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Faculty of Electrical Engineering
Department of Economics, Management and Humanities

Modeling of Electricity Markets Using an Agent-Based Simulator

Master Thesis

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1. Hamill L., Gilbert N.; Agent-Based Modelling in Economics; 2016; Surrey; John Wiley & Sons, Ltd.
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3. Santos G., Pinto T., et al.; Multi-agent simulation of competitive electricity markets: Autonomous systems cooperation for European market modeling; 2015; Porto, Denmark; ELSEVIER

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III. Assignment receipt

The student acknowledges that the master's thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the master's thesis, the author must state the names of consultants and include a list of references.

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"I hereby declare that this master's thesis is the product of my own independent work and that I have clearly stated all information sources used in the thesis according to Methodological Instruction No. 1/2009 – "On maintaining ethical principles when working on a university final project, CTU in Prague".

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Abstract

The creation of a fully integrated European electricity market is barred by physical constraints which are caused by the special character of the traded good. Capacity congestions between different European market areas require an economically efficient approach to exploit the available cross-border capacity optimally. Building larger coupled regions using the same clearing mechanisms, the European electricity markets are in constant transition. The available cross-border capacity can be determined with nodal, Available Transmission Capacity (ATC), or flow-based market coupling. In Europe, however, only ATC market coupling and the flow-based approach are in use.

Besides these technical complexities, from economic perspective, the energy sector is, due to the liberalization, a complex system as well. It is characterized by many interacting actors seeking to maximize their own profit. Classical top-down approaches lack to properly model the dynamics of the behaviors of single entities in the system. Thus, with respect to new business models, enabled by the reform of regulations, bottom-up approaches are a good approach to model electricity markets flexible. Moreover, the new business models, such as arbitrage trading and providing network services with storages and decentralized generation units, require an intelligent response to market signals. Besides the complex environment with several agents, the special characteristics of electricity trading itself make the electricity markets an interesting field of application of agent-based modeling. Revolving auctions with a uniform good to be traded is an interesting use case for strategic bidding and the adjustment of strategies.

The above-mentioned aspects are the motivation for this thesis to develop a model that is capable to model the European electricity markets including different market coupling schemes. Therefore, different machine learning algorithms are applied with respect to the strategic bidding of market actors. Exemplary studies, comparing different market coupling settings, indicate, that an extension of the current market coupling might be a beneficial result in an increase of the social welfare.

Keywords: market coupling, flow-based approach, wholesale electricity markets, agent-based modelling, neural networks

Contents

Declaration	V
Abstract	VII
Contents	IX
List of Abbreviations	XI
1 Introduction	1
1.1 Background and Motivation.....	1
1.2 Targets and Structure.....	2
2 Analysis	3
2.1 Electricity Markets.....	3
2.1.1 Characteristics of electricity markets.....	3
2.1.2 Market Coupling.....	16
2.1.3 Modeling approaches.....	40
2.2 Agency Systems.....	43
2.2.1 Basic principles of agent-based models	43
2.2.2 Different agent-based Approaches for Energy Markets	44
3 Model Development	57
3.1 Development of a model to simulate electricity markets.....	57
3.1.1 Modeling of different entities	57
3.1.2 Modeling of optimization procedure for welfare maximal electricity supply	61
3.1.3 Modeling of different agent-based approaches	63
3.2 Review of functionality and practicality.....	64
4 Exemplary Studies	67
4.1 Parameterization of the test scenarios	67
4.2 Application of different configurations.....	70
4.2.1 Determination of welfare maximal supply.....	70
4.2.2 Comparison of results of different agent-based methods.....	72
4.2.3 Comparison of results for calculations with different market coupling approaches.....	73

4.3	Review and effects of more realistic modeling	75
4.3.1	Plausibility check	75
4.3.2	Required computing power and memory of model.....	76
5	Conclusion and Outlook	77
	References	79
	List of Figures	87
	List of Tables	89

List of Abbreviations

4M MC	Four Markets Market Coupling
ABM	Agent-based modelling
ACER	Agency of energy regulators
ANN	Artificial Neural Network
API	Application-Programming-Interface (API)
ATC	Available Transfer Capacity
CACM	Capacity allocation and congestion management
CMM	Capacity management module
CS	Consumer surplus
CWE	Central Western Europe Market Coupling
DSO	Distribution System Operator
ELIX	European electricity index
ENTSO-E	European network of TSOs for electricity
FAV	Final adjustment value
FBMC	Flow-based market coupling
FCA	Forward capacity allocation
FRM	Flow reliability margin
GSK	Generation shift key
LMP	Local marginal price
LP	Linear program
LTS	Local trading system
MCP	Market clearing price
MCV	Market clearing volume
MIC	Minimum income condition
MIP	Mixed integer program
MIQP	Mixed integer quadratic program
MRC	Multi-Regional Coupling
NEMO	Nominated electricity market operator
NP	Net exchange position
NTC	Net Transfer Capacity
NTF	Notified Transmission Flows
OTC	“Over-the-Counter”
PCR	Price coupling of regions
PS	Producer surplus
PTDF	Power Transmission Distribution Factor
PUN	“Prezzo Unico Nazionale”
PX	Power exchange
RAM	Remaining Available Margin
ReLU	Rectified linear unit
REMIT	Wholesale energy integrity and transparency
SFE	Supply function equilibria
SM	Shipping Module
SOB	Shared order book
TRM	Transmission Reliability Margin
TSO	Transmission System Operator
TTC	Total Transfer Capacity

1 Introduction

This chapter introduces the topic of the thesis explaining the background and the motivation based on which the thesis is elaborated. In chapter 1.2, the target of this thesis and its structure is explained.

1.1 Background and Motivation

The superior aim of the European Union, to create an Internal European Market also affects the energy sector with electricity as one of the most important goods for modern economies. Driven by the aim to increase the overall welfare by building competitive markets the liberalization of the energy sector was issued at the end of the last century. By breaking up the naturally grown monopolies encouraged by a capital-intensive sector, competition regarding the electricity generation was increased and wholesale electricity markets were created. However, paying tribute to the special characteristics of electricity as a good, the way towards a fully integrated European electricity market remains barred. This is due to congested interconnections of the different European electricity markets. Although intermeshed and synchronized across whole Europe, the European grid was designed to fit the purposes of single zones. Thus, between markets in the EU there are limited transmission capacities. In order to exploit these constrained transmission capacities economically efficient, different bidding zones regionally agreed on common market coupling schemes. Over the last ten years, more and more of these coupling regions merged creating larger collaborations and using advanced market coupling procedures. On top of that, although the liberalization was issued to create fully competitive markets, still there are distortions that allow the exploitation of market power.

Additionally, with respect to European efforts addressing the climate change, the energy markets are facing transitions which are increasing the complexity and moreover the uncertainties of the system. Decentralized renewable generation units are challenging exciting business models and the existing electricity landscape turn upside down. Their volatility challenges investments, both, regarding grids and production capacity, as well as grid operators that must balance a system which is more and more difficult to predict. Roles and market power which were previously distributed rigidly and one-sided, are now shifting. Consumers turn into prosumer reacting according to market signals or producing their own electricity.

In this complex environment market participants seek to find strategies to maximize their profits exploiting any opportunity to exceed market power. The emerging field of artificial intelligence, and

machine learning in particular, thus, offers new opportunities to simulate the actions and reactions of a range of entities affecting each other.

1.2 Targets and Structure

The target of this thesis is to develop an agent-based model which is capable to simulate market coupling in a wholistic European electricity market. The model should be employed to compare the impact of different market coupling schemes with regard to the achieved social welfare. In the agent-based approach machine-learning algorithms are supposed to be implemented in order to simulate individual behaviors multiple entities in a complex environment. The scope of this thesis is to model a strategic bidding approach for the supplier side. However, with respect to a paradigm shift towards a demand side that is responding to market signals, it should be designed in a way enabling further extensions.

In chapter 1 the European electricity markets are analyzed at first. After that, agency systems are introduced and learning algorithms examined. In chapter 3, then, the simulation model is developed and reviewed according to its functionality. Therefore, at first, the different entities, simulated by the model, are introduced. Subsequently, market clearing algorithm as well as the implementation of the learning algorithm is explained. Finally, several scenarios, simulating different learning algorithms, as well as different learning algorithms are investigated in chapter 0.

2 Analysis

In this chapter, the theoretic foundations for the model, that is about to be developed in chapter 3, are explained and analyzed. Chapter 2.1 is stating the features of the European electricity markets. Its followed by chapter 2.2 where agency systems are introduced and explained.

2.1 Electricity Markets

In the following the general characteristics of electricity markets are examined explaining the developments of the European electricity sector starting from its liberalization. Moreover, the different actors in the energy landscape as well as the European electricity trading are explained. The chapter is closed by explaining strategic bidding. The subsequent chapter 2.1.2 introduces the basic market coupling schemes. Finally, the traditional modeling approaches of electricity markets are examined in order to leading to the approach of agency systems.

2.1.1 Characteristics of electricity markets

The EU's strive for a European Single Market also affects the European electricity markets and resulted in an enormous restructuring process 25 years ago. It resulted in a complex multiarea system with several zones, the bidding zones. These are the smallest organizational entities in which electricity is traded resulting in a single price. Price differences between bidding zones are mainly caused by grid congestions between them although the European electricity grid is highly intermeshed across whole continental Europe. The congestions are due to the grown grids which were historically designed to satisfy the electricity demand within a single bidding zone. The congestions impede the strive for an internal energy market with respect to a single price. However, with respect to the superior target, growing social welfare, congestion only mark an additional constraint in the price determination process as it is explained later. [1]

In general, electricity markets are a special kind of good markets due to the characteristics of the traded good. Electricity is a standard good that cannot be distinguished, and its trading is constrained by physical laws. The transport of electricity is bounded by transmission lines and the good itself cannot be stored in its specific energetic form in large amounts. Furthermore, electricity is considered a crucial good with respect to public wealth and security. This is due to the high level of electrification of major parts of human civilization. From this importance, a field of tension can be derived comprising the

triangle with the security of supply, environmental sustainability, and economic competitiveness as its cornerstones. [2]

Liberalization

For years and especially before the liberalization of electricity markets, the European electricity landscape was shaped by a centralistic approach. Large generation units were installed on the highest voltage levels. The transmission networks transmitted the energy toward lower voltage levels and into distribution networks and finally to the consumers. Energy flows occurred only in one direction. Due to high investment costs and long planning horizons for large generation units and required infrastructure, the electricity markets became geographically natural monopolies. It is neither economically nor ecologically reasonable to operate two parallel grids. The capital-intensive investments in both generation and infrastructure themselves marked high market entry barriers. [3]

The monopolies were state-owned to a large extent and the national markets were divided by only a few large energy suppliers according to geography. The suppliers, thus, consolidated all steps of the electricity value chain. This value chain consisted of generation, transmission, and distribution. Especially, there was no wholesale electricity market. This, as well as the consolidation of all steps, was changed by the liberalization of the electricity sector from 1997 onwards. [4]

The liberalization marks a milestone in the history of European electricity markets reshaping the markets fundamentally. It is meant for the utilization of economic benefits of competitive markets. The main concepts of the market liberalization are unbundling and the introduction of a wholesale electricity retail market. Unbundling stands for the separation of grid operation and electricity distribution and its generation in terms of organization, company law, and proprietary. It only applies to suppliers above a certain limit of customers. The concept allows electricity trading on the distribution side but requires strict regulation on the grid side. The latter is necessary, as the operation of electricity grids remains a natural monopoly for familiar reasons. The regulation aims at preventing the abuse of market power as well as on establishing a competitive market by granting free access to the electricity network and, thus, opening the market for more actors. At the same time, incentives for investments into the infrastructure are set to ensure its development. The remuneration of grid operators is made by network usage charges, which are paid by electricity distributors and forwarded to the end consumer. The charge is paid for the energy consumed and its height is determined by a special regulation scheme in order to prevent the mentioned abuse of market power by grid operators. Although the grid charge schemes vary across Europe, they are all based on the same concept. [4, 5]

As the grid usage is charged according to the consumed energy, the main concern of investors into power generation is not necessarily the minimization of grid usage. Instead, there is an incentive to minimize the electricity production cost. Thus, plants were historically located close to the resources instead of close to the load centers, in order to minimize transportation costs. This is especially valid for lignite. This allocation contributes to the need for grid expansion measures as it is increasing the power flows inside the grids causing congestions. This reinforces the need, which is already induced by non-transportable resources like wind or solar radiation. [6]

Market Actors

The actors in electricity markets are, due to the liberalization, manifold. First, there is a regulator trying to shape the market in a competitive way. It controls and supervises the market and the grid operators which can be divided into transmission system operators (TSO) and distribution system operators (DSO) controlling the respective grid levels. The national regulators are cooperating in the Agency for the Cooperation of Energy Regulators (ACER). The agency supports the regulatory authorities for the European Parliament striving for the realization of an integrated European electricity market. Furthermore, ACER is in charge of REMIT (wholesale energy market integrity and transparency). It is a department of ACER and tracks market manipulation and insider trading as the competition regulator. [7]

The TSOs are supervising the transmission system. Their various tasks can be summarized by ensuring the balance of supply and demand and the security of supply. To do so, the TSOs, among others, are in the long run developing the grid according to periodic grid expansion plans and utilize market-based balancing power and congestion management in the short run. The latter includes redispatch as well as feed-in management. Redispatch is a temporary measure to relieve grid constraints by relocating generation capacity relative to the point of physical constraint. To ensure reliable operation of the transmission grids, information on the energy trade on the various markets introduced below are submitted to the respective TSO affected by the flow of the traded electricity. Based on that, the TSO can plan their congestion management beforehand. [8, 9]

With respect to a European internal electricity market, the different TSOs founded the ENTSO-E (European Network for Transmission System Operators for Electricity) in 2008. This was issued by the Regulation (EC) No 714/2009 of the European Parliament. Its purpose is to initiate cooperation between the European TSOs to ensure the highest possible degree of security of supply. On a non-profit based level, the TSOs commit their selves to develop a sound European electricity network under highest standards regarding its operation and management. Therefore, network codes are set up by

the TSOs containing rules for operation, cooperation or emergency situations. The ENTSO-E consist of 43 members from 36 countries, including Turkey as an observer member. On top of that, there is cooperation with neighboring regions as well as with TSOs and organizations from overseas, like in the USA, in Japan or in China. Within the framework of coupling the different zones in Europe, the TSOs conduct the required calculations for their regions to determine the available cross-border capacities. This is done in order to prevent situations of congestions caused by inter-zonal electricity trading. [10, 11, 12, 13]

The DSOs operate the grids below the maximum voltage level. Historically, they distributed the electricity to the consumer with a unidirectional energy flow top-down. Especially, coupling points with higher grid levels were designed for feed-in from these higher levels. Due to the transitions in the electricity sector toward decentralized generation at lower voltage levels, the DSOs face an increasing amount of electricity fed-in into their grids bottom-up. This fundamentally changes the usage of a specifically designed grid. With respect to different subsidy schemes regarding renewable generation, the DSOs have to forward the electricity, which is not marketed by the generator itself to their respective TSO that has to sell the electricity. This implicates the need to expand and adjust their grid to new requirements demanding enormous planning and investment efforts. [14, 15]

The digitization, in this respect, is a cross-branch development accelerating and enabling the decentralized energy generation, on the one hand. On the other hand, the digitization also brings the means for grid-operators to handle the new use-cases and the challenges accompanying the decentralization of electricity supply. Traditionally passive and analog steered networks are equipped with smart elements that turn the grids into smart grids. This includes consumer that turn into prosumer who can steer and shift their consumption and generation. Digitization enables the trading of electricity and at the same time offers new technologies, like the Block Chain technology, to disrupt it. [16]

Besides the actors of the physical layer of electricity supply, there are the actors of the economical layer conducting the trading of electricity. These are the power generators, often comprising several generation units, selling their electricity as well as the electricity supply companies. The latter purchase electricity, often additionally, to their generation portfolio and sell it to the consumer which are located at the end of the value chain. The generators try to maximize the utilization of their generation units by selling their produced electricity with different time horizons on different markets. Besides the generators optimizing the dispatch of their large generation units such as nuclear, lignite or hard coal power plants, the decentralization of energy generation enabled the introduction of new actors

such as virtual power plants. Virtual power plants bundle distributed generation units of smaller scales, compared to the large conventional generation units. Due to a larger portfolio, the impact of fluctuating energy resources such as wind or solar power can be compensated and with larger ensured batch sizes additional markets such as balancing markets can be approached. [4, 17]

The large quantity of consumers is located at the lowest voltage level. These are household as well as smaller factories or offices. Across Europe, the household sector together with the trade, commerce and services sector comprises roughly 58 % of the overall electricity consumption. The industry sector with fewer consumers but with large demand are located at the middle and high voltage level and consumes about 37 % of the overall consumption. The rest is consumed by the transport and agriculture sector. Traditionally, the demand side of electricity trading did not participate in wholesale electricity trading due to small batch sizes of electricity demand. The electricity was and still widely is purchased on the retail market from electricity suppliers. For large industrial consumers, however, there is the incentive to avoid the retail market and to purchase their required electricity on their own by trading or own generation. Moreover, they can provide rewarded flexibility for the market. Aluminum smelters, which are located on the high voltage level, are one example in this respect as they mark high load due to their furnaces. According to grid requirements, they can adjust their production. However, trends like digitization and decentralized energy generation combined with subsidies for renewable generation also offer saving potentials for smaller consumers turning them into prosumers as well. [4, 18]

Energy Trading

Due to the special characteristics of the traded good, electricity is traded in advance to the desired time of delivery and, moreover, in advance to its production as the supply always has to meet the demand. Supply offers are referred to as bids, whilst demand offers are referred to as asks. Offers for a specific time interval basically include information on the volume of electricity and the price at which the volume is desired to be sold at least or purchased at most. The offers can be traded in different settings with respect to the marketplace, time until the delivery and the market clearing. In terms of the market clearing, in general, trading is conducted in auctions of different characters, which differ according to the clearing process. During continuous trading, a bid-ask pair is merged immediately when suitable. On markets with auction character, all offers are gathered until the market is closed and then cleared, which is the merging of bids and asks. Moreover, auctions can be, among others, distinguished according to price determination. In pay-as-bid auctions, after the market clearing, participants pay the price they offered, which is especially relevant for auctions with single-sided bids.

However, continuous trading as well uses the pay-as-bid mechanism with two parties agreeing on volume and price. Regarding the later, the bids are not sealed, and participant bid nothing but the negotiated price. Single-price-auctions, or uniform price auctions, determine a non-discriminatory market clearing price (MCP) which is valid for all accepted bids and offers with sealed bids in a single round. The price is determined by the price of the last bid-ask pair. The cumulated volume of all accepted offers is referred to as the market clearing volume (MCV). The clearing is conducted with respect to maximal social welfare. To do so, bids and asks are cumulated to the supply and demand curve, respectively. The supply curve, thus, is ordered with ascending prices whilst the demand curve is ordered descending.

Figure 1 shows a particular supply and demand curves for two bidding zones. The intersection marks the market clearing point with the respective MCP and MCV for each market. Moreover, the figure shows the consumer surplus (CS) and the producer surplus (PS) in each zone.

