 6320,- (Tesla Motors, 2015b). This corresponds to 253 €/kWh. Nissan offered owners of their EV, the Nissan Leaf, a replacement battery for 204 €/kWh (MyNissanLEAF.com, 2013). Anderman (2013) reported a battery price of 266 €/kWh, including a profit margin of 21%.

On the other hand, basing cost projections solely on experience curves may also be too optimistic (and unrealistic, if you do not take into account a range of LRs) (see EXP CURVE book, 2010). A first reason is that the cost development of LiBs for (PH)EVs may have benefited from a spillover effect from knowledge on LiBs for consumer electronics. This effect may subdue in later stages of development. A second reason to handle the found LR with care is the scarcity of data on the cost development of EV. In this research, the experience curve is largely based on the research and development team of DOE[13]. Despite the fact that this is a reliable source, the experience curve is vulnerable for the possibility of the influence of chance on the learning trajectory of DOE. The LR found was confirmed by Bloomberg (2014a), who based their experience curve on prices. However, a serious theoretical remark can be made: there is no linear relation between prices and costs (see Figure 18). Therefore, it is recommended to accompany an experience curve based on prices with analysis of the market (Sark, et al., 2010a). In this case, it is very well possible that the EV battery market experiences a shakeout, which would lead to an overestimation of the LR. Mean reason to believe this, is the current overcapacity of LiB production. According to Anderman (2013), already in the end of 2013 there was capacity of more than 23 GWh, while only 3 GWh was produced. The 23 GWh annual LiB demand is not expected to be reached before 2018 (Pillot, 2014). With this current overcapacity, it seems

[13] Regarding cumulative production, the worldwide amount is taken. Therefore the resulting curve can still be considered an experience curve, instead of a learning curve, which would be appropriate for an analysis of a singular company.

reasonable to think different producers are competing on price (Bloomberg, 2014b). And more practically: if the needed capacity for producing batteries is already installed, this leaves less room for cost reduction by technological learning. [14]

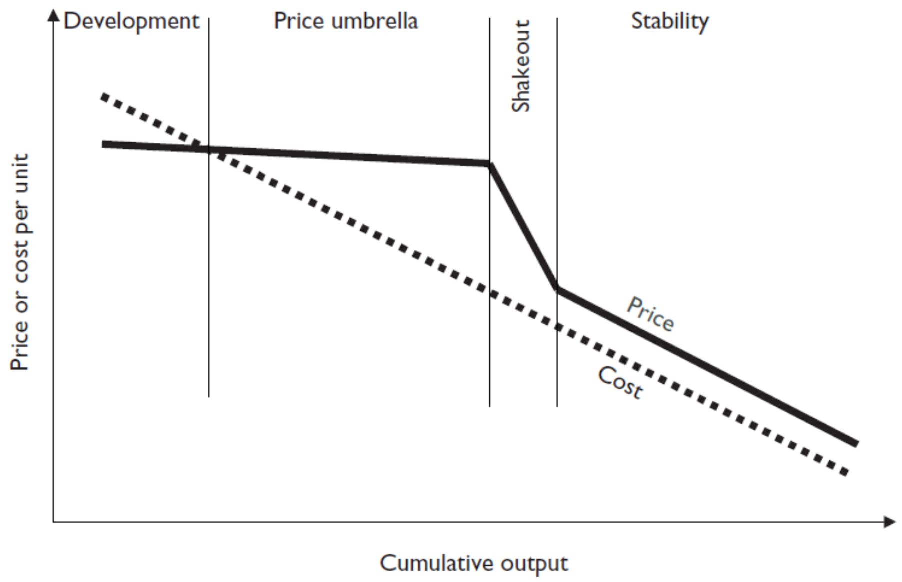


Figure 18, Price-cost relations for a new product. Source: Boston Consulting Group (1968). Adapted from van Sark et al. (2010b)

Since the literature predicts LiB prices to be around 250 €/kWh, but experience curves indicate costs around 150 €/kWh, for the remainder of this research the base cost of Lithium-ion batteries in 2020 will be assumed to be 200 €/kWh.

3.1.2.3 Future cost reductions

As recommended by van Sark et al. (2010a), in this research the experience curves are supported by bottom-up engineering studies. The studies in the literature study often were bottom-up engineering studies. For example, DOE (2014) predicts no change is possible in their current production costs of thermal management, pack integration, and packaging & transportation. However, they aim for a 50% cost reduction in manufacturing and in material costs, resulting in a target of 132 $/kWh compared to their current costs of 212 $/kWh. A more detailed analysis can be adopted from McKinsey (2012), see Figure 19. Regarding "Manufacturing and overhead improvements", McKinsey estimated 23 percent of the 2011 costs could be reduced by manufacturing at scale; mostly in the period 2011-2015. Through economies of scale, 60-70% can be saved on the per unit labor costs. Furthermore, higher unit sales provide the opportunity to spread fixed costs (e.g. Research & Development) over more products, resulting in a possible 30-50% costs reduction in overhead. Larger-scale production indeed seems to take place: in the end of 2013 there was already an installed (PH)EV LiB production capacity of 23 GWh/year (Anderman, 2013) – the cumulative production including 2014 is 16 GWh. Next, McKinsey estimated around 18% of the 2011 costs could be reduced by "Material and component cost reductions". 60% of this reduction is represented by margin compression; in 2011 the margins of component suppliers was 20-40%, while typical margins in the automotive suppliers industry are more than twice as low. The rest of the savings in Material and component cost can be made by manufacturing-productivity improvements. For example, manufacturers can move their business to countries with lower factor costs. Finally, "Technology improvements" can reduce 2011 battery costs with 30%. An example is the so-called "layered-layered" structures; the layering of an electronically

[14] On the other hand, Van Sark et al. (2010) emphasize that plants undergo significant learning in the first years of operation.

inactive component with an electronically active component. Reportedly, this could increase battery capacity by 40 percent.

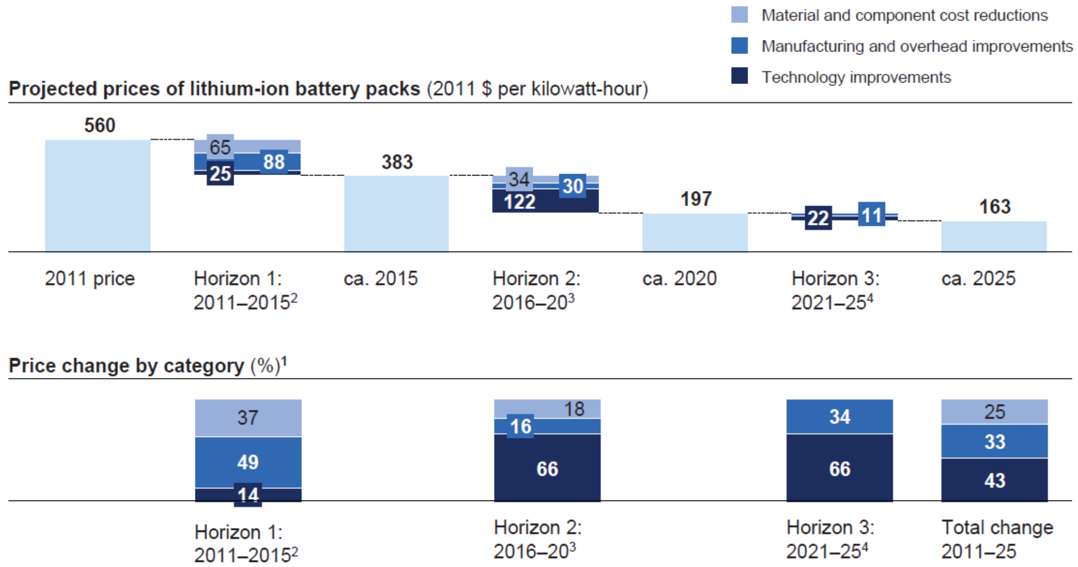


Figure 19, McKinsey analysis of potential cost reductions

3.1.2.4 EV batteries versus stationary batteries

While the EV battery market may be an immature market, the stationary battery market is a premature market – especially in Europe. This is reflected in the extreme spread in current prices of stationary batteries. In Germany, batteries are sold in a niche market as a luxury product. Costs are € 17,000 for a 7.1 kWh (usable capacity) battery, a whopping 2394 €/kWh (Solaranlagen-Portal, 2015). In the American market, batteries are also sold because they are a necessity for remote locations rather than a luxury product. This is reflected in the price which is five times lower than the German price: 480 €/kWh (Balqon, 2015). Reportedly, one can even order 10 kWh batteries for $1500 + 15 $/month for 10 years. This relates to Net Present Costs of 265 €/kWh[15] (Shahan, 2014). Furthermore, Tesla plans to use its Gigafactory to also produce stationary batteries (Bloomberg, 2014c), which could further decrease the price.

Due to this extreme variation in stationary battery prices, in this research the assumption is made that stationary battery prices are comparable to EV battery prices. Although batteries are modular products, there is some scaling effect regarding the assembly of battery cells into a battery pack. This would result in a somewhat higher per kWh cost for stationary batteries as compared to EV batteries, because of the larger size of EV batteries. On the other hand, stationary batteries have lower performance requirements. Regarding power rating, EV batteries need a multiple of the required power rating for stationary batteries. The power rating can also be translated into cost. Related, the heat generation in EV batteries is much higher than in stationary batteries. Therefore, EV batteries have much higher cooling requirements.

All in all, it seems reasonable to assume similar costs for EV batteries and stationary batteries. This was also confirmed by battery experts from Vito (De Beuckere, personal conversation). However, in reality it may take some time before these costs are realized for stationary batteries, just like it took some time for EV batteries to surpass the cost of consumer batteries.

[15] Using a discount rate of 6%

3.2 Determining optimal storage size

2. What is the relation between increasing storage size and marginal benefits of storage for different types of PV households and how would that influence PV self-consumption?

From the 77 households, 67 had a business case for a battery (i.e. a positive Net Present Value (NPV) was found). The optimal sizes for a battery ranged from 1 to 7 kWh, with an average of 3.18 kWh and a standard deviation of 1.23 kWh. Looking at households with a positive NPV for a battery, Figure 20 shows the distribution of optimal sizes of the batteries is somewhat right skewed, with 3 as modus.

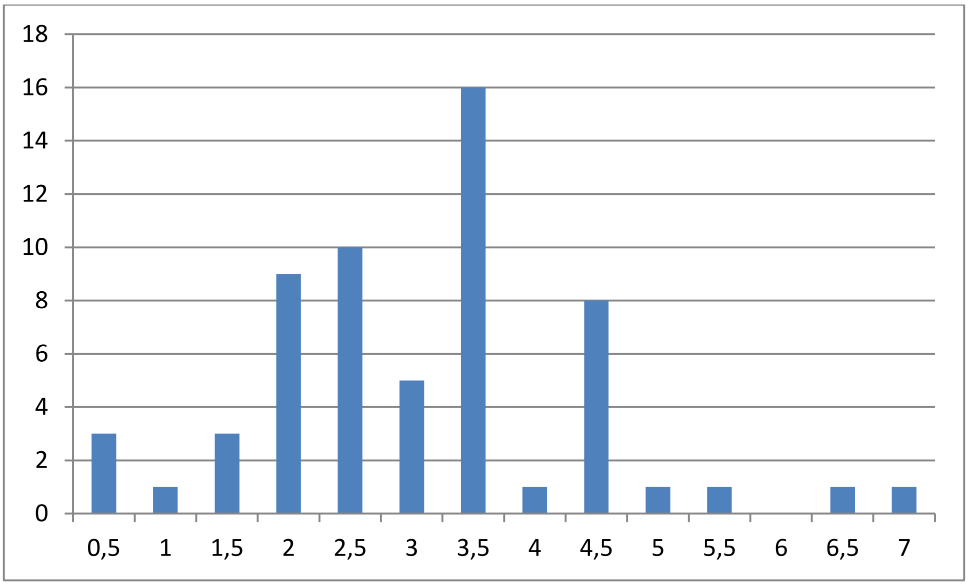


Figure 20, overview of occurrence of various optimal storage sizes.

The NPVs ranged from 33 € to 1704 €, with an average of 699 € with a standard deviation of 278. Not surprisingly, average NPV increases with increasing optimal storage size (see Figure 21); households with larger optimal batteries have more overproduction, hence higher benefits of storage. However, the relation is not one on one: the household with an optimal storage size of 5 kWh seems to have a relatively high NPV. Hence, individual profiles play a role: it is most optimal when the full battery capacity is used as many times as possible. This was confirmed by examining the amount of days that the full capacity of the battery was used: 120 days for the household with a battery of 5.5 kWh, 132 days for the household with a battery of 6.5 kWh, but 166 days for the household with a battery of 5 kWh.

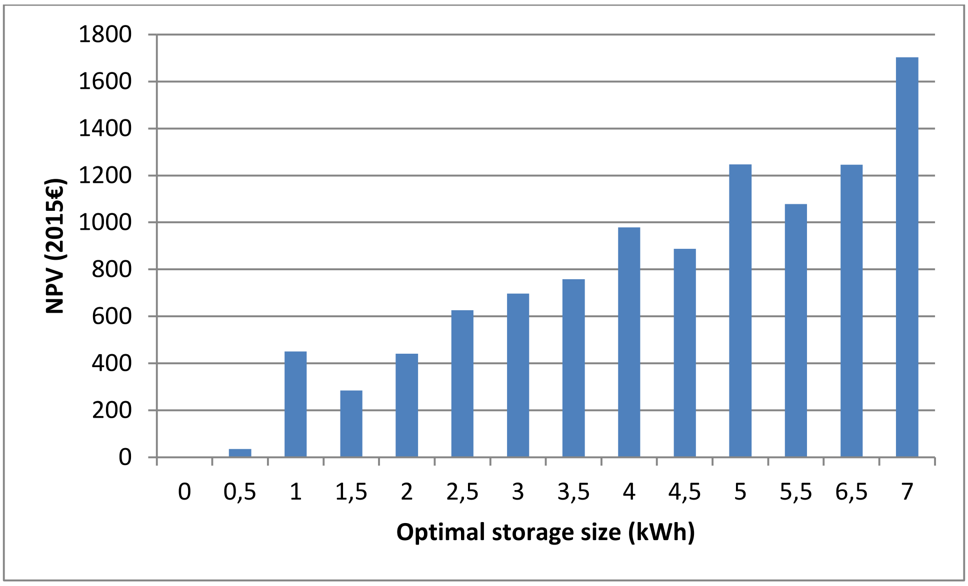


Figure 21, relation between Optimal battery size and NPV. There were no households with an optimal size of 6 kWh, so this value is left out of graph.

Figure 22 shows the relationship between increasing the storage size and the NPV for four individual households. Although individual differences are apparent, all curves show the same pattern: steepest increase in NPV for the lowest storage sizes, diminishing increase until the maximum is reached, and subsequently a gradual decline in NPV. Hence, Marginal benefits are declining with increasing storage size (see Figure 23).

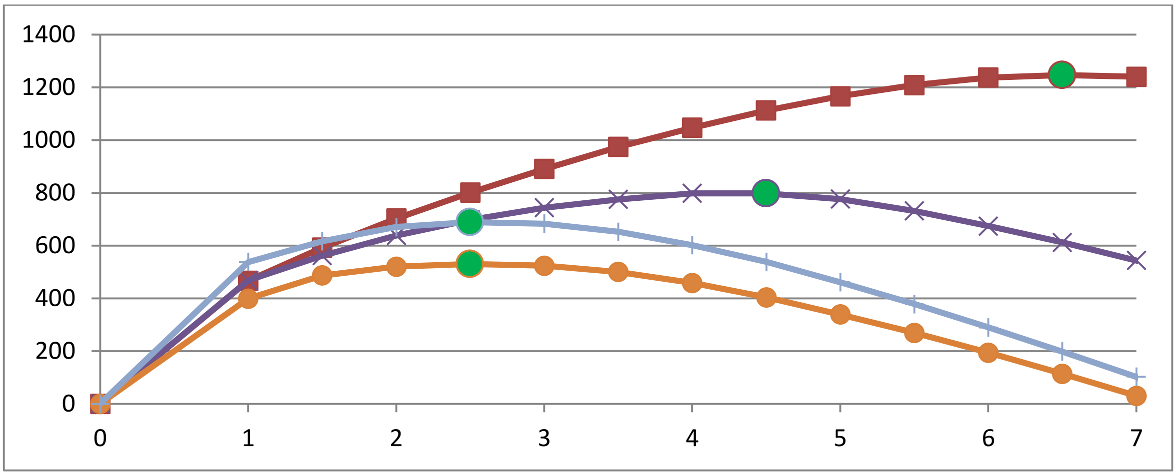


Figure 22, Relation storage size and Net Present Value of adding a battery. Green dots represent maximum values (optimal storage sizes)

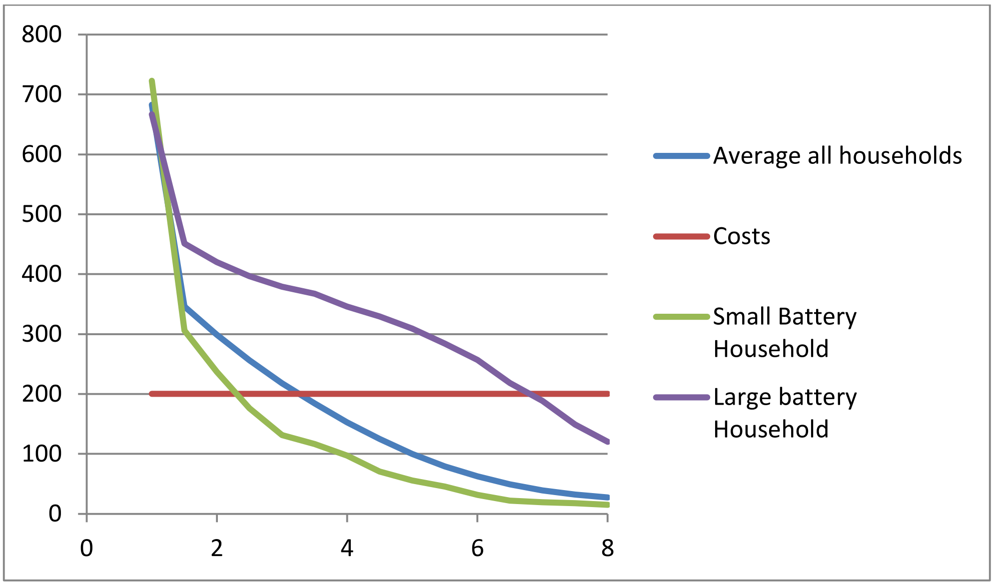


Figure 23, Marginal Benefits curves and Marginal Cost curve. Optimal storage sizes can be found Marginal Costs = Marginal benefits, hence the intersect between the cost curve and the benefit curves

Instead of opting for the battery with the highest NPV, one could also opt for a larger battery. This would result in a somewhat lower NPV. However, when the difference between the NPV of the optimal size and the NPV of a larger size is small, this could be an interesting investment opportunity for an external party. For example, consider the following situation. For a prosumer, the NPV of the battery decreases with 100 € when it is sized 2 kWh above the optimal size. For a net operator, there would be a business case for storage at investment costs of 150 €/kWh, while battery costs are 200 €/kWh. For both parties individually, it would be irrational to invest in storage capacity. However, when they would both pay half of the additional storage costs and place the battery at that prosumer, both *would* have a business case for the additional storage. Therefore, it is interesting to analyze what these decreases in NPV with additional storage for a prosumer would be. The very low slopes after the peak (Figure 22) already indicate that these decreases can be very small.

