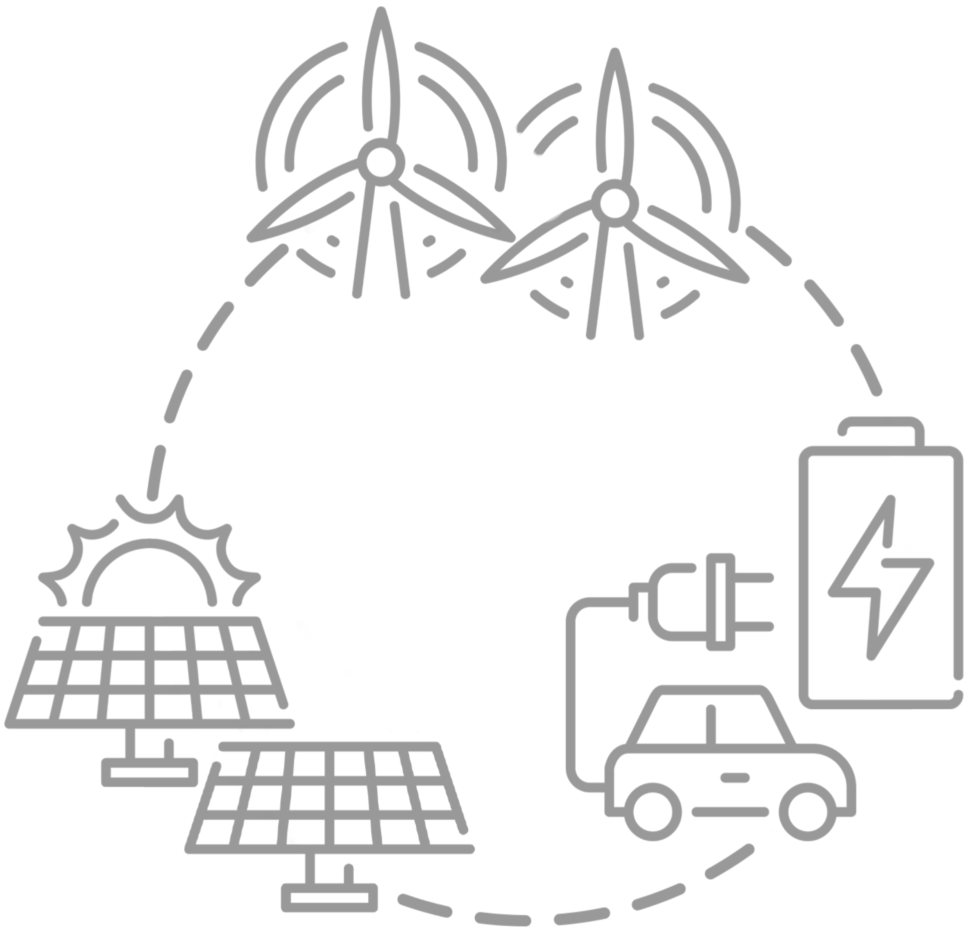
A Price-Dynamic Model of Flexibility in the Electricity Market of the Future

Economic Engineering

W. S. Slits

Master of Science Thesis



Delft University of Technology

Delft Center for Systems and Control

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For the degree of Master of Science in Systems and Control at Delft University of Technology

W. S. Slits

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Faculty of Mechanical, Maritime and Materials Engineering (3mE) · Delft University of Technology

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A Price-Dynamic Model of
Flexibility in the Electricity
Market of the Future

by

W. S. Slits

in partial fulfillment of the requirements for the degree of

Master of Science Systems and Control

Dated: 25-03-2022

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Abstract

To match supply from intermittent renewable energy sources (RES) with demand, it is proposed in literature to introduce flexibility in the electricity market of the future. Flexibility can be provided by energy storage, demand response and cross-border transmission. In this thesis flexibility is modeled explicitly through the price mechanism of demand and supply. This price mechanism can be made explicit with the principles of Economic Engineering. With that price mechanism a price-dynamic bond graph model of the electricity market of the future is built. This model can be used with the various tools that control engineering has to offer to aid investors and regulators in designing the electricity market of the future. It can aid specifically in determining the adequate generation capacity, but also in determining the necessary power and energy capacity of storage, demand response and cross-border transmission.

As an example of application, this thesis demonstrates the use of the price-dynamic model by simulating a future scenario. By simulating trading behavior of a market participant the change of prices for a market with flexibility can be quantified. It is shown that passive control does not represent realistic trading behavior, so optimal control is used. To this end, an Economic Model Predictive Controller (EMPC) is designed to simulate how market prices change when a trader maximizes his profits through energy arbitrage. Based on these price changes it is advised that the Transmission System Operator (TSO) implements an energy storage reserve market to account for risk and ensure grid stability in the electricity market of the future.

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Preface

Climate change starts to be undeniably present in our daily lives now. Tackling climate change is possibly the most interesting and fascinating challenge of the upcoming decades, since it concerns everyone and requires the collaboration of all countries across the globe. For this thesis, I got to dive into the economics behind the energy transition on the electricity market. Through that process I learned a lot about the many challenges, but also about the many opportunities that lie ahead of us. This has made me truly enthusiastic about all which is going on right now. "Smart" solutions seem to be key, and this is where Systems and Control techniques can definitely take an important role. The future is exciting!

I would like to thank my supervisors Max Mendel and Coen Hutters for introducing me to the field of Economic Engineering and letting me carve out my own thesis topic and project from beginning to end. The endless discussions and many hours in the Wiener Hall have been eye-openers, but also forced me to be sharper and more precise in both speech and writing. Beyond the serious discussions, I would also like to thank them for the many fun times, especially during a corona pandemic where nothing else was really possible.

A similar gratitude goes out to the Economic Engineering group that consistently showed up on Tuesdays and Thursdays for discussions and input. It forced me to really get the story straight and clear, and they came up with many useful suggestions when my research was stuck or I was looking for a different view.

Furthermore I like to thank many people that were available for one-time input about the electricity market and other thesis related topics, such as Laurens de Vries (TBM), Nikita and Anne Sjoerd (Shell), Roel Dobbe (TBM), and Sjoerd Boersma (WUR).

And last but not least, a small shoutout to the "Taxi Wouter"-crew for the many entertaining drives back-and-forth between Rotterdam and the TU Delft the past year, and actually trusting me as their chauffeur.

Delft, University of Technology
13-03-2022

W. S. Slits

"The day when we shall know exactly what electricity is will chronicle an event probably greater, more important than any other recorded in the history of the human race. The time will come when the comfort, the very existence, perhaps, of man will depend upon that wonderful agent." — *Nikola Tesla*

Chapter 1

Introduction

1-1 The Need for Flexibility in the Electricity Market

As climate change becomes more apparent, the need for cleaner electrical energy sources increases. Renewable energy sources (RES) are deployed to reduce CO_2 emissions, while still providing sufficient energy to meet the electrical energy demands [4], [5]. There are several forms of RES, but in most of Europe, and especially in the Netherlands, wind farms and solar panels are the most promising techniques [6]. As costs are dropping for these technologies [7] and they are deployed on a larger scale, the effects it has on the market start becoming apparent.

Both wind and solar energy sources have the major drawback that their energy production is weather dependent, and therefore highly intermittent. Even when wind farms are built at sea where wind blows more stable, this is still a problem [8]. Meanwhile electrical energy demand is following its own schedule, while demand is also increasing due to electrification. Demand certainly does not match the intermittent character of RES. This is a problem on the electricity market for two reasons: The electricity market has the unique feature that demand and supply must meet in real-time to prevent blackouts on the electricity grid, and the electricity market is in place to provide this grid stability at least cost to consumers [9].

These differences between demand and the supply will cause highly volatile prices with high uncertainty [2], [10], [11]. This results in economic uncertainty for market players and therefore negative economic effects will be inevitable. Additionally, if prices become very volatile with high uncertainty, grid balance is compromised and the risk for black-outs increases [12].

To make demand and RES supply match closer, more flexibility must be added to the market. Flexibility is described as the ability of a power system to deal with variability and uncertainty in supply and demand, while maintaining an acceptable level of reliability at a reasonable cost [13]. This can ensure grid stability and prevent extremely volatile prices. Market mechanisms that increase flexibility include electrical energy storage, demand response and cross-border transmission [13], [14]. Implementing these three solutions will change the economic system structure of the electricity market substantially. These effects have to be accounted for when modeling the electricity market.

1-2 Modeling the Electricity Market of the Future

Models of the electricity market are used for day-to-day trading as well as long-term investments and strategies [15]. These economic activities rely on an accurate model to reduce price uncertainty. A common modeling technique is to use historical data to forecast upcoming prices and market behavior through statistical or machine learning methods [16], [17]. These approaches result in a black box model of the electricity market.

A black box model is a useful approach if the economic system (the market) that this model describes remains similar. However if the system structure changes substantially in the future, as is bound to happen on the electricity market due to increased flexibility, this does not provide a strong basis for accurate forecasting [18]. This is similar to how two mechanical systems with different dynamic structures behave differently. A black box model lacks interpretability [19], so it is virtually impossible to adapt it to future scenarios. An interpretable model does not have this problem.

Using Economic Engineering it is possible to explicitly model market dynamics using engineering first-principles modeling, instead of using a black box approach. In Economic Engineering economic systems are modeled as causal dynamic systems, similar to how mechanical and electrical systems are modeled [20]. This leads to a modular model with elements that have an economic interpretation. The changing dynamics in the electricity market provide a unique opportunity to use Economic Engineering to its full potential. Statistical regression or machine learning methods with historical data will not be representative for the new market dynamics in the electricity market.

Explicitly modeling the market dynamics is not a new concept in the electricity market. System Dynamics modeling is an established field used primarily to model different scenarios for policy assessment or to help make investment choices on generation capacity expansion [18], [21]. [22]. The main difference with System Dynamics modeling is the inclusion of price dynamics in Economic Engineering. Economic forces are used to describe how prices change, something that is not present in System Dynamics modeling. Using Economic Engineering a modular first-principles bond graph model can be build that includes price dynamics and accounts for the increased flexibility.

1-3 A Price-Dynamic Economic Engineering Model

In Chapter 2, an Economic Engineering model is developed for the current electricity market. This is done by first analyzing the electricity market, and introducing and substantiating several model assumptions. Then the electricity market is formulated as a control problem, that is subsequently controlled with a passive proportional controller.

In Chapter 3, the problems that arise on the electricity market of the future are discussed. According to literature storage, demand response, and cross-border transmission will be deployed to keep the grid stable and the costs for electricity within reasonable limits. It is then demonstrated for storage what the price mechanism is, and how this can be used with the passive controller. In the simulations economic incentive for using passive control is however shown to be limited. The trader that owns the storage cannot optimize for profit, so the trading behavior of the trader implemented by this passive controller is not very realistic.

By using optimal control more realistic trading behavior can be simulated. In Chapter 4 modeling techniques for storage, demand response and cross-border transmission are developed using Economic Engineering to find a modular first-principles model that is suitable for optimal control. The modular design of the model offers versatility to the user. Storage, demand response and cross-border transmission can be added as separate building blocks to the model, allowing for a model design that closely matches predicted future scenarios.

1-4 Quantifying Market Price Changes

With a modular model of the electricity market of the future, the price changes due to new market dynamics can be quantified. This is achieved by simulating trading behavior on the electricity market using optimal control. In Chapter 5 a trader with electrical energy storage and demand response is modeled by combining several modular building blocks. A Model Predictive Controller (MPC) is then used to maximize profits and simulate more realistic trading behavior.

These simulations will show what potential there is for a trader to make profits using storage. Secondly, this provides insights in how the market prices in the future will change with respect to the current market. Ultimately this will assist in making investment choices in renewable energy sources. More certainty in RES investments speeds up the energy transition.

Additionally, the model can support regulators in designing the market of the future. The flexibility that is added to the market of the future can solve many of the problems with intermittent RES, but at the same time introduce new risks. Especially the risk of having too little energy available in storage due to forecast errors can pose problems. Because risk is explicitly taken into account in the design of the MPC, it is possible to quantify it. This leads me to formulate a regulatory advice for an energy storage capacity reserve market at the end of Chapter 5 to regulate risk-taking with storage.

Chapter 2

An Economic Engineering Model of the Current Electricity Market

The electricity market is the place where produced electrical energy is sold to electrical energy consumers. Similar to other commodity markets, electrical energy is traded on this electricity market in various ways and with several timescales, with the main difference being that supply and demand must meet at all times in real-time, otherwise power outages might occur. The electricity market is therefore serving two main goals [9]:

- Ensure grid stability to prevent blackouts by matching demand with supply.
- Supply electricity to consumers at least cost.

This chapter will go into depth how the electricity market is built up. The information in this chapter is used to establish relevant modeling assumptions. Then the analogies between the mechanical and economical domain are used to analyze the electricity market. At the end of this chapter the matching of demand and supply on the electricity market is formulated as a control problem using these modeling assumptions. This is the basis for building a first Economic Engineering model of the electricity market.

Chapter Goals

- Provide relevant background information for determining modeling assumptions.
- Analyze the electricity market using Economic Engineering.
- Formulate matching demand and supply as a control problem.
- Build an Economic Engineering model of the current electricity market.

2-1 Structure of the Electrical Energy System

To sell and transport electricity, there is an extensive electricity system in place. The electricity system as a whole can be structured into three segments. The first segment is the wholesale market. This is where electrical energy produced by different electricity generators is sold 'in bulk' to large consumers such as big industry players and retail companies. The energy is then transmitted from the generators to different areas in the country and distributed among consumers. This transmission-distribution process is the second segment of the energy system and represents the physical electricity grid. Retail companies then sell that distributed electricity to private parties, such as households and small businesses in a third segment called the retail market. Figure 2-1 shows a visual representation of the market.

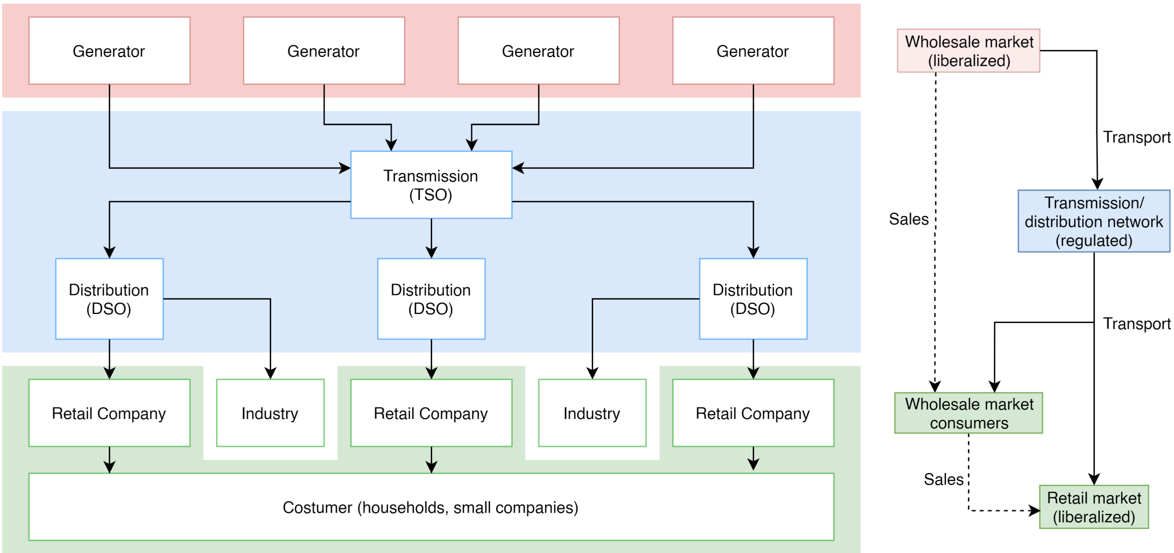


Figure 2-1: Structure of the electrical power system

The information here focuses on the Dutch electricity market, which is a decentralized market. This means that transmission and economic activities are strictly separated [23]. Electricity markets in other European countries are also decentralized markets, but outside Europe electricity markets are often organized differently. For instance in the United States the markets are integrated electricity markets, meaning that electricity generation is centrally dispatched and economic activities and transmission are interconnected [23]. Information provided here may therefore not apply directly to non-European energy markets.

The current electricity market is a relatively young market and still continuously developing. This is because until the end of the 20th century, the entire Dutch electrical power system was still regulated by the government, and costumers could not choose their electricity retailer. The wholesale market was liberalized in 2001, allowing for competition between electricity generators. Then in 2004, the retail market was also liberalized, making sure that costumers could choose who they would buy power from. The transmission-distribution process is still regulated by the government, thus a natural monopoly [24].

The focus of this research will be on the wholesale market, since this is where the day-to-day trading of electricity takes place. It consists of all the electricity generators, electricity retail companies and large industry players. Participants on the wholesale market can be generating and selling electricity, as well as buying electricity. Also traders are active on the electricity market; they do not generate or consume electricity, but only buy or sell certain volumes in order to buy or sell the same volume later. The Transmission System Operator (TSO) and Distribution Systems Operators (DSOs) are prohibited from market activities.

2-1-1 The wholesale market divided in four markets

To make sure energy supply and energy demand meet, and power outages do not occur, electricity in the wholesale market is traded on different timescales. Electricity can be bought or sold years, months or weeks ahead of time on the futures and forwards market. Prices can be either peak or base prices.

As real-time T approaches and predicted demand and supply become more certain, buyers and sellers can buy or sell electricity on the spot market. If necessary they can correct their purchases and sales from the futures and forwards market. The spot market consists of the day-ahead market (DA) and an intra-day market (ID). The first being a market that trades for the next day and the second being a market that trades up to 15 minutes before real-time (which is the lead time n). For the day-ahead market, the next day is divided into 24 blocks of one hour, so the traded electrical power is for an entire hour. On the intra-day market trading happens in blocks of 15 minutes to provide more flexibility.

Finally mismatches between demand and supply are corrected by the TSO in real-time on the balancing market. Figure 2-2 shows a simplified timeline of the electricity market.

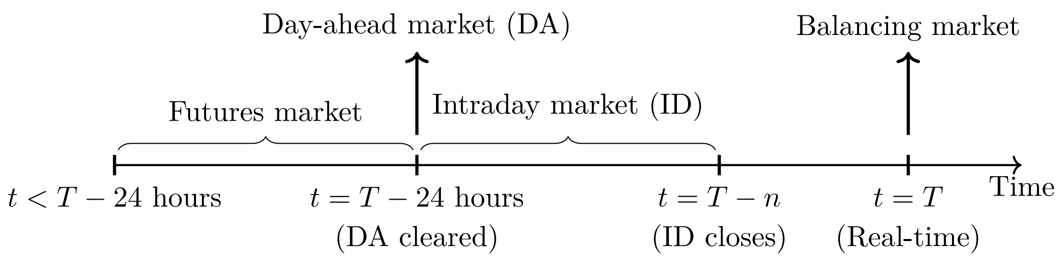


Figure 2-2: Simplified timeline of the electricity market

The futures market is still rather small and most electricity futures are actually traded over-the-counter (OTC) on the forward market. These are non-standard contracts between two parties that are also non-transparent, so there is little insight in the details such as prices for energy forwards [25]. Prices for most forward contracts are said to be based upon current spot prices on the day-ahead market[1].

The spot market is much more transparent, especially the auction-based day-ahead market. The day-ahead market accounts for about 35% of total energy supplied and the intraday market for only about 3-4% [25]. Finally, the balancing market is a crucial element in electricity system, but from a trading perspective less interesting because of the smaller volumes.

[1] Literature on electricity futures is scarce, these insights are therefore based on claims by experts.

The focus of this thesis will be on the day-ahead market, because of its large trading volumes, one market clearing price for all buyers and sellers, and full transparency on the supply and demand curves (the aggregated curves for supply and demand bids per hour) [26].

Model Assumption

Modeling using only data from the day-ahead market of the wholesale market.

Upcoming chapters will specifically discuss the day-ahead market of the wholesale market, however for a broader understanding of the electricity market a more detailed description of both the electrical power system and the entire structure of the wholesale market is given in Appendix A.

2-1-2 Different market policies

Since electricity is such a crucial commodity in modern society, countries choose market policies to ensure stability, yet keep costs down for consumers [9]. Electricity markets can sell energy (in MWh) and/or power capacity (in MW). Also different pricing schemes may be used for bidding. Since there are no universal optimal policies for electricity trading, the specific policies differ per country. Nevertheless the chosen policies are mostly aligned throughout Europe.

The Dutch day-ahead market is just like most European markets an energy-only market. This means that only electrical energy is sold here, so consumers only pay for energy that is actually consumed [27]. So even though the electricity market is often referred to as the power market, the actual product which is traded is electrical energy and not electrical power.

Model Assumption

Modeling an energy-only market, no power capacity trading.

The pricing scheme is a uniform pricing scheme. This means that the auction-based market is cleared using one market clearing price for all sellers and buyers, irrespective of their bids. So as long as buyers bid above the market clearing price and sellers bid below the market clearing price, their bids will be fulfilled at the market clearing price [26].

Model Assumption

A uniform pricing scheme with one market clearing price per hour.

Capacity markets and pay-as-bid pricing schemes are alternative market policies that are discussed in more detail in Appendix A.

2-2 Demand and Supply on the Current Electricity Market

Similar to other markets [28] the objective on the electricity market is to match demand and supply. However, since quantity supplied and quantity demanded actually have to always meet in real-time to prevent power outages, this objective of matching demand and supply is enforced much stricter than on other markets. The different markets as discussed in subsection 2-1-1 all contribute to keeping the power grid stable despite uncertainties in planning. This section will discuss how demand and supply are matched on the day-ahead market.

2-2-1 Energy demand

Electrical energy is a product that is consumed by many households and smaller companies without ever really taking the wholesale energy market prices into account. Many households will switch on their light or turn on their televisions whenever they want, and since they pay a fixed price for energy on the retail market, their consumption is almost completely disconnected from energy prices on the wholesale market.

The energy demand therefore varies constantly and these variations are typically divided in four timescales. The demand differs per minute, per hour of the day, the day of the week and the month of the year [29]. The differences are dependent on what most people and companies are doing, but also on the weather. Especially seasonal differences are caused primarily by weather and temperature differences between winter, spring, summer and autumn.

Model Assumption

Demand is price-inelastic and very volatile over time.

The physical demand of electricity on the electricity grid is called the load. An example of a typical load curve for one day is given in Figure 2-3. This shows that demand consists of a constant base load (of 14 GW in this case) and a peak load (close to 18 GW for this day). Usually the peak load occurs in the morning around 09:00 and in the evening around 19:00. Energy demand variation is discussed in more detail in Appendix B.

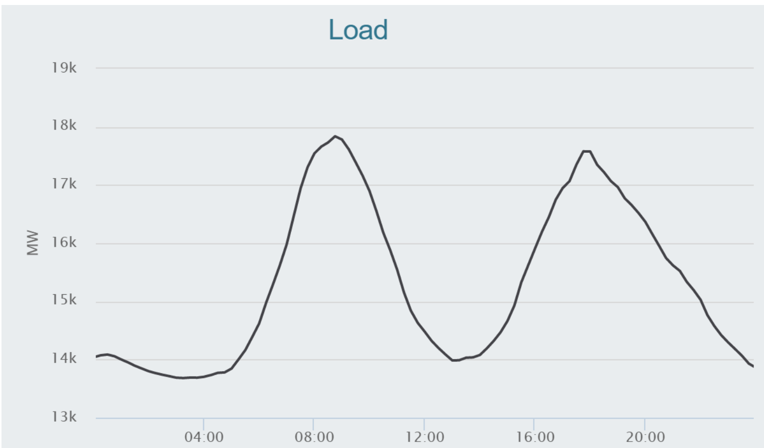


Figure 2-3: Load curve on the Dutch electricity grid on Thursday 11 february 2021 [1]

2-2-2 Energy supply

There are many different ways to produce electrical energy to match the energy demand, each having different costs, flexibility in usage, and side-effects to for example climate or landscape. To accommodate a stable and cost-effective electricity network, most countries have a diverse portfolio of electricity generators to meet the different requirements the market has [23]. This ranges from renewable energy sources (RES) such as wind and solar power, to traditional nuclear, coal and natural gas plants.

RES have running costs close to zero, reasonable capital costs, but their intermittent weather-dependent generation makes their energy production less constant and less reliable. Coal and nuclear are typical base load generators with high capital costs, low to medium running costs, and slow dispatch-ability. Gas plants are commonly used as peaking plants, they are often cheaper and easier to build than coal and nuclear plants, have fast dispatch-ability, but also high running costs.

Appendix C goes into more detail on these different generators. For a deeper understanding of why the portfolio is mixed as it is, this is useful to read. However, for understanding the upcoming modeling part of this thesis the provided information here is sufficient.

Model Assumption

Electricity is supplied by a diverse portfolio of generators.

2-2-3 Using the merit order to match supply with demand

To make sure the supply matches the demand each hour on the day-ahead market, the energy suppliers bid how much energy they are willing to supply at what price for each hour during the next day. All available generators are ranked by their bids, which leads to an aggregated supply curve. The generator with the lowest bid is deployed first, and the generator with the highest bid is deployed latest, if at all. This is called the merit order [23]. When modeling the electricity market, a merit order model often forms the basis. It shows the price bid of a specific generator and how much energy it can supply during one time block.

The merit order model has bidding price with units €/MWh on the y-axis. The quantity on the x-axis usually has units of power capacity in MW [23]. However, economically a flow of electrical energy in MWh/h is more precise. Although flow of energy and power are similar, flow of energy more explicitly and accurately depicts the actual trading of the product. MWh/h on the x-axis matches with a price per MWh on the y-axis. The merit order model used in this thesis will therefore use flow of energy MWh/h on the x-axis. The x-axis will be labeled "quantity" instead of "capacity" to make this distinction more explicit.

In Figure 2-4 a fictive merit order model is shown that roughly represents the current world-wide generation mix. For the Netherlands the generation mix consists of more natural gas and less coal, but the working principle behind the merit order model remains the same. In most countries the consumers on the demand side also place bids, which will then be sorted from high to low, but for now demand is assumed perfectly inelastic. This assumption is acceptable since most consumers will not base their energy consumption on current prices.

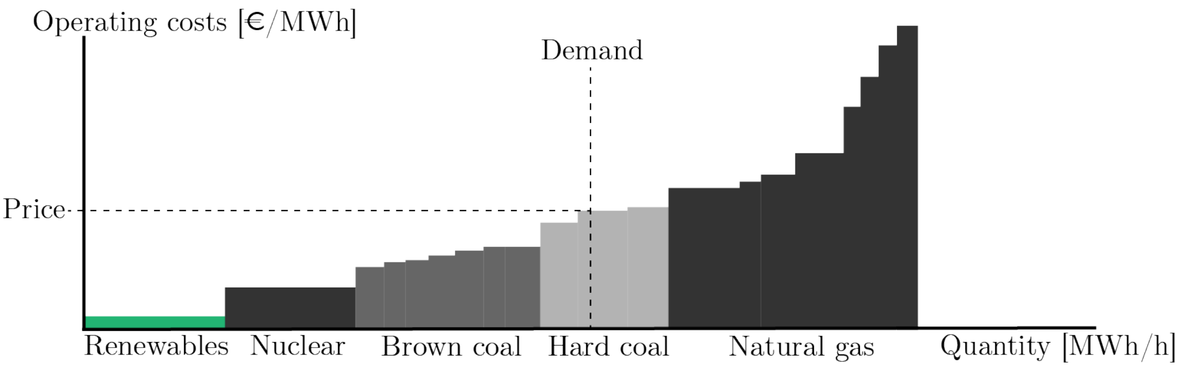


Figure 2-4: Example of what a merit order model looks like

By matching the quantity supplied with the quantity demanded, a market clearing price is found. This clearing process is executed by the power exchange or a clearing house connected to the power exchange. This happens in accordance with the TSO. [26], [30]

> Model Assumption
>
> **Demand and supply must be matched closely, this is enforced by the TSO/ clearing house.**

Perfect Competition

For the merit order model, perfect competition is assumed. According to [31], perfect competition for the electricity market assumes, among other things, that:

- All players have perfect information.
- There is a sufficient number of market players, so that no individual player can influence the market price.
- Market players can freely enter and exit the market.
- Electricity is a homogeneous product.
- The cost of transmission and distribution are constant and are not taken into account.

If perfect competition is assumed and a uniform pricing scheme is used (see subsection A-3-2) to find the market clearing price, all suppliers will bid their operating costs. Bidding above their operating costs does not yield any benefits, since all participating suppliers during a certain hour will receive the market clearing price for their product anyways.

> Model Assumption
>
> **Because of perfect competition all suppliers bid at their operating costs.**

Since the available generators, and thus the shape of the merit order, can differ per hour, and the demand also varies greatly across the day, the market clearing price will fluctuate heavily throughout the day. Figure 2-5 shows the prices for one week (the demand curve of this week is shown and discussed in the Appendix in Figure B-3). The typical shape with peaks in the morning and the evening can be seen, so demand certainly has a strong influence on prices. Meanwhile Thursday 11th of February is an outlier, so on this day not only demand was high, but there were also some cheaper generators unavailable (for example no wind or solar power). During such moments the generators on the utmost right of the merit order are deployed and market clearing prices rise steeply.