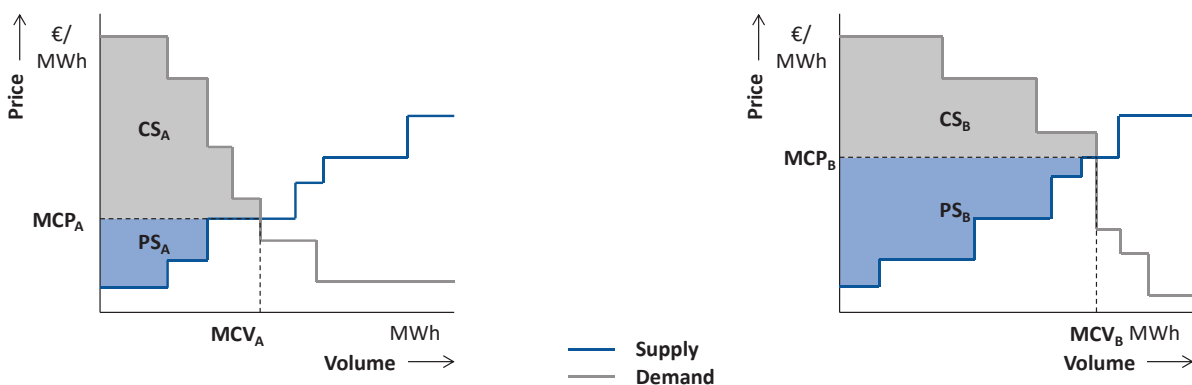


Figure 1: Market Clearing (own figure)

A surplus is calculated as the difference between the offered and the market clearing price multiplied with the offered volume. Regarding the consumers, the offered price represents the willingness to pay, whilst for the producers, it represents the marginal costs of production in a fully competitive market. The supply curve, then, is determined by the different technologies which are in use for generation and is called merit-order. Although shown differently in Figure 1 for illustration reasons, the demand for electricity can be characterized by small price elasticity. Electricity can barely be substituted, although there is the trend towards an active demand side. The supply side, instead, is more flexible and facing a shift due to the growing share of renewable generation. The supply curve is shifted right as renewable generation face nearly zero marginal cost. With a constant demand, this pushes other technologies with higher marginal costs out of the market. This effect is referred to as the merit-order effect and his varying with respect to the volatility of fluctuating renewable resources. The social

welfare (SW), which is supposed to be maximized by an auction, equals the sum of consumer and producer surplus for a single market as equation (2.1) shows. [19, 20]

$$SW = CR + PR \quad (2.1)$$

Finding the maximal social welfare, now, is an optimization problem which can be solved by linear programming in its simplest form for a single bidding zone. The objective function for a single-price, social welfare-maximizing electricity auction is shown in equation (2.2). The indexes d and s , thus, indicate whether a particular offer is from the set of asks D or from the set of bids S , respectively. P stands for the specific price for an offer, whilst Q represents the offered quantity. The decision variable q is the rate of acceptance for an offer and, thus, is bounded between zero and one. This approach assumes that each offer can also be fulfilled partly and represents the most flexible bids. These bids are called single-part bids. Multipart bids, in comparison, are complex orders, e.g. comprising several hours or including price limits or even characteristics of certain technologies. Automatically, in situations where a market is cleared at a price, which is offered by several bids, the residual volume of market clearing and already accepted volume is spread equally among the bids.

$$\max_q \sum_{d \in D} P_d * Q_d * q_d - \sum_{s \in S} P_s * Q_s * q_s \quad (2.2)$$

Beside the bounding of the decision variable, the objective function is subject to the clearing constraint which is shown in equation (2.3). The constraint is referring to the physical characteristics of electricity explained above. Demand and supply always have to be balanced.

$$\sum_{d \in D} Q_d * q_d - \sum_{s \in S} Q_s * q_s = 0 \quad (2.3)$$

With respect to the marketplace, trading of electricity is conducted in two ways. On the one hand, there is the over-the-counter (OTC) trading, which is based on bilateral contracts between two traders e.g. a power plant operator and an electricity supplier. On the other hand, there are electricity exchanges. In terms of OTC trade, the actors know each other and often have long-term contracts, which can be designed individually. Nevertheless, there are issues of high transaction costs and credit risk. The high transaction costs are due to efforts regarding the search for a counterpart and negotiations in terms of the contracts. This credit risk is due to the possibility of infringement. OTC trading can be conducted by various channels. Brokers operate platforms, where bids and asks can be

submitted and merged providing a comparably high degree of transparency due to standardized products. In order to participate, a trader needs to have permission. In direct OTC trading, trading is conducted via phone directly between two parties offering higher flexibility regarding the contracts which is paid with less transparency. [21]

Credit risk and transaction costs are diminished by the services of power exchanges. Power exchanges are providing a voluntary market place where bids and asks can merge. A clearinghouse steps in as an intermediary and, thus, as the contractor for both traders. The latter do not know each other, but they have the security that either money or electricity is flowing. Each contractor just trades with the power exchange, which requires securities by the trading parties themselves. In order to ensure certain liquidity of the market, the products at power exchanges are standardized. Traders only submit their orders containing quantity and price electronically to a trading platform. The clearinghouse matches these orders with regard to the characteristics of a particular market and, thus, clears the market. Clearinghouses provide their services regarding the reduction of economic risk for OTC-contracts as well in some cases. [22, 23, 24, 25]

The electricity trading is based on several products defining a set of trading features each. These trading features comprise, among others, the time horizon, both, regarding the traded time periods, which can comprise hourly, quarter-hourly, or block deliveries, and the time until delivery that can be years, quarters, month or weeks in advance. On top of that, there is, depending on the respective power exchange, a variety of complex orders, which complicate the basic linear program to a mixed integer quadratic program (MIQP). Such complex orders are orders with a minimum income condition (MIC), merit or PUN ("Prezzo Unico Nazionale") orders. MIC orders are designed for suppliers and ensure, that a minimum income will be obtained to cover variable as well as fix costs. The whole MIC bid set is refused if the clearing price does not meet the minimum income. Merit orders are orders with an assigned number showing the priority of fulfillment in uncongested situations. A special type of merit orders are PUN orders, which are cleared according to a PUN price that might be below the market price of the particular bidding zone. The trading of electricity itself is done by contracts, which are instances of related products in time. Besides the time of day, for which a product should be purchased, contracts determine the amount of electricity traded and the price. [20, 26]

As already explained, electricity trading can be conducted with different time horizons regarding the time of delivery. This is valid for both, OTC as well as exchange trading. In general, the different time horizons are addressed by two fields of markets. On the one hand, there is the future and forward trading where products are traded from years down to weeks in advance. On spot markets, on the

other hand, products are traded from a day down to minutes before delivery. The closer the time of trading to the time of delivery, the smaller is the time horizon of the products traded. Whilst on future markets weekly blocks of hours, namely baseload and peak load for the workweek, are traded, on spot markets, daily blocks of hours, single hours and quarter-hours are traded. Futures are traded on power exchanges and are, therefore, highly standardized and anonymously. Mainly, they are traded as financial products without any physical delivery of energy. The latter is used for hedging purposes with a daily margin, which is the payment of the win or loss of the position relative to the previous day. By this, the credit risk of a participant is reduced, causing a high cash flow for the contract parties. Forwards, instead, are traded OTC and have higher degrees of freedom at higher credit risk. They are combined with physical delivery of the traded energy exclusively and payment after delivery. Forwards are reducing the price risks of spot markets by selling or purchasing the required amount of electricity in advance to the delivery. Both, future as well as forward markets are, thus, important measures for risk management. For both, the pricing mechanism is pay-as-bid. [4, 21]

As it is mentioned before, on spot markets energy is traded close to the time of delivery. The closer the time of delivery, the higher is the share of electricity which is traded on power exchanges. The biggest European spot market is the EPEX Spot as the central spot market for France, Germany, United Kingdom, the Netherlands, Belgium, Austria, Switzerland, and Luxembourg. These markets comprise 50 % of the European electricity consumption although just a comparably small amount of electricity is traded on the spot market. Due to risk management issues, by far, the electricity to be delivered physically is traded on forward markets. The spot market of energy exchanges consists of the day-ahead market and intraday markets. The day-ahead market is organized as a single round, sealed auction with uniform pricing with demand and supply bids, which is scheduled at noon the day before the physical delivery. During the auction, the electricity trade for every single hour of the next day is contracted. The specific hours are traded separately as well as in different blocks of several hours. By that, e.g. the baseload and peak load can be satisfied as individual products without trading every single hour. The energy is delivered to the respecting transmission system operator of the region the purchaser is located. The minimum volume per order is 0.1 MW with a minimum price increment of 0.1 €/MWh at EPEX Spot. [20, 21]

The intraday market is organized both with a single round auction as well as in continuous trading of time intervals of hours and quarter-hours. By continuous trading, short-term purchases can be realized. The increasing share of renewable resources in the grid, increasing the importance of his short-term markets. This is due to the limited prediction accuracy of highly volatile generation by renewable resources. The continuous trading starts after the result of the day-ahead auction was

published. Electricity can be traded until 30 minutes before delivery on the next day. The constraints for traded volume and price changes are the same as for the day-ahead trading. The clearing algorithm, instead, is pay-as-bid. An intraday auction is only offered for the British and German market. It follows basically the same rules as the day-ahead auction regarding minimum traded volume or price change. Whilst it is scheduled in the afternoon with the start of the continuous intraday trading in Germany exceptionally, for Britain, there is another auction in the morning of delivery. [20]

Besides the wholesale markets, cultivating the benefits of competitive markets, there is the physical layer of electricity supply. As electricity cannot be stored in a sufficient degree, demand and supply always have to be balanced to guarantee a reliable electricity supply. As the electricity is traded in advance to the delivery, there is always a certain inaccuracy between the estimated and, thus, purchased electricity, and the final load. The markets with different time horizons try to address these inaccuracies with products of higher granularity and shorter time horizon but lack to do so perfectly at the latest in an unexpected situation such as an outage. The final balance of demand and supply is, independent from wholesale trading, the task of the transmission system operator. To ensure the balance, even in the case of generation outages or unexpected demand, the transmission system operators provide balancing power. This type of power is purchased independently from wholesale trading by transmission system operators, e.g. by websites as it is the case in Germany, on separate markets. The usage of this power is squared according to the causing principle the day after application. That the cost of balancing power is higher than wholesale prices is emphasizing the importance of continuous intraday trading for electricity suppliers. Figure 2 shows a symbolic load coverage by electricity purchased on the different markets. It illustrates the decreasing amount of electricity traded with the oncoming time of delivery. [21, 27]

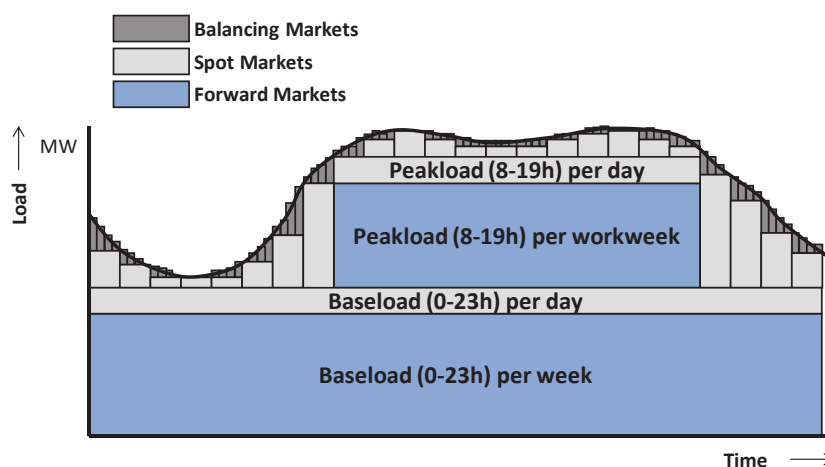


Figure 2: Load coverage according to different markets (according to [21])

The European-wide transition of the energy sector carries risks and uncertainties that are detrimental for the planning horizon of investments. Due to the rapid change of the energy sector, long-term investments of roughly 60 years, which have been typical in the energy sector in case of large generation units, become unattractive. Thus, there is the fear of lacking investments into these large generation units with typical high reliability regarding the electricity generation but relatively expensive resources with regard to the merit order. They, though, are required to ensure a secure energy supply with respect to highly volatile renewable generation. The effect is reinforced by the shift of the merit-order. One opportunity to incentivize the investment into long-term projects is the introduction of capacity markets as it is the case in France. Besides electric energy, also capacity is traded. The German approach, instead, is a capacity reserve. Plants, which are about to be shut down but considered to be system relevant are shifted into the capacity reserve before their final shut down. By that, the electricity market remains an energy-only market. [28]

Strategic bidding

The liberalization of the energy sector aimed at the utilization of benefits related to a competitive market. These benefits, however, can only be cultivated entirely under perfect competition. Perfect competition in an electricity market implicates that no actor in the market can exercise market power meaning that all actors are price takers. For such status of competition, bidding according to marginal cost is the optimal bidding strategy. However, especially regarding European electricity markets, the concept of perfect competition is a theoretical construct only. This is due to the oligopolistic character of the European electricity markets explained above. Competition can only emerge regarding the trading of electricity as the transmission is a regulated monopoly. In European oligopolistic electricity markets, market power is slightly shifted toward the suppliers. This market imperfection condenses in strategic bidding schemes of suppliers seeking to increase their profits by bidding above cost. By bidding above marginal costs, the suppliers are capable to cover their fix costs. Due to the competitive character of the auction, suppliers need to include all their costs into the prices of their bids. An additional concept, in this respect, is the inclusion of startup costs for large scale conventional power plants on short-term markets. Dependent on whether they are baseload or peak load power plants, they deduct the startup costs from the price or add them, respectively. With respect to baseload power plants, this even results in negative prices. These plants are characterized by a high number of full load hours and by comparably small load gradients. Thus, it might be more economically efficient for plant operators to even pay for energy consumption if the price drops below marginal costs in single hours compared to reducing energy consumption. The willingness to pay for consumption is limited by the startup costs. For peak load plants, however, this is the other way around. Peak load plants have a

lower number of full load hours but steeper load gradients. In situations, where they are about to be started, besides their variable costs, they have to earn the startup costs. The startup costs can be added, as the peak load plants are just in the money as the last technology defining the price. Assuming, that other plant operators with similar technology are acting economically reasonable as well, the startup costs do not shift the plants out of the money. Due to the single-round, sealed character of day-ahead markets, adding or deducting the startup cost is based on price assumptions. Equation (2.4) shows the price determination for a supplier s from the set S for each generation unit i from its portfolio I . The variable cost and the startup cost for each generation unit of a supplier are denoted as $c_{var,s,i}$ and $c_{startup,i}$, respectively. M_s is the markup a supplier adds to its bid. [29, 30]

$$P_s = \begin{cases} c_{var,s,i} - c_{startup,i} + M_s & \text{baseload} \wedge \hat{P}_s \leq c_{var,s,i} \\ c_{var,s,i} + c_{startup,i} + M_s & \text{peakload} \wedge \hat{P}_s \geq c_{var,s,i} \\ c_{var,s,i} + M_s & \text{otherwise} \end{cases} \quad \forall s \in S \wedge \forall i \in I \quad (2.4)$$

The demand side, instead, which is rather price inelastic, is the price-taker. However, larger consumers are already active bidders and small and medium consumer are about to become it, shifting their demand or potentially providing grid service with new technological opportunities. The attraction of strategic bidding is conditioned by the explained characteristic features of electricity markets, in general, and the European electricity markets in particular. These characteristics result in the pool trading character of the electricity market with the sealed, single-round auction schemes mainly applied. The frequent, at least daily, repetition of these auctions for the same uniform product in a continuously changing sector is a fertile ground for strategic bidding and adaption of bidding strategies. [29]

In general, three bidding strategy developing approaches can be distinguished considering a bidding strategy as the choice of markup. However, dependent on the portfolio of a supplier strategic bidding might also imply capacity withholding. Capacity withholding is theoretically relevant to suppliers with generation units of different technologies. These suppliers, in a not fully competitive market, might have the incentive to not fully offer the available capacity of a cheaper plant in order to push a more expensive one into the money according to the merit-order principle. By, then, covering the sold electricity of the expensive plant by the cheaper one, a higher revenue might be achieved. This approach, however, is highly risky against the background of volatile production by renewable resources and forecast inaccuracies. [31]

At first, the bidding strategy can be based on estimations regarding the market clearing price of the respective bidding period. This, however, is subject to high uncertainties as predictions and assumptions regarding them need to be made. The main assumption is that the market price cannot be influenced by bidding. This is the fundament of any strategic bidding efforts. The second approach rests the bidding strategies on two different game theories. At first, there is a matrix game. Here, a payoff matrix for several discrete strategies is developed enumerating all combinations of possible strategies in order to find an optimal equilibrium. For real problems, due to the continuity of strategies, this is only partially applicable. The model is more interesting for analyses applications. The same is valid for oligopolistic games due to simplifying and distorting assumptions made. The latter, however, enables the determination of equilibrium states that, theoretically, can be implemented as bidding strategies. Common equilibrium models, in this respect, are Cournot models or supply function models. The third, and most widely applied approach is the development of bidding strategies according to the estimated behavior of rivals. Strategy development is mainly based on probabilistic modeling regarding the expected behavior of competitors. Moreover, due to rising computation capacities, intelligent agents relying on genetic programming algorithms or machine learning applications also subject to research. The agents adapt their strategies autonomously according to market output. This also includes the intelligent application of supply function models. In this work, these agents will be considered and explained later. [29]

Besides the liberalization as well as the transition of electricity generation with all its implications explained above, the European market integration is a major issue. The concept aims at the introduction of a European electricity market by coupling the existing electricity markets. Market coupling is explained in detail in the following chapter.

2.1.2 Market Coupling

In order to increase the overall social welfare, there are basically two options considered to develop the existing electricity markets. These are market coupling and market splitting, which aims at the same output in contrary ways. Market coupling seeks to combine two or more markets to one wholistic one accepting congestions between the different market. Market splitting, instead, divides a market area based on congestions into several zones. Both methods, then, try to clear the market in a way optimizing the use of the congested lines between the zones or market areas, respectively, economically, if there are any congestions. If there are no, the electricity prices are the same for both considered overall markets. Particularly in the case of market splitting, first, the market is cleared without paying attention to possible constraints. If the results cause congestion, the market clearing is conducted again separately for the zones divided by congestion. Bids and offers are collected by a single power exchange. Market coupling, instead, collects bids and offers from several power exchanges and, thus, uses price signals from different market areas in order to steer the power flow economically efficient and clears all markets at a time in a single optimization process. [23]

Although e.g. the EPEX Spot is the power exchange for several European electricity markets, naturally defined by national borders, this does not necessarily include trade between these markets. Nevertheless, the European electricity network, since it is intermeshed over the whole of Europe, provides the opportunity to transfer electricity between different countries and, thus, different markets on the physical layer. Thereby, the definition of markets by national borders marks an artificial isolation of electricity trading, letting an opportunity pass to raise economic potentials by creating larger markets. Thus, the European Union initiated the efforts to mesh the European electricity system on an economic level as well by market coupling. It is a major step in order to form an Internal European market in the long-run. Thus, the market coupling is, besides the liberalization, a further milestone in the development of European electricity markets. [32]

Figure 3 shows the bidding zones from Figure 2 in a coupled situation without congestion. As the market price in zone A, originally, is smaller than in zone B, electricity is flowing from zone A to zone B. The export of zone A is represented by additional demand and, thus, a demand curve shift to the right. The import of electricity in zone B results in additional supply and a shift of the supply curve. Whilst in zone B this shift results in a price decrease from MCP_B to MCP_B^* at constant volume, in zone A it results in a volume shift from MCV_A to MCV_A^* at a constant price in this scenario. The difference between the market clearing volumes with and without market clearing, the difference in consumption, equals the net exchange position of zone A with zone B. The net exchange position is the sum of all electricity

exports and imports form a bidding zone to or from each neighboring bidding zone. A negative value indicates a net import, whilst a positive value indicates a net export. Thus, the net exchange position of zone B is negative, as it is importing from zone A exclusively in this bilateral example. The net exchange position is hidden in the additional production capacity causing the shift of the supply curve. In scenarios of no congestion, electricity is exported or and imported until there is price convergence between the markets. This might even result in a price increase in the exporting zone. Moreover, the figure expresses the surplus in social welfare market coupling entails.

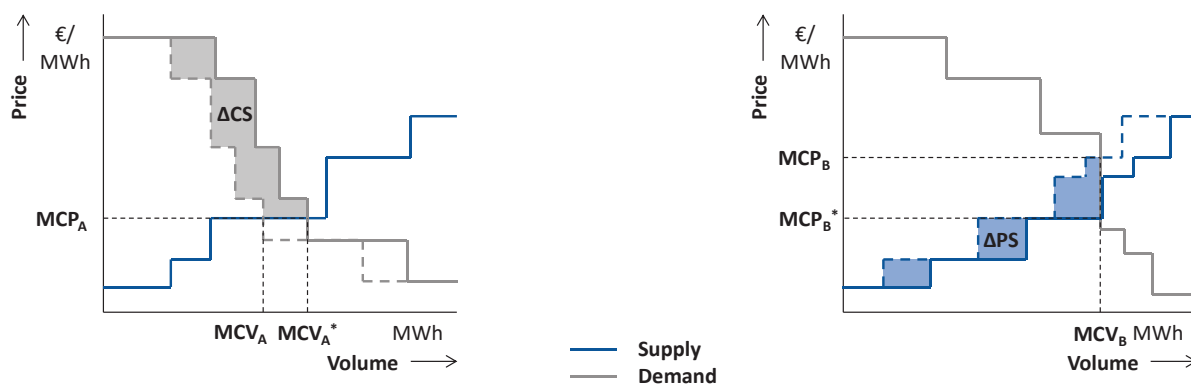


Figure 3: Market Coupling (own figure)

As it was mentioned before, the European grid was evolved over time serving the needs of particular nations, and, more precise, bidding zones. The idea of an internal European electricity market was not considered at first. Thus, between especially between nations there are congestions regarding the transferable capacities. The congestions are hindering the electricity markets to fully merge without jeopardizing the security of supply. Bidding zones, in this respect, are areas considered as having no internal congestion and, thus, a single price as no capacity needs to be allocated. The division of bidding zones is, due to the explained reasons, done according to congestions as the market signals are used to handle the congestions social welfare maximal. That is why some countries are split into several bidding zones already or considered to be split.

