Optimal Energy Resource Control in Congested Areas

A Stochastic Resource Dispatch Optimization Model Considering Flexible Robust Constraints

Victor van Doorn

Thesis Report

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A Stochastic Resource Dispatch Optimization Model Considering Flexible Robust Constraints

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Abstract

Future energy systems are expected to rely increasingly more on distributed energy resources (DER). Prosumers that own energy resources such as photovoltaic (PV) generation and energy storage systems, will play a crucial role in the realization of DER's in future power systems. Limited grid connections due to local electricity congestion make it more difficult for prospective industrially-sized prosumers to find suitable locations for their business operation. Energy resources such as batteries and PV, can be used to fulfill the desired electricity demands while adhering to the congestion related limits. By combining multiple energy resources and controlling them together the operational cost is drastically reduced. This thesis develops a stochastic optimization model that is able to find the optimal dispatch strategy for energy resources while adhering to constraints set by the DSO in a congested area. Also, a deterministic model is developed to be used as a comparison to the stochastic model. A deterministic model is simple and fast but it does not accurately represent the stochastic nature of PV generation, electricity consumption, and market prices. The stochastic model uses a set of different input scenarios for each time step and finds the optimal strategy considering all scenarios. In this thesis two models that consider stochasticity are developed: a stochastic and a robust model. For the robust model, the imposed grid constraints from the Distribution System Operator (DSO) have to be respected at each time step for each scenario and are classified as hard constraints. The model is able to find a optimal strategy for a week in each season when considering 11 scenarios. All predetermined constraints are respected for each simulation and while this makes the strategy reliable it also makes it conservative. For the second stochastic model, the DSO grid supply constraint is designed to be flexible and allow for occasional overshoot. In this case, flexibility is obtained by constraining the statistical distribution of grid power rather than the value at each time step and scenario. The calculated control strategy results in a simulated revenue increase between 3.67% and 4.78% depending on the season. For each season the objective cost reduces relatively more than the occurrence of grid overshoot. The term grid overshoot is used to indicate a situation where the DSO imposed grid limit is exceeded for a time step. The overshoot remains within the predetermined value threshold of 4% for all simulations of the stochastic optimization model.

Preface

This thesis report is the result of my graduation internship at Sunrock Investments BV. Working on my thesis at Sunrock meant I was surrounded by highly motivated people that gave me a lot of guidance for the duration of the project. I am lucky to have had the opportunity to end my masters at a place that has given me valuable working experience and companionship in times of COVID pandemic restrictions. I am also happy to have received the opportunity to stay on as a full-time employee and help Sunrock to work towards a clean energy future after my thesis. My personal graduation project goal was to develop valuable skills at the same time as contributing to relevant current academic work. The first months were overwhelming in terms of seeing the bigger picture but also in developing the hard skills required to finish my stochastic optimization models. After a few months I noticed significant improvement and I began to understand the full potential of this topic. Through this realization I knew I was on track of achieving my thesis goal which was to develop a valuable skill.

First of all, I want to thank my daily supervisor Dr. Pedro P. Vergara Barrios for his outstanding guidance throughout this thesis project. I am grateful for having had the ability to have weekly meetings and getting his valuable feedback on a regular basis. Moreover, I want to thank my Sunrock supervisor Noud Jaspers for his daily guidance within Sunrock and always making time to help me improve my mathematical modelling skills. I would also like to thank my colleague Ayush Verma for sharing his interesting insights during our daily meetings. I would also like to thank Dr. ing. Jose Rueda Torres and Dr. Hesan Ziar for their feedback and for being part of my thesis committee. Lastly, I want to thank my extended family and friends for their support throughout the entirety of my time at Delft University of Technology.

Victor van Doorn
The Hague, November 2022

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Nomenclature

β_t^c	binary variable for battery charging at time t
β_t^d	binary variable for battery discharging at time t
$\beta_t^{G,in}$	binary variable for feeding into grid at time t
$\beta_t^{G,out}$	binary variable for supplying from grid at time t
Δ^t	time step size (granularity) [kW]
ϵ^{bat}	price/cost for battery dispatch [€/MW]
ϵ_t^b	price for buying energy at time t [€/MWh]
ϵ^f	fine for exceeding grid limit [€/MW]
ϵ_t^s	price for selling energy at time t [€/MWh]
η^b	battery roundtrip efficiency [%]
γ^{max}	battery maximum state of charge [%]
γ^{min}	battery minimum state of charge [%]
$\mu_{P,grid}$	mean grid power taken over all scenarios s and time steps t [kW]
$\rho^{B,c}$	battery charge limit [kW]
$\rho^{B,d}$	battery discharge limit [kW]
$\rho^{G,in}$	grid limit for power feeding into grid [kW]
$\rho^{G,out}$	grid limit for power supplying from grid [kW]
$\sigma_{P,grid}$	standard deviation grid power taken over all scenarios s and time steps t [kW]
$BESS$	battery energy storage system
CPP	critical peak pricing
DER	distributed energy resources
DLC	direct load control
DoD	depth of discharge
DOE	Department of Energy
DP	dynamic programming
DR	demand response
DSO	Distribution System Operator
EMS	energy management system
$EPEX$	European Power Exchange
ESS	energy storage system

FCR Frequency Containment reserve

$HVAC$ heating, ventilation, and air-conditioning

LP linear programming

LV low voltage

$MILP$ mixed-integer linear programming

$NMCO$ Lithium Nickel Manganese Cobalt Oxide

NP nondeterministic polynomial

$O\&M$ operation and maintenance

$P^{B,c}$ battery power charged [kW]

$P_t^{B,c}$ battery power discharged at time t [kW]

$P^{B,d}$ battery power discharged [kW]

$P_t^{B,d}$ battery power discharged at time t [kW]

P_n^B nominal battery capacity [%]

$P^{G,in}$ grid power feeding into grid [kW]

$P_{t,s}^{G,in}$ grid power feeding into grid for scenario s at time t [kW]

$P_t^{G,in}$ grid power feeding into grid at time t [kW]

$P^{G,out}$ grid power supplied from grid [kW]

$P_{t,s}^{G,out}$ grid power supplied from grid for scenario s at time t [kW]

$P_t^{G,out}$ grid power supplied from grid at time t [kW]

P^L load power [kW]

$P_{t,s}^L$ load power for scenario s at time t [kW]

P_t^L load power at time t [kW]

P^{PV} pv power [kW]

$P_{t,s}^{PV}$ pv power for scenario s at time t [kW]

P_t^{PV} pv power at time t [kW]

$POPF$ probabilistic optimal power flow

PV photovoltaic

R_F robustness factor

RTP real time pricing

RV random variable

SoC state of charge

TOU time of use pricing

TSO Transmission System Operator

1
Introduction

The 7 years with the highest average global temperature have all occurred since 2015, with 2016, 2019 and 2020 making up the top three [1]. Greenhouse gas emissions (GHG) need to drop drastically in order to prevent any more disastrous effects of global warming. The energy sector is by far the largest GHG emitting sector and accounts for 73.2% of global GHG emissions. [2]. As part of the Dutch national climate law, the Netherlands has set the ambitious goal of a 49% carbon emission reduction by 2030, compared to 1990 levels. For the Netherlands to reach this goal, it is crucial to significantly ramp up the generation of electricity and heat from renewable sources. Solar PV will play a major role in the European transition to clean power of which an annual installed capacity of 21–22 GW is needed to reach EU goals [3]. Due to the inherent intermittent nature of most renewable energy sources, energy storage is also a key player in the European energy system. For the EU to reach its current carbon emission goals, they will need more than 100 GW of battery storage capacity by 2030. This was one of the key findings in a study on energy storage by the European Commission's Directorate-General for Energy[4].

1.1. Thesis background

Traditionally, an electrical power system consists of generation, transmission, distribution and consumption. This unidirectional process of matching electricity producers to consumers is known as centralized power generation. The main assumption of centralized power generation is that power is produced at one location and consumed at another. The power can only flow in a unidirectional manner from producer to consumer often over large distances which can lead to numerous problems especially when using renewable energy sources. For example, the loss of power categorized as transmission losses occur when transporting electricity over larger distances. The increasing amount of distributed energy resources (DER) such as roof-tied solar PV, wind generation and battery storage does not suit the the unidirectional nature of centralized power generation. Today's power grids are not designed for this new way of distributed power generation and connecting them to the power grid becomes increasingly difficult by the day.

Similar to other countries, Distribution System Operators (DSO) in the Netherlands are required to ensure safe, reliable and affordable operation of the distribution network by law (article 16 Elektriciteitswet 1998). When the DSO is having difficulty balancing capacity demand and availability, new connections are rejected or limited as the region is considered congested. A distribution system is congested when distribution cables, transformers, and other crucial resources, reach their maximum capacity. In other words, there is a mismatch in supply and demand that can not be solved without exceeding the limits of the distribution system. Because of congestion, large consumers in congested regions do not get the required grid size connection allocated by the DSO. A commercial building cannot be used without an electricity-connection, meaning that the development is not realized if the connection is not allocated. In addition to limiting supply capacity, congestion can also result in limitation of feed-in capacity and often both simultaneously. Many industrial-sized consumers want to realize large PV parks on their roof but without a grid connection the development of large-scale roof-tied PV parks is put to a halt. The current solution is to postpone the development of large-scale roof-tied PV parks in feed-in congested areas until capacity is made available again. Extra capacity can be made available through expensive investment into the electrical infrastructure and can take multiple years to complete.

Limiting the allocation of new connection to reduce the capacity used in the distribution system is only a temporary solution for DSOs. Waiting a couple of years to increase grid capacity in a region will be an endless loop as the electricity demand of such a region could have increased in those years as well. Both the DSO and power consumers in the region should make an effort to utilize the current grid more efficiently. There are some pilot project that use methods such as using batteries for peak-shaving, curtailment or relying solely on the consumption of the building underneath the roof-tied PV system [5]. Also, if congestion only effects a region temporary, a special type of connection should exist where both parties adapt so that the current distribution network is sufficient for a few years. Current solutions are often economically unfavourable, lack robustness or are only effective for short time spans.

1.2. Problem statement & research objective

Industrially-sized prosumers require a sufficiently large grid connection to support the growth of sustainable energy especially with the current electrification process. Currently, most parties situated in congested areas have no way to get a large enough connection allocated by the DSO. Many renewable energy projects are either postponed or canceled. Extra supply capacity is acquired by using non-sustainable production methods. Reliable energy resource dispatch cost optimization models that adhere to local congestion constraints are therefore, needed. The research objective is to develop a stochastic model using flexible constraints that is able to limit grid limit overshoot to a predefined percentage of time. Implementation of such a model in real life can be used to show the DSO that a new grid connection will not aggravate local congestion issues if certain rules are adhered. At the same time, the prosumer implementing such a model receives a more favourable connection for a fixed percentage of the time.

1.3. Scope, research questions and contribution

This work done in this thesis will only consider the situation as it is in the Netherlands. PV production is assumed to come from large-scale roof tied PV, located on the rooftop of commercial buildings located in business parks. the energy consumption profiles used in this thesis are from industrial-sized scale only. Every resource should be sized in a financially realistic way (no drastic over sizing).

The key issues that this thesis aims to solve can be captured in the following research questions:

- *How can an industrially-sized prosumer optimally dispatch energy resources while adhering to constraints set by the DSO in a congested area?*
- *How can a stochastic energy dispatch model implement flexible robust constraints where the grid limit is exceeded in less than a predefined probability or value?*
- *How does a stochastic hard constrained energy resource optimization model compare to one with flexible robust constraints?*

The scientific contribution from this thesis, can be summarized as follows:

A stochastic energy resource cost optimization model that adheres to congestion constraints. The models can accurately find the optimal dispatch strategy for a situation where grid limitations are implemented as hard constraints. The energy resources are PV, energy storage and electrical loads. Also a stochastic energy resource optimization model that is able to find the optimal dispatch strategy while using flexible constraints. This model will use statistical distribution properties to find an optimal dispatch strategy that can exceed the grid limit a set percentage of the time. If it is possible to show that the grid limit will only be exceeded a predetermined percentage of the time, the DSO might be able to give a larger connection that will only be used in emergency situations.

1.4. Thesis process and report outline

The thesis project process can be seen in Figure 1.1. The project is divided into three different time blocks that each contain a part of modelling, analysing and reporting. The thesis report starts with a more in depth

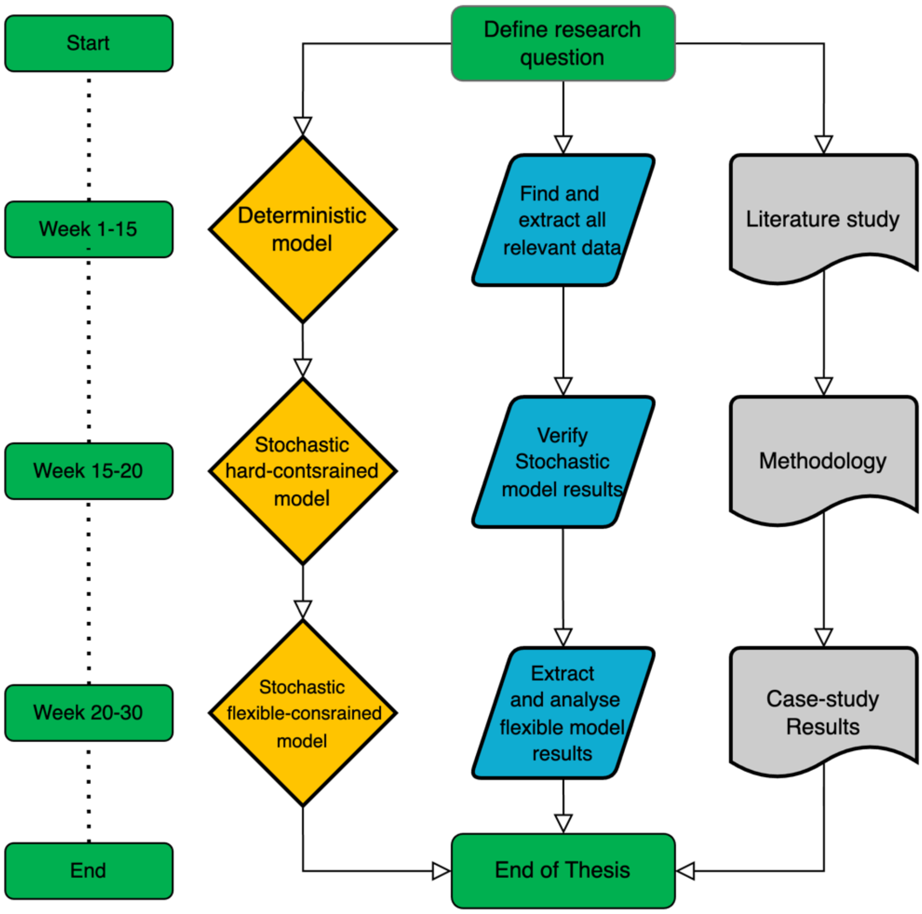


Figure 1.1: Flowchart describing the thesis process

background discussion in Chapter 2. The background chapter contains background information on electricity grid congestion and energy resource optimization modeling. Without understanding the problem, it is extremely challenging to comprehend why certain solutions perform better than others. The state of the art is presented in chapter 3, which includes a comprehensive overview of what has been done in the field of energy resource optimization, especially focusing on energy storage models. The state of the art will also discuss various options in the modelling of energy resource components but also analyse current energy resource optimization models and techniques. The design of the proposed energy resource optimization models is presented in Chapter 4. The models are tested by working out a case-study using real historical data in chapter 5. By working out a case-study, the models can be compared which enables an in-depth appreciation of the model performance in a natural real-life context. Chapter 6 summarizes the key finding, possible recommendations, research question answers and discusses future research.

2

Congestion & Modelling Background

This chapter contains background information on electricity grid congestion and energy resource optimization modeling. The first section gives an overview on electricity grid congestion in general and presents a number of causes. The next section describes the electricity grid congestion situation in the Netherlands. Next, the challenges and considerations related to energy resource modeling are presented. The final section in the background chapter discusses existing energy resource optimization models. The information in the background chapter is provides the necessary knowledge to understand the work presented later in the thesis report.

2.1. Electricity grid congestion

Numerous countries are transitioning from a regulated electricity market to a deregulated one. Previously, most electricity markets where considered a monopoly, where a single player has control over distribution, generation and transmission [6]. The dismantling of these vertically integrated utilities is necessary to meet the ever-growing demand for electricity at affordable prices. The term congestion is used for a situation where a physical flow is blocked or overcrowded. Electrons travel through power lines similar to cars using roads, however electrons do not cause congestion the same way cars cause a traffic jam. A distribution system is congested when distribution cables, transformers, and other crucial resources, reach their maximum capacity. In other words, there is a mismatch in supply and demand that can not be solved without exceeding the limits of the distribution system. The limits of a distribution system, often referred to as distribution constraints, are linked to congestion but are indisputably different. The U.S. Department of Energy (DOE) [7], identify three main distribution constraint concepts:

1. A single or group of components that limits power flows in distribution system;
2. An operational limit imposed on an element (or group of elements) to protect reliability;
3. The lack of adequate distribution system capacity to deliver electricity from potential sources of generation (either from new sources or re-routed flows from existing sources when other plants are retired) without violating reliability rules.

Distribution constraints, as defined above in (1), are a result of many factors including load level, generation dispatch, and facility outages. Jointly, these conditions establish a specific level or limit—as in (2)—to the permissible flow over the affected element(s) in order to comply with reliability rules and standards established to ensure that the grid is operated in a safe and secure manner. Managing congestion in the distribution network is more complicated compared to congestion in the transmission network [8]. The current strategy for Distribution System Operators primarily relies on network reconstruction which are expensive and can take a long time to complete. In this scope network reconstruction means adding extra power capacity to transformer stations and power lines in a congested area. In addition to long project times and high construction cost, this method of alleviating congestion comes with high management cost and fails to increase flexibility [9]. Distribution system congestion has a direct impact on the accessibility of power as well as negative economical consequences. Congestion in a distribution system describes a situation where the local distribution network does not posses sufficient capacity to allow new connections on the current network. This means that power distribution in the affected area can not cope with the market demand resulting in economical consequences in the area. A more in depth analysis of the congestion situation and consequences is presented in the next section.

2.2. Congestion in the Netherlands

The Dutch government pledged a 49% reduction of the Dutch greenhouse gas emissions by 2030, compared to 1990 levels, and a 95% reduction by 2050 [10]. Increasing the share of renewable energy in the Dutch electricity mix is crucial if these ambitious goals are to be reached. Table 2.1, shows the expectation of the International Energy Agency for the Dutch solar PV market [11]. The standard scenario prognosis is an installed PV capacity of 28.0 GWp while the accelerated scenario goes as far as 30.9 GWp.

Netherlands (GWp)	**Scenario 'standard' (GWp)**	**Scenario 'accelerated' (GWp)**	**Total installed 'standard' (GWp)**	**Total installed 'accelerated' (GWp)**	**Utility-scale (GWp)**	**Residential-scale (GWp)**	**Commercial-scale (GWp)**
2021	3.4	4.0	13.5	14.1	1	1	1.5
2022	3.3	3.7	16.8	17.8	1	0.8	1.5
2023	3.2	3.6	20.0	21.4	0.9	0.8	1.4
2024	3.1	3.5	23.1	24.9	1	0.6	1.5
2025	2.7	3.2	25.8	28.1	0.9	0.5	1.4
2026	2.3	2.9	28.0	30.9	0.8	0.4	1.1

Table 2.1: The International Energy Agency (IEA) forecasts for the Dutch PV market up to 2026

A rapid increase in renewable energy production combined with growing industrial electrification leads to significant demand for new electricity connections in the Netherlands. This is the case for both grid-supply and feed-in connections, causing problems in the development of new renewable energy projects [12]. When a solar- or wind project has no connection allocated before starting development, the project becomes increasingly more difficult to finance because there is no way to sell the produced electricity to the grid. This problem does not only limit the renewable energy production of a plant, it results in the whole project not being funded as there are no profits. It becomes an even bigger issue when generation plants that are already connected needs to be curtailed (or disconnected) due to congestion. The existence of grid-supply congestion means that large consumers are not able to receive the required energy they need for their property. In many areas, these larger consumers such as logistical hubs, small-scale industrial and warehouses get offered a connection that is insufficient or often no connection at all. Grid congestion is closely monitored by netbeheer Nederland and published to the public through the congestion-map [13]. Figures 2.1 and 2.2 show the respective grid-supply and feed-in congested areas in the Netherlands.

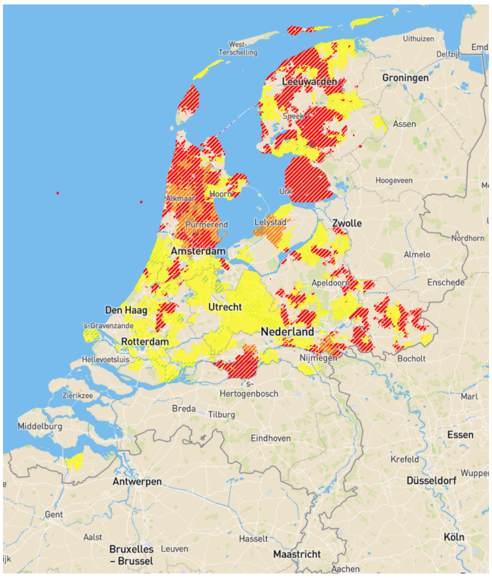


Figure 2.1: Grid-supply congestion situation in the Netherlands

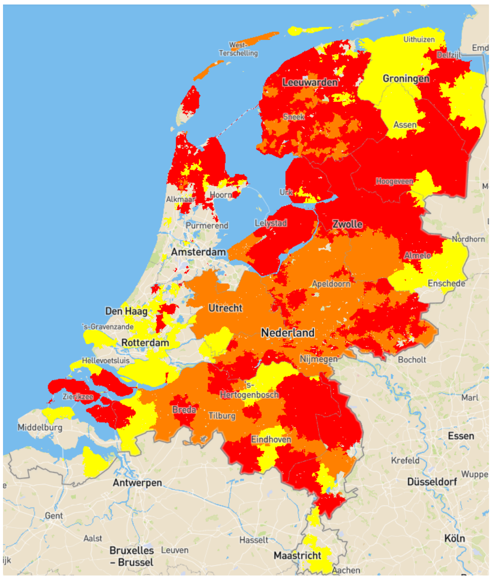


Figure 2.2: Feed-in congestion situation in the Netherlands

Color-codes used in the congestion map:

- Yellow: transport congestion warning, reduction in offered electricity connections.
- Orange: Advance notice of structural congestion to the Authority for Consumers & Markets.
- Red: structural congestion, new connection applications will not be honored.

Grid-supply congestion predominantly occurs in areas where there is a high demand for electricity. Densely populated areas and industrial hubs frequently experience congestion problems [14]. This is also illustrated in Figure 2.1, where most congestion occurs around the highly populated cities of Amsterdam, Utrecht and The Hague. At the same time there seems to be little to no supply congestion in less populated areas, mostly situated in the east. From the situation illustrated in Figure 2.2, it can be seen that feed-in congestion is a lot more common than grid-supply congestion. Also, feed-in congestion appears to emerge in contrasting areas with respect to grid-supply congestion. Most areas that do not accept new connection applications due to structural congestion, are located in less densely populated areas in the east. One reason for this is that the land is cheaper in these areas which makes it financially attractive for developing solar and wind projects. Also, these areas have a significant amount of distribution centers with large roofs which is a desirable place for roof-tied solar projects.

2.3. Challenges and considerations in energy resource modeling

This section presents background information with respect to energy resource modeling and optimization, primarily focusing on energy storage. There are many challenges that should be considered when developing energy resource models. There are a considerable amount of different design options for modeling the physical characteristics of an energy resource. In addition to physical characteristics, there is also a broad range of different optimization strategies for the integration of different energy resources.

2.3.1. Generic optimization modeling

The characterization of an optimization problem is a crucial first step before developing the model. Characterization is crucial because it decides the algorithm used for solving the optimization problem, which is not the same for all problems. An optimization problem requires a tailored solver as per category the nature of the problem can be attributed to. By understanding the differences between various types of optimization problems, one can design a model in such a way it becomes solvable. Also, this knowledge is essential for comparing and analyzing other optimization models.

Continuous Optimization vs. Discrete Optimization

As the name suggests, models using discrete variables are discrete optimization problems and models with continuous variables are continuous optimization problems. In mathematical optimization problems, discrete values are often a subset of integers. The variables used for continuous models can take on any real value. Solving continuous optimization problems is easier compared to solving their discrete counterpart. However, computing technology advancements have made it possible to efficiently solve discrete optimization problems of greater size and complexity.