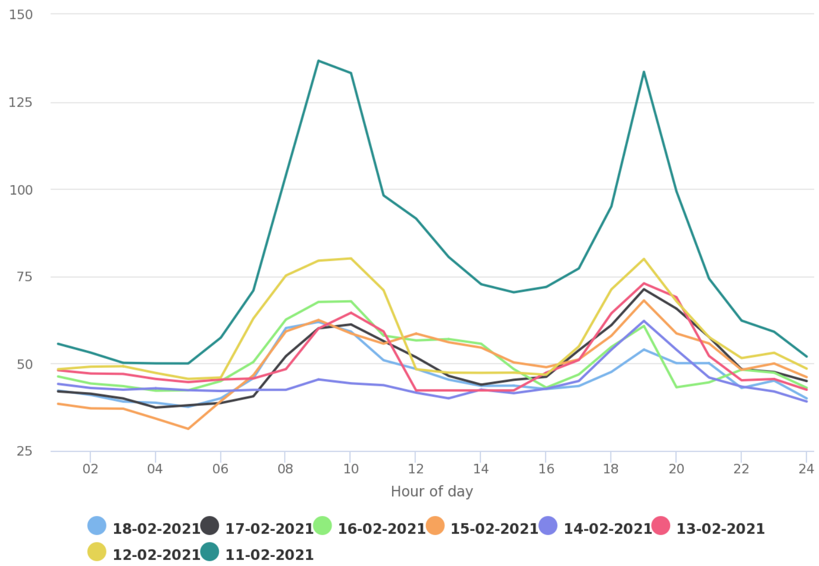


Figure 2-5: Nord Pool day-ahead prices per hour for 24 hours plotted for several days

2-2-4 Limitations of the merit order model

The surplus that a generator makes is the difference between the market clearing price and the operating costs per MWh (which will be its bidding price) multiplied by the quantity supplied by that generator. In Figure 2-6 this is shown for a large nuclear generator. Any generator that has been built already will try to maximize its surplus for the upcoming days or weeks by supplying whenever the price is above its operating costs. This is regardless of whether enough surplus will be accumulated to cover the capital costs. This shows the limitations of the merit order, since it can only account for short-term market dynamics.

In the long run it is important to know for investors if they earn their capital costs back, else they will not invest anymore in that type of generator. The merit order will therefore change shape in the future if a generator consistently makes too little surplus, because these generators will disappear. Likewise the number of very profitable generators in the market may increase. These changes are difficult to capture using only the merit order. So even though merit order is a useful tool for analyzing the demand and supply behavior on the energy market, the broader picture of electricity suppliers wanting to earn their investments back is important as well.

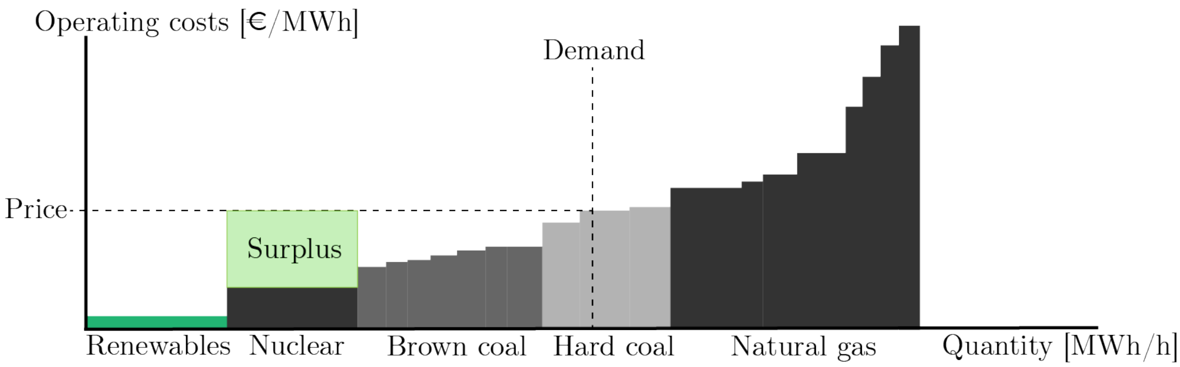


Figure 2-6: Surplus made by a generator

2-3 Using Economic Engineering to Demonstrate Constrained Dynamics

Economic Engineering is a new field of study that models economic systems in a similar way as engineering systems, as already introduced in Section 1-2. It has useful tools for analyzing market dynamics from an engineering point of view. This section will show how I use Economic Engineering for looking at the current electricity market and will also show how constrained market dynamics currently result in static pricing when modeling the electricity market.

Mechanics		Economics		Electricity Market	
Variable	Units	Variable	Units	Variable	Units
Force (F)	N	Want (F)	€/ #	Bidding (F)	€/(MWh·h)
Momentum (p)	Ns	Price (p)	€/ #	Price (p)	€/MWh
Velocity (v)	m/s	Flow (Q)	#/h	Quantity (Q)	MWh/h
Displacement (x)	m	Inventory level (q)	#	Energy stored (q)	MWh

Table 2-1: Analogs between mechanical domain and economic domain

In Economic Engineering bond graph modeling is used as a domain neutral modeling tool. In bond graph modeling the different components of a dynamic system are graphically represented using I-, C- and R-elements. The I-element is the inertance element, which is for example a mass or an inductor. The C-element is the compliance element, which is for example a spring or a capacitor. The R-element is the resistance element which is for example a damper or a resistor.

The different elements are connected using power bonds that have an effort and a flow component. These components are force and velocity, or voltage and current for the mechanical and electrical domains respectively. Table 2-1 shows the analogs between the mechanical domain and the economic domain.

2-3-1 Demand and supply on the energy market using engineering principles

The supply and demand curves are analogous to looking at masses in mechanics, and represented by I-elements in bond graph modeling. A mass can store momentum p by integrating a force F over time, a supply curve can store price by integrating a market force F over time:

$$p = \int F \, dt \tag{2-1}$$

The price elasticity ϵ_S of the supply curve is used to determine the quantity supplied Q_S at a certain price:

$$Q_S = p\epsilon_S \tag{2-2}$$

This relation can be shown in a p, Q-diagram where the price elasticity is the slope of the supply curve. Likewise their is also a price elasticity for the demand curve. Q_S and Q_D represent the quantity supplied and quantity demanded respectively. In bond graph modeling the size of the I-element represents the price elasticity through $\epsilon = 1/\mathrm{I}$.

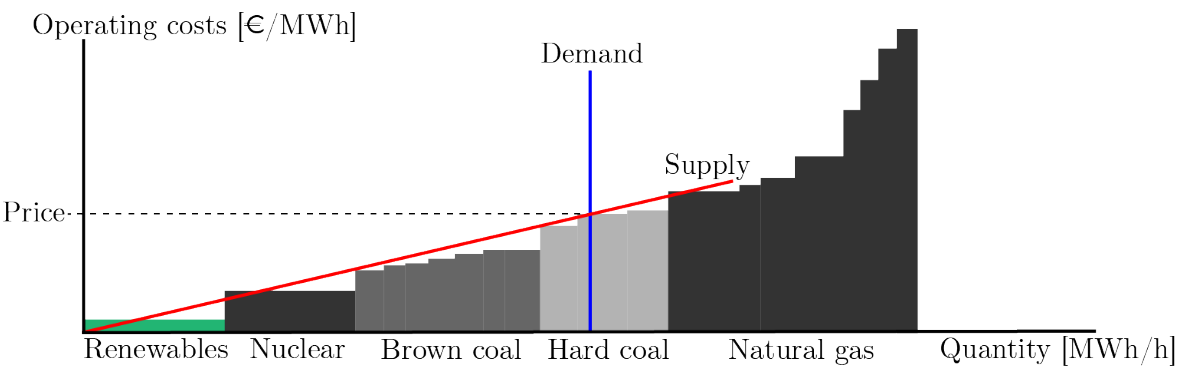


Figure 2-7: Merit order with simplified demand and supply curve

The most suitable p, Q-diagram for the electricity market is the merit order model for the day-ahead market as introduced in subsection 2-2-3. This staircase-shaped merit order model can be approximated with linear demand and supply curves. The demand curve is assumed perfectly inelastic for now, so price elasticity is infinite, or similarly a mass in the mechanical domain that represents demand has an infinite size and does not move upon applying force. Figure 2-7 shows the merit order model from subsection 2-2-3 with linear supply and demand curves.

Model Assumption

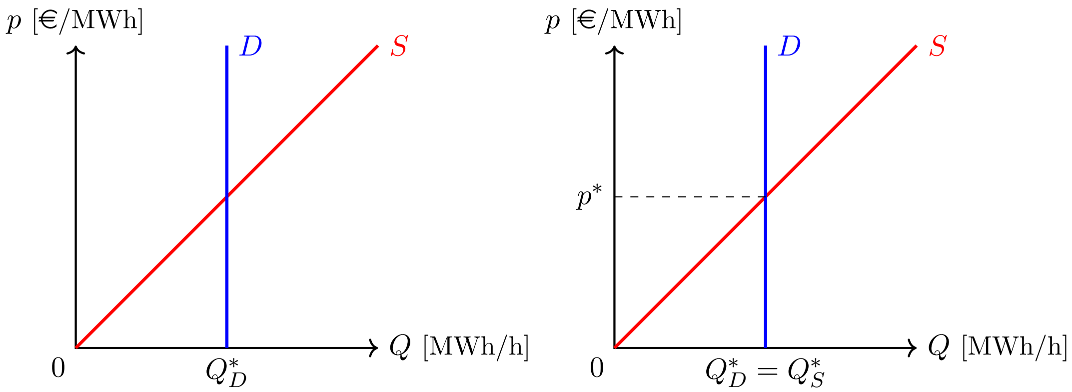
The supply curve is a linear function of price.

Since suppliers bid their operating costs, the price bid per supplier is equal to operating costs. As explained in Section 2-2, the objective of the energy market is to match demand and supply at all times, to prevent power outages. This objective is enforced by the TSO by letting a clearing house on the power exchange match quantity demanded with quantity supplied to find a market clearing price for each hour in the day-ahead market:

$$\text{Current objective:} \quad Q_D^* = Q_S^* \tag{2-3}$$

2-3-2 Constrained dynamics leading to static pricing

With $Q_D^* = Q_S^*$ and the price following from this relation, the dynamics in the system are currently constrained in my view. An abstract representation of the merit order model is given in Figure 2-8 that depicts this constraint.



(a) Demand is perfectly inelastic

(b) Price p^* follows from $Q_D^* = Q_S^*$

Figure 2-8: Abstract representation of merit order model

The demand can be seen as a mass with infinite size in the form of a fixed wall that cannot move within its own frame since it is fixed. It already has an infinite amount of momentum, and no force within the system can change this. It only has a velocity with respect to an external reference frame. The velocity of this reference frame is the quantity demanded. The supply side is a second mass that does have a non-infinite size, so it does have a price elasticity, but it is directly bolted to the wall with a stiff rod. This is graphically shown in Figure 2-9.

As a result the mass representing the supply curve will always move along with the wall. In this way the momentum/price on this second mass cannot be influenced by introducing a force on this mass. The velocity of the second mass, the quantity supplied, also follows directly from the velocity of the reference frame.

For now I make the assumption that the objective of quantity demand equals quantity supplied is modeled as a strict constraint. The demand side is assumed perfectly inelastic, and the supply curve is assumed to continue into infinity, so it is possible to always match demand with the supply. Therefore the relationship between quantity demanded and quantity supplied will be represented with a stiff rod for the remainder of this section.

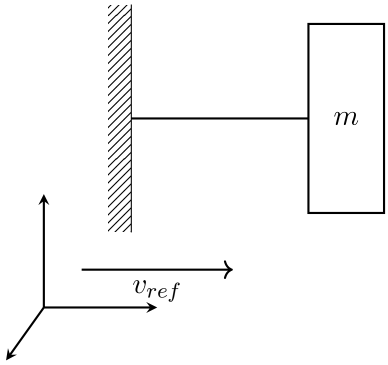
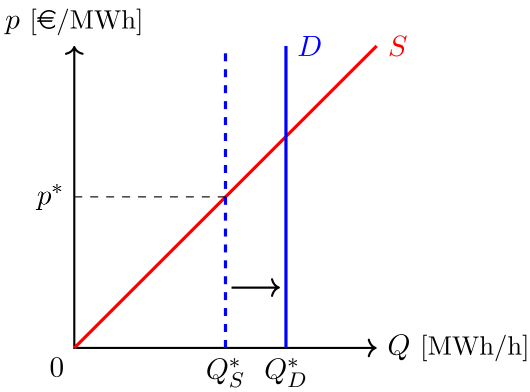


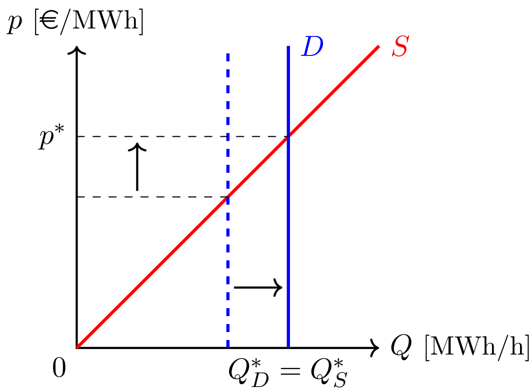
Figure 2-9: Mechanical diagram of the demand and supply with respect to the reference frame

When the demand shifts to the right in the p,Q-diagram it means the velocity of the reference frame is increased. The quantity supplied will acquire the same amount of velocity, which is additional product flow, since they are connected with a stiff rod and cannot move independently. The momentum stored in the second mass must now be higher as well. This is because now the mass moves at a higher velocity, but only with respect to the reference frame.

In economic analogous terms the price went up because the quantity supplied increased as shown in Figure 2-10. This is actually an anti-causal relation between quantity supplied and price, and is caused by the stiff rod. This stiff rod which represents the $Q_D^* = Q_S^*$ constraint enforced by the TSO takes the dynamic price behaviour out of the system. Prices now only change because of changes with respect to the reference frame. The internal dynamics are completely constrained and pricing within the merit order model is subject to what I call static pricing modeling.



(a) Q_D^* is shifted



(b) Q_S^* follows, and p^* adjusts accordingly

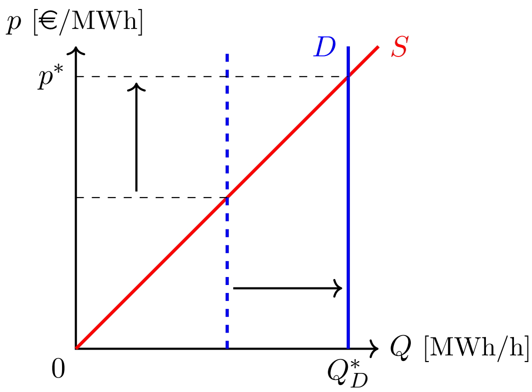
Figure 2-10: Shift in price follows from shift in demand

2-3-3 External effects causing price volatility

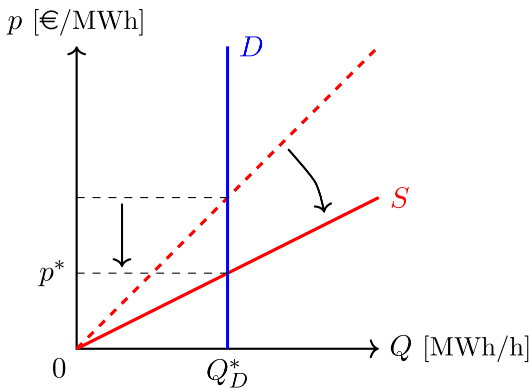
Despite the pricing in the model being static, prices still vary greatly across the day. This is not due to internal price dynamics, which have been shown to be constrained in subsection 2-3-2, but because of external effects. It is the velocity of the reference frame that dictates changes in price. The price elasticity then returns how much change in the price takes place when the velocity of the reference frame has changed.

In Figure 2-11 it can be seen that shifts of the demand curve and rotations of the supply curve have a major influence on the price. A shift in the demand curve in the economic domain is a change of the velocity of the reference frame in the mechanical domain. This happens when the demand fluctuates from hour to hour.

A change in the price elasticity, or actually a rotation of the supply curve, is a change in the size of the mass. This happens when the available electricity generators vary greatly from hour to hour or when more expensive generators have to be deployed. Intermittent renewable energy sources play a major role in this, because their availability is strongly dependent on the weather. The use of expensive gas turbines as peaking plants is a second reason.



(a) Shift of demand curve



(b) Rotation of supply curve

Figure 2-11: Prices are still volatile because of external effects

2-4 Formulating the Electricity Market as a Control Problem

The electricity market has the objective to match the quantity supplied Q_S very strictly with the quantity demanded Q_D. In subsection 2-3-2 this was represented with a stiff rod to show the constrained dynamics from a modeling perspective. In that way the objective becomes an actual constraint on the system dynamics. This is in line with how quantity demand and quantity supplied are always perfectly matched upfront on the futures market, the day-ahead market and the intra-day market. Every MWh of energy bought is matched to a seller. The balancing market then corrects any differences between the market schedule and the actual supply and demand. So in reality $Q_D^* = Q_S^*$ is not truly a strict constraint, but the clearing house and TSO are actively correcting any differences.

2-4-1 Clearing house and TSO actively matching demand and supply

To simplify the whole market setup and uncover the dynamics behind the electricity market I make the assumption that there is just one market, not four. On this one market the clearing house and TSO are actively matching demand and supply by matching available bids. Through this process they find a market clearing price for each hour. It will be based on the day-ahead market, so the aggregated supply curves from the day-ahead market are still used as basis for the price elasticity of supply. However, it will have the dynamic behavior from the entire market. This is a substantial simplification, though a crucial one to say anything about the price dynamics in later chapters.

Model Assumption

The electricity market is seen as one large dynamic market, instead of four separate markets.

From a control engineering perspective this assumption of one dynamic market makes it possible to formulate a control problem. Since the excess demand Q_E is now the error signal e and the clearing house is the controller trying to minimize the error signal. It uses the excess demand that is given by:

$$Q_E = Q_D - Q_S \tag{2-4}$$

This does break with the strict day-ahead market hour-to-hour approach, because in the actual day-ahead market demand and supply are matched upfront for each hour. There is no error and no feedback behavior. Electricity sold during one hour can be seen as an economically different product from the electricity sold the next hour (with the exception of dispatchable limitations of large coal and nuclear generators). This is because of lack of flexibility possibilities. Each hour is economically independent. As flexibility options are introduced in Chapter 3, different hours will become economically dependent. The control formulation as stated here becomes more suitable, so it is established here already.

2-4-2 Designing a passive controller

Using the modeling assumptions that were established in Section 2-1 and Section 2-2 a block diagram can be drawn that represents the current market.

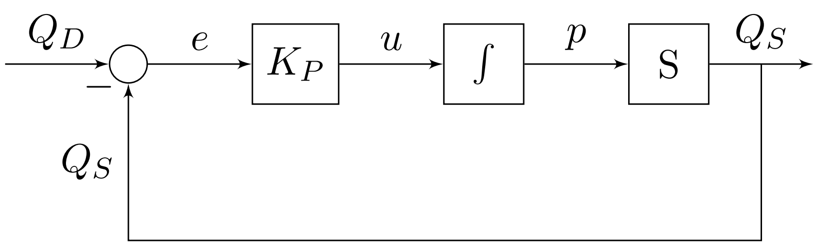


Figure 2-12: Block diagram of the electricity market with the clearing house as controller

Model Assumptions

- Modeling using data from the day-ahead market.
- Energy-only trading, no power capacity trading.
- Uniform pricing scheme (one market clearing price per hour for all suppliers and consumers).
- The supply curve is an aggregated linear curve.
- Demand is price-inelastic and very volatile over time.
- Demand and supply must meet, this is enforced by the TSO/clearing house.
- Because of perfect competition suppliers only bid at their operating costs (no strategic bidding).
- The electricity market is one dynamic market, instead of four separate markets.

The clearing house acts as a controller with only a proportional gain K_P to minimize the error e:

$$F = Q_E K_P \tag{2-5}$$

The control input u is a market force F imposed by the clearing house that appreciates or depreciates the market clearing price p:

$$p = p_0 + \int F dt \tag{2-6}$$

Suppliers are willing to supply more or less electrical energy per hour depending on the price. They submit bids for the supply side beforehand. These supply side bids are used by the clearing house to create the supply curve S with price elasticity ϵ_S. With the market clearing price, a quantity supplied Q_S is then found using:

$$Q_S = p\epsilon_S \tag{2-7}$$

So by appreciating or depreciating the price, the size of the traded quantities changes. The cash flow (which is the amount of economic energy in the system in [€$/h$]) is also increased or decreased constantly. In case of an increase in economic energy this is additional total cash flow to the suppliers, that has to be paid by the consumers. In case of a decrease in economic energy the total cash flow is reduced, which benefits the consumers.

The proportional gain K_P is similar to an R-element in bond graph modeling. So a damper with high damping coefficient between the mass and the wall. The block diagram in Figure 2-12 can be represented with the bond graph model in Figure 2-13 where the excess demand Q_E over the 0-junction results in a market clearing force according to:

$$F = Q_E R \tag{2-8}$$

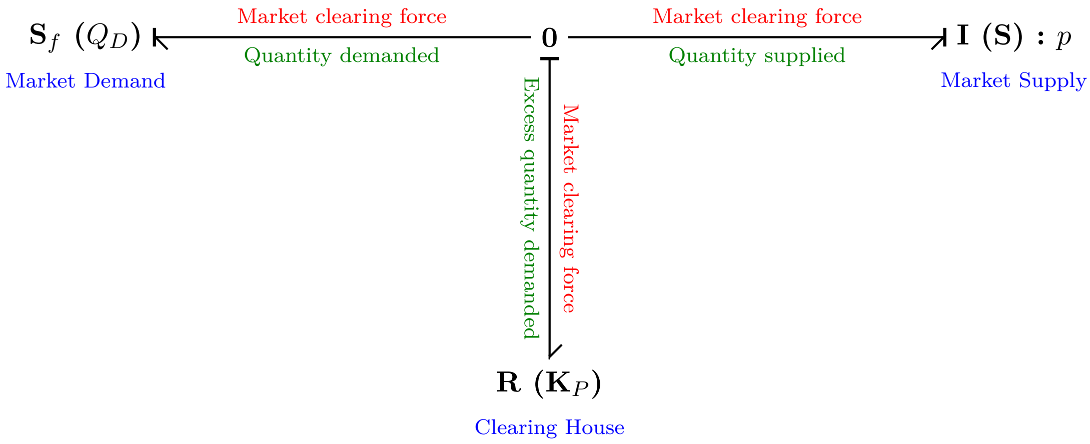


Figure 2-13: Bond graph model of the electricity market in the block diagram in Figure 2-12

For clarity, the notation in the block diagram in Figure 2-12 will be changed from typical control engineering notation such as error e and control input u, to the Economic Engineering notation Q_E and F in Figure 2-14. This will be the base model:

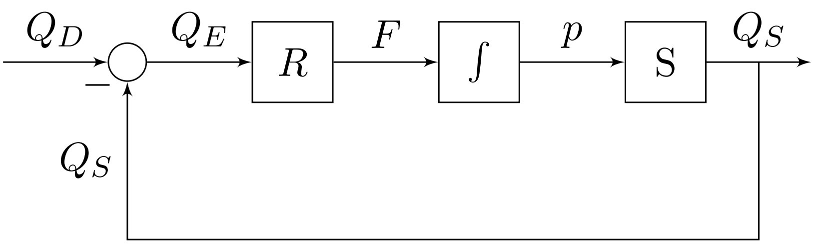


Figure 2-14: The base model of the electricity market

2-4-3 Simulating demand and supply using the controller

To run simulations the base model is discretized using Forward Euler. The development of the price is given by:

$$p[k+1] = p[k] + T_s(Q_D[k]R - p[k]\epsilon_S R) \tag{2-9}$$

Where T_s is the sampling time. The sampling time is a choice between simulation accuracy and computation time. For now computation time is no issue, so a short sampling time causes no problems, since there is no optimization necessary. In subsection 5-2-5 when tuning a Model Predictive Controller (MPC) the computation time does become relevant.

The sampling time cannot be too long either, otherwise simulation accuracy is compromised. A sampling time of 1 means that each timestep represents 1 hour (since units of time in the model are hours). In that case the effect of an hour would only be included the next hour. A sampling time of 0.25 is chosen, so timesteps of 15 minutes. This is sufficient for now and is very usable in terms of computation time when the optimization becomes more complex.

To guarantee stability R must be larger than 0 and the input Q_D must be bounded. For the discrete system, there is also an upper limit on R dependent on the sampling time T_s. R is given by:

$$0 < R < \frac{1}{T_s \epsilon_S} \tag{2-10}$$

To guarantee a close match between Q_D and Q_S at all times, the proportional gain R is chosen relatively large. Thereby the error Q_E is minimized quickly and effectively, preventing power outages. This is shown in figure Figure 2-15 for an example with several extreme demand shifts; Q_S follows Q_D closely. Q_D is the input vector and R is chosen at 0.015 with an elasticity ϵ_S of 200.

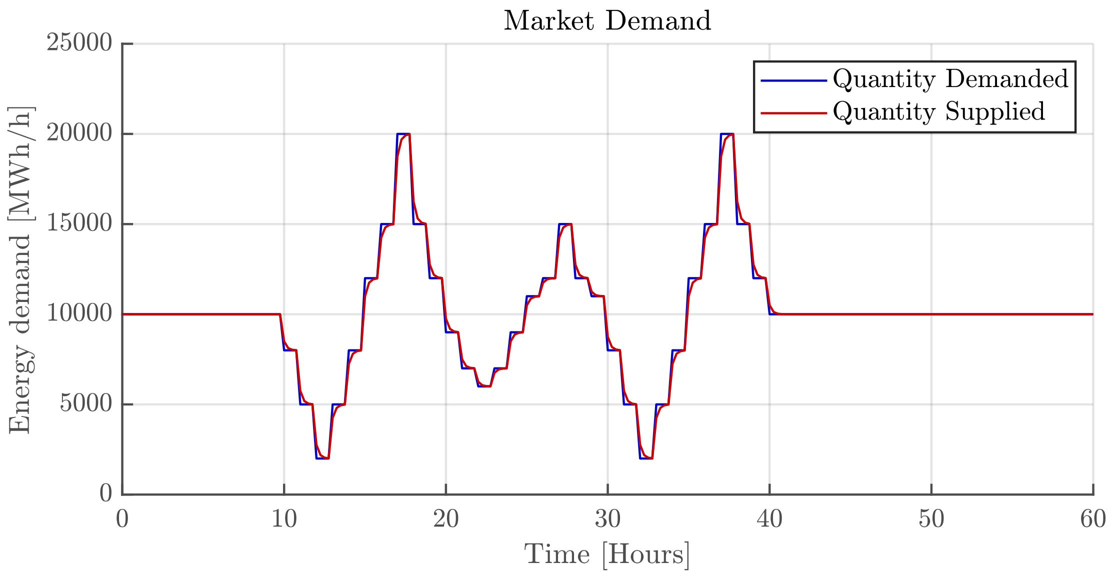


Figure 2-15: Quantity supplied following the quantity demanded closely during demand shifts.

This can result in very large control inputs from the clearing house however, which means consumers have to increase or decrease their payments a lot from hour to hour. This potentially large control input given by the clearing house is the direct cause for very volatile prices in the electricity market. Figure 2-16 shows the price development for the demand in Figure 2-15.

2-5 Conclusions

The current market is modeled with a static pricing mechanism. This is because there are no market mechanisms in place that provide flexibility in trading to allow for dynamic pricing. The market is constrained by the strict objective that demand should match supply. This lack of flexibility creates highly volatile prices when the demand fluctuates or when market penetration of intermittent energy sources such as wind and solar increases.

Figure 2-16: Price development of a market with several demand shifts.

Chapter 3

The Price Mechanism of Flexibility in The Electricity Market

As governments and industry are pushing for cleaner energy sources, renewable energy sources are expected to take a more dominant position in the electricity market. With a higher RES market penetration the intermittent behavior of RES and the corresponding problems also become more noticeable, and require smart solutions.

The Dutch government aims for 20 GW of wind power and 20 GW of solar power in 2030, to produce about 70% of total electrical energy supply throughout the year. Of this 20 GW installed wind power, 11 GW will be offshore. Offshore wind turbines are predicted to contribute to about 40% of total energy generation in 2030. Onshore wind and solar power are expected to deliver about 30% of energy generation [2], [32]. This has major effects on the electricity prices if market dynamics remain constrained, resulting in more volatile prices.

This chapter elaborates on these problems and discusses what solutions are proposed in literature. These solutions contribute in working towards more flexibility for the electricity market. Then it is shown how this adds price dynamics when modeling the electricity market using Economic Engineering and how they fit in the passive control design of Section 2-4.

Chapter Goals

- Elaborate on the upcoming problems in the electricity market due to high market penetration of RES.
- Present solutions from literature and show how they lead to an increase in flexibility.
- Show how flexibility leads to price dynamics and use it in the passive control design.

3-1 Problems in the Electricity Market of the Future

With more wind turbines and solar panels being installed, and traditional fossil fuel generators such as coal plants being shut down, the production of electrical energy will start to fluctuate more based on local weather. This causes prices to become more volatile. On the one hand prices will become very low when there is a lot of wind and solar energy available. On the other hand prices will peak extremely high when there is no wind or sun, since generators with high running costs need to be deployed as energy becomes scarce temporarily [33].

The constrained nature of the current market dynamics make sure there is no way of preventing these highly volatile prices. These problems are illustrated perfectly in the predicted price-duration curve for 2030 in Figure 3-1 [2]: very high prices on the left during some hours per year, but also very low prices on the right for a substantial amount of hours per year. Especially compared to the situation in 2017, RES have a negative influence on the prices.

Additionally there might even be moments when supply from RES is so low and demand is so high that the remaining traditional generators simply cannot meet the energy demand, and the power grid could potentially black-out as a result. More information on the price-duration curve is provided in Appendix E.