Figure 4 shows the different bidding zones of continental Europe plus the Ukraine and Turkey. Boxes sharing edges are linked with each other. The figure is derived from available data on offered cross-border capacities in implicit and explicit auctions for the shown bidding zones. The data is provided by the ENTSO-E on a transparency platform. [33]

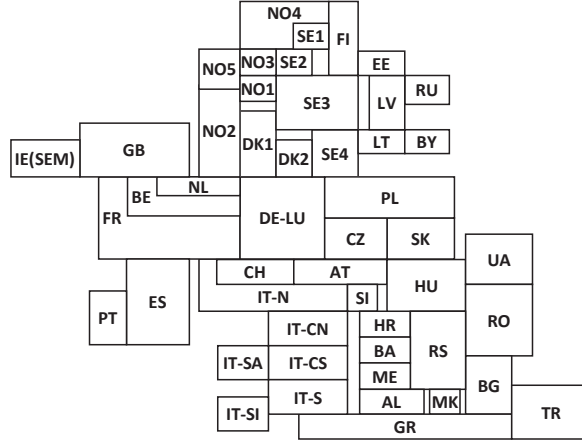


Figure 4: Bidding zones of continental Europe (according to [33])

With the opportunity of cross-border trading under the assumption of no congestion, the original linear problem is depicted in equations (2.2) and (2.3) can be adjusted according to equations (2.5) and (2.6). Z , in this respect, is the set of bidding zones or market areas, respectively. Each market area has a single clearing constraint which is added by the net exchange position shown in equation (2.6).

$$\max_q \sum_{z \in Z} \left(\sum_{d \in D} P_{d,z} * Q_{d,z} * q_{d,z} - \sum_{s \in S} P_{s,z} * Q_{s,z} * q_{s,z} \right) \quad (2.5)$$

$$\sum_{d \in D} Q_{d,z} * q_{d,z} - \sum_{s \in S} Q_{s,z} * q_{s,z} + NEP_z = 0 \quad \forall z \in Z \quad (2.6)$$

In order to derive the market clearing prices from the optimization problem, the concept of duality can be employed. The market clearing prices for each bidding zone are given by the shadow prices of the market clearing constraints. The shadow prices, thus, are the prices for an additional marginal unit of volume in the respective bidding zone which equals, per definition, the market price.

The economic exploitation of limited cross-border capacities can be handled either by implicit or explicit auctioning. In explicit auctions, cross-border capacity and electricity are traded separately from each other. Before the several market coupling efforts in Europe, this market design has been

exclusively used to trade electricity across borders. In order to trade electricity with contractors of another market area, first, the required capacity needs to be purchased. This implies the risk of potentially not being able to use all the purchased transmission rights. Moreover, there is the concept of “use-it-or-lose” it, which allows the system operator to sell purchased but unused capacities from long-term markets on short-term markets again. The implicit auction, instead, eases the bidding, as the cross-border capacity is allocated together with the energy by a single order. Compared to explicit auctioning, implicit auctioning bundles the information about capacities and markets. This improves the market liquidity and reduces both the complexity of the system and the risk of trading as there is just one clearing but no temporal offset. Furthermore, the line capacity is used more efficiently as the capacity is not allocated externally but based on market signals. Implicit auctioning is the base of market coupling and market splitting. [22, 23]

A market can either be coupled according to volume or according to price. These two approaches differ in terms of which part of the market clearing, price or volume, is calculated by the coupling entity superior to the participating markets. In both approaches, the local power exchanges submit the orders received to the market coupling system. With respect to volume coupling, a price independent volume bid is calculated and transmitted to each power exchange. The power exchanges, then, clear their markets based on this volume bid. This market coupling system is a price taker whereas the price coupling system is clearing the market for all received orders from local exchanges as a whole at a time. While price coupling bears a higher degree of complexity due to coordination efforts, volume coupling is subjected to a similar basic problem as explicit auctioning. This problem is the lack of simultaneity, either regarding capacity relative to energy or volume relative to price, ending up in non-optimal market clearing results. Another issue is the manifold algorithms used by the local power exchanges for market clearing. This leads to price differences among the participating markets, which might cause the paradox of energy flows from high price areas to low price areas. [23]

To overcome these issues, several markets and TSOs in Europe built coupling areas parallelly which continuously merged over the years building larger coupled areas. The efforts regarding central-western European market coupling started at the end of 2006 with the Tri-Lateral Market Coupling (TLC) between the day-ahead markets of France, Belgium, and the Netherlands. This trio enlarged by the German day-ahead market in 2010 forming the Central West Europe market coupling (CWE). This market coupling scheme, again, was expanded to the North Western Europe Price Coupling (NWE) with the Nordic region which started their market coupling already in the nineties, the Baltics, and Great Britain. By that, the Price Coupling of Regions project (PCR) was founded. During this, a uniform clearing algorithm was developed that can be used for flow-based as well as ATC market coupling. The

algorithm is called EUPHEMIA and is used by all PCR members. By 2014, the NWE was extended by Spain and Portugal founding the multi-regional coupling (MRC). It was extended one year later by Italy and Slovenia. Since 2015, the CWE region, as a subset of all regions coupled in the MRC, uses the flow-based coupling algorithm explained below. By now, the MRC comprises 19 countries and 85 % of the overall European electricity consumption. As it was already explained, the orders are collected by several power exchanges, whilst EUPHEMIA is matching bids and asks. The clearing itself is conducted by several power exchanges again. Besides the mentioned coupling collaborations, the Four Markets Market Coupling (4M MC) exists in parallel. It is the implicit coupling of the Czech, the Slovak, the Hungarian, and the Romanian electricity market. [32, 34]

By coupling of markets in the day-ahead PCR project, the European Union seeks to maximize the social welfare through the creation of a larger market. That increases the competition among the suppliers as well as the liquidity of the market, affecting a decrease in electricity prices. A further benefit is the decrease of price volatility and the implicit allocation management. Although the European electricity network is intermeshed, there is still a limitation of cross-border transmission capacities, which need to be allocated in the most efficient way in terms of social welfare. Due to that, and due to the remaining responsibilities for national PXs and TSOs in terms of other markets or backup in case of failures, there is no single power exchange, replacing all the other power exchanges. Figure 5 shows the different coupled regions as well as applied coupling schemes at each border. [35, 36]

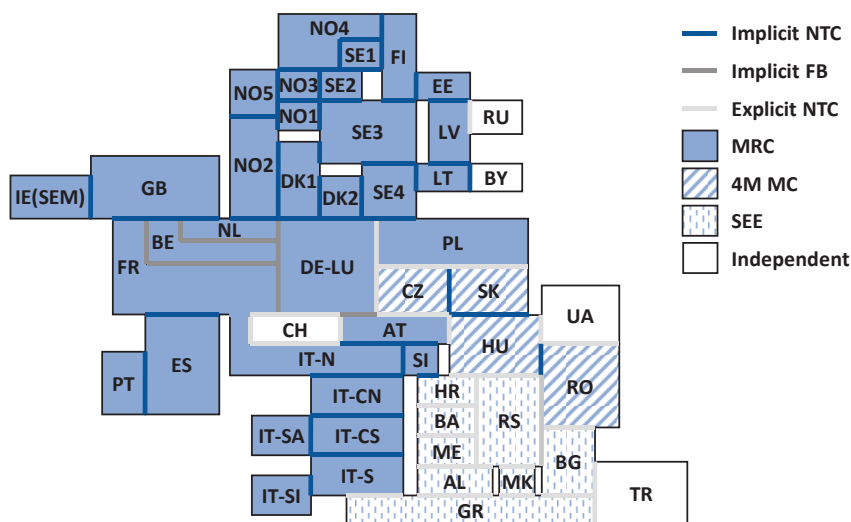


Figure 5: Market Coupling: Status Quo (according to [33])

The mentioned congestions mark, as mentioned at the start, additional constraints to the optimization problem of social welfare maximal market coupling. The constraints limit the net exchange positions of two coupled bidding zones to the available capacity of the branches between them. The general

constraints are shown below. Equation (2.7), thus, defines the capacity CAP_l allocated to a particular line l by market signals as a function dependent on the net exchange positions NEP_z of all bidding zones from the set of bidding zones Z . Equation (2.8) limits the capacity of a line according to a minimum CAP^{min} and a maximum value CAP^{max} . The available capacities or the capacity limits, respectively, are determined beforehand by the TSOs. The set of considered lines L , thus, is subject to the applied coupling scheme. With respect to the constraints on available line capacities, the shadow prices mark the congestion prices. This is equivalent to the amount of money market participant would pay for an additional marginal unit of capacity on the respective line. [37]

$$CAP_l = f(NP_z) \Leftrightarrow CAP_l - f(NEP_z) = 0 \forall l \in L \tag{2.7}$$

$$CAP^{min} \leq CAP_l \leq CAP^{max} \forall l \in L \tag{2.8}$$

Figure 6 shows a scenario with congested market coupling resulting in a price difference between the considered zones. Although zone B is importing from zone A , the clearing price MCP_B^{**} remains higher than the market clearing price in the exporting zone. CR is the congestion rent, which is the product of the price difference and the net exchange position of the two zones as equation (2.9) shows. It is also referred to as congestion income or congestion revenue. Like consumer and producer surplus, the congestion rent contributes positively to social welfare. [38]

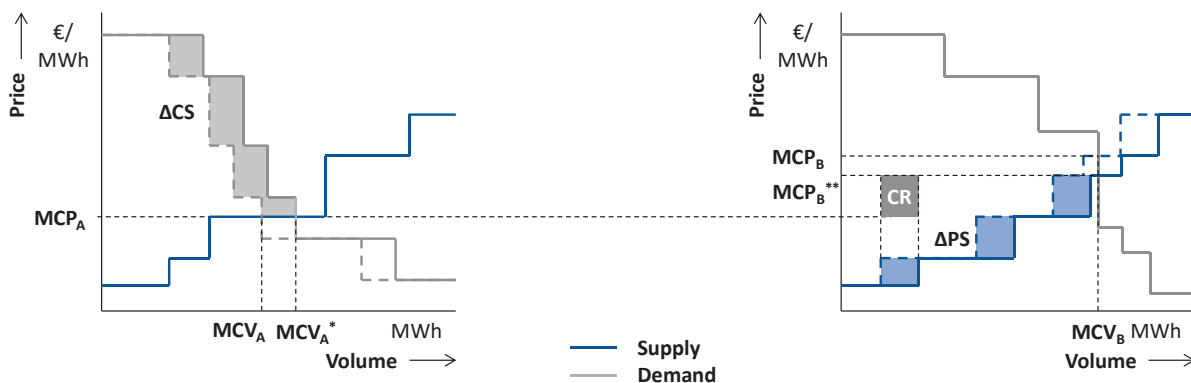


Figure 6: Congested Market Coupling (own figure)

$$CR = (MCP_B^{**} - MCP_A) * NEP_{A,B} \tag{2.9}$$

The concerns of market coupling with respect to congestions that need to be exploited economical efficient, basically three network codes which became regulations where issued by the EU. Commission Regulation (EU) 2015/1222 is the guideline on capacity allocation and congestion management

(CACM), also referred to as the regulation on the market coupling. It determines the capacity allocation methods and sets the framework for the operation of cross border capacity allocation markets. By this, competitiveness, as well as the integration of renewables, is supposed to be promoted. An integral part in this respect is the nomination of one power exchange per bidding zone as the nominated electricity market operator (NEMO). These are the respective power exchanges, which are meant to contribute to the market coupling in their particular bidding area. The European exchanges organize themselves in the Europex, the Association of European Energy Exchanges. The CACM is the foundation for market coupling of day-ahead and intraday markets. The guideline on forward capacity allocation (FCA), Commission Regulation (EU) 2016/1719, is the respective extension of the guidelines for capacity allocation with respect to long term markets. It enables participants to secure the required cross border capacity for forward cross border trades in advance. With respect to a European balancing market, Commission Regulation (EU) 2017/2195 issues the introduction of a European electricity balancing market. Basically, the guideline opens the balancing markets for new actors enabling demand response and renewable resources to balance demand and supply. By this, new revenue sources for these low-emission technologies are opened, on the one hand, increasing their competitiveness. On the other hand, the security of supply is enhanced not increasing the costs of consumers at limiting emission at a time. [39, 40, 41]

Nodal Pricing

Although there are basically three approaches existing, in Europe only two allocation approaches are in use. These differ regarding their accuracy of modeling the interactions between the economic and physical perspective of market coupling. On the one hand, this is represented by the time the capacity limit allocation takes place relative to the market clearing. On the other hand, this is evidenced by the sharpness of detail regarding the nodes and branches of a grid which are considered for the allocation. This comes down to the size of the considered set of lines L . The approaches can be divided, globally, into nodal and zonal pricing. The latter, as already explained, is in use in Europe and coupling according to a reduced set of considered lines. The most accurate approach, however, is nodal pricing, where every single node of a network is treated as a market zone. The net exchange positions of a single node, in this respect, is the injected power in that node. By this approach, every line is considered in the market clearing algorithm. By using nodal pricing, the allocation of capacity is conducted simultaneously with the market clearing. As no assumptions on the market outcome are required for determination of the available line capacities, the capacity allocation is not biased by reliability margins. With the high level of detail, a high number of variables and constraints goes along in the optimization problem. Thus, there is a significant increase in computation time with an increase of

node in the considered grid. Nevertheless, due to a comprehensible market clearing algorithm, nodal pricing offers a high degree of transparency while the exercise of market power is finite. Again, complexity is reduced by clearing the market uniquely and, thus, the cost of congestion can be reduced as capacity allocation and electricity trade happen simultaneously. Zonal pricing instead requires more congestion management efforts and carries more complexity due to simplifications made leading to a not necessarily optimal solution. The nodal pricing was first applied in New Zealand and is now in use in several market coupling projects in the USA as well. That the nodal approach isn't in use in Europe is issued by the concerns of politicians who do not accept different electricity prices within a country. This, however, might be the output of nodal pricing considering even capacity constraints within sub-areas of the same market area. Nevertheless, nodal pricing can set more targeted incentives to reduce capacity constraints effectively. It reveals needs for action in a remarkable sharpness of detail. [23, 37]

Nodal prices can also be referred to as local marginal prices (LMPs). Their calculation is based on a reference node with a mark-up on congestion and losses. In order to clear the market in a nodal pricing approach, Nodal Power Transfer Distribution Factors (PTDFs) are calculated. These sensitivity parameters are a relative measure representing the change of power flow in a particular branch of the grid according to injection changes in different nodes. They are derived from the current power flow on a branch and the injection or withdrawal of electricity at the respecting start and end nodes of the particular line.

Figure 7 symbolically shows the resulting flows in the whole grid resulting from an electricity transfer between the neighboring nodes i and k from two different bidding zones. The intended transfer between the two nodes is the net exchange position $NEP_{i,k}$. The $PTDF_{i,l}$ represents how much the injection change in node i influences the flow over the red branch l from node m to node n . [42, 43]

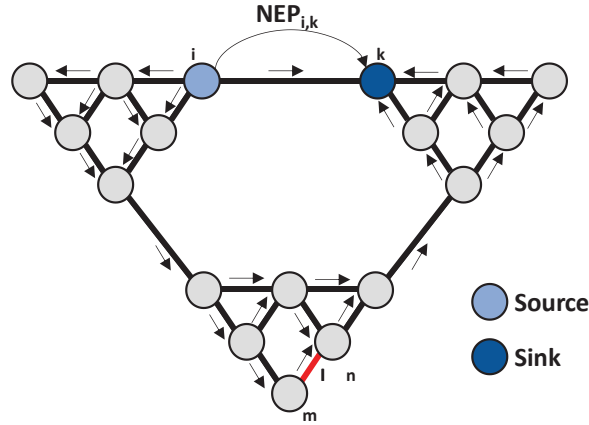


Figure 7: Nodal Capacity Allocation (according to [37])

For a particular energy network, the PTDFs are calculated in a matrix format with one PTDF relative to every node of the grid for every branch. Starting from AC power flow balance equations for active (P_i) and reactive power (Q_i) for a node i in a network, linearization leads to a DC power flow equation from which the PTDFs finally are derived. Equation (2.10) and equation (2.11) show both, the active and reactive power flow in a node i , dependent on the flow on connected branches. V , thus, marks the voltage magnitude whilst δ represents the voltage angle of a specific node. The variables G_{ik} and B_{ik} represent the conductance and the susceptance between the considered node i and each node k respectively. The conductance and the susceptance regarding the same node are the sums of the respective quantities of all connected nodes. [44]

$$P_i = V_i \sum_{k=1}^n V_k (G_{ik} \cos(\delta_i - \delta_k) + B_{ik} \sin(\delta_i - \delta_k)) \quad (2.10)$$

$$Q_i = V_i \sum_{k=1}^n V_k (G_{ik} \sin(\delta_i - \delta_k) + B_{ik} \cos(\delta_i - \delta_k)) \quad (2.11)$$

The conductance and the susceptance of a branch between two nodes determine the complex admittance can be calculated from the resistance and the reactance of a branch as equation (2.12) indicates. [44]

$$Y = G + jB = \frac{r}{r^2 + x^2} + j \frac{-x}{r^2 + x^2} \quad (2.12)$$

In order to linearize the active and reactive power flow equations, three approximations can be conducted under the assumption of a stable network operation. At first, since the resistance of a branch can be assumed to be much smaller than its reactance, the conductance can be neglected and the susceptance can be simplified. This is shown in equation (2.13). [44]

$$r \ll x \Rightarrow G \approx 0 \wedge B \approx \frac{-1}{x} \quad (2.13)$$

Due to the small-angle approximation, the trigonometric terms can be removed from the equations (2.10) and (2.11) according to equation (2.14). The small-angle approximation is applicable since the voltage angles difference between two neighboring buses is assumed to be close to zero.

$$\sin \delta \approx \delta \wedge \cos \delta \approx 1 \quad (2.14)$$

A small difference between two neighboring nodes also can be assumed for the voltage magnitude difference between two buses. Under the usage of the per unit system, the voltage magnitude variables can be removed following equation (2.15).

$$\text{p. u. : } V_i, V_k \approx 1 \quad (2.15)$$

The mentioned before, the approximations linearize the power flow equations as the trigonometric terms are removed. Equation (2.16) and equation (2.17) show the final equations. As the approximations change the reactive power flow Q_i into a constant, only the active power flow remains for the calculation of the required voltage giving this method its name. [44]

$$P_i = \sum_{k=1}^n B_{ik}(\delta_i - \delta_k) \wedge P_{ik} = B_{ik}(\delta_i - \delta_k) \quad (2.16)$$

$$Q_i = \sum_{k=1}^n -B_{ik} \quad (2.17)$$

Based on the remaining equation (2.16), the bus admittance matrix can be defined. For every node and the connection between to nodes, it contains the susceptance. The diagonal elements, therefore, are the sum of all susceptances of the connected branches to a node. The diagonal elements are the negative susceptances of the lines between the two nodes as equation (2.18) shows. [44]

$$\begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} = \begin{bmatrix} B_{12} + \dots + B_{1n} & -B_{12} & \dots & -B_{1n} \\ -B_{21} & B_{21} + \dots + B_{2n} & \dots & -B_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ -B_{n1} & -B_{n2} & \dots & B_{n1} + \dots + B_{(n-1)n} \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_n \end{bmatrix} = [Y_{bus}][\delta] \quad (2.18)$$