Table 5 elaborates on this. In this case, costs were defined as the decrease in NPV compared to the situation with the optimal battery size. Table 5 shows these costs for various storage sizes, averaged over all households with a business case for battery storage. If all batteries were enlarged with 4 kWh (so on average more than doubled), it would costs an external party 119 €/kWh to compensate for the NPV loss of a prosumer. However, it makes more economical sense to look at the incremental storage costs: an external party could increase the storage sizes of this neighborhood until the incremental costs are equal to the value the external party attaches to storage capacity. On average, the 'costs' of increasing storage sizes until 1.5 kWh stay below 100 €/kWh. Considering that the average optimal storage size is 3.18 kWh, this already would be a very significant increase.

Table 5, Economic effect of increasing storage size above optimal size. Averaged over all households with a business case for battery storage

Expansion above to optimal storage size (kWh)	Average decrease NPV (€)	'Storage costs' external party (€/kWh)	Incremental 'storage costs' $(^{\Delta €}/_{kWh})$
0.5	14	27	27
1	46	46	65
1.5	94	63	97
2	155	77	121
2.5	225	90	140

3	302	101	155
3.5	385	110	165
4	477	119	185

To answer the research question, linear regression was performed. Variables taken into account were *Yearly Overproduction*, *Yearly Net metered consumption*, and *Watt Peak*. The best predictor of the optimal storage size is *Yearly Overproduction*, with an adjusted R^2 of 0.698 (see Figure 24). This is not surprising, because overproduction is direct input for the battery, and therefore determines the benefits of the battery. Still, 30 percent of the variance in optimal storage size cannot be explained by yearly overproduction. This can be explained by the individual differences between households regarding the specific profile. Households with a constant overproduction of 4 kWh would have a very different optimal storage size than households with 0 kWh oversupply on half of the days and 8 kWh oversupply on the other half of the days, despite having the same yearly oversupply.

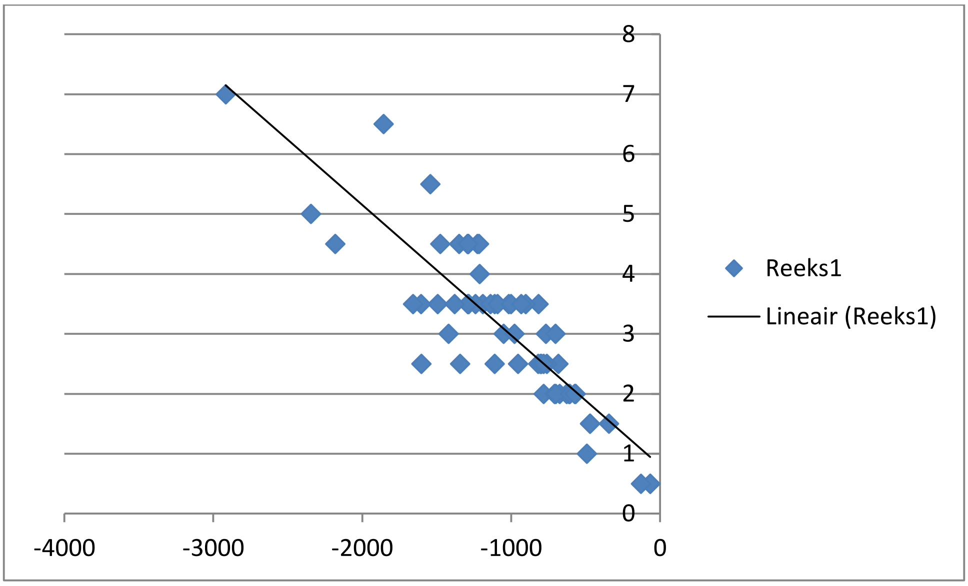


Figure 24, relation between yearly overproduction and corresponding optimal storage size of a prosumer. Yearly overproduction is defined as a negative. Adjusted R^2: 0.742

In reality, the yearly overproduction mostly will not be available. Watt Peak would be a more practical predictor for optimal storage size. Figure 25 shows the relation between Watt Peak and optimal storage size. Watt Peak predicts optimal storage size also reasonably well, with an adjusted R^2 of 0.484. Comparing to yearly overproduction, a larger part of the optimal storage size remains unexplained. This is due to the fact that consumption is not taken into account. If one household has a PV system with the same Watt Peak as a second household, but much less electricity consumption, this household will have more overproduction and therefore have a larger optimal size. Therefore, it is reasonable to add a second factor to the regression model: *Net metered consumption*. Like Watt Peak, this variable is readily available for most households. Using multiple regression analysis, the regression model would become[16]:

$$Optimal\ Size\ (kWh) = \ 0.45 - 2.47\ *\ 10^{-4} * Net\ Metered\ Consumption\ \left(\frac{kWh}{year}\right) + 1.24\ * PV\ System\ Size\ (kW_{peak})$$

	Value	Standard Error
Intercept	0.45	0.42

[16] kW_{peak} is now defined as a positive number

Net Metered Consumption	$2.47 * 10^{-4}$	$9.7 * 10^{-5}$
PV System Size	1.24	0.16

The predictions based on this regression model are plotted against the actual optimal storage sizes in Figure 26. The adjusted R^2 of this model is 0.527. Evidently, this regression model makes no physical sense. However, it does make logical sense: the larger the PV installation, the higher the optimal size. And the lower the net metered consumption, the higher the optimal storage size. Low net metered consumption relates to high overproduction, which makes larger storage systems more attractive.

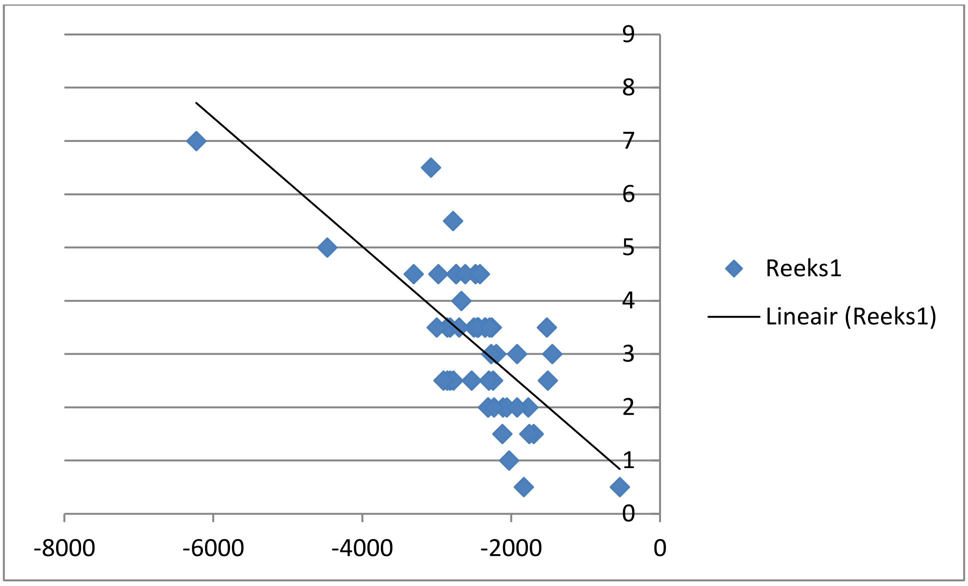


Figure 25, relation between Watt Peak and corresponding Optimal storage size of a prosumer. Watt Peak is defined as a negative number. Adjusted R^2 = 0.481

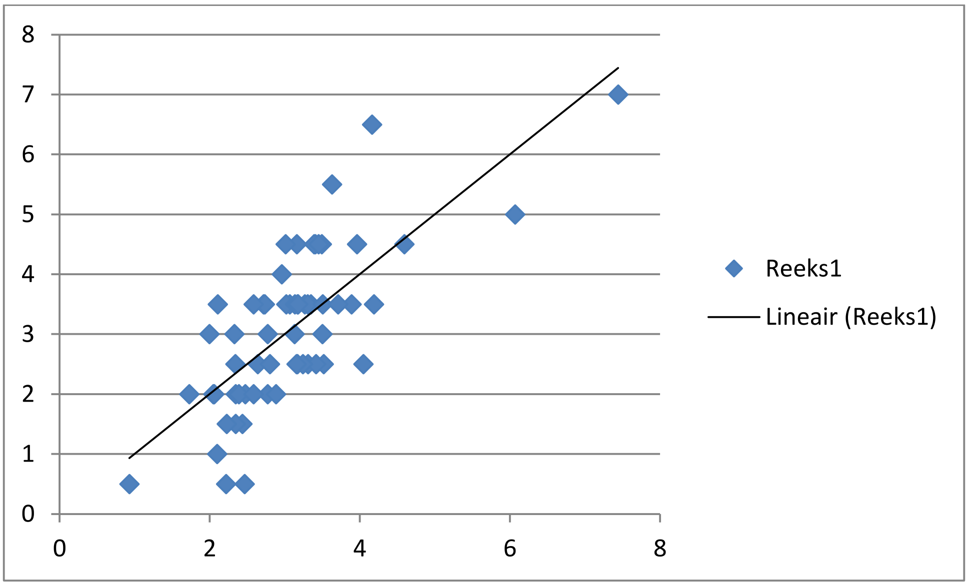


Figure 26, Model Predictions of Optimal Size (x-axis) versus Optimal Size (y-axis)

3.3 Simulation Optimal Batteries

3.3.1 Overproduction

The overproduction that is covered by the battery for individual households range from 34.3% till 73.7%. On average, a battery covers 53.8% of the overproduction of a household, with a standard deviation of 8.5%. Smaller batteries cover a larger part of their specific overproduction than larger batteries; there is a correlation of -0.24 between Optimal battery size and percentage of overproduction covered. This seems counterintuitive, however it is due to the high absolute overproduction on very sunny days for households with large PV systems.

Since the initial self-consumption without batteries of the households is not known, the effect on self-consumption cannot be determined. Figure 27 shows what an 53,8% decrease in overproduction would mean for various amounts of self-consumption. If the initial average self-consumption of PV electricity within the neighborhood was 30%, the optimally sized batteries would increase this with 130%. Hence, the new average self-consumption would be 69%. Evidently, the impact on self-consumption is much higher for low initial values of self-consumption.

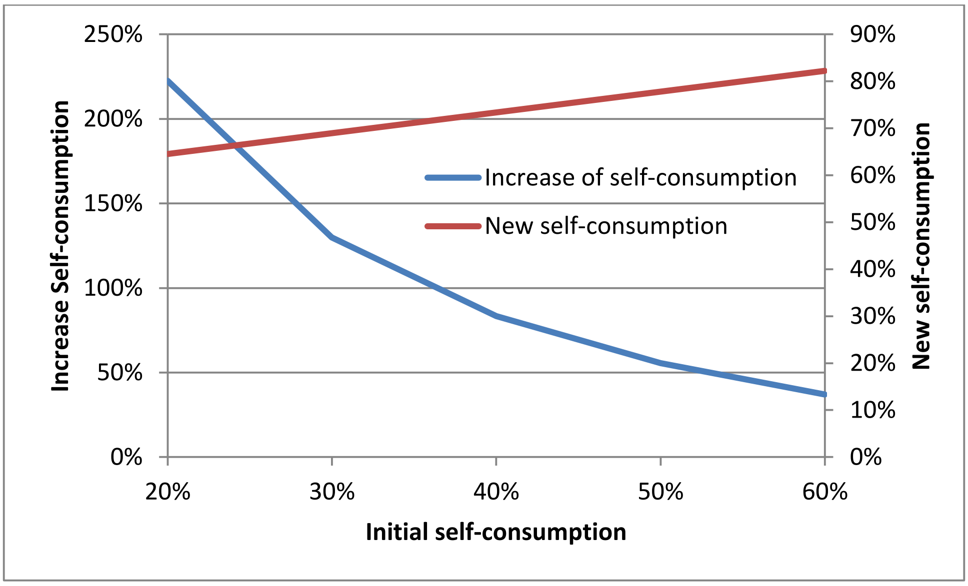


Figure 27, increase of self-consumption for various initial self-consumptions

3.3.2 Peak shaving

Table 6 shows information on production and consumption peaks for a system without batteries, and a system where PV systems are equipped with optimally sized batteries. When comparing production and consumption, it is notable that the overall yearly production and consumption peaks are somewhat equivalent in both system configurations: 111,4 kW and 107,5 kW for the system without batteries, 105,1 kW and 96,5 kW for the neighborhood with batteries.

A next important notion that can be made from Table 6, is that it is really important at which indicator one looks. Regarding consumption, on average the optimally sized batteries have a substantial impact on the peaks. However, it makes more sense to look at the overall peak of the entire year. To prevent brown- or blackouts the yearly peaks are more relevant the electricity system is designed to be able to have the capacity to cover all demand at all time. Looking at the yearly consumption peak, impact of the battery is much smaller; just 5,7%. The same holds for the production peaks. Overall, many of these peaks are shaved in a system with batteries: on average the peaks lie more than 50% lower than in a system without batteries. However, the overall maximum is just 10,2% lower in a system with batteries. This is due to the nature of optimization on consumer economics; the batteries are aimed to obtain as much value for money as possible. On that one day with extreme overproduction, many batteries will be fully charged in an early stage of the day. When the batteries are fully charged, overproduction will be exported to the grid resulting is similar potential production peaks as a system without batteries. Overall, it can be concluded that batteries have a substantial impact to the stability of the system; on many days the consumption and production peaks are much lower in a system with batteries. However, the impact of having batteries on the needed capacity of the system is just marginal.

Table 6, overview consumption and production peaks for neighborhood with and without batteries

Daily peak	No Batteries (kW)	Batteries (kW)	Difference
Consumption (average)	70,7	57,5	-18,7%
Consumption (max)	111,4	105,1	-5,7%
Production (average)	-61,5	-29,7	-51,7%
Production (max)	-107,5	-96,5	-10,2%

3.3.3 Load shifting

The average consumption in the four peak hours for the neighborhood without batteries was 203 kWh. When the PV systems were equipped with optimally sized batteries, this average peak load was reduced to 158 kWh: a decrease of 22,2%. This means that for this neighborhood, over an entire year 16,4 MWh of load could be shifted from the peak hours.

The total consumption[17] of the neighborhood for one year is 256 MWh. So on average, per four hours 117 kWh is consumed. Hence, incorporating batteries shifts the peak load substantially; decreasing the difference between peak load and average load by more than half.

3.3.4 Battery degradation indicators

The indicators of battery degradation were examined: average Depth of discharge (DoD), average State of Charge (SoC) and total energy throughput.

The average DoD over all household and the entire year was 52,9%. The occurrence of various DoDs shows a typical double peak profile, most often the battery is either fully used, or hardly used. Figure 28 shows a distribution of various categories of average DoD on for all households with a battery. For 31.7% of the days, the battery capacity was used for less than 20%. On the other hand, on 28.4% of the days, the full capacity of the battery was used. This is not surprising, as the battery size was economically optimized. This could be a problem for battery technologies that cannot handle deep (dis)charges well.

[17] Consumption from grid. So excluding self-produced directly consumed PV electricity

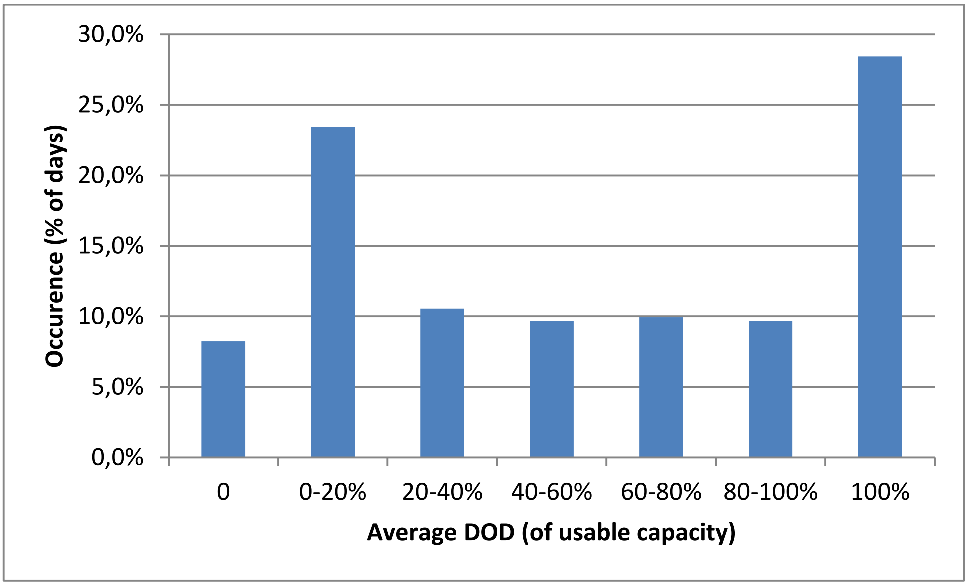


Figure 28, occurrence of various categories of average Depth of Discharge.

The average SOC varied per battery; from 3,7% to 41,0%. On average, the households had a battery with an average SOC of 22,2% (standard deviation 8,6%). Larger batteries had a higher average SOC: a correlation of 0,51 between storage size and average state of charge was found. These are rather low average SOCs, which is positive for the battery lifetime. However, one should notice that these low values are mainly caused by the fact that batteries are empty for large part of the year.

Possibly the best indicator for battery degradation is the total energy throughput. On average, the optimally sized batteries had an total energy throughput of 1441 kWh in one year. The total energy throughput can be predicted accurately from the optimal size, as can be seen in Figure 29; there is a correlation of 0,98. This is not surprising, since the optimal size was determined by the amount electricity that could be used from a battery of various sizes.

