Optimisation Based Design of an Integrated Energy System in the Netherlands

A casy study at Picnic

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Technische Universiteit Delft

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by

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Executive summary

As the share of solar and wind in the energy mix increases, the inherent intermittency of these energy sources pose a great challenge for the Dutch power grid. The occurrence of problems with congestion and balancing power supply and demand are becoming more common. Companies in the Netherlands show potential to implement means for smart use of energy to alleviate these kind of problems. However, the gap between academic solutions and the industry is often too large. This research presents a method to find the optimal design of an integrated energy system in the Netherlands. A use case at Picnic is used to apply the proposed method. A flexible load scheduling optimisation algorithm is presented to explore the financial benefit of an integrated energy system that combines a photovoltaic system, an energy storage system, a cold storage system and a fleet of electric vehicles. The financial performance of different system designs are compared. Results show that the optimised load schedules for the EV fleet and CS system achieve a 2.6% decrease of energy costs with respect to the benchmark of Picnic. A PV system turns out to be beneficial for every size that the grid connection allows. This research finds 600 square meters to be optimal in the case of Picnic. An energy storage system would make optimised load schedules obsolete due to its flexibility. An energy storage system with a capacity of 250 kWh is found to be optimal according to the performance analysis. However, significant limitations in the assumptions of the storage system advise against installing it. Further research is required to elaborate the different elements in the proposed model. Different markets are suggested to use as a basis for load scheduling and a broader set of system designs is suggested to analyse their performance.

Preface

Writing this thesis was the last step for graduating from the Masters program Sustainable Energy Technology. I would like to take this opportunity to express my sincere gratitude to a number of people without whom this research would not have been possible. First, I would like to thank my family for their encouragement and support to follow my academic aspirations in Delft. I would especially like to thank my direct supervisor at the university, Petra Heijnen, for her time, patience and critical view on my work. Also, I would like to thank the rest of my thesis committee, Zofia Lukszo and Simon Tindemans, for their time and feedback during the meetings we had. I would like to thank my friends and academic collegues Marnix and Frederik for all the times we spent studying together, it was always a pleasure. I am very grateful for the opportunity to carry out this research during an internship at Picnic where I was surrounded by incredibly talented and inspiring people. I would like to thank my supervisors at Picnic, Amy Klein and Frank Gorte, for their effort, advice and new insights they gave me during this project. During this period I developed a significant amount of soft and hard skills and learned a lot about the energy markets and e-commerce business. Learning Python feels like a great achievement since I had no prior experience with it. Furthermore, organising a workshop about the Picnic smart grid during the *All energy day* and attending a number of conferences about smart energy like *the Future of Charging*, *the FLEXcon* and *Aperi'Tech* gave me a good insight in modern developments regarding the energy transition and how to implement academic research in practice. As a closing remark, I am very excited to announce that I will start my career at Picnic and will continue to further work on this project in the future.

Frank Vollering
Amsterdam, August 27, 2019

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Acronyms

aFRR	Automatic frequency restoration reserve
BRP	Balance responsible party
BSP	Balance service provider
CAPEX	Capital expenditures
CS	Cold storage
DAM	Day ahead market
DC	Direct current
DER	Distributed energy sources
DoD	Depth of discharge
DR	Demand response
DSO	Distribution system operator
EMS	Ennergy management system
EPEX	European power exchange
ESS	Energy storage system
EC	Energy costs
EV	Electric vehicle
FCR	Frequency containment reserve
GHG	Greenhouse gas
ICES	Integrated community energy systems
IES	Integrated energy system
kW	Kilowatt
kWh	Kilowatt hour
LCOE	Levelised cost of energy
LEC	Levelised energy costs
mFRR	Manual frequency restoration reserve
MILP	Mixed integer linear programming
MW	Megawatt
MWh	Megawatt hour
OPEX	Operating expenditures
PPA	Power purchase agreement
PRP	Program responsible party
PV	Photovoltaic
RES	Renewable energy source
SOC	State of charge
TSO	Transmission system operator

1 Introduction

"We are the first generation to feel the effect of climate change and the last generation who can do something about it."

- Barack Obama

1.1. Energy transition

It is evident that the emission of carbon dioxide and other greenhouse gases due to human activity is increasing global average surface air temperatures and is changing the earths climate (Stocker et al., 2013). Efforts to reduce these effects cause the share of renewable energy sources (RES) in the worlds energy mix to become larger. The use of RES emits less or even no carbon dioxide. However, RES are often decentralised and strongly dependent on weather conditions, particularly the availability of wind and solar irradiance. In their study about wind energy generation forecasting, Ernst et al. (2007) state that the existing electricity supply system was mainly designed for large units of fossil fuel and nuclear power stations and therefore integration of renewable energy sources leads to challenges with regard to capacity and balancing.

Generally, problems that arise due to the introduction of RES are divided in two categories: *(i)* balancing of generated power and consumption and *(ii)* capacity related issues for energy transportation infrastructure. First, balancing issues occur when supply doesn't meet demand. Such events happen more often with a high share of RES in the energy mix. On the other hand, there can be too much generation of power while there is no consumer to alleviate the grid from its oversupply. Second, capacity issues are related to peak loads that are too big for grid connections. When there is an overload of energy and the infrastructure is not capable of handling this, it is commonly referred to as congestion. This can occur for example due to quick and unexpected installation of large scale solar parks, large increase of demand for electricity due to clustering of data-centres or more locally an increase of solar panels on roofs, EVs and heat pumps. In their paper about smart charging of EVs, Zheng and Jian (2016) state that it has been shown that uncoordinated charging of large scale EVs will threaten the stability and security of the power grid. Future grid analyses predict that peak loads will start to increase and current connections are not able to handle these high capacities. To renew all transmission lines, connectors, cabling and transformers would require an investment that often is not cost-efficient.

Therefore, the transition from conventional fossil fuel based energy sources to the more unpredictable RES calls for a new way to structure the energy grid. Heard et al. (2017) write in their comprehensive review of the feasibility of 100% renewable-electricity systems that efforts to date seem to have substantially underestimated the challenge and delayed the identification and implementation of effective and comprehensive decarbonisation pathways. It follows that with the expected rise of RES, a reformation of our current energy system is inevitable to enable the energy grid to handle the intermittent character of generation and balance it with energy demand. According to Sechilariu et al. (2013), a solution to this problem is to expand the role of integrated energy systems (IES) that interact with the utility grid and operate adjusted to limited availability of energy during peak hours or operate independently in case of power outage. IES often include one or more renewable energy sources, integrated with energy storage systems (ESS) and other technologies.

Therefore, more research is needed to stimulate the implementation of IES to decrease future problems due to grid balancing and congestion. Some companies possess the potential to ameliorate the complexities caused by the energy transition. The availability of free roof space creates an opportunity to install a solar system and locally generate electricity. High energy consumption that is flexible creates the opportunity for demand response and grid balancing. To further research the potential of companies in the Netherlands this research uses a case study at Picnic.

1.2. Picnic

Picnic is an online supermarket that exclusively delivers groceries, hence they have no physical stores where customers can buy their groceries. They deliver the groceries with small electric vehicles right up to the customers' front door. In 2019, they had roughly 800 EVs in operation spread out over 30 distribution hubs in the Netherlands and Germany.

To enable the use of RES like wind and solar, policies and regulations within Europe stimulate the transition to more use of electric vehicles as well as smarter and more efficient use of energy to compensate for the intermittent character of these RES. Picnic shows great potential for the implementation of a smart grid due to their large fleet of EVs, a lot of roof space suitable for PV, cold storage facilities and overall large energy consumption. That is why Picnic has been awarded a grant for sustainable energy use in transportation from the Dutch government to set up a collaborative project with ENGIE, a French multinational electric utility company, and Dexter Energy Services, who provides energy price forecasting and demand-side control services. Together they will test the possibilities for smarter energy use. The goal is to develop and test an experimental setup where a fleet of small electric trucks can be charged in the most efficient and least costly way possible within the planned logistical boundaries, along with local energy generation with a PV system, smarter energy use by the cooling systems and opportunities for energy storage.

The Picnic supply chain consists of a number of processes. Starting with ordering stock and inbound product delivery to the fulfilment centres. Here, the fulfilment of the individual customers' orders takes place. Next, the orders are transported to distribution hubs for preparation of last mile delivery to the customers' home. A graphical representation is shown in Figure 1.1. The experimental location will be at a distribution hub of Picnic in the city of Zaandam, the Netherlands. At this location there will be an integrated combination of an on-site PV system for energy production, an energy storage system and demand-side control activities applied on the cold storage facilities and EV charging stations based on forecasts of energy prices.

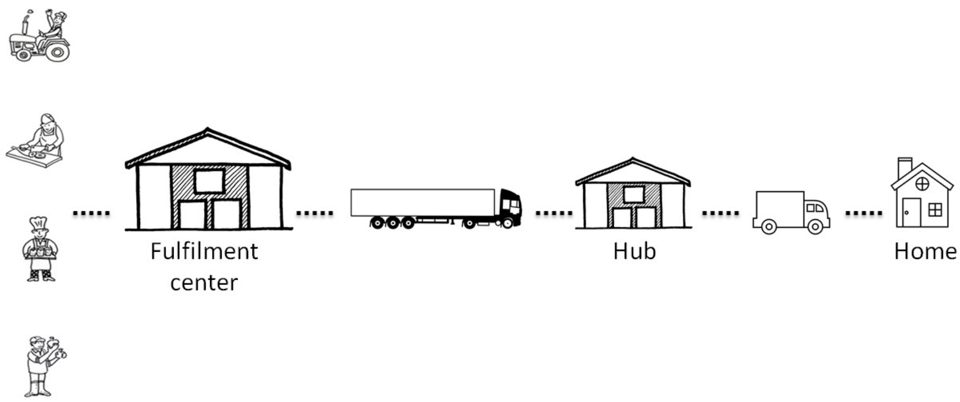

Figure 1.1: Graphical representation of the Picnic supply chain flow

1.3. Knowledge gap and problem statement

Research shows that there are numerous options for optimising energy use. However, a direct approach to combine energy storage, cold storage, EV charging and local energy generation in an integrated energy system has not yet been investigated. Besides, Picnic is new in the world of smart energy use and is in need of an analysis of the technical implementation for their integrated energy system. Therefore this research will focus on how to find the optimal design for an integrated energy system for companies like Picnic.

1.4. Research outline

This thesis will focus on how to determine the optimal design for an integrated energy system for e-commerce food distribution hubs. The following research question will be answered:

How can the optimal design for an integrated energy system for e-commerce food distribution hubs be determined?

In order to lead to an answer to the main research question, the following six subquestions are constituted:

I. *What elements are involved in an integrated energy system for e-commerce food distribution hubs?*

II. *What are the characteristics of the energy flows between the elements in the integrated energy* *system?*

III. What are the criteria for an optimal design of an integrated energy system?

IV. What method can be used to find the optimal sizing requirements of all physical components within an integrated energy system?

V. How can the method for finding optimal sizing requirements be applied?

VI. What is the optimal design of an integrated energy system for the use case of Picnic?

1.5. Report framework

The objective of this research is to find a method to design an integrated energy system in the Netherlands. The study will concentrate on integrated energy systems for e-commerce food distribution hubs and how to optimise such a system. The situation at Picnic will be used as a case study in this research. The experiments in this research are performed over the most recent full year, 2018, and an advice is constructed taking into account the present energy landscape.

- Chapter 2 describes relevant literature concerning this research.
- Chapter 3 describes the electricity landscape in the Netherlands, the electrical power systems and the actors in the energy markets.
- Chapter 4 describes the design of the research and the method that is used.
- Chapter 5 documents the data that is used as input for the experiments.
- Chapter 6 documents and discusses the results of this research.
- Chapter 7 formulates the conclusions of this research and gives recommendations for further research.

2

Literature review

This chapter provides an overview of modern literature concerning integrated energy systems (IES), demand response (DR) strategies and optimisation methods with respect to integrated energy systems.

2.1. Integrated energy systems

Integrated energy systems are commonly understood as a location specific design for the integration of different renewable energy sources and other innovative technologies for smarter use of energy. An integrated energy system is also known as a *smart grid*. Hatziargyriou (2014) states the definition of a smart grid as follows:

"A smart grid is an electricity network that can intelligently integrate the actions of all users connected to it - generators, consumers and those that assume both roles - in order to efficiently deliver sustainable, economic and secure electricity supplies."