Deterministic, Stochastic and Robust Optimization

Deterministic optimization is a category of optimization where the output is causally determined by preceding events. Stochastic programming is used to solve optimization problems that include a set of plausible scenarios or probabilities. For Deterministic optimization problems the outcome is determined completely by known parameter values and initial conditions. However, sometimes data is not known precisely as a lot of processes are random or follow a specific probability distribution. Optimization problems that consider data from stochastic process such as weather or economic markets, can be solved using stochastic programming. Parameter uncertainty in stochastic programming is captured by a number of discrete probabilistic scenarios. The probability distribution of these functions are assumed to be known *a priori* which makes it possible finding the optimal expected outcome by minimizing or maximizing the objective function. Optimization problems that have to deal with data uncertainty can use robust optimization. Robust optimization is a sub-type of optimization that uses data from uncertainty sets, which are continuous sets of which the probabilities are unknown. As the probabilities for the uncertainty set are unknown, another measure is optimized. Most cases use robust optimization to find the optimal value with the worst-case values from the uncertainty set. The aim is to find a solution that is feasible regardless of the constraints, and optimized for the worst-case scenario.

Linear Programming
Linear programming is a particular classification for solving optimization problems. The name linear programming refers to the optimization problem having both a linear objective function and linear constraints. A linear optimization problem is solved when the objective function is either minimized or maximized, depending on the problem [15]. The objective function, often called cost function depends on certain variables that can be controlled called decision variables. Decision variables used in the objective function are subjected to certain linear constraints that indicate the range these variables can take. Theoretically it is possible for some decision variables to reach infinity (e.g. weight, time) however practically they can be limited to a certain finite value.

$$
\begin{aligned}
Maximize:& \sum_{j=1}^{n} c_j x_j \\
Subject\ to:& \sum_{j=1}^{n} a_{ij} x_j \leq b_i, \ \ i = 1...m \\
& x_j \geq 0, \qquad j = 1...n
\end{aligned}
\tag{2.1}
$$

Quadratic Programming
It is possible for an objective function to be in a quadratic form, this particular classification of optimization problems is called quadratic programming. While the objective function is quadratic, the constraints remain linear. Quadratic programming is often referred to as nonlinear programming in literature.

$$
\begin{aligned}
Maximize:&\ \ f(x) \\
Subject\ to:&\ \ g_i(x) \leq 0, \ \ i = 1...m \\
& h_j(x) = 0, \ \ j = 1...n
\end{aligned}
\tag{2.2}
$$

Convex versus concave function
The complexity of a an optimization problem depends on the how the objective function and the constraints are structured. An objective function that is either convex or concave will be rather easy to solve due to the function having a global maximum/minimum.

$$f((1-t)u + tv) \leq (1-t)f(u) + tf(v), \ \ \forall u, v \in K, \ \ t \in [0,1] \tag{2.3}$$

$$f((1-t)u + tv) \geq (1-t)f(u) + tf(v), \ \ \forall u, v \in K, \ \ t \in [0,1] \tag{2.4}$$

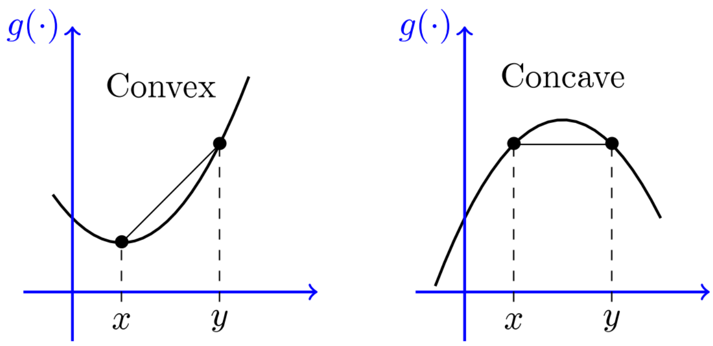


Figure 2.3: A convex function (Left) and a concave function (right)

2.4. Existing energy resource optimization models

This section gives a background on existing energy resource optimization models. The section starts with discussing common design choices found in deterministic optimization models. Next is a more in-depth analysis on stochastic optimization models and a discussion on number of stochastic optimization design choices.

2.4.1. Design choices for optimization models

There are a variety of different energy resource optimization model implementations used today, especially in sizing and control. Most people approach energy storage models as a highly time-coupled process meaning different time steps depend on one another. When a system with energy storage is modeled as time-independent, it will fail to make optimal use of energy storage. Linear programming (LP) is a common approach that is used to optimize the economic dispatch of energy resources. Using LP for energy resource models is advantageous due to its converging properties and ability to solve problems with a large amount of variables in a short amount of time [16] In addition to LP, some energy resource optimization implement dynamic programming to find the optimal economic dispatch strategy. Dynamic Programming (DP) is an algorithmic technique that breaks down a complex problem into simpler sub-problems so that the results can be re-used. This method utilizes the fact that the optimal solution to the overall problem depends upon the optimal solution of the previously solved sub-problems. Dispatch problems based on dynamic programming are considered very powerful but have the disadvantage of being computationally intensive resulting in long solving times for models with a large number of variables [17]. In addition to high computational time and intensive use of memory, dynamic programming algorithms do not necessarily guarantee to have found the global minimum. Another method used for energy resource optimization is mixed-integer linear programming (MILP). A disadvantage of MILP is that the problem becomes NP hard (nondeterministic polynomial time) which means solving the problem is more time intensive than LP problems [18]. A problem is considered NP-hard when the solving algorithm can be translated into one for solving any NP-problem. Figure 2.4 shows the different problem classes in computational complexity theory [19].

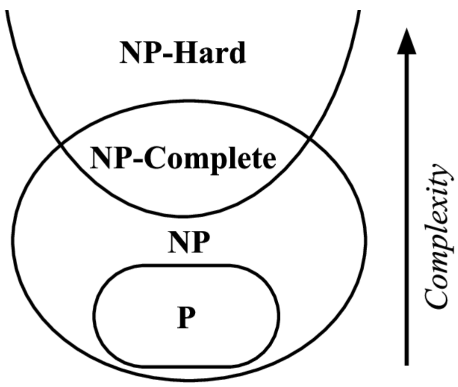


Figure 2.4: Diagram of intersection among classes P, NP, NP-complete and NP-hard problems

Energy resource optimization models often use bidirectional power flow, which can lead to certain constraints not suitable for regular LP models. A battery cannot charge and discharge at the same time, the same way it is not possible to import and export electricity at the same time when using a single connection. With MILP it is possible to use boolean variables ensuring the model adheres to certain physical constraints. Hence, even though MILP is computationally intensive, it is still a popular method used in energy resource optimization models. Authors in [20] used an adaptive deterministic approach for finding the optimal sizing of a battery system connected to PV and EV charging. The model developed in [21] is a deterministic approach for finding the optimal dispatch scheduling of a battery connected to residential PV system. Deterministic optimization models can also be used for optimal scheduling of battery energy storage systems considering degradation cost [22].Participating on multiple markets with the same energy storage resource is interesting as value stacking can potentially lead to higher returns [23].

2.4.2. Stochastic optimization models

Deterministic models are fast, computationally non-intensive and produce the same exact results for a particular set of inputs. However, there is one main disadvantage with using deterministic optimization models for energy storage resource optimization. Energy storage resources use many parameters that are inherently intermittent from nature. PV generation, wind power, demand and energy prices are not known in advance which makes deterministic optimization unrealistic to implement in real-life applications. Stochastic programming is used to solve optimization problems that consider a set of plausible scenarios or uncertainties. A stochastic optimization problem involves finding the optimal variable values that minimizes the expected value of the objective function. When solving stochastic optimization problems that consider probability, the probability distribution of the uncertainty parameters is assumed to be known *a priori*. Uncertainty parameters are parameters of where the exact value is not known in advance. Electricity production from intermittent sources such as wind and solar can only be forecasted but it is not possible to know the exact production output in advance. For models with parameters that are assumed to follow a certain distribution, these distributions and expected values can be used for stochastic optimization. Whenever an uncertainty parameter does not follow a specific distribution, the model can also use a large number of scenarios as an input. In order for stochastic programming to be effective, the number of scenarios must be large, even after scenario reduction techniques. Unfortunately, using a large set of uncertainty scenarios makes the model highly complex and therefore computationally demanding. Stochastic optimization can be implemented in various operation strategies and resource sizing models. Examples are: optimal day-ahead trading strategies, optimal dispatch strategy, sizing of a battery and residential PV system, and battery degradation cost optimization. Another possibility is to use an approach that is simulation- or scenario-based such as a forecast. In such cases the optimization problem can use the forecast as an input.

2.5. Energy storage valuation and model types

There is no generic approach for quantifying the performance of energy storage model. The key energy storage performance indicator that is used for evaluating the result of an energy resource in a specific case is subjective. Certain models are interested in maximizing financial performance, others in minimizing degradation or optimizing grid interaction. Energy storage valuation can be done by defining value streams and evaluating business models which is commonly used by energy storage models [24].

2.5.1. Energy storage revenue streams

Depending on the configuration, energy storage resources can be used for generating revenue or reducing costs. When an energy storage resource is in a front-of-the-meter configuration it is able to generate revenue from services such as energy arbitrage and ancillary services. Energy arbitrage is a basic form of trading where energy is bought when prices are cheap and sold when energy prices are high. In the Netherlands this can be done on the imbalance market which falls under the responsibility of the Dutch TSO. Using energy storage resources for ancillary services such as the Frequency Containment Reserves (FCR) and Frequency Restoration Reserves (aFRR) is also a popular way to generate revenue. Participating on multiple markets with the same energy storage resource is interesting as value stacking can potentially lead to higher returns. Energy storage in a behind-the-meter configuration can be used for cost reduction techniques such as demand response, reduction of transportation cost and higher self-consumption meaning less grid interaction [25].

2.5.2. Energy storage costs

There are various types of energy storage costs however there are two main categories of interest for energy resource modeling. These categories are capital expenditures and O&M (operation and maintenance) costs. Capital expenditures for energy storage depends on the type of technology used and on the size. Different technologies use different materials and for certain technologies these materials are more expensive. The costs related to O&M predominantly depend on the rate of depreciation of the battery and what the battery is being used for. If an energy resource is used in a significant extensive way, it can result in faster degradation.

2.5.3. Price taking models

Price-taking models are a commonly used form of energy storage models, where the value of energy storage is estimated for providing market-priced services. A price-taking model is implemented for situations where energy storage is sufficiently small to not impact market prices or other major external influences. This situation allows the model to optimize its objective function without taking the power balance into account. The objective function for a generic price-taking model is shown in 2.5. A generic energy resource price-taking model is bounded by device constraints, external constraints and market-design constraints.

$$max \sum_{t} [revenue_t - operational\, cost_t] \tag{2.5}$$

3

State of the Art

The state-of-the-art chapter starts by discussing different kind of congestion management approaches being implemented in the Netherlands. Beginning with the importance of DSO operation flexibility and an analysis on a currently proposed framework for cost-effective operation. Next several congestion management techniques are presented compared. the remainder of the state-of-the-art chapter discusses and compares current stochastic congestion management optimization models. The chapter ends with a summary on the scientific contribution of this thesis.

3.1. Congestion management in the Netherlands

The congestion problem in the Netherlands can be categorized more as an infrastructure problem rather than a regulatory one. By interpreting the problem in such a way, the solution will be expensive and take a long time to solve as this is the case for increasing grid capacity. When there are too much passengers in public transport during rush hour, it will be more cost effective to increase the tariff during rush hour then to increase the amount of trains [26]. With dynamic pricing or a subsequent related reward system, people that are able to shift their transport to another time will do so more often. By optimizing how you control the current resources, people can still arrive on their destination while massive and expensive infrastructure projects are averted. The same way it is less expensive to change the way the trains are used then to increase the amount of trains or railway tracks, the electricity grid can be utilized better.

3.1.1. Flexibility

When there is a risk of structural bottlenecks occurring in the electricity gird, the DSO can benefit from implementing congestion management methods. Congestion management, refers to market based mechanisms that are implemented to prevent overloading of the electricity network. Rather than declining new connection applications in areas with structural congestion, congestion management could potentially increase the number of allocated connections. The conventional method of distributing electricity in a transmission system is based on the principle that production follows consumption. Due the fast growing share of intermittent generation sources (e.g. solar, wind energy) in the Dutch electricity mix, this has become increasingly difficult. In the current Dutch electricity system, demand is made to be highly inelastic due to the lack of incentives for adapting consumption to available production. Flexibility allows the DSO to adjust both consumption and production with the goal of maintaining grid stability. The role of the DSO is becoming increasingly important with the electricity system shifting to a more flexible type. European Energy Regulators recommend the role of the DSO to be neutral market facilitators focusing on regulated operations and staying out of activities that can be

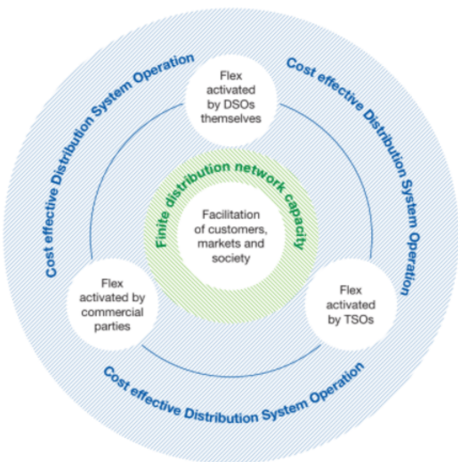


Figure 3.1: Flexibility framework for cost-effective Distribution System operation

carried out by a competitive market [27]. According to the authors in [28], one advantage of using a competitive market system is that competitive markets result in more affordable energy prices compared to regulated markets. It is important that the DSO remains neutral and does not get involved in such competitive markets so that there is no unfair advantage. Otherwise the DSO would benefit from favouring their own resources over potentially more affordable services. Having such an unfair market participant could deter potential investments and prevent innovation [29].

There are 3 main groups that have the ability to implement flexibility: DSO, TSO and market participants. Market participants can be producers, consumers but also a participant who both produces and consumes, called prosumers. Figure 3.1, shows the flexibility framework for cost-effective distribution system operation. In this framework the three main parties operate on the same network, implying that a reaction from one party has an impact on the other two. Even though each party in this framework has different reasons for implementing flexibility, the overarching goal is the same for all. The goal of flexibility can be defined as facilitating customers, markets and society operating in the distribution network. The European associations representing DSOs (CEDEC), EDSO (for Smart Grids), eurelectric, Eurogas and GEODE – have proposed 2 different options for DSOs to implement congestion management [30]. The first option is separate DSO & TSO congestion management, which has several advantages. Option one enables the DSO to tailor products for distribution level congestion management without taking care of transmission level specific requirements. Also, This method enables low entry barriers for smaller market aggregators he product will be tailored for small local market parties like aggregators or Flexibility Service Providers. The main disadvantage is that market parties can only participate in the smaller DSO congestion management market. The second option is combined DSO & TSO congestion management, which leads to easy access for market participants on both congestion market places. Communication between the DSO and TSO makes it more difficult to agree on product specifications and governing the markets.

3.1.2. Consumption or Generation Curtailment

Although counter intuitive, curtailment could increase the amount of PV power injected into the grid. Curtailment is the act of reducing or restricting something, which is energy production or consumption in the scope of this thesis. When a certain area has feed-in congestion, the DSO is unable to guarantee that new connections will not pose problems in a worst case scenario. For feed-in congestion that would mean high production and low consumption at a certain moment in time. In these situations an entire project could be postponed or canceled due to the inherent uncontrollable nature of PV production. A solution to this could be for the DSO to remotely control PV output so that the output can be limited in times of emergency. According to authors in [31], Curtailing PV production does not necessarily mean that the annual energy production is severely limited. To test this statement, an arbitrary 1.5 MWp rated PV system [1] is analyzed for various curtailment percentages. Figure 3.2 shows the AC power output from the 1.5 MWp rated PV system with an AC inverter rating of 990 kVA, which is coincidentally the maximum power output. As can be seen in Figure 3.2,

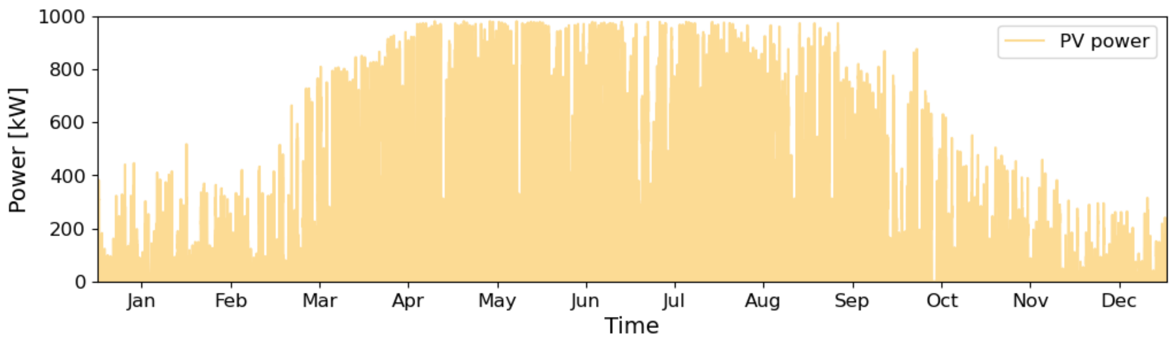


Figure 3.2: The 2020 power output for an arbitrary 1.5 MWp rated PV system

the PV system only operates at the maximum rated system output occasionally. Table 3.1 shows how often the PV system in Figure 3.2 exceeds a certain threshold. Notice that a PV system only exceeds 95% of its rated power 1.57% of the time. If only hours where the sun is shining are considered this is still only 3.18% of the

[1] PV system is owned and operated by Sunrock, the data has been taken directly from the internal Sunrock database

time. In the case of feed-in congestion, the DSO would curtail a PV park when the cables are in danger of overloading. This does not mean that the whole park is limited at 95% or any similar value throughout the whole year. The values presented in Table 3.1 illustrate exactly how infrequent PV peaks actually occur during operation. When a PV system is only a potential threat 5% of the time, it is better to reduce its power during these moments than to not develop the system at all. A study by authors in [32], showed that a reduction of the generation from wind power plants to 70% of their maximum power output would decrease their total energy output by only 1.3% in the year 2011. The same study also concluded that a power reduction to 80% of the maximum rated power would have led to an energy output reduction of 0.5%.

Power reduction [%]	**Max power [kW]**	**Occurrence in year [%]**	**Occurrence when producing [%]**
0%	990	0.014%	0.029%
5%	940.5	1.57%	3.18%
10%	891	2.71%	5.5%
15%	841.5	3.87%	7.85%

Table 3.1: A study on how often a certain threshold is exceeded in a year and when the sun is shining

Also, a PV park that is able to remotely curtail or completely shut off has cost benefits for the park owner as well [33]. Increasing renewable energy production has resulted in an increase of negative electricity wholesale prices [34]. Negative prices commonly occur during peak solar energy production hours, meaning that the ability to curtail during these times mitigates the costs of selling power to the grid. While this does not relate to direct profit for the plant operator, it does enable the plant owner to reduce cost of feeding energy into the grid during negative prices. Note that this is only true for cases where curtailment is combined with day-ahead production forecasting or imbalance price forecasting. According to a study by the Copernicus Institute of Sustainable Development, the installed capacity of a PV system can be increased by up to 130% on the same connection[35]. This is thanks to a combination of curtailment and azimuth angle changes. This method is easy to implement and does not require investing in infrastructure. The study also mentions that above 130%, curtailment becomes less cost-effective compared to increasing grid capacity. However, PV parks located in congested areas do not have the opportunity to increase their connection capacity and rely on the DSO to invest in such infrastructure.

Consumption curtailment, or load curtailment, is a congestion management technique designed by a DSO to potentially reduce the power demand or electrical energy usage during the peak load periods. By curtailing consumption in a congested area, the DSO is able to remotely reduce capacity on the distribution system and lower the possibility of outages. The author in [36], proposes a form of consumption that can be divided into two main load curtailment categories: explicit and implicit demand response (DR) programs. Explicit DR is a form of load curtailment where the DSO has control over specific loads and can turn these off if necessary. Implicit DR is a form of load curtailment where the DSO controls the consumption during a specific time slot with a fine or some form of price incentive. To make sure the consumer loads are actually controlled correctly, a form of direct load control (DLC) is used where an external entity uses a two-way communication link to directly control the controllable loads [37]. This method has a significant effect on consumers' privacy and autonomy, however this is necessary minimize the uncertainty of accurate consumer response [38]. It is possible that certain types of consumers have other priorities than reducing electricity costs or mitigating congestion. The consequence of having limited participation in DLC, is that the DSO can not control enough load and have a significant effect on congestion in the region.

3.1.3. Peak shaving & load shifting

Matching production and consumption is becoming increasingly difficult due to the inherent intermittent nature of renewable energy production and the inelasticity of energy consumption. For energy producers, peak shaving is leveling out the electricity production peak of a power plant. Figure 3.3 shows an arbitrary solar PV production curve where the peak production is stored and discharged during off-peak hours. After storing the energy that is produced during peak hours in an energy storage resource, it can be dispatched at a later more suitable time. This method enables a solar production plant to use a significant smaller feed-in connection while the energy that is supplied to the grid stays roughly the same [2]. The main difference between peak

[2] Depending on the size of the energy storage resource and the alternative feed-in connection rating

shaving and curtailment is that curtailment essentially wastes the energy while peak shaving stores it for later use. Note that peak shaving requires an energy storage resource with sufficient capacity which is not cheap. From the DSOs perspective peak shaving is a relatively simple way to keep the costs of network expansion low. Utilizing a distribution network more efficiently requires less expensive raw-materials and labour hours for the installation of power lines and distribution points. Authors in [39] combined a battery with a novel forecast-based control scheme to reduce the required feed-in connection capacity. By simulating the battery operation over a 12 month period using a wide range of battery capacities, installed PV capacities, and different domestic load profiles, it was shown that the grid connection could be reduced by up to 70% without exorbitant losses.

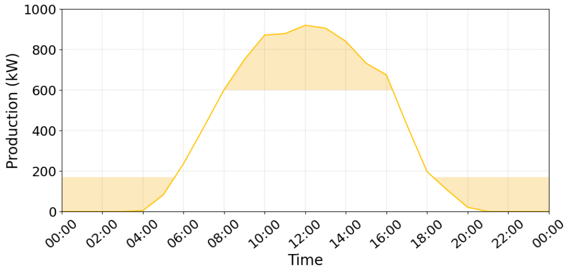


Figure 3.3: Peak shaving a large-scale roof tied PV installation

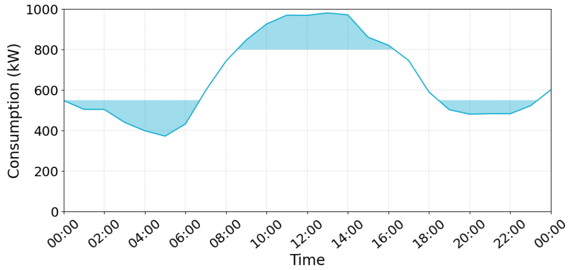


Figure 3.4: Load shifting for an industrially sized consumer

The main energy consumption contributors in large-scaled logistical buildings are heating, lighting, cooling and ventilation [40]. Heating in the industrial and logistical sector is still predominately done with gas boiler systems [41], meaning that the electrical consumption profile is not directly affected by heating demands. Lighting, ventilation and indoor climate cooling are linked to the amount of employees in the building to reduce unnecessary consumption. According to authors in [42], approximately 80% of energy consumption is consumed during working hours. Excluding data centers it is unlikely to find a logistical building with a constant consumption profile curve. The common energy consumption profile of a logistical building follows working hours when there are no large appliances working constantly. Constantly matching production to extremely inelastic demand is not a feasible method when an energy system uses significant intermittent energy sources. With an energy storage resource a consumer is able to adjust their consumption to a more constant profile, this method is called load-shifting. Load-shifting is a load management technique where demand is "shifted" from peak hours to off-peak hours in a certain time frame. Figure 3.4 shows an arbitrary demand curve where the peak consumption is supplied with a battery. The result is a consumption profile that is considerably more flat with a significant decrease in required peak consumption power. When congestion leads to there not being sufficient supply capacity available in the region, load shifting can be used to continue business operation. Authors in [43], worked out a simple load-shifting technique where energy storage was used to reduce the required connection and related costs. In their simulation a battery with a 51 kWh capacity and 150 kW rated power was used to shave 243 peaks representing 6% of the maximum load peak. The issue with this method is that it is not a robust solution for overcoming the effects of supply congestion. The economic benefits heavily rely on the tenant load profile and is not reliable enough for lowering the physical grid connection. This is a great method for lowering transportation costs and hedging against high peak energy prices however, a industrially scaled prosumer cannot rely its entire business operation on this method without drastically over sizing the battery. The authors in [44] propose district heating as an additional flexibility option.