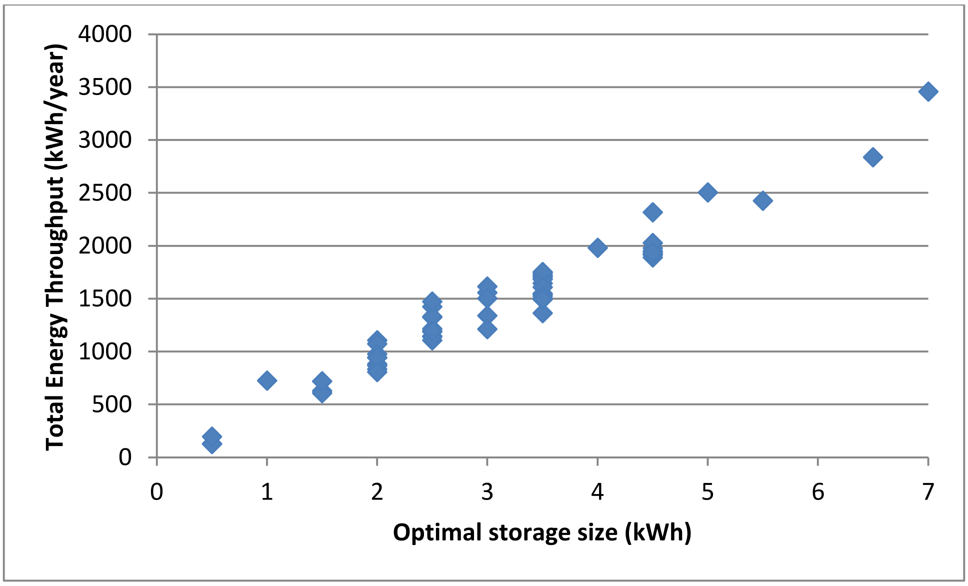
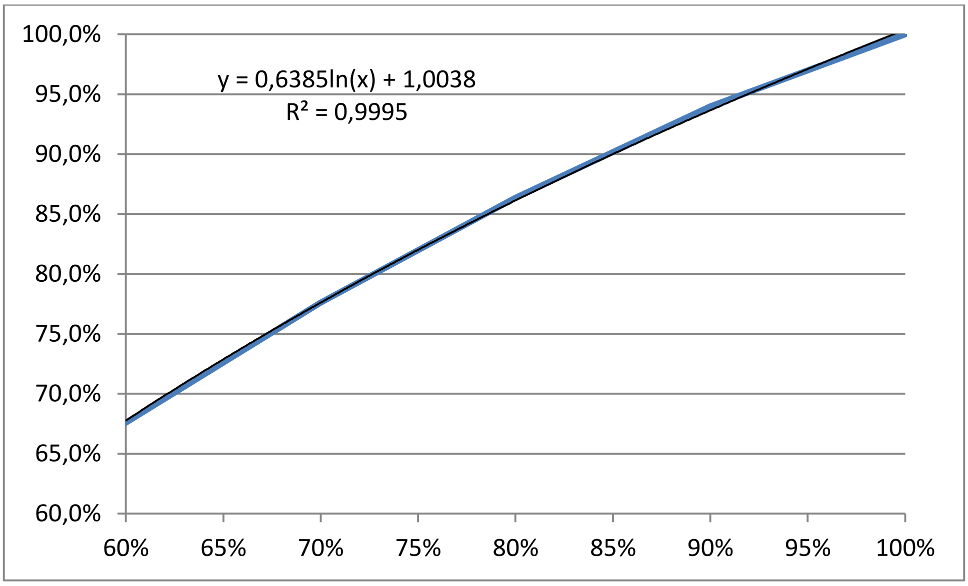


Figure 29, relation between optimal storage size and total energy throughput

A second notion that can be made from Figure 28 is that also a degraded battery is able to cover a large part of the 'demand'. Based on manufacturer warranties, industry targets and simulations, Heymans et al. (2014) predict that EV batteries would lose 20% of their capacity after 8 years, and would no longer be used in vehicles. If the same would be true for PV integrated batteries, the battery with 80% of its capacity would still be able to cover 86.4% of demand that the initial battery would. A clear empirical relation between capacity loss and functionality loss was found:

$$1 - \mathit{Functionality\ loss}\ (\%) = 0{,}6385 * \ln\left(1 - \mathit{Capacity\ loss}\ (\%)\right) + 1{,}0038$$



3.4 Simulation precharged battery

As mentioned before, residential energy storage appears to be a natural partner for peak shaving. Electricity is stored during daytime, and can be used after daytime when sunlight is not available; approximately at the same time as when the peaks occur. In reality, this is only true to some extent: when there is sufficient overproduction of solar electricity. As we have seen in the previous paragraphs, and This can have economic value regarding the reduced deployment of power plants with high marginal cost (*load shifting,* 3.3.3). However, it has no value regarding the prevention of investment cost (*peak shaving,* 3.3.2). Therefore,

3.4.1 Peak Shaving and load shifting

Figure 30 shows the development of the neighborhood's aggregated consumption peaks throughout the year. In all graphs, it can be observed that these peaks are higher in winter than in summer. In the optimized 'Dumb' batteries, this trend is most pronounced. Peaks of the 'Dumb' battery coincide with peaks of the base scenario in the winter, and this gradually alters to match the graph of the 'Smarter' battery in the summer.

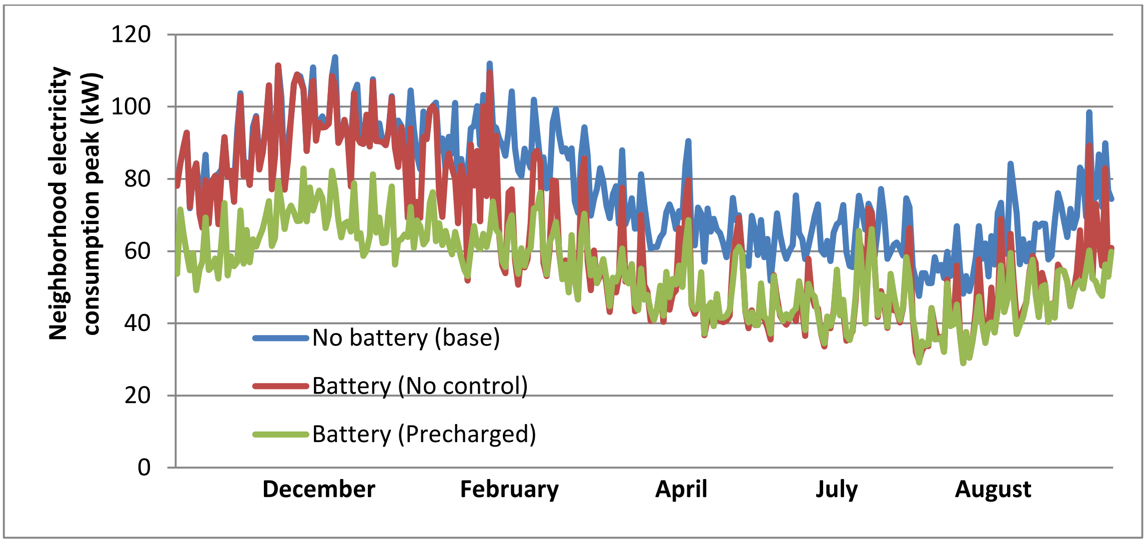


Figure 30, Neighborhood daily consumption peaks from November 2013 until September 2014. For illustrative purposes, these peaks are displayed as a continuous graph – in reality the peaks are discrete points.

As can be observed in Figure 30, peaks of electricity use occur in winter, and it is unrealistic that enough PV electricity will be produced on winter days to prevent peaks. Hence, the same back-up capacity and grid capacity would have to be built to maintain the current electricity requirements. This was reflected in the overall peak of consumption of the neighborhood without batteries, and the neighborhood with non-controlled batteries as described in paragraph 3.3.2.

To illustrate this, a day with substantial overproduction (30 April 2014, Figure 32, Cumulative electricity demand of neighborhood for various configurations of)) and a day with marginal overproduction (5 February 2014, Figure 31, Cumulative electricity demand of neighborhood for various configurations of 5 February 2014.) are analyzed in more detail. The neighborhood's aggregate grid use is shown. On 30 April, there is substantial overproduction. When comparing the situation with a battery and without a battery, some peak shaving can be observed. However, on 5 February there is much less overproduction. On this day, the patterns of the neighborhood without batteries and the neighborhood with the non-controlled batteries were very equal. Also with the storage capacity, the peak demand from the grid is higher than the peak on the day before without storage capacity.

To make optimal use of the solar batteries, these batteries have to be precharged. When it is ensured that all batteries are fully charged at 17 o'clock, the effect of the storage capacity on peak shaving is (1) much larger and (2) not dependent on overproduction (see Figure 31, Cumulative electricity demand of neighborhood for various configurations of 5 February 2014. and Figure 32, Cumulative electricity demand of neighborhood for various configurations of). Table 7 shows the resulting impact on the four hour peak and the peak electricity demand. The neighborhood with precharged batteries have 39% lower four hour peak load than the neighborhood without batteries and 21% lower than the neighborhood with non-controlled batteries. The peak load is almost entirely shifted and is just slightly higher than the average four hour load over the whole year (117 kWh). The peak electricity demand is decreased to 75,2 kW. So in contrast to the non-controlled batteries, this is a substantial difference to the situation without batteries (-33%, compared to -6% when batteries are not precharged). The load duration curves of Figure 33 provide more insight in this. Where the neighborhood without batteries and with non-controlled batteries start at similar demands, the curve of precharged batteries start substantially lower. From 2000 hours, the curve of the system with precharged batteries lies higher than the curve of the non-controlled batteries. This is due to the many hours of precharging, which results in a slightly higher electricity demand during from 10 till 17.

Table 7, comparison between neighborhood without batteries, with non-controlled batteries, and with precharged batteries on four hour peak load, and peak power

	No batteries	Batteries (no control)	Batteries (precharged)
Average 4 hour peak (kWh)	203	157	124
Peak power (kW)	111	105	75,2

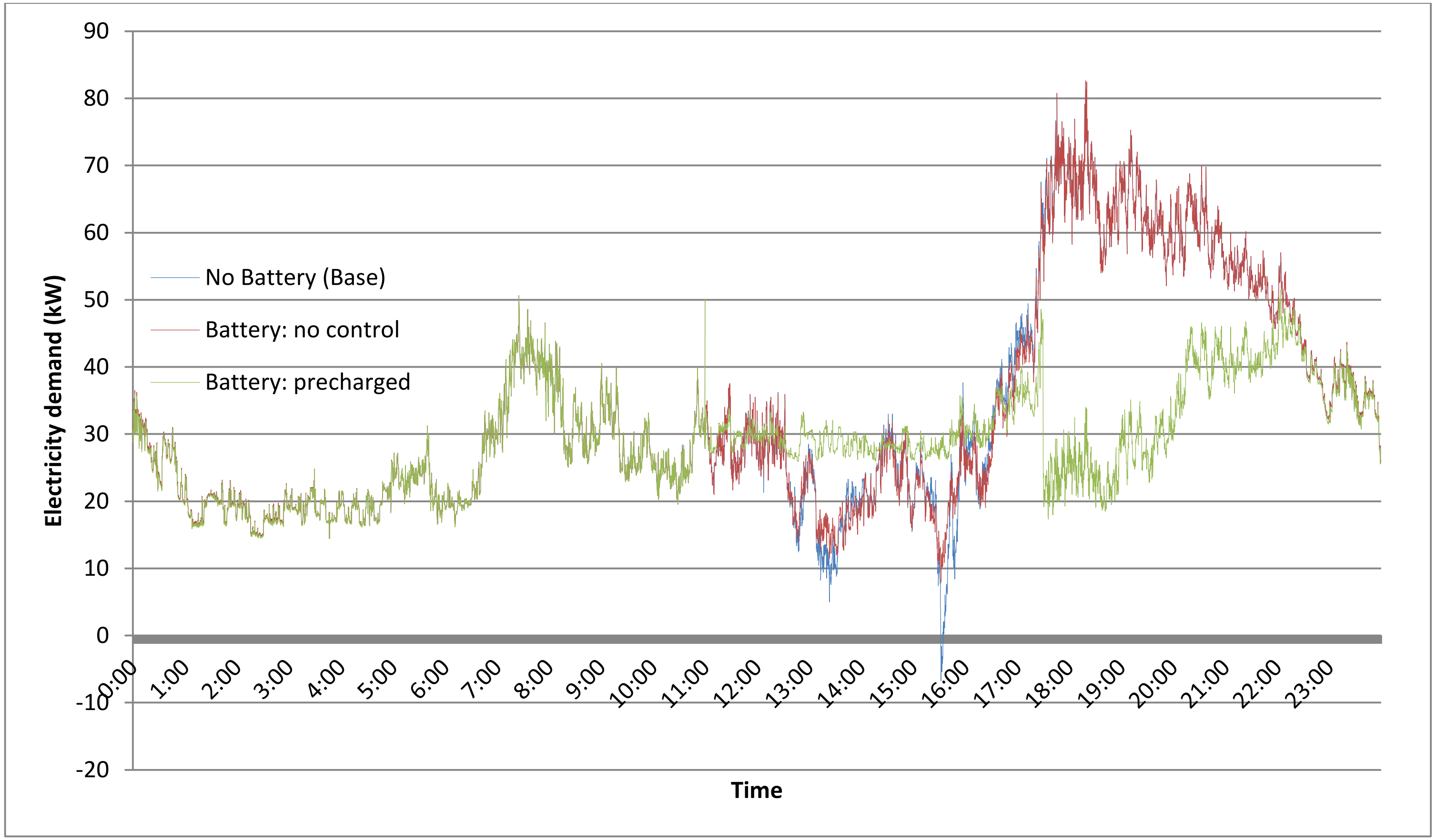


Figure 31, Cumulative electricity demand of neighborhood for various configurations of 5 February 2014.

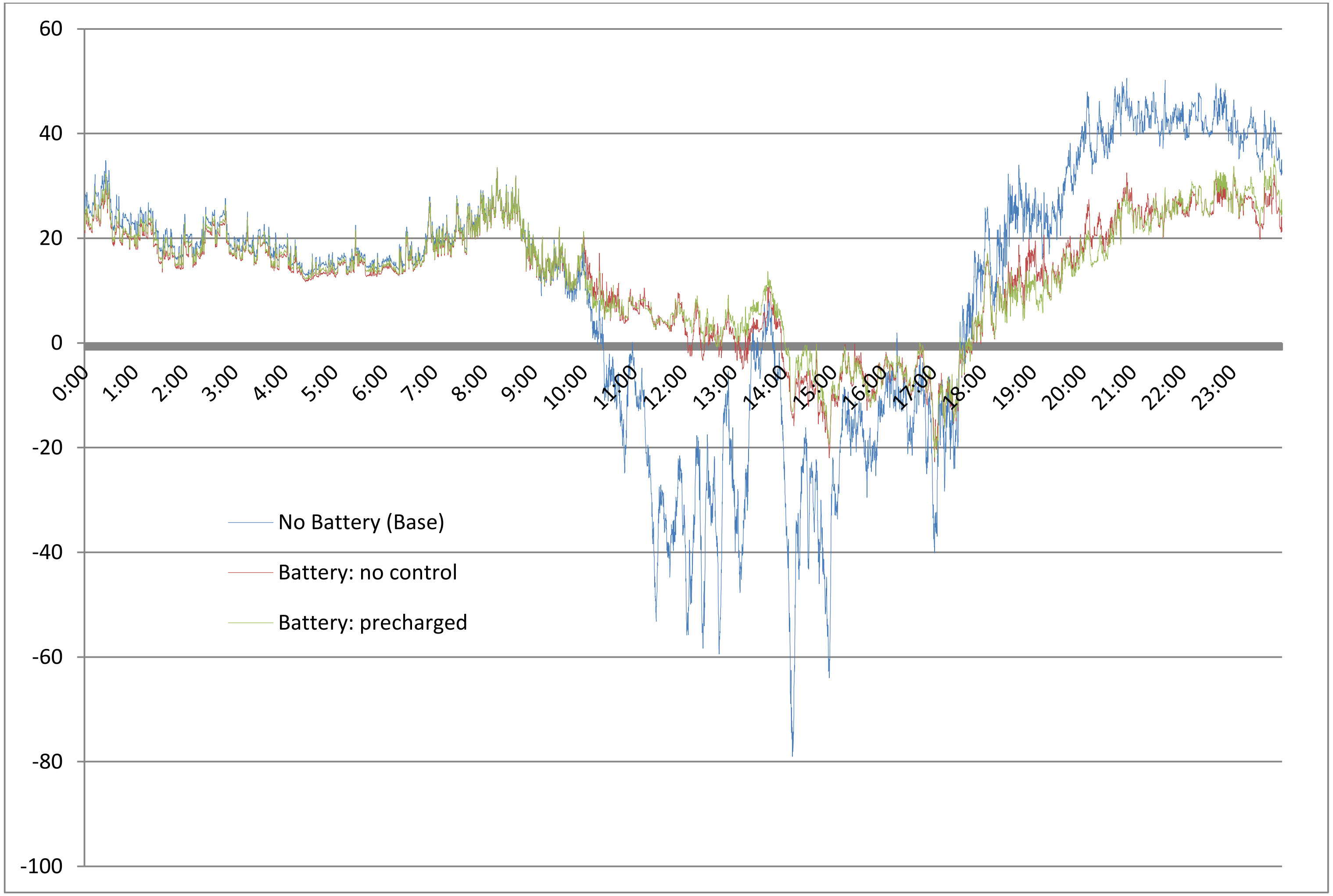


Figure 32, Cumulative electricity demand of neighborhood for various configurations of