From this definition, three key concepts can be distilled, namely the energy generation source, the energy end user and intelligent integration between those two to balance generation and consumption. Intelligent energy use beholds that the power system is monitored, controlled and that there is some sort of communication between the generator and consumer. According to Verzijlbergh and Lukszo (2013), intelligent energy systems are often a combination of the elements of flexible electricity demand anticipating on real-time prices and distributed generation. Consequently, to anticipate on price stimuli, a suitable system needs to be developed to control energy flows. Koirala et al. (2016a) describe the modern development to re-organise local energy systems where they focus on integrated community energy systems (ICES) and distributed energy resources. They present a model-based framework to assess the value of ICESs for local communities and use it to assess the value of an ICES in the Netherlands. In June 2016, Koirala et al. (2016b) describe the same framework but for a combination of ten households in Spain. In both articles, grid-connected ICESs are preferred over the alternative of solely being supplied from the grid, both in terms of costs and carbon dioxide emissions. It follows that the use of intelligent energy systems attractive in terms of costs. Verzijlbergh et al. (2014) investigated possible congestion management mechanisms for price-responsive EV demand in electricity distribution networks. They find that in order to yield desirable outcomes, it is a necessity to have optimal dynamic grid tariffs. This way, the volatility of energy costs and price signals can be used to stimulate or discourage the use of energy by the end user. Therefore, in this research dynamic grid tariffs will be used as an input parameter for the optimisation problem. Lund and Münster (2006) present the analysis of different ways of increasing flexibility in the Danish energy system by the use of local regulation mechanisms. They find that it can increase grid flexibility in an energy system and that it can benefit from energy trading. Also, it stimulates a better use of wind and other types of renewable energy. It follows that the use flexible assets is able to be financially preferred. According to Farhangi (2010), the smart grid is required to be self-healing and resilient to system anomalies. Khan and Khan (2013) state that a robust communication infrastructure is the touchstone of a smart grid that differentiates it from the conventional electrical grid by transforming it into an intelligent and adaptive energy delivery network.

Concluding, different research shows that the implementation of integrated energy systems can be financially desirable. Typical technologies in an IES include energy storage, local renewable energy production (e.g. PV systems) and demand management on basis of dynamic grid tariffs. It shows that for the design of an integrated energy system, there is a need for a robust control system that can schedule load for flexible assets and control other energy flows. Dynamic grid tariffs are needed to create value when scheduling this load. Chapter 3.4 elaborates further on the dynamic grid tariffs in different energy markets.

2.2. Demand response

As concluded in Section 2.1, part of the implementation of IES involves load scheduling based on dynamic grid tariffs. This practise is also referred to as demand response (DR). DR is a form of load management that focuses on the demand side and often uses flexible assets to solve congestion or imbalance between demand and supply. In this section the way of restructuring the load is reviewed. The basic principle of demand response is to lower energy demand during specific time intervals as a response on price signals which are determined by the supply and demand of energy. Carreiro et al. (2017) focus in their paper on the role of energy management systems aggregators. They review recent literature and projects to put perspective the role of energy management systems aggregators in the context of intelligent energy systems. They find that the involvement of end-users is a key element for the implementation of demand response, as a way to enhance the energy efficiency of the electricity infrastructure also enabling to cope with the intermittency of renewable energy sources. There are multiple types of demand side management that can help alleviate capacity constraints in the electricity grid. Figure 2.1 gives a graphic illustration of different demand management techniques as described by Eid et al. (2016).

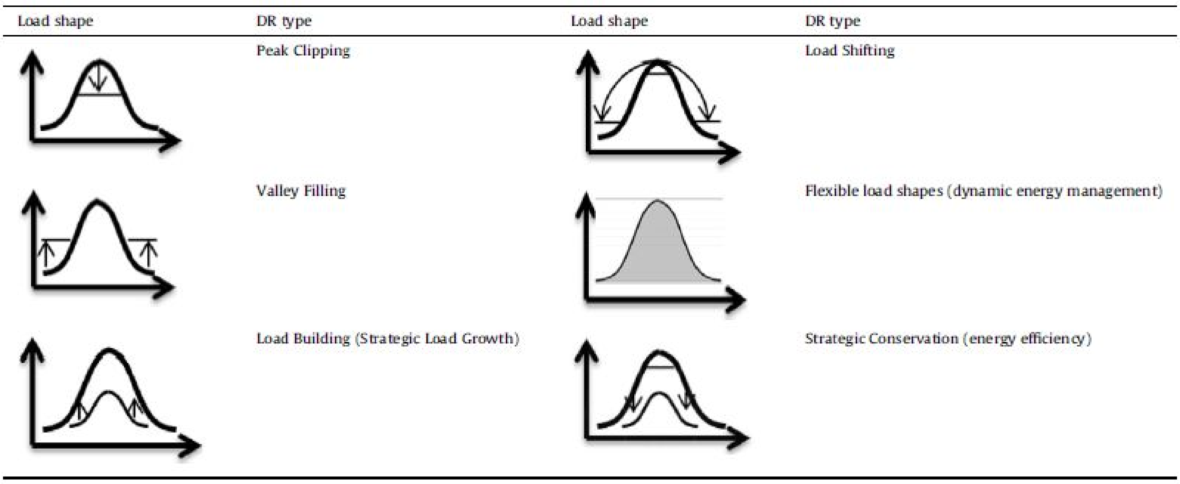

Figure 2.1: Demand response load shapes (Eid et al., 2016).

Considering the various approaches of demand response described, it is concluded that the main goal in designing an integrated energy system is to have the opportunity to adjust the load profile of energy consuming assets. The problems with most strategies and the application for flexible assets is that their energy demand during a specific time period is fixed. Meaning that when at one point in time the demand is decreased, it needs to be increased in another point of time. Resulting, the only applicable demand response strategy for these assets is load shifting. The basic concept as described by Eid et al. (2016) is decreasing peak demand and shifting it forward or backward in time. Concluding, DR can be used to schedule load on basis of dynamic grid tariffs in a smart energy context.

2.3. Load scheduling techniques

Previous sections conclude that flexibility is key in integrated energy systems and demand response can be applied to schedule load based on dynamic energy tariffs to achieve a financial advantage. In this section different techniques with respect to load scheduling in integrated energy systems are reviewed. Three main techniques are discussed to create load schedules for assets within integrated energy systems: optimisation with linear programming, model predictive control and stochastic optimisation.

2.3.1. Load schedule optimisation

Zhu et al. (2012) propose a consumption scheduling mechanism for home area load management in a smart grid based on integer linear programming. Their objective is to minimise the peak hourly load in order to achieve an optimal daily load schedule. Their simulation results demonstrated the effectiveness of the optimisation technique. Logenthiran et al. (2012) present a demand side management strategy based on load shifting technique for demand side management of future smart grids with a large number devices of several types. They propose a day-ahead load shifting technique formulated as a minimisation problem. They find that their proposed strategy achieves substantial financial savings. Ng and Sheble (1998) present a linear programming based algorithm for a scheduling problem that maximises profit by customer loads. They find that it is an inexpensive and powerful approach. A similar conclusion is found by Kurucz et al. (1996) who have developed a linear programming model to optimise the amount of power system peak load reduction thorough scheduling of industrial and residential loads. Concluding, (mixed integer) linear programming proves to be a inexpensive and powerful approach for day ahead scheduling of loads to minimise energy costs.

2.3.2. Model predictive control

In the research of Okur et al. (2019), a model predictive control approach is applied and employed in combination with an optimisation model in a smart energy use context. It uses a rolling horizon approach to optimise imbalance for aggregators for a certain time period based on solar irradiance input that is updated between consecutive runs of the optimisation model. Mayne et al. (2000) state that MPC is a form of control in which the current control action is obtained by solving a model for a finite horizon in multiple consecutive sampling instants. The output of a current model output is used as an input for the next instant. Garcia et al. (1989) states that MPC designs have the ability to yield high performance control systems capable of operating without expert intervention for long periods of time. When making a load schedule with day ahead linear programming optimisation, the input parameters could consist of forecasts of energy prices or solar irradiance. Because these forecasts are generally more accurate as the time for which is forecasted comes closer, a model predictive control approach could result in a better performance in comparison with a single day ahead load schedule.

2.3.3. Stochastic optimisation

When working with forecasts of energy demand, energy generation by PV systems or energy prices, there is some degree of variability due to possible inaccuracy forecasts of weather, energy demand or energy prices, which causes optimisation techniques to be not completely accurate. To be able to deal with variations in input parameters, stochastic optimisation is often introduced. In their paper, van der Linden et al. (2018) present a model to minimise operational costs and propose a stochastic optimisation method of an EV aggregator that models the uncertainty of the imbalance price, the reserve prices and the probability of acceptance and deployment of reserves. Their experimental evaluation shows that the proposed stochastic optimisation method results in lower costs than deterministic and quantity-only bid solutions. Four classes of load optimisation strategies are described in a two-part tutorial on stochastic optimisation in energy (Powell and Meisel, 2015a) (Powell and Meisel, 2015b). These classes are control theory, dynamic programming, stochastic programming and robust optimisation. They conclude in the first part that each of these classes may be best, depending on the optimisation problem. In the second part they propose a fifth hybrid policy that illustrates the ability to combine the strengths of multiple policy classes. Concluding, stochastic optimisation is a technique that can be used for load scheduling in smart energy settings to illustrate the stochastic nature of forecasts related to weather, demand or energy prices.

2.4. Literature review conclusion

Concluding from the literature study, load scheduling and measuring total energy costs is a suited approach to test the performance of integrated energy systems and load shifting is proved to be an effective demand response strategy. A requirement is the availability of dynamic tariffs for energy taken from the grid. Three techniques are reviewed for load scheduling in integrated energy systems. The main approach used in different load scheduling algorithms and demand planning is linear programming. It proves to be an inexpensive and powerful approach for day ahead load scheduling. Model predictive control and stochastic optimisation show potential for load scheduling with forecasts. These approaches are suited when optimising with a limited horizon forecast of e.g. imbalance prices.

3

Dutch electricity landscape & context

This chapter creates an overview of the electricity landscape and the context of this research. This research focuses on integrated energy systems in the Netherlands with a case study at Picnic. It is concluded that there is a requirement for dynamic grid tariffs. There are multiple ways to achieve this. Therefore, in this chapter, the Dutch electricity system will be explained as well as the markets on which electric energy is traded and the different actors who fulfil key roles in this system.

3.1. The Dutch power system

Generation is the first step in the electricity supply chain. Electricity is conventionally generated in steam generators fuelled by coal or gas but renewable energy sources are gaining a larger share in the energy mix. The energy is transported via a transmission network managed by Tennet. TenneT is the Dutch transmission company, or transmission system operator (TSO), controlled and owned by the Dutch government. It is TenneT's responsibility to balance the grid and prevent the Netherlands from power outages. They manage 110 kV, 150 kV, 220 kV and 380 kV AC grids and control interconnections with neighbouring countries. This is referred to as the high voltage grid and covers all of the Netherlands. Distribution in specific regions or among households is the responsibility of the distribution system operators (DSOs) and is done via distribution networks. They take care of transforming the high voltage to medium and low voltage of 230 V and distributes it to the consumer who applies a load to the grid. There are seven DSOs in the Netherlands who are each operational in a specific region: Rendo, Coteq, Liander, Enexis, Stedin, Westland and Enduris. Communicating energy demand by consumers with the TSO is managed by program responsible parties (PRPs). A PRP is a legal entity that manages at least one physical connection the the grid. The PRPs can bid supply as well as demand they are the party that correspond with TenneT. The supplying of energy is managed the the retail company. This party takes care of direct contact with the end user and manages the trading between the PRP and the end user. Figure 3.1 shows an illustration of the power system in the Netherlands with the different actors and physical systems.