3.1.4. Dynamic pricing

Another promising congestion management technique is dynamic pricing, which is considered an efficient mechanism for relieving peak demand through demand response [45]. The main forms of dynamic pricing found in scientific literature are time-of-use (TOU) pricing, critical peak pricing (CPP) and real time pricing (RTP). TOU pricing works by splitting a day into peak and off-peak hours where prices depend on which part of the day it is. Its common for utility companies maintain their peak- and off-peak prices for a longer period, only to change on a seasonal frequency [46]. CPP is a method that identifies a number of peak hours within a year where the peak is considered critical. The aim of CPP is to relieve stress on the system during these identified peak moment by implementing temporary higher prices. The difference between CPP and TOU is that the price blocks in TOU are divided two categories peak - and off-peak, while CPP has multiple possible peak blocks during they day [47]. Consumers in a system with RTP pay a price that changes on a hourly basis which is the same granularity used for the wholesale market for electricity [48]. Sunrock has implemented this technique in a flexible energy contract where clients pay a tariff based on the EPEX day-ahead called Sunrock Energy [3]. As the tariffs are based on the day-ahead market, the prices are known a day in advance. Knowing prices in advance enables the consumers to adjust their consumption according to the prices and potentially save money.

Authors in [49] propose a dynamic pricing demand response control strategy for mitigating congestion problems in low-voltage (LV) networks. Load consumption profiles are developed 24 hours in advance based on the expected overloading cost. The authors reveal up to 82% reduction in distribution grid congestion, without decreasing the quality of supply in the network. The proposed system works by utilizing the scalable architecture agent-based systems. The main issue with this method is that consumers in the area need to invest in smart control hardware that allows to remotely control the loads according to the day-ahead strategy. Also, the proposed method depends on everyone connected to the feeder to participate because the day-ahead control strategies are calculated with the assumption that they can shift a large part of the consumption. When the controllable load becomes smaller, the uncertainty of the load profile increases and distribution grid congestion is decreased less.

3.2. Existing energy storage component modelling techniques

All energy storage models should accurately represent the technical capabilities of the chosen storage system. Modeling energy storage resources depends on design choices made by the author and whether physical attributes such as dc/ac conversion, real- or reactive power control and various other power electronics are part of the model scope. Other energy storage models avoid simulating such components, choosing a more simplified approach. This section discusses several component modeling design choices found in state-of-the-art energy storage models.

Dependency of efficiency on current

Energy-storage models generally include a method for accurately representing process efficiencies. For simple models efficiencies are considered to be constant throughout the operation of the energy storage model. However, efficiencies of energy storage systems can be related to charging and discharging currents [50]. Authors in [51] developed a non-linear charge-based battery storage optimization model where battery efficiency is not considered to be constant throughout operation. The proposed model treats voltage and current as individual variables, rather than only considering dispatch power flows. With the battery voltage depending on both state of charge (SOC) and discharge current, the battery efficiency is also depended on those. Authors that develop linear models typically simplify certain battery properties and cannot independently represent voltage and current [52]. An example of this is an optimization model where the authors propose a method to enhance the representation of lithium-ion batteries in MILPs [53]. One challenge with a system that makes use of such a simplification, is the practical implementation of an energy management system that could operate using these methods in near real time.

Temperature effect on energy storage performance and cycle-life

Temperature has a significant impact on the performance of many energy storage systems, with a common example being lithium-ion batteries. Different temperature conditions result in different adverse effects severely limiting the application of lithium-ion batteries [54]. Generally, the use-independent efficiencies of a battery are considered to be constant. However, metallic lithium plating causes electrolyte decomposition resulting in the battery losing capacity to provide the same power at low temperatures [55]. Figure 3.5 illustrates the non-linear relation between temperature and capacity reduction for the case of Li-ion batteries [56]. On the other end, high temperatures significantly decrease the cycle life for Li-ion batteries. High operating temperatures result in a higher solid electrolyte interphase film accumulation, increasing battery aging process and cycle life reduction [57]. Figure 3.7 illustrates the relation between temperature and cycle life for Li-ion batteries operating at a 50% DoD, which has been found by authors in[56]. Notice that similar to high temperatures, extremely low temperatures have a detrimental effect on the cycle life. The priority of accurately representing the impact of temperature in energy storage models again depends on the scope of

[3]https://sunrock.com/en/energy/

the model. In the case of the authors in [58], the temperature impact was one of the top priorities. The authors developed a model that accurately represents Lithium Ion Battery commonly found in electric vehicles. Their focus was on the effect of temperature on battery operation behaviour and optimizing processes based on this impact. When a model optimizes control based on physical characteristics, it is crucial to accurately model the effects of such physical characteristics for potential practical implementation.

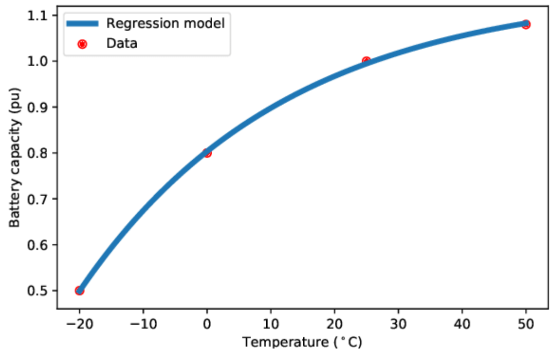


Figure 3.5: Effect of temperature on Li-ion battery capacity

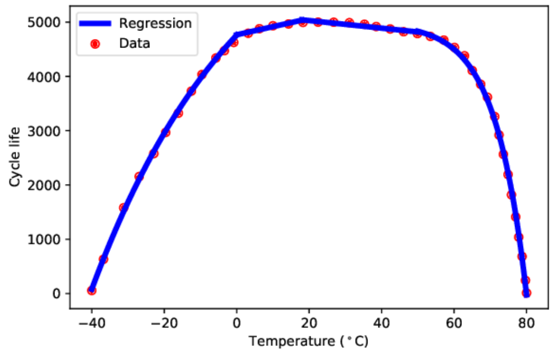


Figure 3.6: Effect of temperature on Li-ion battery life at 50% DOD

Degradation

Models that use batteries as energy storage resource have to decide on the method of modelling battery degradation. Battery manufacturers use the amount of battery cycles to give an estimation of the battery life. The cycle life is the number of complete charge/discharge cycles that the battery is able to support before that its capacity falls under 80% of it's original capacity. There are two main type of battery degradation models used in majority of energy storage models. The first commonly used degradation class is a power-based, linear degradation model. An example of a such a power-based degradation can be found in [59], where a general convex cost for battery demand response has been adopted. Another similar implementation is used [60] where an energy system that is used for peak shaving and regulation services, uses linear degradation. Power based degradation models regard degradation cost as time independent which keeps solving the model computationally simple.

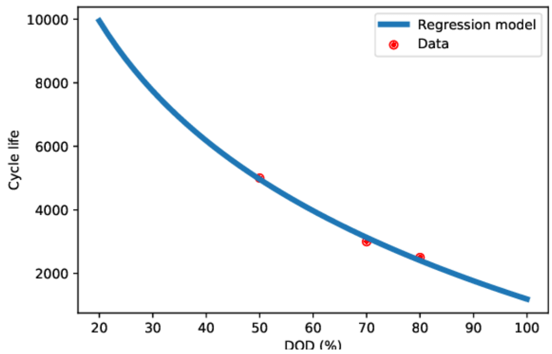


Figure 3.7: Regression curve of Li-ion battery cyclelife vs DOD

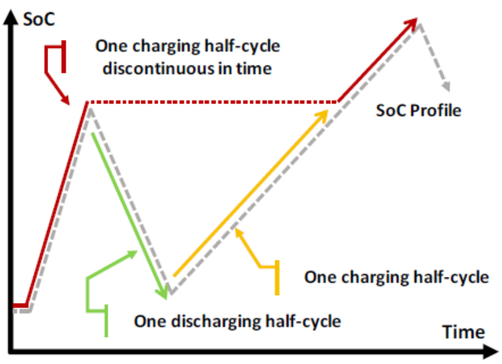


Figure 3.8: Rainflow cycle counting example

The primary drawback of the power-based method is that it does not a accurately capture the degradation of an energy storage system. Data from a study into the actual degradation of a Lithium Nickel Manganese Cobalt Oxide (NMC) battery showed a significant higher degradation when operated at near 100% cycle depth of discharge (DoD) compared to operation at 10% DoD [57]. Figure 3.7 shows a regression curve of a Li-ion battery cycle life for cycles at different DoD's [56]. The correct method for counting battery cycles is illustrated in 3.8. This cycle counting algorithm is called rainflow-counting and is frequently used for fatigue analysis. Modeling battery degradation using a rainflow-counting algorithm has one major problem when implemented in energy storage models. The non-linearity characteristic of such a method results in computational complexity and long optimization times. Another model that considers degradation as a non-linear process is proposed by authors in [61]. The model optimizes the dispatch of lithium-ion batteries in grid applications such as Frequency Containment Reserve (FCR), imbalance trading and peak shaving. The practicality if this model will be discussed further in 3.3

3.3. Existing stochastic congestion management optimization models

Section 3.2 focused on various energy resource modelling design choices and discussed decisions made by state-of-the-art optimization models found in literature. This section analyses the performance of existing stochastic congestion management optimization models. Rather than discussing the design choices, this section sheds light on implementing the model as a whole.

3.3.1. Stochastic battery dispatch models using hard constraints

As discussed in Section 3.2, the authors in [61] developed a battery model that optimizes dispatch control for operating in different energy markets. The model optimizes the dispatch of lithium-ion batteries in grid applications such as FCR, imbalance trading and peak shaving. In energy resource optimization models, it is common to oversimplify degradation processes due to lack of data and the necessity of fast computation. The proposed model used experimental aging data of a commercial battery to develop a battery dispatch control model, which according to the authors could operate under constraints of the investigated market models. Even though the presented battery degradation method is not 100% equal to the real case, it is able to make an efficient compromise between computational complexity and model accuracy. The main issue with the model is that although it is able to to optimize within the time horizons of market trading in theory, it is highly unlikely to be fast enough in practice. The model oversimplifies important time constraints for certain energy markets, most notably the imbalance market. For example, the Dutch market imbalance prices are settled for 15 minute blocks but this price is only known after the period is completed. Every minute Tennet publishes the actual imbalance price and these values can be used to forecast the 15 minute imbalance price. This does mean that for imbalance trading the optimization model should run at least every minute and this does is not possible with the proposed model. In other words, sometimes a model has to make simplifications because practical applications are constrained by time and decision making needs to be sufficiently fast. Implementing a complex model on the day-ahead market is a much better fit as it has at least a few hours to calculate an optimal strategy for the next day.

The model proposed in [62] is a stochastic hard constrained optimization model that calculates the optimal day-ahead scheduling for a grid-tied microgrid which includes energy resources such as a generator, PV, wind turbines, batteries and a limited grid connection. Due to limited grid supply, the microgrid could run into the same problem that a prosumer in a congested areas might have. The authors provide a model that is simple so that relevant time constraints are respected, but at the same time manages to model the resources with significant detail. However there is at least one oversimplification that could hinder practical implementation of the proposed model. The model uses a probabilistic constrained approach where uncertainties in consumption and weather forecast errors are estimated as a single value. This means that the model optimizes for input data that has a high probability of occurring but does not include worst case scenarios that have a low but non-zero probability of occurring. In order for stochastic programming to be effective, the number of scenarios must be large, even after scenario reduction techniques. Unfortunately, using a large set of uncertainty scenarios makes the model highly complex and therefore computationally demanding [63].

Stochastic optimization can be implemented in various operation strategies and resource sizing models. The Authors in [64] derive optimal day-ahead trading strategies in a multi-market environment. The problem is solved using stochastic optimization as it is subject to different levels of uncertainties such as variable generation output and various market prices. Instances of using stochastic optimization for problems considering optimal operation strategy and sizing are also common in literature. In [65], the authors propose a stochastic mixed integer nonlinear programming (MINLP) to determine optimal operation strategy and sizing of a battery and residential PV system. Another common implementation of stochastic optimization in energy resource related problems is battery degradation cost optimization. Authors in [66] developed a two-stage stochastic mixed-integer linear problem (MILP). Here, the uncertainty of electricity prices, solar irradiation, wind speed, and conventional loads are taken into account. Another possibility is to use an approach that is simulation- or scenario-based such as a forecast. In such cases the optimization problem can use the forecast as an input [67]. Some authors view energy resource dispatch as a non time-coupled process, meaning they consider each time-step independently [68]. When a system with energy storage is modeled as time-independent, it will fail to make optimal use of energy storage making the optimization model flawed [69].

3.3.2. Stochastic battery dispatch models using flexible constraints

Stochastic optimization is a broad mathematical optimization type and two arbitrary stochastic models can differ significantly in various rules and considerations. This thesis focuses on two kind of stochastic optimization methods where the only difference is the way the constraints are defined. The first method is a stochastic model using hard constraints, which was discusses in the previous section. The second model is a stochastic optimization where certain constraints are considered flexible. A flexible constraint does not always have to be respected and is generally modelled by adding a cost to a variable when it falls outside of a flexible constraint. For example a 100€fine for each additional kg of emissions that a factory produces over the flexible limit. Another way is to design a flexible limit in such a way that a predefined amount can fall outside the flexible limit. An example of this would be a consumer that has to adhere to a maximum grid constraint 95% of time.

The author in [70] proposes using hard constraints to solve an optimal power flow (OPF) model. An OPF model is used to determine the best operating levels for electric power plants in order to meet system energy demands. Robust optimization is found to be computationally less intensive because it solves the robust equivalent instead of using scenarios [71]. However, robust optimization mostly results in a solution that is too conservative. If a system is not constrained to a certain threshold 100% of the time, it could potentially result in significant better results compared to a system that is. Batteries are expensive, thus it would be financially challenging to get an additional 20% capacity for a event that happens only 1-2% of the time in a year. The author in [72] proposes a probabilistic optimal power flow (POPF) for unbalanced three-phase electrical distribution systems considering flexible robust constraints. Here the author considers the voltage and current fluctuation to be normally distributed and can therefore implement a statistical measure to translate a hard constraint into a flexible constraint.

Equation 3.3 shows the general formulation of a Gaussian distributed probability density function. It uses both the expected value (μ), defined by equation 3.1 and the standard deviation (σ), defined by equation 3.2

$$\mu = \sum \frac{x}{N} \tag{3.1}$$

$$\sigma = \sqrt{\frac{\sum (x-\mu)^2}{N}} \tag{3.2}$$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right) \tag{3.3}$$

- x - The value of a specific time-step in in the data distribution
- μ - The expected value or mean of the distribution
- σ - The standard deviation of the respective distribution
- N - The total number of of observations

A random variable (RV) which is part of a normally distributed set is most likely to have a value close to its expected value. Figure 3.9, 3.10 and 3.11 show the probability density function of a normal distributed set with $\mu = 1$ and $\sigma = 1$. The shaded areas in the figures show the respective confidence interval of $\pm 1\sigma$, $\pm 2\sigma$ and $\pm 3\sigma$ from the expected value μ. For a RV that has a normal distributed probability function, roughly 68.26% of the realizations will differ from their mean value by one standard deviation, 95.45% by two standard deviations and 99.73% by three standard deviations.
Optimization problem that contain uncertainty sets, that can be considered normally distributed, can use this statistical characteristic to find a less conservative solution. The probabilistic OPF model proposed in [73],

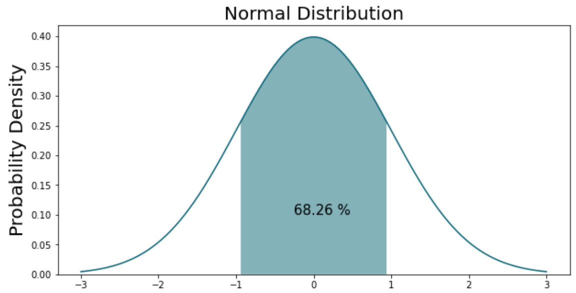


Figure 3.9: Normal distribution confidence interval at 1σ from μ, where μ=1 and σ=1

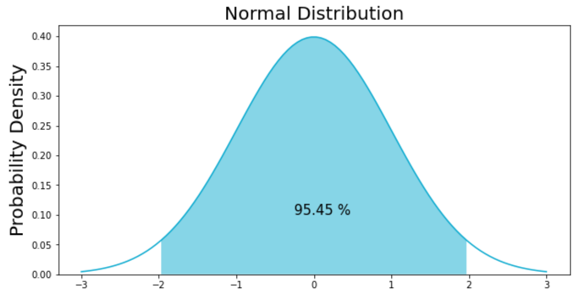


Figure 3.10: Normal distribution confidence interval at 2σ from μ, where μ=1 and σ=1

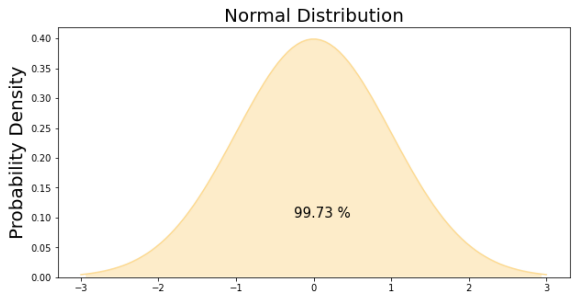


Figure 3.11: Normal distribution confidence interval at 3σ from μ, where μ=1 and σ=1

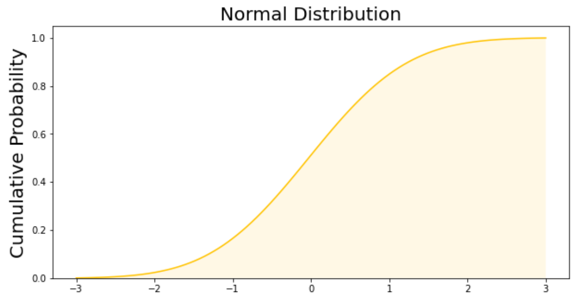


Figure 3.12: Normal cumulative distribution function from μ, where μ=1 and σ=1

implements this characteristic in voltage magnitude constraints shown Equations 3.4, and 3.5. For $\alpha^V = 1$, approximately 68.2% of the realizations deviate from their mean value. When using $\alpha^V = 1$ for the constraints in 3.4 and 3.5, this translates into at least 68.2% of the realizations should be below the maximal voltage threshold $\overline{V}$. For $\alpha^V = 2$ this would be 95.4% and so on [74].

$$\mu^V_{k,f} + \alpha^V \sigma^V_{k,f} \leq \overline{V}, \quad \forall k \in \Omega_b \tag{3.4}$$

$$\mu^V_{k,f} - \alpha^V \sigma^V_{k,f} \geq \overline{V}, \quad \forall k \in \Omega_b \tag{3.5}$$

- $\mu^V_{k,f}$ - Expected value of the RV at node k and phase f
- α^V - Level of robustness
- $\sigma^V_{k,f}$ - Standard deviation of the RV at node k and phase f
- Ω_b - Set of nodes
- $\overline{V}$ - Maximum voltage magnitude [p.u.].

3.4. Scientific contribution

The aim of this thesis is to contribute to the field of congestion management research by adding and extending current work. The main contribution is the development of a stochastic energy resource optimization model using flexible robust constraints. Considerable research is being conducted into developing both deterministic and stochastic optimization models aimed at integrating renewables into the power grid. Despite these efforts, there is little to no information to be found on cases where such models have been implemented in actual energy systems. General robust optimization models yield results that are too conservative due to the hard constraints and the high number of scenarios that have to adhere to these constraints. The work in this research attempts to make these constraints more flexible in order to improve the optimal solution while adhering to the constraints in all but a few instances. The idea is that this method provides a solution that is more likely to be implemented in real life cases through to the combination of robustness and improving the optimal solution. Also, energy resource models that use stochastic optimization generally use hourly data as granularity when optimizing over more than a day. All models developed in this thesis use data of 15min granularity, except for the day-ahead EPEX prices as these are cleared for every hour. This makes the problem more complex to solve but it gives a more detailed solution that can be used for a more in depth result analysis. The model also incorporates bi-directional power flows which enables different prices for buying and selling energy. Different prices for trading energy and a 15min granularity is already a step forward towards reflecting reality.

4

Methodology

The methodology chapter describes the methods used for developing the proposed mathematical optimization models. The first section gives an overview of the different resources used in this thesis and discusses any limitations imposed for the different tools. The first section also describes the energy resource configuration and several location specific parameters. The next section explains the deterministic, hard constrained stochastic and flexible-constrained stochastic optimization models used to solve the energy resource dispatch problem.

4.1. System overview

Figure 4.1 shows the different energy resources that are part of the optimization problem. The configuration also shows the possible directions of the power in the system. The energy resources connected to the system are solar PV (P^{PV}), battery storage (P^{B}), load demand (P^{L}) and a grid connection (P^{G}). Note that the PV and battery are connected in a behind-the-meter configuration. The energy resources are dispatched according to the control strategy determined in the smart control resource. The bidirectional flow, shown in Figure 4.1, is used to indicate the two-flow of data instead of power as is the case in the other resources.

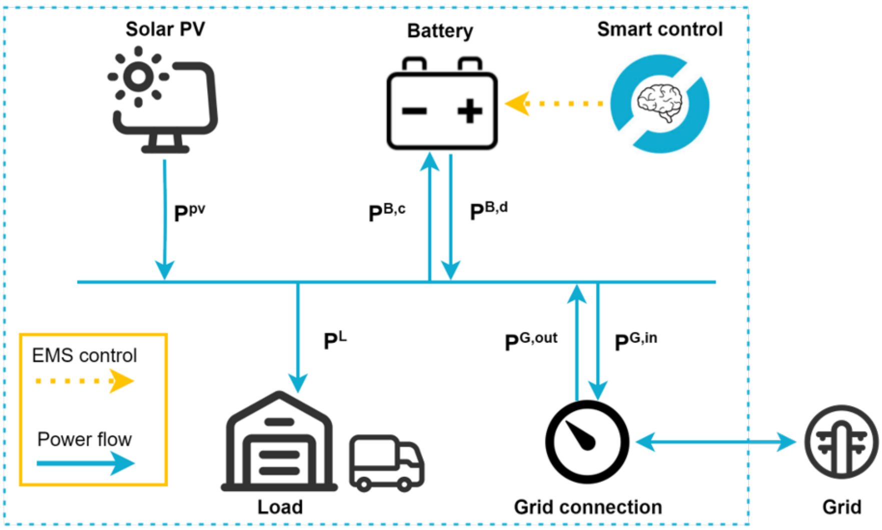


Figure 4.1: The energy resource configuration layout with corresponding power flow direction

The proposed configuration is a closed system meaning that power should be balanced at each time step t, shown in Equation 4.1. All power flows in the system are of the AC kind with PV and battery power already being transformed from DC to AC before it enters the local distribution system. The efficient losses for converting DC to AC are also already taken into consideration.

$$P_t^G = P_t^L - P_t^{PV} + P_t^B \qquad \forall t \in T \tag{4.1}$$

Figure 4.2 shows the higher-level process of the proposed optimization models. The vertical arrows indicate the chronological order of how the model treats data, the horizontal arrows are used to show the data feed into the system and outputs.

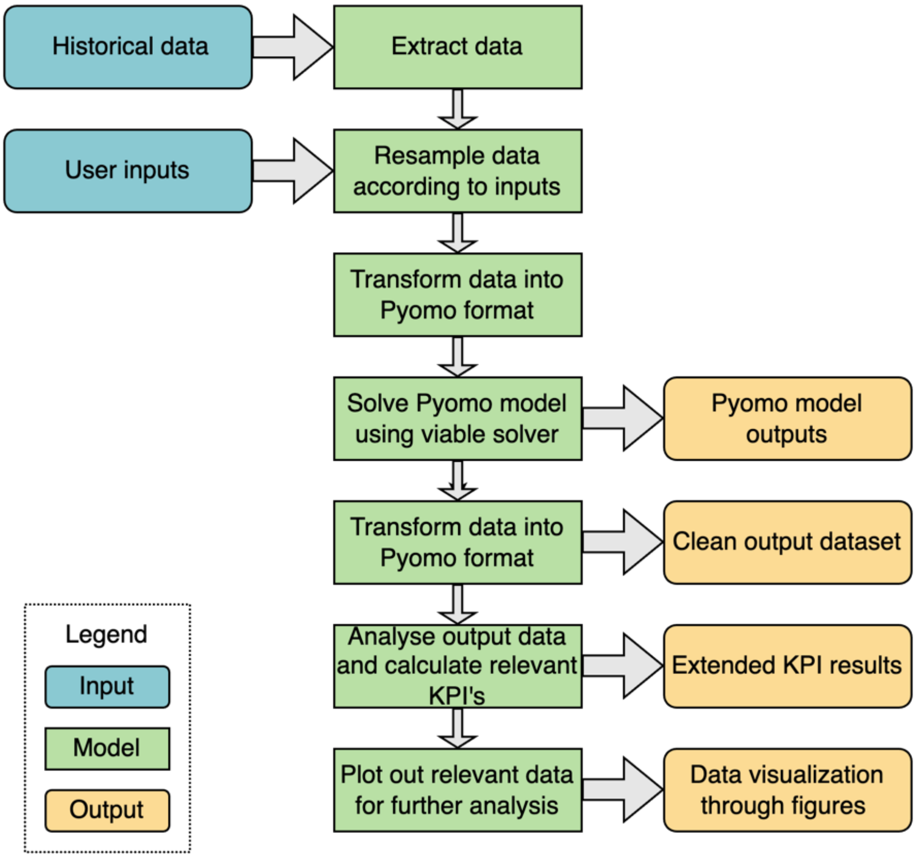


Figure 4.2: Flowchart representing the higher-level process of the proposed optimization models

4.2. Mathematical optimization

This section describes the mathematical optimization models that are developed in this research study starting with the proposed deterministic optimization model. Optimization components such as objective function and constraints are analysed, and relevant design choices are explained. After the deterministic model design, both the hard constrained and flexible constrained stochastic models are analysed using the same method as per deterministic model. The last section describes the implementation of the proposed theoretical optimization models into the Pyomo environment. The final section also describes dependencies, packages and other programming related design choices.