In order to calculate the voltage angles, the bus admittance matrix needs to be inverted to the bus impedance matrix in equation (2.19). [44]

$$\begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_n \end{bmatrix} = \begin{bmatrix} B_{12} + \dots + B_{1n} & -B_{12} & \dots & -B_{1n} \\ -B_{21} & B_{21} + \dots + B_{2n} & \dots & -B_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ -B_{n1} & -B_{n2} & \dots & B_{n1} + \dots + B_{(n-1)n} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} = [Z_{bus}][P] \quad (2.19)$$

As the bus impedance matrix is singular, a slack bus as a reference point needs to be chosen in order to ensure a unique solution. Therefore, in the diagonal element of the slack bus, which is the node 1 in the example depicted in equation (2.20), a one is added. [44]

$$\begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_n \end{bmatrix} = \begin{bmatrix} 1 + B_{12} + \dots + B_{1n} & -B_{12} & \dots & -B_{1n} \\ -B_{21} & B_{21} + \dots + B_{2n} & \dots & -B_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ -B_{n1} & -B_{n2} & \dots & B_{n1} + \dots + B_{(n-1)n} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_n \end{bmatrix} = [Z_{bus}][P] \quad (2.20)$$

Equation (2.20), finally, is the base from which the PTDF matrix can be derived. The matrix contains the PTDFs of a node relative to each line of the system showing the change of active power flow on each branch caused by a change the respective node. According to equations (2.16) and (2.20) the PTDF for node i regarding the line from node i to node k can be calculated as shown in equation (2.21). [44]

$$PTDF_l^i = \frac{\Delta P_{ik}}{\Delta P_i} = \frac{B_{ik}}{\Delta P_i} (\Delta \delta_i - \Delta \delta_k) = B_{ik} (Z_{bus_{ii}} - Z_{bus_{ki}}) \frac{\Delta P_i}{\Delta P_i} = B_{ik} (Z_{bus_{ii}} - Z_{bus_{ki}}) \quad (2.21)$$

In matrix form, the PTDFs can be handled easily or further. The columns, thus, are representing the nodes, whilst the rows represent the lines. A $PTDF_l^i$ of 0.2, therefore, indicates, that 20 % of an injection in node i would flow on line l from node i to node k . The basic constraints of the clearing problem introduced above are adjusted to the equations (2.22) and (2.23). Like in the nodal approach, no bidding zones are considered the net exchange position of a node equals the power injected. It is multiplied with the respected nodal PTDF of node n regarding line l . A negative active power P_i , thus, indicates a consumption in a specific node. Also, the bids and asks of the objective function are considered per node.

$$CAP_l = \sum_{i \in I} PTDF_l^i * P_i \forall l \quad (2.22)$$

$$-CAP_l^{max} \leq CAP_l \leq CAP_l^{max} \forall l \quad (2.23)$$

The other two approaches, which are applied to the European market, are the zonal approaches, comprising several network nodes to bidding zones. Applied to European markets they are used with the common clearing algorithm EUPHEMIA (pan-European Hybrid Electricity Market Integration Algorithm). Zonal approaches simplify the grid structure to different degrees. The Available Transfer Capacity (ATC) method reduces the coupling markets to one node per bidding zone, just modeling the interconnection lines. Thus, it is the highest degree of simplification. The available capacity of each considered interconnector is calculated ex-ante to the market clearing and determined for every cross-border line independently from the others. ATC also takes into account the ramping limits for particular lines as not just the flows but also the flow changes are constrained physically. Furthermore, line losses and tariffs for line usage are considered. Tariffs, therefore, are treated as losses as well. As the calculations are conducted before market clearing, it is based on both, assumptions regarding the market outcome and heuristic rules. Thus, in order to avoid line overloading, the ATC value estimate

is conservative letting economic potentials unexploited in order to not jeopardize the security of supply. The outcome of the capacity allocation is likely to not be optimal. The ATC is widely in use in European electricity markets. Only the day-ahead market is organized in a different way in some bidding zones. [26, 37]

ATC- Market Coupling

Equation (2.27) shows the formula of the ENTSO-E NTC-Procedure applied to calculate the ATC. The ATC of a line equal its Net Transfer Capacity (NTC) deduced by the already contracted and allocated capacities referred to as the Notified Transmission Flows (NTF). The NTCs of a line, again, are calculated from the Total Transfer Capacity (TTC) from which the Transmission Reliability Margin (TRM) is deduced. The TRM is determined for each border individually by both affected TSOs. [45]

$$ATC_l = NTC_l - NTF_l = TTC_l - TRM_l - NTF_l \tag{2.24}$$

Figure 8 shows the network of a three-area system using ATC capacity allocation. The system is reduced to bidding zones, comprising several nodes. The exchange between bidding zone A and B is considered to equal the flow on the line l in between.

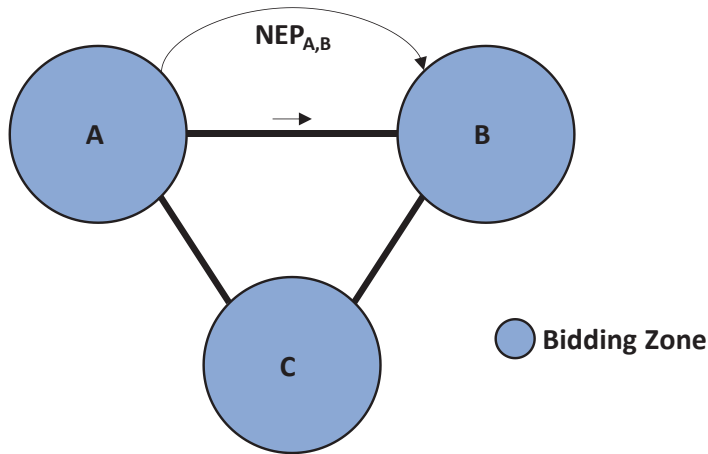


Figure 8: ATC capacity allocation (according to [37])

For market areas coupled by using ATC capacity allocation, the line capacity constraints can be defined as described in equations (2.25) and (2.26). The line capacity constraint indicates, that a bidding zones net exchange position is dependent on the flow on the lines connecting the bidding zone with the neighboring zones. The factor $A_{l,z}$, thus, is steering, whether an interconnector is considered to start ($A_{l,z}=1$) or to end ($A_{l,z}=-1$) in a particular bidding zone. A factor $A_{l,z}$ equaling zero indicates no connection of a line to the respective bidding zone. The capacity limits ATC_l^{min} and ATC_l^{max} , not necessarily the negative equivalent of each other, are derived from an adjacent matrix containing the cross-border capacity from any bidding zone to another bidding zone in the system.

$$NEP_z = \sum_{l \in L} A_{l,z} * CAP_l \quad \forall z \quad (2.25)$$

$$ATC_l^{min} \leq CAP_l \leq ATC_l^{max} \quad \forall l \quad (2.26)$$

Flow-Based Market Coupling

The European market coupling of the day-ahead markets is organized by ATC-coupling most widely. However, in the CWE region, a flow-based market coupling (FBMC) is in use as mentioned before. It is a hybrid between the ATC and the nodal allocation, being partly simultaneously to the market clearing and partly ex-ante relating to assumptions made on critical lines beforehand. The algorithm earmarks the interconnections between markets by one node per market like in the ATC approach. Moreover, critical network elements within the several coupled markets are considered. The slightly higher degree of detail eases the requirement for conservative determinations of cross-border capacities. Thus, higher cross-border flows, which are not independent of other cross-border flows for a particular line anymore, can be achieved. In the flow-based approach, the cross-border capacities are dependent on the net exchange positions of the different market areas like in the ATC approach. The capacity allocation is based on two parameters. These are the zonal PTDFs derived from the nodal PTDFs introduced above and the Remaining Available Margin (RAM). As these factors are required for market clearing whilst the result of market clearing need to be known to calculate the parameters, there is a circulation problem. To address this problem, a forecast estimating the status of the electricity system is considered to calculate the parameters. This is the point, where the allocation process is partly conducted in advance to the market clearing itself. The forecast is the so-called base case, which is a congestion forecast made two days prior to the delivery day and which is derived from the SCADA systems including power flows, currents and voltages. However, due to an increasing amount of renewable and volatile generation, the difference between the forecast and the realized flows can be

high. As security factors are required in order to address these uncertainties with regard to a possible overload of the grid, the zonal PTDFs are distorted, influencing the final market margin. However, the latter is expected to be greater than for the ATC model. The zonal PTDFs, again in a matrix, and the RAM are submitted to the market clearing algorithm as the line capacity constraints. [37, 44]

Figure 9 shows the simplified network using the flow-based market coupling. By a net exchange position NEP_{AB} between two zones, all interconnectors between all bidding zones and several critical network elements are considered.

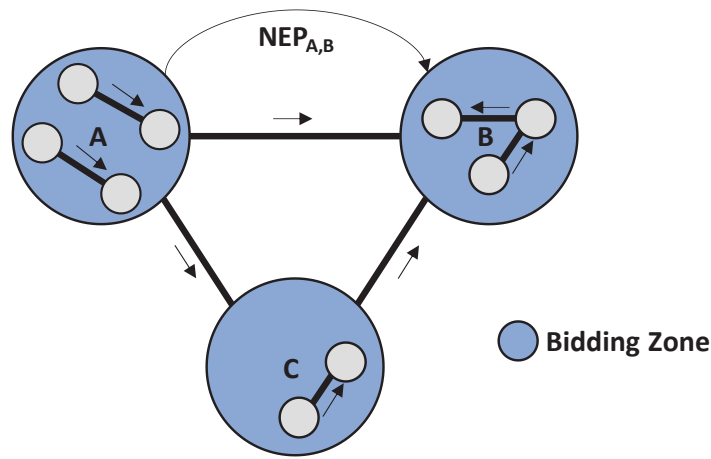


Figure 9: Flow-based Capacity Allocation (according to [37])

The nodal PTDFs are translated into the zonal PTDFs by a weighted sum which is shown in Equation (2.27). Each nodal PTDF of a particular zone is weighted with a specific generation shift key (GSK). In general, several generation shift key sets can be considered referring to consumption, technology, or the generation itself. The sum of all GSKs in a bidding zone, however, equals one. The weights are indicating the influence of a change in the net exchange position of the zone in the specific node. THE GSKs, thus, represent the expected impact a zonal net exchange position has on the injection in a specific node. This is dependent on the particular zone and system state and is defined relative to a defined base case. The zonal PTDFs, again, are indicators for the influence of zonal balance changes on the grid constraints. As the weighting impacts the calculation of the zonal PTDFs, the choice of the GSK is crucial with respect to the later market margin. The inaccuracies, which are caused by any choice of the GSK are due to the fact, that the GSK method is a linear approximation and thus a simplification of a relation which is non-linear itself. [44]

$$PTDF_l^z = \sum_{n \in N} GSK_z^n * PTDF_l^n \quad \forall z \in Z \wedge \sum_{n \in N} GSK_z^n = 1 \quad \forall z \in Z \quad (2.27)$$

For the GSK method, only marginal nodes are considered. Marginal nodes are those nodes influenced by a change of the net exchange position within an area relative to the base case net exchange position. Dependent on the expected system state, for a particular bidding zone, this e.g. might those nodes, offering peak load generation assuming that all base load generation is fully in use. In this case, the GSKs for nodes with base load generation are set to zero as they are not affected by a net exchange position change. For the remaining peak load nodes, the GSKs represent the coverage of the change in the net exchange position, which equals a change in demand by the considered peak load plants. Thus, the GSKs represent the merit-order to a certain extent considering the marginal nodes with their generation units and differing marginal costs. In Europe, the choice of GSKs differs with different characteristics of each bidding zone and node from zone to zone and from TSO to TSO. [46]

The influence of a zone on the real flow on a considered critical network element is a function of the net exchange position of the particular zone. With respect to market-based coverage of a change in the net exchange position, only the set of contributing marginal nodes are considered. The dependency only represents the merit-order around the point of market clearing. The considered nodes are topologically located closer to or farther from the considered line, influencing its flow differently with injection in their place. Thus, the flow function is not linear. The flow-based method linearizes this function starting from the assumed base case using a single zonal PTDF per line and zone defined by the chosen GSK strategy. [44]

For the final determination of GSKs among the set of marginal nodes, basically, the marginal and the average GSK strategy can be distinguished. Both resulting linear approximations, however, intersect in the net exchange position of the assumed base case as Figure 10 indicates. According to the marginal strategy, starting from the base case, the GSKs are chosen under the assumption that the marginal technology determines the zonal PTDF. The slope of the real flow function at that point, thus, equals the slope of the linear approximation. The marginal technology is the last technology, which is in use according to the function of the real flow based on the merit-order. The average strategy, in contrast, defines the PTDF according to the average slope of the original flow function. Thus, it is taking into account all the technologies of the merit-order. Whilst the average strategy is more robust in terms of big changes in the net exchange position because of that, the marginal strategy is more accurate close to the base case. As the real flow might differ a lot from the base case, the goodness of the forecast defines the strategy to be chosen. In order to reduce risks, the average strategy is widely in use whilst efforts are conducted to improve the forecasts. However, for different time slots and different areas, different strategies can be applied. The right choice depends on the characteristics of a specific area regarding its power plant park as already explained. Therefore, ex-post analyses of the realized capacity allocation and the calculated capacities is necessary in order to improve the strategies. Again, the PTDFs are structured in a matrix whose rows again are the lines whilst the columns represent the zones. [44]

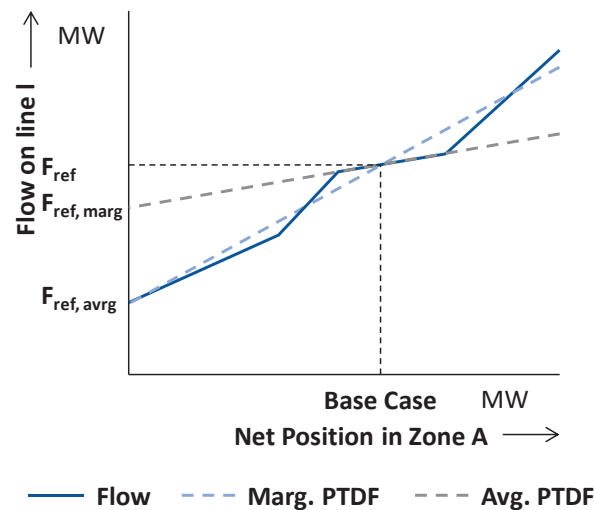


Figure 10: Marginal and Average PTDF strategy (according to [44])

The second parameter required for the flow-based method is the Remaining Available Margin (RAM) for each line. Basically, it is the available transmission limit on a critical line including security margins with respect to the inaccuracies regarding the made assumptions on the base case. The parameter is submitted to the clearing algorithm as a vector with entries for each critical network element. Equation (2.28) shows in vector form that for each branch the RAM vector is derived from the maximal possible flow of the respective line minus the mentioned security margins. The RAM for a particular line, usually positive, may become negative, as well indicating pre-allocated congestion. The clearing algorithm, then, relieves it considering physical interests before economic interests. [44]

$$\mathbf{RAM} = \mathbf{F}_{max} - \mathbf{FRM} - \mathbf{FAV} - \mathbf{F}'_{ref} \quad (2.28)$$

\mathbf{F}'_{ref} in this equation is the vector of the flows on each line at a net exchange position of zero in each zone. It is derived by moving from the base case points of each zone to the intersection of the y-axis and the chosen linear approximation of the real flow for each zone. The respective formula is shown in equation (2.29). \mathbf{NEP}^{BC} is the vector of the base case net exchange positions of all considered zones and needs to be multiplied with the respective row of the PTDF matrix. \mathbf{F}_{ref} is the vector containing the flows of each branch in the base case. \mathbf{F}'_{ref} is deducted for each branch in order to remove pre-allocated capacity, which has been allocated independently from the algorithm. [44]

$$\mathbf{F}'_{ref} = \mathbf{F}_{ref} - \mathbf{PTDF} * \mathbf{NEP}^{BC} \quad (2.29)$$

The Flow Reliability Margin (FRM) is a factor for each line deducted in order to cope with the uncertainties coming along with the flow-based method. These mainly arise from the limited precision of the forecasts made by the power system operators and the linear approximation of the real flow function as already explained. Thus, the uncertainties manifest in the thread of line overloading threatening the operation of the grid. The \mathbf{FRM} vector, therefore, is a buffer reserved in order to give space for real flow differing upwards on each line. The size of each entry is determined by statistical analysis of observed deviations of flows estimated by the flow-based method and the real flows. [44]

Qualitative indicators like operational skills and experience can be included in the calculation by the Final Adjustment Value (FAV). It is the only parameter in the equation, which is set manually, and which is, thus, not calculated. Per default, the value equals zero and changing requires the agreement of all affected TSOs. The \mathbf{FAV} vector allows to adjust the RAM on each line either positive or negative when e.g. security computations reveal additional risks of congestion. \mathbf{F}_{max} is the vector of the maximal flows each line can carry physically. The maximal flow on a branch, as equation (2.30) shows, dependent on

the operating voltage, the thermal current limit and the ration of reactive and active power on a specific line. From the ratio of reactive and active power, the angle φ can be derived. However, since the reactive power is neglected in the flow-based method like in the nodal approach assuming stable operating voltages, the cosinus term equals one. The errors arising from this are troubleshot by the **FRM**. [44]

$$Fmax = \sqrt{3} * \text{operating voltage} * \text{thermal current limit} * \cos \varphi \quad \text{with } \varphi = \tan^{-1} \left(\frac{Q}{P} \right) \quad (2.30)$$

Equations (2.31) and (2.32) show the adjusted constraints for the clearing algorithm derived from the zonal PTDFs and the RAMs. Since each row in the PTDF matrix represents one line, there is one constraint per row submitted to the clearing algorithm. [44]

$$CAP_l = \sum_{z \in Z} PTDF_l^z * NEP_z \quad \forall l \in L \quad (2.31)$$

$$-RAM_l \leq CAP_l \leq RAM_l \quad \forall l \in L \quad (2.32)$$

EUPHEMIA

EUPHEMIA is the central algorithm applied for market clearance on the coupled European day-ahead markets. For this purpose, it requires certain information about the status of the power transmission system in the form of parameters forming constraints delivered by FBMC or ATC. These constraints need to be satisfied while social welfare is about to be maximized. The algorithm calculates for each bidding area a market clearing price as well as a net exchange position. The latter is the difference between the demand and supply quantities in a particular bidding area as already explained. In 2015 the algorithm cleared 53 bidden areas with 67 interconnectors. Besides hourly orders, EUPHEMIA is able to deal with block orders as well as with more complex orders such as MIC, PUN or Merit orders which are explained above. The algorithm finds a first good solution rapidly and seeks to improve it afterward. To ensure an acceptable computation time, EUPHEMIA uses heuristics and assumptions of market prices to reduce both the number of constraints as well as the number of orders. Furthermore, it uses decomposition in order to solve several smaller optimization problems instead of one large one. The algorithm itself was derived from COSMOS, a clearing algorithm applied for the CWE market coupling. The company, that developed both algorithms is N-SIDE. [26, 47, 36]

Due to the complex structure of the market coupling problem, EUPHEMIA operates a combinatorial optimization process rather than a single optimization program. It consists of a master problem with three sub-problems in order to quickly find a feasible solution. The master problem is the welfare maximization, which is the overall target of the European market coupling approach. The welfare, thus, consists of the consumer and the supplier surplus from an economic perspective, and a congestion rent referring to physical constraints. The congestion rent comprises possible charges for electrical flow through specific interconnectors. The master problem includes physical as well as economic constraints neglecting the requirements for PUN and merit orders at first. Consisting of continuous as well as decision variables to select or dismiss block and MIC orders, a Mixed-Integer Quadratic Program (MIQP) needs to be solved. To do so, a branch-and-cut algorithm is applied. It is a branch-and-bound algorithm with the opportunity to insert cutting planes. In order to find an upper bound for the first integer solution from the solution space, an integer relaxation is conducted. Practically, for the moment, this can result in block orders being executed partly. This approach, however, can also lead to an optimal solution immediately. The branch-and-cut algorithm uses four methods to find the first integer solution. At first, there is the branching, which is conducted starting from the upper bound in order to find a solution which sticks to the constraints. Therefore, from each node representing a certain solution, two new instances are derived rounding up and off a particular integer variable whose integer characteristic has been relaxed before. The new instances equal new constraints. By this, a tree structure develops exploring the solution space solving the relaxation problem for each instance using branching again if necessary. In doing so, the actual best value of the objective function is marked. The latter is required for the fathoming. Here, nodes are identified whose successors can improve the solution. Thus, the branching algorithm can stop at the respective node by pruning the tree. The cutting is an operation removing undesirable solutions by adding a new constraint and thus a new instance by introducing cutting planes. This is the case if the integer solution of the master problem submitted to the sub-problems is infeasible for any of them. The cutting planes render a particular solution as infeasible. Finally, there is the stopping that is determined by a time limit or by the full exploration of the branch-and-bound tree. However, if there is no solution found within the time frame the calculation continues until the first solution is found. The output of the master problem is an integer solution containing a selection of block and MIC orders maximizing the social welfare. It is submitted to the first sub-problem, the price determination. [26]