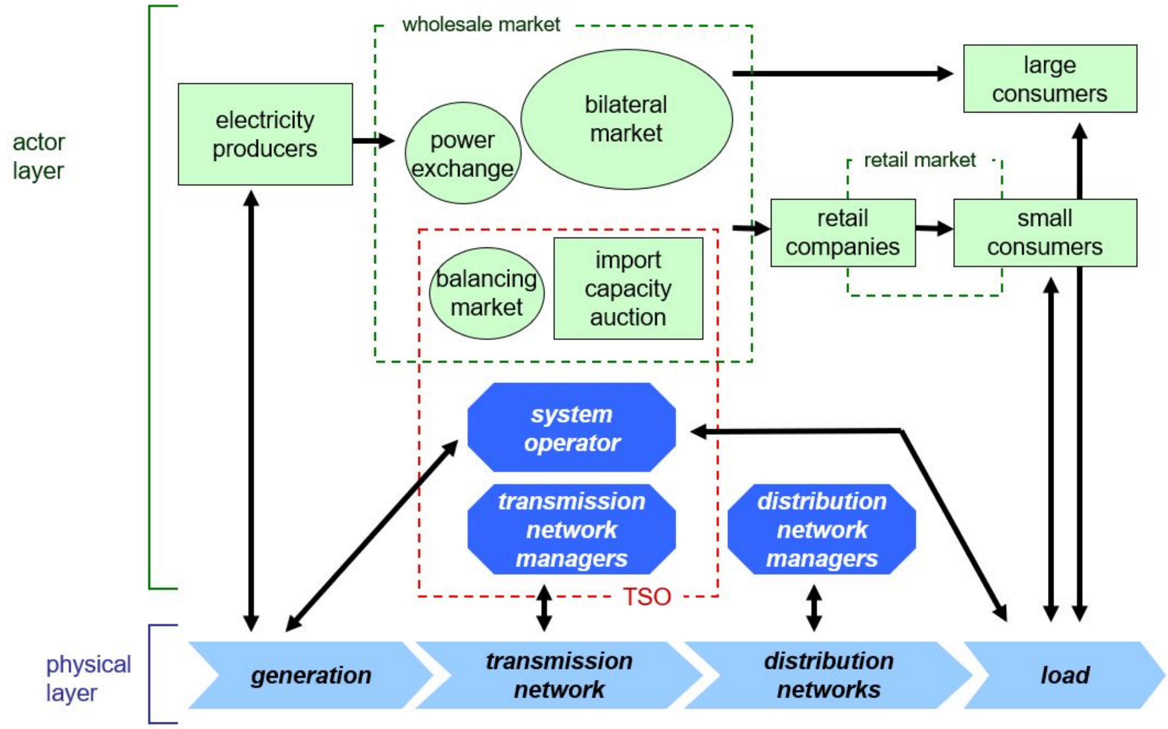

Figure 3.1: Representation of the Dutch power system (De Vries, 2018)

3.2. Wholesale markets

For the situation in the Netherlands, there are generally three main types of markets distinguished: the bilateral market, the power exchanges, and balancing markets. In these three segments there are different markets that are accessible to trade energy.

Bilateral market

On the bilateral market market bilateral contracts are traded. These are long term purchase agreements between energy producers and utility companies. Bilateral contracts are also referred to as power purchase agreements (PPAs). The majority of electricity is traded bilaterally between producers and industrial consumers or retail companies. The use of this construction reduces the investment risk of price changes. Most of these contracts have a duration not longer than 3 years but they can be as long as 10 years. These type of contracts are private, this means that it is hard to know the price that is agreed upon. Producers and consumers can avoid uncertainty of short term price variations. For the producer, these contracts reduce the risk of sudden low prices and for the consumer it reduces risk for sudden high prices.

Day ahead market

Most of the energy is traded on the day ahead market (DAM), this is a type of spot market and in the Netherlands the largest exchange is the European power exchange (EPEX), known as the EPEX SPOT. They also operate the markets in Germany, Austria, Luxembourg, France, the UK, Belgium and Switzerland. On the DAM, the market price is determined by pairing supply and demand bids with a method called market clearing. For every hour in one day a different price is determined. The market closes at noon the day before the concerning day. Since all bids are based on a prediction of supply or demand, deficits or surpluses in bids are not uncommon. These deviations are settled on the intraday market and the balancing market.

Intraday market
The intraday market has a similar structure as the day ahead market and trading also happens on the EPEX SPOT. The main difference is that energy is traded within the concerning day. Prices determined hourly via the same bidding structure and market clearing. The intraday market is not used as much as the DAM and is therefore not as liquid.

3.3. Balancing markets

When load profiles that are communicated by the PRP to TenneT are not fulfilled, the imbalance in the energy grid that arises is balanced with help of the different balancing markets.

The frequency containment reserve
The frequency containment reserve (FCR) is the first link in balancing the energy grid and is focused on keeping the frequency of the grid at 50 Hz. PRPs can submit bids for a certain power capacity, starting at 1 MW. The PRP is required to be able to activate the offered capacity within 30 seconds for at least 15 minutes. The PRPs are required to monitor the frequency themselves and act upon changes and document this and send it to TenneT. The contracted time for which a bid is selected is one week.

Automatic and manual frequency restoration reserve
The automatic frequency restoration reserve (aFRR) is designed to control substantial imbalances in the frequency of the energy grid. Bidding is done for time units of 15 minutes. There are two ways to participate in the aFRR. These are as a contracted bidder or on voluntary basis. With a contracted participation there is a contract compensation plus a compensation when you are requested to supply energy. Regulation takes place on voluntary basis, only when regulation takes place the bidder is compensated TenneT (2018). The manual frequency restoration reserve (mFRR) serves the same purpose as the aFRR but is activated in a later stadium and is manually controlled.

TenneT imbalance
Based on day ahead and intraday markets, load profiles are communicated by the program responsible party (PRP) to TenneT who balances the transmission grids with this information. The imbalance market is where deficits or surpluses of the initial bids are settled. Imbalance prices are determined by TenneT and are based the tariffs of the balancing services FCR, aFRR and mFRR.

3.4. Context conclusion

In order to create a financial incentive to apply demand response, dynamic grid tariffs need to be available. These tariffs need to be easily predictable to create a schedule up front. The different markets as decribed in this section are considered to act as a basis to create a schedule for the energy flows within an integrated energy system. Starting with the bilateral market, it is obvious that when prices are fixed for long periods of time there is no advantage to steer energy demand. Next, the day ahead market shows high potential to steer energy demand on. The prices differ every hour of the day and a forecast can be obtained of adequate quality. The intraday market has similar qualities except for the fact that the market liquidity in the Netherlands is deficient. When a bid is made on the day ahead market or intraday market, the deviation of this bid is settled on the imbalance market. The prices on this market differ every period of 15 minutes and are highly volatile. Negative prices, which mean that one receives a benefit when consuming energy, are not uncommon. These prices are based on costs that are made on the ancillary markets. To create a load schedule based on this market shows great potential due to the high volatility. However, to predict these prices is often problematic. Furthermore, the ancillary markets require a more involved bidding system. The FCR market is only accessible when providing services for a week. This would largely constrain daily operation of most assets. The aFRR seems to have potential. However, there are high fines involved with not complying with obligations regarding the bids. This is simply a too large risk for commercial company's that do not pursue these activities as their core business. The 1 month contract duration of mFRR markets are a direct limitation to the usability of this system.

Concluding from this analysis, because of the hourly different prices and the availability of price forecasts, the day ahead market is the most suitable trading platform for the scheduling of energy demand based on energy prices. Therefore, these market prices will be used as an input for the load scheduling model. Total costs from the energy grid will be minimised by shifting energy load. A perfect foresight of the day ahead prices is assumed in the model.

In order to make a bid on the day ahead market, there is the need of a PRP. In this case study, ENGIE takes up this role and communicates the load schedule of Picnic to TenneT. This research only considers the system design performance with the generation of a load schedule, the actual simulation of the application of the load schedule with the accompanying forecast errors and imbalance settlement is not covered in this research.

4
Methodology

In this section a methodology presented to find the optimal design of an integrated energy system in the Netherlands. No parameters are given a value so that the complete methodology can be replicated in further research with different data. Chapter 5 gives an overview of the input data used in this research.

A set of different system designs for an integrated energy system (IES) is proposed in which the presence of a photovoltaic (PV) system, an energy storage system (ESS) and the ability for optimised load scheduling for electric vehicle (EV) charging and a cold storage (CS) system load is varied. The energy flows between all system elements are determined by the load scheduling algorithm. The energy flows are controlled by an energy management system (EMS). A mixed integer linear programming (MILP) optimisation problem is designed to determine the load scheduling for the integrated energy system as well as the resulting performance for each system design in terms of average costs per unit of energy, taking into account investment costs. Figure 4.1 shows the system with all elements that are included in the IES. The arrows indicate the direction of energy flows.

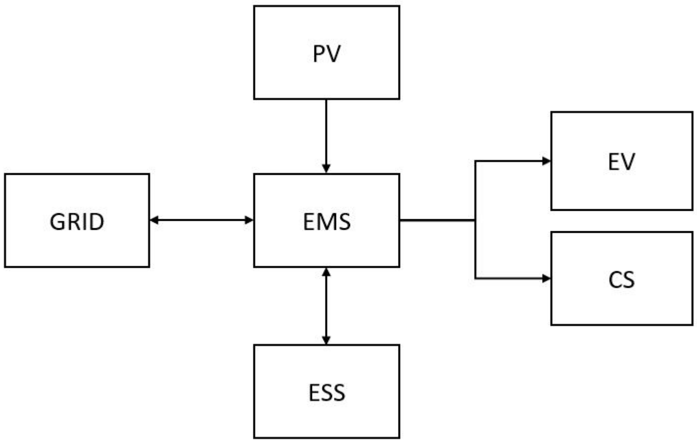

Figure 4.1: Schematic representation of the energy flows within an integrated energy system

4.1. System designs

For the experiments in this model, there are four elements of the system design selected that have two variations, present or absent. These are:

1. Smart charging
   EV smart charging is tested both optimised for costs and for a charging schedule that resembles the conventional charging schedule. Flexibility for smart charging is created by extending the end-time of the charging session.
2. CS load scheduling.
   The optimised CS load schedule is compared to the conventional cooling demand schedule. Flexibility is created by increasing the peak power of the CS system.
3. PV system
   The PV system is tested for both presence and absence in the integrated energy system.
4. ESS
   The presence and the absence of the energy storage system are included in the set of system designs.

All these variations result in a set of sixteen different system designs which are shown in Table 4.1.

Table 4.1: Set of system designs

System design	**EV**	**CS**	**PV**	**ESS**
1	EV	CS		
2	EV smart	CS		
3	EV	CS smart		
4	EV smart	CS smart		
5	EV	CS	PV	
6	EV smart	CS	PV	
7	EV	CS smart	PV	
8	EV smart	CS smart	PV	
9	EV	CS		ESS
10	EV smart	CS		ESS
11	EV	CS smart		ESS
12	EV smart	CS smart		ESS
13	EV	CS	PV	ESS
14	EV smart	CS	PV	ESS
15	EV	CS smart	PV	ESS
16	EV smart	CS smart	PV	ESS

For each system design the total costs of energy per day is determined with the load scheduling algorithm that is introduced in Section 4.2. From there, section 4.5 explains how the performance is determined for each system design in terms of levelised average costs per unit of energy.

4.2. Model design

The load scheduling for each element in the IES is determined with an optimisation problem that is solved using mixed integer linear programming. The optimisation problem in this research is based on a time period of 24 hours, starting at 00:00. This is modelled as such because EV have to be fully charged each day and day ahead prices are determined on daily basis. The model determines the daily load schedule for the grid connection, the fleet of EVs, CS system and ESS. Figure 4.2 provides a schematic representation of the solver. The output is modelled in such a way that the schedules can be used by the manager of the IES to control the energy use of the different assets. Resulting from the optimised load scheduling, the total cost of electricity is determined over the day. To anticipate on variations in terms of solar irradiation and energy price between days, the daily model is run for a series of days to find the cumulative result. How this is used to determine the performance of the different system designs is explained in Section 4.5.

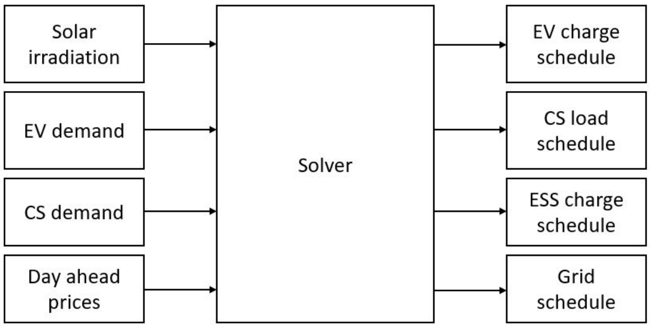

Figure 4.2: Schematic representation of the solver

4.3. Parameters and indices

The proposed model requires a number of input parameters and model parameters to determine the value of the decision variables. These parameters are described in this section.

4.3.1. Indices

To specify the different parameters, four indices are used to indicate the program time units (PTUs) within a day, the PTUs that are not available for EV charging, the day for which the model is run for and for each vehicle in the simulation. These indices are listed in Table 4.2 where t_{max} indicates the number of PTUs in a day, t_{end} indicates the last PTU of an EV charging session, d_{max} indicates the number of days in the experiment and n_{max} indicates the number of vehicles in the experiment.