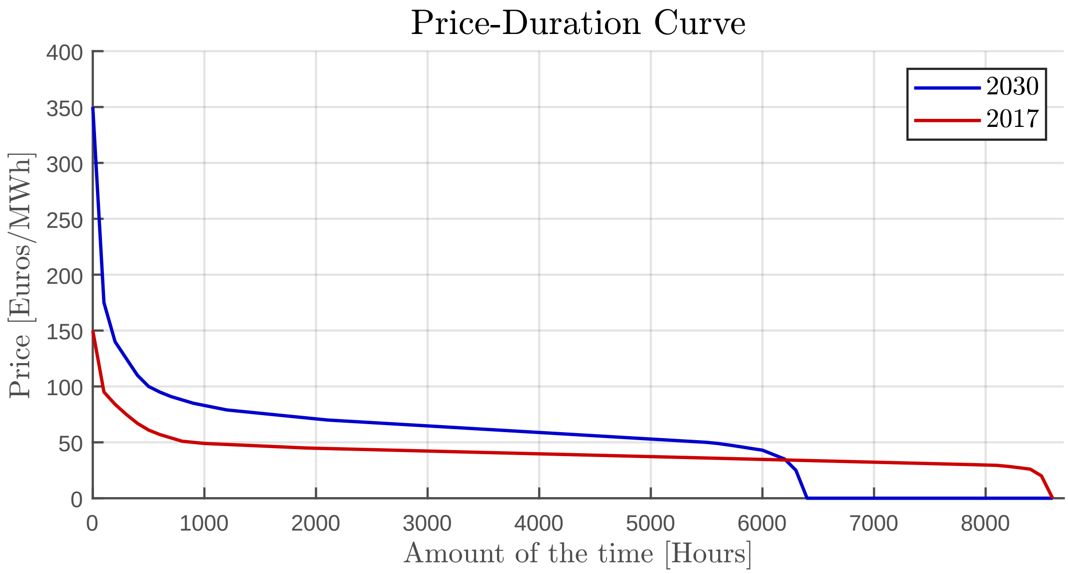


Figure 3-1: Predicted price-duration curve for NL in 2030 if no measures are taken [2].

The problems are actually two-fold: Both on the high-supply low-demand side, and on the low-supply high-demand side. Extremely high prices during peak hours are undesirable for the consumer, in particular because it may hinder the electrification of many processes which is required for decarbonization. Extremely low prices may be able to compensate for this though.

The actual problem lies with the investors; investors can only earn money when they have energy to sell. For investors in wind farms and solar panels this is only when the sun shines or the wind blows. But when the sun shines and the wind blows prices are low or even zero. Additionally, when they do not have anything to sell, prices are high [33].

The merit order in Figure 3-2 shows how prices drop when renewable energy supply is increased. This makes it difficult to earn investments back, and could stall investment in RES in the future [2]. Likewise, if there are more periods of lower prices, base generators with high capital costs and average marginal costs such as coal plants will see less opportunity to earn money. Combined with the rising CO_2 emission prices (see Section C-2), coal plants will eventually have to close down.

Plants with lower capital costs but higher marginal costs such as gas turbines will take over during peak hours. From an environmental point of view this is actually regarded desirable, at least as a temporary transition fuel, as gas turbines emit less CO_2 than coal plants [34]. However from an economical point of view this provides some challenges.

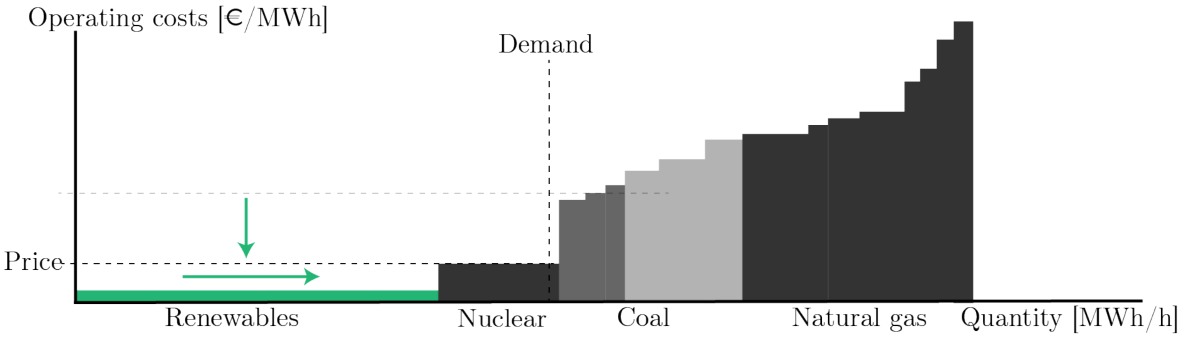


Figure 3-2: Shift in the merit-order due to decrease in coal production and increase in renewables.

Despite this shift from coal towards natural gas, investors in these fast-switching generators can only sell energy when the wind turbines or solar parks do not produce energy. This means a large part of the year they may be inactive, while only making marginal surplus when they are online, since running costs will typically be high for generators that can be switched on or off quickly. Therefore they will often be the highest bidder on the day-ahead market, or close to the highest bidder, and make hardly any surplus. With little incentive to build such peak hour generators, the total national capacity might shrink too far to provide all the required energy during peak hours.

3-2 Solutions That Increase Flexibility in the Electricity Market

To make sure demand and supply meet in the electricity market at all times flexibility is required. In [13] flexibility is described as the ability of a power system to deal with variability and uncertainty in supply and demand, while maintaining an acceptable level of reliability at a reasonable cost.

Traditionally flexibility was provided on the supply side by the portfolio of different generators that could ramp up or down [14]. The amount of flexibility this provides is however limited. From an economic point of view the flexibility this provides is certainly limited, because price is linked directly to quantity demanded through the merit order, as shown in Section 2-3. With high RES penetration this leads to the high price volatility and price uncertainty, as demonstrated in Section 3-1.

With more intermittent RES in the market more flexibility will be necessary. Several solutions have been proposed in literature to provide more flexibility within an electricity market. Electrical energy storage and demand response are the main solutions that can provide this flexibility [14]. Alternatively flexibility can be added by looking beyond one electricity market, either by connecting several markets through cross-border transmission, or by cross-sector coupling the electricity market with other energy markets such as the heat market [35].

All these flexibility solutions are already used right now, but at very limited scale. Their effect on the market is therefore also limited. When up-scaling these solutions in the future they will start influencing the market and its prices, so in my view they have to be included when modeling the electricity market of the future.

For this thesis research the focus will be on storage, demand response and cross-border transmission. Including cross-sector inter-connectivity will unnecessarily complicate the research and require even more background knowledge of the complete energy system. Thus for now the scope of this thesis will be limited to purely the electricity market. The three flexibility solutions that are the basis for the model in Chapter 4 are discussed in more detail below using literature.

Model Assumption

The flexibility solutions that are included in the model are storage, demand response and cross-border transmission.

3-2-1 Electricity storage

Overproduction of energy at a certain moment can be stored to be used later; when there is a high demand and little available supply [36]. This can be done on a short-term basis for minutes [37] and medium-term basis for hours, so for example storing in the morning and using that stored energy in the evening [38]. It could however also be done for longer time spans, for example storing in the summer and supplying in winter [39].

Although storing energy seems the most obvious solution for intermittent RES, costs for large-scale deployment are currently still too high. Costs are dropping rapidly though, and within a few years large-scale deployment is expected to become reality in some form (this may well be batteries from electric vehicles for example) [40].

3-2-2 Demand response

Instead of adapting on the supply side using storage, it is also possible to adapt on the demand side to the available energy and current electricity prices [41]. This is called demand response (DR). Demand response can be utilized by large consumers by reducing or increasing their electricity consumption. Moreover DR is an important reason why smart grid (SG) technology is currently extensively researched [42]. DR for smaller consumers and households would preferably use smart devices that actively monitor the electricity market in real-time and adjust their energy usage automatically accordingly. There are various applications of

DR. The most notable example of DR for households is electric vehicles charging at night when there is little demand [43], [44], [45]. Furthermore, many types of machinery and industrial processes could be temporarily switched off to alleviate a peak demand, such as heating systems in buildings that stop heating for half an hour [46], heat storage bricks that can be heated in isolation at night and give off their heat during the day [47], [48], a washing machine that only starts when electricity prices have dropped, or a steel producer that stops producing for a few hours during peak demand [49], [50].

Some of these energy demands can only be shifted to a slightly later moment, such as the charging of the car and heating of the building [51]. At some point in the morning the consumer wants the car to be charged. Likewise a building cannot go extremely long without heating before temperature drops significantly and reaches unpleasant temperatures. An aluminum producer will be more flexible and will for most part base his production schedule on electricity price levels and corresponding economic choices. Apart from this being the most economic choice, DR participation fees can be payed to industry providing fast short-term demand response [51].

3-2-3 Cross-border transmission

In Europe import and export of electrical energy has become common practice in the past decade. Most countries are connected to their neighbors for transporting smaller volumes of energy. Energy could however be transmitted over longer distances and in larger volumes across countries that are connected to the same electricity network [52]. If one country has an excess energy demand at one moment, while another country has excess energy supply, energy could be transmitted between countries to smooth out demand and supply in both countries and keep the power grids stable.

Cross-border transmission as a solution does become problematic when both countries have excess demand or excess supply at the same time. This is a realistic scenario if two neighboring countries are highly dependent on for example solar and it is sunny or it rains in both countries. Also the international electricity grid should be heavily reinforced to support large amounts of energy to be transported between countries over large distances. Nevertheless even heavy intercontinental connections are proposed, for example transporting solar energy from the Sahara to Europe [53].

3-3 The Price Mechanism of Flexibility

These new flexibility market mechanisms add price dynamics to market, which can be modeled using Economic Engineering. This section demonstrates this for storage and uses it for expanding the passive controller introduced in Section 2-4. The limitations of this passive controller approach are discussed at the end of this section.

3-3-1 The price dynamics introduced by storage

Replacing the infinitely stiff rod that connects the wall and the mass with a spring in Figure 2-9 immediately introduces dynamics. In the economic domain this removes the constraint between quantity supplied and quantity demanded, and therefore introduces price dynamics. A graphical representation of this is given in Figure 3-3. Now it is possible to put a force F on the mass m and change the momentum p and velocity v of this mass with respect to the wall.

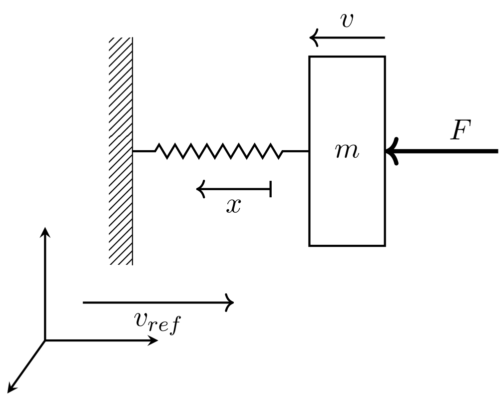


Figure 3-3: Mechanical diagram of the demand and supply with respect to the reference frame

Such a spring in mechanics can store position x by integrating velocity v over time:

$$x = \int v\, dt \tag{3-1}$$

In bond graph this is represented by a C-element and the equivalent in economics would be a trader or seller with a storage unit that stores a flow of products Q. If this flow is the excess quantity demanded Q_E than the stock q is given by:

$$q = \int -Q_E dt \tag{3-2}$$

The market clearing price can be increased by a trader by exerting a market force; in case of the electricity market a bid on the demand side. This price increase will make the suppliers supply more product. The excess quantity supplied can then be stored in the storage. Likewise, the market price can be decreased by a negative market force, which is a bid on the supply side. This causes the suppliers to supply less product. The excess demand will be supplied from storage.

Model Assumption

A positive force from the trader is a bid on the demand side, a negative force from the trader a bid on the supply side

For now I assume there is only one trader with storage and he will store all excess supply, and sell from storage to cover for all excess demand.

Model Assumption

The storage belongs to a trader who stores all excess supply on the market, and sells from storage to cover all excess demand on the market.

3-3-2 Energy in storage influences the market through convenience yield

For a general economic system, the amount of stored product influences the modeled market forces. If the storage belongs to a trader, then this trader will have the benefit of having the product physically available in storage. This is his convenience yield, and because of this the trader will impose a negative economic want on the market. So if there is product in storage the trader will bid on the supply side to decrease the market clearing price. The quantity supplied by the suppliers will be decreased. Therefore the trader will start supplying more product from his storage. The size of the C-element represents the slope of the convenience yield curve, analogous to the spring constant:

$$F_{\text{storage}} = -\frac{1}{C}q \tag{3-3}$$

For many commodity markets the convenience yield is a well-established concept when relating futures prices to spot prices [54], but for the electricity market this is not the case [55]. This is primarily because it is difficult to store electrical energy. In [17] the concept of convenience yield is investigated for hydropower on the Scandinavian Nord Pool market, where the water level represents storage of energy. Although the expected correlation between prices and water level seems to be there, the paper states it cannot draw hard conclusions, as the observed relationship may also be caused by market inefficiency.

My assumption is that with the introduction of large-scale electrical energy storage the concept of convenience yield will also become relevant on the electricity market.

> Model Assumption
>
> **Energy in storage results in convenience yield for the trader holding the actual energy.**

The trader will have a preferred storage level; an optimal amount of energy in storage. This will be modeled as "zero" product in storage, analogous to the spring being in its rest state. At this point no force is exerted on the market. The trader is able to drop below this optimal storage level, but then he is having less product in storage than desired. In that case the amount of product in storage is "negative". The trader imposes a positive force on the market to drive up the price and increase the amount of product supplied by the suppliers. This in turn will increase the amount of product he has in storage.

> Model Assumption
>
> **The trader will have an optimal energy storage level, which will be modeled as the zero level.**

3-3-3 Extending the passive controller with a trader

In Figure 3-4 the block diagram from Figure 2-12 is extended with a trader with storage. The trader with storage acts as an integral action by integrating excess demand Q_E and multiplying with an integral action K_I. Combined with the proportional action from Section 2-4 this is a Proportional Integral (PI) controller. So the clearing house and the trader together function as a PI controller

Integrating Q_E actually results in the backlog; the inverse of the storage level. This is $-q$. The amount in backlog is multiplied by K_I, which is $\frac{1}{C}$. The new market force is the sum of the market clearing force by the clearing house, and the convenience yield by the trader.

$$F = Q_E R + \frac{1}{C}\int Q_E dt \tag{3-4}$$

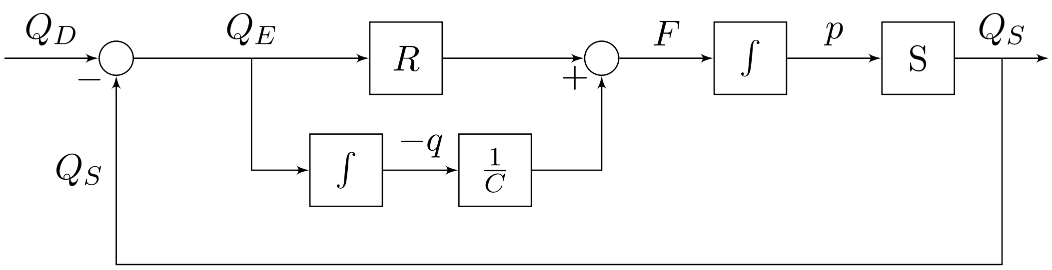


Figure 3-4: Block diagram of the electricity market with an energy trader with storage

The PI controller is able to keep the market clearing price more constant. The size of the R-element (so the proportional action) is reduced compared to Figure 2-12, so it acts less aggressive. This means the clearing house is appreciating or depreciating the price less actively. Demand and supply still meet because of the new integral action. This is the trader, who places additional bids on the demand or supply side depending on his convenience yield.

Ultimately these bids by the trader lead to a more constant market clearing price. He is continuously filling the gap between quantity supplied and quantity demanded as the quantity demanded changes. The bond graph similar to this block diagram is given in Figure 3-5.

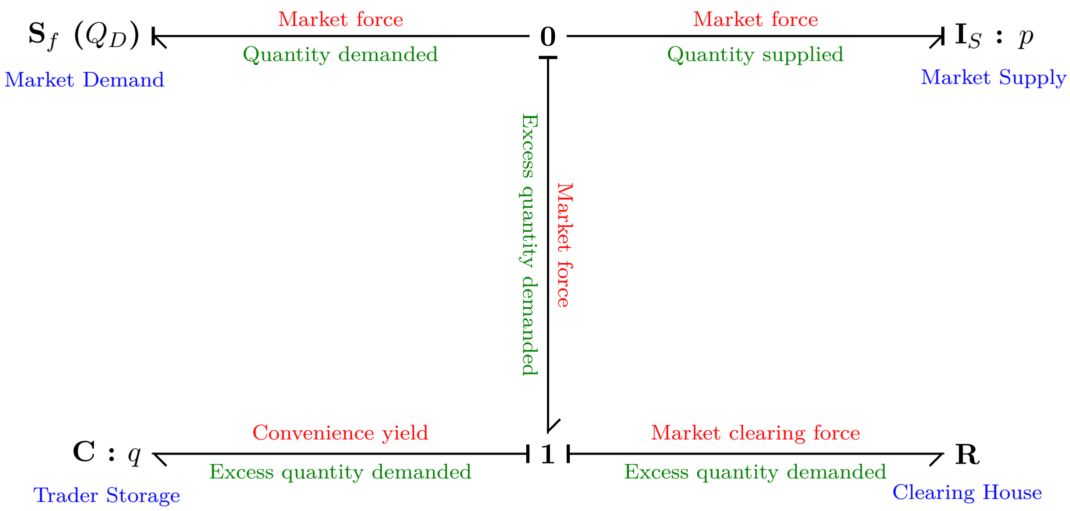


Figure 3-5: Bond graph model of the electricity market with a passive trader

The state space model with controller is given by:

$$\begin{bmatrix} \dot{p} \\ \dot{q} \end{bmatrix} = \begin{bmatrix} -\epsilon_S R & -1/C \\ \epsilon_S & 0 \end{bmatrix} \begin{bmatrix} p \\ q \end{bmatrix} + \begin{bmatrix} R \\ -1 \end{bmatrix} \begin{bmatrix} Q_D \end{bmatrix} \tag{3-5}$$

3-3-4 Simulations with a passive trader

The model is discretized with Forward Euler for simulations:

$$\begin{bmatrix} p[k+1] \\ q[k+1] \end{bmatrix} = \begin{bmatrix} p[k] \\ q[k] \end{bmatrix} + T_s \begin{bmatrix} -\epsilon_S R & -1/C \\ \epsilon_S & 0 \end{bmatrix} \begin{bmatrix} p[k] \\ q[k] \end{bmatrix} + T_s \begin{bmatrix} R \\ -1 \end{bmatrix} \begin{bmatrix} Q_D[k] \end{bmatrix} \tag{3-6}$$

The aggressiveness of the clearing house is decreased: $R = 0.0005$ for the upcoming simulations. The convenience yield rate is chosen at C = 5000. Sampling time T_s is still at 0.25 (so 15 minutes). The excess demand Q_E is now completely compensated for by the trader. He will supply any excess demand and store any excess supply. Using the demand from subsection 2-4-3, the storage level of the trader develops as follows:

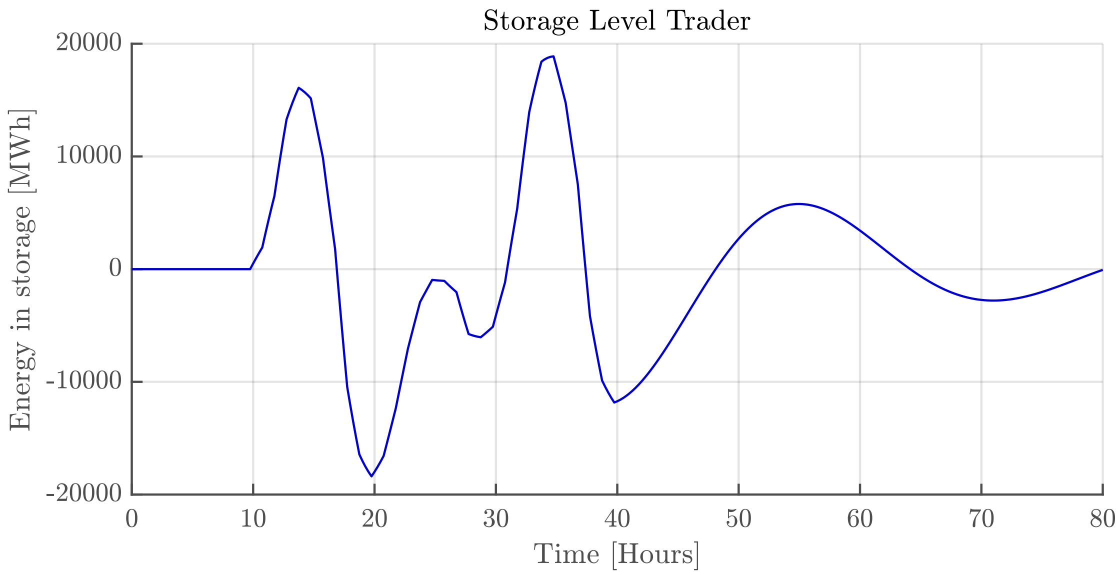


Figure 3-6: Storage level of the passive trader through several demand shocks

As a result, the price on the market remains more stable as can be seen in Figure 3-7. Reducing the clearing house aggressiveness and convenience yield rate further can reduce the price volatility even more.

To see the economic consequences for the trader of his trading behavior, it is best to look at his income. At this moment all costs are neglected except for the costs for buying the electricity. The development of his income over time is calculated using:

$$\text{Trading income} = \sum_{k=1}^{T} Q_E[k]p[k] \tag{3-7}$$

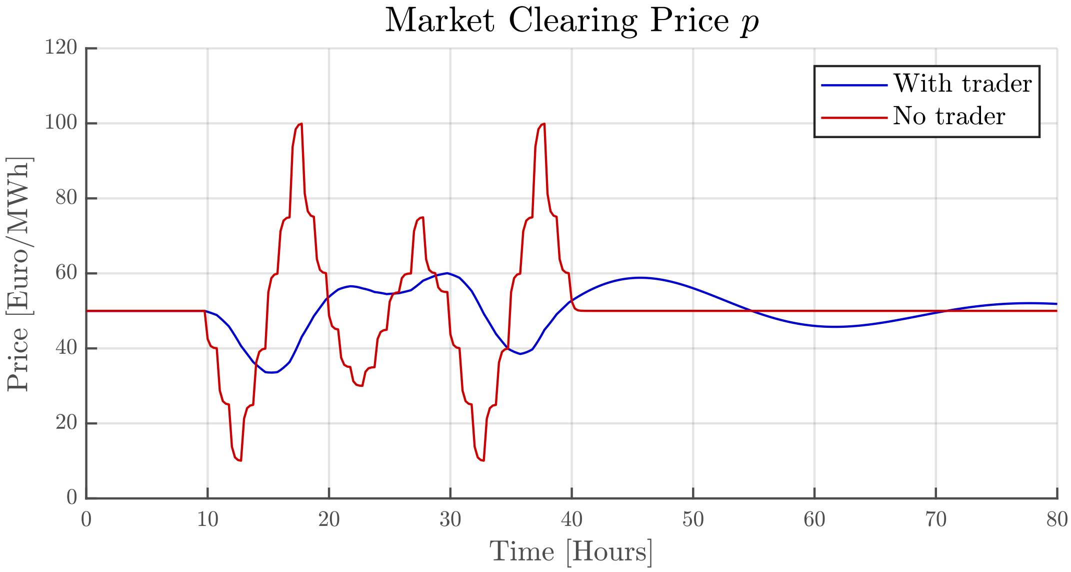


Figure 3-7: Price development of the market with and without a passive trader

Even though the trader is storing and selling a lot of energy he is still losing money as can be seen in Figure 3-8. He does not choose the best moments for buying and selling. This means that his current trading behavior is economically irrational. Clearly, the control objective here was to minimize the error between quantity demanded and quantity supplied. Economic goals are not included.

3-3-5 Limitations of passive control

Although the trader helps overcome high price volatility, the clearing house still has to appreciate and depreciate the price. Due to the trading behavior of the trader, the price remains much more constant. However, the trader is now serving the market, but not necessarily benefiting from this financially himself. Passive control is unable to maximize for his profits. It is only doing reference tracking of the error. Additionally it is difficult to put constraints on for example the power and energy capacity of the storage if desired [56].

Lastly, more complex optimization problems cannot be solved by a passive control system. For example, if the trader can choose between different storage solutions, each with different costs and different round-trip efficiencies, a passive system has no way to optimize this choice over time. This will supposedly be a common trade-off. For example choosing between hydrogen storage and battery storage. Hydrogen has low round-trip efficiency and low storage costs. Batteries have high round-trip efficiency and high storage costs [57]. This requires active optimization.

These limits to PI control can be solved by using optimal control [56]. Using optimal control the trader can perform energy price arbitrage: buying electrical energy at low prices and selling later at high prices [58], [59], [60]. This requires a model that can be used for optimal control. In Chapter 4 a model is developed for all three market mechanisms. Then Chapter 5 discusses the use of a Model Predictive Controller (MPC) for profit maximization through energy arbitrage for the trader.

Figure 3-8: Accumulated income of the trader as he stores and sells from storage.

3-4 Conclusions

High market penetration of RES is going to cause problems on the electricity market, so flexibility in the electricity market must be increased and therefore also included when modeling. This adds new dynamical effects to the electricity market. The passive controller from Section 2-4 is extended with a trader with storage, but this approach lacks the economic incentive for the trader to participate in the market. Additionally constraints are difficult to include. A controller that actively optimizes the profit for the trader solves these problems.

Chapter 4

A Price-Dynamic Economic Engineering Model

The flexibility mechanisms introduced in Chapter 3 fundamentally change the system structure of the market dynamics. Forecasting how the market in the future will behave using data from the current market will not be suitable [18]. This is because data from the current market lacks the effects of storage, demand response and cross-border transmission. An Economic Engineering first-principles model of the electricity market can be designed such that it includes these new market mechanisms. Through Economic Engineering price dynamics of these mechanisms will be included. This model can then be used to forecast different future scenarios using optimal control.

This chapter develops the modeling techniques for the three new flexibility mechanisms using Economic Engineering. The mechanisms will be discussed separately and their effects are modeled in isolation. This leads to a modular model design, where the different mechanisms can be added as individual building blocks.

Chapter Goals

- Discuss the relevant model assumptions for storage, demand response and cross-border transmission.
- Develop modeling techniques for the new flexibility mechanisms.
- Build a modular Economic Engineering model of the electricity market of the future.

4-1 Modeling Electricity Storage

Currently electricity storage is not used on a large-scale. This is mostly due to the high costs of storage, energy losses associated with storing and/or spatial limitations [36], [57],

[61]. Also the market penetration of renewable energy sources (RES) is still relatively low, so the need for energy storage is currently limited, especially on the day-ahead market. Storage is already a useful option for providing ancillary services on the balancing market [62]. As extensive research into electricity storage is driving down storage costs and reducing energy losses when storing, large-scale energy storage for the day-ahead market is assumed to become economically feasible within the upcoming decade [57], [40].

The new price dynamics introduced by storage have to be included in a model of the electricity market to make reliable predictions. In Section 3-3 the effects of storage were included through passive control, but this has limited application to the electricity market. Through passive control the trader is completely in service of the market and has no economic benefit himself. In this section a storage model for optimal control is proposed. This can be used for profit maximization by a trader with storage and therefore results in a more realistic trading behavior by the trader.

Model Assumption

The trader does not use his storage to cover all excess demand or supply anymore, but focuses on his own economic benefits instead.

4-1-1 Model assumptions for storage

Since there will never be an infinite amount of energy capacity for storage available, the amount of energy in storage is going to be constrained. In the mechanical analogy this is the maximum extension of the spring; it cannot extend any further than a certain distance. At 0 MWh in storage, it is completely empty. This is analogous to the spring being compressed as far as possible. These limits of compression and extension can be implemented as constraints.

Model Assumption

The trader will have an upper and lower bound on his storage levels.

There is also a limit to power capacity. This is the speed at which a storage can be filled or emptied. For example for a battery this is the amount of electrical energy that can be stored or supplied per hour. For pumped hydroelectric energy storage it is the speed at which pumps can pump up water for storage or how much water can be released through the turbines for supply. For hydrogen storage this is determined by the size of the electrolyser [57].

For batteries the properties of the battery usually determine both the energy capacity and the power capacity. This scales, so larger energy capacity batteries have higher power capacity. For pumped-hydro and for hydrogen storage, the energy capacity and power capacity are more independent design choices. Increasing energy capacity, so increasing the size of the water reservoir or using an additional cavern in which the hydrogen is stored, is usually relatively cheap. Increasing power capacity, so increasing the size of the pumps or increasing the size of the electrolyser, is more expensive [57].

Model Assumption

The trader will have a maximum quantity that he can store or sell per hour.