4.2.1. Deterministic model

The deterministic model is used to calculate the optimal energy resource dispatch strategy without considering the influence of probabilities or uncertainty. The goal of the deterministic model is to find the variable results that minimize the objective function, which is shown in Equation 4.2. The variable results that produce in the optimal objective function are also referred to as optimal control strategy. As was explained in 4.1, the grid and battery have a bidirectional power flow. At each time step t, the battery can either discharge, charge denoted by respectively $P_t^{B,d}$ and $P_t^{B,c}$. Note that another possibility is for the battery to sit idle, which would mean that both $P_t^{B,d}$ and $P_t^{B,c}$ are 0. Similarly the grid can import or export power at each time step t denoted by respectively $P_t^{G,in}$ and $P_t^{G,out}$. The main reason for splitting the grid power into a variable for import and export, is due to the different price for selling and buying electricity. The selling price of electricity to the grid is denoted by ϵ_t^s, while the buying price is denoted by ϵ_t^b. As prices of electricity are related to energy and not power, the objective function uses Δ_t to correctly transform power into energy. By implementing the time factor Δ_t, the model is able to input data of different granularity's. Equation 4.3 is an extension of 4.1 that is used to ensure the model is adhering to the power balance at each time step t. The energy dispatched by the battery can be given a fixed weight denoted by ϵ^{bat}.

$$min \sum_{t \in T} \Delta_t.(P_t^{G,in}.\epsilon_t^s + P_t^{G,out}.\epsilon_t^b) + (P_t^{B,c} - P_t^{B,d}).\epsilon^{bat} \tag{4.2}$$

$$subject\ to:$$

$$P_t^{G,out} + P_t^{G,in} = P_t^L - P_t^{PV} + P_t^{B,d} + P_t^{B,c} \qquad \forall t \in T \tag{4.3}$$

Equations 4.4-4.8 are constraints related to battery operation. The constraint shown in Equation 4.4 ensures the value for $P_t^{B,c}$ remains below the maximum rated charge power $\rho^{B,c}$. Similarly $P_t^{B,d}$ is constrained by $\rho^{B,d}$ as can be seen in Equation 4.4. During one time step the battery can only discharge or charge but it cannot do both at the same time. To ensure the mutual exclusivity, the binary variables $\beta_t^c, \beta_t^d \in \{0,1\}$ are introduced in Equations 4.4-4.6. Equation 4.6 is used to make sure the binary variables can only take the allowed value. The constraints in 4.7 and 4.8 guarantee that the discharge power is always negative and charge power positive for each time t.

$$P_t^{B,c} \leq \rho^{B,c}.\beta_t^c \qquad \forall t \in T \tag{4.4}$$

$$-P_t^{B,d} \leq \rho^{B,d}.\beta_t^d \qquad \forall t \in T \tag{4.5}$$

$$\beta_t^c + \beta_t^d \leq 1 \qquad \forall t \in T \tag{4.6}$$

$$P_t^{B,d} \leq 0 \qquad \forall t \in T \tag{4.7}$$

$$0 \leq P_t^{B,c} \qquad \forall t \in T \tag{4.8}$$

The grid interaction is modeled by Equations 4.9-4.13 and is constrained in a similar way compared to the battery. As mentioned before, P_t^G is split into import- and export power denoted by respectively $P_t^{G,out}$ and $P_t^{G,in}$. By Implementing the constraint shown in Equation 4.9, the grid import power never exceeds the maximum grid limit $\rho^{G,out}$. For grid feed-in power $\rho^{G,in}$ this is achieved through the constraint shown in Equation 4.10. The binary variables $\beta^{G,out}, \beta^{G,in} \in \{0,1\}$ used in Equation 4.11 ensure that at each time step t, the grid is exclusively supplying or importing energy. The constraints shown in Equations 4.12 and 4.13, ensure positive values for importing energy and negative for exporting energy. The only time $P_t^{G,out}$ and $P_t^{G,in}$ have the same value is when they are equal to 0.

$$P_t^{G,out} \leq \rho^{G,out}.\beta^{G,out} \qquad \forall t \in T \tag{4.9}$$

$$-P_t^{G,in} \leq \rho^{G,in}.\beta^{G,in} \qquad \forall t \in T \tag{4.10}$$

$$\beta^{G,out} + \beta^{G,in} \leq 1 \qquad \forall t \in T \tag{4.11}$$

$$-P_t^{G,out} \leq 0 \qquad \forall t \in T \tag{4.12}$$

$$P_t^{G,in} \leq 0 \qquad \forall t \in T \tag{4.13}$$

The constraints describing the battery state of charge SoC_t for each time step t are shown in Equations 4.14 - 4.15 below. Looking at constraint 4.14, SoC_t depends on the previous value denoted by SoC_{t-1}. The new state of SoC_t is calculated by adding the charged energy or subtracting the dispatched energy during time step t. The efficiency of the battery system is included in the calculation through the parameter η^b. The SoC limits, denoted by γ^{min} and γ^{max} and are implemented using the constraint shown in 4.15.. When t=0, the first term in Equation 4.14 is set to $SoC_{t=0-1}$, which is known as the initial battery state of charge. The initial state of charge is defined before solving the model and can be taken anywhere between γ^{min} and γ^{max}.

$$SoC_t = SoC_{t-1} + \frac{(\frac{P_t^{B,d}}{\eta^b} + \eta^b.P_t^{B,c}).\Delta^t}{P_n^B} \qquad \forall t \in T \tag{4.14}$$

$$\gamma^{min} \leq SoC_t \leq \gamma^{max} \qquad \forall t \in T \tag{4.15}$$

One possible method for limiting the amount of grid power exceeding a certain threshold, is to define the limit as a soft constraint. This means that, in this case the grid limit, can be exceeded but the extra power is given a cost. The idea is that the limit will only be exceeded when the profit out ways the cost of overshooting the grid limit. Also, when the cost is sufficiently large, the exceeding power P_t^E is limited to be used when absolutely necessary. The deterministic model developed in this thesis has been extended to include this soft grid limit constraint. Analysing the impact of different values gives valuable insight to the performance of such a method and also sheds light on possible limitations. To transform the grid limit into a flexible constraint instead of a robust one, the exceeding power P_t^E in the model is weighted by the predetermined grid fine ϵ^f. To allow the grid power to exceed the grid limit, Equations 4.16 - 4.18 are added to the model. The objective function is changed to 4.16, so that it also considers the grid fine when optimizing the cost function. The power balance also needs to include the extra grid power P_t^E, thus the power balance is rewritten to the one in Equation 4.17. The focus of the case study is on supply congestion, meaning the grid fine ϵ^f is only relevant when taking energy from the grid. To ensure P_t^E has the same sign as $P_t^{G,in}$ the constraint in Equation 4.18 is used.

$$min \sum_{t \in T} \Delta_t.(P_t^{G,in}.\epsilon_t^s + P_t^{G,out}.\epsilon_t^b) + (P_t^{B,c} - P_t^{B,d}).\epsilon^{bat} + (\epsilon^f + \epsilon_t^b).P_t^E \tag{4.16}$$

$$subject\ to:$$

$$P_t^{G,out} + P_t^{G,in} + P_t^E = P_t^L - P_t^{PV} + P_t^{B,d} + P_t^{B,c} \qquad \forall t \in T \tag{4.17}$$

$$-P_t^E \leq 0 \qquad \forall t \in T \tag{4.18}$$

4.2.2. Stochastic model using hard constraints

The stochastic optimization model developed as part of this thesis, is able to calculate the optimal energy resource dispatch strategy while considering parameter uncertainties. The realized stochastic robust model is able to optimize a problem that has different scenarios s for the same time step t. The stochastic robust model is essentially an extension of the deterministic model with the addition of multiple scenarios per time step. Each variable used in the stochastic robust model should be defined as being either scenario dependent or scenario independent. The value of a scenario dependent variable can be different for each scenario of the same time step. Unlike dependent variables, scenario independent variables are the same for each scenario in a time step. In other words, the optimal solution contains only one value for a dependent variable in each time step. The stochastic parameters that are used in the optimization problem are $P^L_{t,s}$ and $P^{PV}_{t,s}$.

$$s \in S \qquad\qquad S_s = \begin{Bmatrix} (P^L_t, P^{PV}_t)_1 \\ ... \\ (P^L_t, P^{PV}_t)_s \end{Bmatrix} \tag{4.19}$$

Compared to the deterministic objective function, the stochastic objective function in Equation 4.20 includes two scenario dependent variables denoted by $P^{G,out}_{t,s}$ and $P^{G,in}_{t,s}$. The solution to the optimization problem will therefore include a value for each different scenario s at a certain time t depending on the stochastic parameter for a certain scenario. The battery variables $P^{B,c}_t$ and $P^{B,d}_t$ are scenario independent and the solution includes only a single value for each t. The goal is to find a battery dispatch strategy that works best when combining all possible scenarios. The battery is the only controllable load in the system which makes it the only energy resource that is modeled as scenario independent.

$$min \sum_{t\in T, s\in S} \Delta^t.(P^{G,in}_{t,s}.\epsilon^b_t + P^{G,out}_{t,s}.\epsilon^s_t) + (P^{B,c}_t - P^{B,d}_t).\epsilon^{bat} \tag{4.20}$$

$$subject\ to:$$

$$P^{G,out}_{t,s} + P^{G,in}_{t,s} = P^L_{t,s} - P^{PV}_{t,s} + P^{B,d}_t + P^{B,c}_t \qquad \forall t \in T,\ s \in S \tag{4.21}$$

The battery constraints in Equations 4.22-4.26 are the same as the battery constraints for the deterministic model. There are no stochastic parameters and all variables are scenario independent. The grid constraints in Equations 4.27-4.31 are similar to the battery constraints for the deterministic model but not exactly the same. The power balance constraint in Equation 4.21 shows that both grid power variables $P^{G,out}_{t,s}$ and $P^{G,in}_{t,s}$, are directly dependent on stochastic inputs parameters. Therefor, the constraints in Equations 4.27-4.31 show a dependency on both time and scenario (t,s).

$$P^{B,c}_t \leq \rho^{B,c}.\beta^c_t \qquad \forall t \in T \tag{4.22}$$

$$-P^{B,d}_t \leq \rho^{B,d}.\beta^d_t \qquad \forall t \in T \tag{4.23}$$

$$\beta^c_t + \beta^d_t \leq 1 \qquad \forall t \in T \tag{4.24}$$

$$P^{B,d}_t \leq 0 \qquad \forall t \in T \tag{4.25}$$

$$0 \leq P^{B,c}_t \qquad \forall t \in T \tag{4.26}$$

$$P^{G,out}_{t,s} \leq \rho^{G,out}.\beta^{G,in}_{t,s} \qquad \forall t \in T,\ s \in S \tag{4.27}$$

$$-P^{G,in}_{t,s} \leq \rho^{G,in}.\beta^{G,out}_{t,s} \qquad \forall t \in T,\ s \in S \tag{4.28}$$

$$\beta^{G,in}_{t,s} + \beta^{G,out}_{t,s} \leq 1 \qquad \forall t \in T,\ s \in S \tag{4.29}$$

$$-P^{G,out}_{t,s} \leq 0 \qquad \forall t \in T,\ s \in S \tag{4.30}$$

$$P^{G,in}_{t,s} \leq 0 \qquad \forall t \in T,\ s \in S \tag{4.31}$$

The variable SoC_t is calculated from the battery variables $P^{B,c}_t$ and $P^{B,d}_t$. Looking at Equations 4.32 and 4.33, it can be seen that SoC_t depends exclusively on deterministic parameters. With SoC_t only depending on deterministic parameters and scenario independent variables, the state variable SoC_t is scenario independent itself. Since SoC_t is scenario independent, the constraints in Equations 4.22-4.26 are identical to the state-of-charge constraints used in the deterministic model.

$$SoC_t = SoC_{t-1} + \frac{(\frac{P^{B,d}_t}{\eta^b} + \eta^b.P^{B,c}_t).\Delta^t}{P^B_n} \qquad \forall t \in T \tag{4.32}$$

$$\gamma^{min} \leq SoC_t \leq \gamma^{max} \qquad \forall t \in T \tag{4.33}$$

4.2.3. Stochastic model with flexible constraints

The third and final model developed in this thesis, is the stochastic model using flexible constraints optimization model. The flexible constrained model is similar to the hard constrained stochastic model with the difference being the method of defining the constraints. The idea is to implement a method similar to what authors in [72] used in a probabilistic optimal power flow (POPF). The proposed method combines statistical distribution from the grid power and grid supply limits, resulting in flexible constraints usable for the energy resource dispatch problem addressed in this thesis. First step is to define the mean value for the power flowing to and from the grid denoted by $\mu_{P,grid}$. The model calculates the value for $\mu_{P,grid}$ by using Equation 4.34. Here $T_{steps}.S_{tot}$ is used to indicate for the total amount of data points for $P^{Grid,-}$. The next step is to derive the standard deviation for grid power denoted by $\sigma_{P,grid}$. The value of $\sigma_{P,grid}$ is obtained taking the root of the sample mean $\sigma^2_{P,grid}$, which is calculated using Equation 4.35. The standard deviation is an absolute value so the constraint in Equation 4.36 is used to guarantee a positive value.

$$\mu_{P,grid} = \sum_{t\in T,s\in S} \frac{P^{G,out}_{t,s} + P^{G,in}_{t,s}}{T_{steps}.S_{tot}} \qquad \forall t \in T,\ s \in S \tag{4.34}$$

$$\sigma^2_{P,grid} = \sum_{t\in T,s\in S} \frac{((P^{G,out}_{t,s} + P^{G,in}_{t,s}) - \mu_{P,grid})^2}{T_{steps}.S_{tot}} \qquad \forall t \in T,\ s \in S \tag{4.35}$$

$$-\sigma_{P,grid} \leq 0 \tag{4.36}$$

The difference between the stochastic flexible and hard constrained model, is the method of imposing the grid limit. The stochastic robust model uses a hard constraint that cannot be exceeded for any scenario or time step. The stochastic flexible model implements flexible robust constraints where the constraint can be exceeded occasionally. The stochastic flexible model uses the same constraints as the stochastic robust model with the exception of Equations 4.27 and 4.28. These constraints are replaced by the constraints in Equations 4.37 and 4.38. The robustness factor is a positive integer value that can be used to specify how flexible a certain constraint is. As was previously explained in Subsection 3.3.2, the realizations of a Gaussian distributed random variable can be approximated. When R_F=1 this mean that approximately 68.2% of the realizations fall inside the confidence interval of $[\rho^{G,in}, \rho^{G,out}]$. For R_F=2 this would be 95.4% of the realizations and for R_F=3 this would be 99.7%. When relating this to the robust optimization model, this would mean that with a robustness factor of R_F=1, at least 68.2% of the realizations should adhere to the flexible grid constraint. In case R_F=2, a total of 95.4% of the realization for $P^G_{t,s}$ should adhere to the flexible grid constraint.

$$\mu_{P,grid} + \sigma_{P,grid}.R_F \leq \rho^{G,out} \tag{4.37}$$

$$\mu_{P,grid} - \sigma_{P,grid}.R_F \leq \rho^{G,in} \tag{4.38}$$

The theory is based on the assumption that the input variables will follow a Gaussian distribution, which is most likely not the case. Nevertheless, by considering the central limit theorem (CLT) the value for $P^G_{t,s}$ can be approximated to follow a Gaussian probability density function [75]. The CLT states that the distribution of a given sample mean is approximately similar to a Gaussian distribution under certain conditions. The central limit theorem applies when the variables are random, independent and the sample size is sufficiently large (n≤30). Considering the optimization problem in this thesis, the assumption is that the CLT can be applied since the sample size of input RVs in the form of P^L and P^{PV} is sufficiently large. There is a situation where the method fails to ensure flexible robust constraints. For a situation where $\sigma_{P,grid}$=0, this would mean that the data set has no spread. No spread indicates a situation where all values are the same and thus you do not have a stochastic model, but rather a deterministic one.

4.2.4. Battery degradation estimation method

There are numerous ways to estimate battery degradation ranging from complex non-linear functions to simplified linear methods. The method chosen for defining battery cycles in this thesis, is the rainflow cycle counting algorithm. Considering the available resources for this thesis, rainflow cycle counting has not been implemented in the model directly as it is to computationally complex. This means that degradation is not taken into consideration when calculating the optimal strategy. Instead the rainflow cycle counting algorithm is used to calculate the cycles post optimization. The deterministic model does include the ability to define a cost on using the battery. This cost is however not linked to the rainflow cycle counting algorithm. Changing the battery cost will limit the overall use of the battery but it will not consider the method of counting cycles when calculating the optimal dispatch strategy. Equation 4.39 shows the part of objective function that limits the battery usage.

$$(P_t^{B,c} - P_t^{B,d}).\epsilon^{bat} \tag{4.39}$$

Note that $P_t^{B,d}$ is always negative or zero and $P_t^{B,c}$ is zero or positive. This means that there is a cost taken into account in the objective function every time the battery charges or discharges power. The deterministic model is also used for a sensitivity study in section 5.2.1, on how the model results are affected by different battery dispatch costs.

4.3. Implementation of models in Pyomo

The deterministic, stochastic and stochastic flexible model, are all implemented using the python-based, open-source optimization modeling language Pyomo [76],[77]. The basic steps of developing a mathematical optimization model in Pyomo are shown below.

- Create model and declare components (set,parameter, variable, objective and constraint)
- Represent an abstraction by a concrete instance otherwise known as instantiating the model
- Depending on the formulation and type of model, apply a solver that fits the criteria
- Extract solver results and transform results into relevant performance indicators

In addition to built-in python libraries, additional libraries and software packages are used in the development of the models. The Pandas package is required for data analysis and associated manipulation of tabular data in Dataframes. Pandas also allowed for efficiently importing data from various file formats. Working with arrays was done with the Numpy python library. Numpy has functions for working with linear algebra, fourier transforms, and matrices. All figures have been made using Matplotlib, which is a cross-platform, data visualization and graphical plotting library for Python. A handful of statistical calculations were done using the SciPy library. SciPy stands for Scientific Python and it provides utility functions for optimization, stats and signal processing statistics. The battery cycles were calculated post optimization by using the rainflow cycle counting algorithm package for fatigue analysis called rainflow [78].

5
Case Study

This chapter presents the results of various proposed mathematical optimization strategies when implemented for a logistical building in the Zaandam region. The case considers a distribution center that is home to a major e-commerce company which has been unable to obtain the minimal grid supply connection required for normal business operation. The first section discusses the data collection process and also presents interesting data analysis results. Next, the results of three different optimization models are presented and the performance of various key indicators is analysed. The final section evaluates model limitations and compares the results of the different proposed optimization models.

5.1. Data used in case study

This section focuses on the input data used in the case-study. First, the historical PV production and electricity consumption data is presented and analysed. Understanding the model inputs is useful for understanding the results and performance of the system. Next is a discussion on the local congestion constraints and parameters related to the energy storage resource. The last section discusses the implementation of the day-ahead energy market for both selling and buying electricity. A summary of the inputs used for the case study can be found in Table 5.1.

Type	Size	Unit	Type	Size	Unit
Installed pv capacity (DC)	2000	kWp	Battery capacity (usable)	2000	kWh
Installed pv capacity (AC)	1280	kVA	Battery charge power max	2000	kW
Yield	900	kWh/kWp	Battery charge power max	2000	kW
Peak consumption	550	kVA	Initial state of charge	50	%
Supply grid limit	450	kVA	minimum state of charge	10	%
Delta timestep	0.25	N/A	maximum sate of charge	100	%

Table 5.1: General system inputs used in case study for all models

5.1.1. PV production

Company X is located just north of Amsterdam in an area known as the Zaandam region. This specific region has not yet encountered issues due to feed-in congestion as is the case in many other regions in the Netherlands. Because of this company X has been allocated a feed-in connection rated at 2000 kVA. Building X has a total usable roof area of 15,000 m^2 with an installed PV capacity of 2000 kWp translating into a PV density in approximately 135 Wp/m2. The array-to-inverter ratio is approximately 1.56 resulting in a maximum AC output of 1280 kVA. Figure 5.1 shows a similar building compared to company X and Figure 5.2 shows the E/W oriented PV system layout as viewed from the roof.

Figure 5.1: Logistical building similar to company X

Figure 5.2: PV system layout for building similar to company X

The PV system consists of 7000+ Talesun Solar TP660P-275 panels (A.2) and uses 16 Sungrow SG80KTL inverters (A.3) rated at 80 kVA each. The availability of the PV park has been 99.98% during 2020 which has resulted in an annual yield of 1,800 MWh/yr and performance of 900 kWh/kWp. Figure 5.3 shows the 2020 monthly output for the PV system located on the roof of building X. The monthly PV production output illustrates the expected seasonality with peaks in summer and low yield in winter. It is interesting to see that the yield in May was significantly higher than the yield during the summer months. The reason for this difference was that May was an exceptionally good month for PV production. During May 2020, the KNMI recorded 324 solar hours while the monthly average since 1989 is only 213 solar hours, which is the 2nd most in recorded history. For comparison, August had the 2nd most available sun hours in 2020 with only 229 recorded by the KNMI [79]. The monthly data for PV production can be found in Appendix Table B.1.

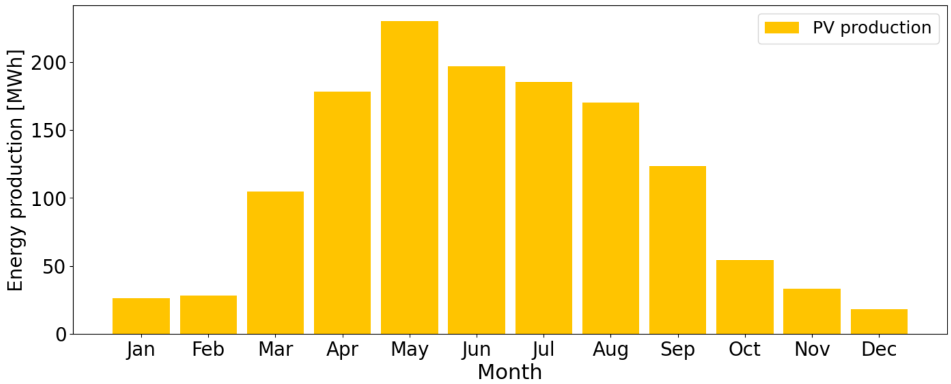


Figure 5.3: Company X's PV system production output in MWh throughout 2020

Figure 5.4 shows the average PV production compared to the minimum and maximum value for each season. The granularity of the historical production data is 15min, which is the same as the consumption data. Note that the maximum power in spring and summer seems to be curtailed during peak production times due to the maximum rated inverter power of 1280 kVA. Although the PV profile for spring and summer look similar, there is an additional 26.8% PV production in summer compared to spring. The seasonal increase is mostly likely attributed to the different sunrise and sunset times as the peak seems similar. In summer the PV system produces energy between 6:30 and 22:45 while the production in spring occurs between 7:00 and 22:00. In addition to the wider production curve in summer, the figure shows that the minimum PV output during summer is also substantially higher compared to spring.