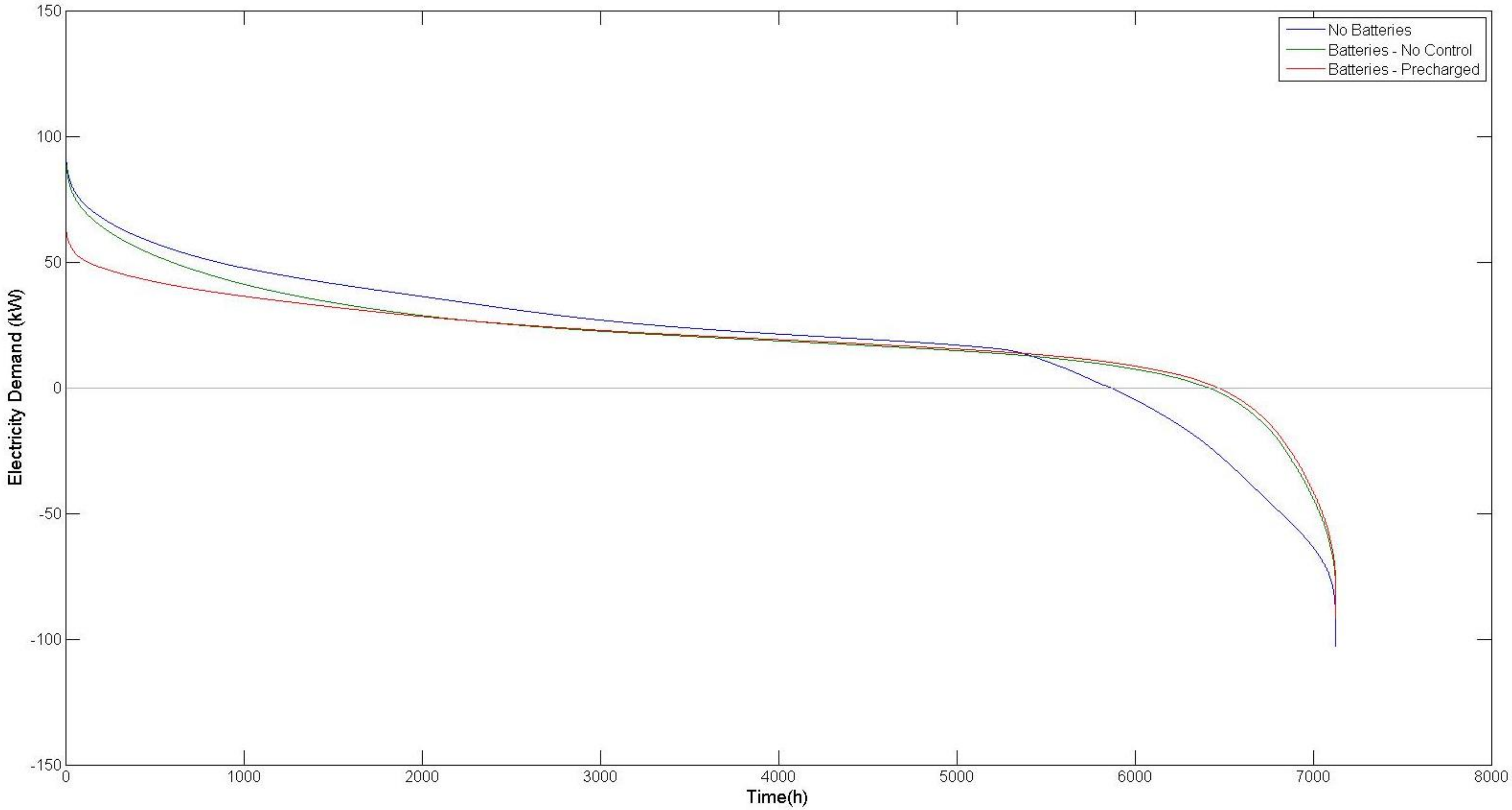


Figure 33, Load duration curves for neighborhood without batteries, with non-controlled batteries, and with precharged batteries. Data from 297 between November 2013 and September 2014

3.4.2 Battery degradation indicators

Table 8, overview battery degradation indicators for optimally sized batteries with (a) no control and (b) prechargingTable 8 shows the performance on battery degradation indicators when the battery is precharged to meet the peak demand. Not surprisingly, when incorporating precharging, the batteries perform worse on all battery degradation indicators. Note that the batteries are programmed to meet the entire evening demand. With an average optimal storage size of 3,17 kWh, many prosumers need the entire battery capacity to cover for their evening demand

Table 8, overview battery degradation indicators for optimally sized batteries with (a) no control and (b) precharging

	No control	Precharging
Average DoD	53%	85%
Average SoC	22%	30%
Total energy throughput (kWh/year)	1441	2074

3.5 Sensitivity analysis

Three sensitivity analyses were performed. Figure 34 shows the impact of the various input parameters on the average optimal storage size (research question 2). Note, this is the impact on the average of the entire neighborhood, so also the households with an optimal storage size of 0 kWh taken into account.[18] The positive impact on optimal storage size taken only the households with a business case for batteries into account, would be somewhat higher.

It can be concluded that the parameters with the largest impact on the optimal storage size, are the life time of the battery, the cost of the battery and the benefits of storage (=ΔElectricity price). All these parameters are quite uncertain. The life time of the battery is subject of current scientific debate (e.g. Barré et al. (2013)). To increase complexity for the residential battery, this debate is mostly focused at car batteries. These batteries operate under different circumstances than residential batteries. Most importantly, the operating temperature of residential batteries will be lower due to the lower power requirements. This would be positive for the life time of a residential battery as compared to a car battery. Furthermore, the lifetime of the battery is often expressed as the time a battery can meet certain performance requirements (i.e. 80% of initial capacity). However, as was shown in paragraph 3.3.4, the functionality loss of a residential battery would still be limited. The uncertainty in investment costs of the batteries was extensively reviewed in paragraph 3.1. An important uncertain factor here is the development of demand for batteries. This can be influence by various factors, e.g. EV charging infrastructure, oil price and policy support. Lastly, the benefits of storage is completely dependent on future policy decisions. Mostly the possible abolishment of net metering, but also for example incorporating a more advanced dynamic pricing regime. Substantial difference between the retail price and the feed-in tariff is needed: when this difference is €0,08 the average optimal storage size decreases with almost 70%.

[18] Reason to do the analysis this way, was that otherwise an increase from optimal storage size for a specific household from 0 kWh to 0,5 kWh would be negative for the average of the neighborhood.

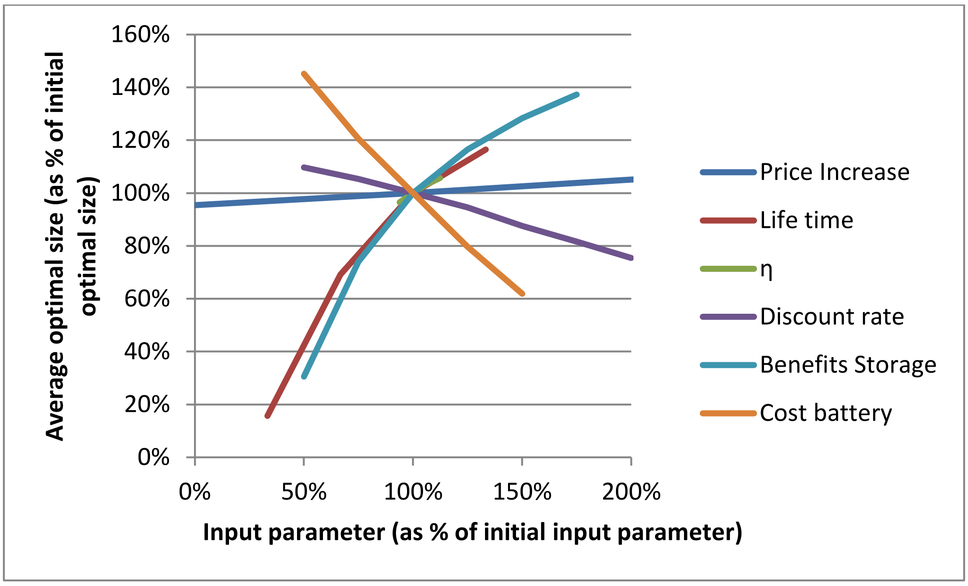


Figure 34, Sensitivity analysis on average optimal storage size

The next step is to look at the impact of these changed optimal storage sizes on the results of research question 3 and 4. The impact on peak electricity demand of the system with no control is very small. This is logical, since the impact of the non-controlled batteries on the peak electricity demand without batteries was also limited. The same holds, to a lesser extent, for the impact on the four hour peak of the non-controlled batteries. Smaller battery sizes have a larger impact on the peak electricity demand and peak four hour load of the neighborhood with precharged batteries. The impact on for hour peak is somewhat robust: when the optimal sizes of the batteries decrease to 44% of the initial optimal sizes, the four hour peak is 13,4% higher than the initial four hour peak. This is still much lower than for the neighborhood without batteries; 96 kWh versus 158 kWh. The peak electricity demand of the neighborhood with precharged batteries is 84 kW when the optimal sizes are decreased to 44% of the initial optimal sizes, and 96 kW when the batteries are decreased to 72% of the initial optimal sizes (compare: 111 kW in the neighborhood without batteries). The relationship between optimal size and Peak demand has a peculiar shape; surprisingly, when the optimal sizes are increased further, the peak demand *increases*. This is due to the fact that more precharging is possible with larger batteries. Apparently, the precharging during the day –which is programmed to meet the evening demand– results in higher peaks than the evening peaks.

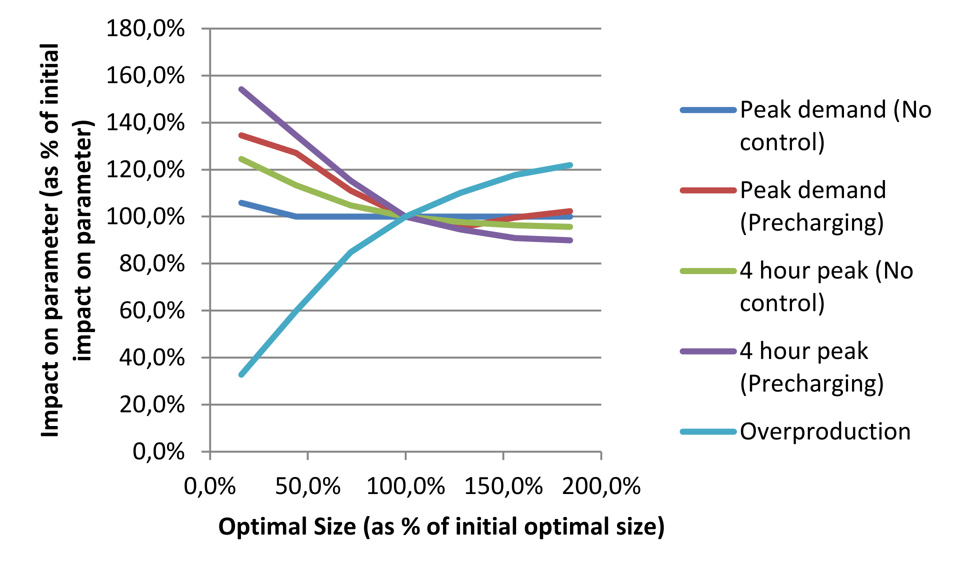


Figure 35, Impact of storage size on peak electricity demand and four hour peak load of neighborhood with (a) non-controlled batteries and (b) precharged batteries

Lastly, a special sensitivity analysis was performed. Using solar irradiation data, the input data for this research was transformed to match a neighborhood of different self-sufficiencies. In Figure 36, the value of 1 on the x-axis represents a self-sufficient neighborhood that produces as much electricity as it used. With abolishment of net metering, the average optimal size of this neighborhood would be 5,1 kWh. Note that for self-sufficient households with high absolute consumption and production (e.g. households with electric heating or an electric car), the optimal size can be much higher. One household in the investigated neighborhood would have an optimal battery size of 10 kWh.

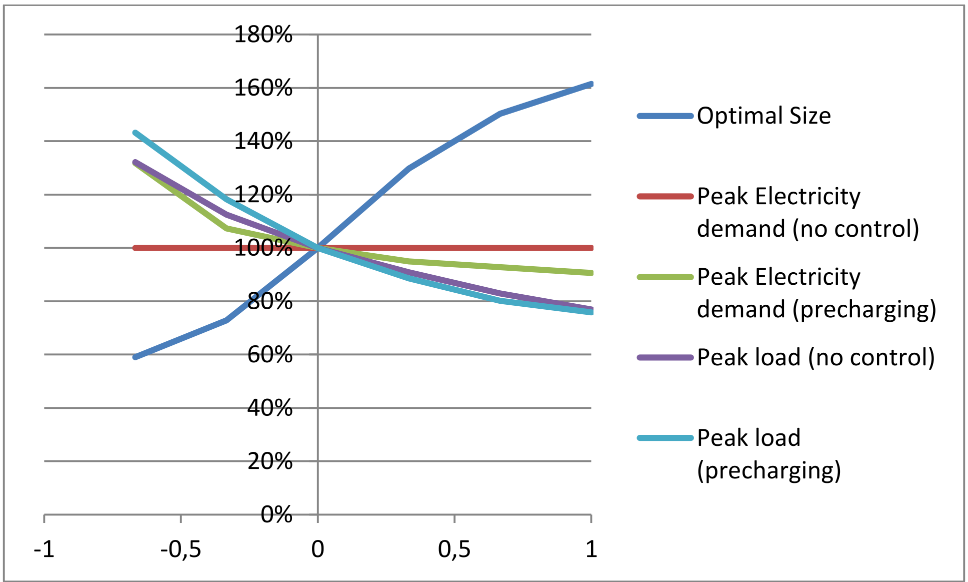


Figure 36, impact of varying self-sufficiency of neighborhood on main results research question 2-5

3.6 Social acceptance

In the course "Consultancy Project", a survey (N = 168) was performed on different residents of the Netherlands about characteristics of Domestic Energy Storage (DES). In this section, the data of perceived *importance* and *concerns* is analyzed.

3.6.1 Importance

When investigating the importance respondents attach to different characteristics, a general conclusion can be made that all characteristics were, on average, deemed important. *Space used* was evaluated as the least important characteristic, still on average scoring 3,41 on a 5-point scale. *Product lifetime* and *Safety* were considered most important, followed by *Maintenance friendliness*, *Environmental impact, Noise level* and *User friendliness.* After *Space used,* the least important characteristics are *Structural change* and *Grid independence.* However also notable regarding *Grid independence*; while on average it scored relatively low, the standard deviation was the highest. This means there is more controversy about this variable: some respondents deem it not that important, while others think it is very important. This is also reflected when respondents are asked to rank a top three of most important characteristics: 11,9% of the respondents see grid independence as the most important characteristic; only *Safety*, *Product lifetime* and *Noise level* score higher (see Appendix A).

	Mean	Std. Deviation
Space used	3,41	0,94
Structural change	3,58	0,94
Grid independence	3,61	1,13
User friendliness	3,95	0,75
Noise level	4,07	0,95
Environmental impact	4,16	0,88
Maintenance friendliness	4,19	0,73
Product lifetime	4,44	0,67
Safety	4,45	0,71

Table 9, Mean importance and standard deviation attached to different characteristics in survey by 168 respondents on a 5-points scale.

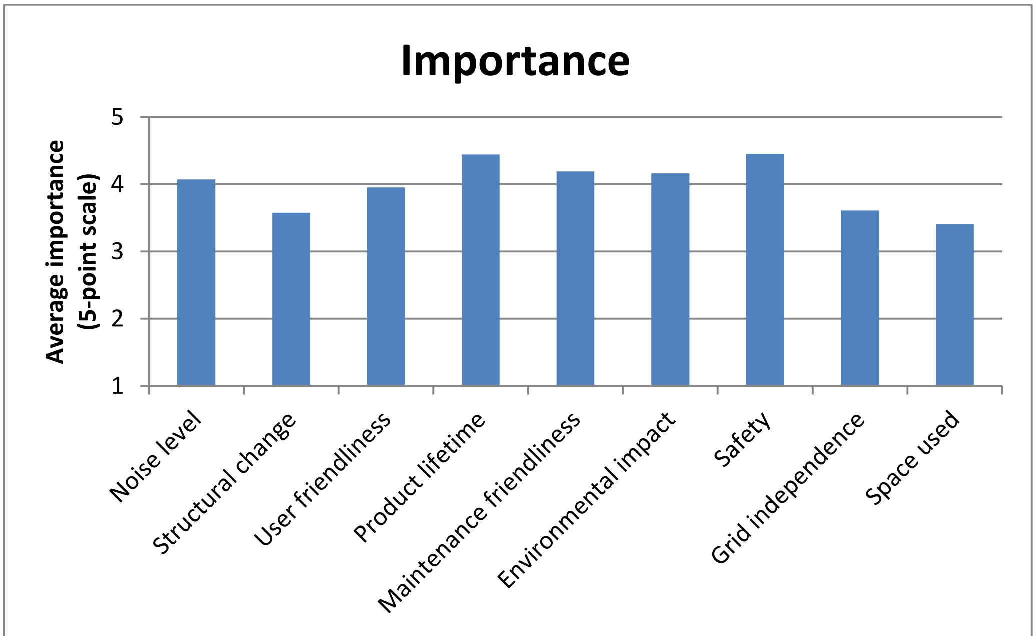


Figure 37, average importance attached to different characteristics regarding Domestic Energy Storage. 169 respondents rated each characteristic on a 5-point scale.

To test whether the differences between the importance attached to characteristics were significant, a Friedman ANOVA was executed. The differences were significant: χ^2 (8) = 304,177, p < 0,01. To determine which characteristics differed statistically significant, Wilcoxon Signed-Rank Test was executed. Effect sizes (Corder & Foreman, 2009) and significances are shown in Table 10. 27 of the 36 comparisons were statistically significant (p<0,01), and effect sizes were high: 24 scored above medium (=0,3) and 12 even scored above high (=0,5) (Corder & Foreman, 2009).

	Noise	**Structure**	**UserFr**	**Lifetime**	**Mainten**	**Evironm**	**Safety**	**Indep**	**Space**
Noise		0,41*	0,13	0,35*	0,11	0,07	0,35*	0,30*	0,52*
Structure			0,34*	0,66*	0,55*	0,42*	0,67*	0,03	0,15
UserFr				0,52*	0,30*	0,22	0,51*	0,30*	0,46*
Lifetime					0,39*	0,30*	0,02	0,58*	0,72*
Mainten						0,03	0,36*	0,42*	0,62*
Evironm							0,32*	0,38*	0,54*
Safety								0,56*	0,73*
Indep									0,17
Space									

Table 10, Effect sizes of differences between characteristics. To determine the direction of the difference, see Table 9. Asterisks (*) indicate whether differences are statistically significant (after Bonferroni correction, p <0,01).

Next step was to determine whether PV owners differ from non-PV owners regarding the importance they attached to different characteristics. This is relevant, because these represents two different target markets, and the attractiveness of each market depends on policy.