Table 4.2: Indices for the mathematical formulation

Index	Definition	Values
t	PTU in day	$t \in T = \{1, 2, \dots, t_{max}\}$
t	PTU after end of charging session	$t \in T_{na} = \{t_{end} + 1, \dots, t_{max}\}$
d	Day	$d \in D = \{1, 2, \dots, d_{max}\}$
n	Vehicle	$n \in N = \{1, 2, \dots, n_{max}\}$

4.3.2. Decision variables

The optimisation model is designed to find the optimal value for four decision variables that are determined for each PTU in a day. These decision variables are listed below along with their upper and lower limit constraints.

- $E_t^G \quad \forall t \in T$ Energy flow from the grid [kWh]
  These continuous decision variables represents the energy consumed from the grid connection per time interval. This is all the energy that is consumed minus the energy that is locally generated and drawn from the energy storage system. Constraints 4.1 show the minimum and maximum of the decision variable.

$$E_{min}^G \leq E_t^G \leq E_{max}^G \qquad \forall t \in T \tag{4.1}$$

- $b_{n,t}^{EV} \quad \forall n \in N, \forall t \in T$ EV charging [binary]
  These binary decision variables represent whether EV n during PTU t is charging or not. Constraints 4.2 show the binary values of the decision variables.

$$b_{n,t}^{EV} = \begin{cases} 1, & \text{if EV } n \text{ is charging during PTU } t \\ 0, & \text{otherwise} \end{cases} \qquad \forall n \in N \qquad \forall t \in T \tag{4.2}$$

- $E_t^{CS} \quad \forall t \in T$ Energy flow Cold storage [kWh]
  These continuous decision variables represent the energy that is used by the cold storage system during PTU t to meet the daily CS demand. Constraints 4.3 show the upper and lower limits of the decision variables.

$$E_{min}^{CS} \leq E_t^{CS} \leq E_{max}^{CS} \qquad \forall t \in T \tag{4.3}$$

- $E_t^{ESS} \quad \forall t \in T$ Energy flow of energy storage system [kWh]
  These continuous decision variables represent the energy drawn from or consumed by the energy storage system during PTU t. Constraints 4.4 show the upper and lower limits of the decision variables.

$$E_{min}^{ESS} \leq E_t^{ESS} \leq E_{max}^{ESS} \qquad \forall t \in T \tag{4.4}$$

4.3.3. Input parameters

The four sets of input parameters that are used to solve the optimisation problem are listed below.

- $\hat{p}_t \quad \forall t \in T$ Energy price forecast [€/kWh]
  These input parameters represent the forecasted prices per kilowatt hour for each PTU.
- $\hat{E}_t^{irr} \quad \forall t \in T$ Solar irradiance forecast [kWh/m^2]
  These input parameters represent the solar irradiance forecast that is used to determine the energy generation of the PV system during each PTU.

- $\hat{E}_n^{EVd}$ $\forall n \in N$ EV demand forecast [kWh]
  These input parameters represent the daily forecasted energy demand for each EV in the fleet.
- $\hat{E}^{CSd}$ CS demand forecast [kWh]
  This input parameter represents the daily forecasted demand of the cold storage system.

4.3.4. Model parameters

The supplementary parameters that are required for the model are described below.

- P^{EV} EV charging rate [kW]
  The charging rate determines the charging power of the EVs and is fixed.
- L^{PTU} Length of one PTU [h]
- E^{EV} EV energy charged in a single PTU [kWh]
  The energy charged during a PTU is equal to the charging power and the length of one PTU. Equation 4.5 shows that the energy charged during a single PTU is equal to the power times the length of a PTU.

$$E^{EV} = P^{EV} \cdot L^{PTU} \tag{4.5}$$

- C^{ESS} Capacity energy storage system [kWh]
  This is the capacity of the energy storage system.
- SOC_0^{ESS} Initial SOC of energy storage system at $t = 0$ [%]
  The state of charge (SOC) of the energy storage system at the beginning of a day.
- A^{PV} Surface PV [m^2]
  This is the total surface that is used for the PV system.
- η^{PV} PV efficiency [%]
  This is the percentage of energy that is converted from the irradiation to electric energy.
- $\hat{E}_t^{PV}$ PV system energy generation [kWh] This parameter represents the energy that is generated by the PV system and is equal to the product of the solar irradiation energy, the surface of the PV system and the system efficiency as represented by Equation 4.6.

$$\hat{E}_t^{PV} = \hat{E}_t^{irr} \cdot A^{PV} \cdot \eta^{PV} \qquad \forall t \in T \tag{4.6}$$

- P_{max}^{CS} Cold storage system maximum power [kW]
  This parameter represents the maximum power drawn by the CS system.
- E_{max}^{CS} Cold storage system max energy during a PTU [kWh]
  This parameter represents the maximum energy drawn by the CS system during one PTU and is defined by Equation 4.7

$$E_{max}^{CS} = P_{max}^{CS} \cdot L^{PTU} \tag{4.7}$$

4.4. Optimisation problem

The optimisation problem is represented as an objective function with a set of constraints.

4.4.1. Objective function

The objective Function 4.8 minimises the cost paid for energy from the electricity grid during a single day.

$$\min \sum_{t=1}^{t_{max}} \hat{p}_t \cdot E_t^G \tag{4.8}$$

The help Functions 4.9 state that the energy taken from the grid is equal to the sum of the energy demand of the EVs, the cooling system and the ESS minus the PV system during each PTU.

$$E_t^G = \Big(\sum_{n=1}^{n_{max}} b_{t,n}^{EV}\Big) \cdot E^{EV} + E_t^{CS} + E_t^{ESS} - E_t^{PV} \qquad \forall t \in T \tag{4.9}$$

4.4.2. Constraints

Constraints 4.10 ensure that the sum of energy charged during each PTU meets the daily energy demand. Since it is not always the case that the daily demand has no remainder when it is divided by the amount of PTU's needed to meet this demand, the sign used is *greater or equal* to make sure there is a feasible solution. A condition accompanying this modelling choice is that there should be no negative prices so there is no incentive to charge the EV further than the minimum demand.

$$\sum_{t=1}^{t_{max}} b_{t,n}^{EV} \cdot E^{EV} \geq E_n^{EVd} \qquad \forall n \in N \tag{4.10}$$

Constraints 4.11 state that for each EV, there is a time period where the EV is out driving so it is not connected to the charger and cannot be charged.

$$b_{t,n}^{EV} = 0 \qquad \forall n \in N \qquad \forall t \in T_{na} \tag{4.11}$$

Constraint 4.12 makes sure that sum of the energy supplied each time unit to the CS system is equal to the daily cooling demand.

$$\sum_{t=1}^{t_{max}} E_t^{CS} = E^{CSd} \tag{4.12}$$

Constraints 4.13 make sure that the SOC of the ESS for each PTU are equal to the sum of the SOC during the precedent PTU and the energy delta during that PTU.

$$SOC_t^{ESS} \cdot C^{ESS} = SOC_{t-1}^{ESS} \cdot C^{ESS} + E_t^{ESS} \qquad \forall t \in T \tag{4.13}$$

Constraints 4.14 state the minimum and maximum SOC percentages of the ESS.

$$SOC_{min}^{ESS} \leq SOC_t^{ESS} \leq SOC_{max}^{ESS} \qquad \forall t \in T \tag{4.14}$$

Constraint 4.15 makes sure that the energy storage systems initial SOC is equal to the SOC at the end of the day.

$$SOC_0^{ESS} = SOC_{t_{max}}^{ESS} \tag{4.15}$$

4.5. System performance

Section 4.4 introduces the optimisation problem which is used for finding the load schedule that minimises the objective value; the total energy costs per day. To assess the system design performance, this optimisation is carried out for a series of days and the cumulative objective values of each day are divided by the total energy used by the two energy consuming assets; EV fleet and the cold storage system. Equation 4.16 shows the calculation for the energy costs (EC).

$$EC = \frac{\sum_{d=1}^{d_{max}} \sum_{t=1}^{t_{max}} (\hat{p}_{t,d} \cdot \hat{E}_{t,d}^{G})}{\sum_{d=1}^{d_{max}} \sum_{t=1}^{t_{max}} (\hat{E}_{t,d}^{EV} + \hat{E}_{t,d}^{CS})} \tag{4.16}$$

The presence of a PV system and an ESS require investment costs. The costs to control the system and apply the load scheduling are assumed to be negligible. Therefore, to determine the levelised energy costs (LEC), only the investment costs are taken into account. The ESS and PV system are are assumed to have a certain lifetime, respectively indicated by l^{ESS} and l^{PV}, by which the payment of the capital expenditures, respectively $CAPEX^{ESS}$ and $CAPEX^{PV}$, are divided. The amount of days in this equation is assumed to be 365, equal to one year. The lifetimes are expressed in years. Equation 4.17 shows the calculation of the LEC.

$$LEC = \frac{\sum_{d=1}^{d_{max}} \sum_{t=1}^{t_{max}} (\hat{p}_{t,d} \cdot \hat{E}_{t,d}^{G}) + \frac{CAPEX^{ESS}}{l^{ESS}} + \frac{CAPEX^{PV}}{l^{PV}}}{\sum_{d=1}^{d_{max}} \sum_{t=1}^{t_{max}} (\hat{E}_{t,d}^{EV} + \hat{E}_{t,d}^{CS})} \tag{4.17}$$

Both metrics are used to determine the performance of the proposed set of system designs.

4.6. Sensitivity analysis

In order to determine the robustness of the optimisation model, a sensitivity analysis is carried out. For the sensitivity analysis of the model that is proposed in this research, the effect of changing different parameters is tested. Parameters that actively constrain the outcome of the model are assumed to have a significant effect on the system design performance; the EC and the LEC. In order to test the effect of changing these parameters, they are changed to become smaller and larger and are respectively compared to the change in performance. The relation between these percentages give an indication of the sensitivity of that specific parameter. The parameters that are tested in this research are listed in Section 6.3.

5

Data

This chapter documents the data that is used for the experiments carried out in this research. The case at Picnic is used as motivation for most parameter values. All motivations are argued in this chapter.

5.1. Picnic test location: distribution hub Zaandam

The location where Picnic will carry out the different test for smart energy use will be the distribution hub in the city of Zaandam. The reason why this location is chosen is because the roof strength is high enough to support the installation of a PV system, there is a good cooperation with the owner of whom Picnic rents the building and because the electricity infrastructure is installed in such a way that is easily altered for new systems that might be required for smart energy use. At the hub there are 9 EVs in operation that on average use 9 kWh per day each and a cool cell is installed to cool cold products that have arrived from the fulfilment centres and are waiting to be delivered to the customer the same day. This cool cell uses 96 kWh per day on average. The size of the PV system according to the project plan is 300 square meters and the capacity of the ESS is 500 kWh. The grid connection has a capacity of 80 kW. These values are used as initial parameters for the experiments of this research.

5.2. Input parameter datasets

In contrast to the model parameters that are fixed for each optimisation, the input parameters can change every PTU during the optimisation. In the experiments in this research a perfect forecast is assumed of hourly day ahead energy prices and hourly solar irradiance. Also, the energy demand of both the EV fleet and the cold storage system is assumed to be known in advance. In these experiments, the daily load of the EVs and the CS system is assumed to be constant every day, however the model allows to have varying data per day and per individual EV. The data that is used for the input parameters is listed below.

- **Energy price**
  For the input of the energy prices, the historic hourly day ahead prices from the year 2018 as

traded on the EPEX SPOT market platform are used as input (ENTSO-E, 2019). In the experiments in this research a perfect foresight of energy prices is assumed to create the load schedules.

- **Solar irradiation**
  The historic solar irradiation data of the year 2018 of the KNMI weather station in Schiphol is used as an input (KNMI, 2019). A perfect foresight of these data is assumed for the model.
- **Cooling demand**
  Based on average data by Picnic, the CS system demand in this research is assumed to be 96 kWh per day and constant throughout the year.
- **EV demand**
  At Picnic, an average of 75% of a 12 kWh battery capacity is assumed to be demanded for trips every day, thus 9 kWh per EV per day.

5.3. System design parameters

Table 4.1 shows the different system designs that are proposed to compare their performance. Below, the values are described that characterise the different system designs. Three experiment setups are proposed, case A represents the case as introduced in the Picnic case. Case B and case C are respectively a twice as small and twice as large setup of the PV system surface and ESS capacity. The values for case A are described below. Tables 5.1, 5.2 and 5.3 show the system design parameters for case A, B and C respectively.