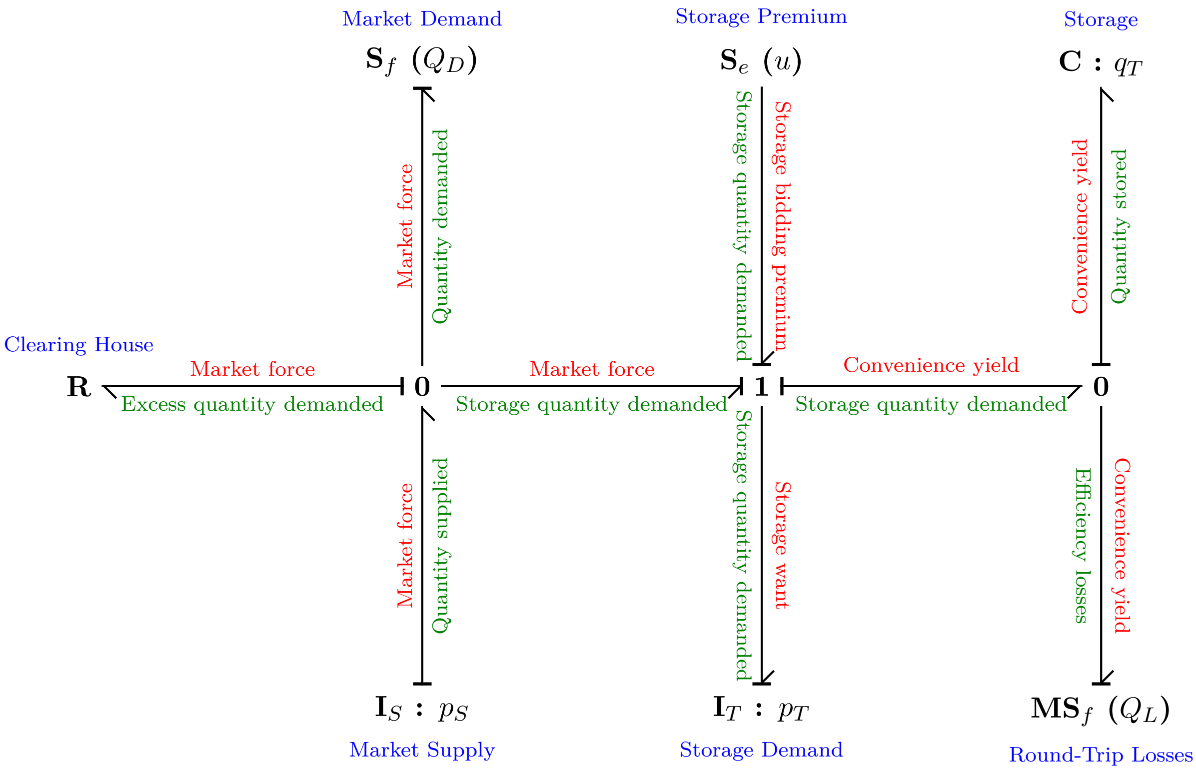


Figure 4-1: Bond graph model of the electricity market with an active trader with storage

4-1-2 A bond graph model for a trader with storage

For the purpose of profit maximization with active optimization a different modeling approach is used from Section 3-3. The trader needs a control input that can be actively controlled to optimize his profits. The bond graph for a trader with storage that can be used for optimal control is shown in Figure 4-1.

The trader determines a reservation price for himself using his own I-element representing the demand of the trader for this particular storage. This will be his bidding price on the market. This trader I-element does have the same price elasticity ϵ as the supply curve, since all market participants have to trade with the same aggregated curve. This price elasticity is given by:

$$\epsilon_S = 1/I_S = 1/I_T \tag{4-1}$$

Depending on the difference between the reservation price p_T of the trader and the market clearing price p_S the trader will buy from the market or sell from his storage. This is a quantity Q_T.

$$Q_T = (p_T - p_S)\epsilon_S \tag{4-2}$$

The excess quantity demanded becomes:

$$Q_E = Q_D + Q_T - Q_S \tag{4-3}$$

The efficiency losses Q_L with round-trip efficiency η are given by a modulated flow sink MS_f . This value is divided by two because losses are subtracted when storing and also when selling from storage:

$$Q_L = \frac{|Q_T(1-\eta)|}{2} \tag{4-4}$$

The amount of energy in storage is given by:

$$q_T = q_{T0} + \int (Q_T - Q_L)dt \tag{4-5}$$

The reservation price p_T consists of a base reservation price and a bidding premium. The base reservation price is determined by the change in market price (due to the market force F) plus the change due to the convenience yield. The size of the convenience yield is generated by the amount of energy in storage, this concept was introduced in subsection 3-3-2.

The trader can deviate his bid from this base reservation price by adding or subtracting a bidding premium, which will be the control input u for the optimal controller. The market force F, the convenience yield from storage and the bidding premium combined determine the want of the trader, which is shown in his bidding behavior. This want of the trader leads to a change in reservation price. In this way the trader can exploit the fluctuating prices to make a profit.

The initial trader price p_{T0} is the same as the initial market price p_{S0}:

$$p_{S0} = p_{T0} \tag{4-6}$$

The price for the trader is given by:

$$p_T = \underbrace{p_{T0} + \int (F - \frac{q_T}{C})dt}_{\text{base price}} + \underbrace{\int udt}_{\text{premium}} \tag{4-7}$$

The state space model is then given by:

$$\begin{bmatrix} \dot{p_S} \\ \dot{p_T} \\ \dot{q_T} \end{bmatrix} = \begin{bmatrix} -2\epsilon_S R & \epsilon_S R & 0 \\ -2\epsilon_S R & \epsilon_S R & -1/C \\ -\epsilon_S & \epsilon_S & 0 \end{bmatrix} \begin{bmatrix} p_S \\ p_T \\ q_T \end{bmatrix} + \begin{bmatrix} R & 0 & 0 \\ R & 1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \begin{bmatrix} Q_D \\ u \\ Q_L \end{bmatrix} \tag{4-8}$$

4-2 Modeling Demand Response

Demand response can be implemented for both industry/large businesses and households/smaller businesses. Demand response by industry and larger businesses is already happening to some extent, because they place demand bids on the wholesale market (contrary to the model assumption in Chapter 2 that demand is perfectly inelastic). This will become even more useful when prices start fluctuating more in the near future.

Demand response for households and smaller businesses should be feasible from an economic perspective, since it promises to make the market more efficient and save consumers money.

However it requires practically every demand-response suitable device to be connected to a centralized system that tells it when energy demand is low enough, thus rendering a complex smart network of many different devices and users [42].

Also it is still unclear which parties are going to carry out this kind of micro-management. In a simpler implementation the costumers could switch on and off their electrical equipment manually, based on the prices, but this still requires an energy meter that records hourly usage and communicates current prices. Without this the incentive for the consumer to use demand response would be absent.

Although widespread implementation of DR is still some years away, it is inevitable that it will influence the electricity market in the future. Many small-scale control solutions have already been proposed, mostly optimization-based, such as [47], [48], [63]. Models showing the influence on the market clearing price are missing though. This section will demonstrate how the price mechanism of accumulated demand response can be implemented in a model.

4-2-1 Model assumptions for demand response

Demand response in this thesis is divided in two categories [22]. The first is strictly price dependent, where the price dictates (a part of) the demand. In case of high prices this is called "Load reduction". The second form is postponed or sped-up demand; energy consumption is moved to a different time frame. This is demand that typically will have to be fulfilled, but that can be fulfilled sometime within a certain time frame [51]. In case of high prices this is called "Load shifting". Both are discussed separately below.

Price dependent demand response

The most direct form of demand response is a rotation of the demand curve. This means that the demand is not perfectly inelastic anymore, but the quantity demanded will actually be price dependent [64]. Some costumers will only buy energy below a certain price, otherwise they will not use electrical energy. A good example of this is an aluminum producer that only produces when prices for electricity are acceptable, otherwise his product becomes too expensive. This is a direct form of load reduction. Additionally consumers can increase demand when prices are low.

The analogy in the mechanical domain is that the fixed wall now becomes a (large) mass as well, that does not have an infinite amount of momentum anymore. Therefore applying a force will be able to change the momentum of the demand mass as well.

> Model Assumption
>
> **Through demand response the demand is not perfectly inelastic anymore, but it becomes price dependent as well.**

The demand curve represents bids on the day-ahead market by consumers or retailers for buying electricity. This is something that is actually happening already in the current market, although most demand bids are at such a high price level that they will be cleared practically all of the time. This is especially true for energy retailers that often have no choice but to provide their costumers with electricity.

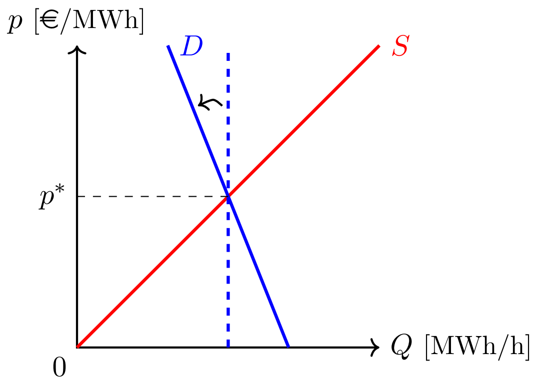


Figure 4-2: The demand curve becomes elastic through demand response

Shifted demand

A second type of demand response is price dependent postponed or sped-up demand. Also referred to as moving or shifting the energy consumption in time [51]. So if for example a car needs to charge its battery before the next day, and it is plugged into a charger between 7 o'clock in the evening and 7 o'clock in the morning, energy has to be bought at some point during these 12 hours. The exact time of charging is not relevant, but in the morning the car needs to be charged [65]. Since the price will probably be very high in the evening, a moment at night is preferred.

This shifted demand (SD) can be represented by a very stiff spring that can temporarily be extended to delay demand. When used, this stiff spring returns a large market force to make sure the energy demand is not delayed any longer than necessary. The interpretation is very similar to that of storage, except for that energy demand is now kept in backlog instead of an inventory. A backlog is the inverse of an inventory. The amount of demand that can be shifted in this way is referred to as the responsive load [66].

> Model Assumption
>
> **Through demand response some of the demand is shifted in time to a more preferable moment.**

The idea of seeing part of the demand response as a form of storage is actually used in real applications. In [67] a heat system uses concrete core activation (CCA) for demand response. This literally uses a form of storage (heat storage) to shift demand.

The big difference with actual energy storage is the inability to transform this heat energy back to electrical energy efficiently. Therefore the distinction between energy storage and shifted demand is explicitly made in this thesis. The effects are also different; energy storage leads to lower prices because there is additional cheap supply available. Shifted demand leads to lower prices because the total demand is temporarily decreased.

Alternatively demand during different hours could be coupled through price cross-elasticity, which is proposed in [68]. The price of each hour is linked to the demand of all other hours in the day. So if price is high during one hour, this will reduce the demand in this hour, but

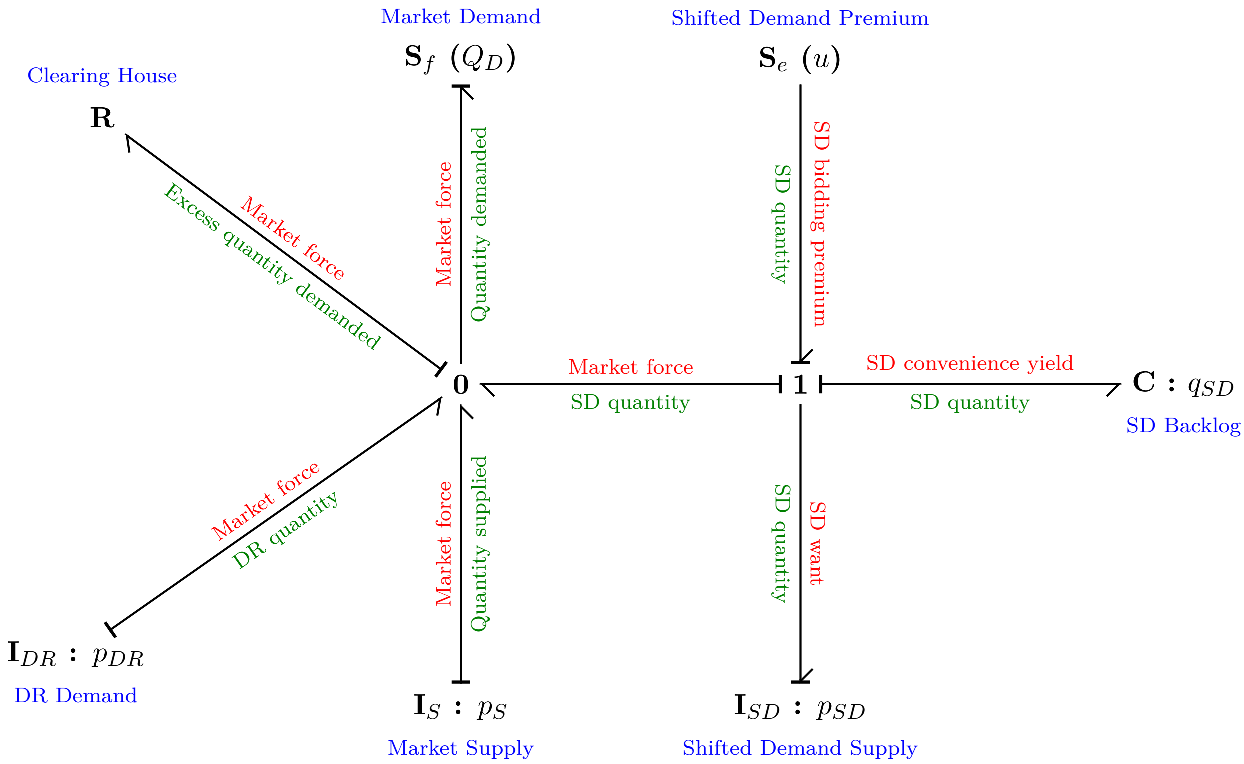


Figure 4-3: Bond graph model of the electricity market with demand response

subsequently increase the demand in other hours through cross-elasticity. This does require a price cross-elasticity matrix of 24-by-24 hours of the day.

A combination of a demand response backlog and demand cross-elasticity is probably the most suitable approach for shifted demand. However, to reduce complexity for this model only the demand response backlog is used here. Cross-elasticity is introduced in Section 4-3 more thoroughly to describe how prices in neighbouring countries affect each other. This however is completely unrelated to demand response cross-elasticity.

To perform shifted demand response with enough energy and power capacity, a market participant will have to combine many suitable machinery and devices from costumers and control their power demand. A trader could for example accumulate a costumer base of 100.000 electric vehicles and through smart charging control when these cars are charged. Participating costumers can receive part of the profit in return. In this way the trader can have access to enough capacity.

Model Assumption

A trader performs shifted demand response with the machinery and devices of an accumulated costumer base.

4-2-2 A bond graph model for demand response

Demand response can be added to the base model. To show the effect of demand response in isolation, storage is now left out. The price dependent demand response is represented by an elastic demand curve I_{DR} with price elasticity ϵ_{DR} and quantity demanded Q_{DR} to market. The shifted demand response (SD) is a trader with a backlog q_{SD} with quantity supplied Q_{SD} to market.

$$Q_E = (Q_D - Q_{DR} - Q_{SD}) - Q_S \tag{4-9}$$

$$q_{SD} = \int Q_{SD}\, dt \tag{4-10}$$

The initial price for the supply curve, the demand curve and the shifted demand response are the same:

$$p_{S0} = p_{DR0} = p_{SD0} \tag{4-11}$$

Consequently, the price at the supply curve and at the demand curve become the same, so one market price:

$$p_S = p_{DR} \tag{4-12}$$

The reservation price p_{SD} for shifted demand is built up similarly to how the reservation price p_T for storage is built up. Also here a convenience yield and a bidding premium determine the reservation price that the trader uses.

The main difference is that here the trader needs to trade on behalf of a large costumer base with demand response suitable machinery and devices instead of his own storage. Availability may therefore be restricted at times. The big benefit is the lack of efficiency losses for most forms of demand response, since demand is simply shifted, and not stored in some form that has inherent round-trip losses. Some losses may occur though, for example if demand is shifted forward through pre-heating of buildings.

The quantity supplied plus the amount of reduced quantity demanded through demand response are given by:

$$Q_{DR} + Q_S = p_{DR}\, \epsilon_{DR} + p_S \epsilon_S = p_S(\epsilon_{DR} + \epsilon_S) \tag{4-13}$$

This gives the following state space model:

$$\begin{bmatrix} \dot{p_S} \\ \dot{p_{SD}} \\ \dot{q_{SD}} \end{bmatrix} = \begin{bmatrix} -(\epsilon_{DR} + \epsilon_S)R & -\epsilon_{SD}R & 0 \\ -(\epsilon_{DR} + \epsilon_S)R & -\epsilon_{SD}R & 1/C \\ 0 & \epsilon_{SD} & 0 \end{bmatrix} \begin{bmatrix} p_S \\ p_{SD} \\ q_{SD} \end{bmatrix} + \begin{bmatrix} R & 0 \\ R & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Q_D \\ u \end{bmatrix} \tag{4-14}$$

4-3 Modeling Cross-Border Transmission

Since the European electricity markets have been liberalized and are mostly connected, an approach could be to model them as one large market. However rules for using interconnectors vary from regular national market transmission access, so this one-market approach is unrealistic [69]. The markets are connected through interconnections, but cross-border trade has constraints, so the markets are linked incompletely. An approach with separate markets is more accurate for the foreseeable future. At least as long as international transmission is limited compared to national transmission [22]. This is in accordance with the fact that each country has its own Day-Ahead market on the EPEX Power Exchange [26].

Model Assumption

National markets are linked incompletely, so there is not one international market, but many national markets with constrained connections

4-3-1 Model assumptions for cross-border transmission

The assumption I make here is that suppliers can choose to sell (part of) their electrical energy in neighboring countries. Consumers on the other hand have to buy electricity in the country of consumption.

Model Assumption

Suppliers can sell (some) electricity across neighboring countries, consumers have to buy in the country of consumption

Each country still has its own price for electricity, which confirms that the markets are linked incompletely. The prices of neighboring countries do however influence each other. This is modeled through cross-elasticity matrix E.

$$E = \begin{bmatrix} 0 & \epsilon^{NL/DE} \\ \epsilon^{DE/NL} & 0 \end{bmatrix} \tag{4-15}$$

In this way, the price in one country will influence the quantity supplied in another country through this cross-elasticity. If the price increases in a country due to high demand, suppliers from a neighboring country will want to supply there. As a result they will want to supply less in their own country. This will ultimately result in an increasing price there as well. This can be visualized in a block diagram as shown in Figure 4-4.

The full price elasticity matrix (consisting of S^{NL}, S^{DE} and E) looks as follows:

$$\begin{bmatrix} Q_S^{NL} \\ Q_S^{DE} \end{bmatrix} = \begin{bmatrix} \epsilon^{NL} & \epsilon^{NL/DE} \\ \epsilon^{DE/NL} & \epsilon^{DE} \end{bmatrix} \begin{bmatrix} p^{NL} \\ p^{DE} \end{bmatrix} \tag{4-16}$$

This elasticity matrix can be extended to multiple countries. Poland for example is a neighboring country of Germany, but not directly connected to the Netherlands.

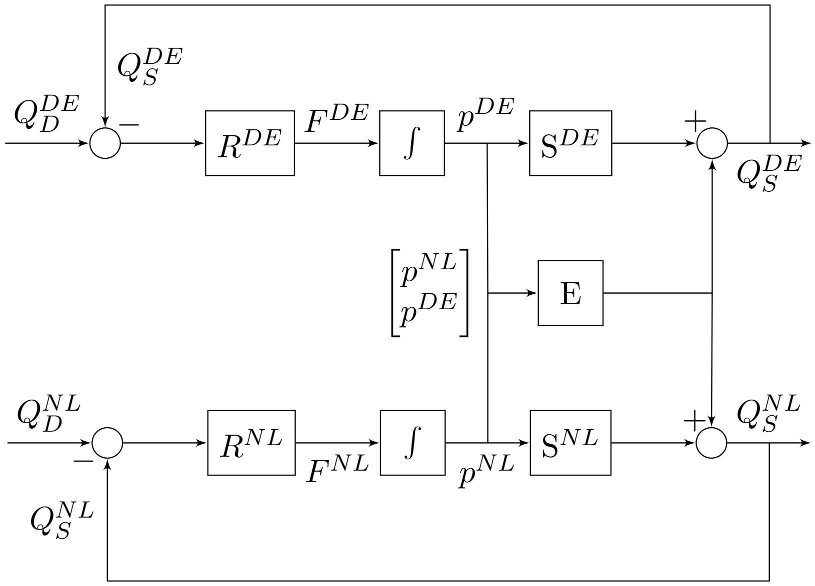


Figure 4-4: Block diagram of the electricity market with cross-border transmission

$$\begin{bmatrix} Q_S^{NL} \\ Q_S^{DE} \\ Q_S^{PL} \end{bmatrix} = \begin{bmatrix} \epsilon^{NL} & \epsilon^{NL/DE} & 0 \\ \epsilon^{DE/NL} & \epsilon^{DE} & \epsilon^{DE/PL} \\ 0 & \epsilon^{PL/DE} & \epsilon^{PL} \end{bmatrix} \begin{bmatrix} p^{NL} \\ p^{DE} \\ p^{PL} \end{bmatrix} \tag{4-17}$$

This means that prices in the Netherlands and Poland do not directly influence each other. However through changing quantity supplied/price in Germany, the price in the Netherlands will influence the price in Poland slightly.

4-3-2 A bond graph model for cross-border transmission

The bond graph model for cross-border transmission in Figure 4-5 uses a multi-port I-element. This I-element holds a price for each bond connected to it. Quantities to each bond are then determined using a elasticity matrix such as in Equation 4-17.

The state space model for cross-border transmission is given by:

$$\begin{bmatrix} \dot{p}^{NL} \\ \dot{p}^{DE} \end{bmatrix} = \begin{bmatrix} \epsilon^{NL} R^{NL} & \epsilon^{NL/DE} R^{NL} \\ \epsilon^{DE/NL} R^{DE} & \epsilon^{DE} R^{DE} \end{bmatrix} \begin{bmatrix} p^{NL} \\ p^{DE} \end{bmatrix} + \begin{bmatrix} R^{NL} & 0 \\ 0 & R^{DE} \end{bmatrix} \begin{bmatrix} Q_D^{NL} \\ Q_D^{DE} \end{bmatrix} \tag{4-18}$$

In this case there are no traders in either of the countries. Prices are completely determined by demand and price elasticities in both countries. Flexibility provided by cross-border transmission differs from storage and demand response in that it requires no active optimization over time. If prices in one country are higher than in the other, suppliers will want to supply in the country with the highest price.

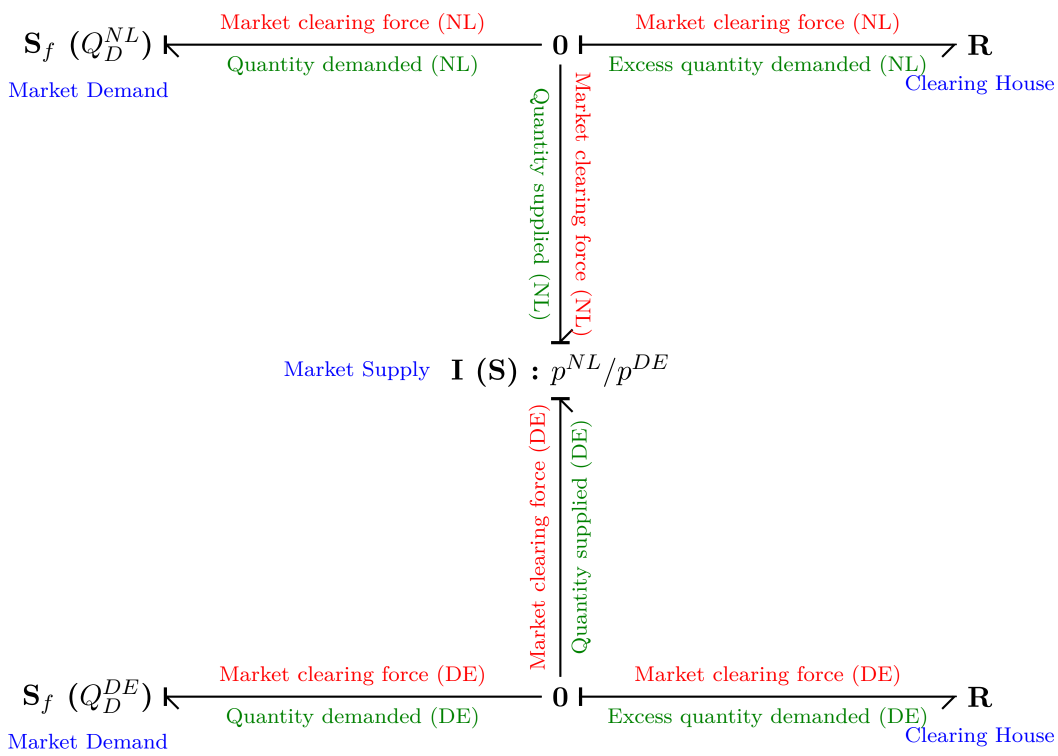


Figure 4-5: Bond graph model of the electricity market in the block diagram in Figure 2-12

4-4 A Modular Bond Graph Model for the Electricity Market

By combining all the different building blocks created in this chapter a complete model can be designed. This is shown in Figure 4-6. Buildings blocks for each mechanism can be added or left out to match a predicted future scenario. So to add hydrogen storage next to battery storage, an extra green storage block can be connected to the blue market. This hydrogen storage block will have different values for the storage costs and a different round-trip efficiency.

Also storage and demand response can be added to different countries. So a new orange demand response block and a new green storage block can be connected to the 0-junction in the red box. Then both countries will have storage and demand response while the markets do influence each other.

The market itself has 1 state, the price p_S. Each storage or demand response block introduces 2 states. The cross-border transmission block adds 1 state. It is assumed that all states are completely known at all times.

The current model is limited to the electricity market, but the modular design allows for integration with different energy markets as well. The gas market, the heat market, the hydrogen market and many other energy markets can be connected through a transformer to the 0-junction in the middle of the model to create a multi-sector model. The idea of integrating different energy market is called Smart Energy Systems [70]. This thesis will stick to the electricity market, but further research could focus on developing cross-sector models.

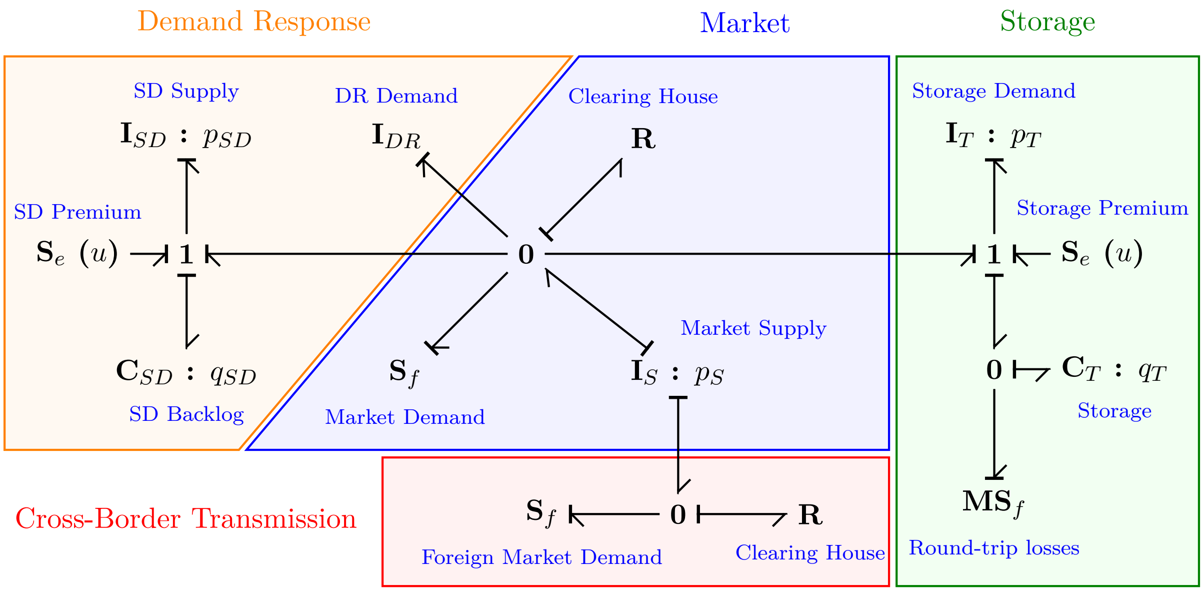


Figure 4-6: Complete bond graph model of the different building blocks. Blue is the market, green is storage, orange is demand response and red is cross-border transmission.

4-5 Model System Identification

The lack of data of the electricity market of the future makes data-driven modeling difficult, so therefore this first-principles Economic Engineering model was built in this thesis. The parameters of this first-principles model still have to estimated though and the lack of data provides a challenge here as well. Parameter estimation through typical grey-box system identification is not possible. Also verification of the model becomes difficult. Parameters will have to be estimated using literature and expert input.

These problems however are not exclusive for first-principles modeling; any method will be struggling when trying to forecast a future scenario that is very different from now. The big advantage of first-principles modeling remains that the known causal relations between the different elements can be explicitly included. And the parameters that are unknown do have an actual economic interpretation, which helps choosing appropriate values.

Since accurate parameter estimation is not within the scope of this thesis, there will not be an extensive search to find the proper values. In Chapter 5 the model is used as a proof-of-concept, so in that chapter rough estimates for the various parameters will be used.

4-6 Conclusions

It is important to explicitly model new market mechanisms to predict how the market will behave in the future. In this chapter the necessary building blocks for an Economic Engineering model that works with optimal control were built. These can be combined to create a modular model. By combining several building blocks a model can be created that matches a predicted future scenario. These building blocks are used in Chapter 5 to perform optimal control.

Chapter 5

Optimizing Profits through Energy Trading with Economic MPC

The model developed in Chapter 4 can be used for various applications such as day-to-day trading, scenario forecasting and/or policy making. Since the size of storage, demand response and cross-border transmission is currently still limited, using this model for day-to-day trading is not useful right now. Scenario forecasting on the other hand is a very important application to support investment decisions and assist with designing future regulations.

This chapter quantifies how prices change when a trader tries to optimize his profits on the electricity market of the future. The trader uses the price-dynamic Economic Engineering model in combination with an Economic Model Predictive Controller (MPC) to maximize his profits from energy arbitrage. This provides insights in how market players may adapt their strategies and investments in the future, and what precautions must be taken to ensure grid stability.

Chapter Goals

- Design an Economic MPC for optimizing a trader's profits using the Economic Engineering model.
- Quantify the price changes that occur when trading with storage and shifted demand, and analyze the effects it has on the market.
- Formulate a regulatory advice to reduce the grid stability risk that comes with flexibility through a new storage capacity reserve market.

5-1 Energy Arbitrage for Profit Making

Electrical energy storage can be used for multiple applications at grid level, such as energy arbitrage, peak shaving, ancillary services, costumer energy management and renewable energy integration [71]. Most of these applications are to assist the transition to RES by ensuring grid stability and provide power quality. Of these different applications energy arbitrage is the application with the largest and most direct economic incentive, which makes it the most interesting use of electricity storage for energy traders. Energy arbitrage will indirectly also contribute to the other applications, because grid stability is improved in the process.