The price determination sub-problem is meant to determine the market clearing price for each bidding area while meeting the two constraints. On the one hand, the market clearing price is constrained by the price spread of demand and supply. On the other hand, it is limited by the minimum and maximum

price bounds of a particular bidding area. On top of that, then, it has to be ensured that neither block and complex orders are accepted paradoxically, nor non-intuitive flow-based results occur. This is done by cutting. The sub-problem may determine negative prices for certain bidding areas. This would encourage the bi-directional electricity flows back and forth on interconnectors in order to destroy electricity by the line losses. To overcome this issue, the flow of one direction is set to zero. If no solution can be found for this sub-problem, the integer solution of the master problem is rejected, and a cutting plane is inserted in order to render the solution as infeasible. The type of cutting plane, thus, depends on the reason for having an infeasible solution, which is investigated by the solving algorithm. Then the master problem is starting again. A successful outcome of this sub-problem is a feasible integer solution, which is then submitted to the next sub-problem. [26]

The second sub-problem is the PUN search for valid PUN volumes and prices asserting strict consecutiveness in terms of the accepted PUN orders. The PUN search is constrained by the PUN imbalance and an iterative process. If no feasible PUN solution is found, again, the solution is rendered as infeasible by a cutting plane and the master problem starts again. After a PUN solution is found, first the list of rejected complex orders and, after that, the respective block order list which is ranked by price and volume are checked. By piecewise activation of the orders and de novo execution of the price determination, possible reinsertion is analyzed. This functions as a shortcut in the branch-and-bound tree by jumping from node to node in order to prune nodes due to a new better objective function value of the master problem after reinsertions. If the objective function value is decreasing by reinsertion, the order is dismissed again. Regarding the checking of block order reinsertions, a new PUN search may be required as the imbalance is not respected by a constraint. Finally, the solution is submitted to the volume indeterminacy sub-problem. [26]

The last sub-problem is the volume indeterminacy sub-problem. At this point, a feasible integer solution with PUN has been found including market clearing prices, volumes and a selection of orders to be executed. The volume indeterminacy sub-problem now seeks to find a coherent solution from a set of equivalent solutions yielding the same social welfare with a focus on four aspects. These aspects are curtailments, the merit order of as well as the traded volume regarding hourly orders and the flows on ATC lines. The curtailment minimization and the curtailment sharing are addressing the curtailment. Curtailment in this respect are situations in which the market clearing price is at one of the constituted order price limits of a particular area whilst not all hourly orders submitted at this price are accepted. These orders are the price-taking hourly orders accepting any market clearing price in order to fulfill their order. Regarding demand, these are hourly orders submitted at the maximum price and regarding supply, these are orders submitted at the minimum price. The curtailment ratio is the measure to

determine the degree of curtailment by the proportion of the not accepted price-taking orders. The curtailment minimization sub-problem, thus, matches price-taking hourly orders with opponent orders locally within the same bidding area. This equals a constraint marking the lower bound of accepted price-taking orders in a bidding area. It is considered in the master problem already. [26]

The curtailment sharing, instead, aims at the harmonization of curtailment ratios among all bidding areas. At least partly, it is implemented in the master problem. A term is added to the objective function of the master problem in order to penalize the non-acceptance of price-taking demand orders. The penalizing term is the sum of the highest curtailment ratio of each bidding area enforced by a large factor. Thus, the curtailment sharing is addressed automatically in the solution finding process. In the volume sub-problem, the harmonization of curtailment ratios is conducted as well but for the ATC method, exceptionally. It is necessary in that case because the master problem is indifferent between different bidding areas for equal price taking orders. Curtailment minimization and curtailment sharing on volume sub-problem level are excluding each other regarding their application on a bidding area. In terms of the latter, the contribution of a particular bidding area happens in the form helping to carry the higher curtailment of other bidding areas. The approach of this volume problem is to minimize the curtailment ratios of the respective areas by weighting them with the volumes of only those orders, which are price taking. However, all other constraints remain respected. [26]

The volume maximization addresses the traded volume by seeking to optimize the accepted volume considering all possible orders except block orders. The solution regarding the latter has already been optimized. The volume can be increased if there is more than one intersection between demand and supply. Practically, this is the case, when demand and supply intersect whilst both ask and bid the same price for a similar range of volume. The market clearing price is not affected at all. Thus, it just affects orders which are at-the-money accept price-taking orders which have been fixed by curtailment minimization or curtailment sharing before. [26]

After that, hourly orders at-the-money are rearranged according to their merit order numbers if it does not change the feasible solution respecting the PUN constraint. Finally, whilst all other variables have been determined, the flows will be re-attributed for ATC lines according to their cost coefficients. The flow indeterminacy problem needs to be solved when several flows are capable to translate the solution of the economic level onto the physical level. Only in areas with intermeshed networks and full price convergence this might be the case. After the volume indeterminacy sub-problem has been passed through entirely, a feasible solution from a set of equivalent solutions has been found which is

obeying all constraints and which is in line with the mentioned volume related criteria. In the next step, the process will start again in order to improve the solution. [26]

Besides the day-ahead market coupling, the idea of integrated European electricity markets also aims at the introduction of coupled intraday markets. These markets are crucial for actors on the market for balancing their own portfolio in order to avoid being charged for balancing power by the TSOs. The single intraday coupling started its operation in 2018 and its design was also manifested in the CACM regulation from 2015. The system operated to provide the intraday market coupling is called XBID system, which was designed by the Deutsche Börse AG. It is based on three modules ensuring the seamless trading backed up by the national intraday markets in case of failure. The three modules comprise the physical, the economic and the informational layer of market coupling. The first module is the Shared Order Book (SOB), which is related to the economic layer. It is a commodity trading system providing flexible trading services according to the special needs of energy markets continuously. The SOB is the core of the XIB system including four different fields of duty. At first, it is a superior order book, consolidates the orders of local exchanges in order to match them for execution cross-regionally if enough capacity is available. Thereby it implicitly allocates the cross-border capacities. The matching of orders happens according to the Price-time-capacity priority criteria ensuring that at first the orders with the best prices are executed. Orders with the same price are ranked by the time of submission and finally, the capacity criterion ensures, that an order is executable in terms of volume. In general, XBID offers quarter-hourly, half-hourly, hourly, and block products. Based on that, the SOB conducts capacity routing to determine the order execution flow. This is determined by the shortest path rule according to the ATC as the market coupling approach for this particular market. Finally, the SOB provides an interface to local trading systems (LTS) making the closed contracts and matched order available for them. [48]

The Capacity Management Module (CMM) is responsible for allocating cross-border capacities continuously with a direct connection to the SOB. This service is offered both implicitly via SOB as well as explicitly by requests of independent users. On top of that, it provides two interfaces for TSO and explicit traders. The interface for TSOs is the Capacity Management Integration Application (CMI) monitoring market activities in real time. The interface for explicit participants enables the submission of orders. In general, the CMM is structured into an area, connection and user management addressing the different functional entities participating in the continuous intraday market coupling. The area management administrates the concerns of market areas which might include several delivery areas which themselves are managed by a TSO each. The fourth entity in this field of administration are the virtual delivery areas. The connection management administrates the borders, the connections

between two market areas, as well as the interconnectors, the connections between two delivery areas. The connections are managed according to physical and administrative characteristics like default capacity or leading TSO. The last field of administration is the user management, which handles with the TSOs and the explicit participant both groups of users. [48]

The last module is the Shipping Module (SM) representing the communication layer. The module comprises the market clearing and thus the energy transfer both within and across the participating areas. This includes the financial as well as the physical market clearing. Shipping, thus, is the change of ownership regarding energy and the respective payments. [48]

As it was already explained, the market coupling is the try to establish a fully integrated European power market with a single European electricity price. This, however, is not achieved due to cross-border capacity constraints between several markets, which comes down to differing prices between them. This issue is subject to efforts of transmission system operators to reduce these constraints by expanding the European transmission network. In order to show the welfare losses due to capacity constraints, the EPEX Spot calculates the European Electricity Index (ELIX). The index is based on all bids and offers which are also cleared within the constrained market coupling process but it neglects the constraints. The differences between actual and ELIX prices indicate the benefit a constraint reduction can bring in terms of the overall welfare. In other words, the difference between market prices and ELIX are the congestion cost of a specific border. Thus, the index helps to indicate market coupling performance and proves its benefit. Compared to the total amount of congested hours, it is a monetary parameter. By that, it can support policy and investment decisions. In particular, compared to the PHELIX, the ELIX comprising, with France, Germany, Austria and Switzerland, 36 % of the European electricity consumption, the gap is already quite low. [49, 35]

2.1.3 Modeling approaches

The liberalization of the energy sector triggered the development of new modeling approaches due to its special characteristics already explained above. Due to privatization and the introduction of wholesale trading, actors face economical risks whilst regulators face increasingly complex analysis tasks. Both require support on their tasks in terms of decision-making or monitoring the market performance. Traditionally, pre-liberalization-models are not able to model the interactions among market actors driven by decentralized decisions. The key motivation for companies, thereby, is profit maximization. Due to that, the requirement for models describing electricity markets is that the economics perspective is always constrained by physical-technological aspects. This is due to the special characteristics of electricity as a good that have been described above. Thus, each model describing the electricity markets needs to have at least a physical layer influencing subordinated layers like the economic layer. Furthermore, despite market liberalization, even wholesale electricity markets are imperfect markets due to relatively few actors. Capacity constraints and the presence of large players artificially decrease markets and competition. In order to meet these special requirements, basically, three trends of modeling approaches have developed. These are optimization, equilibrium, and simulation models, which are, due to their different characteristics, relevant for different use cases. The models differ in terms of the modeled degrees of competition or uncertainty, the considered time scope or the linkage between periods. With respect to electricity markets, they also differ regarding the ability to model transmission constraints. On top of that, they provide different degrees of detail regarding the modeling of a market and of the entities within a generation system. [50]

Optimization models consider only one company or actor. Therefore, they consider the pricing as an exogenous variable or as dependent on the respective quantity of electricity supplied by oneself. By this, the number of variables and subordinate optimization problems is reduced significantly. Due to this and due to proven optimization algorithms, these models offer a fast calculation and are thus relevant for short-term considerations regarding difficult and detailed problems. An example in this context is the building of bid curves. Within optimization methods, two streams can be distinguished. At first, there is the approach that all prices are given exogenously meaning that the respective company cannot influence them and, thus, is a price-taker. The price is an input parameter for a linear or a mixed integer linear optimization problem with a linear objective function dependent on a company's production exclusively. This approach assumes a perfectly competitive market. Within this approach, there are two ways of modeling the input price. On the one hand, the price can be modeled as deterministic. This approach allows the division of the company's optimization problem into sub-

problems considering its different generation units. This results in the submission of bids according to marginal costs. On the other hand, there is the stochastic approach considering prices determined but uncertain. In this respect, there are several models dealing differently with this risk of uncertainty. The second approach considers the market price to be dependent on the company's decision on its production scheme. The residual demand function is the decision scheme illustrating the amount of electricity that can be sold at a given price by the company. Input parameters, therefore, are the demand curve as well as competitors' supply curves. Again, these can be deterministic or stochastic. The residual demand function is determined by the difference between competitors' supply and the demand. The stochastic approach considers, thus, a probability function for the input parameters in order to seek for an optimal bidding strategy for the company in terms of its offers. Thus, these models are applied to determine hedging strategies facing short-term uncertainties. [50]

Since equilibrium models consider all actors of a market environment, these approaches are capable to model competition and to support market power analysis. Thus, they focus on long-term issues. Nevertheless, these models are subjected to a high number of variables and constraints due to the illustration of complex systems. This necessitates laborious mathematical programming methods in order to find the desired equilibria. Again, within this approach, there are two different streams. On the one hand, there is the modeling by Cournot equilibria assuming that companies follow quantity strategies setting an optimal output. This approach is considered to be capable of dealing with imperfect competition in markets, although it is an application on electricity markets, in particular, is discussed controversially. Models in this category are based on a set of algebraic equations, thus equilibria can be found with little computation effort. The fields of application, thus, are manifold. They stretch from market power analysis over hydrothermal coordination and electric power networks toward single risk analysis applications. In terms of market power analysis, equilibria can be found by a revolving algorithm. Considering a market with different actors, the profit-maximizing output for each company is determined repetitively and successively one at a time. The outputs of the other companies are considered as fixated during the calculation of a particular company's output. This procedure is repeated until no company can improve its output and thus equilibrium is reached. Nevertheless, there are algorithmic deficiencies and other skewing inaccuracies especially with respect to hydroelectric plant operation. Regarding electric power networks, this approach is used to model congestion pricing. Therefore, it takes into account the power-flows framed by Kirchhoff's laws. Nevertheless, this includes the assumption that companies only generate in a single node. This, however, is an exception in electricity markets. The controversies regarding this approach mainly focus on the fact, that prices are only determined by and highly sensitive to demand. This results in higher

clearing prices than yielded by real markets. This bias is sought to be overcome by conjectural variations regarding competitors' behavior. On the other hand, within the approach of equilibrium models, there is a stream of modeling by supply function equilibria (SFE). Compared to the Cournot approach, here a range of residual demand is considered. Thus, the company prepares a bidding strategy offering different quantities at different prices in a supply function. To find an equilibrium a set of differential equations need to be solved causing issues regarding their numerical tractability. That is why detailed modeling of complex generation system is not possible. However, there are streams using linearization or a stepwise definition of supply curves in order to overcome these issues. For this approach, there are three use cases with market power analysis, electricity pricing, and electric power network analysis. Basically, inelastic demand is assumed for whose covering suppliers provide a daily supply curve. However, the demand does not need to be known in advance and the supply curves are also valid for changing demand as they determine the price for different quantities sold. In terms of electricity networks, for each generation unit of a company in a particular network node. Transmission constraints can also be modeled in the form of transaction costs. However, the high flexibility of SFE models is paid by tractability issues, computational efforts, and simplifications of analyzed systems. Furthermore, there is a bunch of different not standardized ways of SFE usage. Due to the complex numerical setting, it is hard to prove solutions of SFE models in terms of uniqueness or even existence. On top of that, the assumption of inelastic demand is crumbling with regard to demand-response applications. [50]

In contrast to equilibrium or optimization models, simulation models offer higher flexibility in terms of modeling competition as no equations put limitations of any kind on it. Simulation models are a proper approach to deal with highly complex systems as they model the decision dynamics of agents by predefined rules of behavior. Again, there are two sub-categories. Firstly, there are models, closely related to equilibrium models as the decision rules are based on Cournot and the setting of quantities. Secondly, there are agent-based models. They are determined by the adaptability of agents learning from their past decision. Their field of application is manifold. Due to its higher flexibility regarding the modeling of competition with neither taking supply and demand curves nor prices as given this particular type of simulation models will be applied to the European electricity market in the following. [50]

2.2 Agency Systems

This chapter introduces the concept of agency systems. To do so, at first, the basic principles are explained in chapter 2.2.1. It is followed by the presentation of several agency systems which are applied to the energy markets.

2.2.1 Basic principles of agent-based models

Agent-based systems can model aspects of markets, traditional approaches lack to model. It is an approach developed by increasing computational capacities and research on artificial intelligence as well as on non-linear dynamics. At first, agent-based modeling (ABM) can illustrate heterogeneity in markets in terms of diverse independent and individual actors with unique sets of characteristics and specific behavior. In traditional, especially economic approaches, this is often simplified by aggregation. However, heterogeneity is a crucial characteristic of markets, making trading possible at all. Another aspect is that of dynamics in terms of adaptive processes. Traditionally, in economics, equilibriums are analyzed or compared whereas the process of changing between equilibria is typically not considered. This, again, agent-based modeling provides by setting simple rules. Last, traditional models neglect the interactions between market participants in terms of behavioral approaches. Actors in markets influence and copy each other. Interaction of actors, though, is the core principle of ABM. With these three fundamental characteristics, ABM is able to close the gap between micro- and macro-economic considerations, which are often conducted separately in traditional economic approaches. [51]

Agents themselves have four substantial characteristics, which determine the features of ABM mentioned above. At first agents have the ability of perception. Thus, they recognize the neighboring agents in their environment. With them, an agent can communicate and interact, which is one aspect of the ability of Performance. On top of that, agents can act in order to achieve their goals. Furthermore, agents have a memory allowing retrieving past actions and past states. According to this and according to the issue of artificial intelligence, agents can learn and adapt to a new behavior. Finally, agents are subject to several rules determining their behavior. [51]

Besides the introduced features of ABM compared to traditional approaches, ABM breaks with a common characteristic style of models searching for equilibria and optimums. Since optimization problems require a set of assumptions, which distort the reality significantly, this a major concern of traditional economic models. ABM instead allows the introduction of other rules than simple

maximization of a target value. These rules may be simple pricing rules for actors in a retail market or management of budgets instead of maximizing its utility for households, just to mention some. This might be far from optimal solution, but closer to reality as the mentioned rules are referring to the issue of uncertainty and missing information for actors on real markets. Optimization problems instead, with regard to unrealistic assumptions, assume traditionally certainty regarding the input data. [51]

However, there are several issues discussed related to the application of ABM in economic research. First, there is the issue of complexity. Often agent-based models are black-boxes not revealing the processes inside. Here more transparency and explanations, e.g. by publishing code, are requested. On top of that, critics argue that ABM is not based on equations, which are solved or optimized and concurrently considering too many variables. These points of criticism, in fact, point out the benefits of ABM. First of all, ABM is based on equations, but the models do not seek to optimize target value but provide other decision criteria. Furthermore, the high number of variables pays attention to the benefit of a high sharpness of detail. Thus, ABM is closer to reality. [51]

Another aspect is the lack of standardization translating into several decision criteria and rules besides the common one of optimization. In fact, there are many different behavioral rules already considered. Theoretically, the number of different behaviors is unbounded. That is why researchers call for standardization of ABM in terms of transparency and scientific rules. Besides a standardization, new input data is requested, as the focus with ABM shifted from purely economic values to behavioral aspects. These need to be defined more accurately in order to enable the development of ABM. Behavioral economics, anyhow, is an emerging field of study. [51]

2.2.2 Different agent-based Approaches for Energy Markets

In terms of the application of agent-based models on the electricity sector, several approaches can be distinguished which differ mainly regarding the utilized learning and adaption algorithms. At first, there are the model-based adaption algorithms. These are algorithms designed individually for specific applications and can hardly be generalized. They are neither based on psychological research nor on machine learning. Instead, they are referring to naïve and intuitive formulations. Another approach are genetic algorithms imitating the rules of biology in terms of evolution. By this, these learning algorithms use heuristic decision criteria creating new strategies which are not chosen from a predefined set of given strategies. With regard to strategic bidding at markets, only successful strategies are considered furthermore as offsprings in subsequent generations. A strategy in this

analogy is a gene consisting of several chromosomes which are bit strings including the strategy information. Crossover and mutation procedures take into account genetic dynamics. On top of that, there are approaches applying the Erev-Roth reinforcement learning algorithm. This algorithm is based on three parameters derived from psychological findings on human learning including features like experimentation and forgetting. Furthermore, there is the concept of Q-learning, which was first issued in 1983. Learning Classifier Systems instead are hybrids of reinforcement learning and genetic algorithms using the benefits of both approaches. Finally, there is the supply function optimization heuristic. Here, under the assumption that the competitors do not adjust their supply function over time, the agents solve their profit optimization problem by adjusting their supply function. Another approach are artificial neural networks, which are referring to deep learning. The different approaches are explained in detail below, based on applications on electricity markets. [52]