5.1.2. Consumption

As was mentioned before, company X is a distribution center housing a major Dutch e-commerce company located in the Zaandam West region in the province of North-Holland. The bulk of energy consumption can be attributed to 4 main processes which are HVAC (heating ventilation and cooling), lighting, IT network with relevant equipment and operating machinery (e.g. charging forklifts). Note that the building heating system

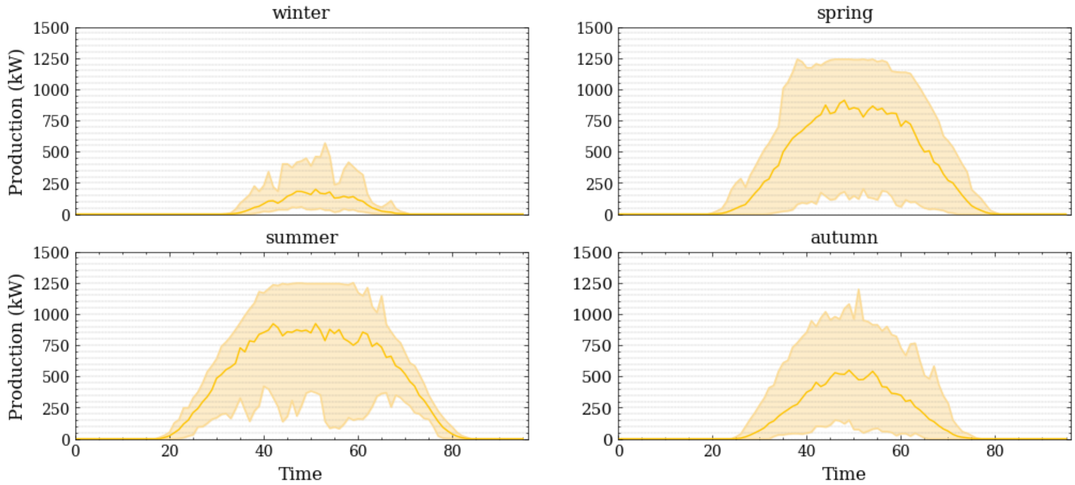


Figure 5.4: Daily average, minimal and maximum PV production in 2020, compared by season

for this case study runs on gas so a significant chunk of the building energy consumption is not reflected in the electricity consumption data used in this thesis. A useful analysis tool that can result in better understanding time series data is seasonal decomposition. Here a time-series data set is broken down in systematic and non-systematic components. Systematic components show consistency that can be mathematically described, which allows for accurate modeling. For non-systematic components, there is no logical consistency making it difficult to accurately model, often known as noise. Systematic components include trend, seasonality and level. Figure 5.5 shows an additive decomposition of the electricity demand in 2020 for company X. The additive model implies that the different components added together make up the actual data. Looking at the trend plot, it can be seen that company has higher electricity demand in summer months compared to winter months. This seasonality is advantageous when a company wants to make direct use of the rooftop PV as the consumption profile trend is similar to that of PV. A monthly consumption profile can be found in Appendix B.1, which also shows a similar trend. The seasonality component in seasonal decomposition is defined as the repeating short-term cycles in a time series data set. Looking at the seasonal component in Figure 5.5, the plot demonstrates the same frequency and amplitude indicating linear seasonality. The last plot in Figure 5.5 shows the noise and considering it is not a straight line, it means that there is some noise in the data. However, the noise seems to fluctuate between -0.1 and 0.1 which still indicates a reasonably consistent consumption profile. Having a consumption profile that is consistent throughout the year is useful when that data is used for optimization models. If a profile is consistent, chances are history repeats itself which makes a strategy based on this historical data more reliable. Also when a model is consistent, it becomes easier to make different forecast for the time series data as it becomes more predictable. Note that this does not mean an optimization model is not required to be robust against unlikely events.

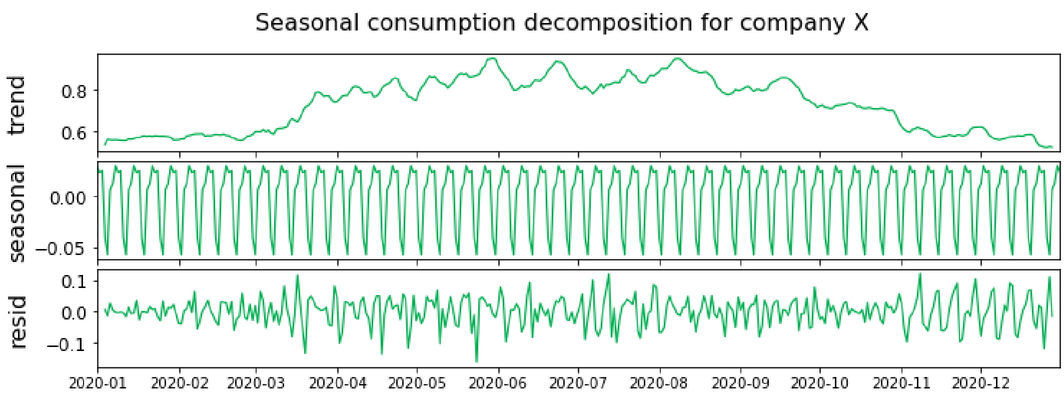


Figure 5.5: A seasonal decomposition of Company X's electricity demand in 2020

Figure 5.6 shows the 2020 weekly average, minimal and maximum power demand for each season. The thick line is the average consumption profile and the light green indicates the bound between the minimum and maximum, for a certain day in the week. The granularity of historical consumption data is 15 min, which was the same as PV production. With only slightly lower consumption during the weekend, the consumption profile can still be categorized as 7 day constant. This means that business operation for company X is essentially the same for each day during the week. Consumption during summer and spring months is considerably higher compared to other months in the year. Also, the power demand for company X never falls below 100 kW during winter and 160 kW for summer. The profile can thus be categorised as a 7 day profile that follows working hours with a base load of approximately 50% of the peak. Note that the spread in winter is significantly lower compared to other seasons.

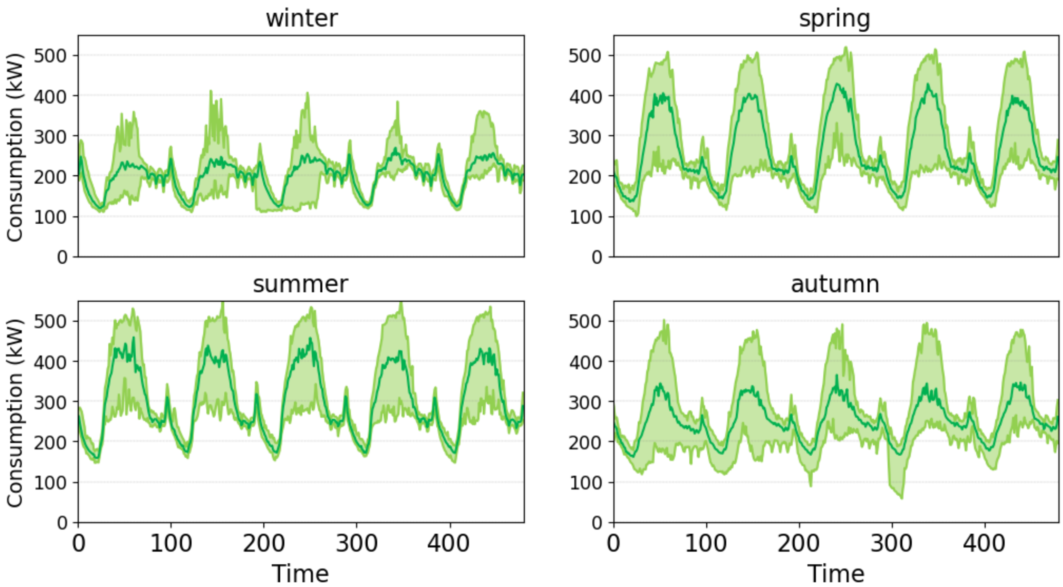


Figure 5.6: Daily average, minimal and maximum power demand in 2020, compared pby season

5.1.3. Local grid congestion

As was previously discussed in Section 3.1, grid congestion has become a significant bottleneck for increasing the share of renewable energy. Company X is located in the Zaandam West region which is experiencing structural supply congestion. As of now, there are no issues related to feed-in congestion but the allocation of new supply connections has been stopped indefinitely. The expectation for the earliest allocation of new large supply connections is in the 4th quarter of 2027, but could also be as late as 2030 [80]. The current existing and contracted capacity for the substation in congestion area Zaandam West is shown in Table 5.2. These values are reported by Liander in a 2021 study into the congestion issues emerging in the region [80]. Note that theoretical maximum power peak is already 9.6 MVA above the 50 MVA available capacity.

Table 5.2: Current existing and contracted capacity in congestion area Zaandam West

Type	**Power [MVA]**
Available capacity for electrical substation	50
Current existing peak load on the electrical substation origination from electricity consumption	59.6
Current existing peak load on the electrical substation originating from electricity feed-in	1.3
Total contracted supply capacity for large consumers (>3x80A)	5.3
total contracted feed-in capacity for large consumers	12.5
Total contracted supply capacity for small consumers (<3x80A)	10207

If the current existing power peak would be the same for coming years, this would be a problem but a manageable one. The issue becomes a real problem when the peak rises further which is expected to happen due to two main reasons. The first reason is the backlog of contracted capacities actually being used. A grid connection is applied for before construction of a new building starts. Liander stopped allocating new connection but there are still some buildings in the area which have not yet started operation. The second, more pressing issue is the current electrification movement putting more pressure on the current connections. Table 5.3 shows the expected yearly energy that will not be able to be transported due to supply congestion as reported by regional DSO Liander in 2021 [80]. So even if you have a grid connection it could be beneficial for continuous business operation to become less dependent on the grid and use as much locally produced energy as possible. In some cases the investment cost of a battery could be considered small or reasonable when compared to shutting down business because of a grid blackout. Company X in this case study has a supply connection of 450 kW but has a peak of 550 kW. They also have plans to electrify certain processes such as HVAC and add EV trucks to their fleet. The current connection cannot even handle the current demand let alone the demand that is required for these future plans. Adding a gas generator for charging electric trucks is counter productive, thus the problem needs to be solved with local green generation and storage.

Table 5.3: Expected amount of electricity that cannot be transported in congestion region Zaandam West

Year	Expected yearly non-transported energy [MWh]
2022	26
2023	45
2024	1300
2025	1876
2026	2441

5.1.4. Energy storage

There are many different energy storage resources to choose from, each with their own advantages and disadvantages. Company X opted to go with a battery system as its energy storage resource. Table 5.4 and 5.5 show the respective specifications for the DC and AC equipment in the chosen battery system. Appendix A.1 shows the data sheet for the C&I 1MW 1.15MWh BESS Solution developed by the Chinese based company LP energy. The setup in the case study actually consists of two C&I BESS solution battery connected in a behind the meter setup. The initial SoC for each simulation is set at 50%, using the same starting position for each simulation ensures fair and consistent results when comparing different models.

DC side	
Rated power (kW)	1000
Rated capacity (kWh)	1152*
Rated voltage (Vdc)	640
Minimum SoC (%)	10%

Table 5.4: Battery specifications DC *Rated capacity actually set to 1000 kWh for improving battery life

AC side	
Rated power (kVA)	1000
Rated voltage (Vac)	400
Roundtrip efficiency	85%

Table 5.5: Battery specifications AC *Rountrip efficiency includes the losses for inverting between AC en DC power

5.1.5. Day-Ahead Energy Market

The case study uses different prices for importing and exporting energy although both are based on the EPEX day-ahead energy market. In most cases, the electricity from commercial developed PV parks is sold on this wholesale day-ahead market in combination with the spot imbalance market. The production for the next day is forecasted and hourly bids of the forecasted volume are put into the market. Depending on the forecasting error, the mismatch will be automatically settled on the imbalance market on a 15 min scale. For the case study in this thesis the client has a market conform power purchasing agreement (PPA) with an undisclosed utility company. The agreement states that the the energy produced on the roof of company X is sold at the EPEX price with a cost of 8%. This 8% is used to cover the potential losses on the imbalance market from forecast errors but also a small portion is revenue for the utility company for acting as the middle man. Company X is assumed to have implemented the real time pricing contract called Sunrock Energy. Consumers with Sunrock energy pay a price that changes on an hourly basis in the same way as the EPEX day-ahead market [1]. With the prices being directly related to the day-ahead market, the prices are known a day in advance. The fee payed on top of the EPEX settlement price is 5 €/MWh, but the client also receives 2.5 € worth of GVO (guarantee of origin) for each MWh bought. These GVO's can be sold for 2.5 €/MWh on

[1] https://sunrock.com/en/energy/

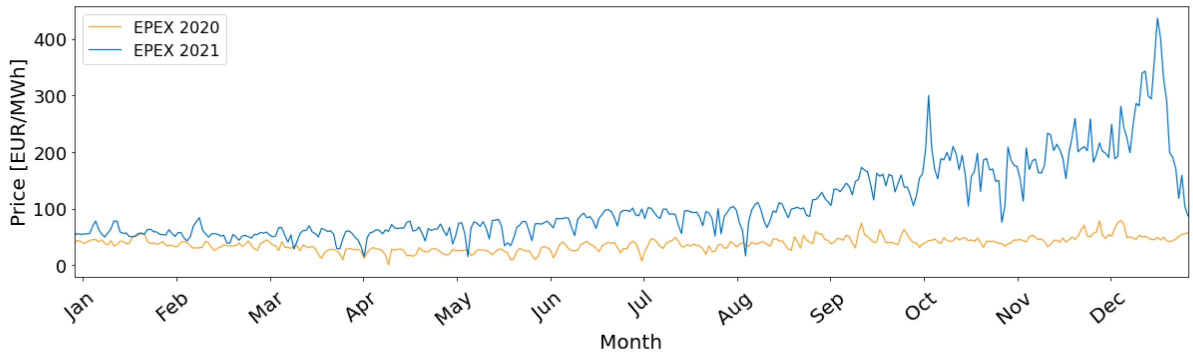


Figure 5.7: The daily average EPEX SPOT settlement prices for 2020 and 2021

the market as companies are required to have enough of them for relevant emission laws. Figure 5.7 shows the average daily EPEX settlement prices for 2020 and 2021. The price data for 2020 seems to be fluctuating slightly but still fairly constant throughout the year. Around August 2021 the prices start rising heavily and the local minima and maxima seem to be growing further apart. The daily average price has increased from 42.10 €/MWh in 2020 to 242.80 €/MWh in 2021, which is a 476.7% increase. The daily standard deviation has increased from 9.92 €/MWh in Jan 2020 to 102.12 €/MWh in 2021, which is a 929.4% increase. Appendix B.2 shows how the mean and standard deviation for the EPEX settlement price increase over the course of two years.

The case study in this thesis analyses three different scenarios for EPEX prices. The first scenario is shown in 5.8 and is referred to as scenario A during the remainder of this report. In scenario A, the EPEX data from 2020-06-01 to 2020-06-05 is used.

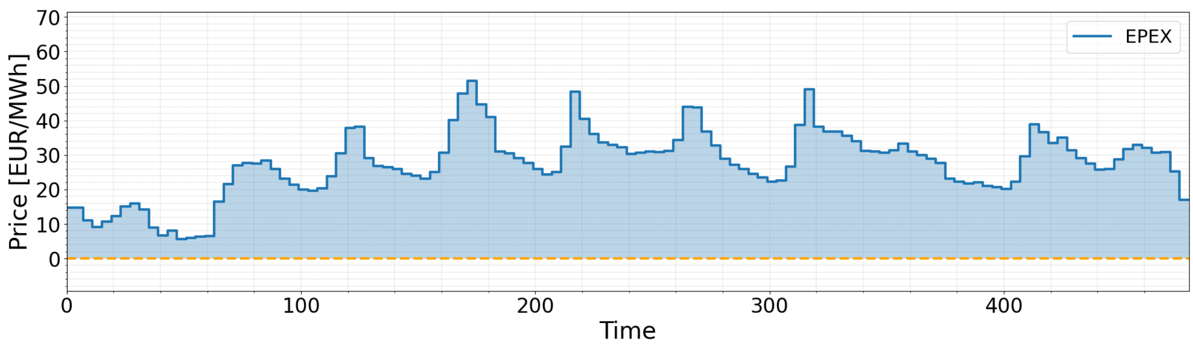


Figure 5.8: Epex day-ahead price data for 2020-06-01 - 2020-06-05, scenario A

The second scenario is shown in 5.9 and will be referred to as scenario B for the remainder of this report. Scenario B is used to for a single day of data and represents a single regular summer day on 2020-06-01. The third and final scenario is the settlement prices that occurred on 2021-12-01, from here on referred to by scenario C.

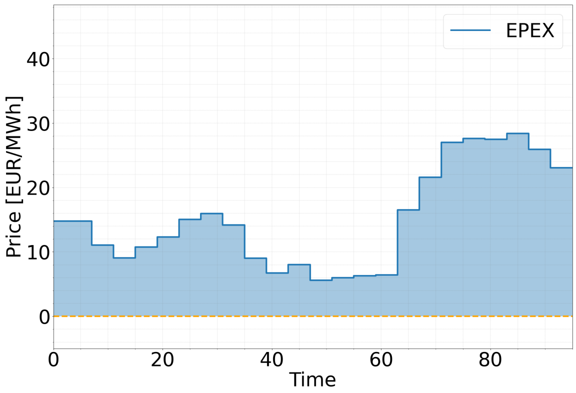


Figure 5.9: summer 2020 1 day, scenario B

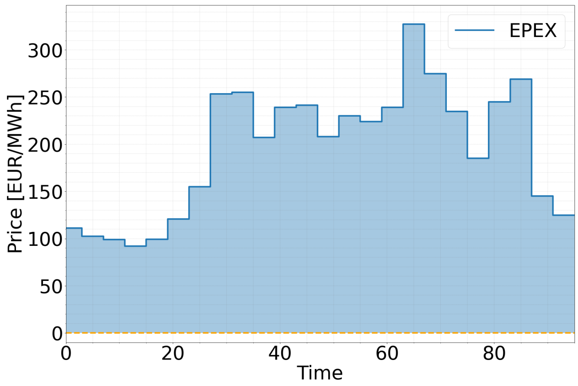


Figure 5.10: winter 2021 1 day, scenario C

5.2. Results

The results section aims to show the performance of the deterministic, stochastic hard constrained and stochastic flexible-constrained optimization models. The deterministic model is used to find the optimal dispatch strategy considering a single input scenario for a week of operation. The model is also used for a sensitivity study on the impact of different battery costs an grid fines. The hard constrained model is used to find the optimal dispatch strategy considering multiple scenarios for a week of operation. The parameter uncertainty impact is analysed for four different seasons when considering multiple scenarios. The stochastic flexible constrained model will introduce flexible constraints and find the optimal strategy considering multiple scenarios. Lastly the models are compared in terms of electricity cost, grid interaction, solving speed and other key model performance indicators.

5.2.1. Deterministic model

As mentioned, the deterministic model calculates the optimal energy resource dispatch strategy for a scenario without the involvement of probabilities or randomness. Figure 5.11, shows the optimal power flow results for input scenario A at each 15 minute time step. For scenario A the EPEX prices, electricity demand and PV production are the historical values that occurred from 2020-06-01 to 2020-06-05. The grid interaction P^G is shown in subfigure (a), with positive values indicating importing energy from the grid and negative values used for feeding-in to the grid. The grid import limit $\rho^{G,out}$= 450 kW is indicated in the figure with the red dashed line. The grid feed-in limit $\rho^{G,in}$= 2000 kW is not specifically shown in the figure because there is no feed-in congestion problem. If company X want a larger feed-in connection it can get one with relative ease. There are some time steps where the full grid connection is being used, but the grid limit is never exceeded. With the battery being the only true controllable resource, the battery dispatch shown in subfigure (b) is the only direct controllable variable in the optimization model. The maximum battery charge power is capped at $\rho^{B,c}$= 780 kW, with the maximum battery discharge power being capped at $\rho^{B,d}$= 2000 kW. The electricity demand is shown in subfigure (c), where a significant base load can be seen. The minimum load power during scenario A is P^L= 155 kW and the peak load is P^L= 530 kW. A load of 530 kW when the grid can only supply 450 kW means that the battery and PV setup is required to supply the load peaks. The PV production profile that was used as an input is shown in Appendix Figure B.3.

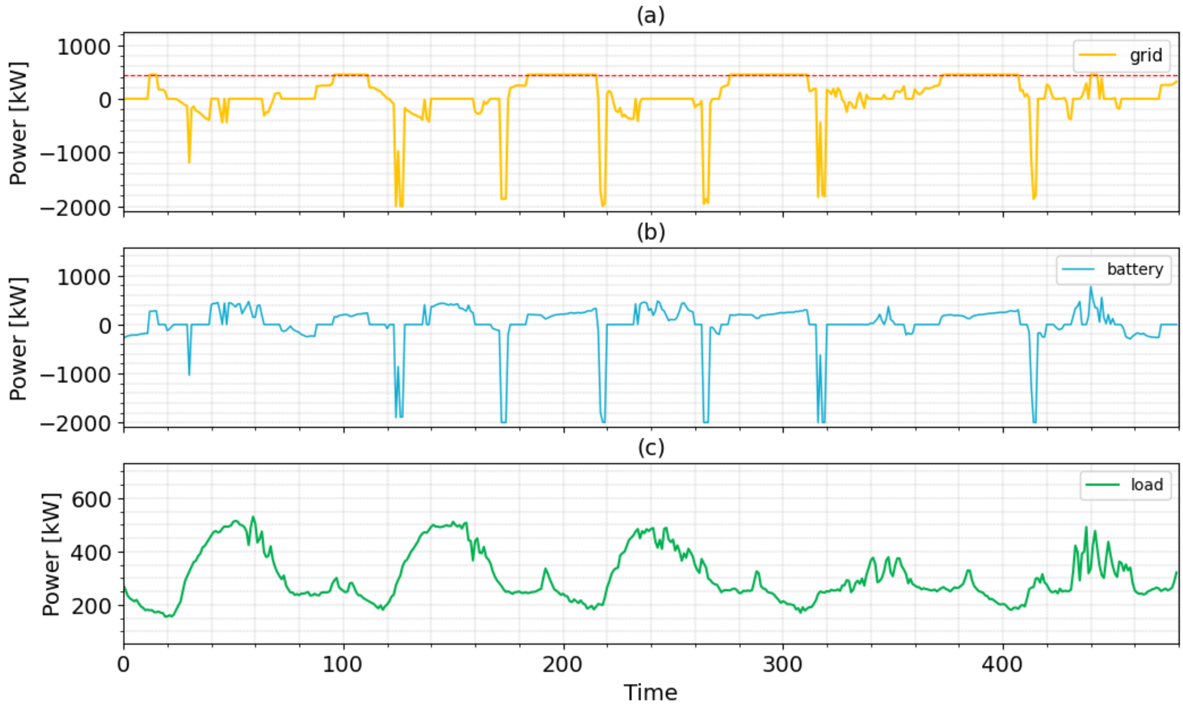


Figure 5.11: Individual power flows resulting from the deterministic model for scenario A and 11 scenarios in summer

Figure 5.12 shows the optimal power flows for scenario A combined in the same plot. Note that each day follows a similar battery dispatch strategy. The battery discharges before PV production starts and charges during peak production hours. When the sun goes down the battery discharges again, before following a more constant profile during the night. Comparing the battery strategy to the prices in Figure 5.8, it can be seen that the battery dispatches during times when prices are high and charges when prices are low. This behaviour can also be seen in the battery state of charge results shown in Figure 5.13. The SoC never falls below 10% which is the lowest SoC value allowed denoted by γ^{min}.

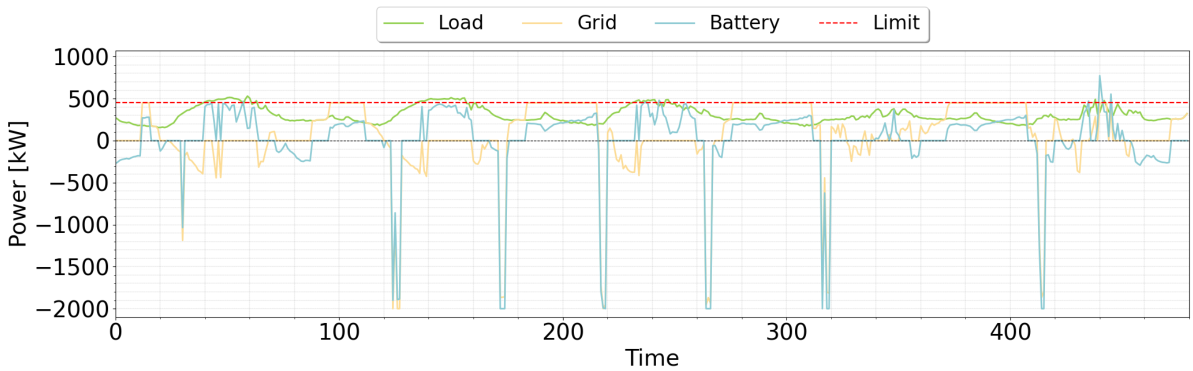


Figure 5.12: Combined power flows from the deterministic model for scenario A and 11 scenarios in summer

Table 5.6 shows the results of a sensitivity analysis for battery cost ϵ^{bat} and grid fine ϵ^{f}. Most inputs used in the deterministic model are predefined by location specific characteristics or design decisions by the owner. The parameter ϵ^{bat} is not predefined and is used to give a weight to using the battery. There is no direct variable cost linked to using a battery but degradation is heavily dependent on the amount and way it is used.