Arbitrage in finance is a practice that aims to make money from price differences between different markets [58]. By buying in one market with a lower price and selling in another market for a higher price, the imbalance between markets is exploited to earn money.

Energy arbitrage is a slightly different practice; energy is still bought at low prices and sold at high prices, however these price differences are now exploited on the same market, but in time [58]. As prices are highly volatile throughout the day, energy arbitrage is primarily used to buy at night when prices are low and sell during the day when prices are high. But energy arbitrage can take place on many different scales, even buying and storing in the summer and selling in the winter is done.

Model Assumption

The trader optimizes his profit through energy arbitrage.

The model from Chapter 4 is used to simulate a trader maximizing profits through energy arbitrage with MPC, or more specifically an Economic Model Predictive Controller (E-MPC). This allows to optimize profit over time using a custom objective function, while including dynamic pricing through the model. Additionally with MPC constraints can also be added easily to account for limitations to either states or inputs (for example storage size). More literature background on energy arbitrage optimization is given in Appendix D.

5-2 Economic MPC Design for Energy Arbitrage

In this section an Economic MPC is designed that can maximize profits for trader. By having this trader maximize his profits, realistic trading behavior can be simulated. These simulations are then used to quantify the market price changes at the end of this chapter.

The MPC is a controller that can solve optimal control problems using a receding horizon. It differs from other optimal controllers in that it can solve the optimal control problem online for the current state of the system [72]. In Model Predictive Control an open-loop optimal control problem with finite horizon is solved in which the initial state is the current state of the system.

A diagram of an MPC is shown in Figure 5-1. Since the market that was modeled does not exist yet, the model and "the system" will be the same. For an Economic MPC the cost function will be an economic objective function. Constraints include the power capacity and energy capacity of storage. The demand (strongly dependent on the weather) is the main disturbance in this case.

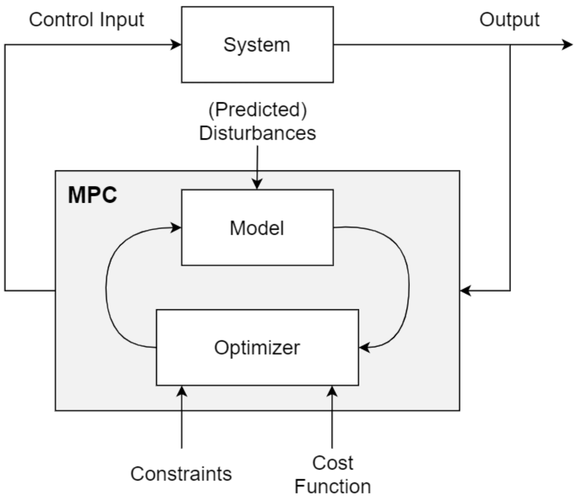


Figure 5-1: Diagram of a Model Predictive Controller

5-2-1 Economic Model Predictive Control

The Economic MPC is a development specifically in the past decade to explicitly include economic goals in control, in particular in chemical plant control [73], [74]. The traditional method for controlling chemical plants as economically optimal as possible used to be a two layer design. First, a layer of real-time optimization (RTO) determines the optimal economic steady-state and then an MPC layer uses this optimal economic steady-state as a reference input. The big disadvantage of this approach is that the steady-state that the system moves to may be economically optimal, but the path to this steady-state is most probably not economically optimal (and instead is primarily determined by the tuning of the MPC).

The Economic MPC merges these two steps by finding both the optimal steady-state and optimal transient in the same optimization step. The objective function is not the traditional trade-off between driving the state to the reference state and minimizing the control input; the objective function has a direct economic interpretation. Although the theory is promising, [74] points out that use-cases should be researched where Economic MPC actually has a large enough advantage over the traditional two-layer design.

For the economic systems researched in Economic Engineering where price is dynamic, the two-layer design of RTO and traditional MPC will not be sufficient, so Economic Engineering proves a good use-case for Economic MPC. This is because the price is dynamic, and therefore the price is present in the objective function as well as it being a state of the system. This means the path of the transient has an influence on the price and therefore RTO as a separate first step is not possible. The economically optimal transient as well as steady-state have to be computed at the same time, which an Economic MPC can do.

Alternatively offline optimization could be used, since the application for this thesis currently only concerns simulating a market of the future. Real-time trading cannot be optimized yet with the model, since the market that the model describes does not exist yet. Offline optimization assumes perfect information of the future though. To simulate realistic trading behavior it must be assumed that the trader does not have perfect information of the future, therefore a MPC with receding horizon is designed instead of using offline optimization.

5-2-2 Discretization of the model

The optimization will be performed for a trader with a battery storage (variables with the letter B), a hydrogen storage (variables with the letter H) and a shifted demand backlog (variables with the letters SD). This is an electricity market with 3 building blocks attached.

For the model to be used with Economic MPC it needs to discretized. This is done with Forward Euler:

$$\begin{bmatrix} p_S[k+1] \\ p_B[k+1] \\ p_H[k+1] \\ p_{SD}[k+1] \\ q_B[k+1] \\ q_H[k+1] \\ q_{SD}[k+1] \end{bmatrix} = \begin{bmatrix} p_S[k] \\ p_B[k] \\ p_H[k] \\ p_{SD}[k] \\ q_B[k] \\ q_H[k] \\ q_{SD}[k] \end{bmatrix} + T_s \begin{bmatrix} -(4\epsilon_S+\epsilon_D)R & \epsilon_S R & \epsilon_S R & \epsilon_S R & 0 & 0 & 0 \\ -(4\epsilon_S+\epsilon_D)R & \epsilon_S R & \epsilon_S R & \epsilon_S R & -1/C_B & 0 & 0 \\ -(4\epsilon_S+\epsilon_D)R & \epsilon_S R & \epsilon_S R & \epsilon_S R & 0 & -1/C_H & 0 \\ -(4\epsilon_S+\epsilon_D)R & \epsilon_S R & \epsilon_S R & \epsilon_S R & 0 & 0 & 1/C_{SD} \\ -\epsilon_S & \epsilon_S & 0 & 0 & 0 & 0 & 0 \\ -\epsilon_S & 0 & \epsilon_S & 0 & 0 & 0 & 0 \\ \epsilon_S & 0 & 0 & -\epsilon_S & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_S[k] \\ p_B[k] \\ p_H[k] \\ p_{SD}[k] \\ q_B[k] \\ q_H[k] \\ q_{SD}[k] \end{bmatrix}$$

$$... + T_s \begin{bmatrix} R & 0 & 0 & 0 & 0 & 0 \\ R & 1 & 0 & 0 & 0 & 0 \\ R & 0 & 1 & 0 & 0 & 0 \\ R & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Q_D[k] \\ u_B[k] \\ u_H[k] \\ u_{SD}[k] \\ Q_{L_B}[k] \\ Q_{L_H}[k] \end{bmatrix}$$

With T_s, ϵ_S, R and C parameters. u the control inputs, Q_D a disturbance, and Q_L also a disturbance, but that one depends on the states p_B/p_H and p_S according to:

$$Q_{L_B}[k] = \epsilon_S(1-\eta) \cdot |p_B[k] - p_S[k]| \tag{5-1}$$

$$Q_{L_H}[k] = \epsilon_S(1-\eta) \cdot |p_H[k] - p_S[k]| \tag{5-2}$$

5-2-3 Objective function

In [60] an objective function for optimizing energy arbitrage with battery degradation is formulated as follows:

$$J = \sum_{t=1}^{T} p(t)(E^S(t) - E^P(t)) - \Delta c(t) \tag{5-3}$$

Here p is the market price for electricity per hour, E^S is the electrical energy sold per hour, E^P the electrical energy purchased per hour and Δc the costs for battery degradation per hour. For Δc different models are proposed. I will use a simple fixed price model, where each MWh that is stored costs a certain fixed amount of money.

Objective function for my model:

$$J = \sum_{k=1}^{T} \underbrace{-p_S[k]Q[k]}_{\text{Energy Arbitrage}} - \underbrace{|cQ[k]|}_{\text{Storage Costs}} \underbrace{-\frac{1}{2}u^T[k]R_{risk}u[k]}_{\text{Risk Aversion}} \tag{5-4}$$

The most important part of this objective function is the variable for the market price p_S. This price is continuously changing based on the bids of the trader and external disturbances such as demand. The price dynamics included in the Economic Engineering model therefore immediately influence the objective function. This also shows the importance of an Economic MPC compared to the two layer RTO-MPC design; an economically optimal steady-state within the horizon of the MPC cannot be computed if the price is continuously changing as a result of control inputs and disturbances. The system is therefore controlled to move along the economically optimal path over the time horizon of the Economic MPC.

For now competition is not included, so the trader is the only market participant using storage to optimize his profits. This assumption is very much simplifying the optimization, but incorporating game theory at this point is deemed too complex. Ultimately the trader would have to come to some Nash equilibrium with competitors. This is included in the recommendations in Section 7-1.

Model Assumption

The trader does not have to compete with other traders.

Income from energy arbitrage

The income from energy arbitrage is the revenue from selling electricity minus the expenditure for buying electricity, represented by $-p_S[k]Q[k]$. For multiple storage blocks, $p_S[k] = \begin{bmatrix} p_S[k] & p_S[k] & p_S[k] \end{bmatrix}$ and $Q[k] = \begin{bmatrix} Q_B[k] & Q_H[k] & Q_{SD}[k] \end{bmatrix}^T$. If Q is positive the trader is storing energy, so buying energy on the market. When Q is negative he is selling from storage to the market.

This part of the objective function is linear, so the trader can make income from energy arbitrage by selling electricity at a higher price than what he bought it for. Maximization of income through energy arbitrage is achieved by finding the optimal moments to sell and buy.

Storage costs

To use storage, the trader will have to calculate costs for this storage. This is either for depreciating his own storage, or for using the storage of someone else. The storage costs are defined in the c-vector and have units €/MWh, so it represents a fixed price. If there are multiple storage options, such as batteries and hydrogen storage, and a backlog without costs, the vector looks as follows:

$$c = \begin{bmatrix} c_{\text{battery}} & c_{\text{hydrogen}} & 0 \end{bmatrix} \tag{5-5}$$

This part of the objective function is an absolute function, because costs are calculated both when storing ($Q > 0$) and when selling ($Q < 0$). The function is concave, since the negative absolute of a linear function is given by the minimum of two linear functions:

$$-|Q| = \min\{Q, -Q\} \tag{5-6}$$

Maximization of a negative absolute function can be solved using quadratic programming by recasting the function with a dummy variable Q_T^* and corresponding constraints [75].

$$|Q| = Q^* \tag{5-7}$$

Subject to:

$$\begin{aligned} Q &\leq Q^* \\ -Q &\leq Q^* \end{aligned} \tag{5-8}$$

The optimal point for storage costs lies at $Q_T = 0$, meaning no trading. However as long as the income from energy arbitrage outweighs the storage costs, the trader will trade. This immediately reveals the trade-off between energy arbitrage and storage costs.

Risk aversion

The trader has a base reservation price, which is the market price plus the price difference caused by the convenience yield over time due to having product in storage or backlog (see subsection 4-1-2). The trader can add a premium to this base reservation price to determine his actual reservation price. This is the price at which the trader bids. The premium is a control input in the form of an economic want that will change the reservation price over time.

By deviating from the base reservation price, the trader takes an economic risk. His reservation price is not strictly dependent on the market price and his storage level anymore. If the demand and weather predictions appear to be off, the trader could be stuck with too much or too little energy in storage to still make profit.

How easily the trader can differentiate from the base reservation price determines his willingness to take risk. If the penalty R_{risk} on the control input u is high, the trader will bid risk-averse. Meanwhile if the penalty on the control input is close to zero, the trader will change his reservation price to any price he sees fit. This means he will trade practically any quantity he wants that fits within the constraints of his storage.

This risk can differ per storage medium. The trader may for example see more risk in having additional energy in his batteries compared to his hydrogen storage, depending on several factors. In this way the trader can prefer one storage medium over the other, aside storage costs and round-trip losses. This choice can be explicitly made by choosing the risk factor.

$$R_{\text{risk}} = \begin{bmatrix} R_{\text{battery}} & 0 & 0 \\ 0 & R_{\text{hydrogen}} & 0 \\ 0 & 0 & R_{\text{SD}} \end{bmatrix} \tag{5-9}$$

This part of the objective function that penalizes the control input is quadratic and also shaped concave. Also here an input of zero economic want is the optimal choice. Once again the trade-off between making income from energy arbitrage and the penalty on economic want determines how much trading takes place.

An important note here is that economic risk does not solely come from the penalty on control input. The choice of what the optimal storage level is, as well as the choice of the constraints, also determines how well the trader can deal with uncertainty, and thus how risk averse he trades. Risk averse trading is by no means the optimal way of trading. In control engineering this is the trade-off between performance and robustness.

5-2-4 Constraints

The maximization problem is given by objective function J maximized over time with constraints. The state equations, as well as capacity constraints on storage and a terminal constraint are constraints on the system. The optimization of one iteration looks as follows:

$$\begin{aligned} \underset{u}{\text{maximize}} \quad & \sum_{k=1}^{T} -p_S[k]Q[k] - cQ^*[k] - \frac{1}{2}u^T[k]R_{risk}u[k] \\ \text{subject to} \quad & x[k+1] = Ax[k] + Bu[k] + E\hat{w}[k], \\ & x[0] = x_0, \\ & q[T] = 0, \\ & Q[k] \leq Q^*[k], \\ & -Q[k] \leq Q^*[k], \\ & q_{min} < q[k] < q_{max} \end{aligned} \tag{5-10}$$

Where Q, q and u are vectors (i.e. $Q[k] = \begin{bmatrix} Q_B[k] & Q_H[k] & Q_{SD}[k] \end{bmatrix}$). $\hat{w}$ is the expected quantity demanded Q_D.

After the optimal control sequence for $k \in [0, T]$ has been calculated for one iteration, the control input for the first timestep is implemented and the new states are determined. The updated states are used as the new initial condition x_0. The optimal control sequence for $k \in [1, T+1]$ is determined, and the process repeats.

Since the control variable is not explicitly in the entire objective function, the state equations need to be included in the objective function to be able to solve the optimization problem. This is achieved using a costate variable $\mu[k]$ according to Pontryagin's maximum principle [76].

In this way the state equations become soft constraints on the objective function, and the maximization problem is solved for both $u[k]$ and $\mu[k]$. This is similar to how Lagrangian multipliers $\lambda[k]$ are used for optimization problems with non-dynamical constraints. The resulting objective function H has the following format:

$$H[x, u, k, \mu] = J[x, u, k] + \mu[k]f[x, u, k] \tag{5-11}$$

Where J is the original objective function and f represents the state equations. H is the formal solution.

Terminal constraint

To improve performance, the economic cost that is beyond the prediction horizon has to be considered [77]. By implementing a terminal constraint the system converges to a specified state that is deemed as an optimal rest state. For economic systems this could be considered as the economically optimal steady-state at the end of the horizon [77] (where knowledge of what is beyond the horizon is missing). In case of the trader this means his storage levels return to the optimal storage levels at the end of the horizon (which have been defined as $q_T = 0$).

Therefore there is a terminal constraint $q_T(T)$ on the storage levels. It prevents the trader from maximizing his profits by selling his storage empty. Although selling his storage empty may optimize his profits over the given prediction horizon, this is not a useful strategy in the long run (so beyond the prediction horizon). Therefore the trader has the freedom to trade within the time span of the prediction horizon, but must be at the optimal storage level again at the end ($q_T[T] = 0$).

For a risk-averse trader with a high R_{risk} parameter this terminal constraint is less relevant. He will keep his storage levels close to the optimal storage level by design. The storage levels of a risk-taking trader will drift off far into the negative values without a terminal constraint. The terminal constraint is able to provide additional stability when the penalty on the control input is low.

5-2-5 MPC tuning

Sampling time

The sampling time is a choice between simulation accuracy and computation time. A sampling time of 1 means that each timestep represents 1 hour (since units of time in the model are hours). This is too slow, since the effect of one hour would only be included in the next hour. The sampling needs to be at least 0.5 the dominant frequency (so 30 minutes), but since computation time permits a sampling time of 0.25 is chosen (15 minutes).

Prediction and control horizon

The length of the prediction horizon T is a trade-off between performance and computation time. The prediction horizon must be long enough for the trader to see an arbitrage opportunity within the horizon. So at least one moment of expected high prices and one moment of expected low prices within the foreseeable future.

The dominant frequency in the price signal will therefore play an important role. If prices go up and down tremendously between day and night, a prediction horizon of one or two days can be enough. If weekend and weekdays are the differentiating factor, then the prediction horizon must be at least a few days, but preferably more than a week. For seasonal effects the prediction horizon must be months, but this can become too computationally intensive.

Additionally, looking too far in the future and including these inputs with the same weight as inputs in the near future may also compromise performance, because these far future inputs will suffer from higher uncertainty than the near future inputs. A weighted objective function that reduces the contribution of far future inputs by giving them less weight can help prevent these problems. A weighted objective function in combination with a terminal constraint is not possible though, because the terminal constraint will be ignored as a result of the weighted function. The best solution to this problem is a Stochastic MPC (SMPC) which is discussed in Section 7-2.

In contrast with common MPC design, the control horizon for the Economic MPC is chosen equal to the prediction horizon. The control horizon for a typical MPC is chosen shorter than the prediction horizon to reduce computation time. The length of the control horizon is chosen such that the system can reach steady state within the time frame of the control horizon. After the control horizon, the control input will remain constant for the remainder of the prediction horizon. This is suitable for tasks like reference tracking. For an economic system where the controller tries to maximize profit this steady state is never reached, so choosing a control horizon shorter than the prediction horizon can cause very poor performance.

5-2-6 Stability

For an Economic MPC, the system is stable if the system converges to the optimal trajectory. A sufficient condition for optimal operation is that a system is dissipative [74]. A system is dissipative if the energy stored by the system along any solution (for all states x within set $\mathcal{X}$) is less or equal the amount of energy supplied from outside [74], [78]. A system is called strictly dissipative if this holds for all trajectories (also those moving beyond $\mathcal{X}$). The dissipativity condition can be met by finding a correct storage function λ such that:

$$\lambda(f(x,u)) - \lambda(x) \leq s(x,u) \tag{5-12}$$

Where s is the supply function and λ is the storage function.

This requires a definition of what the optimal regime of operation is. If the optimal regime of operation is a steady-state, then finding a storage function and satisfying the dissipativity condition is described in detail in [74]. For a system with periodic orbital optimal regions, or even more general optimal regimes of operation, this is much less straight-forward [78].

Economic Engineering systems fall in the latter category of general optimal regimes of operation. This is because the market price is essential for determining optimal operation. As a result of the price dynamics, the market price is continuously changing. Therefore there is no optimal steady-state within the prediction horizon. Determining if the system always converges to its optimal trajectory, by proving the dissipativity condition for general optimal regimes of operation, is well beyond the scope of this research. At this point, Economic MPC for Economic Engineering deserves a thesis on its own.

Some final thoughts on stability of the Economic MPC can be provided though. The terminal constraint does guarantee that at least the storage levels return to their steady-state at the end of the prediction horizon. Also, since the current application of Economic MPC in this thesis is restricted purely to simulation, convergence behavior can be verified through trial-and-error with simulation. This is a reasonable way of determining if the system converges to some optimal path. For operation of real-life systems, such as chemical plants, a stability proof is of greater importance for obvious safety and economic reasons.

5-3 Simulations

For simulations two demand signals are created. The first demand signal is the demand signal already introduced in Figure 2-15. The second demand signal is a fictive yet more realistic demand throughout two weeks.

The simulations are performed in Matlab using the YALMIP toolkit to program the MPC [79]. The optimization problem is solved using "quadprog" solver with the interior-point-convex algorithm. The default settings for the interior-point-convex algorithm are sufficiently fast, such that no additional tuning is required. Simulations are run on an Intel i9-9900k processor.

The simulations for the first demand signal finish within in a minute (more than 300 iterations, so less than 0.2 seconds per iteration) and the simulations for the two week demand signal finish within ten minutes. Ultimately the computation has to be fast enough to perform at least one iteration of MPC per 15 minutes if the model were to be used in real-time trading.

The simulations will be performed for a trader with a battery storage, a hydrogen storage and some machinery that can be used to shift demand in time. The battery storage is given a capacity of 5000 MWh, has a round-trip efficiency of 90% and storage costs of €25/MWh. The hydrogen facility also has 5000 MWh of storage capacity available, has a round-trip efficiency of 50% and storage costs of €5/MWh. The machinery available for shifting demand is 1000 MWh in size at any time. It has no round-trip losses and is also free of costs.

These storage parameters are purely illustrative and no hard conclusions should be drawn on the feasibility of specifically batteries or hydrogen from these simulations.

The other model parameters are chosen as follows:

For demand scenario 1:
$C_B = C_H = C_{SD} = 200$, $R = 0.01$, $\epsilon_S = 1/0.005$, $\epsilon_D = 1/0.02$, $R_{\text{risk}} = 20$, $T = 24$ hours,
Initial conditions: $p_{S_0} = p_{B_0} = p_{H_0} = p_{SD_0} = 50$, $q_{B_0} = q_{H_0} = q_{SD_0} = 0$.

For demand scenario 2:
$C_B = C_H = C_{SD} = 200$, $R = 0.01$, $\epsilon_S =$ Varying, $\epsilon_D = 1/0.02$, $R_{\text{risk}} = 100$, $T = 48$ hours,
Initial conditions: $p_{S_0} = p_{B_0} = p_{H_0} = p_{SD_0} = 50$, $q_{B_0} = q_{H_0} = q_{SD_0} = 0$.

5-3-1 Demand dependent price elasticity

To approximate the staircase shape of the merit order, the price elasticity ϵ of the supply curve is made dependent on the quantity demanded Q_D. This will make the model time-variant. The supply curve is split in different sections, and the curve gets steeper as the quantity demanded increases. As a result the price will shift more when demand and prices are high, and will shift less when demand and prices are low. Figure 5-2 visualizes the idea behind a piecewise linear supply curve.

For demand scenario 2:
$Q_D > 15500$, $\epsilon_S = 1/0.008$
$Q_D > 11000$, $\epsilon_S = 1/0.0035$
$Q_D < 11000$, $\epsilon_S = 1/0.002$

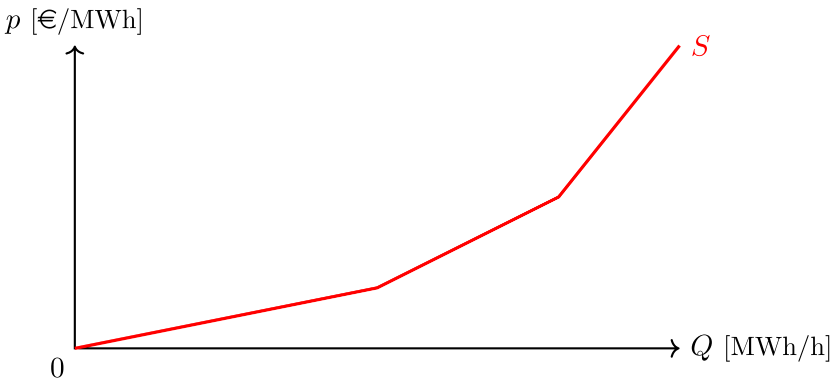


Figure 5-2: Piecewise linear supply curve

5-3-2 Brownian noise

The MPC uses a predicted input quantity demanded Q_D for the upcoming hours. This prediction will never be perfect and therefore this predicted quantity demanded vector is adjusted as real-time approaches. This is simulated by adding Brownian noise to the demand vector after each timestep. Values further in the future will be more uncertain, so more deviation is added to values further in the future. The optimal control input vetor is calculated for the current demand vector. Then the timestep is executed, the demand vector is updated with brownian noise and the new timestep is calculated with the updated demand vector.

Brownian noise is chosen over white noise, because the deviation in the demand signal should not be completely random. By using Brownian noise a random deviation is added to the demand signal, but the deviation per step is not completely independent from the previous step. Brownian noise can be seen as low-pass filtered white noise, so more low frequencies. In Figure 5-3 the demand signal is shown without noise as well as two runs where random Brownian noise is added.

5-3-3 A simple demand signal

For demand scenario 1, as shown in Figure 5-3, the storage (q_B, q_H and q_{SD}) and price levels (p_S, p_B, p_H and p_{SD}) develop as shown in Figure 5-4 and Figure 5-5.

It can be seen that shifting demand is the preferred method of providing flexibility. This is no surprise, since in these simulations there are no costs or losses when shifting demand. The trader will therefore always make full use of the available capacity in shifting demand.

For the battery storage and hydrogen storage the trader has to account for losses and costs. For battery storage the costs are the main factor, so the absolute price spread between the selling and the buying price must be large enough to arbitrage. This so-called bid-ask spread must be at least €25,- (actually, slightly higher to compensate for the losses as well).

For the hydrogen storage the round-trip losses are most important. This means the relative price spread between the buying and the selling price is the most important. Since 50% of the electricity is lost in a round-trip conversion, the selling price must be at least twice the buying price (once again slightly higher to compensate for the costs as well).

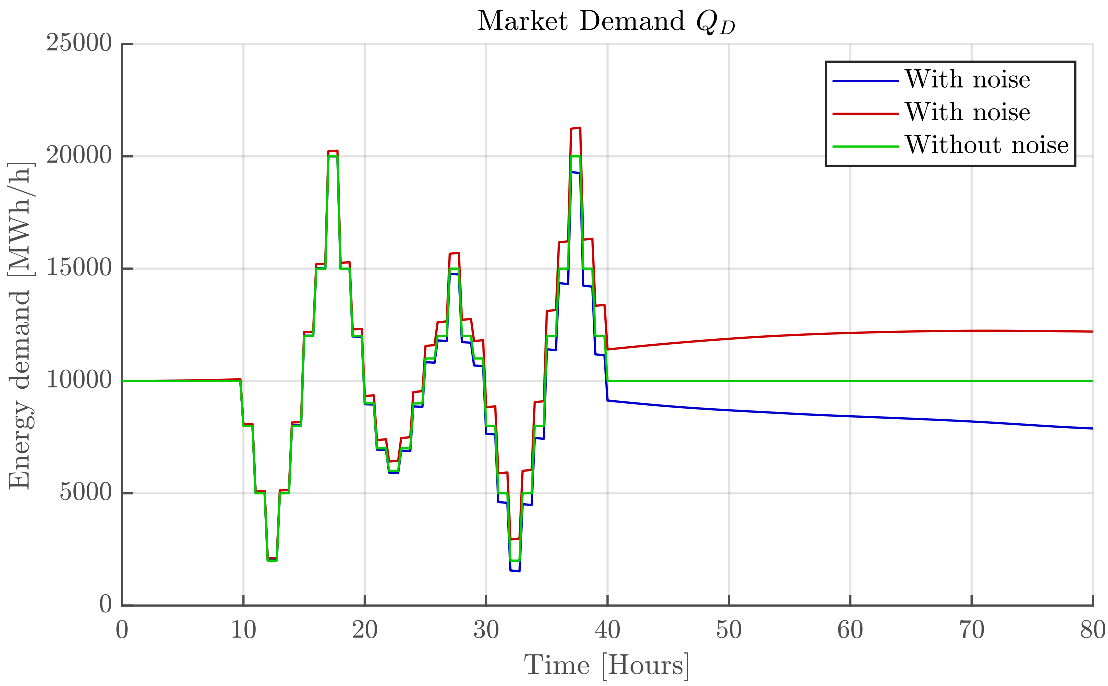


Figure 5-3: Three fictional demand signals, two with Brownian noise and one without noise

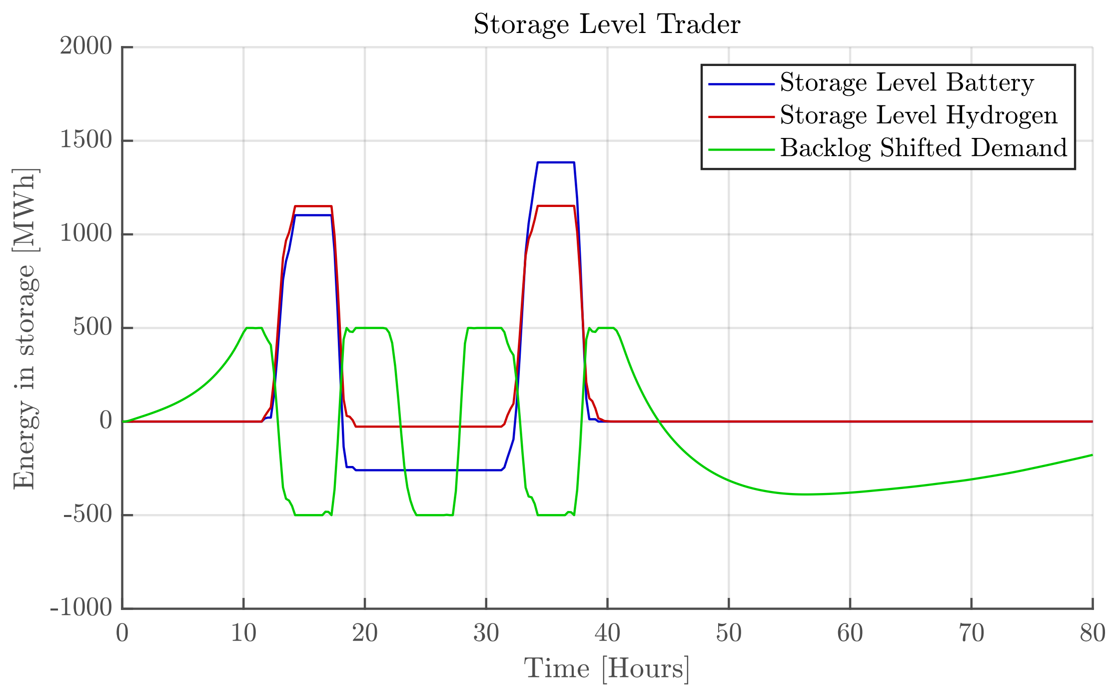


Figure 5-4: Storage levels for the different methods

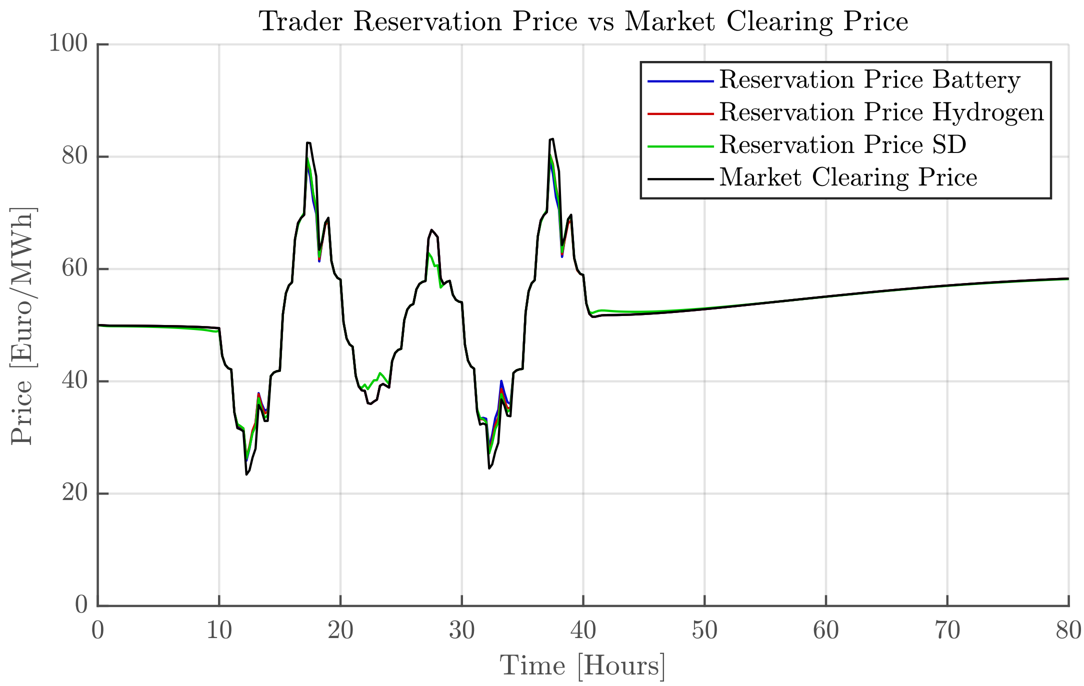


Figure 5-5: Reservation prices for the different methods

In these simulations the absolute and relative price spreads are both large enough for arbitrage at two moments, without one being much more advantageous compared to the other. The price spread between 20 and 30 hours is not big enough for either storage methods.