1. *'EV & EV smart'*

   Smart charging and regular charging is distinguished by changing the length of the charging session. Two options are tested: 4:15 ($t = 17$) or 14:00 ($t = 56$). The optimisation and the start of the charging sessions of the EVs start at 00:00. In 4:15 hours the EV meets it's energy demand. Therefore this test has no flexibility and represents charging according the standard charging schedule. At 14:00, the EVs leave to drive their trips, this time indicates the length of the charging session with flexibility; *'EV smart'*.

$$t_{end} = \begin{cases} 17, & \text{Normal charge schedule} \\ 56, & \text{Optimise charge schedule} \end{cases}$$

2. *'CS & CS smart'*

   For the cold storage unit, the demand is 96 kWh. To test smart and non-smart energy use the maximum cooling power is changed from 4 kW for non-smart and 16 kW for smart energy use. Which results in maximum energy during one PTU of 1 and 4 kWh respectively.

$$E^{CS}_{max} = \begin{cases} 1kWh, & \text{Normal cooling schedule} \\ 4kWh, & \text{Flexible cooling schedule} \end{cases}$$

3. *'PV'* For the PV system, the base system is 300 square meters. The absence and presence of this system are tested in the system designs.

$$A^{PV} = \begin{cases} 0m^2, & \text{No PV system} \\ 300m^2, & \text{PV system} \end{cases}$$

4. *'ESS'* For the ESS, the base system has a capacity of 500 kWh. The absence and presence of this system are tested in the system designs.

$$C^{ESS} = \begin{cases} 0kWh, & \text{No ESS} \\ 500kWh, & \text{ESS} \end{cases}$$

5.3.1. Case A

Concluding from these parameter values, for case A, Table 4.1 translates into Table 5.1 as shown below.

Table 5.1: Case A set of system designs

System design	$t_{end}[\#]$	$E^{CS}_{max}[kWh]$	$A^{PV}[m^2]$	$C^{ESS}[kWh]$
1	17	1	0	0
2	56	1	0	0
3	17	4	0	0
4	56	4	0	0
5	17	1	300	0
6	56	1	300	0
7	17	4	300	0
8	56	4	300	0
9	17	1	0	500
10	56	1	0	500
11	17	4	0	500
12	56	4	0	500
13	17	1	300	500
14	56	1	300	500
15	17	4	300	500
16	56	4	300	500

5.3.2. Case B

Table 5.2: Case B set of system designs

System design	$t_{end}[\#]$	$E^{CS}_{max}[kWh]$	$A^{PV}[m^2]$	$C^{ESS}[kWh]$
1	17	1	0	0
2	56	1	0	0
3	17	4	0	0
4	56	4	0	0
5	17	1	150	0
6	56	1	150	0
7	17	4	150	0
8	56	4	150	0
9	17	1	0	250
10	56	1	0	250
11	17	4	0	250
12	56	4	0	250
13	17	1	150	250
14	56	1	150	250
15	17	4	150	250
16	56	4	150	250

5.3.3. Case C

Table 5.3: Case C set of system designs

System design	$t_{end}[\#]$	$E^{CS}_{max}[kWh]$	$A^{PV}[m^2]$	$C^{ESS}[kWh]$
1	17	1	0	0
2	56	1	0	0
3	17	4	0	0
4	56	4	0	0
5	17	1	600	0
6	56	1	600	0
7	17	4	600	0
8	56	4	600	0
9	17	1	0	1000
10	56	1	0	1000
11	17	4	0	1000
12	56	4	0	1000
13	17	1	600	1000
14	56	1	600	1000
15	17	4	600	1000
16	56	4	600	1000

5.4. Model parameter data

This section discussed the assumptions that underlie the input parameters of the model in the experiments.

- **Efficiency of PV system**
  The efficiency with which the PV system converts solar irradation to energy is assumed to be 15%.

- **Surface PV system**
  The surface of the PV system is assumed to be 300 square meters, based on specifications of the project requirements.

- **Capacity ESS**
  The capacity of the ESS is 500 kWh based on the project specifications at picnic.

- **CAPEX ESS**
  The CAPEX of the ESS are assumed to be €200 per kWh capacity as provided by the project specifications.

- **CAPEX PV system**
  The CAPEX of the PV system are assumed to be €150 per square meter as provided by project specifications.

- **Number of days in test**
  The number of days in the experiments for determining the EC and LEC is 365, representing the whole year 2018.

- **Energy demand per day CS system**
  The energy demand per day by the CS system is assumed to be 96 kWh based on average consumption by Picnic.

- **EV charge rate**
  The charging rate is assumed to be 2.2 kW, derived from specifications of the Picnic vehicles. Figure 5.1 shows a charging curve of one EV measured on the 9th of January 2019. The shape closely resembles a square charging curve. The manufacturer specifies a peak charging power of 2.2 kW while the actual peak power is slightly less. When the charging cycle ends a small inaccuracy is seen and for the time the EV plugged in there is a small power measured of a few watts. Figure 5.2 shows the assumption of a perfect square charging shape that is used in this research with a constant charging power of 2.2 kW.

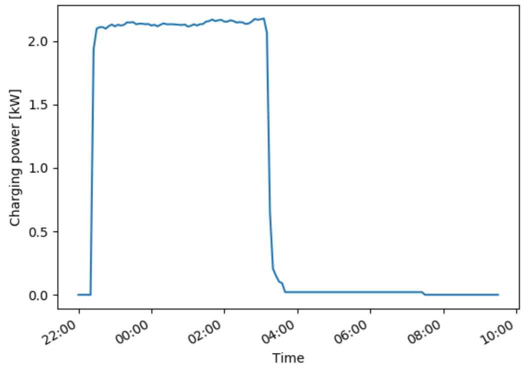

Figure 5.1: Actual charging curve of a single EV

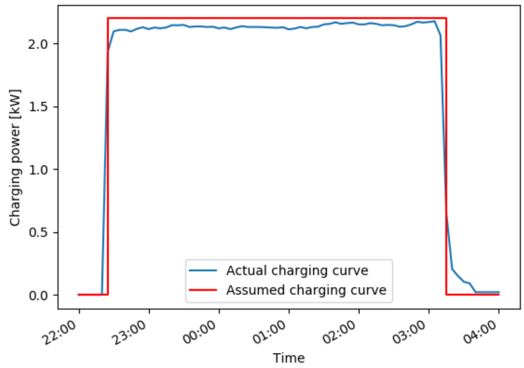

Figure 5.2: Actual and assumed charging curve of a single EV

- **Energy per PTU charged to EV**
  The charging power is 2.2 kW, a PTU has a length of 15 minutes. The energy per PTU is therefore 0.55 kWh.
- **Energy demand per day for single EV**
  The energy demand for each EV is 9 kWh per day.
- **Lifetime ESS**
  The lifetime of the ESS is assumed to be 10 years as provided by the project specifications.
- **Lifetime PV system**
  The lifetime of the PV system is assumed to be 25 years as provided by the project specifications.
- **Length of PTU**
  The length of the program time units is 00:15 hours.
- **Number of EVs**
  The number of EVs in the experiments in this research is assumed to be 9, the same number of EVs in the test location hub in Zaandam.
- **ESS (dis)charge rate**
  The discharge and charge rate of the ESS are set to 1 C, meaning that it can (dis)charge with one kW per kWh of capacity.
- **Grid connection maximum and minimum**
  As provided by the specifications of the Picnic test location in Zaandam the grid connection allows a limit of 80 kW to be consumed or fed into the grid.
- **CS system maximum power**
  In this research the maximum power assumed is 16 kW. This creates high flexibility. For the scenario of low flexibility, 4 kW is assumed.
- **Energy storage system initial SOC**
  The ESS is assumed to have a SOC of 50% at the beginning of the optimised day and will end up with with the same SOC at the end of the day.

- **ESS max SOC**
  The maximum SOC of the ESS is set to 100%.
- **ESS min SOC**
  The minimum SOC of the ESS is set to 0%.
- **EV charging session end**
  For the daily cost optimisation is assumed that EVs are connected to the chargers from 00:00 till 14:00.
- **Number of PTUs in experiment**
  Since a PTU is 00:15 hours, there are 96 PTUs in one day.

The parameters are summarised in Table 5.4

Table 5.4: Parameter assumptions

symbol	Assumptions	Value
η^{PV}	Efficiency PV system	15 %
A^{PV}	Surface PV system	300 m^2
C^{ESS}	Capacity energy storage system	500 kWh
$CAPEX^{ESS}$	Capital expenditures of ESS	€150 $\cdot C^{ESS}$
$CAPEX^{PV}$	Capital expenditures of PV system	€200 $\cdot A^{PV}$
d_{max}	Number of days in test	365
E^{CSd}	Energy demand per day for cooling system	96 kWh
E^{CS}_{max}	Maximum energy per PTU	1, 4 kWh
E^{EV}	Energy per PTU charged to EV	0.55 kWh
E^{EVd}	Energy demand per day for single EV	9 kWh
l^{ESS}	Lifetime ESS	10 years
l^{PV}	Lifetime of PV system	25 years
L^{PTU}	Length of PTU	00:15 h
n_{max}	Number of EVs	9
P^{ESS}	ESS (dis)charge rate	500 kW
P^{EV}	EV charge rate	2.2 kW
P^{G}_{max}	Grid connection maximum	80 kW
P^{CS}_{max}	Cooling max power	4 kW, 16 kW
P^{G}_{min}	Grid connection minimum	-80 kW
SOC^{ESS}_{0}	Energy storage system initial SOC	50%
SOC^{ESS}_{max}	Energy storage system maximum SOC	100%
SOC^{ESS}_{min}	Energy storage system minimum SOC	0%
t_{end}	EV charging session end	17, 56
t_{max}	Number of PTU's in experiments	96

6 Results and discussion

This chapter documents the results for the sixteen different system designs that are tested for the year 2018. To create an understanding of how the model works, the first section gives a detailed overview of the load schedules for a single day. The second section gives the results of the performance analysis for the system designs for case A, B and C and the third section discusses the sensitivity analysis.

6.1. Load scheduling demonstration for a single day

This subsection gives a detailed overview of the behaviour of the optimisation model for a single day. The sytem is run for 1 January 2018, all figures show the outcome for this date. The optimised results are based on *system design 16*, *case A*, as described in Table 5.1. Smart charging and optimised CS system schedules are also compared to conventional load schedules.

6.1.1. Hourly energy price data

The model proposed in this research optimises on basis of day ahead prices. Figure 6.1 shows the hourly day ahead prices within one day. It can be observed that there is large variation between prices for different hours. There is a peak during noon and prices are lower during the night and early morning. It is expected that the load scheduling will follow these variations and will schedule loads on times where prices are relatively low.

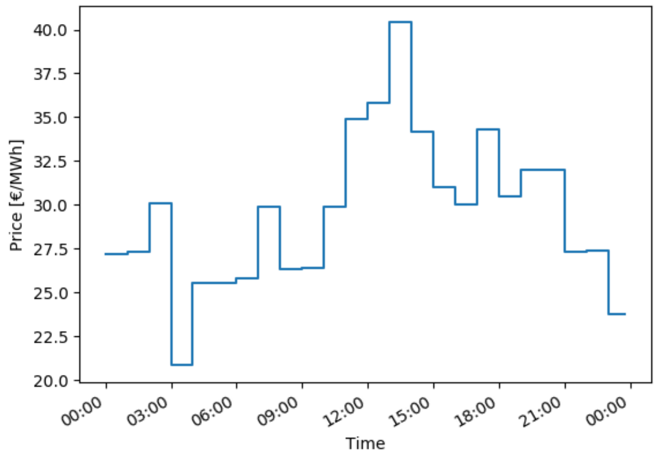

Figure 6.1: Hourly day ahead prices 01-01-2018

6.1.2. Power output of PV system

The power generated by the PV system is used as input for the optimisation as is shown in Figure 6.2. This data clearly shows a typical solar bell curve for the output of the PV system, apparent between roughly 9:00 and 17:00; a short day with low maximum power output, which is expected during the winter season.

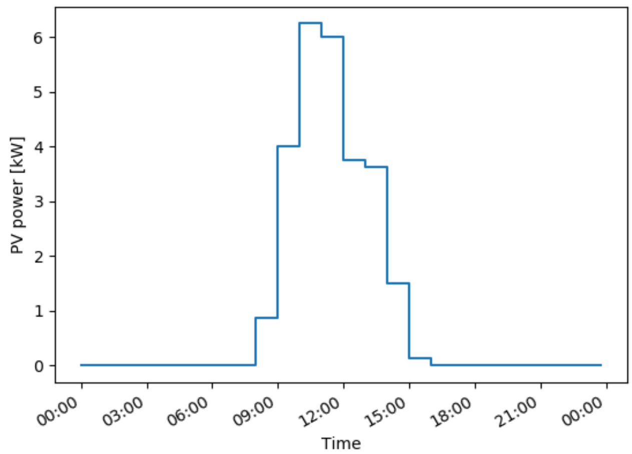

Figure 6.2: Power output by PV system 01-01-2018

6.1.3. EV charge schedule

In Figure 6.3 the normal charging curve is shown for a single EV, considering no flexibility or optimised scheduling as in *system design 1*. Figure 6.4 shows the optimised charging schedule for a single EV as in *system design 16*. It shows that the optimised charging schedule does not charge during T_{na} and avoids high prices during the middle of the day as depicted by Figure 6.1, as expected.