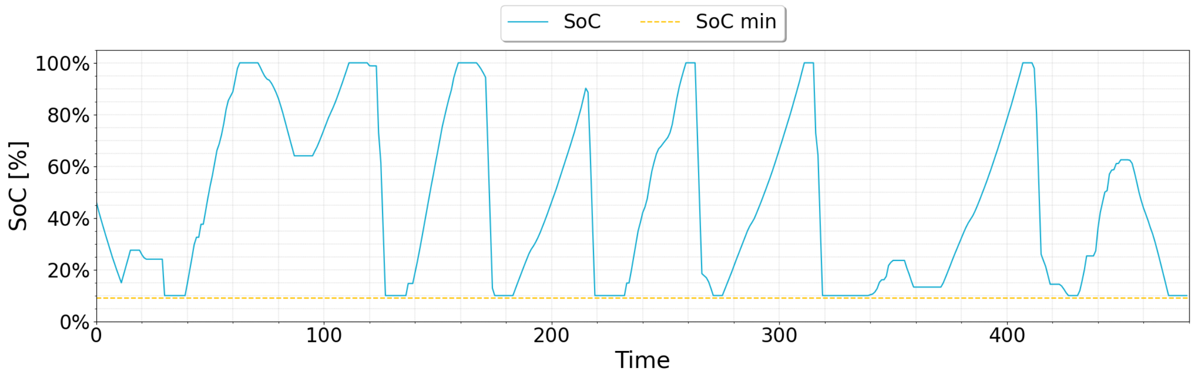


Figure 5.13: Battery state of charge results from the deterministic model for scenario A and 11 scenarios in summer

Table 5.6: Sensitivity study for grid fine and bat cost in deterministic model *negative means profit

Bat cost (€/MW)	Grid fine (€/MW)	Objective	Total cost (€)*	# Cycles	Grid overshoot (%)	Grid overshoot (MWh)	Fine cost (€)
0	-	-190.53	-190.53	3.375	0%	0	0
0	1	**-206.37**	**-310.29**	3.625	3.33%	4.49	17.95
0	5	-195.14	-238.18	3.375	1.67%	1.53	30.61
0	10	-191.09	-203.95	3.375	1.04%	0.39	15.43
5	-	-87.07	-140.74	1.625	0%	0	0
5	1	-92.51	-228.7	1.625	2.08%	2.92	11.69
5	5	-87.07	-140.74	1.625	0%	0	0
5	10	-87.07	-140.74	1.625	0%	0	0
10	-	-61.2	-88.63	0.25	0%	0	0
10	1	-61.19	-88.63	0.25	0	0	0
10	5	-61.19	-88.63	0.25	0	0	0
10	10	-61.19	-88.63	0.25	0	0	0

As was discussed in subsection 4.2.4, the model uses a different method for taking battery degradation into account during simulation and actually estimating battery degradation post optimization. The value of ϵ^f is a hypothetical cost for exceeding the grid limit which is used to implement a form of static flexibility. Static flexibility in the way that it is limited by a single value and is not robust to unforeseen changes. When a grid fine is determined to be 2 €/MW and EPEX prices rise by 200% or reduce to 50%, the previously determined fine does not have the same impact as before. In the scope of this thesis, the parameter ϵ^{bat} is implemented with the aim of limiting the cycles to an acceptable amount. The general industry standard for acceptable battery cycles is approximately 1 full cycle per day however, this is not a rule. Even when ϵ^{bat} is set to 0, the cycles for 5 day of operation are 3.375. A cycle count of 3.375 for 5 days is well inside the limit of 1 cycle per day and thus it is not necessary to impose a value for ϵ^{bat} under these case-study circumstances. Note that higher values for ϵ^{bat} limits the objective function and system revenue, making it undesirable to impose a battery cost if it is not necessary in terms of battery cycle limitation. The sensitivity analysis in Table 5.6 presents the optimization results for 4 different values of ϵ^f. The first scenario, indicated in the table by a dash, is the original scenario where there is no possibility of exceeding the limit, meaning grid limit is a hard constraint. The other 3 scenarios are a fine of 1, 5 and 10 €/MW of power that exceeds the limit. The scenario with a grid fine of 1 €/MW results in the best objective function value with an increase of 8.31% compared to the hard constrained connection scenario. A grid fine of 5 €/MW leads to an increase of 2.4% and 10 €/MW leads to an increase of 0.29%, when compared to the the hard constrained connection scenario. It should be noted that for these cases an increase in objective function results are also accompanied by an increase in grid limit violations.

5.2.2. Stochastic model using hard constraints

The deterministic model is simple and fast, however it does not accurately represent the uncertainty for realistic input parameters. Finding the optimal dispatch of a battery when already knowing the production and consumption input *a priori* can not be implemented in real life as the parameter values are not known in advance. The stochastic optimization model developed in this thesis, is able to calculate the optimal energy resource dispatch strategy including the involvement of probabilities or randomness. By optimizing over enough scenarios, the optimal dispatch strategy for sufficient known possibilities is determined. A strategy based on a sufficient amount of scenarios is inherently more robust compared to a deterministic model with just one scenario. The different PV and consumption scenarios are sorted by season, similar to the figure shown in 5.6. Each time step for a certain day in the week is grouped together and separated by season, which makes sure consumption data from a given weekday is separated from other days in the week. Business operation for Company X is structured and automated, ensuring it closely follows weekly procedures. Defining different scenarios this way ensures that all scenarios for a specific time step during the week, accurately represent business operation. For example, if forklifts are automatically charged on 10:00 on a Tuesday it would not be accurate to group that time step with data another day of the week. The scenarios for PV production are defined in a similar way even though the sun is not influenced by business operation like consumption is. The reason is that the model works by taking the same amount of scenarios for production and consumption. The production scenarios are separated by season so that seasonality is accurately represented in the optimization problem. The optimal power flows for the stochastic optimization problem are shown in Figure 5.14. The main difference between the deterministic model solution and the stochastic models, is that the stochastic model results are optimized over multiple scenarios.

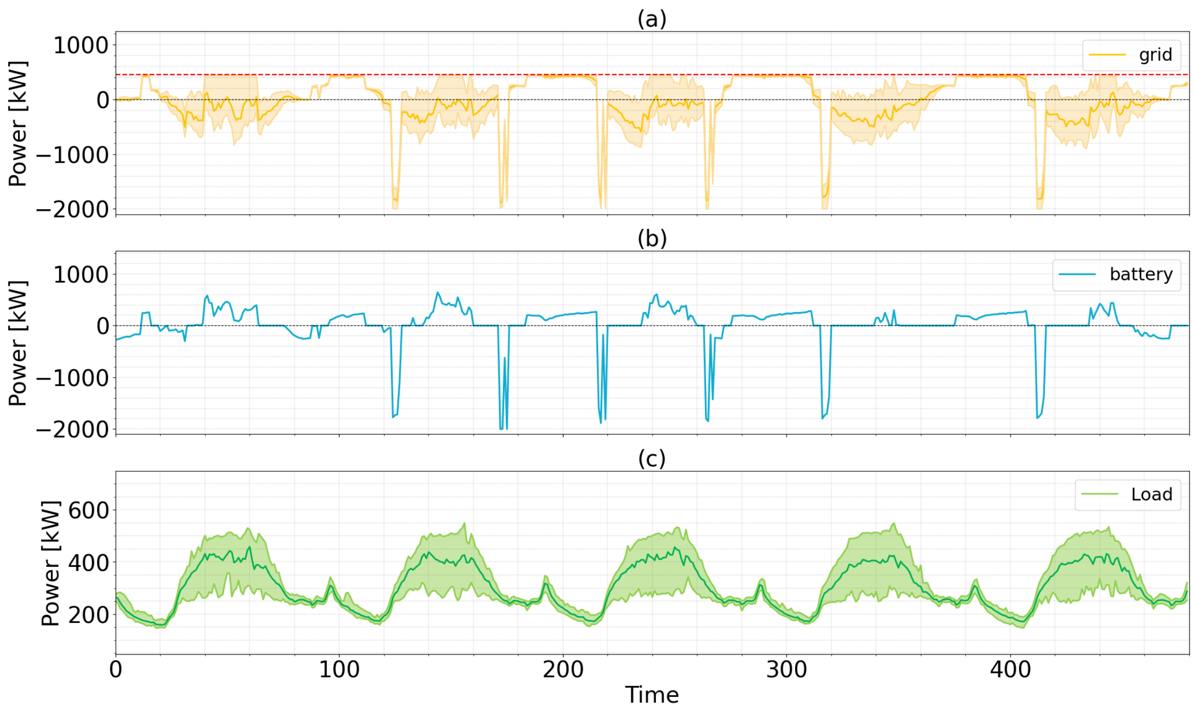


Figure 5.14: Individual power flows from the stochastic model using EPEX scenario A and 11 scenarios in summer

Looking at subfigure (a), the grid power flow resulting from the optimal battery dispatch strategy is presented in the form of a range rather than a single line. The range represents the grid power results for all scenarios by showing the the maximum and minimum values. The darker line is used to indicate the mean value which gives information on the variable distribution. The red dashed line represents the grid supply connection limit which has been set at 450 kW. The figure shows that constraint is not exceeded at any instance for the stochastic hard constrained model, which is expected as the grid limit is designed as a hard constraint. Subfigure (b) shows the battery dispatch strategy which is, unlike the grid power in subfigure a, represented by a single profile. A single line is used because the battery power is scenario independent meaning that there is only a single result for all defined scenarios at each time step. The highest value for battery charge $P^{B,c}$= 643.14 kW while the maximum battery discharge power that occurred in simulation was $P^{B,c}$= 2000 kW. Subfigure (c) shows the power consumption data for 5 weekdays under 11 different scenarios in summer. Similar to the grid power, the consumption is illustrated by plotting the maximum and minimum values, and the darker line is used for the mean values. The maximum value for consumption is 549.74 kW while the peak of the average consumption power is capped at a lower value of 458.25 kW. The different PV production scenarios that were used as input are shown in Appendix Figure B.4. The PV production is presented using the same visualization method as for consumption and grid power. Figure 5.15 shows the stochastic optimization power flow results combined in a single figure. The battery strategy and resulting grid flows show similar dispatch behaviour compared to the deterministic model shown in 5.12.

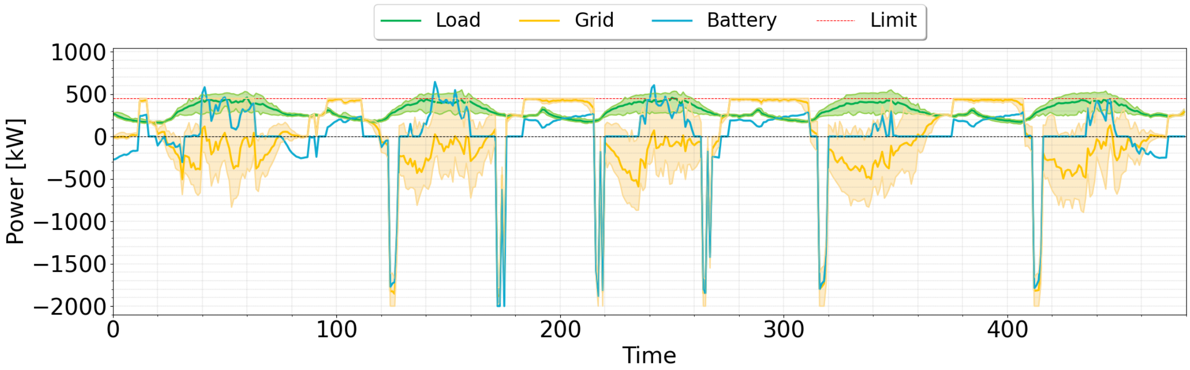


Figure 5.15: Combined power flows from the stochastic model using EPEX scenario A and 11 scenarios in summer

The battery dispatch strategy resulting from the stochastic hard constrained model is expected to be similar, but also slightly more conservative. Conservative due to the dispatch strategy having to make sure the grid limits are respected for each scenario. Figure 5.16 shows the battery state of charge results for scenario A and 11 scenarios in summer. As is expected the profile seems relatively similar to the deterministic model profile shown in 5.13. Note that the stochastic model demonstrates different behavior between t= 340 and t= 360, with the deterministic model showing an extra cycle compared to the stochastic model. Taking a more in depth look at the SoC results reveals more smaller deviations from the deterministic profile. This can also be seen in the amount of battery cycles for both models. Table 5.7 shows various optimization results for the stochastic model at different scenarios. The results show that the stochastic hard constrained model uses only 2.375 cycles for scenario A in summer, which is 29.6% lower then the deterministic results under the same circumstances[2].

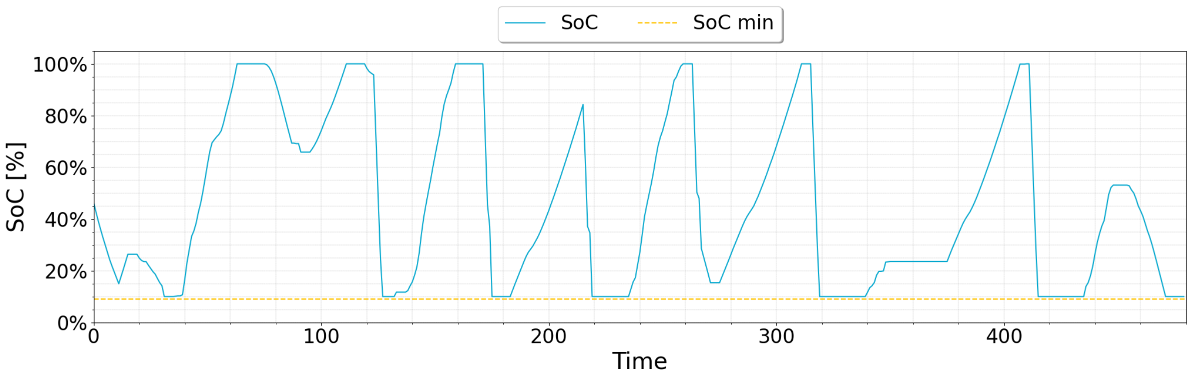


Figure 5.16: Battery state of charge results from the stochastic model for EPEX scenario A and 11 scenarios in summer

The optimal objective costs for the different scenarios presented in Table 5.7 vary significantly when comparing each season. This difference can be expected as the PV production yield is higher during summer and spring, compared to winter and autumn. A higher PV production yield results in additional PV energy sold to the grid but also less electricity bought from the grid to cover consumption demand. There is also a big difference in objective cost between scenario B and C, which is due to the increased EPEX prices for scenario

[2]Compared to the deterministic model with no battery cost and not including a grid fine

C. The difference in prices made the biggest impact during spring where the objective revenue increased 7722.9% compared to scenario B. Also note that during autumn the objective function result went from positive to negative, indicating operating the resources went from costing money in B to generating revenue in scenario C. The mean grid power in scenario B and C is actually approximately the same, but it is the standard deviation that changed in these scenarios. The standard deviation in scenario C is higher compared to scenario B indicating a wider spread in grid power. This increased spread can also be seen when comparing the grid power distribution plots shown in Figure 5.17 and 5.18. As mentioned before, in the stochastic hard constrained model the grid power is not allowed to exceed this threshold at any time. Appendix B.6-B.9 shows the grid power distribution for all seasons under scenario B. Here the implementation of the hard constraint is clearly demonstrated with no grid power exceeding the limit at any time.

Table 5.7: Stochastic optimization results for each season under price scenario A, B and C *negative means profit

Result	**Objective cost**			**Mean grid power**			**Sdev grid power**			**# of cycles**		
Scenario	A	B	C	A	B	C	A	B	C	A	B	C
winter	3936.05	258.76	3085.48	160.92	137.82	136.18	405.0	272.78	390.91	2.375	0.625	0.75
spring	-1438.11	-111.8	-8746.0	-10.7	-52.79	-54.92	462.18	285.37	488.92	2.625	0.625	0.75
summer	-2534.19	-214.53	-11189.92	-40.94	-87.12	-87.76	489.25	314.7	551.45	2.375	0.625	0.75
autumn	2788.3	204.6	-476.65	117.46	85.78	83.67	399.87	246.33	425.57	2.375	0.625	0.75

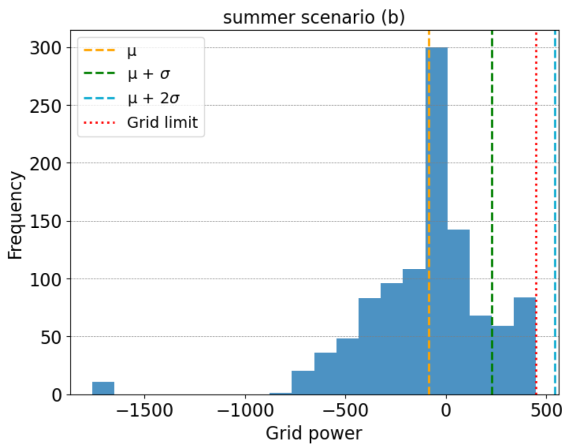


Figure 5.17: Grid power distribution for scenario B with 11 scenarios in summer

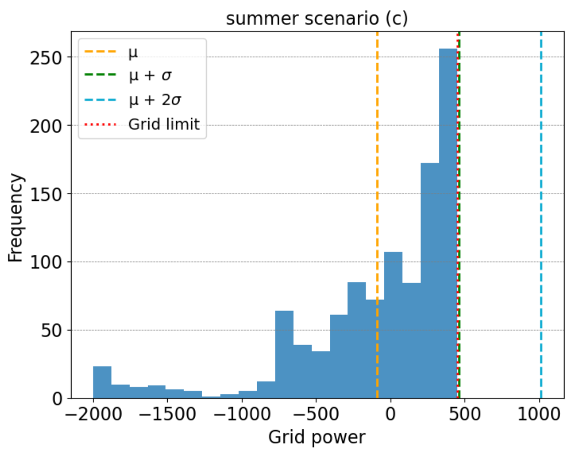


Figure 5.18: Grid power distribution for scenario C with 11 scenarios in summer

5.2.3. Stochastic model using flexible constraints

The hard constrained stochastic model is a great way to accurately represent the uncertainty of certain input parameters. However, the stochastic model discussed in section 5.2.2 only uses hard constraints. Hard constraints ensure that the limit is never exceeded but it also leads to conservative solutions due to the lack of flexibility. The flexible constrained model is similar to the hard constrained model with the addition of flexible robust constraints. One common way to implement flexible constraints is by giving a certain cost to a variable where a higher cost results in a higher objective function cost if not limited. In this thesis the flexible constraints are implemented in a different way where the threshold is based on statistical distribution instead. The main idea is that by exceeding the grid supply limit on a few occasions, the objective function cost will reduce relatively more. The main disadvantage of using statistical distribution to implement flexible constraints is that it requires a substantial longer time to optimize compared to stochastic optimization with hard constraints. For this reason, it was decided to only optimize for a single day while maintaining 11 different input scenarios. The flexible constrained model is analysed for each season using EPEX price scenario B, which is later compared to the stochastic results in section 5.3. It was decided to use a robustness factor of Rf= 2 for all simulations in subsection 5.2.3 to ensure the same situation for all scenarios. The subsection ends with an analysis on the impact of using different robustness factors for the flexible grid supply limit constraint.

The individual power flow results for the flexible constrained optimisation problem are presented in Figure 5.19. The resulting power flows represent a single day in summer using EPEX price scenario B. Subfigure (a) shows the grid power where the main difference with the previous models can clearly be seen around t= 50. The grid power exceeds the imposed grid limit on occasion but adheres to the constraint for most of the simulation time. The grid limit is exceeded 1.42% of the times meaning the grid power is less than the DSO imposed constraint 98.58% of the time. Interestingly, this moment of that coincides with the lowest electricity price which can be seen in Figure 5.9. The battery dispatch result is shown in subfigure (b), where the general strategy can be seen to resemble that of the previous models. The battery dispatch strategy of the flexible constrained model predominantly varies in amount of charging/discharging, instead of timing like the previous models. The consumption demand for a single day is shown in subfigure (c). The profile represents a shorter time range but is otherwise similar to the consumption input used in the previous models. The PV production scenarios that were used as inputs are shown in Appendix Figure B.5, where the same visualization method is used as the consumption and grid power. Note that even with 11 different scenarios, the consumption before t= 25 and after t= 75 is exceptionally constant. The mean squared error (MSE) between the average and max consumption is for the whole day is equal to 3112.8. Looking at the consumption data before t= 25 and after t= 75 the MSE is only 585.8. The MSE between the average and max consumption is 5959.7 for the whole period and only 228.9 when only considering before t= 25 and after t= 75. This constant demand profile coincides with the absence of significant production or any production at all as the sun has not risen before t= 25 and has started to set after t= 75. As a result of this behaviour the grid exchange in subfigure (a) is also exceptionally constant between these hours.

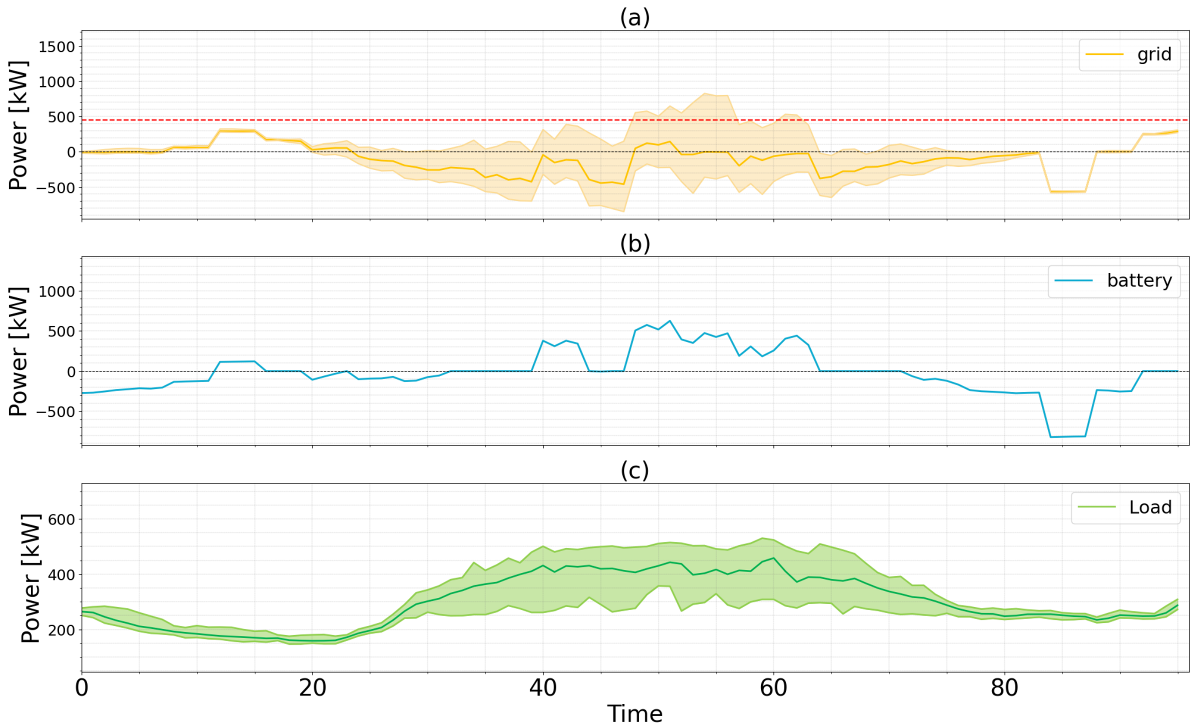


Figure 5.19: Individual power flows from the flexible constrained model using EPEX scenario B and 11 scenarios in summer

The combined power flow plot in Figure 5.20 also shows the constant grid interaction before t=25 and after t= 75. Note that the average grid power does not exceed the grid supply with its peak limited to only 290 kW, which is 160 kW lower than the grid limit. The highest grid supply power for all scenarios is almost double the imposed grid limit at 827 kW. In addition to creating direct extra revenue, the flexible grid constraints have another valuable impact. With the maximum consumption power reaching 550 kW and the grid only able to supply 450 kW the residual 100 kW comes from either direct PV production or stored battery capacity. The ability to continue business operation at all times is crucial for a company as delays can be costly. If there is no sun or energy resource malfunction, the flexible constraints still allows for the consumer to exceed the limit when at times of need. When the DSO allows for 4% grid limit overshoot in a month, this means that the limit can be exceeded a total of 30 hours in a month. The maximum consumption profile exceeds 450 kW for 6 hours in a summer day. Hence, the 30 hour grid overshoot allowance results in an extra 5 days of normal operation for a worst case scenario. Under normal circumstances 5 days should be sufficient to fix or replace the broken resources. The state of charge resulting from the different battery dispatch strategies for each season is shown in Figure 5.21. The strategy for each season appears to be similar when using the same prices. Both the minimal and maximum state of charge is reached at the same time steps for each season. During the morning, the state of charge in winter is diverging slightly from the other seasons no other major differences can be spotted.