In Figure 5-6 the market clearing price as a result of the trader's behavior is compared to a scenario without this trader. The market prices are squeezed inwards because of the trader's behavior. This is as expected; when the trader sells, the prices go down, when the trader buys, the prices go up.

As the trader needs to fill up his storage first, he first has to invest some money. As can be seen in Figure 5-7 his total profit over time starts out negative as a result. Ultimately, the trader makes a profit from performing energy arbitrage on the electricity market.

5-3-4 A more realistic demand signal

For demand scenario 2 shown in Figure 5-8, the demand represents two weeks of demand. This includes daily peaks in the morning and the evening, a low demand at night and a lower demand in the weekends compared to the weekdays. In this way a fictive, but realistic scenario is simulated.

The trader now uses his storage levels primarily to sell during the peaks hours and store during the off-peak hours. The shifted demand is used at between every peak. The battery and hydrogen storages are filled up at night and then sold empty around the peaks during the day. During the weekends the price spread is not large enough to use the storage and the trader cannot look far enough in the future. If the prediction horizon would be increased from two days to a full week, the weekends could be used to fill up the storage already.

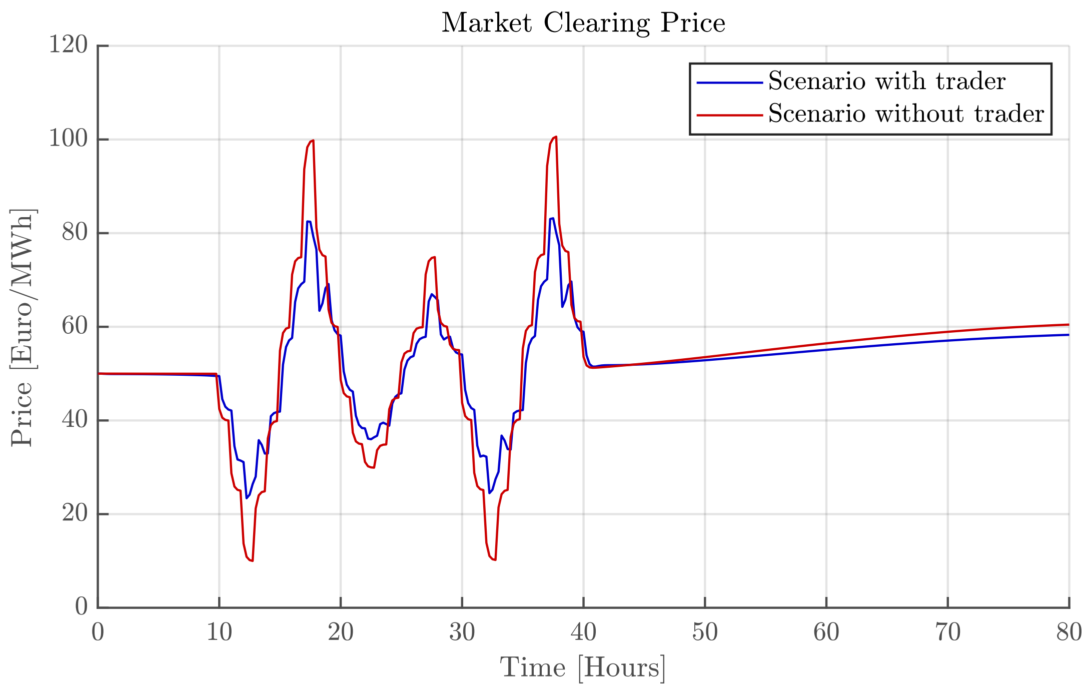


Figure 5-6: Comparison of the market prices if there is trader introducing flexibility, compared to the scenario without a trader.

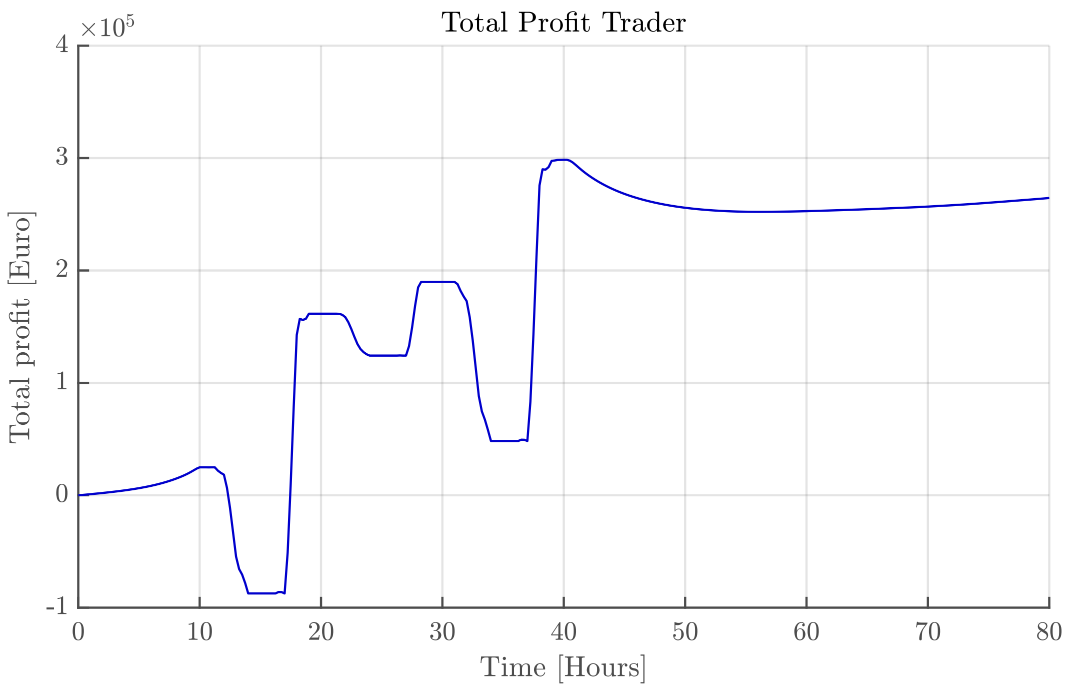


Figure 5-7: Profit made by the trader

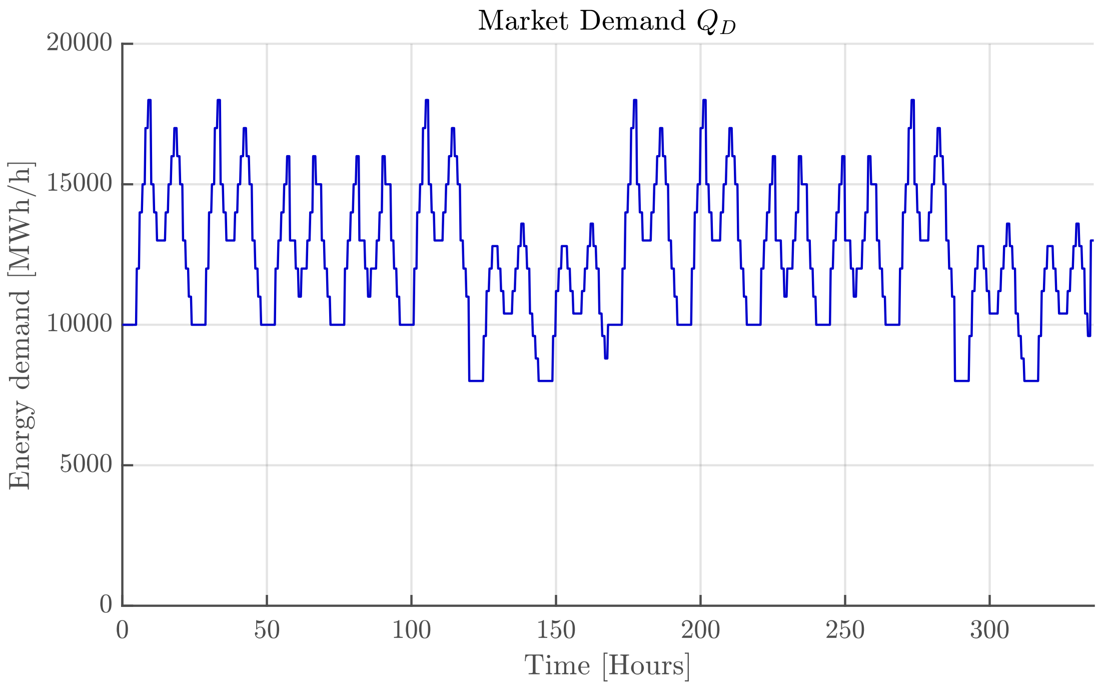


Figure 5-8: A fictive but realistic demand signal

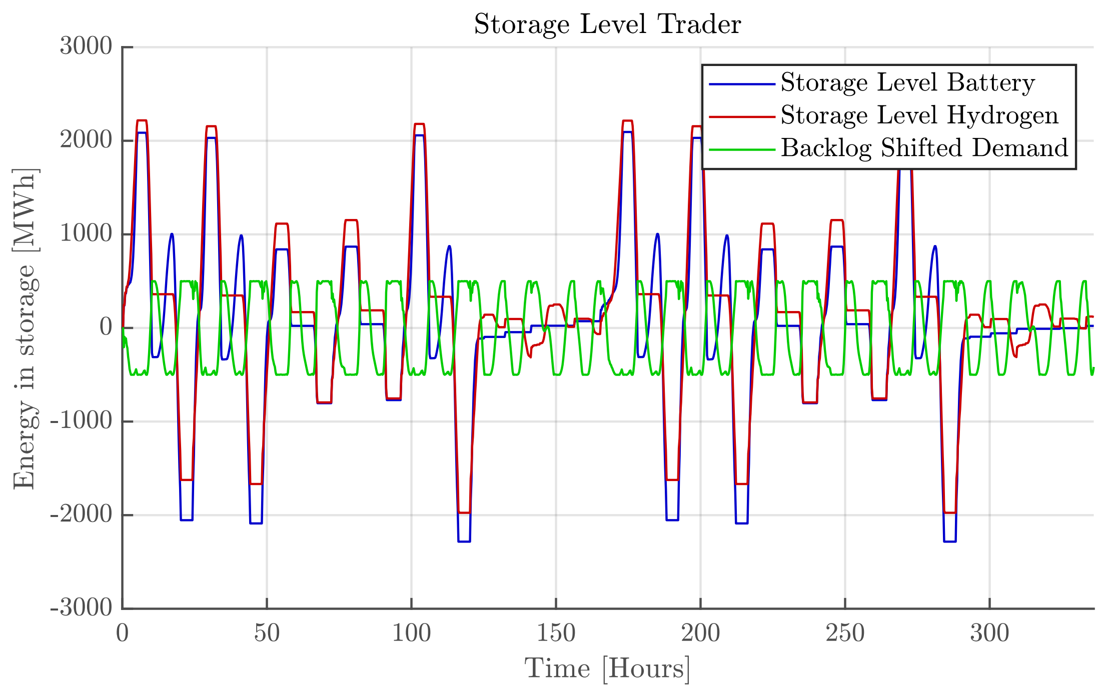


Figure 5-9: Storage levels of the trader over two weeks of trading

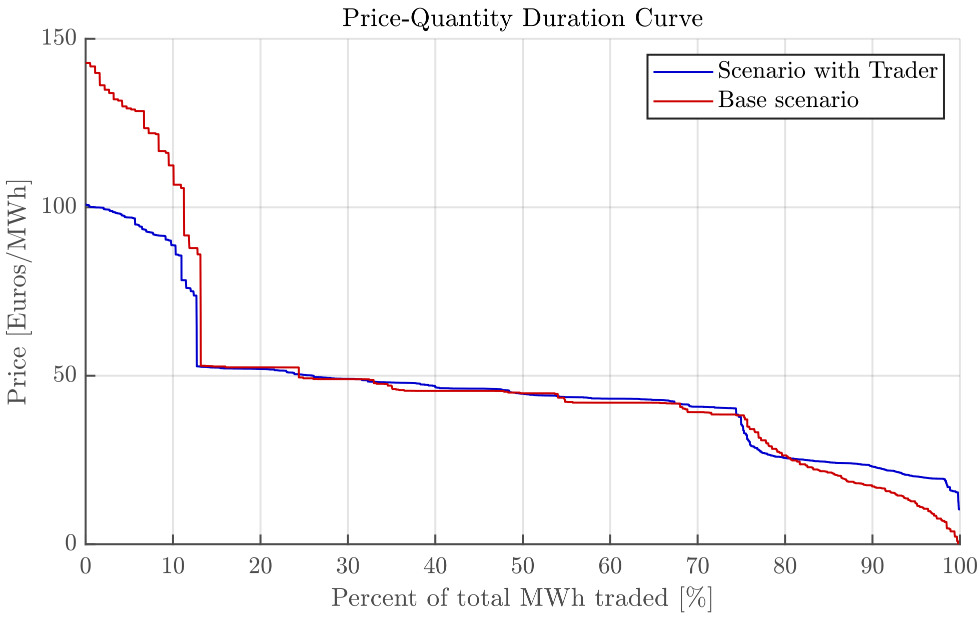


Figure 5-10: Price-quantity duration curve of the simulated electricity market in scenario 2

5-4 Consequences of the Price Changes due to Added Flexibility

To analyze the effects of new market mechanisms have on the electricity market, a price duration curve holds useful information about the price development. More details on the price duration curve can be found in Section E-1. It misses the amount of energy supplied at each price though. I propose using a price-quantity duration curve instead, which is a weighted price duration curve. This idea is explained in more detail in Appendix E as well.

Figure 5-10 is a price-quantity duration curve for the demand in scenario 2. This helps explain several things that will happen with the prices and the market participants when a trader starts using his storage for energy arbitrage:

- First of all, the trader has a positive impact on the average price of electricity over the entire time horizon. The average price is slightly decreased. This is because due to the demand-dependent price elasticity high prices drop more when selling from storage than low prices rise when storing. This means that the electricity market goal of providing electrical energy to consumers at least cost is improved. Also extreme price peaks are avoided, which is beneficial to all sorts of consumers that can hardly adjust their electricity usage and have to pay whatever the price is.

- Secondly, the profitability of RES is improved. Investors will receive higher prices for their renewable electricity, since they will often sell when prices are typically low. This is when traders store, so these prices rise. Electricity suppliers with RES will therefore also be the parties that benefit most from investing in storage. If they have storage themselves, they can make profit from energy arbitrage by "buying" from themselves. At the same time they will increase the price of the remainder of the electricity that they do sell directly.

- Thirdly, the amount of traditional generators will decrease for economic reasons (regardless of the decrease due to environmental reasons). This is because plants such as gas peaking plants are only selling when prices are high enough. So with less high prices the investment becomes less viable and therefore some peaking plants will be shut down. This is a well-known problem and is called 'the missing money problem' [2].

  Grid stability is improved nonetheless, because the loss of generation capacity is compensated by the introduced flexibility. Periods of little wind and sun can be covered with stored energy and reduced demand. This is a service that is inherently provided by the trader with storage and demand response because it is also in his economic best interest when prices are high.

- Finally, there is however an important downside to the added flexibility: Electricity systems may become too dependent on storage if the capacity of the traditional generators shrinks too far. In contrast to traditional generators that are simply there, storage actually needs to be filled with energy at the optimal moments to be able to supply enough energy when necessary later on. For doing this correctly, traders are dependent on the accuracy of for example their weather forecast models or demand forecast models.

  The amount of risk they take is also relevant. If the forecast models are off, or the trader took too much risk in trading, grid stability may be compromised. The trader cannot supply enough energy because it is not in his storage. And due to his presence on the market some traditional generators that could previously guarantee grid stability have closed. Capacity adequacy becomes more complex with large-scale storage, since not only the power capacity needs to be there, but also the energy itself.

5-5 Regulating Risk through a Storage Capacity Reserve Market

The importance of capacity adequacy and the benefits of flexibility are well-reported [80] [81], but the risks of flexibility are underexposed. In [82] the benefits and some of the risks of flexibility through hydropower are discussed, but the risk of having no energy in storage is not mentioned explicitly.

Currently the balancing market is in place to correct any planning errors and prevent blackouts. However if due to storage mismanagement from a large energy trader the energy necessary to meet the demand is not there, then available capacity on the balancing market will not be sufficient to cover for this mismanagement. In such a scenario prices will explode and black-outs may even appear.

Once storage has acquired a large market share, it becomes the backbone of the electricity grid. For stationary grid storage this can already pose problems if the required energy is not in there, but for mobile storage such as electric cars this may be even more troublesome. Mobile storage will contribute to pushing traditional power capacity out of the market because they can be used for trading most of the day. However the total power capacity from storage may be temporarily reduced heavily if a lot of cars start driving at 9 o'clock in the morning or 5 o'clock in the evening. And with that flexible yet crucial role for storage, some regulation will be necessary to guarantee grid stability.

Traders must be financially incentivised to reduce their risk. As explained in subsection 5-2-3 this thesis defines two different ways the trader can take risk. The first is through the tunable parameter for risk in the objective function. This determines how risk averse the trader is in his planning and trading behavior by setting a penalty for deviating from his base reservation price. This is difficult to regulate without conflicting too much with the free market. The second form of risk is the optimal storage level and the constraints on the storage size. By setting these storage levels higher than economically optimal the trader can build a buffer. This means that even when the model/controller thinks the storage is empty, there is in fact still some reserve energy left. The trader must be financially compensated by the TSO for this buffer.

This compensation is similar to the reserve capacity market of the balancing market. On the reserve capacity market participants receive a financial compensation for keeping some power capacity available at all times [81], [83]. The height of the compensation is determined through bidding, so the free market is also present on this additional regulatory reserve market. The TSO determines the size of the reserve power capacity on this market and pays the compensation.

A new market for reserve energy storage would be coupled to the day-ahead market instead of the balancing market. If prices on the day-ahead market are bound to explode or bids on the supply side cannot even be matched with bids on the demand side, because traders have not kept enough energy in storage, the TSO can activate the buffer energy. The price level or moment at which this buffer energy is activated should be communicated beforehand (for example at the start of each month).

The coupling with the day-ahead market instead of the balancing market provides the TSO with enough time to prevent potential black-outs. The Economic Engineering model developed in this thesis can be used to quantify the risk and determine the size of the reserve energy storage market.

More ideas for a reserve storage market could be borrowed from the gas market. There the TSO has a “-9/-17 rule” [84], which means that if the temperature drops below -9 degrees Celsius for more than 24 hours, the TSO is responsible for gas delivery. The TSO tenders this flexibility from the market. The rest of the year is left to the market. In this way there is a back-up mechanism in place for extreme situations with transparent conditions. A similar approach could be used for reserve energy storage.

5-6 Conclusions

Flexibility, introduced by a trader that optimizes his own profits through energy arbitrage, provides mainly benefits to the market. In particular, profits of RES suppliers increase and electricity costs for consumers drop.

It is important to stay aware of the risk that comes with storage on a free market. This risk being that traders have too little energy in storage due to poor forecasting. The main advantage of the Economic MPC developed in this chapter is that risk is explicitly in there, so it can be identified more easily. This helps a TSO determine the best strategy and format for regulation to reduce this risk.

Chapter 6

Conclusions

The Economic Engineering model developed in this thesis is a modular price-dynamic model that can be designed to match the changing system structure of the electricity market of the future. By combining several building blocks, the dynamic effects of storage, demand response and cross-border transmission can be included when forecasting future scenarios. This model can forecast prices for an electricity market of the future, where data-driven models struggle to forecast due to lack of data. The unknown parameters still need to be estimated, but at least they have an actual economic interpretation. The fast-changing nature of the electricity market provides a unique use-case for Economic Engineering.

There is still a lot research required to provide a better fit between the model and the real electricity markets. Currently the model assumes one dynamic market and this makes actual implementation at this point difficult. The actual electricity market consists of four markets where most of the demand and supply is matched upfront. Despite the imperfect fit, new price dynamics are uncovered for the electricity market. The model provides both the TSO and investors with insights in the predicted workings of the electricity market of the future:

- The price dynamics in the model provides investors with more realistic price forecasting. This supports investors in RES investments, given that storage, demand response and cross-border transmission capacity are increased. Additionally the model also shows that RES investors are the market players that benefit most from investing in flexibility mechanisms, since the surplus from RES increases through increased flexibility.
- If capacities of these new market mechanisms are increased, the simulations show that these mechanisms are effective in guaranteeing more grid stability and supplying electricity at lower cost to the consumers in a market with high RES penetration.
- The flexibility provided by the new market mechanisms also require active choices from market participants in the management of their assets. For example, storage capacity may be there, but there also needs to be energy in storage to sell. This increases the risk of a blackout if predicted amounts of energy in storage do not match reality and traditional generation capacity has decreased. A reserve energy storage market is therefore proposed to regulate the risk that energy traders take.

The development of this Economic Engineering model ultimately makes a positive contribution to the energy transition on the electricity market by uncovering new opportunities, but also by exposing the new challenges that require attention such as the regulation of storage risk. The model can be used by both regulators and investors to design a reliable and cost-effective electricity market of the future.

Additionally it allows for the integration of several different energy markets. In this way energy in itself can become the product, and dependent on the application the most economic form of energy or energy carrier can be determined (electricity, gas, hydrogen, heat, etc).

Furthermore this thesis also contributes to usage of controllers in economic systems. The passive controller build in Chapter 2 and Chapter 3 has no option to maximize for profits. In economics this is however a very common goal. The trading behavior in these simulations is helping the market, but is not realistic from the trader's interests.

Active control in the form of EMPC is a useful tool to maximize profit over time, while ensuring constraints are met. Particularly the inclusion of a terminal constraint and the penalty on the control input as a measure of how risk averse the trader is, are important aspects of an economic controller design that were proposed in this thesis.

Chapter 7

Recommendations

There are many opportunities to continue the research started in this thesis or broaden the applicability of Economic Engineering to the electricity market. The recommendations in Section 7-1 and Section 7-2 improve and extend the used control techniques, and are potentially valuable contributions to the field of Economic Engineering in general. Section 7-3, Section 7-4 and Section 7-5 discus new opportunities for applying Economic Engineering to the electricity market, which is an important step towards deploying an Economic Engineering model of the electricity market in a real trading, investment or policy-making setting.

7-1 Including Competition in the Model

The lack of competition was an explicit modeling assumption, but due to lack of competition with other market participants, the trader can make much more profits than realistically possible. This is because the trader now chooses to sell a quantity at a price that maximizes his profits, but he could sell more energy at a lower price while still making a (smaller) profit. A second trader will therefore definitely enter the market to exploit this. As a result they will both want to sell at the same moments, making sure the price drops further during these moments than it does with just one trader in the market.

For realistic results, at least one extra storage building block representing a competitor should be added to the model. This competitor will have his own reservation price, and also influence the market with his bids. The objective function of the MPC will not only have to optimize for the profits of the trader, but also include some game theory to take into account the actions of the competitor. Including competition is currently ongoing research within the field of Economic Engineering, and definitely something that should be added to this model.

7-2 Dealing With Uncertainty Using Economic Stochastic MPC

The current Economic MPC design uses a deterministic objective function, deterministic constraints and deterministic disturbances. The disturbances (the demand/weather) do vary over time using Brownian noise, but at every optimization step, the MPC assumes everything is completely deterministic.

To account for uncertainties when using MPC, there are two common possibilities [85]. The first option is a Robust MPC (RMPC). This can account for uncertainty by using deterministic descriptions of bounded system uncertainties. The solution of the optimal control problem must satisfy the constraints for all possible realization uncertainties. This leads to a large set of deterministic constraints and while robustness against the bounded uncertainty can be ensured, optimal performance of the control objective may be comprised.

A second problem is that often uncertainties are of probabilistic nature. This is why a second type of MPC was introduced; Stochastic MPC (SMPC). In SMPC the objective function is formulated as an expectation and the constraints are formulated as chance constraints. The optimization becomes a trade-off between fulfilling the control objectives and satisfying the constraints, so a mix of performance and robustness [85].

This means that uncertainty can be included in the controller design, while still trying to maximize profits. It means some risk is taken compared to RMPC, but this is very much in line with how an economic agent behaves. The agent will have to take some risk regarding uncertainty when maximizing his profits, because otherwise his competitors certainly will. The SMPC is therefore a useful tool for optimizing profits in economic systems, since any economic system will inherently have uncertainties.

So far in the field of Economic Engineering this has not been looked into, so implementing Economic SMPC is definitely a promising step forward in MPC design for economic systems. Not only for the electricity market model presented in this thesis, but as an addition to the field of Economic Engineering in general.

7-3 More Detail In Electricity Demand and Supply

The focus of this thesis was on the effects of adding flexibility to the electricity market, so the detailed parts of the modeling focused on the storage, demand response and cross-border transmission as individual and stackable blocks. As a result, the used demand and supply curves were assumed to be accumulated for the entire market.

This provides little information of what is actually going on on the production or consumption side of the market. For a more detailed model the demand and supply sides should be split up in at least a few participants. When looking at the supply side for example, it can be split up in various generators. So a supplier for RES, a supplier for coal powered electricity and one for gas powered electricity. They each have their own supply curve and some maximum production capacity which they cannot cross. See Figure 7-1 for a visualisation.

The cheapest generator (RES in this case) will supply until its production capacity is saturated and then the next in line will be activated. Production capacity can vary per hour, which will be the case for RES, or be the same each hour.

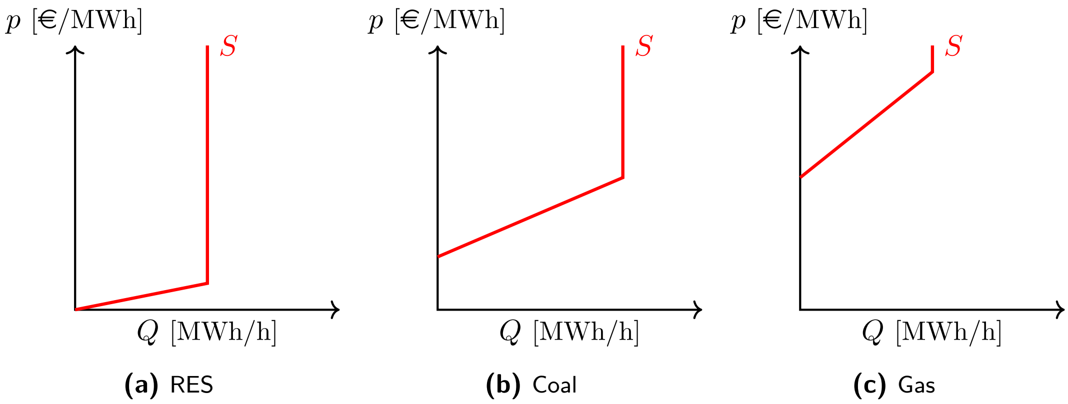


Figure 7-1: Supply curve per production method

7-4 Modeling Different Markets

One of the complexities of electricity trading is its direct connection with many different markets. Using Economic Engineering it could become possible to connect all these markets in one model by adding building blocks on top of each other. This does still require a lot more research.

7-4-1 The four electricity markets

As discussed in Chapter 2, the electricity market is split in four markets over time to make the planning of electricity production possible and adjust as real-time approaches. In this thesis these four markets were assumed to be combined in one dynamic market, but in reality trading has to take place on all these four markets separately. With increased flexibility the choice of trading when and on what market becomes even more complex, but it also means opportunities for earning money increase. A model that can optimize across these four markets would therefore be strongly recommended.