In [53] a genetic algorithm is developed in order to simulate the strategic bidding of electricity suppliers with respect to a social welfare maximal market clearing. Following the Bertrand scheme, agents are adjusting their price bids under uncertainty, whilst the volume bids are fixed. The agents choose their strategy according to their assumptions of the market clearing. As the agents face uncertainty in this respect, several scenarios are developed based on which the agents individually try to maximize their profit using the genetic algorithm each. Each agent, thus, can have a portfolio of several generation units. The scenarios include assumptions on the expected load as well as competitors' behavior. An individual in the genetic algorithm is defined as the bid price for a specific unit from the portfolio of an agent. The range of possible bid prices is defined by a set of different prices with an upper and a lower bound for each particular unit of an agent. The minimum bound, thus, corresponds with the marginal costs for a particular unit. The starting population is derived from three starting solutions. These are bidding the marginal costs for each unit, bidding the maximal price, and bidding the same price for each unit based on the expected outcome of the market. According to the market result, the fitness of each individual is checked, which is basically the earned reward. Based on the information on the population's fitness, iteratively for 90 % of the current population, two individuals are taken as parents according to their fitness rank. The crossover procedure now randomly chooses one gene, from these two individuals creating a new individual. A gene, in this respect, is the price contained by an individual. After 90 % of the required population has been generated as offsprings of the initial population, for 2 % of the newly generated population, the mutation approach is applied. Therefore, their genes or prices, respectively, are adjusted randomly. Additionally, a predefined number of individuals, the paper suggests two offsprings, should be exchanged with individuals from the set of best individuals of the previous generation. The exchange is done using a local search algorithm, be which for random

individuals is checked, whether they are the best within a certain range of individuals around them. A generation, thus, is the population in a particular time step. Finally, the new generation is made up from 10 % of the best individuals of the current population and 90 % of the generated offsprings. [53]

As it was mentioned before, Erev-Roth reinforced learning is an approach which is derived from psychology. By reinforcement learning, learning is based on interactions with the environment and rewards earned according to chosen actions. The two basic rules for learning of living subjects, the law of effect and the power law of practice, are translated into a machine learning concept by an algorithm. The first law states that individuals, assuming that their choice of behavior is probabilistic, will repeat those behaviors, which lead to a higher profit more likely. The second law reflects the fact that learning effects are decreasing over time. The algorithm representing the learning by determining probabilities of executing certain behaviors is scaled by three parameters and dependent on the profit gained by a behavior. The probabilities again are dependent on propensities to execute a certain behavior. Equation (2.33) and (2.34) show the basic formulas to calculate propensity q and probability p regarding each behavior j of a particular agent n . After each execution of any behavior, propensity and probability for each behavior are updated. The propensity function, thus, is mainly referring to the law of effect. For the recently exercised behavior k different propensity function is applied compared to the other behaviors. Both propensity functions consist of a forgetting and an experimentation term. Those are two minor concepts of learning of individuals. Forgetting is modeled by the parameter ϕ and the experimentation by the parameter ϵ . Those are two out of three scaling parameters of this learning approach. The forgetting parameter or recency parameter ϕ , respectively, ensures, that the current behavior has a higher influence on the propensity of future behavior by reducing the contribution of past experiences slowly. This term is equal for both exercised and not exercised behaviors and combines both basic laws. The second term is the experimentation or generalization term, respectively. It is dependent on the reinforcement function R which itself is dependent on the payoff x . As an agent's payoffs are dependent on the competitor's behavior, the reinforcement function automatically includes the competitor's influence on an agent's behavior. The dependency on profits leads to a higher market efficiency as agents adjust their strategies according to their success. The experimentation parameter ϵ is applied differently on the recently exercised behavior k and the other behaviors. It is used to avoid lock-in situations regarding a particular behavior but to ensure the exploration of behavior similar to the current. Thereby, ϵ determines the ratio between exploration, which is the utilization of similar behavior and exploitation. The latter equals focusing on a single profitable behavior until it is not profitable anymore due to the adaption of competitors. The influence of the reinforcement function on the propensity of the currently applied behavior is reduced whilst it

is increased for the other behavior with increasing ε . The former is referred to as the generalization of the experience gained by applying behavior or strategy k , respectively. The parameter M in the latter formula represents the number of possible behaviors. This second term of the propensity function, again, is addressing the first basic law soften it. [52, 54]

The probability function p is representing mainly the power law of practice. The ratio indicates that the propensity and, thus, the reinforcement affects the probability of exercising a certain behavior the more, the smaller time t is. This is due to the decreasing relative increase of the sum over all propensities, which is, due to the nonnegative reinforcement assumption, a function dependent on t . However, with the propensities themselves, also the law of effect is implied in this equation. [52, 54]

$$q_{nj}(t+1) = \begin{cases} (1 - \Phi)q_{nj}(t) + R(x)(1 - \varepsilon) & \text{if } j = k \\ (1 - \Phi)q_{nj}(t) + R(x)\frac{\varepsilon}{M-1} & \text{if } j \neq k \end{cases} \quad (2.33)$$

$$p_{nj}(t+1) = \frac{q_{nj}(t+1)}{\sum_{k=1}^M q_{nk}(t+1)} \quad (2.34)$$

The third parameter is the scaling parameter $s(1)$. Together with the average payoff X for each player n , it determines both the initial choice of propensities and probabilities for each behavior or strategy, respectively. At first, each player assigns the same propensity $q_{jk}(1)$ as well as the same choice probability $p_{jk}(1)$ to each feasible action k . The respective formulas are shown in Equation (2.35) and Equation (2.36) below. [55]

$$q_{nj}(1) = \frac{s(1) * X}{M} = s(1) * X * p_{nj}(1) \quad (2.35)$$

$$p_{nj}(1) = \frac{1}{M} \quad (2.36)$$

The basic Erev-Roth algorithm has two conceptual problems, which need to be addressed in order to make the learning algorithm generally applicable. At first, there is the issue of parameter degeneracy, which is referring to the experimentation term of the propensity function. Basically, it is issued by an inappropriate setting of the experimentation parameter. If ε is set close to the value that is shown in Equation (2.37), the learning process is slowed down or even demolished at equality. This is due to the fact, that the formulas for executed and nonexecuted formulas can be reduced to the same equation which is depicted in Equation (2.38). [55]

$$\varepsilon = \frac{M - 1}{M} \quad (2.37)$$

$$q_{nj}(t + 1) = (1 - \Phi)q_{nj}(t) + R(x) \frac{1}{M} \quad \forall j \quad (2.38)$$

The second problem is related to the experimentation term of the propensity function again, but it is in detail only relevant for updating nonexecuted behaviors. For payoffs close to zero, the choice probabilities are hardly or not changed at all. Again, this is due to the characteristic of the function. Whilst this effect is intended regarding the executed action k , it counteracts the overall concept of the algorithm, as the choice probabilities of the nonexecuted behaviors are changed neither. [55]

Both conceptual problems are addressed at a time by the modified Erev-Roth algorithm shown in Equation (2.39) without violating the learning principles of the basic approach. By this approach, the recency parameter is reduced for nonexecuted behaviors. Thus, there are two different recency parameters for executed and nonexecuted behaviors now by simply replacing the profit term for the latter. Thereby, the degeneracy and the “zero profit” problem are eliminated. Regarding the latter, this is due to the adjustment of the shrinkage speed. For profits close to zero, the propensity and thus the choice probability for the executed behavior shrinks faster than for the nonexecuted behaviors. Thus, the execution of the latter becomes more likely in the following steps. In situations of high profits, instead, the propensity shrinkage regarding the executed behavior is exceeded by the profit term. [55]

$$q_{nj}(t + 1) = \begin{cases} (1 - \Phi) * q_{nj}(t) + R(x) * (1 - \varepsilon) & \text{if } j = k \\ (1 - \Phi) * q_{nj}(t) + q_{nj}(t) * \frac{\varepsilon}{M - 1} = (1 - (\Phi - \frac{\varepsilon}{M - 1})) * q_{nj}(t) & \text{if } j \neq k \end{cases} \quad (2.39)$$

Erev and Roth analyzed a good fit for the three scaling parameters for human-subject games like Equations (2.40) to (2.42) indicate. According to calibrations under application of the modified Erev-Roth algorithm the respective intervals for the scaling and the recency parameter are obeyed. For the exploration parameter, instead, values close to one 1.0 were observed. The calibration was stopped when a single peak in the respective price histogram for each could be observed. To do so, two scenarios were repeated several times with different parameterization whilst the three scaling parameters were changed. The parameterization regarding the fixed values was conducted regarding the number of auction rounds and the number of price offers within each player's price offer range. [55]

$$0 < s(1) < 1000 \quad (2.40)$$

$$0 < \Phi < 0.2 \quad (2.41)$$

$$0.02 < \varepsilon < 0.3 \quad (2.42)$$

The balance between exploration and exploitation can be influenced also by a modified choice probability function by applying the exponential function as Equation (2.43) shows. The function is inspired by the Boltzmann distribution. In this approach, T is a temperature parameter. It defines the player's decisions as explorative at first and exploitative in the long run by decreasing T over time. The parameter steers a player's focus on behaviors with high propensity values dynamically, thus, and introduces the fourth parameter. [52]

$$p_{nj}(t+1) = \frac{e^{\frac{q_{nj}(t+1)}{T}}}{\sum_{k=1}^M e^{\frac{q_{nk}(t+1)}{T}}} \quad (2.43)$$

In [55], a modified Erev-Roth algorithm is developed to simulate the price determination of supply and demand. A particular strategy in this respect is the overall price of the bid. In this paper, however, the strategy of a trading agent will be defined as the markup which is added to the marginal cost of production by a particular agent. This is due to the variability regarding the marginal costs of different technologies. The reward, then, is the revenue or the profit gained by the made choice.

Q-learning, as well, is a reinforcement learning concept. Unlike the Erev-Roth algorithm, though, it is not dependent on a model and probabilities, which the considered agents need to learn beforehand. A model enables an agent to make predictions about future rewards in order to make decisions. Applying Q-learning, a decision can be made without knowing the future handling uncertainties effectively at a time. Furthermore, the impact of market power on the market outcome can be considered using this approach. Q-learning simply seeks to determine the optimal reaction to an actual state or to maximize the expected reward. This is referring to Markov decision processes on which the Q-learning algorithm can be applied only. At first, reinforcement learning is defined by decision making in an environment which can take on discrete states s_t from a finite set of states S in discrete time steps t . Within each discrete time step, according to their sense of the current state s_t , agents can react with actions a_t from a finite set of actions A . Thus, an action might change the current state to a state s_{t+1} or s' , respectively, from the same set of states S resulting in a certain reward for the agent. In Markov decision processes, the transition from one to another state due to a conducted action happens with a probability of $P(s_{t+1}|s_t, a_t)$. By changing the state of the environment through his action, the agent gets the immediate reward $R(s_{t+1}|s_t, a_t)$. Q-learning, now, assigns a value, the Q-value, to each admissible pair of state and action with the updating algorithm shown in equation (2.44). After executing a certain action with earning a reward, the related Q-value for the state-action pair is updated. Basically, the Q-value is the benefit a particular action brings in a certain state including future rewards by considering the value maximizing action for the new state. The Q-values are stored in the Q-value look-up table in which the rows represent the observed states and the columns represent the actions. α is the learning rate of a particular agent and is equivalent to the forgetting parameter in the Erev-Roth algorithm. It balances the impact of the actual Q-value compared to the rewards on the update and, thus, it determines how drastically the updating process is. As for updating the actual Q-values are required, the table needs to be initialized before starting the Q-learning. To do so, there are different approaches e.g. an initialization based on knowledge or random choice. The easiest initialization, however, is an initialization with Q-values of zero. γ represents the discount factor for future rewards. Future rewards, thus, are considered to have less value than actual rewards. According to the formula, in each step, only one value of the q-table is updated representing a state-action pair. An agent, now, chooses its response action to a state according to the maximal Q-value. [56]

$$Q_{t+1}(s_t, a_t) = (1 - \alpha) * Q(s_t, a_t) + \alpha * (R(s_{t+1}|s_t, a_t) + \gamma * \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})) \quad (2.44)$$

According to the optimal Q-value, then, the optimal strategy or policy, respectively, for each state of the system can be derived from the Q-table as it is shown in equation (2.45). Basically, the action, having the highest expected Q-value, is chosen representing the optimal strategy for the considered state. This approach is referred to as a zero-order temporal difference approach assuming a uniform probability of changing to any other state.

$$\pi(s) = \arg \max_{a \in A} (Q(s, a)) \in A \quad \forall s \in S \quad (2.45)$$

Choosing the strategy according to the highest Q-value might cause lock-in situations and, thus, a ϵ -greedy strategy can be applied like in the Erev-Roth algorithm. This strategy balances an agent's decision between exploration and exploitation by using ϵ as a probability to choose an arbitrary action from the set of actions instead of the Q-value maximizing one. The mathematical approach is shown in equation (2.46). [57]

$$a_t = \begin{cases} \pi(s) & \text{with } p = (1 - \epsilon) \\ a \in A & \text{with } p = \epsilon \end{cases} \quad (2.46)$$

Due to the characteristics of Markov decision processes, Q-learning involves the benefit that, theoretically each Q-value converges toward an optimal value definitely. For this, for each state, each action has to be executed infinite times on an infinite run. However, as the assumptions made regarding stationarity and Markov decision processes are simplifications of the reality, Q-learning is at risk of the curse of dimensionality. This can be illustrated by the states of an environment and the actions to be executed whose numbers both are theoretically infinite. Nevertheless, Q-learning is considered as one of the most efficient model-free reinforcement learning algorithms and on top of that as the easiest to implement. [56]

Regarding the simulation of electricity markets, the state of the system can be defined as the market clearing price from which an agent's reward can be calculated according to the sold electricity. The strategy, up to the agent, then, is the choice of a markup on top to the marginal cost. However, as the assumption of stationarity is barely valid, as load and generation by renewables vary significantly from round to round, long time until convergence is expected.

Learning classifier systems (LCS) are combining the characteristics of reinforcement learning approaches and genetic algorithms. Basically, they were designed to advance the genetic algorithm with respect to machine learning. Like in reinforcement learning algorithms, LCSs actions are chosen

dependent on the environment. Thus, the state of the system is classified and based on that classification a strategy is chosen. The behavior of an agent is modeled by a set of classifiers. They link the possible actions of the agent with a certain condition. The different classifiers are referred to as rules. LCSs consist of different subsystems, that are representing, among others, the two mentioned learning algorithms. The Credit Allocation Subsystem is employing reinforcement learning adjust the given rule set or classifier set, respectively, according to the gained reward. The Rule Induction System, instead, extends and changes the existing set of rules using genetic algorithms by adding new and removing existing rules according to their performance. The Performance Subsystem coordinates the other two subsystems and finally chooses the respective strategy according to the outcome of the other subsystems. Formally, a third subsystem handles conflicting situations where different classifiers are issuing contradicting actions. [58]

Supply function optimization agents try optimizing their portfolio bidding according to a piecewise linear supply function. The agents adjust their bids by adjusting the price for only one generation unit between two auctions. The respective generation unit is chosen according to the highest expected reward regarding the observed output of the current auction round. The optimization is done under the assumption that the competitors do not change their strategy at all. [52]

An additional approach in terms of machine learning applications in agent-based modeling is the concept of Artificial Neural Networks (ANNs). ANNs are information processors aligned at human thinking in neural networks. The networks consist of several data processing entities, the neurons which send a signal according to their excitation and which are organized in layers. In a fully intermeshed network, each neuron is linked with each neuron of the previous and the subsequent layer via a weighted connection. Moreover, each neuron is assigned with a bias term, marking a certain excitation threshold. A neural network consists of at least of an input and an output layer. Between the input and the output layer, an arbitrary number of hidden layers can be located. The number of neurons on each layer, thus, is arbitrary as well.

Figure 11 shows the topology of a basic, three-layer neural network. The number of layers is described with the variable d whilst the number of neurons per layer is described with the width w . The connection between neuron i of the input layer and the neuron j of the first and only hidden layer is weighted with the weight w_{ij} . The bias term of neuron j is denoted as b_j . [59]

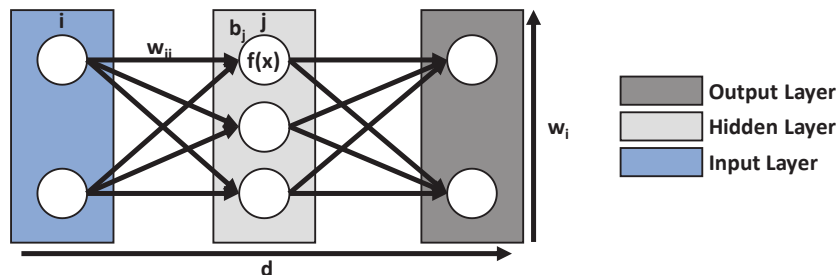


Figure 11: Topology of an Artificial Neural Network (own figure)

The binary information, whether a neuron is activated by the excitation through the signals sent by neurons of previous layers, is stated by activation functions. In general, several different activation functions are in use. They all have in common, that they clearly determine whether a neuron is activated or not. A widely used function, in this respect, is the rectifier function, which is also referred to as “rectified linear unit” (ReLU). The activation for a neuron j dependent on its excitation is shown in equation (2.47). For an excitation x_j smaller or equal to zero, the activation function and thus the neuron, is sending the information of not being activated. An excitation greater than zero leads to an activation greater than zero equal to an activated state. [60]

$$f(x_j) = \max(0, x_j) = \begin{cases} 0 & x_j \leq 0 \\ x_j & \text{otherwise} \end{cases} \quad (2.47)$$

The excitation, again, is determined by the weighted sum of all outputs or information on activation, respectively, of the connected neurons of previous layers plus the bias term b_j as equation (2.48) indicates. Dependent on the use case, the activation functions on the output layer define, whether the neural network is used for classification or for regression purposes. In the case of the latter, the neurons on the last layer are activated linearly if negative values are supposed to be considered. [60]

$$x_j = \left(\sum_{i=1}^n w_{ij} * f(x_i) \right) + b_j \quad (2.48)$$

Machine learning, now, is applied for determining the weights between two neurons and the biases for each neuron. As ANNs are representants of the class of supervised learning frameworks, the weights are updated iteratively according to a given set of data. The output of the ANN to be trained and fed with input features is determined by forward propagation and compared with the observed values. Forward propagation, thus, simply is the calculation of the output vector by stepwise calculating the output of each layer starting with the input layer. According to the difference between calculated and observed values, the weights are updated using backpropagation as a common approach. Here, weights of each connection are updated starting with the last layer. To do so, the basic approach is the gradient descent procedure, updating the weights according to the first partial derivative of the error term weighted with the learning rate η . By updating the weights according to the derivative of the error term, the error is about to be minimized. A typical error term is the sum of squared residuals. The learning rate steers the speed of the convergence process towards a final minimal discrepancy between observed and calculated values. However, in literature, there are many different updating algorithms discussed which are advancements of this the basic approach to a certain extent. [60]

$$w_{ji}(t+1) = w_{ji}(t) - \eta \frac{\partial E}{\partial w_{ji}}(t) \quad (2.49)$$

The choice of the depth and the width of an ANN is subject to many discussions in literature. The basic approach, however, is a combinatory approach testing several configurations of an ANN and finally choosing the best. The training process of ANNs is subjected to overfitting. Overfitted ANNs can predict the output values according to data from the test set with very high precision. New data, however, they fail to predict accurately. To overcome this issue, there are several approaches. The first approach is called regularization and adds an additional term to the used error term. The form of the added term is shown in equation (2.50). It is an adjusted version of the Euclidian norm. The most common configurations in this respect are the "L1"-regularization and the "L2"-regularization, setting q either to one or to two, respectively. The factor λ is the regularization factor, is usually set between one and zero, and steers the impact of regularization. By regularization, smaller weights are preferred during the training process. [61]

$$\lambda * \|w\|_p^q = \lambda * \left(\sum_{i=1}^m |w_i|^q \right) \quad (2.50)$$

An additional approach is to split the available data set into training, a test, and a validation set. Still, the training set is used to train the ANN. Whilst training, the performance which is the difference between the calculated and observed value of the ANN on the validation set is observed. Whilst the error term on the training set is expected to continuously drop by each iteration step, due to overfitting, at some point, the error on the validation set increases again. By “Early Stopping”, the training process is stopped, when the validation set error increases for a predefined number of training steps. A single training step is referred to as “epoch”. The test set, finally, is used to state the generalization ability of the trained ANN. The validation set cannot be employed for checking the generalization ability, as it was used to stop the training process. Thus, the ANN automatically is likely to perform better on the validation set. A common split of the overall set is two thirds for the training set and one-sixth per validation and test set. [62]

3 Model Development

Chapter 3 is stating the model which is developed in this thesis. Therefore, in chapter 3.1 the detailed development of the model is explained. Its practicability is reviewed in chapter 3.2.