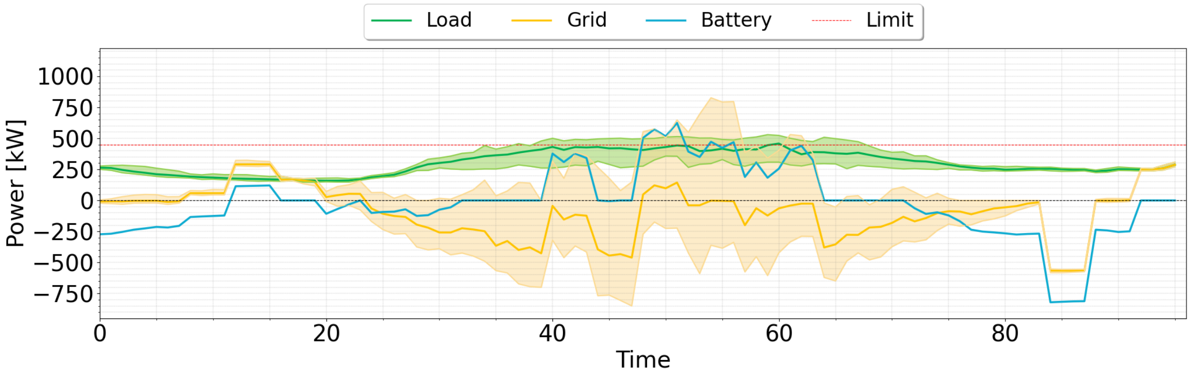


Figure 5.20: Combined power flows from the stochastic model using EPEX scenario B and 11 scenarios in summer

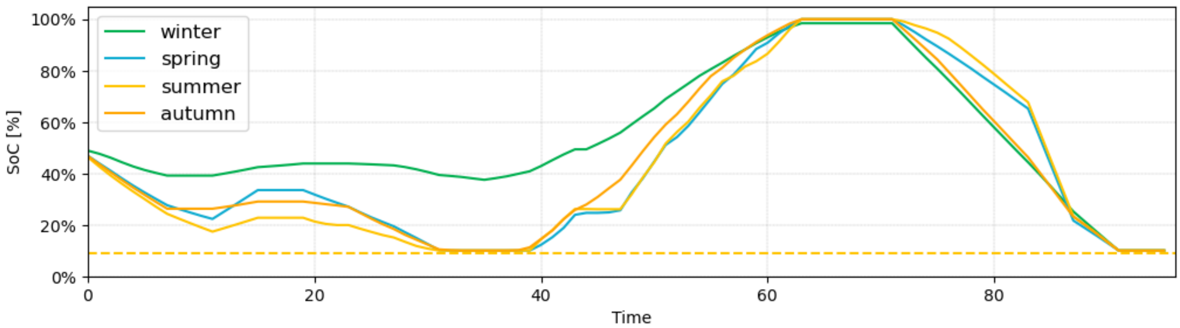


Figure 5.21: Battery state of charge results from the stochastic model with EPEX scenario B and 11 scenarios for each season

The flexible constrained optimization model results for each season are presented in Table 5.8. Similar to the stochastic hard constrained model, the objective function cost for each season follow the same trend as the PV production yield during a season. When there is more electricity generated by PV, there is less grid power needed to match the consumption demand and more electricity to sell to the grid. The values for the mean grid power support this statement, with the highest mean grid power coinciding with the highest objective function cost and vice versa. The last column in Table 5.8 shows the solution gap for each optimization result. The solution gap is used to indicate the gap between the current best solution and the current best dual bound. An optimization solution with a different solution gap than 0% is not necessarily the optimal solution to the problem. With the solution gap for each scenario being less than 1% and not improving for 24hours of simulation, the incumbent objective solution is treated as if it is the optimal solution although this cannot proven. The simulation time presented in the table is the time it took to reach the best incumbent bound.

Table 5.8: Optimization results scenario B with stochastic model using flexible constraints
* time to reach best incumbent objective bound
** after 24 hours of simulation

Result	Objective cost	Mean	Standard deviation	Grid overshoot [%]	Battery cycles	Simulation time*	Solution gap**
winter	246.38	133.52	158.32	0.76%	1.0	120s	0.99%
spring	-118.26	-53.0	251.62	1.33%	1.0	20s	0.49%
summer	-222.92	-87.94	269.1	1.42%	1.25	115s	0.31%
autumn	197.10	84.81	182.68	3.39%	0.75	36s	0.24%

As mentioned before, the main difference between the stochastic hard- and flexible constrained model is the implementation of a flexible grid supply constraint. The grid power distribution in Figures 5.17 and 5.18 show that the hard constraints in the stochastic model are never exceeded. The grid power is allowed to exceed the grid limit occasionally in the flexible constrained model as it uses soft constraints. The grid power distribution for each season is shown in Figures 5.22-5.25. As mentioned before, a robustness factor of Rf= 2 was used for the flexible grid supply constraint. Due to the grid limit being equal to $\mu + 2\sigma$, the vertical lines for both values overlap in each figure. When simulating for a single day using 11 scenarios, it adds up to a total amount of 1056 different grid power variables. For the autumn scenario shown in Figure 5.25, 3.69% of the values are higher than the current supply grid limit of 450 kW. Taking 3.69% of 1056 results in a total of 39 values exceeding the grid limit. The grid distribution shown in Figure 5.25 backs up this statement. By inspecting the distribution for each season, the implementation of flexible constraints is demonstrated.

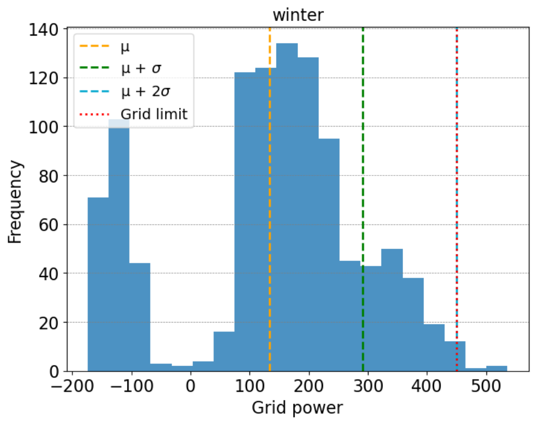


Figure 5.22: Grid power distribution for 1 day with 11 scenarios in winter (0.76% overshoot)

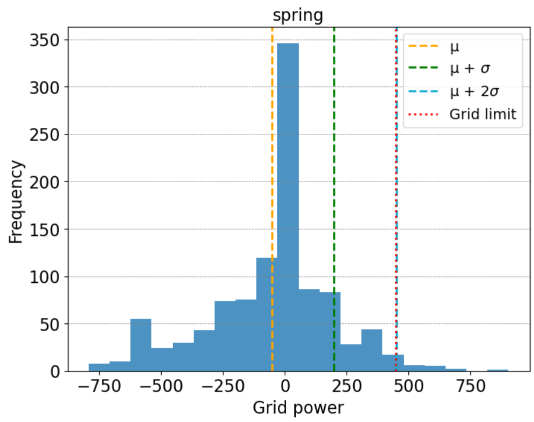


Figure 5.23: Grid power distribution for 1 day with 11 scenarios in spring (1.33% overshoot)

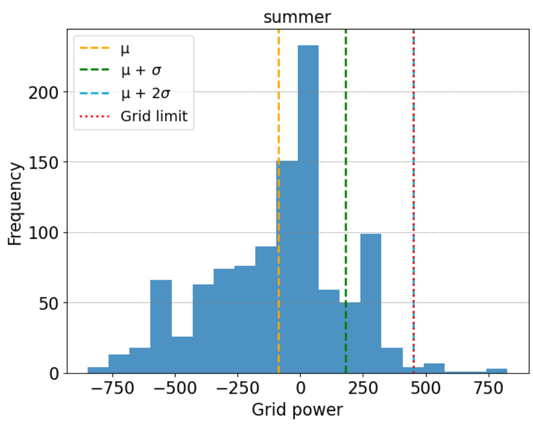


Figure 5.24: Grid power distribution for 1 day with 11 scenarios in summer (1.42% overshoot)

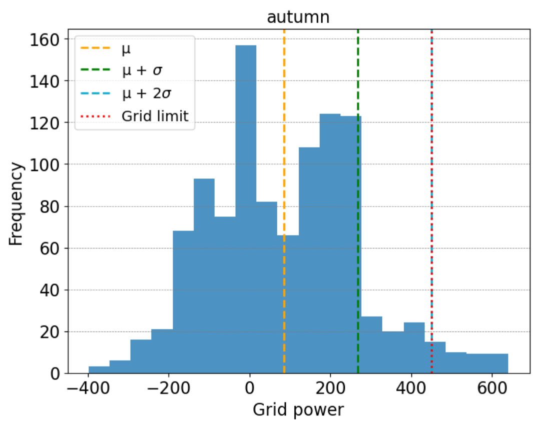


Figure 5.25: Grid power distribution for 1 day with 11 scenarios in autumn (3.69% overshoot)

Comparing the stochastic hard- and flexible constrained model results shows the impact of the proposed flexible constraints. If exceeding the grid limit does not result in a substantial increase of the optimal objective function outcome, justifying the need for a flexible grid limit becomes more difficult. The case for business resilience can still be argued but resilience can also be obtained by over sizing backup energy resources. The results of the flexible constrained model compared to the stochastic model are presented in Table 5.9. The Table 5.9 results are presented as the relative value thus a negative value indicates a reduction when compared to the hard constrained case. By using the proposed flexible constraints, the objective cost for each season increase significantly compared to hard constraints. A reduction in objective cost is expected when the grid limit can be exceeded on occasion but the objective cost reduces relatively more than the grid overshoot. For example, in winter the grid supply limit is only exceeded 0.76% of the times but the objective cost reduces 4.78% which is 6.3 times more. The lowest cost reduction is in autumn but here the objective cost is still reduced 3.67% of the time which is still 1.08 times more then the grid overshoot. The mean grid power decreases for every season, with the mean in spring and summer relatively increasing in negativity when compared to the stochastic results. The mean grid power in winter and summer reduces when using the flexible constraints but are still positive values hence the sign being negative. Unlike the mean grid power, the standard deviation reduces when using the flexible constraints compared to the regular stochastic model. The way the constraints are written, a lower standard deviation increases the possibilities for the mean grid power. For the stochastic model this is not an issue as only the grid power for each time step is of importance for the grid limit constraint. A reduction in standard deviation for the flexible constrained model compared to the stochastic model can thus be expected. An increase in the amount of battery cycles is also not unusual as the flexible constrained model is essentially a less conservative version of the stochastic model. The simulation time is the main issue with implementing this specific method of flexible constraints. Looking at the relative increase in simulation time it becomes clear that the flexible constrained model is severely limited in terms of optimization speed. Because of the increased optimization problem complexity, it was only possible to optimize a single day with 11 scenarios for the flexible constrained model.

Table 5.9: Comparison optimization results scenario B with stochastic model using robust constraints and stochastic constraints * time to reach best incumbent objective bound

Result	Objective cost	Grid overshoot	Mean	Standard deviation	Battery cycles	Simulation time*
winter	-4.78%	0.76%	-3.12%	-42.0	+0.375	+39900.1%
spring	-5.78%	1.33%	0.4%	-11.84	+0.375	+14185.7%
summer	-3.91%	1.42%	0.94%	-14.49	+0.625	+82042.8%
autumn	-3.67%	3.69%	-1.13%	-25.84	+0.125	+25614.2%

The decision to use a robustness factor of 2 was decided early on in the design process. The argument for using an Rf of 2 was that an Rf of 1 would allow to much grid limit violations and an Rf of 3 would be to conservative. Only integers where considered because the research goal was to examine if the flexibility hypothesis works not what value works best. However, the influence of using different robustness factors is of interest as it evaluates the trade-off between revenue and grid overshoot. A comparison in terms of objective function and percentage of grid limit overshoot to the stochastic results is presented in Table 5.10. The values for 1.1, 1.2 and 1.3 are omitted from the table as they gave the same results as the robustness factor of 1. The only value that was changing was the grid overshoot in terms of energy not in occurrence. The lowest robustness factor that actually decreases grid overshoot occurrence is 1.7. When using a robustness factor below 1.7 the only difference is the amount of power that exceeds the limit but not the quantity of times the limited is exceeded. From Table 5.10, it can be concluded that the percentage of scenarios where grid power exceeds the grid constraints increases directly with the value of Rf, as expected. In addition to this, notice that the obtained grid overshoot value falls under the set threshold of 4% for all Rf>= 1.9.

Table 5.10: Scenario B optimization results with stochastic model using flexible constraints for different values of Rf
*Compared to stochastic model for same scenario

Robustness factor (Rf)	Objective cost	Revenue increase *	Grid overshoot [%]	Grid overshoot [GWh]
1.0	-226.55	5.6%	5.682%	14.866
1.4	-224.99	4.88%	5.682%	7.278
1.5	-224.68	4.73%	5.682%	5.798
1.6	-224.39	4.6%	5.682%	4.391
1.7	-224.11	4.47%	5.587%	3.049
1.8	-223.82	4.33%	5.587%	1.754
1.9	-223.52	4.19%	2.083%	0.581
2.0	-222.92	3.91%	1.42%	0.552
2.1	-221.53	3.26%	1.42%	0.548
2.2	-219.01	2.09%	1.042%	0.448

The average cost of the objective function and the amount of grid overshoot energy for the different values of Rf are shown in Figure 5.26. The relation between the level of robustness and the operational cost indicate a trade-off between both variables. In other words, there is a trade-off between Rf and the objective function result as solutions become more expensive as they gain robustness. Note that the grid overshoot between 2 and 2.1 hardly decreases but the revenue decreases 0.65% which is significantly more than the difference between other subsequent Rf values. The optimal Rf value remains subjective as the DSO and company X have different interests in the trade-off between both variables. One could argue that either 1.9 or 2.0 is the optimal value when considering both interests. This is because the difference in revenue increase compared to grid overshoot is largest. If the DSO is more interested in the occurrence of grid overshoot, a robustness factor of 2.0 is probably best. Although in case the DSO is more interested the grid overshoot in terms of energy, a robustness factor of 1.9 would also suffice.

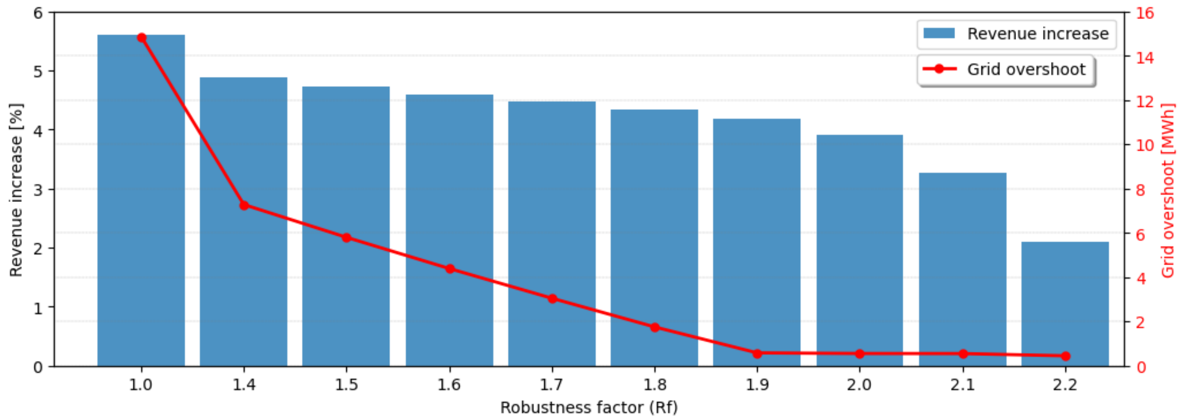


Figure 5.26: Relative increase of the objective function and percentage of grid limit overshoot compared to stochastic constraints for different values of Rf

The optimal dispatch strategy for a case where the grid supply was not limited at 450 kW, would overshoot the grid more often compared to using flexible constraints. Figure 5.27 shows the resulting power flows when there is no grid limit considered in the otherwise same problem. It can be clearly seen that the grid flows are exceeding the grid supply limit on numerous occasions when looking at the figure. For this specific case, the grid is exceeded for 5.78% of the time, which is more than any of the scenarios shown in 5.10. As expected, the objective function cost is lower at -237.77 compared to the cases using flexible constraints. However, the grid overshoot is also significantly higher which is the main reason for limiting the grid connection. The results of this case show that the grid limit of 450 kW has a direct effect on the grid power that limits the flexible constrained optimization models. Because of this limitation, the development of a flexible constrained optimization model with flexible constraints is justified.

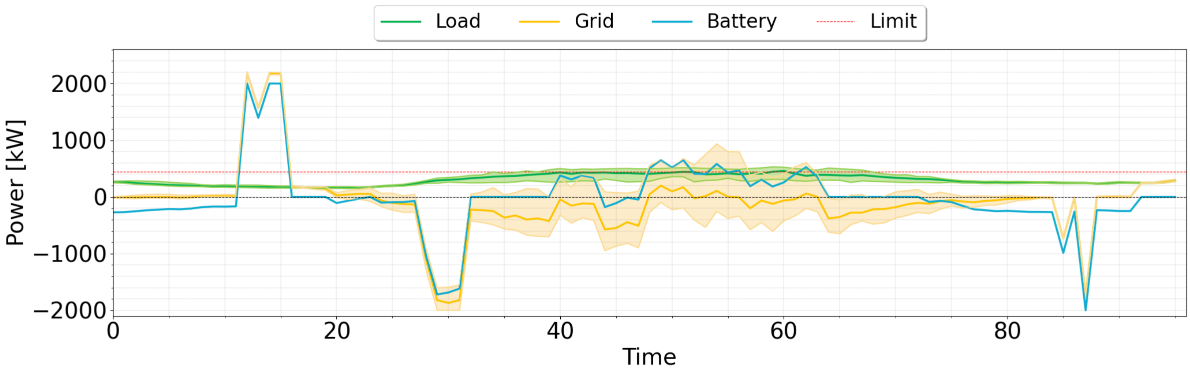


Figure 5.27: Combined power flows from the stochastic model using EPEX scenario B and 11 scenarios in summer

5.3. Discussion

The discussion section aims to delve into the meaning, importance and relevance of the case-study results. The section focuses on explaining and evaluating the findings, showing the relation to the state of the art and research questions. The scope of this thesis was to develop a mathematical optimization model to minimize electricity costs by optimally dispatching energy resources for a predetermined prosumer. The optimization problem considers constraints imposed due to grid congestion in the form of a limited grid connection. Also the possibility of implementing flexible constraints has been researched and a model that is able to optimize operation strategies under these flexible constraints was developed. The deterministic model showed that it was able to optimally dispatch the available energy resources considering predefined deterministic inputs. The deterministic model was also used to conduct a sensitivity analysis for both battery operating costs and grid limit exceeding fines. The sensitivity analysis showed that a battery cost parameter was not necessary as the battery cycles where under the general industry standard of one cycle a day. The sensitivity analysis also showed that a grid fine of 1 €/MW could significantly increase revenue at the cost of only 3.33% grid limit overshoot. The stochastic models where able to accurately represent input parameter uncertainty that exists with PV production and energy consumption. The hard constrained stochastic optimization model results included an optimal battery dispatch strategy for different price scenarios and seasons. The model showed it was able to calculate a strategy that ensured the grid power stayed within the hard constrained grid supply limit for each season when considering 11 different input scenarios. The flexible constrained optimization model was able to successfully demonstrate the ability to stay within the predetermined flexibility bounds according to the flexibility constraints. The flexibility bounds were set at 4% and this limit was not exceeded at any time during simulation. In addition to staying within the predetermined flexible grid limit constraints, the flexible constrained model was able to show it could calculate the optimal dispatch strategy that resulted in an increased revenue stream when compared to the hard constrained stochastic model. A robustness factor sensitivity analysis showed the existence of a trade-off between the robustness factor value and the objective function results. The trade-off meant that objective function solutions become increasingly expensive as the system gains robustness through a larger Rf value.

The deterministic model did not produce any substantial unexpected results or insights. Deterministic optimization is a simple and fast optimization technique that has a wide variety of real life applications. The problem with using deterministic optimization for energy resource dispatch is the fact that the model considers market prices, PV production and consumption as deterministic inputs. Each one of mentioned inputs can be categorized as uncertainty parameters and using a deterministic model to solve such a problem is a drastic oversimplification. The deterministic model can be used if the various uncertainty inputs where forecasted individually and the expected value taken as an input, but this was not the case in this thesis. The deterministic model was able to calculate an optimal dispatch strategy, analyze the impact of different parameter values, and form the basis of both stochastic models. The simplicity of the deterministic model also created a great opportunity to test and verify the different constraints before implementing them in the stochastic models. It would have been interesting to include the imbalance market in addition to the EPEX day-ahead market because it is a more realistic way of battery arbitrage. However, implementing the imbalance market in the model is not necessarily in line with the research scope of this thesis. The hard constrained stochastic model was able to present results from a more realistic set of inputs. The addition of taking into account input uncertainty ensured the resulting battery operation was resilient to multiple scenarios. The grid supply limits were not exceeded for any simulation but this also made the hard constrained stochastic model conservative. With the hard grid limit constraints required to be respected for each time step and scenario, the strategy does not optimally utilize opportunities. By analyzing the results of the flexible constrained optimization model under different values of Rf, it could be shown that there exists a trade-off between robustness and operating cost. This was already expected before developing the flexible constrained model but through simulation results this could be backed by results as well. The expectation of the elasticity between the robustness factor and the grid overshoot occurrence was slightly different then can be seen from the results. Perhaps there would be more possible grid overshoot levels when optimizing for multiple days and over more scenarios. Simulating a stochastic model without grid constraints showed that the previous grid limit would have been exceeded 5.78% of the time during a single day in summer. The results of this case show that the grid limit of 450 kW has a direct effect on the grid power that limits the flexible constrained optimization models. Because of this limitation, the development of a flexible constrained optimization model with flexible constraints is justified.

The research was limited by the complexity of the problem and the resources available for calculating the solution. The flexible constrained optimization model was only analysed for one day with 11 different scenarios. Ideally this would have been at least 5 days, which would have been a similar optimization horizon as the other models. It would have also been interesting to see how the flexible constrained model would perform for a lower grid supply limit, which was not possible with the available resources as the simulation time took to long. Also, complexity constraints prevented introducing more resources in the system such as heat pumps, EV charging or H2 storage. It would have been interesting to see how loads are shifted under different circumstances and how heating demand would impact the control strategy.

5.4. Resources and tools

The analysis of data, development of models and running of algorithms, was conducted using the Spyder 5.15 integrated development environment (IDE). The deterministic, stochastic hard- and flexible optimization models, have been developed using the Pyomo modeling library and handbook. Pyomo is a Python-based, open-source optimization modeling language with a diverse range of optimization capabilities. The optimization problems are solved using the Gurobi Optimizer V9.5 solver obtained through an Academic license. The historical data used in this research project is taken directly from an internal database hosted on a Sunrock server. All data analyses and solving of the optimization models is done on an office laptop with an Intel Core i7 processor and 16GB RAM.

6

Conclusion & Recommendations

6.1. Conclusion

The main goal of this thesis was to develop an optimisation model that minimizes the electricity costs for an industrially-sized prosumer, while adhering to flexible grid limit constraints. Industrially-sized prosumers require a sufficiently large grid connection to power the expected sector growth due to the current electrification process with sustainable energy. As of now, new development projects in congested areas are not able to get a sufficient connection allocated by the DSO. This results in the affected renewable energy projects either being postponed temporally or indefinite. For some cases, additional local supply capacity is acquired by using non-sustainable production methods such as gas or diesel generators. Reliable energy resource dispatch cost optimization models that adhere to local congestion constraints are needed. Such models could potentially ensure normal business operation and business resilience while increasing the share of locally generated renewable energy. This research objective was achieved by solving four separate research questions which have been successfully worked out in the report and the summarized answers are presented below.