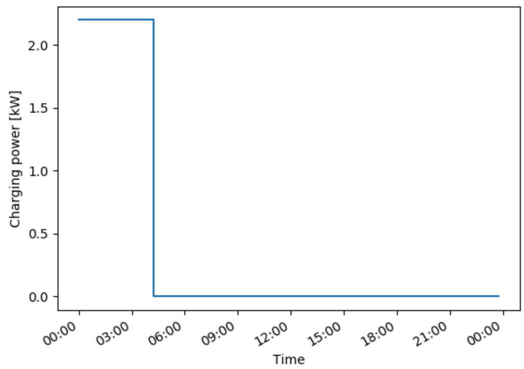

Figure 6.3: Charging curve for a single EV 01-01-2018

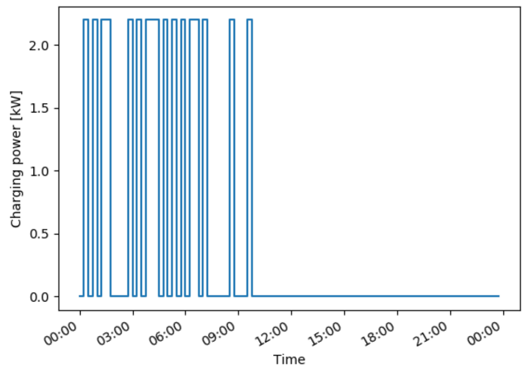

Figure 6.4: Optimised charging curved for a Single EV 01-01-2018

Adding the charging curves for the fleet of 9 EVs together results in Figure 6.5 and 6.6. Showing the cumulative charging curve of the fleet for conventional charging and optimised charging respectively. It is noticed that not all charging curves are the same which would be expected because no constraint is inhibiting simultaneous charging. It is also noticed that at no time all EVs are charging at the same time while there is no constraint limiting this. Both observations can be explained by the presence of an energy storage system which uses its flexibility in such a way that the charging of EVs make no difference because the grid capacity limits the use of available flexibility. In *system design 2* where there is no ESS, all EV charging curves have the same shape.

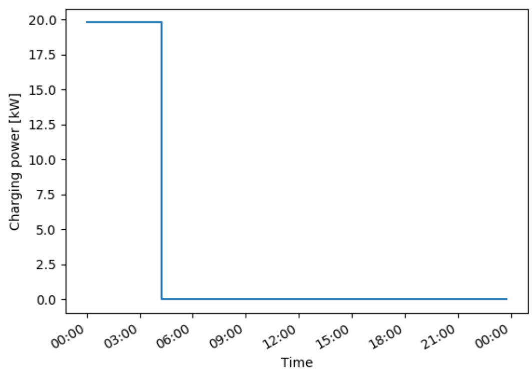

Figure 6.5: Conventional cumulative charging curve for a fleet of 9 EVs 01-01-2018

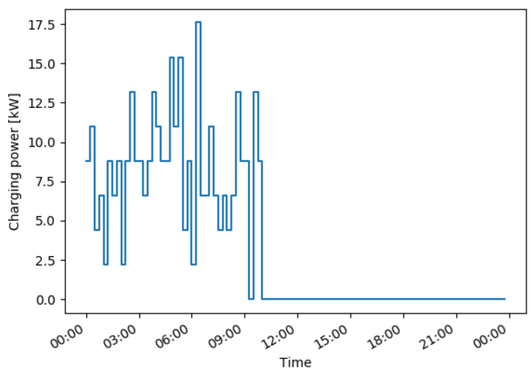

Figure 6.6: Optimised cumulative charging curve for a fleet of 9 EVs in *system design 16* including an ESS 01-01-2018

6.1.4. Cold storage system load schedule

Figure 6.7 shows the assumed normal power curve of the cold storage system and Figure 6.8 shows the optimised energy consumption curve for the CS system. Alike the EV charging schedule, the cold storage schedule avoids the high prices during the afternoon. A consequence of this schedule could be that the temperature would rise significantly during noon and evening since it is not active during that period.

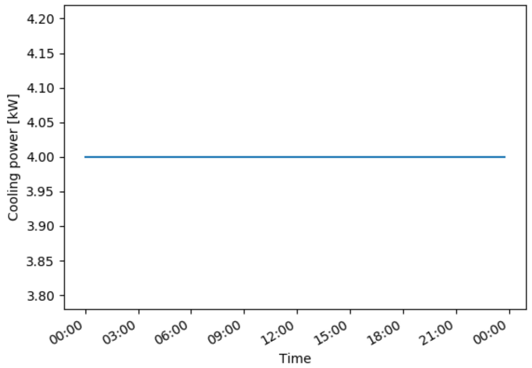

Figure 6.7: Normal CS system load schedule 01-01-2018

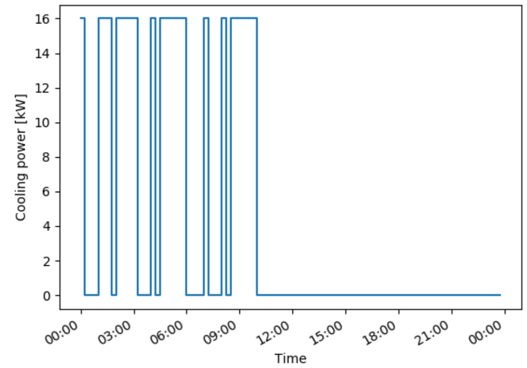

Figure 6.8: Optimised CS system load schedule 01-01-2018

6.1.5. Energy storage system (dis)charge schedule

The charge and discharge power for the energy storage system is shown in Figure 6.9. Positive values increase the SOC of the ESS and negative values decrease the SOC. The resulting state of charge is shown in Figure 6.10. The full capacity of the energy storage system is used, it reaches it's upper capacity twice and is fully discharged at once. It is observed that the ESS is continuously charging and discharging and is discharging energy during the afternoon. The system is feeding energy to the grid at these moments because prices are high.

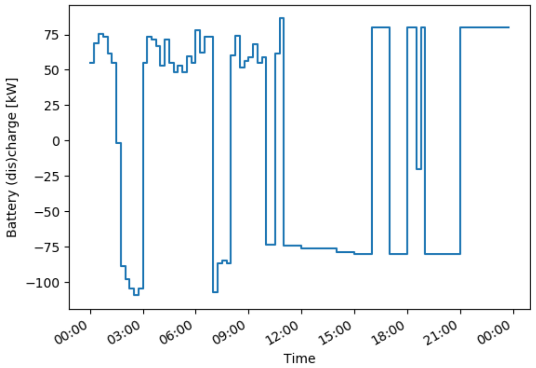

Figure 6.9: The (dis)charge of the energy storage system 01-01-2018

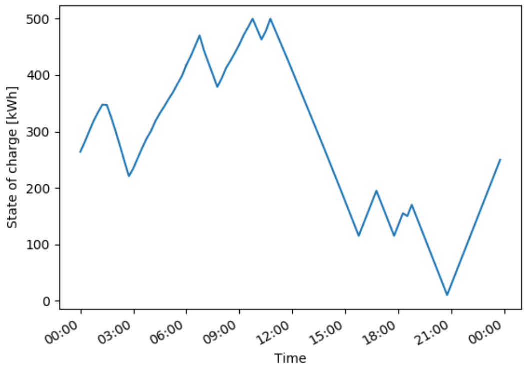

Figure 6.10: The state of charge of energy storage system 01-01-2018

6.1.6. Grid connection

The total energy taken from and fed into the energy grid is shown in Figure 6.11. It is noticed that at nearly all times the system is reaching it's constraints of 80 and -80 kW. This indicates that these are active constraints. When comparing the energy consumption to the energy prices it shows that when prices are high the system feeds energy back to the grid while when energy prices are lower the energy is taken from the grid. This is only possible when the system includes an ESS. With systems that include a PV system, the system shows that energy is fed back in the grid when energy prices are high. When there are no PV or ESS systems included, the system designs do not feed energy back in the grid.

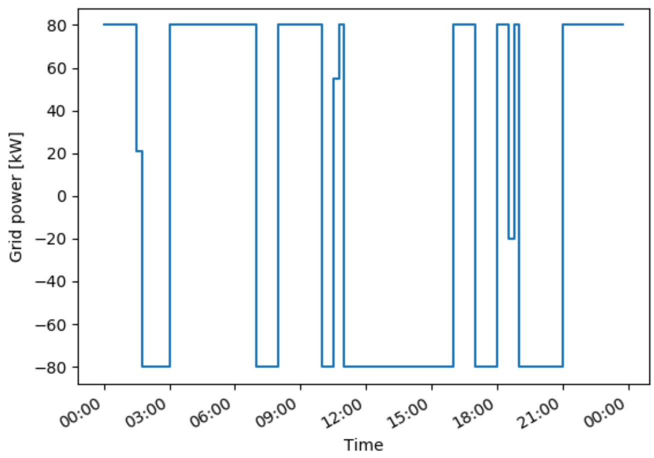

Figure 6.11: Total consumption from and fed into the energy grid 01-01-2018

Concluding from this section, the proposed model seems to work like expected. It is noticed that the grid connection is an important constraint, limiting the power that is drawn to and fed into the energy grid. This is the case because the battery system is 'buying' energy cheap and 'selling' it back when prices are higher, making money in the process. The presence of an ESS limits the benefits of smart charging and optimised CS load scheduling.

6.2. System design performance

This section shows the performance of the set of system designs for case A, B and C.

6.2.1. Case A system design performance

Case A includes 300 square meter for the PV system and 500 kWh as capacity for the ESS, this is the case as provided by the project specifications of the case study. Table 6.1 shows the performance per system design. The EC as well as the LEC for each system design are shown. Figure 6.12 gives a graphical representation of the results. Blue bars and brown bars indicate the EC, orange bars indicate the LEC and the orange and brown bars together represent the CAPEX for each system design. The lowest EC are found for *system design 16*. The lowest LEC and therefore the most preferred system design in terms of costs are found for *system design 8*.

The system design overview shows the impact of smart charging, smart cooling, presence of a PV system and presence of an energy storage system. For each pair of smart charging and non-smart charging system designs, smart charging is more cost reducing than non-smart charging. By an order of around one euro per MWh. This difference becomes smaller when introducing an energy storage system, where the difference is only a few cents. This can be explained by the fact that the flexibility capacity of the storage system greatly exceeds the flexibility of the EV fleet and the limitations of the grid capacity make smart charging obsolete.

The difference between optimised CS load scheduling and conventional CS energy consumption is more significantly in terms of cost reduction. The order of reduction is around 5 euro's compared to conventional cooling. It can be stated that optimised CS load scheduling is beneficial. Simliar to smart charging, the performance of optimised CS energy use is less significant when an ESS is introduced.

The introduction of a PV system is obviously reducing EC significantly. But also, the LEC of system designs with a PV system shows an improvement with respect to all situations without PV. This means that the current payback of the PV weigh up against the investment costs.

What is noticed instantly is that the ESS performs best in terms of EC due to selling and buying of energy. However, the investment costs of the ESS make the LEC the highest for all scenario's including ESS.

Concluding from this analysis, the introduction of optimised charging of the EV fleet and optimised CS load scheduling is recommended as long as there is no energy storage system present. The PV system is recommended since it returns a positive performance. The ESS does return the best EC however it is not recommended since the profits do not weigh up against the investment costs.