- For the futures/forward market trading with long-term electricity storage such as hydrogen becomes possible.
- For the day-ahead market and the intra-day market energy arbitrage would be the main form of income (as demonstrated in this thesis).
- On the balancing market the trader could use parts of his assets to provide ancillary services.

Including the balancing market is of particular interest, since it is bound to grow due to the increased uncertainty of RES.

7-4-2 Smart Energy Systems

The electricity market cannot be seen as a standalone market; apart from cross-border effects it is important to include cross-sector effects as well. In [70] this is referred to as Smart Energy Systems, where electricity, heating, cooling, industry, buildings and transportation are combined. It is hypothesized that least cost solutions for the energy transition cannot be found within single sectors, but can only be achieved through cross-sector coupling.

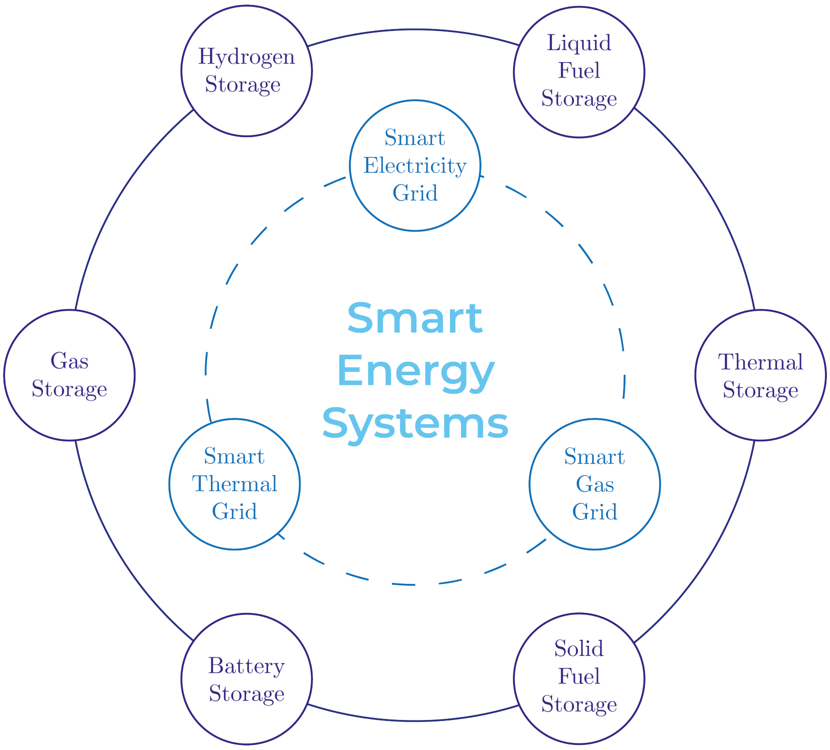


Figure 7-2: Smart Energy Systems connects different markets through smart grids and storage

Using Economic Engineering multiple markets can be connected using 2-port connections such as transformers and gyrators, and by using multi-port I-elements for cross-elasticity effects. For the modular model proposed in this thesis, other markets can be added to the 0-junction in the middle through a transformer. Currently the integration between the electricity market and the hydrogen market is on-going research within the Economic Engineering field, but for a complete picture and better price prediction many more energy markets should be connected.

Ultimately energy itself can become the product, at least within a modeling environment. The exact form or carrier of energy can then be determined by economic optimization. This however requires extensive knowledge of how all forms and carriers of energy interact. Also this is only relevant for long-term optimization; many systems are designed to work with one type of energy carrier and cannot switch from day-to-day (for example a car with internal combustion engine cannot just switch back and forth between petrol, hydrogen and electricity).

7-5 Investment Valuation and Business Cycles

Continuous construction of new plants is necessary to ensure grid stability. Old generators eventually need to be replaced, or power capacity proved insufficient, which requires additional power capacity. Preferably new generators are build long before a capacity shortage is bound to occur. However investors tend to wait, because they want to be certain that their investments are earned back. This results in investment cycles, which is a well-documented problem [81], [69].

Figure 7-3 visualizes the generation capacity of the market over time. The optimal generation capacity lies somewhere in the middle of the maximum and minimum generation capacity throughout time (where demand and supply would be perfectly balanced). At the top of the business cycle there is too much generation capacity (over supply). Existing power plants have difficulty earning their capital costs back. Investors will therefore hold back their investments and may even shut down older plants. As a result the total generation capacity of the market starts shrinking.

When it shrinks below the optimal generation capacity, earning money becomes easier, because demand is higher than available supply and prices rise. Investing becomes interesting again. It takes some time before new plants are in operation, so the total generation capacity may shrink some more, to a level where it can become problematic. Additionally the price signal takes some time to update because of how the merit order works.

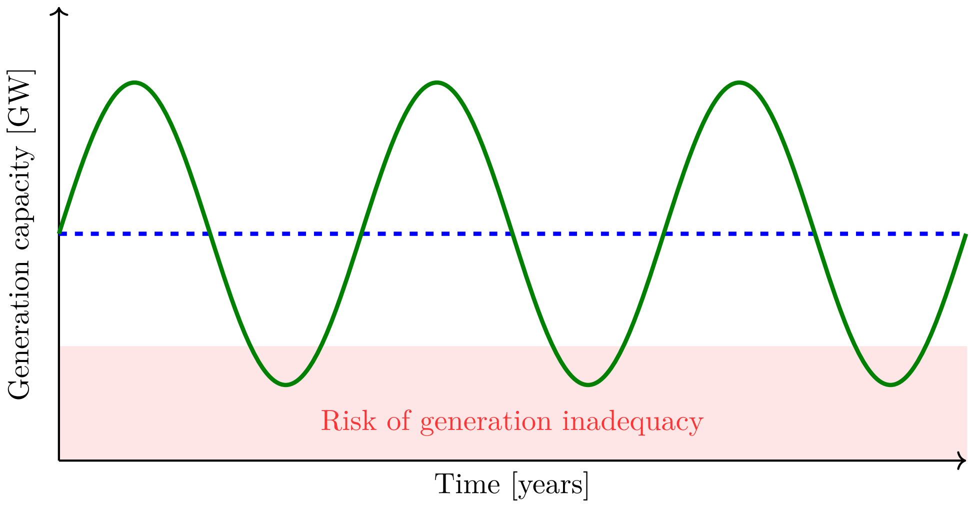


Figure 7-3: Visualization of business cycles in the electricity market. The green line depicts the total generation capacity of the market, the blue dashed line the optimal generation capacity and the red area a risk of generation inadequacy.

At the lowest point everyone wants to invest and because competitor behavior remains uncertain some overshoot in generation capacity occurs. Also prices will rise disproportionate at this point because shortages (power outages) are economically way more harmful to society compared to situations of over supply [69]. The generation capacity returns to its state of oversupply again and the cycle repeats. If the amplitude of the cycle becomes too large, generation adequacy really comes at the stake.

The Laplace transform in the economic domain provides a useful solution to the problem of business cycles. It can do valuation of a project, while also accounting for these business cycles. For the electricity market, the product is energy, expressed in MW-hour. This is similar to how the product on the labor market is labor, expressed in Man-hour. So these goods have units #-hr.

$$V(s) = \mathcal{L}\{p(t)\} = \int_0^\infty p(t)e^{-st}dt \tag{7-1}$$

Taking the Laplace transform of the price of such a good gives the discounted value of the product in €/#. For the electricity market the Laplace transform of the price of energy results in a value in €/MW.

$$s = \sigma + i\omega \tag{7-2}$$

Here σ is the discount rate and ω represents the frequency of the business cycle.

Before building a new generator, the Laplace transform can be used to valuate the project. In combination with the predicted prices of energy that come out of a model, a value can be calculated. In this way a capital cost price for power can be found. A 10 MW wind turbine with a value of €1,500,000 per MW should not cost more than €15,000,000. This is called the net present value (NPV) of the project. The same calculation holds for building for example storage capacity.

The only problem is that here each price is taken into consideration equally, while the quantity sold during each hour is just as relevant as the price. For accurate NPV calculation a weighted price should be used. So the price multiplied with the amount of MWh supplied by a certain generator at that price.

$$C(t) = p(t)Q(t) \tag{7-3}$$

The resulting cash flow C is then discounted using the Laplace transform to find the NPV:

$$\text{NPV}(s) = \mathcal{L}\{C(t)\} = \int_0^\infty C(t)e^{-st}dt \tag{7-4}$$

At this point it is not possible to calculate this since only an aggregated supply curve is available. Quantities supplied by individual generators are not available. Also the influence of business cycles requires more attention.

Because valuation is beyond the scope of this thesis, these topics are recommended for further research. The Economic Engineering model that was build did set the basis for such a research and makes the step towards valuation of building new generators accessible.

When implementing the valuation, it should be discretized. The model is in discrete time, so the Laplace Transform becomes the Z-Transform:

$$\text{NPV}[z] = \mathcal{Z}\{C[k]\} = \sum_{k=0}^{\infty} C[k]z^{-n} \tag{7-5}$$

Ultimately valuation of each generator can be used as feedback for the used merit order model. Generators that are not economically viable in the scenario that was modeled should be removed from the merit order. Simulations are performed again with the updated merit order and using the prices from this second run valuation can be performed again. This process is repeated until all generators that are completely unviable are not part of the simulations anymore.

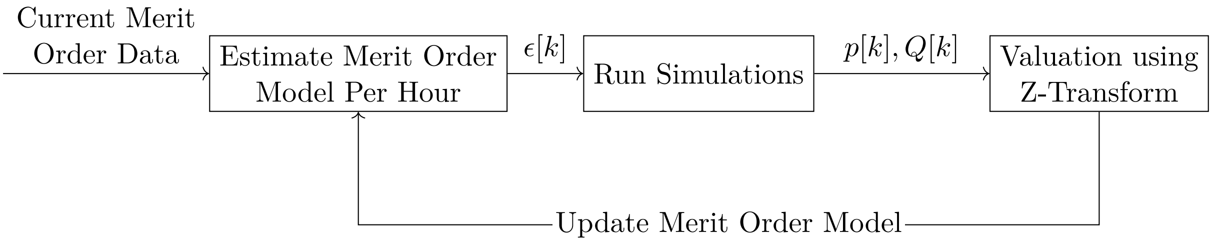


Figure 7-4: Closed-loop modeling procedure

Appendix A

Electricity System in Detail

A-1 The Electrical Power System

A-1-1 Market size

15% of all the power used in The Netherlands is electrical power. With an average power consumption of 100 GW for all types of energy carriers, 15 GW is the average electrical power consumption. The Dutch electrical energy production has been around 110 million MWh annually since 2006 now [86]. In 2019 the average price on the wholesale electricity market was 41.20 €/MWh.

For comparison, the global power consumption averages around 18000 GW for all energy types with also 15% from electrical power. This percentage is expected to rise sharply due to electrification of transport, heating and industry to around 50% in 2050 [41].

A-1-2 The wholesale market

The wholesale electricity market is the market where electrical energy is sold and traded by electricity generators and large consumers. It consists of all electricity generators, electricity retail companies and large industry players. Participants on the wholesale market might be generating and selling electricity, as well as buying electricity. Also traders are active on the electricity market; they do not generate or consume electricity, but only buy or sell certain volumes in order to buy or sell the same volume later.

Electrical energy is traded on different timescales; the futures/forward market, the spot market and the balancing market respectively. Each market has a slightly different purpose, but they function together to sell and buy energy in advance, yet be able to correct for uncertainties in energy consumption and production as 'real-time' approaches in order to secure stability. Because of the uncertainty in energy production and consumption, a large portion of energy is sold on the spot market. However, because it requires some planning to produce and deliver the energy the correct amounts, the spot market is split in a day-ahead market and an intraday market. Most of the energy sold on the spot market is sold on the day-ahead market, which is one day before real-time. The different timescales, and specifically the day-ahead market will be discussed in more detail in the next section. Because the demand differs strongly throughout the day, prices fluctuate from hour to hour and are highly volatile. The price mechanisms will also be discussed more thoroughly in later sections.

When talking about modeling the electricity market in this thesis, sole focus will be on the wholesale market segment of the electricity market. The other two segments, being the transmission-distribution market and the retail market, are assumed 'given' in such models. Below these two segments of the electricity market are shortly touched upon, but thereafter this appendix will continue with more in-depth information about the wholesale market.

A-1-3 Transmission and distribution market

The transmission and distribution market is responsible for transferring the actual physical energy from the generator to the consumer. The energy is transmitted from energy generators to different parts of the country over the transmission network. This is a high-voltage network (above 110kV) managed by the Transmission System Operator (TSO), which is TenneT in The Netherlands. TenneT is a state-owned energy company. They secure stability of the power grid by making sure supply and demand match up in real-time, and that frequency stays around 50Hz, by deploying various instruments such as regulating capacity and reserve capacity.

Transmitting energy from the high-voltage network to consumers is done by distribution networks that gradually lower the voltage as cable lengths decrease, until it is at 230V. These medium- and low-voltage distribution networks are managed by several companies called Distribution Systems Operators (DSOs) and they ensure that everyone has access to electricity. Each DSO has a monopoly in their region and therefore they are being regulated by the state. Financial compensation for the expenses a DSO has, is determined on yearly basis. Part of this is paid by market participants in the form of a monthly fee for being connected and a variable fee based on the amount of energy transported. Stedin, Liander and Enexis are the biggest DSOs in The Netherlands.

The TSO and DSOs in The Netherlands may not participate in market activities such as buying and selling energy for own profits. This ensures their investments remain independent from commercial interests on the energy market.

A-1-4 Retail market

Private costumers such as small businesses and households buy their energy on the retail market. The actual energy is supplied by the DSO in that respective area, but the retailer of choice has to make sure that energy is bought on the wholesale market. Private costumers and retailers often engage in "long-term" contracts of 1-, 3- or 5-years with fixed prices per kWh. Some contracts do have a peak and a base price, based on the time of day, but compared to the wholesale market, prices hardly fluctuate, if they even do. Where electrical energy is sold on the wholesale market for an average around 40 €/MWh, or 0.04 €/kWh, consumers on the retail market pay a much higher price for energy, averaging around 0.21 €/kWh. This higher price on the retail market is for taxes, network and transmission tariffs, and a retailer fee.

Eneco, Essent and Vattenfall are among the larger retail companies in The Netherlands, they have the largest costumer base and also have their own energy generators. Still there are also many smaller retail companies, including a large amount of subsidiary companies. The big retail companies used to also distribute the electricity, but they were forced to split up before 2011 following new laws. This created distribution companies Stedin, Enexis and Liander respectively, among some smaller ones.

A-2 Structure of the Wholesale Market

Energy is traded on the wholesale market in different forms with different timescales. The largest open exchange market for the Western-Europe region is called the European Power Exchange (EPEX). This is where market players from Germany, France, the United Kingdom, the Netherlands, Belgium, Austria, Switzerland and Luxembourg can sell and buy their electricity on a futures market and a spot market. Recently the European Union has allowed multiple power exchanges on the same market, so competitors have joined the market. Since 2019 the Scandinavian exchange Nord Pool is also active on the markets in Western-Europe. Moreover there is a forward market which trades energy on a similar timescale as the futures market, but with non-standardized contracts and in an over-the-counter deal with usually only two parties involved.

The spot market is divided in a day-ahead market and an intraday market, with the day-ahead market accounting for about 35% of total energy supplied and intraday for about 3-4% [25]. There is also a fair amount of over-the-counter (OTC) energy trade, which is non-transparent trading of energy, strictly between two parties. Especially in the forward market and the intraday market a lot of energy is traded OTC. If there is still a miss-match between demand and supply in real-time after all the trading has taken place, the TSO uses the balancing market to guarantee stability on the power grid. Figure 2-2 shows a simplified timeline of the electricity market.

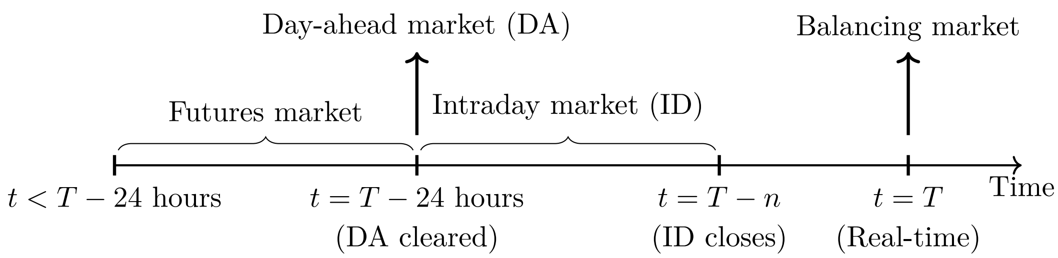


Figure A-1: Simplified timeline of the electricity market

A-2-1 Futures and forward market

The futures market and forward market are places where energy is traded far in advance. On the EPEX, energy futures can be sold no longer than 6 years ahead and only with two prices: peak and base price. The EPEX futures market is still rather small however and most energy futures are actually traded OTC on the forward market, so there is little insight in the precise contracts for energy forwards [25]. Prices for most forward contracts are said to be based upon current spot prices on the day-ahead market[1]. Therefore forward contracts could be seen as a way to speculate on the spot prices going up or down in the coming years. Price calculation methods for energy futures/forwards such as cost-of-carry that are common in other commodities, do not apply to energy futures/forwards since energy can typically not be stored.

For an energy generator, energy futures/forwards are a secure way of getting returns on their capital investment. This way of reducing risk is typically called hedging. For an energy consumer with a practically fixed demand, such as an energy retailer, it can be a good way to avoid extremely high peak prices if they consume most of their energy during peak hours and are unable to change this [25]. Energy consumers that are more flexible, for example steel or aluminium producers, are not in such need of futures/forward contracts, because they can limit their energy usage when prices rise above a certain level. The factory stops producing steel or aluminium temporarily and continues again when energy prices have decreased again. Sticking mostly to the day-ahead market for energy trading is often their most economic strategy.

A-2-2 Day-ahead market

The day-ahead market is where about 35% of total energy volume is traded (around 40 TWh per year in The Netherlands) [25]. It is a blind auction divided in 24 blocks of one hour for each day. Both suppliers and consumers place bids for energy volumes with prices for each hour of the next day. At 12:00 at noon the day before, the supply bids and demand bids are matched on trading volume to ensure grid stability [23]. Clearing is performed by a power exchange or by an organisation related to the power exchange, for the EPEX this is the ECC (European Commodity Clearing). This clearing results in a market clearing price. A merit order is used to sort the bids of the different electricity generators from low to high, which will be elaborated on in more depth in subsection 2-2-3.

The day-ahead market is regarded as the main market for electricity trading since it trades the largest transparent quantities of energy and has most participants [23]. The electricity price on the day-ahead market is therefore also commonly seen as the general price for electricity [25].

A-2-3 Intraday market

After the market has been cleared on the day-ahead market, participants may still want to trade energy because their expected production or expected demand has changed. This can be done on the intraday market. Bids can be submitted on the open exchange or energy can be traded in bilateral contracts. Instead of blocks of one hour, energy is traded in blocks of 15 minutes on the intraday market. The market closes a few minutes before real-time, which is called the lead time. This lead time has decreased significantly over the last years

[1] Literature on electricity futures is scarce, these insights are therefore based on claims by experts.

in many countries. In Germany and the Netherlands the lead time is now 5 minutes. The intraday market is much smaller than the day-ahead market, although the volume traded on the intraday market is growing due to uncertainties in renewable energy production [23], [87].

A-2-4 Balancing market

The balancing market is the final market in place to match demand and supply in real-time. More accurately, its task is to keep the frequency around 50 Hz. This is actively managed by the TSO and achieved through energy suppliers providing ancillary services. There is a variety of services, differing in size and time of deployment. The balancing market is the most complex part of the energy system, involving different products to ensure stability of the power grid. Market participants can submit bids for the different products to not produce planned energy supply when there is excess supply in real-time, and they can submit bids to supply additional energy when there is excess demand [83]. Typically suppliers will bid to the pay the TSO a price to not supply energy that is under their operating costs when there is excess supply. Similarly they will bid to receive a compensation from the TSO that is higher than their operating costs when there is excess demand [23]. For now this market is beyond the scope of this research, so a more detailed description will be left out. Its smaller size and even more volatile prices can however definitely be interesting for future research. Also this market is expected to grow in volume in the upcoming years with higher penetration of RES [88].

A-3 Market Policies

This section will discuss different market policies that policymakers could implement, that would drastically change how energy is traded. Currently in The Netherlands we have an energy-only market with uniform pricing (a market clearing price), and although it is probably not necessary to change this anytime soon even with our energy supply becoming more uncertain in the future [89], it is relevant to understand that different market policies do exist and may actually be implemented somewhere in the future. As a matter of fact, in the United States for example, most markets are capacity markets and only few are strict energy-only markets. Across Europe there is also a variety of different markets.

A-3-1 Energy-only markets or capacity markets

The energy-only market is a market where only energy is traded. Consumers only pay for every kWh of energy they consume. Suppliers have to work efficiently and keep their cost to a minimum to earn money, since they will only make money on the surplus of the actual energy they sell. The biggest drawback is that the demanded energy may not be guaranteed at all times, especially during peak hours, since suppliers may not want to invest in extra generators that they can only use during peak hours [27].

A capacity market on the other hand is one where consumers have to reserve a certain amount of power capacity on long-term basis and pay for this capacity, independent of whether they use up all the capacity in a specific moment or not. If a consumer exceeds its capacity, steep premiums will have to be paid for the extra power, to make sure consumers do not buy too little capacity. This guarantees that demand can always be met, since suppliers receive money for having a generator available, regardless of whether they need to supply.

From a strictly economic consumer point-of-view the capacity market is inefficient, because the consumer needs to pay for power that it often will not use. It can however provide stability to the power grid and prevent black-outs when demand is high. Therefore several countries opt for a hybrid form. France for example uses a capacity market on a number of days each year in winter, when demand is much higher than usual. The rest of the year the energy-only market suffices. In The Netherlands an energy-only market is the only market.

A-3-2 Uniform pricing or pay-as-bid pricing

There are different pricing rules to determine the electricity prices on an open exchange market. The two main pricing rules are uniform pricing and pay-as-bid pricing [90].

The Dutch day-ahead market is cleared for each day around noon on the day before using uniform pricing. The market clearing is done using the merit order that will be discussed in detail in subsection 2-2-3. The supply side bids are matched with the bids on the demand side and a market clearing price is determined, which is the highest bid on the supply side that may still supply. Subsequently all suppliers receive this market clearing price for their supplied energy. As a result suppliers bid at their running costs, since they will get the price of the highest participating bid anyways. Another option is the pay-as-bid market, where bids are directly matched between suppliers and consumers, and everyone receives or pays the price they have bid, instead of a market clearing price. This increases competitive behaviour between suppliers in their bidding, and this would seem beneficial for consumers. However suppliers may start bidding strategically, to secure their profits, thus driving the prices up. This would be even more undesirable if suppliers of RES start bidding strategically, because this could mean that sometimes practically free energy from wind or sun with no emissions is wasted, simply because they had bid higher than fossil fuel generators. Nevertheless RES generators one way or another will have to bid above their running costs to be able to retrieve enough surplus to earn their capital costs back. There is still debate on what the optimal pricing rule actually is, and it seems to depend on the specifics of each market [90].

A similar choice between clearing price and pay-as-bid can be made for the balancing market, where a pay-as-bid system can ensure lower costs for the TSO, since it does not have to pay the price of the highest bidder to all suppliers. It may however actually also cause strategic bidders that bid way above their running costs and push the total costs [91]. This is especially a risk on the balancing market since there are fewer players on the balancing market than on the day-ahead market.

Appendix B

Energy Demand

B-1 Daily demand

In Figure B-1 the demand in The Netherlands throughout one day is shown in a load curve, in this case for a Thursday in February. Peaks can be seen in the morning around 09:00 when the work day starts, and around 18:00-19:00 when people get home after work. These peaks seem larger than they are in absolute figures, because the y-axis in this graph starts with an offset of 13 GW and not at 0 GW. The base load of around 14 GW is in fact much more than the 4 GW difference between the largest and smallest load. This base load consists of many larger household appliances that are always or very often switched on such as refrigerators. Additionally industry has a big contribution to this base load, in the form of for example industrial motors and large furnaces [92].

Looking at a Saturday in Figure B-2 shows a similar pattern, although the peak in the morning is now much smaller than the peak in the evening. This is typical for the weekend, since for most people this is not a work day and many companies are closed. Also the height of the peaks and the base demand are lower on the Saturday than on the Thursday.

B-2 Weekly demand

In a plot of the load throughout a week this difference between days of the week is more clearly visible. Figure B-3 shows the load from Thursday to Thursday. The two weekend days of the week clearly have lower peaks, but also show lower base demand.

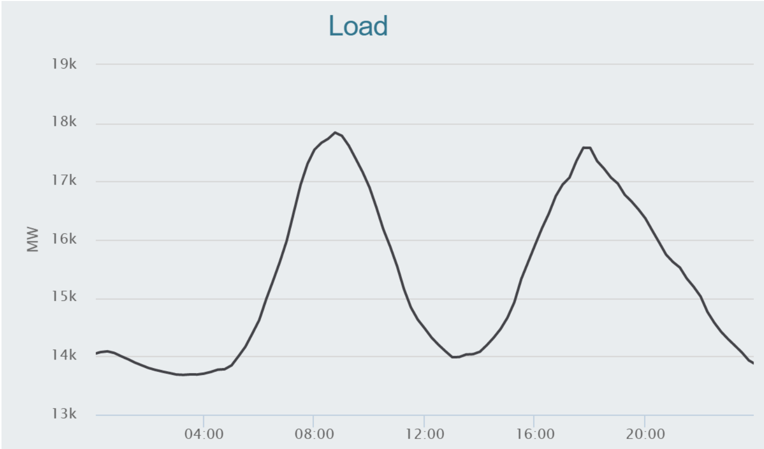


Figure B-1: Load curve on the Dutch power grid on Thursday 11 february 2021 [1]

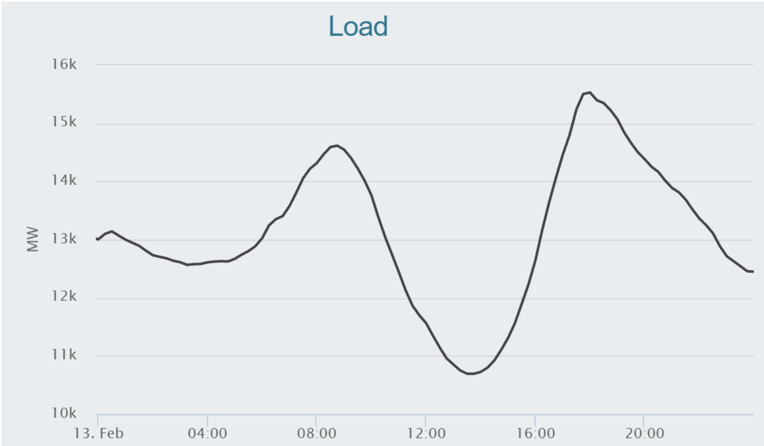


Figure B-2: Load curve on the Dutch power grid on Saturday 13 february 2021 [1]

B-3 Seasonal demand

Yearly demand is shown in Figure B-4. Seasonal effects can be found in the graph on the right, in winter months the demand is about 15% higher than in summer months. A second observation is that during the winter months up to 0.5 TWh of energy is exported and during the remaining months up to 2 TWh is imported. Over the years, demand has been fairly stable, as can be seen in the left plot. Important is that these graphs represent total energy consumption during one month, instead of average power consumption. Dividing the values by the amount of hours in one month or one year gives the average power consumption.

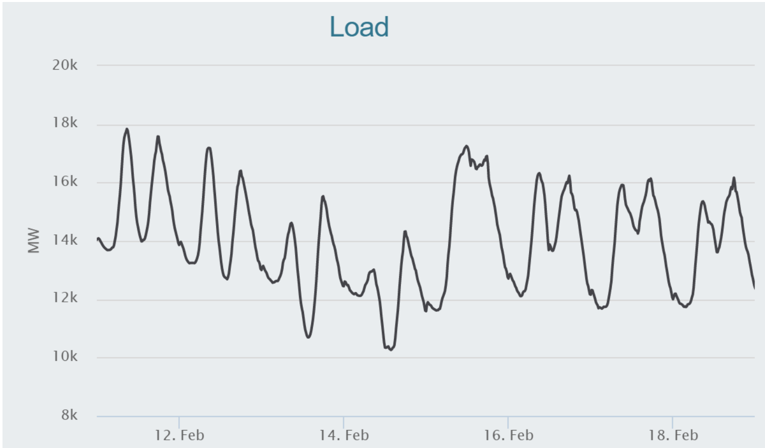


Figure B-3: Load curve on the Dutch power grid over one week in 2021 [1]

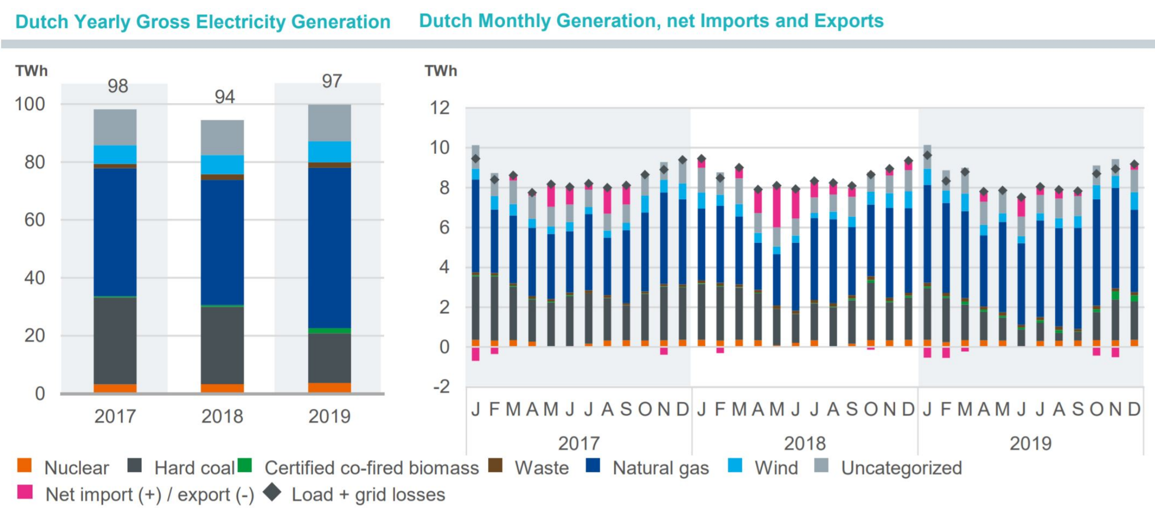


Figure B-4: Generation and load on the Dutch power grid per year (on the left) and per month (on the right) over several years [3]

Appendix C

Energy Supply

There are many different ways to produce electrical energy to match the energy demand, each having different costs, flexibility in usage, and side-effects to for example climate or landscape. To accommodate a stable and cost-effective electricity network, most countries have a diverse portfolio of electricity generators to meet the different requirements the market has [23]. This ranges from renewable energy sources (RES) such as wind and solar power, to traditional nuclear, coal and natural gas plants.