In the survey, it was asked whether respondents own a PV system. This resulted in two independent groups: PV owners (n=112) and non-PV owners (n=53). The differences regarding importance attached to different characteristics are visually represented in Figure 38. In general, PV owners attached more importance to characteristics than non-PV owners. Specifically, PV owners attached more importance than Non-PV owners to the characteristics *Noise level, Product life time, Maintenance friendliness, Environmental impact, Grid independence* and *Space* used. Non-PV owners attached more importance to *Structural change* and *User friendliness.* There is no notable difference regarding *Safety.*

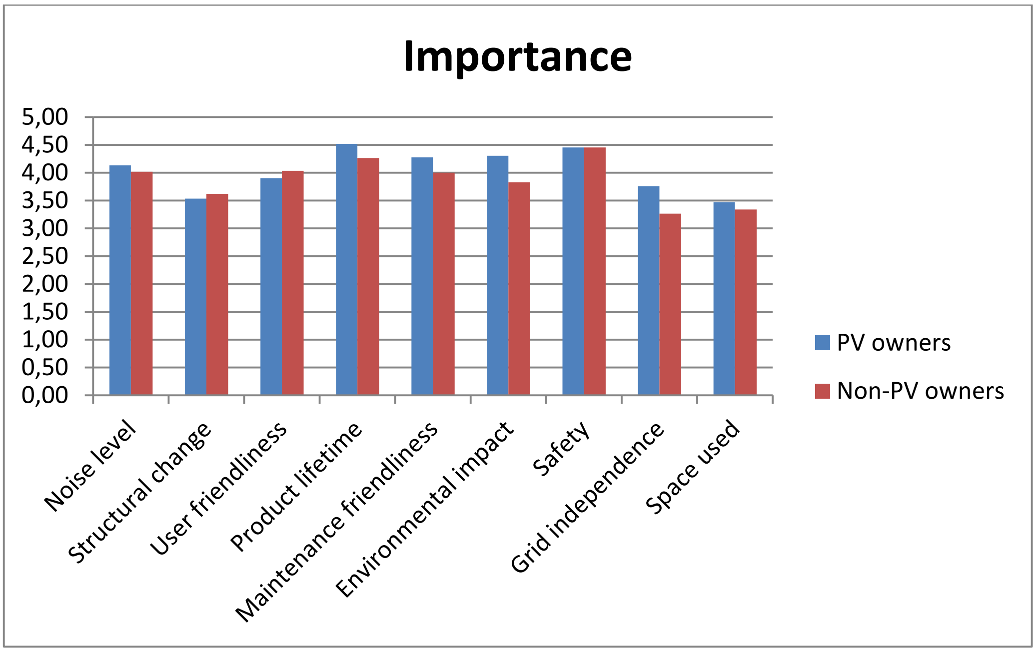


Figure 38, Differences between PV owners and non-PV owners in importance attached to different characteristics of DES.

To determine whether the observed differences were significant, Mann-Whitney U-tests were executed. The results are shown in Table 11. Not surprisingly, PV owners attached significantly more importance to *environmental impact* of a storage system (p<0,01). Furthermore, PV owners found *grid independence* significantly more important (p<0,01). There were non-significant trends (0,05<p<0,10) for three characteristics. PV owners seemed to attach more importance to *Maintenance friendliness* (p=0,084) and *Product lifetime* (p=0,057). There is only one characteristics that seems to be regarded as more important by non-PV owners as compared to PV owners: *User friendliness* (p=0,071).

	Noise	Structure	UserFr	Lifetime	Mainten	Evironm	Safety	Indep	Space
Mann-Whitney U	2893,5	2664,5	2514,5	2486,0	2526,0	2219,0	2714,0	2197,5	2920,5
Z	-0,280	-1,118	-1,809	-1,906	-1,731	-2,819	-1,004	-2,785	-0,176
p (2-tailed)	0,779	0,263	0,071	0,057	0,084	0,005	0,315	0,005	0,860

Table 11, outcome Mann-Whitney U-tests on differences between PV owners (n=112) and non-PV owners (n=53) regarding importance attached to different characteristics

3.6.2 Concerns

As expected, the concerns respondents have are different from the characteristics they found important. 26,2% of the respondents expected most problems from *Structural change* and *Product lifetime*. These characteristics were included in 58,9% and 53,0% respectively of the respondents' top three. 45,2% included *Space used* in their top three, and 35,7% included *Noise level*. Fewer problems were expected with *User friendliness, Maintenance friendliness, Environmental impact, Safety* and *Grid independence*: respectively 19,0%, 23,8%, 23,2%, 19,0% and 22,0% included these characteristics in their top three. Figure 39 gives an overview of how many times characteristics are included in the top three of a respondent.

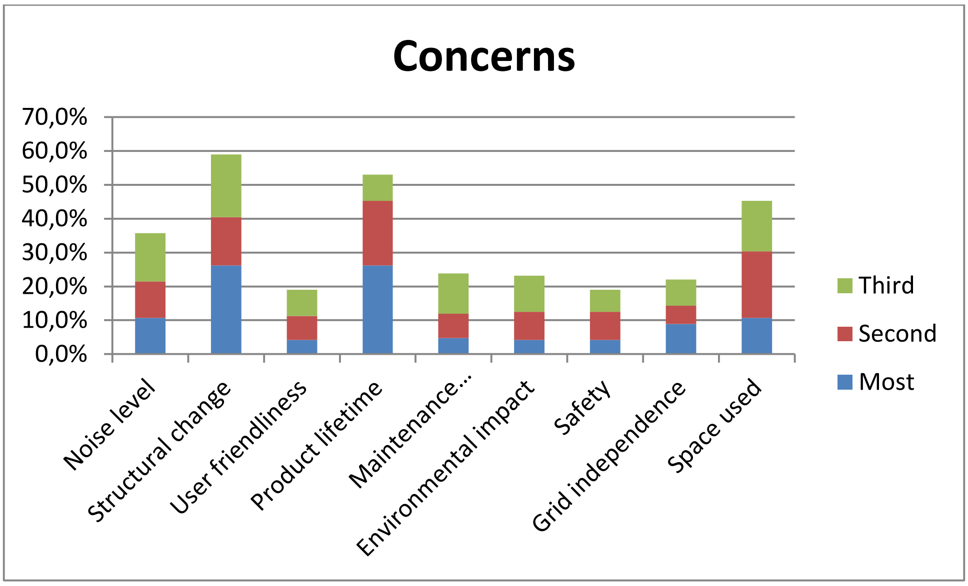


Figure 39, top three of problems expected with domestic energy storage by 168 respondents

To determine whether the differences between the amounts of problems expected with the characteristics were significant, a Friedman ANOVA was executed. The differences were significant: χ^2 (8) = 144,672, p < 0,01. To determine which characteristics differed statistically significant, Wilcoxon Signed-Rank Test was executed. Effect sizes (Corder & Foreman, 2009) and significance are shown in Table 12. 18 of the 36 comparisons were statistically significant (p<0,05), and effect sizes were moderate: most effect sizes were around 0,3. *Structural change* and *Product lifetime* show bigger differences with the other characteristics, which is in line with the visual representation of Figure 39.

	Noise	**Structure**	**UserFr**	**Lifetime**	**Mainten**	**Evironm**	**Safety**	**Indep**	**Space**
Noise		0,31*	0,23	0,29*	0,20	0,18	0,22	0,15	0,10
Structure			0,49*	0,00	0,45*	0,46*	0,49*	0,41*	0,26**
UserFr				0,50*	0,04	0,05	0,01	0,09	0,32*
Lifetime					0,46*	0,49*	0,50*	0,41*	0,21
Mainten						0,00	0,02	0,05	0,30*
Evironm							0,03	0,05	0,30*
Safety								0,08	0,31*
Indep									0,28*
Space									

Table 12, Effect sizes of differences between characteristics. To determine the direction of the difference, see Figure 39. * indicates that differences are statistically significant after Bonferroni correction at p <0,01; ** at p<0,05.

Comparing PV owners with non-PV owners regarding their concerns, the difference between their number one concern was notable: PV owners expect the most problems from the *Product lifetime*, while non-PV owners expect most problems from *Structural change,* followed by *Space used* (See Figure 39).

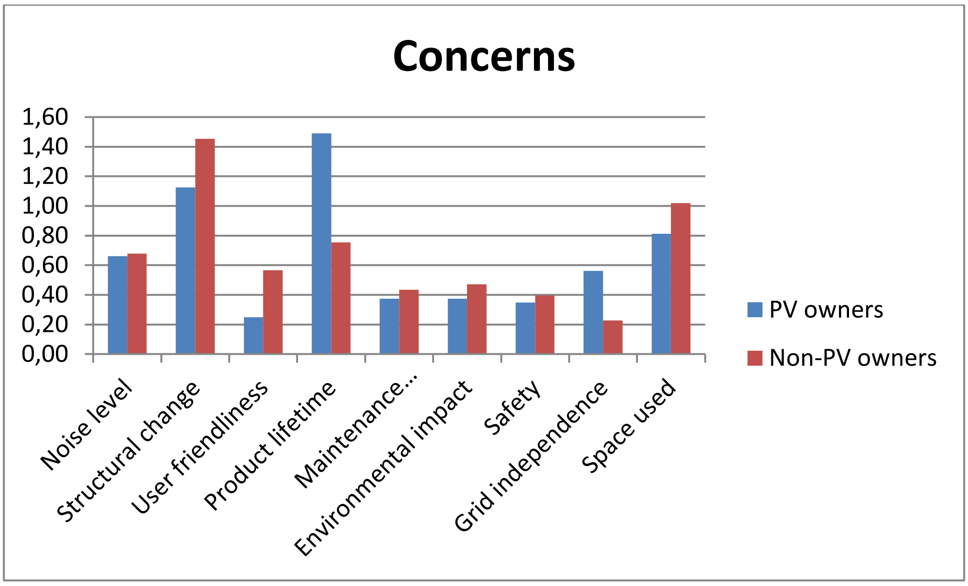


Figure 40, Differences between PV owners and non-PV owners in problems expected from different characteristics of DES. Points are attached for characteristics that are included in the top three's: three points for a first place, two points for a second place, one point for a third place.

Again, to test significance of observed differences a Mann-Whitney U tests were executed. It was found that PV owners expect more problems than non-PV owners with the *Product lifetime* (p<0,01). Non-PV expect more problems than PV owners with *User friendliness*. Interestingly, PV owners expect more problems with *Grid independence* than non-PV owners. At the same time, we saw PV owners find *Grid independence* more important than non-PV owners do. It seems that part of the PV owners see grid independence as a goal, while another part of does not find it important and mainly sees potential problems with it.

	Noise	Structure	UserFr	Lifetime	Mainten	Evironm	Safety	Indep	Space
Mann-Whitney U	2952,0	2575,0	2545,5	2046,0	2898,0	2895,5	2843,5	2561,5	2632,0
Z	-0,066	-1,445	-2,139	-3,445	-0,332	-0,340	-0,630	-1,966	-1,287
p (2-tailed)	0,948	0,149	0,032	0,001	0,740	0,734	0,529	0,049	0,198

Table 13, outcome Mann-Whitney U-tests on differences between PV owners (n=112) and non-PV owners (n=53) regarding problems expected from different characteristics

4 Discussion

As was emphasized by Hoppmann et al. (2014), many studies on integrated PV-battery-systems investigate one aspect in isolation. Hoppmann et al. investigated the impact of multiple economic input parameters to determine optimal PV system and storage size for three-person household in Germany. This research goes further in several aspects. First, because of the data richness. Where other studies focused on a specific amount of consumption (e.g. Hoppmann et al. (2014), Rocky Mountain Institute (2014)), this study incorporated 79 different household with varying amounts of consumption and production. Moreover, instead of using a standard electricity profile (often with total energy use of 15 minutes, averaged over households), this study used power data measured every 10 seconds. This allows to account for differences between households in specific consumption profiles. On the one hand it is valuable to be able to predict an optimal storage size based on parameters like PV system size, on the other hand it is also very important to know which part of the variance cannot be predicted. The empirically formula to determine the optimal storage size, as established in paragraph 3.2, explains 52,7% of the variance in storage size. Hence, 47,3% is dependent on specific profiles, which indicates the value of e.g. a smart meter for determining an optimal storage size.

Furthermore, this research looks beyond implications for households only, but also investigated the possible impact on a larger scale. Important herein was the stepwise approach; first elaborate on the cost development of lithium-ion batteries, and using this information as input for determining the optimal sizes. Subsequently, using these optimal sizes to simulate behavior of a neighborhood equipped with batteries and the resulting impact on peak consumption. Next, comparing the situation of not-controlling the batteries of the neighborhood, with controlling the same batteries by precharging. The value is that more advanced lessons can be learned. For example, it is possible to make statements about what would be the impact of a certain battery price on the potential load shifting of a neighborhood[19].

Policy recommendations

There already has been much speculation about the abolishment of net metering. But before such a decision is to be made, it is important to create knowledge on consequences of the abolishment of net metering. A recommendation about whether it would be a wise decision to abolish net metering, falls outside the scope of this research. In order to make such a statement, the abolishment should be compared to different alternatives.

The main recommendation that can be made, is that an integrated policy approach is needed. Smart grids ask for smart policies. An example is to make it easy for net operators and prosumers to make a joint investment in batteries. Prosumers could benefit from the increased self-consumption, while allowing net operators to operate the battery for peak shaving applications. Such alliances could also be made with energy retailers, enabling load shifting and it's economic benefits. The main recommendation is to make a decision on net metering abolishment and transition scheme well in advance. This time can for example be used by grid operators or energy retailers to convince prosumers of the usefulness of allowing them to operate your in-house battery. As this research has demonstrated, the benefits of distributed storage greatly increase when batteries are smartly operated. This opens the opportunity to form such alliances, and furthermore provide an attractive investment climate for smart grid applications because of long term stability of policy.

Limitations and future research

Limitations include limited generalizability, and assumption of perfect information and economic rational behavior of prosumers. Also, there was some data imperfection. Missing dates; as mentioned in the methodologies, data of the entire month October, 13, 20, 22, 27 and 29 November, 3, 5, 6, 9,

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[19] Evidently

11, 12, 13, 17, 18 and 23 December, 15, 18 and 21 January, 19 and 24 February, 14, 26 and 30 March, 1, 2, 5, 8, 16 and 19 April, 17 May, 23, 25, 28, 30 and 31 July and 8, 20, 26 and 27 August were missing. It was assumed that the remaining dates were representative for a year. The website Polder PV has documented the production of PV electricity from 2002-2014 (Polder PV, 2015). The assumption that the data in this research is representative for a complete year, resulted in a production that was 3,87% higher than the average yearly production over the 13 years.

Possibilities for future research include:

- combination with research about DSM, smart EV charging;
- Add economics of peak reduction from net operator, electricity producer (load shifting and peak shaving;
- Add flexible prices;
- Optimize integration of battery –determine an acceptable peak, and use batteries to stay below that peak. (Optimization based on costs of battery degradation – more research needed);

Connection to existing literature

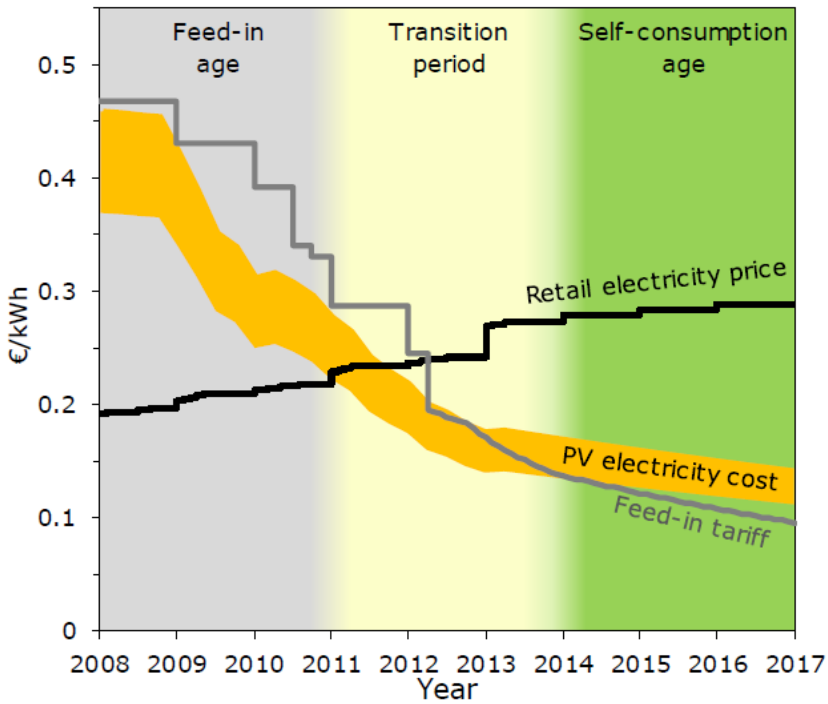

Figure 41, Weniger et al. (2014).

Figure 41 shows the increasing benefits of storage in the upcoming years in Germany. Increasing the retail electricity price (i.e. energy taxes or making network cost dependent from grid use) could be seen as a regulatory option to create financial incentives for electricity storage. However, there is a notable difference with the stimulation of PV electricy. The feed-in tariff is coupled to the PV electricity cost; the feed-in tariff is decreased with decreasing cost of PV. The battery storage incentives on the other hand, would be *increased* with the decreasing costs discussed in section 3.1. The Dutch Minister of Economic Affairs announced a suitable transition period will be put in place when net metering is abolished. It seems more logical to subsidize investment in storage, rather than solely increase taxes on use.

5 Conclusion

In this research, the following main research question was addressed:

How would battery systems in conjunction with PV systems contribute to (economic) value for different stakeholders in the Netherlands?

To answer this research question, several sub questions were investigated.

1. What could be the cost development of residential battery systems?

First, possible cost developments of battery systems were examined. Two methods were used, a meta-analysis of existing cost predictions in literature, and learning theory. A notable finding was that both within and between this methods, there was much differences between individual studies. The meta-analysis showed the Lithium-ion batteries were estimated to be around 250 €/kWh in 2020 (ranging from 125-400 €/kWh). Learning theory and cumulative production predictions resulted in an estimated cost of around 150 €/kWh (range 70-230 €/kWh). Therefore, the prediction of this research is that Lithium-ion costs will lie around 200 €/kWh in 2020.

2. What is the relation between increasing battery size and Net Present Value of storage for different PV households and what would be the optimal storage size for these households?

The following empirical relation between Net Metered Consumption and PV System Size and Optimal storage size was found:

$$Optimal\ Size\ (kWh) = 0.45 - 2.47 * 10^{-4} * Net\ Metered\ Consumption\ \left(\frac{kWh}{year}\right) + 1.24 * PV\ System\ Size\ (kW_{peak})$$

Furthermore, an important finding was that increasing the battery size above the optimal size would result in limited decrease of NPV.

3. For the optimally sized batteries, what would be (a) the impact on overproduction, (b) the results for various indicators of battery degradation (c) the impact on consumption and production power peaks on neighborhood level and (d) the impact on peak loads on neighborhood level?
4. How would precharging of the optimally sized batteries impact the battery degradation indicators, and the peak shaving and load shifting on neighborhood level?

The optimally sized batteries covered 53.7% of the overproduction of prosumers. So the batteries would probably more than double self-consumption of an average prosumer. The performance on peak shaving and load shifting depends for a large part on the charging strategy. The non-controlled batteries have a marginal impact on the peak power, and a limited impact on the 4 hour peak load. The precharged batteries have a substantial contribution to both peak shaving and load shifting (see Table 13).