3.1 Development of a model to simulate electricity markets

In the following chapters, at first, the different entities, simulated by the model are introduced. Subsequently, the optimization procedure of the market clearing is stated before this chapter is closed with an explanation on the implementation of the learning algorithms of the agents.

3.1.1 Modeling of different entities

In this thesis, an agent-based, multiarea market simulation model is developed. It is used to simulate a European electricity day-ahead market-coupling including the capacity allocation. In the latter aspect, the developed model can be distanced from the agent-based approaches introduced in chapter 44 as most of them neglect possible congestions within the system. Moreover, with the European electricity markets a bigger and more specified use case is chosen. In Figure 12, the basic topology of the model is described. The model consists of several market areas, the bidding zones, which are coupled by a superior agent, the market authority. The market authority supervises the coupled markets which are considered by implicit capacity allocation. Each bidding zone contains a bidding zone authority and several trading agents that either supply or demand electricity. The demand of a bidding zone, thus, is modeled as a time series of the load of a particular bidding zone. The supply of a bidding zone consists of several different agents that seek to market their generation portfolio profit maximally. The suppliers are fed by information on the power plant park of a respective bidding zone including the assignment of the power plants to an agent. The availability of the power plants is modeled stochastically.

Hydro Pumped Storage plants have been removed from the set of power plants, as they are assumed to not generate electricity but to make arbitrage trading. Other hydro power plants are simplified to generation power plants not constrained to resource availability.

The renewable fed-in by onshore and offshore wind as well as solar generation is modeled by three different agents assumed to market all generation of a particular resource according to the day-ahead forecast of generation by renewables given by a time series. As well, these agents seek to maximize

their profits. With respect to direct marketing of renewable resources, this simplification can be softened by splitting the renewable generation in further extensions of the model. The agents marketing the renewables trade their electricity entirely on the day-ahead market. The bidding zone authority collects the orders of the trading agents and submits them to the market authority which conducts the market clearing. Moreover, the bidding zone authority is responsible for the cross-border capacities of the respective zone using either NTC-only, flow-based-only or a hybrid clearing with different coupling mechanisms with different neighboring bidding zones. The model allows choosing the market coupling scheme before starting the market simulation.

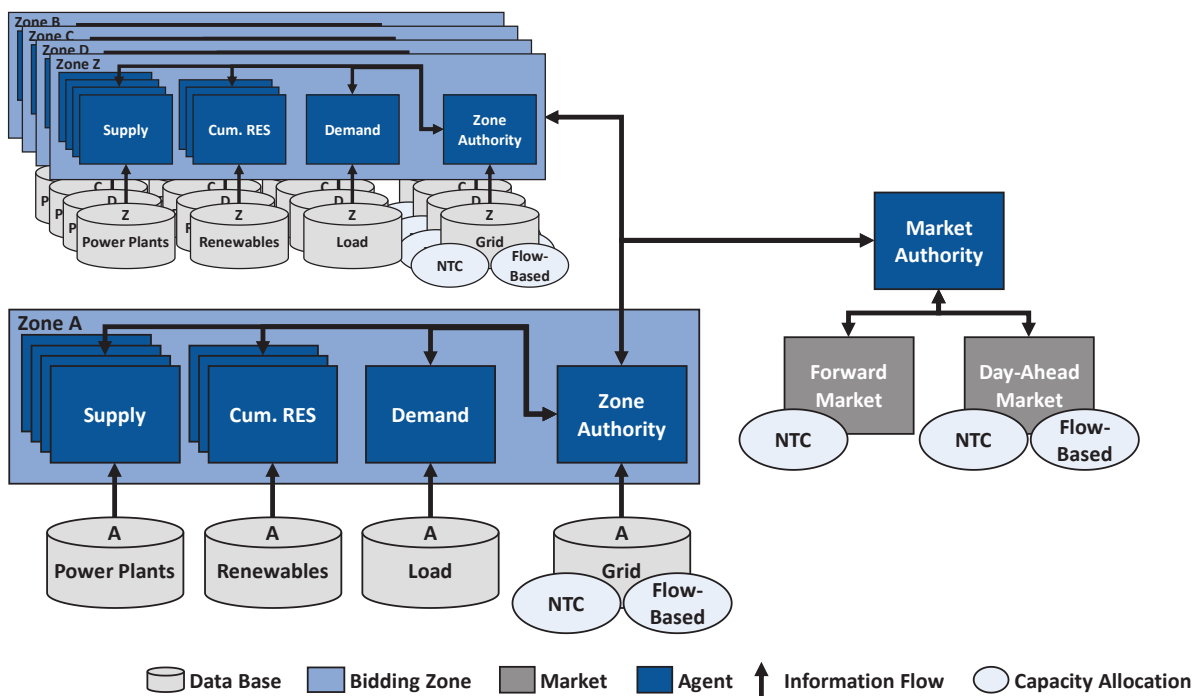


Figure 12: Model Topology (own figure)

The model, so far, simulates a coupled forward as well as a coupled day-ahead market, both, as single-round, sealed auctions per time interval. Forward markets, however, are cleared with a pay-as-bid approach, whilst the day-ahead markets are following the uniform pricing approach. The different products with different time horizons that, generally, can be traded on forward markets are simplified to two. These are the yearly base load and the yearly peak load. Both, yearly base load and yearly peak load are derived from the day-ahead load forecast time series which is the input of the demand side. On the day-ahead markets, the only tradeable products are single hour contracts with flexible fulfillment. Due to the assumption of perfect foresight regarding the load-forecast and due to the assumption of full availability with no outages regarding the generation units, additional markets, like

intraday or balancing markets, are not considered. However, in further extensions of the model, these markets can be considered as well.

The input data on the power plant park of a bidding zone, the generation time series of the renewable resources and the load, as well as the cross-border capacities for each considered bidding zone is provided in different csv-files. This data is the initialization data for each bidding zone. The bidding zones to be initialized are read from an initialization file initiated by the overall market authority. Besides the information on the bidding zones, the initialization file includes the marginal costs and the startup costs for each technology of the overall power plant park. On top of that, the CO₂-emission factors per technology are submitted with respect to CO₂ emission certificates.

During a simulation, at first, for the whole trading period, the forward markets are cleared starting with the base load forward market succeeded by the peak load market. According to the result of the clearing, the supplying agents update their available generation capacity. Moreover, the bidding zone authorities update the available cross-border capacities toward their neighboring zones. Thus, the NTC which is used for the clearing of the base load forward market is adjusted to the ATC. Based on these updates, revolving day-ahead trading is conducted. As the demand is implemented as the load of a traded marginal time interval of a particular market, the demand is modeled as a single ask-offer with a maximal price which is set artificially to 999 €/MWh. By that approach, the demand can be diversified in future extensions of the model easily. The supply side, containing the suppliers with conventional generation and the marketers of wind and solar, try to maximize their profit by adjusting their marginal bids according to equation (2.4). They add a markup to their marginal cost of production and deduce or add the startup cost dependent on the expected price. The expected day-ahead price for each hour of the subsequent day is estimated by each agent by an ANN each. So far, however, per bidding zone, a single ANN is developed used by every agent. Although for all bidding zones a single ANN is developed, all ANNs have the same topology and input features shown in Figure 13. Based on the last three months of 2018, each bidding zone trains its estimation model fed with forecasts on the expected demand on the day-ahead market as well as the expected generation by onshore wind, offshore wind and solar. The training is done prior to the model initialization. For bidding zones, not having day-ahead prices available, a randomly chosen ANN from the set of bidding zones is taken, accepting bad performances regarding the prediction of the prices. Each ANN consists of four layers. On the input layer, the input features are represented by a neuron each, whilst on the output layer only one neuron is located which is linearly activated. Each hidden layer comprises 200 neurons which are fully connected with each neuron on the previous as well as on the subsequent layer. The neurons on the hidden layers are activated by the ReLu function introduced above. Moreover, both, L2-

regularization and early stopping are applied in order to avoid overfitting. In further extensions of the model, easily an individual ANN per agent can be considered which is trained according to the newest available data in defined intervals.

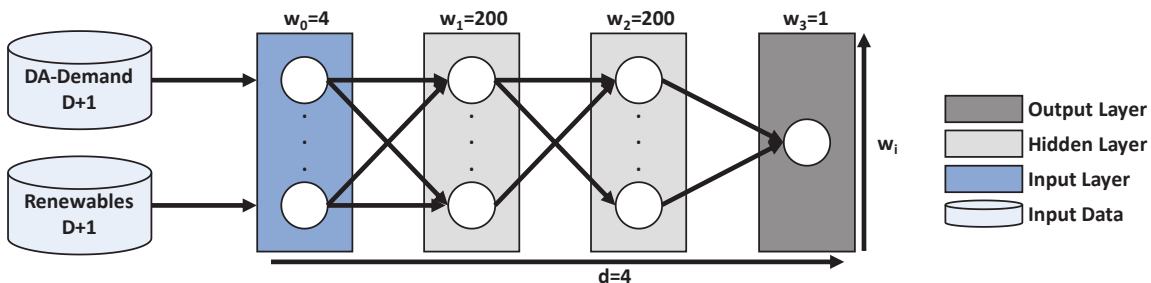


Figure 13: ANN topology for price estimation (own figure)

The output of the model is information on the market clearing prices and market clearing volumes for each auction as well as information on the net exchange positions of each bidding zone. Additionally, information on the congestion prices is stored. Moreover, the revenue and profit as well as the distributed volume for each auction for each agent together with their final strategies which evolve during the trading process, are issued. The orders for each auction are saved as well for evaluation reasons. The output is stored in several csv-Files. Thus, the net exchange positions are stored in matrix form in a separate file for each auction. The same is valid for the respective congestion costs, derived from the dual problem. The information on the market outputs as well as the outputs for the agents is stored in cumulated files per agent.

The model is implemented in python using NumPy as the basic data processing construct. The Python Data Analysis Library (pandas) is used only at the interfaces to the system in order to read or write files. Using pandas for processing the required amounts of data would increase the runtime significantly. Moreover, for the creation as well as the solving of the clearing optimization problem the Application-Programming-Interface (API) PuLP is used. PuLP, thus, uses the standard solver CBC. In order to train the ANNs for predicting the day-ahead prices of the next day, the API Keras embedded in Tensorflow is used. The prediction of the prices, however, inside the model is done independently from Keras importing the trained weights and biases. To do so, a feedforward algorithm is implemented whose output results in the same results as the Keras ANN does. By using the additional algorithm runtime issues, caused by reloading the Keras ANNs are evaded.

3.1.2 Modeling of optimization procedure for welfare maximal electricity supply

The market clearing algorithm used by the model is aligned at EUPHEMIA as the model simulates the market clearing with respect to the respective market coupling approach in use by a particular bidding zone. Due to the assumption of only flexible hourly contracts being traded, the algorithm is drastically simplified compared to EUPHEMIA. Whilst EUPHEMIA is solving a MIQP system, the clearing algorithm employed by the developed model is a linear program (LP) system. In equation (3.1) the objective function of the LP system maximizing social welfare is shown. It is the basic objective function for a social welfare maximal market coupling introduced above.

$$\max_q \sum_{z \in Z} \left(\sum_{d \in D} P_{d,z} * Q_{d,z} * q_{d,z} - \sum_{s \in S} P_{s,z} * Q_{s,z} * q_{s,z} \right) \quad (3.1)$$

The introduced clearing constraint for market coupling, instead, is slightly adjusted according to equation (3.2). In order to be able to determine the net exchange position of one bidding zone to each other, the net exchange position of a single bidding zone z is decomposed. It is the sum of all bilateral net exchange positions of the respective bidding zone which each bidding zone i from the set of linked bidding zones Z_z . For evaluation reasons, for each direction of exchange, a single decision variable is introduced. Complementary net exchange positions are connected according to equation (3.3). This, multiplying the number of constraints of the LP system. This does not result in a significant runtime increase regarding the solving process of the LP system. However, for future extensions of the model, these constraints can be saved by changing the equation system development algorithm accordingly. This might be useful for extensions, like adding complex order types, turning the system into a mixed integer program (MIP) or a MIQP.

$$\sum_{d \in D} Q_{d,z} * q_{d,z} - \sum_{s \in S} Q_{s,z} * q_{s,z} + \sum_{i \in Z_z} NEP_{z,i} = 0 \quad \forall z \in Z \quad (3.2)$$

$$NEP_{z,i} = -NEP_{i,z} \quad \forall z \in Z \wedge \forall i \in Z_z \quad (3.3)$$

According to the update of the clearing constraint, the congestion and capacity constraints have to be adjusted as well. For the day-ahead ATC clearing, this results in a duplication of line capacity constraints as for each bilateral net exchange position a line capacity constraint has to be added as it is shown in equation (3.4). Again, these constraints are just added for each bidding zone with each bidding zone from the set of connected bidding zones Z . Like for the bilateral net exchange position, for the line capacities, a decision variable is created per direction. Due to the complementarity equation regarding the net exchange position, the complementary directions are linked implicitly.

$$NEP_{z,i} = CAP_{z,i} \quad \forall z \in Z \wedge \forall i \in Z_{z,ATC} \quad (3.4)$$

$$ATC_{z,i}^{min} \leq CAP_{z,i} \leq ATC_{z,i}^{max} \quad \forall z \in Z \wedge \forall i \in Z_{z,ATC} \quad (3.5)$$

The decomposition of the net exchange positions for the flow-based line capacity constraint results in the adjustment shown in equation (3.6). In order to derive the PTDF for a net exchange from zone z to zone i , which is referred to as a hub-to-hub PTDF, the respective PTDFs need to be subtracted from each other. More detailed, the PTDF of the receiving zone is subtracted from the PTDF of the injecting zone. It can be done, due to the linearity assumption from which the zonal PTDFs are derived. [46]

$$CAP_l = \sum_{\forall z,i \in Z_{FB}, z \neq i} (PTDF_l^z - PTDF_l^i) * NEP_{z,i} \quad \forall l \in L \quad (3.6)$$

$$-RAM_l \leq CAP_l \leq RAM_l \quad \forall l \in L \quad (3.7)$$

3.1.3 Modeling of different agent-based approaches

Based on the results of the day-ahead market clearing, the trading agents adjust their bidding strategies by changing the chosen markup. The learning is modeled using the two different reinforcement learning algorithms: Erev-Roth-reinforcement learning and Q-learning. Genetic algorithms, as well as supply curve optimization models, are not considered as they are based on heuristics and simplifying the generality excessively. Moreover, the focus of this thesis are machine learning applications for the simulation of multi-agent interaction. Learning classifier systems can be part of further extensions of the model which allows the flexible addition of learning algorithms. However, for the simulation of the European market coupling, reinforcement learning is considered to be a proper choice for a first simulation. They are offering a flexible simulation of a complex environment with several agents making individual decisions. The respective learning algorithm which is supposed to be used can be chosen before the model initialization. Both algorithms choose a markup from a given set of surcharges. Thus, the model is based on a Bertrand scheme with price bids that are adjusted. Volume bids are not altered. Changing volume bids intelligently with respect to concepts such as capacity withholding can be investigated in future model enhancements. The portfolios of the considered suppliers in this model are comparably small due to an incomplete assignment of generation units to particular agents. Thus, the potential for capacity withholding is expected to be small anyway. The markups are considered to be positively exclusively, as the agents are not expected to bid below marginal costs except those, including the startup costs. The choice of markups are the actions each agent might conduct. The reward each agent earns relative to the chosen action is the revenue from sold electricity.

Regarding the Erev-Roth-algorithm, for each hour of the day, a single strategy is supposed to be developed. Moreover, for the model-based learning algorithm, initially, the propensities and probabilities of choosing a respective action need to be initialized. As no knowledge of any propensities and probabilities is known beforehand, the propensities are initialized to zero whilst uniform probabilities are set initially for each markup and hour. Regarding Q-learning, the considered states are the market prices that can be achieved. In order to speed up the learning process, the states are rounded to integers. Moreover, for the first auction, a zero-markup-strategy is chosen. The model-free character is maintained, as new rows can be added to the Q-table as new states of the environment emerge that had not been observed before. These are equivalent to new observed prices. Rows are initialized with Q-values of zero. However, in order to enable agents to leave the initial markup of one, a comparably high greedy parameter should be chosen.

The basic schemes of the implemented algorithms are shown in Figure 14.

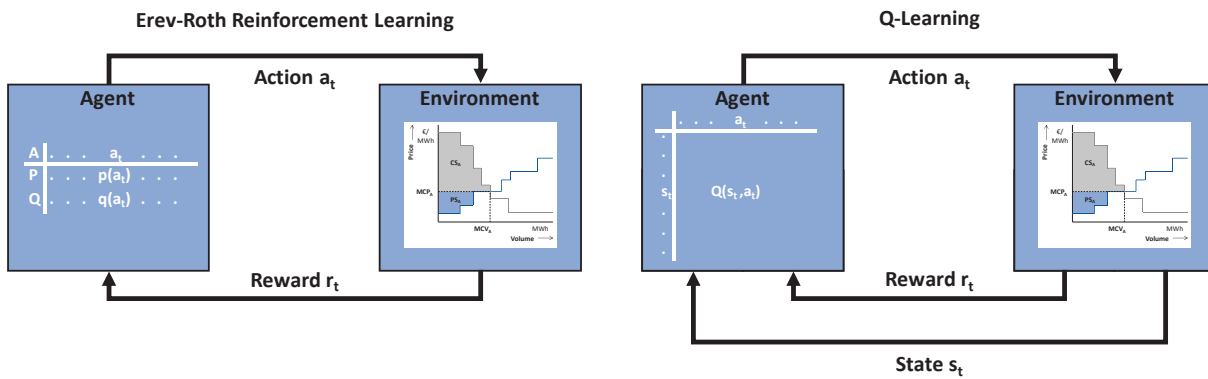


Figure 14: Schemes of implemented learning algorithms (own figure)

3.2 Review of functionality and practicality

The model is steered by a graphical user interface (GUI) allowing to choose the learning algorithm with its parameters and, if desired, a CO₂ price before initialization. After initialization, the trading period is determined by submitting a start and end period and the market coupling scheme can be chosen. So far, four different market coupling configurations are considered, including a European “copper plate” market coupling without any congestion between the bidding zones. The latter can be employed to determine the overall welfare loss due to inter-zonal congestions easily. For calculations using a computation cluster, like it is the case for the investigation in chapter 0, the initializing inputs of the model can be transmitted by an input file.

The developed model is capable to simulate any sequence of single-round auction-based markets, considering both, pay-as-bid as well as uniform pricing. So far, a single market object is implemented simulating the described markets using a market clearing function which is parameterized differently according to the respective requirements. Intraday and balancing markets could be added to the model easily if simplification of continuous intraday trading, like for the forward markets, is accepted. Additionally, the function-based approach can be transferred into an object-based approach creating an instance per market with minimal effort. This is relevant if additional characteristics or clearing schemes are supposed to be considered. The trading agents, as well as the bidding zone and the market authority, are implemented object-based. The trading agents, thus, are subclasses of a superior trading agent. The input file, including the information on the bidding zones and the information on the generation technologies, allows a flexible parameterization of the fundamental model. Thus, multiarea systems of different sizes can be simulated easily.

First tests of the model virtually unexceptionally resulted in negative market clearing prices. This indicates, that the implemented ANN prediction procedure is distorting the model. Another explanation could be the startup costs which might be chosen too higher. To overcome this issue, the ANN day-ahead price prediction is removed for the investigations done in chapter 0 below by setting the startup costs to zero.

Additionally, technical constraints for suppliers as well as Hydro Pumped Storage plants being able to make arbitrage trading between different time steps can be included in the model in future extensions. Moreover, the power plant outages can be modeled more realistically.