RES have running costs close to zero, reasonable capital costs, but their intermittent weather-dependent generation makes their energy production less constant and less reliable. Coal and nuclear are typical base load generators with high capital costs, low to medium running costs, and slow dispatch-ability. Gas plants are usually used as peaking plants, they are often cheaper and easier to build than coal and nuclear plants, have fast dispatch-ability, but also high running costs. Table C-1 provides a summarized overview of the different generators and their characteristics [7], [23]. These categories are simplified and generalized to prevent the information from becoming overly complex. Individual generators within a certain generation category may actually differ to quite some degree, especially for gas plants there is a wide range of options.

Category	Wind	Solar	Nuclear	Coal	Gas
Capital costs	Medium/High	Medium	Very high	High	Medium
Running costs	Very low	Very low	Low/Medium	Medium	High
Dispatch-ability	Very little	None	Slow/Medium	Medium	Fast
Emissions	Low	Low	Low	High	Medium
Landscape usage	High	High	Low	Low	Low
Alternative location	Off-shore	Rooftops	Industrial site	N/A	N/A
Time of day	Depends on wind	Only daytime	All day	All day	All day

Table C-1: Advantages and disadvantages of different energy generators

C-1 Capital costs and running costs

The costs for each generator can be separated in capital costs and running costs.

The capital costs of a generator are all the fixed costs for building and decommissioning a generator, and connecting it to the power grid. These costs are usually large investments and take years to earn back [93].

Running costs involve all costs for operating the generator. These involve fuel and labor costs, but also maintenance costs [93]. Running costs determine whether or not a generator is deployed at a certain moment. Even when capital costs for a generator are relatively low, it may be hardly deployed if running costs are high. When a generator is deployed at a certain hour, the difference between the running costs per MWh and market clearing price per MWh at that hour is the surplus. Accumulated surplus over the years must ensure investment in capital costs is earned back.

The capital costs and running costs can be combined with an expected amount of energy generated over the lifetime of a generator. This results in a Levelized Cost of Energy (LCOE) and represents the total amount of costs divided by the total amount of energy produced [93]. While total capital costs and running costs per MWh may be reasonably easy to compute in advance, predicting the total amount of energy that will be produced is much more difficult, since it depends on unexpected downtime and supply may fluctuate with future market demand. Furthermore different evaluation factors such as job creation or environmental damage may be difficult to express in precise numbers. Especially for generators with a long life span all these factors cause a lot of uncertainty. Also because of this uncertainty, supporters of a certain type of generation may estimate their costs too optimistically and as a result it could be assumed there is some bias in the calculations. So comparisons of Levelized Cost of Energy must be approached carefully and with caution, and possibly taken with a grain of salt if very precise values are given.

For the intermittent energy sources, such as wind and solar, running costs or LCOE of the windfarm or solar panel park alone do not reveal the entire picture. Storage costs must also be taken into account, since large scale energy storage is unavoidable with a high penetration of solar and wind energy [94], [95]. As long as renewable energy is still a small portion of total energy supply, calculating the costs of only wind and solar may be sufficient, but as penetration increases, storage must be included in the calculations as well.

C-2 Greenhouse gas emissions

The goal of moving away from fossil fuels is to reduce the emission of green house gases. The different types of energy production all have different amounts of green house gas emissions. Coal is the most polluting form of electricity generation with around 800-1000 grams of CO_2 equivalent per kWh over lifetime, followed by natural gas at 200-500 grams of CO_2 equivalent per kWh over lifetime. Wind, solar and nuclear generation have no emissions of greenhouse gases during generation. They only emit greenhouse gases during the production of building materials and the construction phase. For nuclear plants there are also some emissions while mining, transporting and enriching uranium. Nevertheless emissions are low at around 10-20 grams of CO_2 equivalent per kWh over lifetime for nuclear and wind. Solar is slightly higher at around 40-50 grams of CO_2 equivalent per kWh over lifetime, although this value is still decreasing. [96], [97], [98]

To make polluting technologies economically less interesting, the European Union introduced CO_2 emission rights. To emit CO_2 companies must have enough allowances. These allowances can be traded on a European CO_2 emission allowances market. As less allowances are given out each year, the price for emitting one tonne of CO_2 rises. This has a large effect on the running costs of very polluting generators [99].

An alternative to using less polluting energy sources is capturing and storing the carbon dioxide before it is released into the air. This process is called carbon capture and storage (CCS) and makes it possible to keep using fossil fuels for energy production [100]. It is a technology that is still actively researched and the first large-scale projects have been build in recent years. In the future, part of the energy demand could be supplied using traditional natural gas generators using this technique if it proves economically viable.

Appendix D

Optimization for Energy Arbitrage

Energy arbitrage is the business of buying electricity when prices are low and selling it again when prices are high [58]. Since prices on the electricity market are very volatile and shifts from high to low prices occur daily energy arbitrage is a useful way to earn money with an electricity storage. To take advantage of this, the buying and selling needs to be performed at the optimal moments. This requires an optimization strategy.

Different approaches have been presented in literature to optimize for energy arbitrage. Early methods were primarily optimization-based [101], [102], [62], [38], [103]. Alternatively a Markov Decision Process (MDP) was formulated and solved using dynamic programming in [104], [105], [106]. More recent approaches include Reinforcement Learning (RL) [107], [108], [109] or a Model Predictive Controller (MPC) [110], [111].

In [111] and [62] it is concluded that using only energy arbitrage is not economically viable at the moment due to high capital costs for energy storage. For now energy arbitrage should be combined with providing ancillary services. As the balancing market is much smaller and therefore quickly saturated, this approach is not scalable. For large-scale grid storage, energy storage costs should drop first. Which explains why large-scale grid storage is still a few years away as discussed in Section 4-1 already.

All the above papers use a price-taking model; it is assumed that the traded quantities are so small that they do not influence the prices. In [112] there is a simple price-making model proposed for the balancing market. This predicts a supply curve for each time step to find how the price adjusts when supplying ancillary services with a battery storage system. In this case the price and the quantity sold are directly related.

This small-scale implementation of price-making usage of storage already shows the importance of including price dynamics. The paper concludes that the concurrent price-taking model overestimates potential profits because it misses the price dynamics. Therefore quantifying price changes becomes important for both consumers and investors. This confirms the importance of the included price dynamics in the Economic Engineering model in Chapter 4.

Appendix E

Price-Quantity-Duration Curve

It is useful to see how prices vary over certain time period. To this end the price-duration curve is often used. This appendix will go into more detail in the price duration curve and discusses an extended version of it.

E-1 Price-Duration Curve

To learn more about prices in the long-term a price-duration curve is used. The price-duration shows how many percent of the time, or how many hours during a certain period of time, the price of energy exceeded a certain price level. It presents a list of price levels during each hour over a certain time span, sorted by price from high to low. Commonly it shows the prices over a time span of a year. The price-duration curve gives insights in the variation in the prices [2].

Figure E-1 shows the price duration curve for the Netherlands in 2017 [2]. Most of the year (around 6000 hours per year) the price is between €50 and €30 per MWh. Some of the time the price drops to very low levels, because demand is very low some hours and because RES with low operating costs already started to provide some fair amounts of the energy production during sunny hours with a lot of wind.

E-2 Load-Duration Curve

Sorting the data on a load curve, by amount of load from high to low, gives a load-duration curve. This is very useful for identifying a practical mix of generators in the generator portfolio. Traditionally coal plants or nuclear energy plants are suitable for covering the base load, since they are fairly affordable to operate continuously. Meanwhile they cannot be ramped up and down as quickly as gas plants, so these gas plants with higher operating costs but lower capital costs are used for load-following and to cover the peaks. In Chapter 4 the price duration and load duration curve are combined to create more understanding of the market. In Chapter 5 these duration curves are used to quantify price changes.

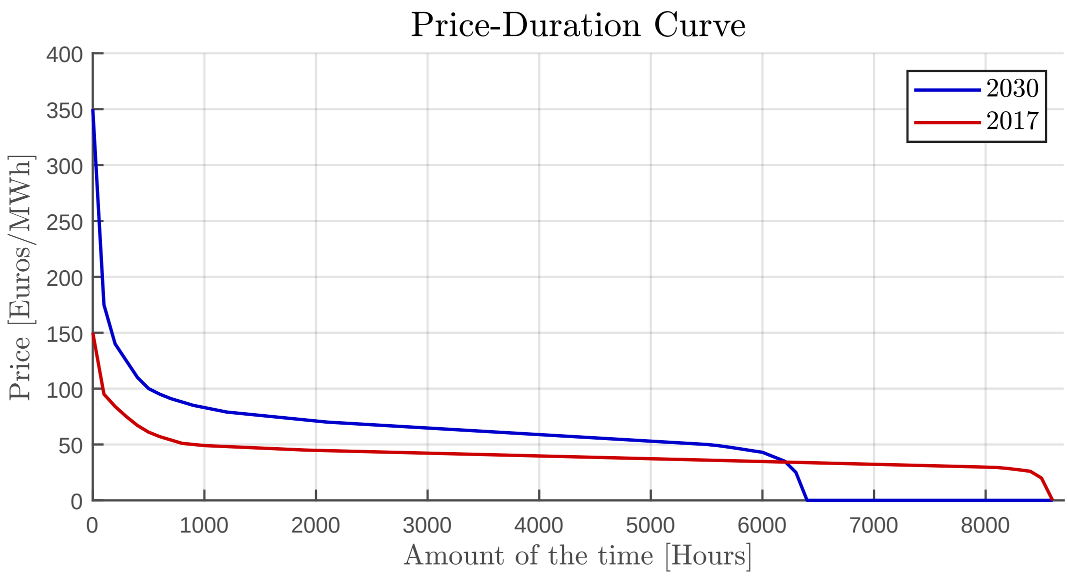


Figure E-1: Price duration curve for The Netherlands in 2017 and a prediction for 2030 [2].

E-3 Price-Quantity-Duration Curve

The price-duration curve as shown in Section E-1 gives information on the price distribution over a certain period of time, commonly one year. It does however miss one critical piece of information: the x-axis is presented in hours, but the amount of electrical energy in MWh sold during such an hour is missing from the graph. The load distribution function shown in Section E-2, does show the load, but now the prices are missing. So I will combine these two distributions to find useful information of the price distribution for all energy sold over a period of time: a weighted price-duration curve. I call this the price-quantity-duration curve.

This new price distribution curve I propose can be found by making a list of the price of each MWh sold during a year. This list is sorted by price from high to low to give a distribution with price on the y-axis and total amount of MWh sold on the x-axis. This distribution shows what amount of MWh or what percentage of MWh was sold above a certain price.

It is possible to build such a graph with real data, by buying the price and load data from the different power exchanges, but for now a fictive graph is drawn to present the main ideas. This graph is shown in Figure E-4, price is on the y-axis and MWh sold on the x-axis. The shape is similar to the price duration curve, although the peak at the top is a bit wider, since the prices will typically be high during hours that the quantity demanded is also high. Although the axis are price and product, this is not phase space. p and z are not directly related as in phase space, so this is merely a list of prices.

If storage is now introduced and if unlimited energy capacity without storage costs is assumed, then every MWh with a price p lower than p^* at h, which is 50% of the total volume sold, will now be stored instead of sold paying price p^* for this to the supplier. Likewise every MWh with a price above p^* will now be sold from storage at price p^*. In this way the total volume stored b and total volume sold from storage a are equal and the price curve is a completely horizontal line now.

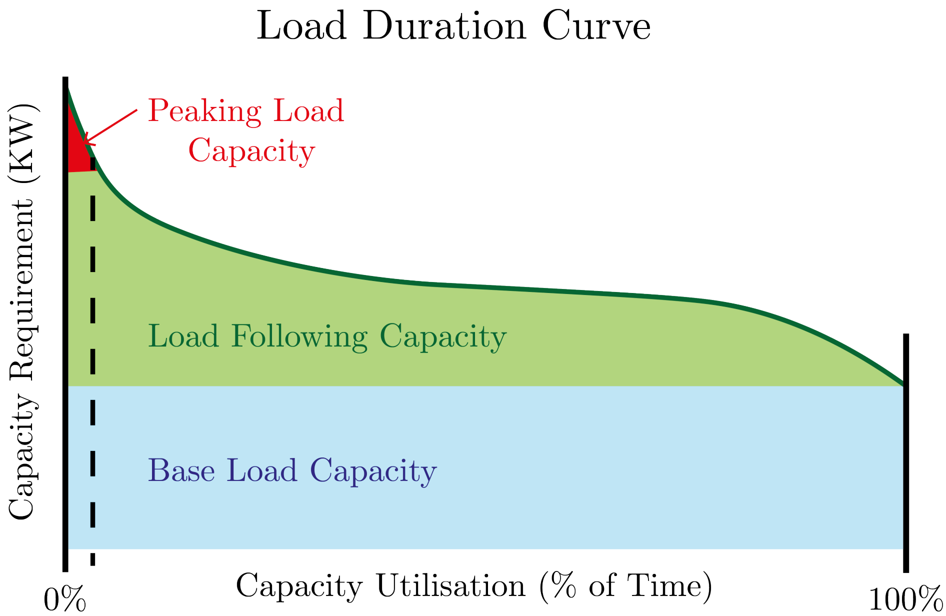


Figure E-2: Load-duration curve showing power capacity distribution over time

The mechanical analogy of this behavior in Figure E-5 can be explained with a spring of infinite length. This is shown in Figure E-3. The whole system is initially moving at velocity v with respect to the reference frame, so the mass has momentum p^*. If the wall decreases velocity with respect to the reference frame, the mass that is connected to this wall with a spring of infinite length will not follow. Instead the spring will start extending and an input force opposite to the changing velocity will keep the mass moving with the original momentum, which is analogous to storing electrical energy in the economic domain. This input force can be seen as bidding on the demand side by the trader. When the velocity of the wall with respect to the reference frame then increases because of a demand shift, the spring will start compressing again, reducing the amount of electrical energy in storage. The momentum of the mass however stays the same throughout these demand shifts and therefore the price will remain at price p^*.

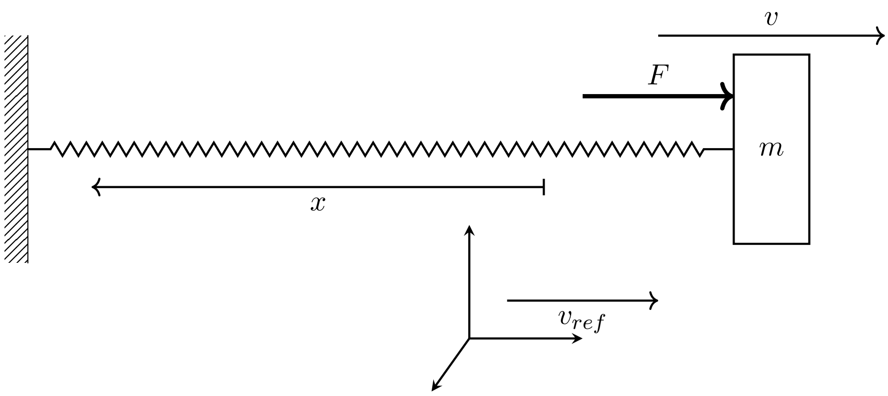


Figure E-3: Mechanical analog of infinite power and energy capacity

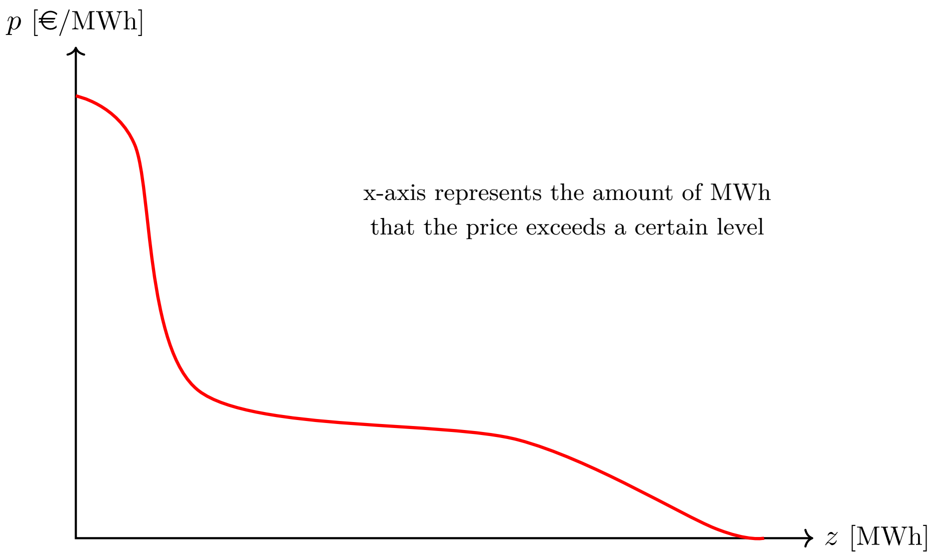


Figure E-4: Fictional price-quantity-duration curve

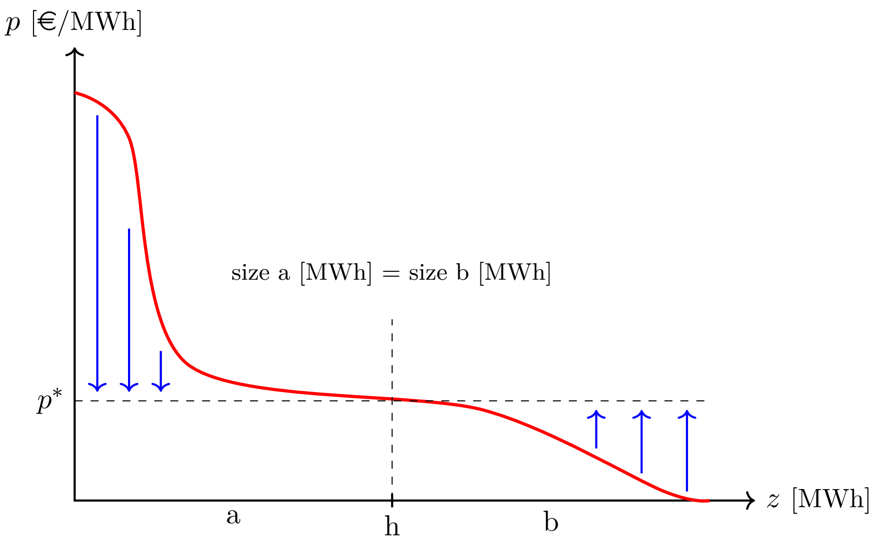


Figure E-5: Distribution for price per MWh sold with storage

Appendix F

Matlab Files

Matlab file for the Economic Model Predictive Controller, written using the YALMIP toolkit [79].

```
%% Economic Model Predictive Controller

yalmip('clear')
close all
clear all
tic

p_S_0                = 50;        % Starting market price
p_B_0                = 0;         % Starting reservation price battery (relative to market price)
p_H_0                = 0;         % Starting reservation price hydrogen (relative to market price)
p_SD_0               = 0;         % Starting reservation price shifted demand (relative to market price)
q_B_0                = 0;         % Starting storage level battery
q_H_0                = 0;         % Starting storage level hydrogen
q_SD_0               = 0;         % Starting storage level shifted demand

C_battery            = 200;       % Convenience rate curve battery
C_hydrogen           = 200;       % Convenience rate curve hydrogen
C_shiftdemand        = 200;       % Convenience rate curve shfited demand
R_element            = 0.01;      % Stiffness of clearing house (bigger is stiffer)
I_D                  = 0.02;      % Price elasticity of demand

c_battery            = 12.5;      % Storage costs
c_hydrogen           = 2.5;       % Storage costs
control_penalty      = 100;       % Risk aversness of trader (higher is more risk averse)
efficiency_battery   = 0.05;      % Round-trip efficiency losses
efficiency_hydrogen = 0.25;       % Round-trip efficiency losses

x0                   = [p_B_0;p_H_0;p_SD_0;p_S_0;q_B_0;q_H_0;q_SD_0];
```

```

Ts                  = .25;
Days                = 14;
Hours               = Days*24;
Timesteps           = (Hours/Ts)+1;
Days_horizon        = 2;
Horizon             = Days_horizon*24/Ts;
default_demand      = 13000;
I_elements          = 0.0035;

dim.N=Horizon;                      %prediction horizon



%% Demand

% Define some demand vector here....

%% Price elasticity vector

I_value = I_elements*ones(Timesteps+dim.N,1);

for j=1:length(u_1)
    if u_1(j) > 15500
    I_value(j) = 0.008;
    else if u_1(j) > 13000
    I_value(j) = 0.0035;
    else if u_1(j) < 11000
    I_value(j) = 0.002;
        end
      end
    end
end

%% Define decision variables
u_B = sdpvar(repmat(dim.nu,1,dim.N),repmat(1,1,dim.N));
u_H = sdpvar(repmat(dim.nu,1,dim.N),repmat(1,1,dim.N));
u_SD = sdpvar(repmat(dim.nu,1,dim.N),repmat(1,1,dim.N));
w = sdpvar(repmat(dim.nw,1,dim.N),repmat(1,1,dim.N));
p_B = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
p_S = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
p_H = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
p_SD = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
q_B = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
q_H = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
q_SD = sdpvar(repmat(dim.price,1,dim.N+1),repmat(1,1,dim.N+1));
I_element = sdpvar(repmat(1,1,dim.N),repmat(1,1,dim.N));
shifted_D = sdpvar(repmat(1,1,dim.N),repmat(1,1,dim.N));

constraints = [];
objective = 0;

%% Define cost function/system dynamics/controller

for k = 1:dim.N

 % Objective Function
```

```
    objective = objective +  (p_S{k} * (-(p_B{k})/I_element{k})) + (p_S{k} * (-(p_H{
        k})/I_element{k})) + (p_S{k} * ((-p_SD{k})/I_element{k})) - abs(c_battery*(
        p_B{k})/I_element{k}) - abs(c_hydrogen*(p_H{k})/I_element{k}) - 1/2*
        control_penalty*u_B{k}^2 - 1/2*control_penalty*u_H{k}^2 - 1/2*control_penalty
        *u_SD{k}^2;

    % Dynamics
    constraints = [constraints, p_B{k+1}   == p_B{k}+Ts*(-q_B{k}/C_battery + u_B{k})
        ];
    constraints = [constraints, p_H{k+1}   == p_H{k}+Ts*(-q_H{k}/C_hydrogen + u_H{k
        })];
    constraints = [constraints, p_SD{k+1}  == p_SD{k}+Ts*(q_SD{k}/C_shiftdemand +
        u_SD{k})];
    constraints = [constraints, p_S{k+1}   == p_S{k}+Ts*R_element*(w{k} + p_B{k}/
        I_element{k} + p_H{k}/I_element{k} + p_SD{k}/I_element{k} - p_S{k}/I_element{
        k} - (p_S{k}-p_S_0)/I_D)];
    constraints = [constraints, q_B{k+1}   == q_B{k}+Ts*(p_B{k}/I_element{k}-
        efficiency_battery*abs((p_B{k})/I_element{k}))];
    constraints = [constraints, q_H{k+1}   == q_H{k}+Ts*(p_H{k}/I_element{k}-
        efficiency_hydrogen*abs((p_H{k})/I_element{k}))];
    constraints = [constraints, q_SD{k+1}   == q_SD{k}+Ts*(-p_SD{k}/I_element{k})];

    %Constraints
    constraints = [constraints, -2500<=q_B{k}<=2500];     % Constraints on storage
        level
    constraints = [constraints, -2500<=q_H{k}<=2500];     % Constraints on storage
        level
    constraints = [constraints, -500<=q_SD{k}<= 500];     % Constraints on storage
        level

    %Terminal constraints
    if k == dim.N && terminal_constraint == 1
    constraints = [constraints, 0<=q_B{k+1}<=0];          % Terminal constraint on
        storage level
    constraints = [constraints, 0<=q_H{k+1}<=0];          % Terminal constraint on
        storage level
    constraints = [constraints, 0<=q_SD{k+1}<=0];         % Terminal constraint on
        storage level
    end
end

% Defining input and output variables
parameters_in = {p_B{1},p_H{1},p_SD{1},p_S{1},q_B{1},q_H{1},q_SD{1},[w{:}],[
    I_element{:}]};
solutions_out = {[u_B{:}],[u_H{:}],[u_SD{:}],[p_B{:}],[p_H{:}],[p_SD{:}],[p_S
    {:}],[q_B{:}],[q_H{:}],[q_SD{:}],objective};

options = sdpsettings('solver','quadprog');

% formulate controller; use minus sign before "objective" to maximize instead
% of minimize
controller = optimizer(constraints,-objective,options,parameters_in,solutions_out
    );

%% Define initial conditions and disturbance vector
x = x0;
demand = u_1(1:dim.N,1)';
```

```
states = [];

brownian_noise = randnd(-2,Timesteps*2,1); %create a vector of brownian noise

%% Run MPC over time
for i = 1:Timesteps

  % Add brownian noise
  if i>1
  demand = [demand(2:dim.N) u_1(i+dim.N-1)+demand(dim.N)-u_1(i+dim.N-2)]; %re-use previous demand vector but shift it one timestep
  end
  deviation = brownian_noise(i);
  for z = 1:dim.N
  demand(z) = demand(z)+(Ts*z*deviation/20);
  end

  I_values = I_value(i:i+dim.N-1,1)';

  % Define current states
  pB     = x(1);
  pH     = x(2);
  pSD    = x(3);
  pS     = x(4);
  q_B    = x(5);
  q_H    = x(6);
  q_SD    = x(7);

  % Solve the optimization problem
    [solutions,diagnose] = controller{pB,pH,pSD,pS,q_B,q_H,q_SD,demand,I_values};

  U_B  = solutions{1};
  U_H  = solutions{2};
  U_SD = solutions{3};
  P_B  = solutions{4};
  P_H  = solutions{5};
  P_SD = solutions{6};
  P_S  = solutions{7};
  Q_B  = solutions{8};
  Q_H  = solutions{9};
  Q_SD = solutions{10};

   x = [pB + Ts*(-q_B/C_battery + U_B(1));
      pH + Ts*(-q_H/C_hydrogen + U_H(1));
      pSD + Ts*(q_SD/C_shiftdemand + U_SD(1));
      pS + Ts*R_element*(demand(1) - (pS-p_S_0)/I_D + pB/I_values(1) + pH/I_values(1) + pSD/I_values(1) - pS/I_values(1));
      q_B + Ts*(pB/I_values(1)-efficiency_battery*abs((pB)/I_values(1)));
      q_H + Ts*(pH/I_values(1)-efficiency_battery*abs((pH)/I_values(1)));
      q_SD + Ts*(-pSD/I_values(1))];

  states = [states x];

end

toc
```

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Glossary

List of Acronyms

RES	renewable energy sources
TSO	Transmission System Operator
DSO	Distribution System Operator
DSOs	Distribution Systems Operators
OTC	over-the-counter
LCOE	Levelized Cost of Energy
EPEX	European Power Exchange
DR	demand response
SD	shifted demand
SG	smart grid
MPC	Model Predictive Controller
RMPC	Robust Model Predictive Controller
SMPC	Stochastic Model Predictive Controller
EMPC	Economic Model Predictive Controller
RL	Reinforcement Learning
MDP	Markov Decision Process
CCS	carbon capture and storage
PI	Proportional Integral
NPV	net present value
RTO	real-time optimization
DA	day-ahead market
ID	intra-day market

List of Symbols

Abbreviations

ϵ	Price elasticity
ϵ_S	Price elasticity of supply
η	Efficiency
C	Convenience yield curve
c	Storage costs
F	Market clearing force
I	Demand or supply
I_D	Market demand
I_S	Market supply
J	Objective function
k	Discrete time
MS_f	Modulate flow source
p_B	Reservation price battery storage
p_H	Reservation price hydrogen storage
p_S	Market clearing price
p_T	Reservation price storage
p_{SD}	Reservation price shifted demand
q_B	Storage level battery
Q_D	Quantity demanded by the consumers
q_H	Storage level hydrogen
Q_L	Quantity lost because of efficiency losses
Q_S	Quantity supplied by all suppliers
Q_T	Quantity demanded by storage
q_T	Storage level
Q_{DR}	Quantity demanded due to demand response
Q_{SD}	Quantity demanded due to shifted demand response
q_{SD}	Backlog shifted demand
R	Aggressiveness of clearing house
R_{risk}	Risk-averseness of trader
S_e	Effort source
S_f	Flow source
T	Length of prediction horizon
t	Time
T_s	Sampling time
u	Control input