Table 13, comparison between neighborhood without batteries, with non-controlled batteries, and with precharged batteries on four hour peak load, and peak power

	No batteries	Batteries (no control)	Batteries (precharged)
Average 4 hour peak (kWh)	203	157	124
Peak power (kW)	111	105	75.2

On the other hand, regarding battery degradation performance indicators, precharged batteries performed much worse (see Table 14).

Table 14, overview battery degradation indicators for optimally sized batteries with (a) no control and (b) precharging

	No control	Precharging
Average DoD	53%	85%
Average SoC	22%	30%
Total energy throughput (kWh/year)	1441	2074

5. What could be non-financial barriers for consumers?

Consumers indicated that the most important non-financial factors were product lifetime and safety.

6 Bibliography

Anderman, M., 2013. *Assessing the Future of Hybrid and Electric Vehicles: The 2014 xEV Industry Insider Report,* Detroit: Advanced Automotive Batteries.

Anderson, D., 2009. *An evaluation of current and future costs for lithium-ion batteries for use in electrified vehicle powertrains,* Durham: Duke University.

Balqon, 2015. *24V Energy Storage.* [Online]
Available at: http://www.balqon.com/store-2/#!/24V-Energy-Storage/c/12269142/offset=0&sort=priceAsc
[Accessed 19 March 2015].

Barré, A. et al., 2013. A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. *Journal of Power Sources,* Volume 241, p. 680–689.

BCG, 2010. *Batteries for Electric Cars - Challenges, Opportunities, and the Outlook to 2020,* Boston: The Boston Consultancy Group.

Bloomberg, 2012. *Battery Prices for Electric Vehicles Fall 14%, BNEF Says.* [Online]
Available at: http://www.bloomberg.com/news/articles/2012-04-16/battery-prices-for-electric-vehicles-fall-14-bnef-says
[Accessed 17 March 2015].

Bloomberg, 2013. *Clean energy investment activity and trends.* London, Bloomberg New Energy Finance.

Bloomberg, 2014a. *Imperial Business Insights.* London, Bloomberg New Energy Finance.

Bloomberg, 2014b. *H1 2014 Clean energy policy & market briefing,* London: Bloomberg.

Bloomberg, 2014c. *Musk Battery Works Fill Utilities With Fear and Promise.* [Online]
Available at: http://www.bloomberg.com/news/articles/2014-12-05/musk-battery-works-fill-utilities-with-fear-and-promise
[Accessed 19 March 2015].

Bosch, 2009. *Battery will drive the world ? and when ?,* Stuttgart: Bosch.

Brouwer, A. S., Kuramochi, T., van den Broek, M. & Faaij, A., 2013. Fulfilling the electricity demand of electric vehicles in the long term future: An evaluation of centralized and decentralized power supply systems. *Applied Energy,* Volume 107, pp. 33-51.

Castillo-Cagigal, M. et al., 2011. PV self-consumption optimization with storage and Active DSM for the residential sector. *Solar Energy,* 2011(85), pp. 2338-2348.

CBS, 2013. *Belang hernieuwbare energie in 2013 niet toegenomen.* [Online]
Available at: http://www.cbs.nl/nl-NL/menu/themas/industrie-energie/publicaties/artikelen/archief/2014/2014-4073-wm.htm
[Accessed 25 September 2014].

CBS, 2014. *Renewable energy; capacity, domestic production and use, 1990-2013.* [Online] Available at: http://statline.cbs.nl/StatWeb/publication/?DM=SLEN&PA=71457ENG&D1=5,8,16-18&D2=0-5,14,22,25-26&D3=10-23&HDR=T&STB=G1,G2&VW=T
[Accessed 22 September 2014].

Chaves-Ávila, J. P., Hakvoort, R. A. & Ramos, A., 2012. Short-term strategies for Dutch wind power producers to reduce imbalance costs. *Energy Policy,* 2013(52), pp. 573-582.

Corder, G. W. & Foreman, D. I., 2009. *Nonparametric statistics for non-statisticians: a step-by-step approach.* Hoboken: John Wiley & Sons.

Deutsche Bank, 2009. *Electric Cars: Plugged In 2,* Frankfurt: Deutsche Bank.

Deutsche Bank, 2010. *The End of the Oil Age - 2011 and beyond: a reality check,* Frankfurt: Deutsche Bank.

DOE, 2012. *Annual Energy Outlook 2012,* Washington: US Department Of Energy.

DOE, 2014. *Overview of the DOE Advanced Battery R&D Program.* Washington, U.S. Department Of Energy.

ECN, Energie-Nederland & Netbeheer Nederland, 2014. *Energietrends 2014,* s.l.: ECN, Energie-Nederland & Netbeheer Nederland.

EEX, 2013. *Auction - EPEX SPOT.* [Online] Available at: https://www.eex.com/en/market-data/power/spot-market/auction#!/2013/06/16 [Accessed 30 9 2014].

European Parliament, 2009. *Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC,* Strasbourg: Official Journal of the European Union.

Fu, R., Choe, S.-Y., Agubra, V. & Fergus, J., 2014. Development of a physics-based degradation model for lithium ion polymer batteries considering side reactions. *Journal of Power Sources,* Volume 278, pp. 506-521.

Geelen, D., Reinders, A. & Keyson, D., 2013. Empowering th eend-user in smart grids: Recommendations for the design of products and services. *Energy Policy,* 2013(61), pp. 151-161.

Gerssen-Gondelach, S. & Faaij, A., 2012. Performance of batteries for electric vehicles on short and longer term. *Journal of Power Sources,* Volume 212, pp. 111-129.

Heymans, C., B, W. S., Young, S. & Fowler, M., 2014. Economic analysis of second use electric vehicle batteries for residential energy storage and load-levelling. *Energy Policy,* Volume 71, pp. 22-30.

Hoke, A. et al., 2011. Electric vehicle charge optimization including effects of lithium-ion battery degradation. *Vehicle Power and Propulsion Conference (VPPC) IEEE ,* Volume September, pp. 1-8.

Hoppmann, J., Volland, J., Schmidt, T. S. & Hoffmann, V. H., 2014. The economic viability of battery storage for residential solar photovoltaic systems - A review and a simulation model. *Renewable and Sustainable Energy Reviews,* 2014(39), pp. 1101-1118.

IEA, 2000. *Experience Curves for Energy Technology Policy.* Paris: International Energy Agency.

IEA, 2009a. *Transport, Energy and CO2,* Paris: International Energy Agency.

IEA, 2009b. *Prospects for Large-Scale Energy Storage in Decarbonised Power Grids,* Paris: International Energy Agency.

IEA, 2011. *Electric and plug-in hybrid vehicle road map ,* Paris: IEA.

IEA, 2013. *Global EV Outlook,* Paris: IEA.

Kamp, H. G. J., 2014. *Beantwoording Kamervragen over avonturen van netbeheerders.* [Online] Available at: http://www.rijksoverheid.nl/bestanden/documenten-en-publicaties/kamerstukken/2014/04/25/beantwoording-kamervragen-over-avonturen-van-netbeheerders/beantwoording-kamervragen-over-avonturen-van-netbeheerders.pdf
[Accessed 24 September 2014].

KEMA, 2011. *Nationaal Actieplan Zonnestroom,* Arnhem: KEMA.

KNMI, 2015. *Klimatologie - Uurgegevens van het weer in Nederland - Download.* [Online] Available at: http://www.knmi.nl/klimatologie/uurgegevens/selectie.cgi
[Accessed 20 April 2015].

Lux Research, 2012. *Li-ion Battery Costs Fall to $397/kWh in 2020; Not Enough for Mass Adoption of Electric Vehicles.* [Online]
Available at: http://www.luxresearchinc.com/news-and-events/press-releases/read/li-ion-battery-costs-fall-397kwh-2020-not-enough-mass-adoption
[Accessed 2 November 2014].

Lux Research, 2014. *Tesla Motors' Gigafactory Will See More Than 50% Overcapacity in its Li-ion Production.* [Online]
Available at: http://www.luxresearchinc.com/news-and-events/press-releases/read/tesla-motors%E2%80%99-gigafactory-will-see-more-50-overcapacity-its-li
[Accessed 20 November 2015].

Matteson, S. & Williams, E., 2015. Learning dependent subsidies for lithium-ion electric vehicle batteries. *Technological Forecasting & Social Change,* 92(2015), pp. 322-331.

McKinsey, 2010. *The role of Battery Electric Vehicles, Plug-in Hybrids and Fuel Cell Electric Vehicles,* New York City: McKinsey & Company.

McKinsey, 2012. *Battery technology charges ahead,* New York City: McKinsey & Company.

MyNissanLEAF.com, 2013. *Update on Nissan LEAF Battery Replacement.* [Online] Available at: http://www.mynissanleaf.com/viewtopic.php?f=4&t=17168#p374490
[Accessed 18 March 2015].

Navigant Research, 2013. *Worldwide Electric Vehicle Sales to Reach 3.8 Million Annually by 2020.* [Online]
Available at: http://www.navigantresearch.com/newsroom/worldwide-electric-vehicle-sales-to-reach-3-8-million-annually-by-2020
[Accessed 18 March 2015].

Peterson, S. B., Apt, J. & F, W. J., 2010. Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. *Journal of Power Sources,* Volume 195, p. 2385–2392.

Pillot, C., 2014. *Battery Market Development for Consumer Electronics, Automotive, and Industrial.* Nice, Avicenne Energy.

Polder PV, 2015. *Monthly solar energy yield: production/month.* [Online]
Available at: http://www.polderpv.nl/nieuws_PVJSS22.htm#2jan2006
[Accessed 26 April 2015].

Pontes, J., 2015. *Battery Makers - Full Year 2014 (Updated).* [Online]
Available at: http://ev-sales.blogspot.ca/2015/02/battery-makers-full-year-2014.html
[Accessed 17 March 2015].

PWC, 2013. *State of the Plug-in Electric Vehicle Market,* London: PricewaterhouseCoopers.

Rijksoverheid, 2011. *Elektrisch Rijden in de versnelling - Plan van Aanpak 2011-2015 ,* The Hague: Rijksoverheid.

Rocky Mountain Institute et al., 2014. *THE ECONOMICS OF GRID DEFECTION - WHEN AND WHERE DISTRIBUTED SOLAR GENERATION PLUS STORAGE COMPETES WITH TRADITIONAL UTILITY SERVICE,* s.l.: Rocky Mountain Institute.

Roland Berger, 2012. *Technology & Market Drivers for Stationary and Automotive Battery Systems.* Nice, Roland Berger Strategy Consultants.

Rooijers, F. J. et al., 2014. *Scenario-ontwikkeling energievoorziening 2030,* Delft: CE Delft.

Sark, W. v., Junginger, M. & Faaij, A., 2010a. Methodological lessons and recommendations for scientists and modellers. In: M. Junginger, W. v. Sark & A. Faaij, eds. *Technological learning in the energy sector - Lessons for policy, industry and science.* Cheltenham: Edward Elgar Publishing Limited, pp. 262-271.

Sark, W. v. et al., 2010b. General aspects and caveats of experience curve analysis. In: M. Junginger, W. v. Sark & A. Faaij, eds. *Technological learning in the energy sector .* Cheltenham: Edward Elgar Publishing Limited, pp. 18-35.

SER, 2013. *Energieakkoord voor duurzame groei,* Den Haag: Sociaal-Economische Raad.

Shahan, Z., 2014. *What Does A SolarCity/Tesla Storage System Cost?.* [Online]
Available at: http://cleantechnica.com/2014/11/03/solarcity-tesla-storage-system-cost/
[Accessed 19 March 2015].

Shinoda, Y., Tanaka, H., Akisawa, A. & Kashiwagi, T., 2011. Evaluation of the Plug-in Hybrid Electric Vehicle Considering Learning Curve on Battery and Power Generation Best Mix. *Electrical Engineering in Japan,* 176(2), pp. 84-92.

Solaranlagen-Portal, 2015. *Prosol Sonnenbatterie.* [Online] Available at: http://www.solaranlagen-portal.com/photovoltaik/stromspeicher/sonnenbatterie-prosol-invest
[Accessed 19 March 2015].

Stewart, A., 2012. *Ultra Low Emission Vans study,* Cambridge: Element Energy.

Tesla Motors, 2015. *Design Studio.* [Online] Available at: http://my.teslamotors.com/nl_NL/models/design
[Accessed 18 March 2015].

Tweede Kamer, 2013. *Conceptverslag van een wetgevingsoverleg over Energie.* [Online] Available at: http://www.tweedekamer.nl/kamerstukken/verslagen/detail.jsp?id=2013D45035&did=2013D45035
[Accessed 1 10 2014].

Verbong, G. P. J., Beemsterboer, J. & Sengers, F., 2013. Smart grids or smart users? Involving users in developing a low carbon electricity economy. *Energy Policy,* Volume 52, pp. 117-125.

7 Appendices

7.1 Appendix A – reassessment experience curves

Table 15, production and price data LiB Matteson & Williams (2015)

Cumulative production (MWh)	Price ($/kWh)
100	2522
300	2111
900	2063
2100	1496
3600	1146
6200	712
10000	615
16000	507
23000	422
33000	422
44000	398
61000	374
78000	338

Table 16, production and price data LiB Mayer et al. (2012)

Cumulative Production (MWh)	Price ($/kWh)
15	2090
50	1750
121	1710
547	1240
1258	950
2288	590
3816	510
5983	420
8505	350
12093	350
17350	330
24526	310
33372	280

7.2 Appendix X – Data literature study

Table 17, data literature study future costs EV battery. Data in 2015€

	2010	2012	2013	2015	2016	2017	2020	2025	2030
IEA (2009)	€ 673					€ 408	€ 369	€ 329	
IEA (2011)	€ 486			€ 365			€ 308		
IEA (2013)			€ 466		€ 393		€ 264		
Anderson (2009)	€ 477			€ 382			€ 318	€254	€207
Bosch (2009)	€ 561						€ 262		
McKinsey (2010)	€ 935			€ 491			€ 322		
McKinsey (2012)		€ 353					€ 128	€103	
Deutsche Bank (2009)	€ 448			€ 336			€ 224		
Deutsche Bank (2010)	€ 310			€ 227			€ 172		
Bloomberg (2013)	€ 676			€ 439			€ 253	€152	€101
Stewart (2012)	€ 754			€ 547			€ 396	€283	€219
Pillot (2014)			€ 392	€ 294			€ 189		
PWC (2013)			€ 477	€ 398			€ 248		
DOE (2012)		€ 689	€ 541	€ 374			€ 271	€217	€175
RMI (2014)			€ 473	€ 365			€ 270	€196	€152
Roland Berger (2012)		€ 500		€ 339			€ 207		
Lux Research (2012)							€ 300		
Lux Research (2014)				€ 207		€ 148			
BCG (2010)	€ 779						€ 312		
Advanced Automotive Batteries (2014)	€ 239		€ 196		€ 172				
Faaij & Gerssen-Gondelach (2012)	€ 810			€ 421			€ 304	€243	
DOE goals				€ 405					€150
Average	**€ 624**	**€ 514**	**€ 431**	**€ 363**	**€ 295**	**€ 148**	**€ 254**	**€207**	**€171**