Table 6.1: Case A system design performance

System design	EC	LEC
1	€ 47.35	€ 47.35
2	€ 46.46	€ 46.46
3	€ 40.84	€ 40.84
4	€ 39.95	€ 39.95
5	€ 4.87	€ 32.24
6	€ 3.97	€ 31.35
7	€ -1.65	€ 25.73
8	€ -2.54	€ 24.84
9	€ -23.97	€ 77.41
10	€ -24.03	€ 77.36
11	€ -27.76	€ 73.62
12	€ -27.80	€ 73.59
13	€ -64.99	€ 63.77
14	€ -65.07	€ 63.69
15	€ -68.54	€ 60.22
16	€ -68.60	€ 60.16

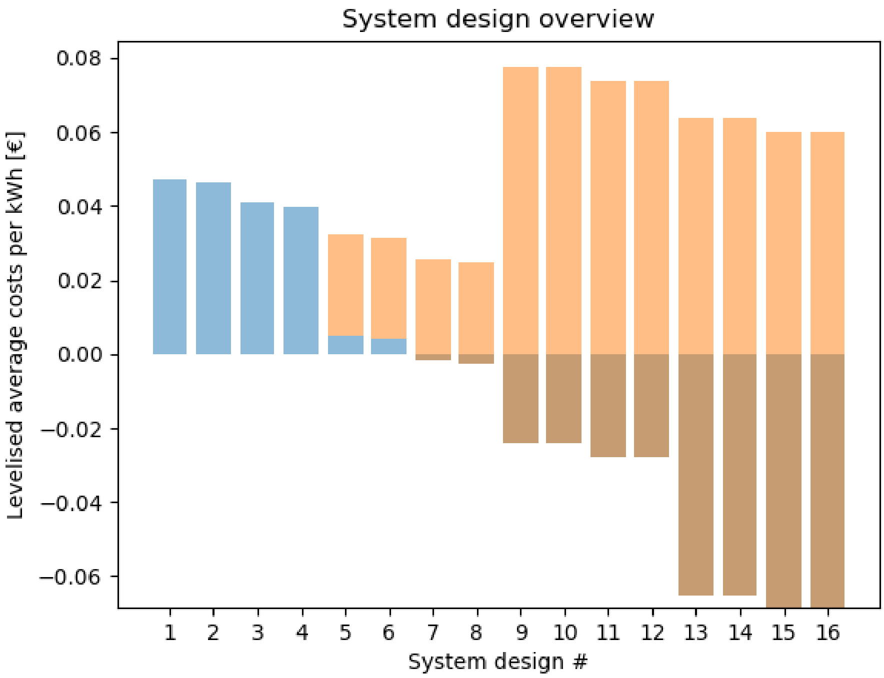

Figure 6.12: Case A system design performance

6.2.2. Case B system design performance

Case B uses 150 square meter for the PV system and 250 kWh as capacity for the ESS, this represents half the capacity as provided by the project specifications of the case study. Table 6.2 shows the performance per system design. The EC as well as the LEC for each system design are shown. Figure 6.13 gives a graphical representation of the results. Blue bars and brown bars indicate the EC, orange bars indicate the LEC and the orange and brown bars together represent the CAPEX for each system design. The lowest EC are found for *system design 16*. The lowest LEC and therefore the most preferred system design in terms of costs are found for *system design 16* as well.

The difference can be explained by the grid connection that is the same size and was limiting the performance of the ESS in case A. Because the performance of the ESS in comparison to its capacity is higher in case B, the LES turns out to be the most preferred. It is concluded that an ESS is recommended with a smaller capacity.

Table 6.2: Case B system design performance

System design	EC	LEC
1	€ 47.35	€ 47.35
2	€ 46.46	€ 46.46
3	€ 40.84	€ 40.84
4	€ 39.95	€ 39.95
5	€ 26.11	€ 39.80
6	€ 25.22	€ 38.90
7	€ 19.60	€ 33.28
8	€ 18.71	€ 32.39
9	€ -6.79	€ 43.90
10	€ -7.08	€ 43.62
11	€ -11.86	€ 38.83
12	€ -12.07	€ 38.62
13	€ -27.76	€ 36.62
14	€ -28.07	€ 36.31
15	€ -32.75	€ 31.63
16	€ -32.99	€ 31.39

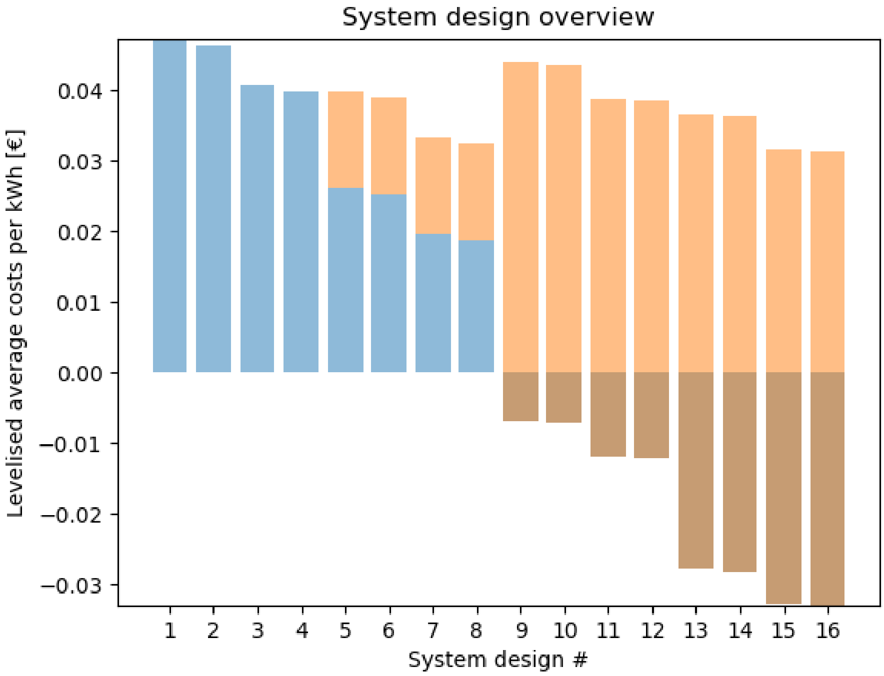

Figure 6.13: Case B system design performance

6.2.3. Case C system design performance

Case C uses 600 square meter for the PV system and 1000 kWh as capacity for the ESS, this represents double the capacity as provided by the project specifications of the case study. Table 6.3 shows the performance per system design. The EC as well as the LEC for each system design are shown. Figure 6.14 gives a graphical representation of the results. Blue bars and brown bars indicate the EC, orange bars indicate the LEC and the orange and brown bars together represent the CAPEX for each system design. The lowest EC are found for *system design 15* and *system design 16*. The lowest LEC and therefore the most preferred system design in terms of costs are found for *system design 8* just like in case A.

6.2.4. Conclusion

When increasing the capacity of the PV system and ESS while keeping the grid connection the same limits the performance of the ESS per unit of capacity. This means that the full capacity cannot be used and investment costs are made while the system is not being used to its full potential. In this case the introduction of a 1000 kWh ESS is not recommended. The PV system decreases the LEC significantly, *system design 8*, returns a lEC of €24.84, €32.39 and €9.73 for case A, B and C respectively. Therefore, it is recommended to install a large PV system of 600 square meters.

Table 6.3: Case C system design performance

System design	EC	LEC
1	€ 47.35	€ 47.35
2	€ 46.46	€ 46.46
3	€ 40.84	€ 40.84
4	€ 39.95	€ 39.95
5	€ -37.62	€ 17.13
6	€ -38.51	€ 16.24
7	€ -44.13	€ 10.62
8	€ -45.02	€ 9.73
9	€ -33.77	€ 169.00
10	€ -33.77	€ 169.00
11	€ -34.02	€ 168.76
12	€ -34.02	€ 168.76
13	€ -114.44	€ 143.09
14	€ -114.44	€ 143.08
15	€ -114.71	€ 142.81
16	€ -114.71	€ 142.81

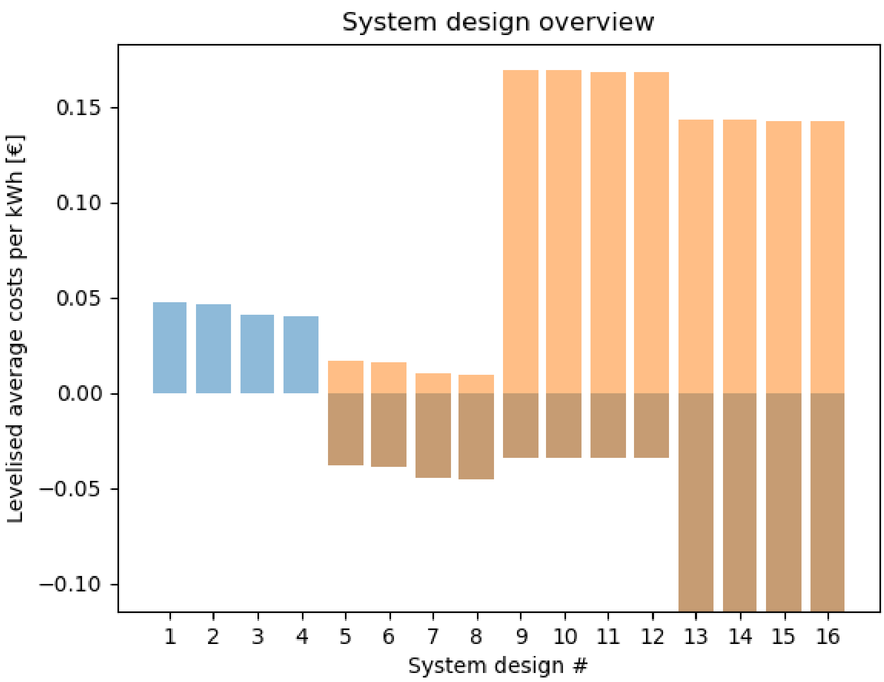

Figure 6.14: Case C system design performance

6.3. Sensitivity analysis

Tables 6.4 and 6.5 and Figures 6.15 and 6.16 show the performance for the sensitivity analysis of the grid capacity parameter for case A. Initially, the power from te grid has a limit of 80 kW. Section 6.1.6 concludes that the grid capacity is a constraint that actively limits the performance of the system design including an ESS. Therefore this parameter is chosen to analyse. This section explains the effect of changes in the minimum and maximum grid capacity parameters of a 10 % decrease and increase, resulting in limits of 72 kW and 88 kW respectively.

The sensitivity analysis for the grid connection is compared to the base case and shows that there is a significant impact when increasing or decreasing the grid constraint. When decreasing the grid capacity the effects are the highest for the EC of *system designs 9 to 12*, the system designs with a PV system but no ESS, which are around 20% higher than the base case. When an ESS is added, the cost increase is slightly lower than 10%. For the LEC, all cost increase lies a little below 10 %. The *system designs 1 to 8* show no change in performance. This is obvious considering that these system designs do not depend on the grid to supply energy back to the grid. When the grid connection is increased, the same pattern shows for all system designs as described above but result in a cost decrease. Percentages are in the same order.

Concluding from this analysis it can be stated that the grid connection is a constraint that influences the performance of system designs that include PV or ESS. The presence of an ESS in the energy system is only interesting when it is in proportion with the grid connection, thus enabling it to work on its full capacity. When there is no ESS present in the system design, the grid capacity has no influence on the system design performance.

Table 6.4: Grid capacity constraint 10% decrease - system design performance

System design	EC	Deviation	LEC result	Deviation
1	€ 47.35	0%	€ 47.35	0%
2	€ 46.46	0%	€ 46.46	0%
3	€ 40.84	0%	€ 40.84	0%
4	€ 39.95	0%	€ 39.95	0%
5	€ 4.87	0%	€ 32.24	0%
6	€ 3.97	0%	€ 31.35	0%
7	€ -1.65	0%	€ 25.73	0%
8	€ -2.54	0%	€ 24.84	0%
9	€ -18.81	22%	€ 82.58	7%
10	€ -18.84	22%	€ 82.55	7%
11	€ -21.80	21%	€ 79.59	8%
12	€ -21.81	22%	€ 79.57	8%
13	€ -59.67	8%	€ 69.09	8%
14	€ -59.73	8%	€ 69.03	8%
15	€ -62.49	9%	€ 66.27	10%
16	€ -62.53	9%	€ 66.23	10%