Answers to the research questions

- *How can an industrially-sized prosumer optimally dispatch energy resources while adhering to constraints set by the DSO in a congested area?* The research process started with understanding the individual resources and investigating the state of the art modeling techniques available in scientific literature. After understanding the different energy resource work, they could be simplified into a number of constraints. The operating boundaries, system efficiencies and various other parameters that accurately represent the physical operation, were defined for each resource in the system. The available historical data for consumption and PV production was transformed so that it could be used as a deterministic input in the model. After accurately modeling the individual resources, the rules for interaction between different resources was defined. An optimization model requires an objective function so that the model can optimize a single function representing different costs in the system. In the case of this thesis, the objective function optimization was a minimization of the costs of operating the resources. Next the method for pricing energy had to be defined and the relevant price data transformed to be used as an input. The model uses mutually exclusive bidirectional power flow in the system so a different variable for each direction was defined. The mutual exclusivity was achieved by implementing binary variables, turning the model into a MILP model. The solver was used to solve the optimization problem for several scenarios and the results were used to calculate other performance indicators. Different parameter values could be tested and the impact analysed through a sensitivity study. All inputs and data used in the optimization problem are part of a case study that focuses on an industrially-sized prosumer that is located in a congested region. By analysing the resulting variables, it could be determined that the developed deterministic model was able to optimally dispatch energy resources while adhering to constraints set by the DSO in a congested area. The deterministic model was used as the foundation for developing the stochastic model. The individual resources and corresponding constraints are similar for the stochastic model as in the deterministic model. The stochastic model does use different input parameters with each time step having a predefined set of scenarios. The stochastic model finds the optimal strategy that yields the optimal objective function outcome when considering all different scenarios. In addition to the optimal cost function outcome, the variables have to adhere to the constraints at each time step and for all scenarios. Each variable in the stochastic optimization model is defined as either scenario dependent or scenario independent. Scenario independent means that the variable does not change value for different scenarios unlike the values of scenario dependent variables that do depending on the specific scenario. Similar to scenario variables, parameters can be scenario dependent or independent as well. PV production and electricity consumption, are scenario dependent and have different values for each scenario in a certain time step. Electricity market prices for buying and selling energy are the same for for each scenario at each time step, making it scenario independent. The optimization problem solution contains a single battery operating strategy that results in the best optimization outcome when considering all scenarios. With only a single value for each time step, the variables for charging and discharging the battery are scenario independent variables. Both the import and export grid power variables are scenario dependent as the same battery dispatch strategy results in different grid exchange outcomes when considering different input scenarios. By analysing various scenarios and cases, it could be determined that the developed stochastic model was able optimally dispatch energy resources while adhering to constraints set by the DSO in a congested area.

- *How can a stochastic energy dispatch model implement flexible robust constraints where the grid limit is exceeded in less than a predefined probability or value?* The stochastic model adheres to the hard grid constraints 100% of time as it is required to do. For the grid power to occasionally exceed the grid supply limit constraint, the hard constraint has to be reformulated into a flexible limit. Implementing a grid fine initially seems like a way this could be obtained but this is not a robust solution. If a certain grid fine is defined and the market prices change drastically the overshoot could go to 0% or more than 4% depending on increasing or decreasing prices. A more robust method is to implement constraints that use statistical distribution variables to ensure adhering to constraints. Because of the central limit theorem, the grid power can be assumed to be Gaussian distributed if the sample set is sufficiently large enough. For a Gaussian distribution, Approximately 95.45% of the realizations are within 2 standard deviations of the mean value. By combining the empirical rule and grid supply limit, the constraints are reformulated into a flexible constraint that allows for approximately 4% of realizations to exceed the limit. A sensitivity study into the robustness factor impact showed the existence of a trade-off between Rf and the objective function result as solutions become more expensive as they gain robustness. Calculating the mean and standard deviation did result in a significantly more complex model to solve. Due to this increased complexity, the simulations were limited to optimizing for a single day instead of the previously used time range of 5 days. Nonetheless, the model was evaluated for different seasons and 11 scenarios which all showed the model's ability to adhere to the grid overshoot limit of 4%.

- *How does a stochastic hard constrained energy resource optimization model compare to one with flexible robust constraints?* The hypothesis for implementing flexible constraints was that it decreased the operational costs for the industrially-sized prosumer. The reason behind this hypothesis is that with flexible constraints the strategy allows for occasional exceeding of the limit when this would improve the objective function result. The limit will therefore only be exceeded if it yields a better outcome compared to not exceeding the limit. Comparing the results for the stochastic model and the robust model showed an improved objective function cost when implementing flexible constraints instead of hard constraints. The optimal objective cost was also relatively higher than the grid overshoot occurrence. In other words, the relative improvement of the objective cost was higher than the percentage of time the grid limit was exceeded. This outcome was true for the operating cost in each different season. The extra grid overshoot did lead to a small increase in battery cycles used but the cycles per day was still under 1 so the increase is not a big problem. The stochastic model with hard constraints did use significantly less time to solve compared to the flexible robust model. As was mentioned earlier, the robust model is more complex than the stochastic model and thus harder to solve. Nevertheless the robust model simulation results show that the flexible constraints improve the objective function significantly compared to the regular stochastic model.

6.2. Recommendations

This research was able to show the models ability to determine a optimal strategy for the available resources while adhering to the hard constraints. Also, the robust model showed the same ability while adhering to hypothetical flexible constraints. However, further research is needed before the proposed models can be implemented in real life scenarios. The following recommendations are given for future research.

- Increase the optimization horizon from a single day to 5 days or more, by using a more powerful computer that is able to handle the complex optimization problems. A more powerful computer would also allow for adding more complex constraints to the problem that are not possible now. The decision to not take into account the rainflow method for determining cycle cost during optimization was taken because it made the problem too complex. If the model would have been able to take into account the cycles during the solving process instead of post optimization, the battery degradation could have been accurately represented in the objective function. Especially when designing the robust model, there was a constant trade-off between complex realistic dependencies and solving time.
- The model uses only a single controllable resource in the form of a battery. The grid is basically as variable that is a result of the battery dispatch and consumption demand, which is also uncontrollable. By including more resources such as heat pumps, EV charging or H2 storage, the model would have included a significantly broader range of options. It would be interesting to see how loads are shifted under different circumstances and how heating demand would impact the control strategy.
- The optimization models developed in this thesis only used a single energy market. The impact of adding a second market like the imbalance market on the control strategy and subsequent revenue is interesting. Also, the price data was known before optimization instead of using it as a stochastic scenario input. Using uncertain price scenarios is another way of making the model more realistic and real life applicable.
- Instead of using the commercial available gurobi solver, a custom build solver could have been developed that would have enabled more flexibility in the solving process. A commercial solver is a black box where calculation happens behind closed doors and only part of the solution is shared with the user. More detailed data from the solving process could have resulted in understanding the model better and how it could have been improved.
- The historical data was limited to that of a single year. If there would have been more data available there could have been more scenarios for the optimization models to use.

A

Product specifications

DC side		
Rated power (kW)	500*2	
Rated capacity (kWh)	1152	
Rated voltage (Vdc)	640	
Voltage range (Vdc)	560~720	
AC side		
Rated power (kW)	500*2	
Rated output voltage (Vac)	400	
Rated frequency (Hz)	50	
Power factor	-1~1	
Connection	Three phase	
Isolation	with isolation transformer	
Others		
Operating mode	On grid/Off-grid	
IP level	IP54	
Altitude (m)	≤2000	
Max. efficiency	85%	
Cycle life	≥4000（25℃, 1C charge/discharge, 90%DOD, EOL≥80%）	
Components	Electrical cabinet	Battery cabinet
Weight (kg)	31500(About)	
Dimension (W*D*H, mm)	40feet Container	

Figure A.1: C&I 1MW 1.15MWh BESS Solution for PV on grid System datasheet

ELECTRICAL PARAMETERS

Performance at STC (Power Tolerance 0 – +3%)

Maximum Power (Pmax/W)	265	270	275
Operating Voltage (Vmpp/V)	31.0	31.3	31.7
Operating Current (Impp/A)	8.56	8.63	8.69
Open-Circuit Voltage (Voc/V)	38.2	38.5	38.7
Short-Circuit Current (Isc/A)	9.04	9.09	9.17
Module Efficiency ηm (%)	16.2	16.5	16.8

Performance at NOCT

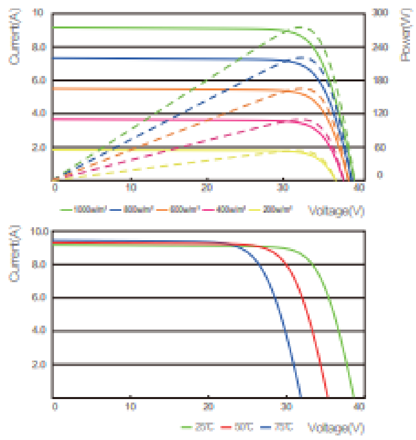
Maximum Power (Pmax/W)	196	199	203
Operating Voltage (Vmpp/V)	28.7	28.9	29.2
Operating Current (Impp/A)	6.83	6.90	6.97
Open-Circuit Voltage (Voc/V)	35.2	35.5	35.7
Short-Circuit Current (Isc/A)	7.32	7.36	7.42

STC: Irradiance 1000W/m², Cell Temperature 25° C, Air Mass AM1.5 NOCT: Irradiance at 800W/m², Ambient Temperature 20° C, Wind Speed 1m/s

MECHANICAL SPECIFICATION

Cell Type	Poly
Cell Dimensions	156.75*156.75mm(6inch)
Cell Arrangement	60(6*10)
Weight	18.5kg(48.5lbs)
Module Dimensions	1650*992*35mm(64.96*39.06*1.38inch)
Cable Length	900mm(47.24inch)
Cable Cross Section Size	4mm²(0.006sq.in)
Front Glass	3.2mm High Transmission, Tempered Glass
No.of Bypass Diodes	3/6
Packing Configuration (1)	30pcs/Pallet,840pcs/40hq
Packing Configuration (2)	30pcs+5pcs/Pallet, 910pcs/40hq
Frame	Anodized Aluminium Alloy
Junction Box	IP68

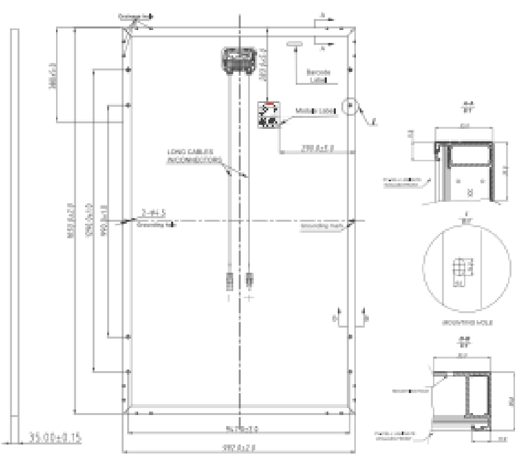
I-V CURVE



OPERATING CONDITIONS

Maximum System Voltage	1000V/DC(IEC)/1500V/DC(IEC)
Operating Temp.	-40℃-+85℃
Maximum Series Fuse	15A
Static Loading	5400Pa
Conductivity at Ground	≤ 0.1Ω
Safety Class	Ⅱ
Resistance	≥100MΩ
Connector	MC4 Compatible

TECHNICAL DRAWINGS



TEMPERATURE COEFFICIENT

Temperature Coefficient Pmax	-0.40%/℃
Temperature Coefficient Voc	-0.31%/℃
Temperature Coefficient Isc	+0.06%/℃
NOCT	45±2℃

TALESUN

Figure A.2: Talesun Solar TP660P-275 datasheet

SUNGROW
www.sungrowpower.com

SG80KTL

Input Side Data

Max. PV input voltage	1000V
Startup voltage	620V
MPP voltage range	570~950V
MPP voltage range for nominal power	570~850V
No. of MPPTs	1
Max. number of PV strings per MPPT	18
Max. PV input current	144
Max. current for input connector	12A

Output Side Data

Nominal AC output power	80000W
Max AC output power (PF=1)	80000W
Max. AC output apparent power	80000VA
Max. AC output current	116A
Nominal AC voltage	3P+PE, 230/400Vac
AC voltage range	310~480Vac
Nominal grid frequency	50Hz/60Hz
Grid frequency range	45~55Hz/55~ 65Hz
THD	< 3% (Nominal power)
DC current injection	<0.5 %In
Power factor	>0.99@default value at nominal power, (adj. 0.8 leading ~0.8 lagging)

Protection

Anti-islanding protection	Yes
LVRT	Yes
AC short circuit protection	Yes
Leakage current protection	Yes
DC switch	Yes
DC fuse	Yes
PV string monitoring	Yes
DC overvoltage protection	DC Type II SPD (40KA)
AC overvoltage protection	AC Type II SPD (40KA)

System Data

Max. efficiency	99.00%
Euro. efficiency	98.70%
Isolation method	Transformerless
Ingress protection rating	IP65
Night power consumption	<1W
Operating ambient temperature range	-25~60℃
Allowable relative humidity range	0~100%
Cooling method	Smart forced air cooling
Max. operating altitude	4000m (>3000m derating)
Display	Graphic LCD
Communication	RS485/PLC
DC connection type	MC4
AC connection type	Screw Clamp terminal
Certification	EN62109-1,EN62109-2,G59/3,BDEW

Mechanical Data

Dimensions (W*H*D)	634*959*267mm
Mounting method	Wall bracket
Weight	60kg

Note: this inverter only be used in industrial area

Efficiency Curve

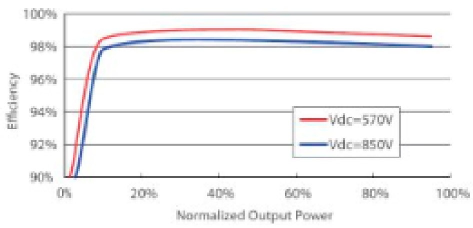


Figure A.3: Sungrow SG80KTL inverter datasheet

B

Additional Data & Results

Monthly production values

The values in Table B.1, represent the monthly data for PV production on the roof of company X in 2020. The monthly PV production output illustrates the expected seasonality with peaks in summer and low yield in winter. Notice the energy production in May was significantly higher than the yield during the summer months. The reason for this difference was that May was an exceptionally good month for PV production, with the KNMI recording record monthly solar hours.

Table B.1: Monthly PV productiona and energy consumption from company X in 2020

Month 2020	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Consumption [MWh]	139.22	135.29	170.4	194.08	216.28	210.42	212.09	217.47	196.82	180.107	144.92	142.51
Production [MWh]	26.28	27.85	104.54	178.35	230.46	196.95	185	170.29	123.54	54.29	32.96	18.17

Monthly consumption data

Figure B.1 shows the monthly energy consumption of company X. The Figure shows that company has higher electricity demand in summer months compared to winter months. This seasonality is advantageous when a company wants to make direct use of the rooftop PV as the consumption profile trend is similar to that of PV.

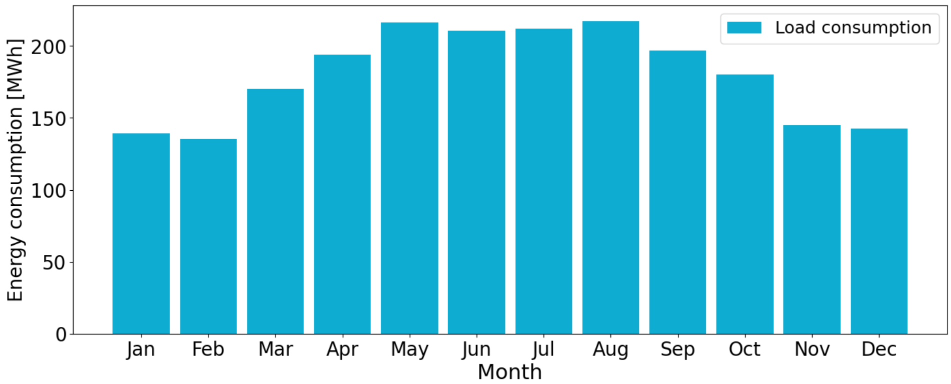


Figure B.1: Company X's electricty consumption in MWh throughout 2020

Monthly EPEX volatility 2020-2021

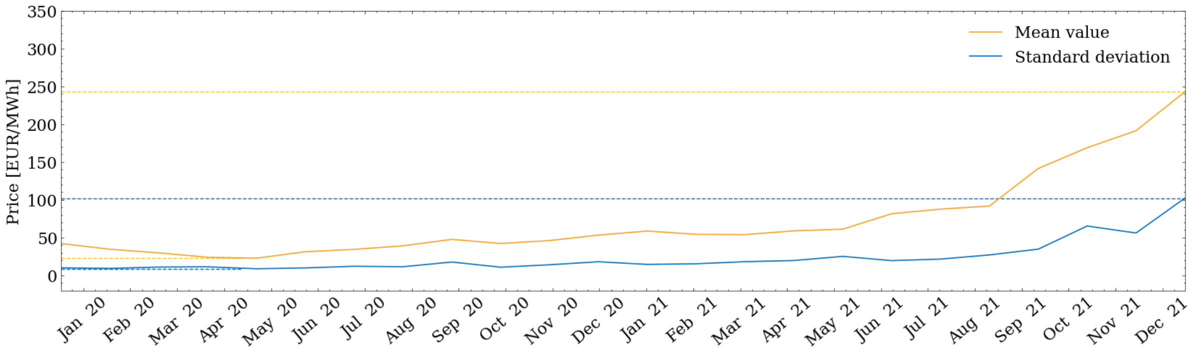


Figure B.2: The monthly average and standard deviation of the 2020-2021 EPEX day ahead prices

PV production for scenario A as used in deterministic model

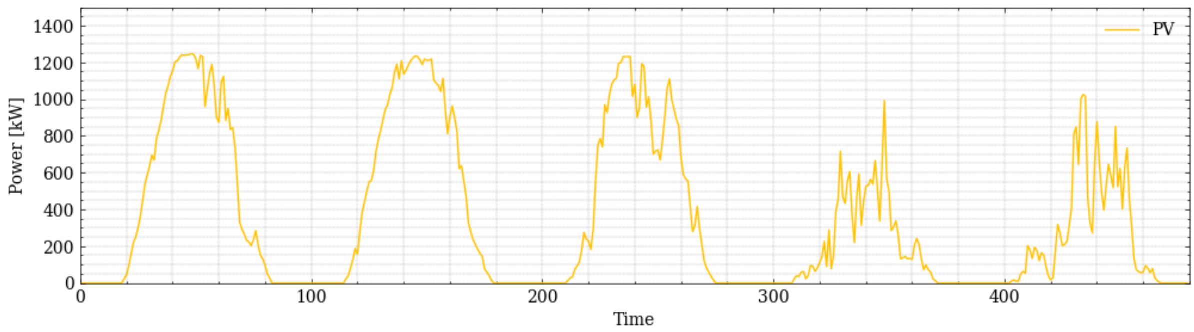


Figure B.3: PV production for scenario A

PV production for 5 days and 11 scenarios in summer, as used in stochastic models

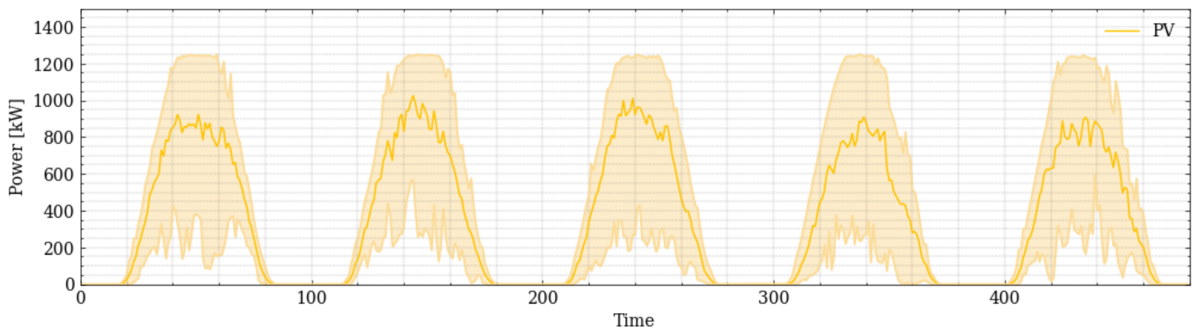


Figure B.4: PV production for 5 days and 11 scenarios in summer

PV production for 1 day and 11 scenarios in summer, as used in stochastic models

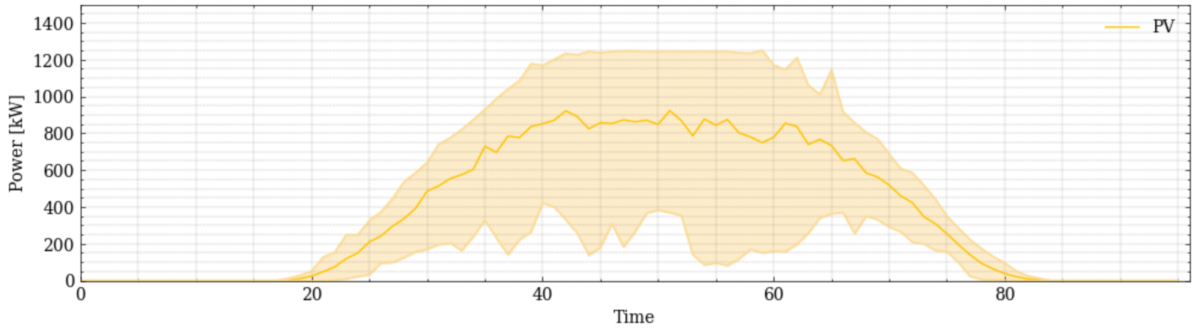


Figure B.5: PV production for 1 day and 11 scenarios in summer

Grid power distribution for all seasons using scenario A resulting from hard constrained stochastic model

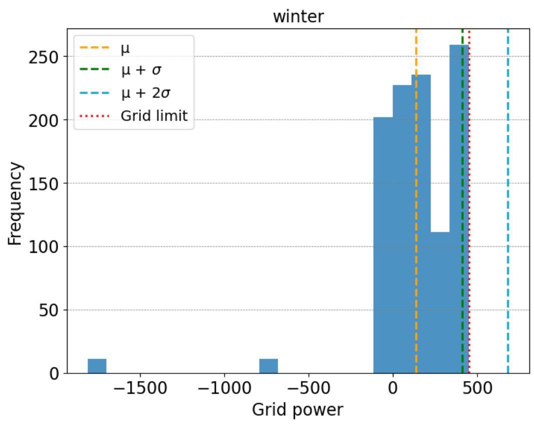


Figure B.6: Grid power distribution for 1 day with 11 scenarios in winter

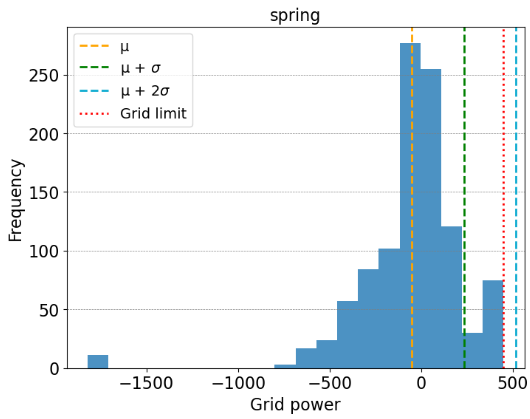


Figure B.7: Grid power distribution for 1 day with 11 scenarios in spring

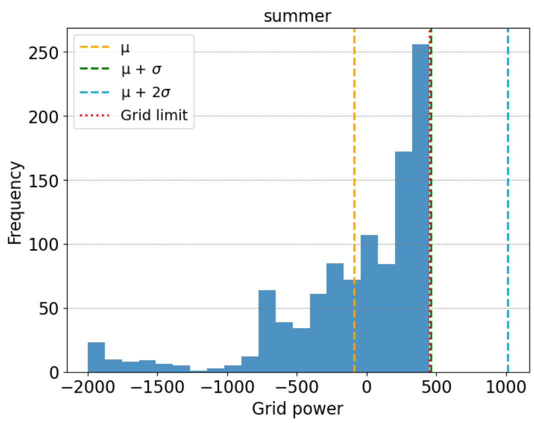


Figure B.8: Grid power distribution for 1 day with 11 scenarios in summer

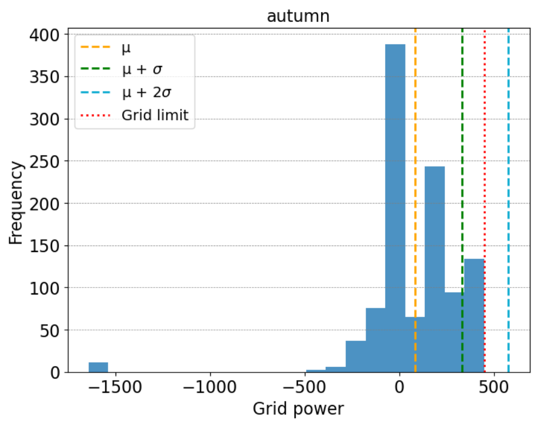


Figure B.9: Grid power distribution for 1 day with 11 scenarios in autumn

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