7.3 Appendix C - MATLAB Code main model

```
clear all
tic
%% About data
% Total number of days: 297

% NOV_tm_JAN
% 01-11-2013 t/m 31-01-2014
% Missing data: 13-11, 20-11, 22-11, 27-11, 29-11, 03-12, 05-12 & 06-12,
% 09-12, 11 t/m 13-12, 17-12 & 18-12, 23-12, 15-01, 18-01, 21-01
% -> Number of days: 74

% FEB_tm_APR
% 02-02-2014 t/m 01-05-2014
% Missing data: 19-02, 24-02, 14-03, 26-03, 30-3, 01-04 & 02-04, 05-04,
% 08-04, 16-04, 19-04
% -> Number of days: 78

% MAY_tm_JULI
% 01-05-2014 t/m 01-08-2014
% Missing data: 17-05, 23-07, 25-07, 28-07, 30-07, 31-7
% -> Number of days: 87

% AUG_tm_SEP
% 01-08-2014 t/m 01-10-2014
% Missing data: 08-08, 20-08, 26-08, 27-08
% -> Number of days: 58
% No double data: 01-08, 09-08, 21-08, 28-08

%!! for data transition and data info, see DataTransitionComplete.m !!

%% %%%%%%%%%%%%%%% INITIALISATION %%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%one-way efficiency
% w=1;
% Optimal_Size_Sens=zeros(7,1);
% AmountBCs_Sens=zeros(7,1);
% MaxConsDumb_Sens=zeros(7,1);
% MaxConsSmart_Sens=zeros(7,1);
% TwoHourPeakDumb_Sens=zeros(7,1);
% TwoHourPeakSmart_Sens=zeros(7,1);
% while w<2

%% Parameters
eta=0.9;
DR = 0.04;                          %Discount rate
PowerMax = 2000/3600000*10;          %converted to "kWh" to be comparable
with other data
LifeTimeBat = 15;                   %Life time battery [year]
C_bat = 200;                        %Cost Battery [euro/kWh_size]
C_elec = 0.16;                     %Benefits of storage (Retail price-FIT)
[euro/kWh_used]
YearlyPriceIncrease=1.01;            %Increase Benefits of storage (Effect
increase energy taxes + effect decrease wholesalemarket prices)
PreChargeTime = 17;                %Time that the battery fully precharged
PreChargeStart = 11;                %Start of precharging
PreChargeEnd = 17.5;                %End of precharging
EveningEnd = 22;                   %IF CHANGED, ALSO CHANGE IN FUNCTIONS!!
```

```
BatteryOnTime = 16;                    %Battery use from
DurationPeak = 4;
DurationPreCharging = 7;

%% Control constants
load('AUG_tm_SEP.mat')
% load('Optimal_Size.mat')
NrDays1=74;
NrDays2=78;
NrDays3=87;
NrDays4=58;
BeginTime = 1;
NrHH = 79;                             %Number of households
NrDays = 58;                            %Number of days
EndTime = NrDays*24*60*6;               %Number of 10 seconds periods
dt = 1;                                %
k = 0;
day = 0;
BatterySizeIni = 2;                    %[kWh]
BatterySizeMax = 22;                   %[kWh]

%% Input matrices
Export2Grid = zeros (BatterySizeMax, NrHH);
ExportPR = zeros (EndTime-BeginTime+1, NrHH);
UsageAbovePR = zeros (EndTime-BeginTime+1, NrHH);
UsedFromBattery = zeros (BatterySizeMax, NrHH);
MaxConsBase = zeros (1,NrDays);                  %Maximum consumption on daily
basis [W]
MaxProdBase = zeros (1,NrDays);                  %Maximum production [W]
TimingMaxBase = zeros (1,NrDays);                %Timing maximum consumption
TimingMinBase = zeros (1,NrDays);                %Timing maximum prodution
MaxConsDumb = zeros (1,NrDays);                  %Maximum consumption on daily
basis [W]
MaxProdDumb = zeros (1,NrDays);                  %Maximum production [W]
TimingMaxDumb = zeros (1,NrDays);                %Timing maximum consumption
TimingMinDumb = zeros (1,NrDays);                %Timing maximum prodution
MaxConsSmart = zeros (1,NrDays);                 %Maximum consumption on daily
basis [W]
MaxProdSmart = zeros (1,NrDays);                  %Maximum production [W]
TimingMaxSmart = zeros (1,NrDays);                %Timing maximum consumption
TimingMinSmart = zeros (1,NrDays);                %Timing maximum prodution
TwoHourPeakBase = zeros (1,NrDays);
TwoHourPeakDumb = zeros (1,NrDays);
TwoHourPeakSmart = zeros (1,NrDays);
BatterySizeM=zeros(1,BatterySizeMax);
BatteryPrecharge = zeros (EndTime+24*60*6,NrHH);
PreCharging = zeros (EndTime+24*60*6,NrHH);
PreChargeM = zeros (EndTime+24*60*6,NrHH);
PreChargingActual=zeros(NrDays,NrHH);
MaxBattery = zeros(NrDays,NrHH);
EveningDemand = zeros(NrDays,NrHH);
BatteryOptimalSmart = zeros (EndTime,NrHH);

HHGridUseBase=AUG_tm_SEP/3600000*10;             %Conversion Power -> Watt to
kWh (Measurements every 10 seconds)
HHGridUseBase(EndTime+1:end,:)=[];                      %Boundary condition
HHGridUseBase(:,NrHH+1:end)=[];
InputBattery=HHGridUseBase;  %Demand  for  battery  use;  can  be  positive
(discharging) or negative (charging)
HHGridUseDumb=HHGridUseBase; %HHKWH_AA = Household consumption from grid (so
total consumption - consumption from battery)
```

```
HHGridUseSmart=HHGridUseBase; %HHKWH_AAA = Household consumption from grid
using smart battery (so total consumption - consumption from battery)

%% PART ZERO: BASE CALCULATIONS (NO BATTERY)
%% Calculation Total Production (excluding self-consumption)%%
HHtotalBase=sum(HHGridUseBase,2);

U1=HHGridUseBase<0; %Production>Consumption
Production=U1.*HHGridUseBase;
TotalProductionHH=sum(Production)*-1; %Total production of one household in
complete time period
TotalProduction=sum(Production,2)*-1; %Total production van de wijk op een
bepaald moment

for i = 1:EndTime
        for j = 1:NrHH
            if InputBattery(i,j)>0
                InputBattery(i,j)=InputBattery(i,j)/eta;      %Input battery
is amount of electricity DEMAND. Regarding transfer losses, more has to be
taken from the battery
            else InputBattery(i,j)=InputBattery(i,j)*eta;    %InputBattery<0
= production. So electricity to battery -> *eta because of transfer losses
            end
        end
end

%% Export P(PV)>PR(Bat)
for i = BeginTime:EndTime
    for j = 1:NrHH
        if InputBattery(i,j) < -PowerMax/eta %Look to InputBattery, because
when PowerMax=2kW, 2.1kW production can still be exporterd to battery
(assumption)
            ExportPR(i,j)=-PowerMax/eta-HHGridUseBase(i,j);  %Assumption: if
production-consumption > PowerMax, the difference is exported to the grid
            InputBattery(i,j) = -PowerMax*eta;
        end
        if HHGridUseBase(i,j) > PowerMax           %Look to HHKWH, because
demand. When demand = PowerMax &Demand = 2000, this can be met with battery
            UsageAbovePR(i,j)=HHGridUseBase(i,j)-PowerMax;
            InputBattery(i,j) = PowerMax/eta;
        end
    end
end

TotalExportPR=sum(ExportPR);

%% Find maxima Houesholds
N=(HHGridUseSmart<0);
ProductionBase=HHGridUseBase.*N;

HHtotalBase=sum(HHGridUseBase,2);
HHProductionBase=sum(ProductionBase,2);

for i = BeginTime-1:EndTime-360*24
    k = k-dt;
    if k < 1
        day = day+1;
        [MaxConsBase(day),              TimingMaxBase(day)]              =
max(HHtotalBase(i+1:i+360*24));       %Possibly adjust HHKWH to HHKWH_A!
```

```
        [MaxProdBase(day),              TimingMinBase(day)]             =
min(HHProductionBase(i+1:i+360*24));
        k = 24*360;
    end
end

for i =1:NrDays
    TimingMaxBase(i)=TimingMaxBase(1,i)+((i-1)*24*360);
    TimingMinBase(i)=TimingMinBase(1,i)+((i-1)*24*360);
end


%% %%%%%%%%%%%%%%%%%%%%%%%%%%%%% DYNAMIC %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% PART ONE - Determining optimal battery size
for BatterySize = BatterySizeIni:BatterySizeMax

    BatterySizePrecise=BatterySize/2;

    Battery = zeros (EndTime,NrHH);
    Export = zeros (EndTime,NrHH);

    for i = BeginTime+1:EndTime
        for j = 1:NrHH

            Battery(i,j)=Battery(i-1,j)-InputBattery(i-1,j);

            if Battery(i,j)> BatterySizePrecise
               Export(i,j)=(Battery(i,j)-BatterySizePrecise)/eta;
            end

            Battery(i,j)= min(BatterySizePrecise,max(0,Battery(i,j)));

        end
    end

    Battery(1,:)=[]; %Removal zeros

    Export2Grid(BatterySize,1:NrHH)=sum(Export)+sum(ExportPR);
    UsedFromBattery(BatterySize,1:NrHH)=(TotalProductionHH-
Export2Grid(BatterySize,1:NrHH)).*eta^2;

    % TotalUsed(BatterySize)=sum(UsedFromBattery);
    % TotalExported(BatterySize)=sum(Export2Grid);

   BatterySizeM(BatterySize)=BatterySize;
end
%% Functions part 1
%%Elapsed time is 205.638725 seconds (functions only).
[UsedFromBattery1,      MaxConsBase1,      MaxProdBase1,      TimingMaxBase1,
TimingMinBase1,    HHGridUseBase1,    InputBattery1]=Function_NOV_tm_JAN(eta,
PowerMax, BatterySizeMax,NrHH);
1;
[UsedFromBattery2,      MaxConsBase2,      MaxProdBase2,      TimingMaxBase2,
TimingMinBase2,    HHGridUseBase2,    InputBattery2]=Function_FEB_tm_APR(eta,
PowerMax, BatterySizeMax,NrHH);
2;
```

```
[UsedFromBattery3,      MaxConsBase3,      MaxProdBase3,      TimingMaxBase3,
TimingMinBase3,   HHGridUseBase3,   InputBattery3]=Function_MAY_tm_JULI(eta,
PowerMax, BatterySizeMax,NrHH);
3;

TimingMaxBase2=TimingMaxBase2+NrDays1*360*24;
TimingMinBase2=TimingMinBase2+NrDays1*360*24;
TimingMaxBase3= TimingMaxBase3+(NrDays1+NrDays2)*360*24;
TimingMinBase3=TimingMinBase3+(NrDays1+NrDays2)*360*24;
TimingMaxBase=TimingMaxBase+(NrDays1+NrDays2+NrDays3)*360*24;
TimingMinBase=TimingMinBase+(NrDays1+NrDays2+NrDays3)*360*24;

UsedFromBattery                                                              =
UsedFromBattery1+UsedFromBattery2+UsedFromBattery3+UsedFromBattery;
MaxConsBase = [MaxConsBase1 MaxConsBase2 MaxConsBase3 MaxConsBase];
MaxProdBase = [MaxProdBase1 MaxProdBase2 MaxProdBase3 MaxProdBase];
TimingMaxBase     =     [TimingMaxBase1     TimingMaxBase2     TimingMaxBase3
TimingMaxBase];
TimingMinBase     =     [TimingMinBase1     TimingMinBase2     TimingMinBase3
TimingMinBase];

HHtotalBase=[sum(HHGridUseBase1,2);sum(HHGridUseBase2,2);sum(HHGridUseBase3
,2);sum(HHGridUseBase,2)];

% for i =1:NrDays
%                      TwoHourPeakBase1(i)=sum(HHtotalBase(TimingMaxBase(i)-
360:TimingMaxBase(i)+360));
% end
NrDays=297;
for i =1:NrDays
TwoHourPeakBase(i)=sum(HHtotalBase(TimingMaxBase(i)-
270:TimingMaxBase(i)+630));
end

clear UsedFromBattery1
clear UsedFromBattery2
clear UsedFromBattery3
clear MaxConsBase1
clear MaxConsBase2
clear MaxConsBase3
clear MaxProdBase1
clear MaxProdBase2
clear MaxProdBase3
clear TimingMaxBase1
clear TimingMaxBase2
clear TimingMaxBase3
clear TimingMinBase1
clear TimingMinBase2
clear TimingMinBase3



%% NPV calculation
SizevsUsed = [BatterySizeM' UsedFromBattery];
I = repmat(SizevsUsed(:,1) .* C_bat,1,NrHH)/2;
NPV = -I;
for t = 1:LifeTimeBat
    B_disc=365/NrDays*(SizevsUsed(:,2:NrHH+1).* C_elec)/(1+DR)^t;    %Remove
6 (
    NPV = NPV + B_disc;
```

```
    C_elec=C_elec*YearlyPriceIncrease;
end
NPV=[zeros(1,NrHH);NPV];

[NPV_Max, Optimal_Row]=max(NPV);
Optimal_Size=(Optimal_Row-1)/2;

AmountBCs = sum(Optimal_Size>0);        %Number of households with a business
case for a battery
% HHBC=find(Optimal_Size>0);                 %Which household has a positive
business case?
% UsedFromBatteryOptimal = zeros(1,AmountBCs);
% Optimal_SizeNew=Optimal_Size(HHBC);
% for i=1:AmountBCs
%     UsedFromBatteryOptimal(i)=UsedFromBattery(Optimal_SizeNew(i),HHBC(i));
% end

%% PART TWO: Redoing calculation with optimal battery size (Dumb battery)
NrDays = 58;

BatterySize = Optimal_Size;

BatteryOptimalDumb = zeros (EndTime,NrHH);
Export = zeros (EndTime,NrHH);

for i = 2:EndTime
        for j = 1:NrHH

            BatteryOptimalDumb(i,j)=BatteryOptimalDumb(i-1,j)-
InputBattery(i-1,j);

            if BatteryOptimalDumb(i,j)> BatterySize(j)
                Export(i,j)=(BatteryOptimalDumb(i,j)-BatterySize(j))/eta;
            end

            BatteryOptimalDumb(i,j)=
min(BatterySize(j),max(0,BatteryOptimalDumb(i,j)));

            if  and(InputBattery(i,j)  >  0,  BatteryOptimalDumb(i,j)  >  0)
%i.e. Usage from battery -> usage from grid = 0
                HHGridUseDumb(i,j) = UsageAbovePR(i,j);
            end

            if  and(InputBattery(i,j)  <  0,  BatteryOptimalDumb  (i,j)  <
BatterySize(j))
                HHGridUseDumb(i,j) = -ExportPR(i,j);
            end

        end
end

%% No battery versus battery
% Consumption from grid with optimal battery (YOBAT) vs no battery (NOBAT)
N=(HHGridUseBase>0);
NOBATCons=HHGridUseBase.*N;
Y=(HHGridUseDumb>0);
YOBATcons=HHGridUseDumb.*Y;
NOBATvsYOBAT=[sum(NOBATCons); sum(YOBATcons)];
```

```
%% Calculating effect Dumb Battery
N=(HHGridUseDumb<0);
ProductionDumb=HHGridUseDumb.*N;
HHProductionDumb=sum(ProductionDumb,2);
day = 0;
k = 0;
% Finding new peaks
HHtotalDumb=sum(HHGridUseDumb,2);
for i = 0:EndTime-360*24
    k = k-dt;
    if k < 1
        day = day+1;
        [MaxConsDumb(day),              TimingMaxDumb(day)]              =
max(HHtotalDumb(i+1:i+360*24));       %Possibly adjust HHKWH to HHKWH_A!
        [MaxProdDumb(day),              TimingMinDumb(day)]              =
min(HHProductionDumb(i+1:i+360*24));
        k = 24*360;
    end
end
for i =1:NrDays
    TimingMaxDumb(i)=TimingMaxDumb(1,i)+((i-1)*24*360);
    TimingMinDumb(i)=TimingMinDumb(1,i)+((i-1)*24*360);
end

%% Functions part 2
% % Elapsed time is 392.435460 seconds.

[MaxConsDumb1,  MaxProdDumb1,  TimingMaxDumb1,  TimingMinDumb1,  ExportPR1,
UsageAbovePR1,                HHGridUseDumb1,                NOBATvsYOBAT1,
BatteryOptimalDumb1]=Function2_NOV_tm_JAN(eta,  HHGridUseBase1,Optimal_Size,
PowerMax,NrHH);
[MaxConsDumb2,  MaxProdDumb2,  TimingMaxDumb2,  TimingMinDumb2,  ExportPR2,
UsageAbovePR2,                HHGridUseDumb2,                NOBATvsYOBAT2,
BatteryOptimalDumb2]=Function2_FEB_tm_APR(eta,  HHGridUseBase2,Optimal_Size,
PowerMax,NrHH);
[MaxConsDumb3,  MaxProdDumb3,  TimingMaxDumb3,  TimingMinDumb3,  ExportPR3,
UsageAbovePR3,                HHGridUseDumb3,                NOBATvsYOBAT3,
BatteryOptimalDumb3]=Function2_MAY_tm_JULI(eta,
HHGridUseBase3,Optimal_Size, PowerMax,NrHH);

MaxConsDumb=[MaxConsDumb1 MaxConsDumb2 MaxConsDumb3 MaxConsDumb];
MaxProdDumb=[MaxProdDumb1 MaxProdDumb2 MaxProdDumb3 MaxProdDumb];

TimingMaxDumb2=TimingMaxDumb2+NrDays1*360*24;
TimingMinDumb2=TimingMinDumb2+NrDays1*360*24;
TimingMaxDumb3= TimingMaxDumb3+(NrDays1+NrDays2)*360*24;
TimingMinDumb3=TimingMinDumb3+(NrDays1+NrDays2)*360*24;
TimingMaxDumb=TimingMaxDumb+(NrDays1+NrDays2+NrDays3)*360*24;
TimingMinDumb=TimingMinDumb+(NrDays1+NrDays2+NrDays3)*360*24;
TimingMaxDumb=[TimingMaxDumb1 TimingMaxDumb2 TimingMaxDumb3 TimingMaxDumb];
TimingMinDumb=[TimingMinDumb1 TimingMinDumb2 TimingMinDumb3 TimingMinDumb];

HHtotalDumb=[sum(HHGridUseDumb1,2);sum(HHGridUseDumb2,2);sum(HHGridUseDumb3
,2);sum(HHGridUseDumb,2)];
NrDays=297;
for i =2:NrDays-1
TwoHourPeakDumb(i)=sum(HHtotalDumb(TimingMaxDumb(i)-
180:TimingMaxDumb(i)+540));
end
```

```
NOBATvsYOBAT=NOBATvsYOBAT1+NOBATvsYOBAT2+NOBATvsYOBAT3+NOBATvsYOBAT;
NOBATvsYOBAT=[NOBATvsYOBAT; NOBATvsYOBAT(1,:)-NOBATvsYOBAT(2,:)];
%% Net Present Costs of increasing battery size
N=Optimal_Size>0;
NPV_BC=NPV(:,N);
NPV_BC_Max=NPV_Max(:,N);
Optimal_Size_BC=Optimal_Size(N);
Optimal_Row_BC=Optimal_Row(N);
for i=1:7
    for j=1:AmountBCs
        ExtraCosts(i,j)=NPV_BC_Max(j)-NPV_BC(Optimal_Row_BC(j)+i,j);
    end
end
[t,indices]=sort(ExtraCosts(:));
[I,J] = ind2sub(size(ExtraCosts),indices);
row_orig = reshape(I,size(ExtraCosts))';
col_orig = reshape(J,size(ExtraCosts))';
sorted = reshape(t,size(ExtraCosts))';

load TotalConsumption.mat
load TotalProduction.mat
load TotalNetMetered.mat
load WattPeak.mat
TotalConsumption_BC=TotalConsumption(:,N);
TotalProduction_BC=TotalProduction(:,N);
TotalNetMetered_BC=TotalNetMetered(:,N);
WattPeak_BC=WattPeak(N,:);
tbl=table(TotalNetMetered_BC',TotalProduction_BC',TotalConsumption_BC',WattPeak_BC,Optimal_Size_BC','VariableNames',{'NetMeteredUse','TotalProduction','TotalConsumption','WattPeak','Optimal_Size'});
mdl=fitlm(tbl);
tbl2=table(TotalNetMetered_BC',WattPeak_BC,Optimal_Size_BC','VariableNames',{'NetMeteredUse','WattPeak','Optimal_Size'});
mdl2=fitlm(tbl2);

clear t
clear I
clear J
clear row_orig
clear col_orig
clear MaxConsDumb1
clear MaxConsDumb2
clear MaxConsDumb3
clear MaxProdDumb1
clear MaxProdDumb2
clear MaxProdDumb3
clear TimingMaxDumb1
clear TimingMaxDumb2
clear TimingMaxDumb3
clear TimingMinDumb1
clear TimingMinDumb2
clear TimingMinDumb3
clear NOBATvsYOBAT1
clear NOBATvsYOBAT2
clear NOBATvsYOBAT3


%% PART THREE: Precharging (smart battery) %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Find maxima Batteries
```

```
3;

NrDays=58;

for i=1:NrDays
EveningDemand(i,:)=sum(HHGridUseDumb(TimingMaxBase(i)-
360:TimingMaxBase(i)+(DurationPeak-1)*360,:));
end

BatterySize = Optimal_Size;

% When not charging further than MaxBat
% day = 0;
% k = 0;
% for i = BeginTime-1:EndTime-360*24
%     k = k-dt;
%     if k < 1
%         day = day+1;
%              MaxBattery  (day,:)=  max(BatteryOptimalDumb(i+1:i+360*24,:));
%Possibly adjust HHKWH to HHKWH_A!
%         k = 24*360;
%     end
% end
%
% PreChargingPotential  = bsxfun(@minus,Optimal_Size,MaxBattery);      % Pre
charging potential = Optimal battery size - Maximum of energy stored in the
specific battery on a specific day

BatteryAtStartPeak=zeros(NrDays,NrHH);
for i=1:NrDays
    BatteryAtStartPeak(i,1:NrHH)=BatteryOptimalDumb(TimingMaxBase(i),:);
end

PreChargingNeed=EveningDemand-BatteryAtStartPeak;    %    Or    EveningDemand-
MaxBattery;
for i=1:NrDays
    for j=1:NrHH
        PreChargingNeed(i,j)=max(0,PreChargingNeed(i,j));
    end
end

for i=1:NrDays
    for j=1:NrHH
        PreChargingActual(i,j)=min(BatterySize(j),PreChargingNeed(i,j));
    end
end

for i = 1:NrDays
PreChargeM(1+(i-
1)*360*24:i*360*24,1:NrHH)=repmat(PreChargingActual(i,1:NrHH),360*24,1);
end
%PreChargeM2=PreChargeM-Battery;

PreChargeM=PreChargeM/((DurationPreCharging)*360);
for i = 1:NrDays
    PreCharging(TimingMaxBase(i)-
(DurationPreCharging+1)*360:TimingMaxBase(i)-360,:)=
PreChargeM(TimingMaxBase(i)-(DurationPreCharging+1)*360:TimingMaxBase(i)-
360,:);              % Create matrix with zeros and every day one value of
```

```
precharging potential. For modelling reasons, assumption is made that
batteries are charged in one go.
end

%% Account for PR(Bat)
InputBatSm=InputBattery-PreCharging(1:EndTime,:);
for i = BeginTime:EndTime
    for j = 1:NrHH
        if InputBatSm(i,j) < -PowerMax/eta
            PreCharging(i,j)=PreCharging(i,j)-(-PowerMax/eta-
InputBatSm(i,j));
        end
    end
end

HHGridUseSmart=HHGridUseSmart+PreCharging(1:EndTime,1:NrHH);

%          BatteryOnOff=[ones(BatteryOffTime*360,NrHH);zeros((BatteryOnTime-
BatteryOffTime)*360,NrHH);ones((24-BatteryOnTime)*360,NrHH)];
% BatteryOnOff=repmat(BatteryOnOff,NrDays,1);
InputBatterySmart=InputBattery;

for i = 1:EndTime
    for j = 1:NrHH
        if PreCharging(i,j)>0
            InputBatterySmart(i,j)=-PreCharging(i,j);
            if and(PreCharging(i,j)>0,InputBattery(i,j)<0)
                InputBatterySmart(i,j)=-PreCharging(i,j)+InputBattery(i,j);
            end

        end
    end
end

%% Smart Battery Dynamic
for i = 2:EndTime
    for j = 1:NrHH

        BatteryOptimalSmart(i,j)=BatteryOptimalSmart(i-1,j)-
InputBatterySmart(i-1,j);

        if BatteryOptimalSmart(i,j)> BatterySize(j)
            Export(i,j)=-HHGridUseBase(i,j);
        end

        BatteryOptimalSmart(i,j)=
min(BatterySize(j),max(0,BatteryOptimalSmart(i,j)));

        if  and(InputBattery(i,j)  >  0,  BatteryOptimalSmart(i,j)  >  0)
%i.e. Usage from battery -> usage from grid = 0
            HHGridUseSmart(i,j) = UsageAbovePR(i,j)+PreCharging(i,j);
        end

        if  and(InputBattery(i,j)  <  0,  BatteryOptimalSmart  (i,j)  <
BatterySize(j))
            HHGridUseSmart(i,j) = -ExportPR(i,j)+PreCharging(i,j);
        end

    end
```

```
end
%% Calculating effect 'Smart' Battery
day = 0;
k = 0;
dt=1;
% Finding new peaks

N=(HHGridUseSmart<0);
ProductionSmart=HHGridUseSmart.*N;

HHtotalSmart=sum(HHGridUseSmart,2);
HHProductionSmart=sum(ProductionSmart,2);

for i = 0:EndTime-360*24
    k = k-dt;
    if k < 1
        day = day+1;
        [MaxConsSmart(day),              TimingMaxSmart(day)]              =
max(HHtotalSmart(i+1:i+360*24));        %Possibly adjust HHKWH to HHKWH_A!
        [MaxProdSmart(day),              TimingMinSmart(day)]              =
min(HHProductionSmart(i+1:i+360*24));
        k = 24*360;
    end
end
for i =1:NrDays
    TimingMaxSmart(i)=TimingMaxSmart(1,i)+((i-1)*24*360);
    TimingMinSmart(i)=TimingMinSmart(1,i)+((i-1)*24*360);
end

BatteryTotal=sum(BatteryOptimalSmart,2);

%
BatteryTotal=[sum(BatteryOptimalSmart,2);sum(BatteryOptimalSmart1,2);sum(Ba
tteryOptimalSmart2,2);sum(BatteryOptimalSmart3,2)];

%% Functions part 3
%Elapsed time is 633.370520 seconds.
[HHtotalSmart1,    HHProductionSmart1,    MaxConsSmart1,    MaxProdSmart1,
TimingMaxSmart1,             TimingMinSmart1,             HHGridUseSmart1,
BatteryOptimalSmart1]=Function3_NOV_tm_JAN(BatteryOptimalDumb1,
HHGridUseBase1, HHGridUseDumb1, eta, PowerMax, Optimal_Size, PreChargeStart,
PreChargeEnd, EveningEnd, InputBattery1, ExportPR1, UsageAbovePR1,NrHH);
3.5;
[HHtotalSmart2,    HHProductionSmart2,    MaxConsSmart2,    MaxProdSmart2,
TimingMaxSmart2,             TimingMinSmart2,             HHGridUseSmart2,
BatteryOptimalSmart2]=Function3_FEB_tm_APR(BatteryOptimalDumb2,
HHGridUseBase2, HHGridUseDumb2, eta, PowerMax, Optimal_Size, PreChargeStart,
PreChargeEnd, EveningEnd, InputBattery2, ExportPR2, UsageAbovePR2,NrHH);
[HHtotalSmart3,    HHProductionSmart3,    MaxConsSmart3,    MaxProdSmart3,
TimingMaxSmart3,             TimingMinSmart3,             HHGridUseSmart3,
BatteryOptimalSmart3]=Function3_MAY_tm_JULI(BatteryOptimalDumb3,
HHGridUseBase3, HHGridUseDumb3, eta, PowerMax, Optimal_Size, PreChargeStart,
PreChargeEnd, EveningEnd, InputBattery3, ExportPR3, UsageAbovePR3,NrHH);

MaxConsSmart=[MaxConsSmart1,MaxConsSmart2,MaxConsSmart3,MaxConsSmart];
MaxProdSmart=[MaxProdSmart1,MaxProdSmart2,MaxProdSmart3,MaxProdSmart];


TimingMaxSmart2=TimingMaxSmart2+NrDays1*360*24;
TimingMinSmart2=TimingMinSmart2+NrDays1*360*24;
```

```
TimingMaxSmart3= TimingMaxSmart3+(NrDays1+NrDays2)*360*24;
TimingMinSmart3=TimingMinSmart3+(NrDays1+NrDays2)*360*24;
TimingMaxSmart=TimingMaxSmart+(NrDays1+NrDays2+NrDays3)*360*24;
TimingMinSmart=TimingMinSmart+(NrDays1+NrDays2+NrDays3)*360*24;
TimingMaxSmart=[TimingMaxSmart1,TimingMaxSmart2,TimingMaxSmart3,TimingMaxSm
art];
TimingMinSmart=[TimingMinSmart1,TimingMinSmart2,TimingMinSmart3,TimingMinSm
art];

HHtotalSmart=[sum(HHGridUseSmart1,2);sum(HHGridUseSmart2,2);sum(HHGridUseSm
art3,2);sum(HHGridUseSmart,2)];
NrDays=297;
for i =2:NrDays
TwoHourPeakSmart(i)=sum(HHtotalSmart(TimingMaxSmart(i)-
180:TimingMaxSmart(i)+540));
end

clear MaxConsSmart1
clear MaxConsSmart2
clear MaxConsSmart3
clear MaxProdSmart1
clear MaxProdSmart2
clear MaxProdSmart3
clear TimingMaxSmart1
clear TimingMaxSmart2
clear TimingMaxSmart3
clear TimingMinSmart1
clear TimingMinSmart2
clear TimingMinSmart3

%% %%%%%%%%%%%%%%%%%%%%%%Visualization%%%%%%%%%%%%%%%%%%%%%%%%%%%% %%
%Time

A = ones(EndTime,1);
for i = 1:EndTime
    A(i) = i+32*360*24;
end

B=datevec(A/8640, 'HH:MM:SS');   %evt. 'DD:HH:MM:SS'

Time=datenum(B);

%Convert to time of day

C = datevec(TimingMaxSmart/8640, 'DD:HH:MM:SS'); %%replace maxInd for minInd
etc.

D = datenum(C);

TimePeak = datestr(D,'HH:MM:SS');

HHtotaltotal=[HHtotalBase HHtotalDumb HHtotalSmart];
HHtotaltotal=HHtotaltotal*3600/10; %in kW
TotalProduction=-1*TotalProduction*3600/10;

% figure(1)
%
plotyy(Time(1*24*360:20*24*360),HHtotaltotal(1*24*360:20*24*360,1:3),Time(1
*24*360:20*24*360),BatteryTotal(1*24*360:20*24*360))
```

```
% datetick('x','dd-mmm HH:MM:SS','keepticks')
% figure(6)
%
plotyy(Time(3*24*360:5*24*360),HHtotaltotal(3*24*360:5*24*360,1:3),Time(3*2
4*360:5*24*360),TotalProduction(3*24*360:5*24*360))
% datetick('x','dd-mmm HH:MM:SS','keepticks')

clear A
clear B
clear C
clear Check
clear D
clear dt
clear i
clear I
clear j
clear k
clear N
clear t
clear U1
clear Y



% Optimal_Size_Sens(w)=mean(Optimal_Size)
% AmountBCs_Sens(w)=AmountBCs
% MaxConsDumb_Sens(w)=max(MaxConsDumb)
% MaxConsSmart_Sens(w)=max(MaxConsSmart)
% TwoHourPeakDumb_Sens(w)=mean(TwoHourPeakDumb)
% TwoHourPeakSmart_Sens(w)=mean(TwoHourPeakSmart)
% w=w+1;
% DR=DR+0.01;
%
% end
% save Optimal_Size_Sens_DR.mat Optimal_Size_Sens
% save AmountBCs_Sens_DR.mat AmountBCs_Sens
% save MaxConsDumb_Sens_DR.mat MaxConsDumb_Sens
% save MaxConsSmart_Sens_DR.mat MaxConsSmart_Sens
% save TwoHourPeakDumb_Sens_DR.mat TwoHourPeakDumb_Sens
% save TwoHourPeakSmart_Sens_DR.mat TwoHourPeakSmart_Sens
%plot(Size_Used(:,1),Size_Used(:,2),Size_Used(:,1),Size_Used(:,3),Size_Used
(:,1),Size_Used(:,4))

% figure(1)
% plotyy(X1,Battery(2:end,1:2),X,Export)
%save Loops2.txt StoreStorage -ascii
toc

MaxBattery1=zeros(NrDays1,NrHH);
BatteryAtStart1=zeros(NrDays1,NrHH);
dt = 1;                                    %
k = 0;
day = 0;
for i = 0:NrDays1*360*24-360*24

    k = k-dt;
    if k < 1
        day = day+1;
        for j=1:NrHH
            MaxBattery1(day,j)=    max(BatteryOptimalDumb1(i+1:i+360*24,j));
%Possibly adjust HHKWH to HHKWH_A!
```

```
            BatteryAtStart1(day,j)=BatteryOptimalDumb1(6*360+i,j);

        end
        k = 24*360;
    end
end

MaxBattery2=zeros(NrDays2,NrHH);
BatteryAtStart2=zeros(NrDays2,NrHH);

k = 0;
day = 0;
for i = 0:NrDays2*360*24-360*24
    k = k-dt;
    if k < 1
        day = day+1;
        for j=1:NrHH

            MaxBattery2(day,j)=    max(BatteryOptimalDumb2(i+1:i+360*24,j));
%Possibly adjust HHKWH to HHKWH_A!
            BatteryAtStart2(day,j)=BatteryOptimalDumb2(6*360+i,j);

        end
    k = 24*360;
    end
end

MaxBattery3=zeros(NrDays3,NrHH);
BatteryAtStart3=zeros(NrDays3,NrHH);

k = 0;
day = 0;
for i = 0:NrDays3*360*24-360*24
       k = k-dt;
    if k < 1
        day = day+1;
        for j=1:NrHH

            MaxBattery3(day,j)=    max(BatteryOptimalDumb3(i+1:i+360*24,j));
%Possibly adjust HHKWH to HHKWH_A!
            BatteryAtStart3(day,j)=BatteryOptimalDumb3(6*360+i,j);

        end
    k = 24*360;
    end
end
MaxBattery=zeros(NrDays4,NrHH);
BatteryAtStart=zeros(NrDays4,NrHH);
dt = 1;                                 %
k = 0;
day = 0;
for i = 0:NrDays4*360*24-360*24
        k = k-dt;
    if k < 1
        day = day+1;
        for j=1:NrHH

            MaxBattery(day,j)=      max(BatteryOptimalDumb(i+1:i+360*24,j));
%Possibly adjust HHKWH to HHKWH_A!
```

```
            BatteryAtStart(day,j)=BatteryOptimalDumb(6*360+i,j);

        end
    k = 24*360;
    end
end

MaxBattery=[MaxBattery1;MaxBattery2;MaxBattery3;MaxBattery];
BatteryAtStart=[BatteryAtStart1;BatteryAtStart2;BatteryAtStart3;BatteryAtSt
art];
DepthOfDischargeKWH=(MaxBattery-BatteryAtStart);
DepthOfDischarge=zeros(NrDays1+NrDays2+NrDays3+NrDays4,NrHH);

k = 0;
day = 0;
for i=1:NrDays1+NrDays2+NrDays3+NrDays4
    for j=1:NrHH
        DepthOfDischarge(i,j)=DepthOfDischargeKWH(i,j)/Optimal_Size(j);
    end
end

N=find(Optimal_Size>0);
DepthOfDischarge=DepthOfDischarge(:,N)
toc
```