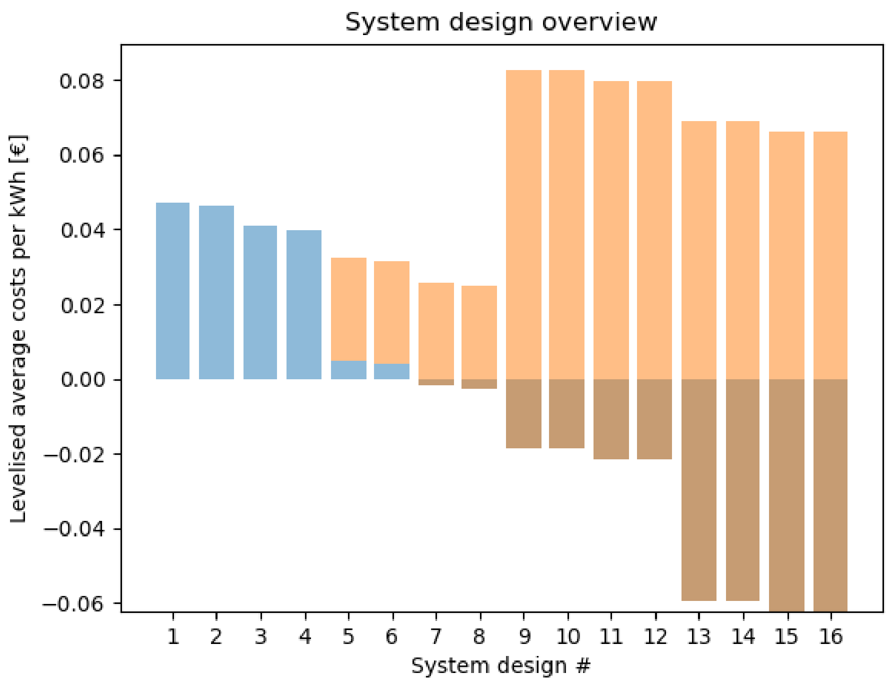

Figure 6.15: Grid capacity constraint 10% decrease - system design performance

Table 6.5: Grid capacity constraint 10% increase - system design performance

System design	EC	Deviation	LEC	Deviation
1	€ 47.35	0%	€ 47.35	0%
2	€ 46.46	0%	€ 46.46	0%
3	€ 40.84	0%	€ 40.84	0%
4	€ 39.95	0%	€ 39.95	0%
5	€ 4.87	0%	€ 32.24	0%
6	€ 3.97	0%	€ 31.35	0%
7	€ -1.65	0%	€ 25.73	0%
8	€ -2.54	0%	€ 24.84	0%
9	€ -28.93	-21%	€ 72.45	-6%
10	€ -29.00	-21%	€ 72.38	-6%
11	€ -33.02	-19%	€ 68.37	-7%
12	€ -33.07	-19%	€ 68.32	-7%
13	€ -70.10	-8%	€ 58.66	-8%
14	€ -70.19	-8%	€ 58.57	-8%
15	€ -73.95	-8%	€ 54.81	-9%
16	€ -74.03	-8%	€ 54.74	-9%

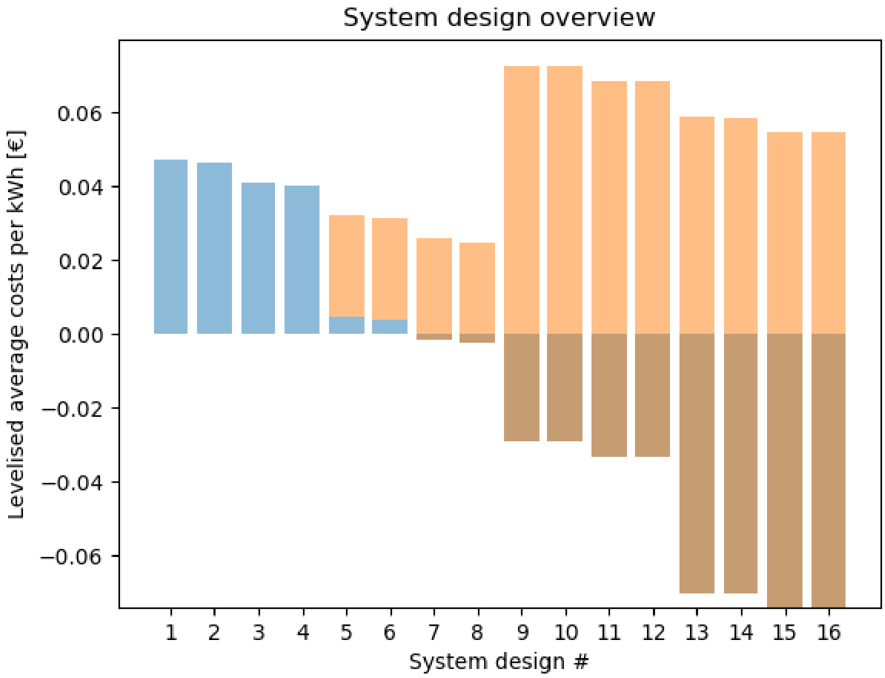

Figure 6.16: Grid capacity constraint 10% increase - system design performance

6.4. Conclusion and comparison to benchmark

This research aimed to propose a method to find an optimal system design of an integrated energy system. It considered the potential of smart charging, smart cooling, local energy generation and energy storage. It found that there is a high potential for optimised load schedules for an EV fleet and a CS system in combination with local energy generation by a PV system. The ESS shows only to be profitable with a grid connection that is in proportion with the capacity of the ESS. The grid capacity is found to be a limiting constraint of which influences the performance of the system designs that include an ESS.

Picnic paid in 2018 an integral commodity price of €41.01 per MWh. Smart scheduling of loads reaches €39.95 per MWh for all tested cases. Therefore, the use of optimised load scheduling of both EV charging and the CS system results in savings of 2.6%. When introducing a PV system the price becomes significantly lower depending of the size of the PV system.

6.5. Discussion

There are several factors that could be more elaborated on or modelled more precisely during this research. Different assumptions for most parameters could return different results. This section gives an overview of the main points of criticism of the used method.

- In the experiments for different system designs, trip planning is not taken into consideration. The assumption is that each EV has the same energy demand each day. However, vehicles often are not used on nonpeak days and energy demand might be higher on peak days. Using real trip planning data would prove more realistic, or even using a week cycle to indicate the difference between peak and nonpeak demand.
- The EV demand has no maximum, so when the model is used with a dataset where prices are negative it could be the case that it will charge more than its capacity. This is a flaw in the model that has no consequences for this research but might cause problems if it is applied in further research.
- The solar production is based on the solar irradiance during specific time intervals. In this calculation the direction in which the system faces is not taken in to account. In reality this leads to a lower energy production because of the angle in which irradiance reaches a PV system. The orientation of the PV system could also increase the direct solar irradiation. Right now the direct irradiation is assumed to be used. But at the moment the respective panels are tilted towards the sun the actual electricity generation could be increased. Here the direction in which it would be aimed is also important. Generally speaking two direction are typical, an east-west facing setup or a south facing setup. Furthermore, historical irradiation data is used assuming it is a perfect foresight during the year which is modelled. In practice this is nearly impossible to forecast on a local scale due to the unpredictability of clouds and the resulting shade. Therefore, in reality it would by nearly impossible to have such a specific forecast for a small scale PV system as in the model in this research. Probably some errors in forecast would have some effect but not significant. The errors could mean that there is more solar, which means less energy from the grid or more feed-in, both not problematic, or less solar which would result in more energy con-

sumed from the energy grid. This could have some negative effects but are assumed not to be significant.

- The ESS is able to consume from and feed-in to the energy grid. When running the optimisation algorithm, it causes the model to maximally utilise the maximum (dis)charge power to buy energy at low prices and sell at high prices. This causes multiple charge cycles per day. Depending on the type of storage, this could cause significant degradation of the system and decreases its lifetime. Furthermore, the efficiency is assumed to be 100% which is difficult to reach.

- The CS system demand in this research is modelled on basis of a fixed daily energy demand. Filling in the energy usage during the day results in meeting this demand. However, in reality there is a constant in and outflow of cold products which results in different demand fluctuations during the day to keep the cooling system at the right temperature. Furthermore, the outside temperature is not taken into account for the cooling system while this has a significant impact on the cooling efficiency of a cold storage system. The variation of cooling demand for seasonal changes on basis of outside temperature would give a better feasibility with respect to PV installation. Because higher solar irradiation would make up for higher cooling demand due to higher temperatures. Furthermore, an optimum may be reached for the size of the PV system when matching production and demand.

- In this research, feed-in of energy to the grid is allowed and the same energy tariffs are assumed as for consuming energy. This is possible with current Dutch *net metering* policy, however this might change in the future. Also, multiple taxes and fees play a role with consuming energy from the grid, these costs are not taken into account during this research, only the bare energy price. It has shown that without the possibility to feed-in, the proposed model returns a number of infeasible days within the year 2018 and is therefore not further investigated. Pursuing these options could however give insights in the performance of a system that is able to minimise energy taken from the grid or be completely self sufficient if there is enough local generation.

- The sensitivity analysis shows usable results but conclusions could be improved by analysing all parameters. Also, different cases for other capacities for the PV system and ESS would provide better conclusions.

- The number of EVs in the fleet at the hub which is used as a case for the simulations of this research is 9. However in 2019, there are more than 800 EVs operational in the fleet of Picnic. To create a better understanding of the costs reduction, the experiments could be carried oud for a larger scale.

- During this research a number of optimisation techniques is reviewed which include model predictive control and stochastic optimisation. In this research only mixed integer linear programming is applied. However, for further research and the implementation of optimisation on basis of imbalance prices these optimisation techniques could be further investigated and applied.

- Bidirectional charging opportunities for electric vehicles are not taken into account. Literature suggests that there is a potential for bidirectional charging to be cost efficient and have a positive impact on balancing the energy grid.

- Interest rate are set at 0 % in the experiments in this research, which is simply not realistic. For more accurate results for the investment costs and LEC, a high percentage should be used.

7 Conclusions and recommendations

This chapter documents the conclusions of this research. The research questions will be answered and recommendations are made for further research and implementation by Picnic.

7.1. Research questions

This research aimed to find a method for optimising an integrated energy system and uses a case study at Picnic to guide the results. The first subquestion asks for the elements in an integrated energy system. In the case study at Picnic these are found to be a PV system, a fleet of EVs, an energy storage system and a cold storage system. The second research question asks for the characteristics of the energy flows. It is found that all elements are connected to a main grid connection, the PV system is solely generating energy, the EV fleet and cold storage system only consume energy and the energy storage system is able to both consume and supply energy. The third research question ask for the criteria for an integrated energy system of which the most important criterion is found to be costs. Subquestion four asks for a method to find the sizing requirements. An optimisation model is proposed to find the performance of a set of sixteen different system designs. The fifth research question asks how this method can be applied, the mixed integer linear programming problem is solved in Python using PuLP as a solver. The last research question ask for the optimal design of an integrated energy system for the case of Picnic. It is found that using an optimised charging schedule for the EV fleet and an optimised cold storage load schedule in combination with a PV system is most desirable. The PV system is advised to be 600 square meters and the capacity of the ESS is optimal at 250 kWh.

The main research question asks for a method for determine the optimal design for an integrated energy system. The proposed methodology gives an overview of sixteen different system designs, varying in the presence of the different system design elements and calculates the performance in terms of levelised costs per unit of energy taking into account investment costs for the PV system and energy storage system. A sensitivity analysis is carried out to determine the robustness of the chosen parameter values. The proposed method can be used by other parties to assess the performance of their integrated energy system designs.

It is found that the grid connection is an active constraint in the design of an integrated energy system when an ESS is installed. Smart charging is obsolete with the presence of an ESS. The presence of a PV systems turns out to be financially desirable in all cases. Increasing the session length for EV charging optimisation increases the performance of a system design. Increasing the maximum power for the CS system increases the performance of the load scheduling algorithm.

7.2. Recommendations for further research

The proposed method proves adequate to assess the performance of different system designs of an integrated energy system. However, concluding from the discussion, to create an adequate overview of system design performance, more cases should be tested and parameter assumptions should be reviewed. The day ahead price optimisation gives a reasonable cost reduction. However, other systems working with balancing markets could provide higher returns. Therefore, the main recommendations are as follows:

- Test more system designs to be able to create a broader view of the possibilities.
- Reconsider parameter assumptions to create a more trustworthy result.
- Research other markets like the imbalance market for the potential implementation of load scheduling algorithms.
- Elaborate on the design of individual system designs to make the proposed model more realistic, e.g. temperature dependency of CS system and losses while charging and storing energy.

7.3. Recommendations for Picnic

Following from this research the following recommendations are formulated for Picnic.

- Optimised load scheduling for the EV fleet and CS system shows to decrease costs by 2.6% based on day ahead prices. However, further research has to be carried out to determine the capabilities for changing the CS system load schedule in practice.
- The flexibility that is available in the operation at Picnic can be exploited with a load scheduling algorithm on basis of day ahead prices like in this research. However, this flexibility might be of much more value to ENGIE to balance their own portfolio. It is advised to further investigate the value for ENGIE and how this flexibility can be 'sold' to them.
- The installation of a PV system is in all cases profitable as long as the grid connection is capable of handling the load to supply energy back to the grid during oversupply. A system with a surface of 600 square meters like in this research shows to be applicable with the grid connection capacity of 80 kW.
- An energy storage system of 250 kWh shows a desirable performance. However, the form of storage is not investigated and the complexity of the system could impose other challenges. Further research is advised on this matter before implementing the system.

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