7.4 Appendix D – MATLAB code 'solar neighborhood'

Solar neighborhood

```
NrHH=79

load 'TotalNetMetered.mat'
load Optimal_Size.mat

load('NOV_tm_JAN.mat')
load 'Sollar irradiation NOV_tm_JAN.txt'
HHGridUseBase1=NOV_tm_JAN/3600000*10;          %Conversion Power -> Watt
to kWh (Measurements every 10 seconds)
HHGridUseBase1(NrDays1*24*360+1:end,:)=[];                     %Boundary
condition
HHGridUseBase1(:,NrHH+1:end)=[];

ExtraPVProduction1=zeros(NrDays1*24*360,1);
for i=0:NrDays1*24-1
ExtraPVProduction1(i*360+1:(i+1)*360)=repmat(Sollar_irradiation_NOV_tm_JAN(
i+1,:),360,1);
end

ExtraPVProduction1=ExtraPVProduction1/(325610*360);

ExtraPVProduction1=bsxfun(@times,TotalNetMetered,ExtraPVProduction1);
ExtraPVProduction1=ExtraPVProduction1*SolarMultiplier;
HHGridUseBase1=HHGridUseBase1-ExtraPVProduction1;

W=find(Optimal_Size>0);
HHGridUseBase1=HHGridUseBase1(:,W);

load('FEB_tm_APR.mat')
load 'Sollar irradiation FEB_tm_APR.txt'
HHGridUseBase2=FEB_tm_APR/3600000*10;          %Conversion Power -> Watt
to kWh (Measurements every 10 seconds)
HHGridUseBase2(NrDays2*24*360+1+1:end,:)=[];                   %Boundary
condition
HHGridUseBase2(:,NrHH+1:end)=[];

ExtraPVProduction2=zeros(NrDays2*24*360,1);
for i=0:NrDays2*24-1
ExtraPVProduction2(i*360+1:(i+1)*360)=repmat(Sollar_irradiation_FEB_tm_APR(
i+1,:),360,1);
end

ExtraPVProduction2=ExtraPVProduction2/(325610*360);

ExtraPVProduction2=bsxfun(@times,TotalNetMetered,ExtraPVProduction2);
ExtraPVProduction2=ExtraPVProduction2*SolarMultiplier;
HHGridUseBase2=HHGridUseBase2-ExtraPVProduction2;

W=find(Optimal_Size>0);
HHGridUseBase2=HHGridUseBase2(:,W);

load('MAY_tm_JULI.mat')
load 'Sollar irradiation MAY_tm_JULI.txt'
```

```
HHGridUseBase3=MAY_tm_JULI/3600000*10;            %Conversion Power -> Watt
to kWh (Measurements every 10 seconds)
HHGridUseBase3(NrDays3*24*360+1+1:end,:)=[];                       %Boundary
condition
HHGridUseBase3(:,NrHH+1:end)=[];
ExtraPVProduction3=zeros(NrDays2*24*360,1);
for i=0:NrDays3*24-1
ExtraPVProduction3(i*360+1:(i+1)*360)=repmat(Sollar_irradiation_MAY_tm_JULI
(i+1,:),360,1);
end

ExtraPVProduction3=ExtraPVProduction3/(325610*360);

ExtraPVProduction3=bsxfun(@times,TotalNetMetered,ExtraPVProduction3);
ExtraPVProduction3=ExtraPVProduction3*SolarMultiplier;
HHGridUseBase3=HHGridUseBase3-ExtraPVProduction3;

W=find(Optimal_Size>0);
HHGridUseBase3=HHGridUseBase3(:,W);

load('AUG_tm_SEP.mat')
HHGridUseBase=AUG_tm_SEP/3600000*10;            %Conversion Power -> Watt to
kWh (Measurements every 10 seconds)
HHGridUseBase(NrDays3*24*360+1+1:end,:)=[];                        %Boundary
condition
HHGridUseBase(:,NrHH+1:end)=[];
load 'Sollar irradiation AUG_tm_SEP.txt'
ExtraPVProduction4=zeros(NrDays4*24*360,1);
for i=0:NrDays4*24-1
ExtraPVProduction4(i*360+1:(i+1)*360)=repmat(Sollar_irradiation_AUG_tm_SEP(
i+1,:),360,1);
end

ExtraPVProduction4=ExtraPVProduction4/(325610*360);

ExtraPVProduction4=bsxfun(@times,TotalNetMetered,ExtraPVProduction4);
ExtraPVProduction4=ExtraPVProduction4*SolarMultiplier;
HHGridUseBase=HHGridUseBase-ExtraPVProduction4;
load Optimal_Size.mat
W=find(Optimal_Size>0);
HHGridUseBase=HHGridUseBase(:,W);
NrHH = 60;
```