4 Exemplary Studies

In this chapter, the different conducted studies, which are conducted based on the introduced model above, are examined. To do so, in chapter 4.1 the parameterization of the test scenarios is revealed. After that, in chapter 4.2, starting from a basic scenario, several configurations are investigated. The chapter closes, with a review of the results of the exemplary studies.

4.1 Parameterization of the test scenarios

Based on the developed model, three scenarios are going to be examined in the following. Starting from a base-case scenario, two additional scenarios are investigated. All scenarios are calculated based on the same basic input data regarding the CWE flow-based market coupling, the NTCs, the load, the renewables, and the power plant parks. The data is provided by the ENTSO-E transparency platform. Explicitly, the NTC data is derived from the information on the offered volumes for the explicit as well as the implicit auctions. Moreover, a single set of capacity values is used for every calculation. This is valid both, for ATC as well for flow-based coupling. The reference day, in this respect, is the 20th of February 2019. This is due to the fact, that the information on an extended flow-based scenario is only available for this date. For the flow-based market coupling, 45 critical network elements are considered. The required data for the extension is provided by the Czech transmission system operator CÈPS. It is based on real data but distorted slightly for data protection reasons. The scenarios, however, are calculated for the months of January and February of 2019. [33]

It is assumed that the power plants are available in 80 % of the cases at maximum capacity. The amount of available capacity, then, is assumed to be distributed normally around an expected value on 100 % available and a standard deviation of 30 %. From the subset of capacities below 100 % of installed capacity, the respective available capacity is determined using the uniform distribution.

Figure 15 shows the parameterization of the marginal costs in an ascending order representing the merit-order according to the technologies. Additionally, the split of the generation according to base and peak load is registered and the specific CO₂ emission per technology is given. For the conducted investigations a CO₂ emission certificate price of 25 €/t is considered based on the current exchange price of the European Emission Allowances on the EEX. [63, 64, 65]

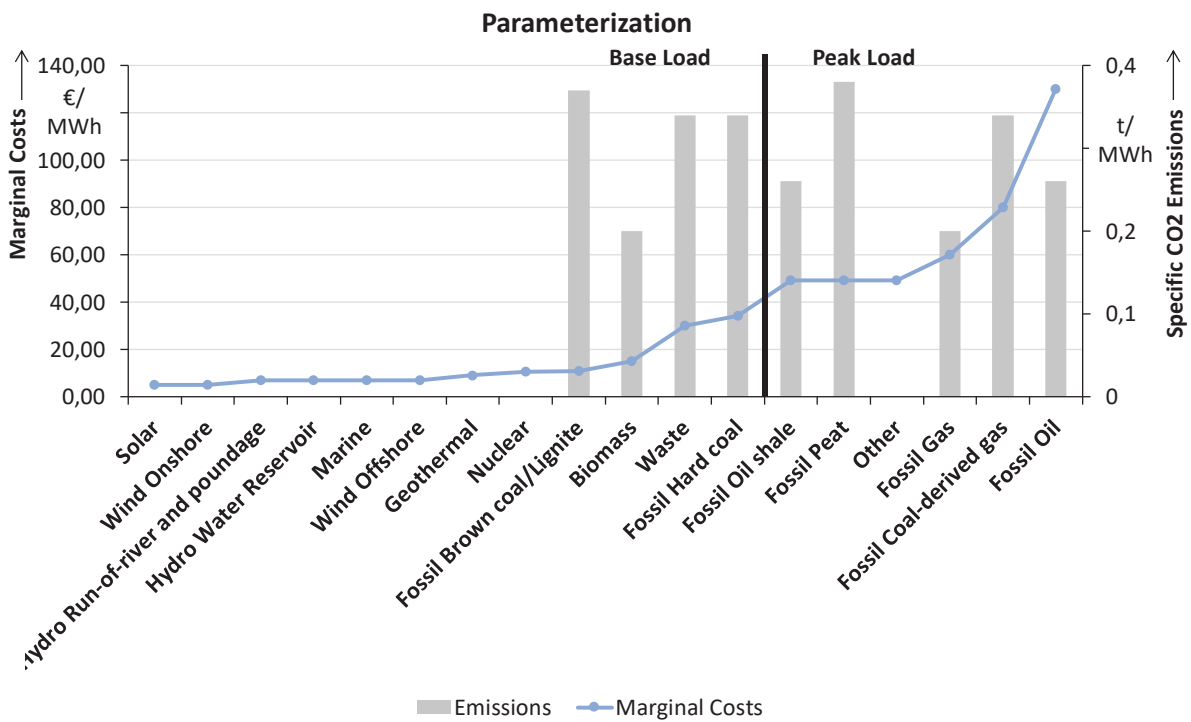


Figure 15: Parameterization (according to [64, 65])

All in all, 2109 trading agents determine the multiarea market system. They are organized in 47 bidding zones. Power plants, that are not assigned an agent are treated as a single trading agent. Figure 16 shows the installed capacity of conventional power plants for the CWE region exemplarily. It shows the heterogenous character of the generation profiles from different bidding zones.

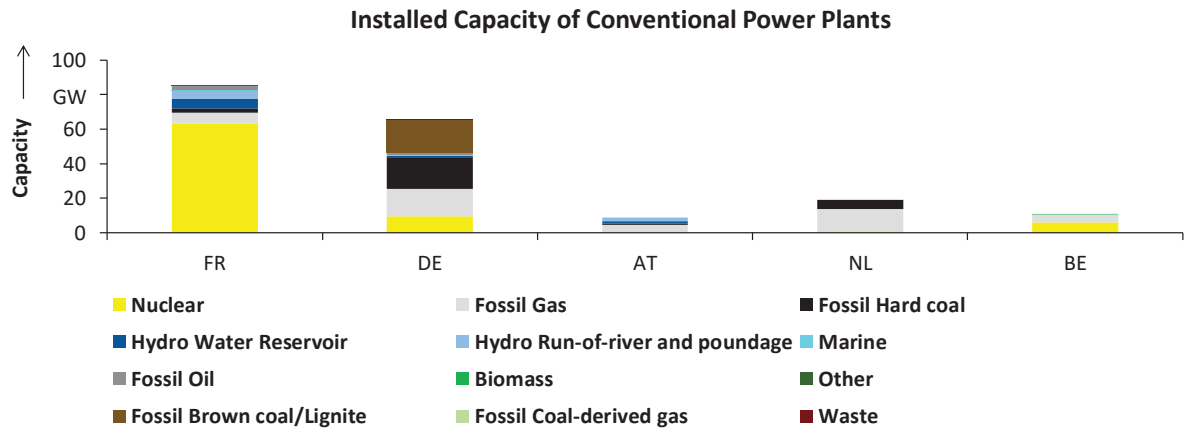


Figure 16: Installed Capacity of Conventional Power Plants in CWE Region(according to [33])

4.2 Application of different configurations

In the following three chapters, different scenarios are evaluated and compared with each other. Starting from a basic scenario, the developed model is run in different configurations, examining different learning algorithms and market coupling schemes.

4.2.1 Determination of welfare maximal supply

The base scenario includes a Europe-wide ATC-day-ahead market coupling with a flow-based market coupling for the members of the CWE region including Austria. Figure 17 depicts the auction type considered for each border. Besides the simplification that all markets are coupled with implicit capacity allocation, this setting represents the current coupling scheme.

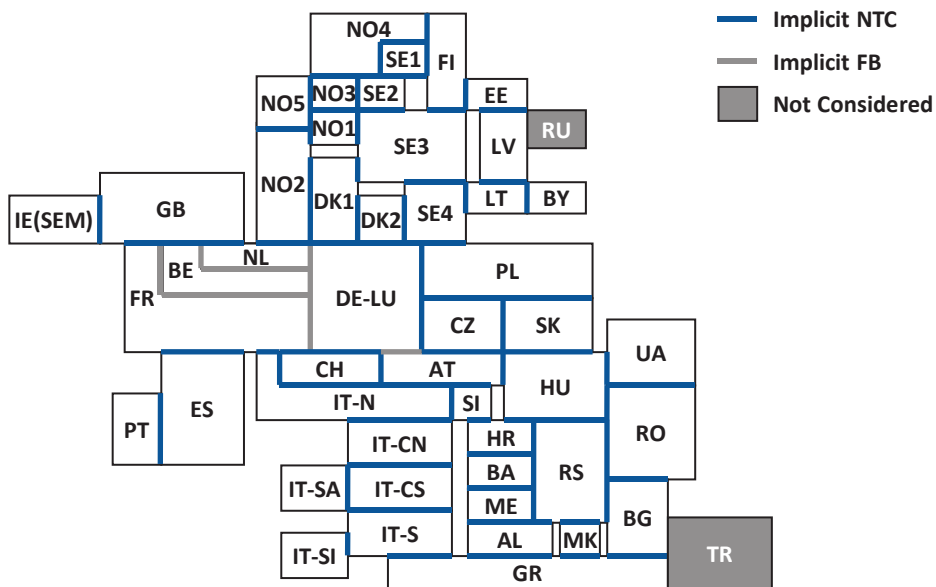


Figure 17: Basic coupling scenario (according to [33])

The basic learning algorithm is Erev-Roth reinforcement learning. The chosen configuration is shown in Table 1. Basically, the choice was made according to the suggestions of literature.

Table 1: Parameterization Erev-Roth Reinforcement Learning

Erev-Roth	Value
Learn rate Φ	0.3
Greedy parameter ϵ	0.1
Cooling parameter M	10000

In Figure 18, the market clearing prices of the bidding zones Germany and the Czech Republic for calendar week eight. The figure shows characteristic price developments of single days including peak prices. Especially, the weekend can be recognized by lower prices. The different prices between the neighboring countries are due to congestions.

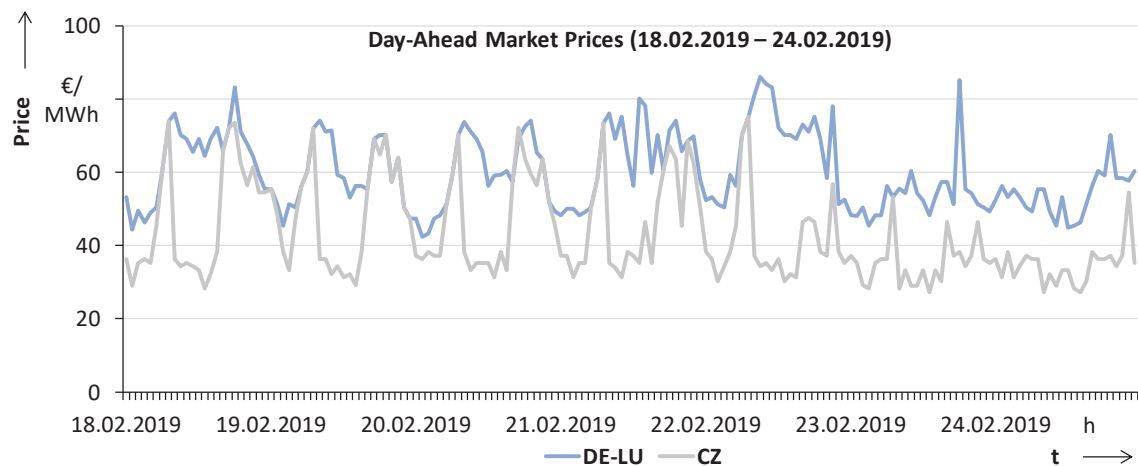


Figure 18: Day-Ahead Market Prices from 18.02.2019 until 24.02.2019 (own figure)

4.2.2 Comparison of results of different agent-based methods

In the first comparison, the implemented reinforcement algorithms are compared with each other applied to the market coupling scenario introduced above. Therefore, in Table 2 the parameterization of the learning algorithm is depicted. Compared to the Erev-Roth reinforcement learning, the Greedy parameter is chosen three times as high. Regarding the learning rate, the same value is applied. The discount factor is chosen to 0.9, which is equivalent to an interest rate of 11,11 %.

Table 2: Parameterization Q-Learning

Q- Learning	Value
Learn rate α	0.3
Greedy-Parameter ϵ	0.3
Discount Factor γ	0.9

Figure 19 depicts the respective frequencies of each markup of the considered set cumulated for all agents. In the Erev & Roth setting, several smaller peaks and of particular volumes can be recognized without being suspected to be a lock-in situation. The peaks can be recognized around a markup of 7 €/MWh, 10 €/MWh and 16 €/MWh. It is assumed, that these peaks mark several technologies within the merit-order. Additionally, the peaks can mark different times of the day, as for each hour different strategies are developed by the agents. However, further investigations on the markups per hour and per technology can be conducted.

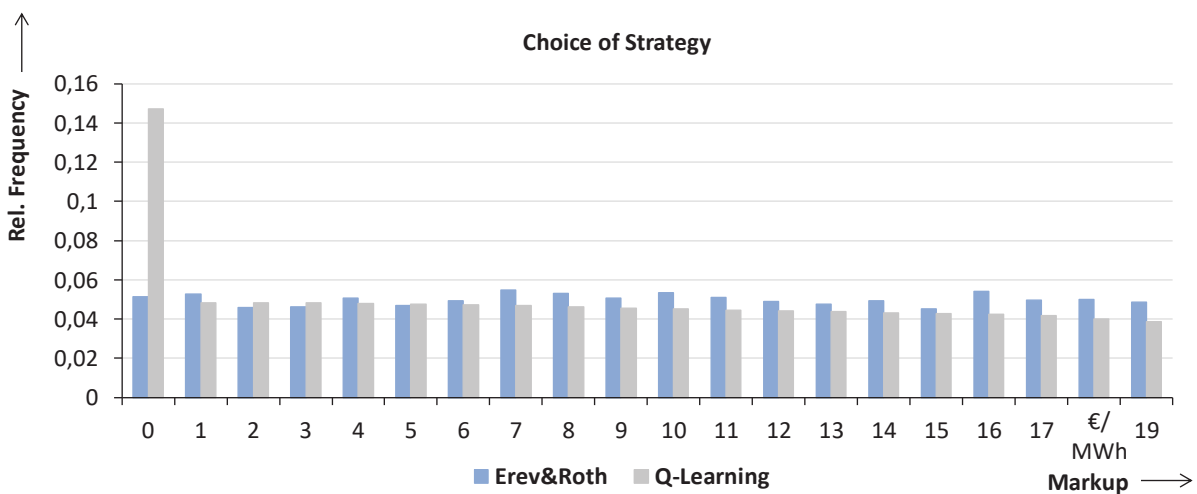


Figure 19: Choice of Strategy (own figure)

Regarding the Q-learning, the highest frequency, by far, is set at a markup of 0 €/MWh, which is equivalent with bidding at marginal costs. The other markups have a continuously decreasing frequency or probability of choice. This pattern would fit the assumption, that suppliers in competition most effectively bid at marginal costs. However, the pattern also might be explained by a lock-in situation. Due to a high greedy parameter, however, this was tackled already by the parameterization. As the Erev & Roth algorithm does not show the same pattern, further investigations are necessary in order to check for plausibility. This can be done by applying both concepts with longer time horizons.

4.2.3 Comparison of results for calculations with different market coupling approaches

Next, the model is run with two different market coupling schemes in order to examine the benefits of one or the other market coupling scheme with respect to social welfare. The respective auction types are depicted in Figure 20. In the first additional scenario, Scenario 2, the market coupling is done implicitly according to the NTC approach at all borders. In Scenario 3, the region using flow-based market coupling is extended by the countries of Central Eastern Europe (CEE). This includes the countries of the 4M market coupling, as well as Slovenia, Poland, and Croatia. The data set for the coupling, provided by the Czech TSO Cèps, comprises 175 critical network elements.

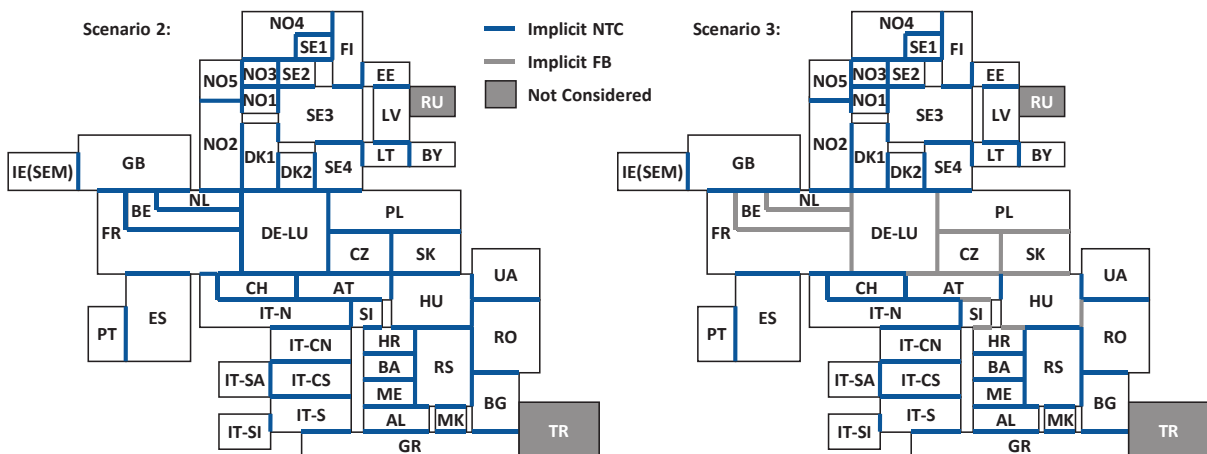


Figure 20: Additional Market Coupling Scenarios (according to [33])

Figure 21 shows the overall net exchange positions for the different scenarios using Erev & Roth reinforcement learning. The figure indicates, that a change from a flow-based market coupling in the CWE region to both, the ATC and the extended flow-based approach, would result in an increase of the cross-border transfers. Whilst this was expected and intended for the flow-based extension, it is not intuitively for the ATC coupling.

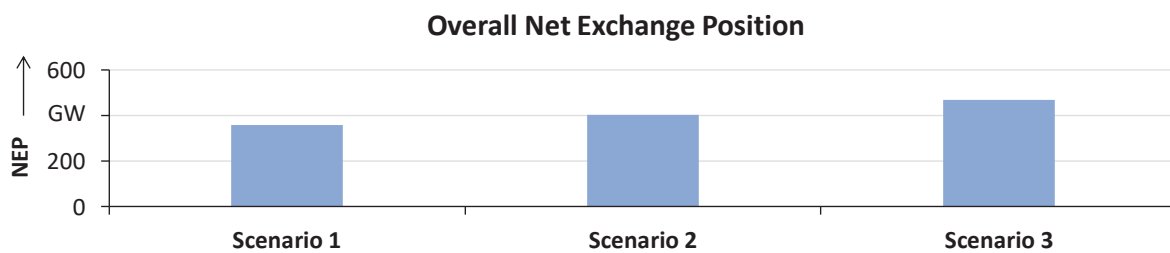


Figure 21: Overall Net Exchange Position (own figure)

Figure 22 shows the net exchange positions for the bidding zones of the CWE region, including Austria for the January 20th. At first, the figure shows different net exchange positions for each bidding zone for each market coupling scheme. E.g. for Germany a change from the flow-based market coupling for the CWE region to an ATC approach would lead to an extremely negative net exchange position and, thus, a net import. A change to the extended market coupling also results in a net import for Germany. However, it is less compared to the ATC market coupling. For Belgium and Austria, the change increases exports. For France, a change to the ATC coupling results in a net import situation but an increased export situation for the extended flow-based scenario. Finally, for the Netherlands, the ATC coupling would decrease the imports, whilst the extended flow-based approach increases the imports.

An increase of the net import might be caused by increased availability of cheap production and more available cross-border capacity. This would indicate, that e.g. Germany has, at least in the chosen parameterization, an expensive power plant park. Germany has few hydro power plants, whilst neighbors, such as Austria or Switzerland do have large capacities in this respect. The Czech Republic, moreover, also has cheap production units with nuclear power plants and lignite. Combined with the particularly chosen parameterization, this might cause the results as shown. Generally, Germany is rather an exporting country. Moreover, as the overall net exchange positions increase for both alternative scenarios, the suspicion can be analyzed more detailed, that the CWE market coupling does not improve the net exchange compared to the basic ATC market coupling. This might be caused by conservative determination of the RAMs for the critical network elements of the CWE region. Regarding the extended flow-based coupling, however, it has to be mentioned, that the values are

artificially distorted, as mentioned before. Moreover, the parameterization of the scenario highly influences the final output. Thus, scenario analyses should be done, and the input data to the model should be updated.

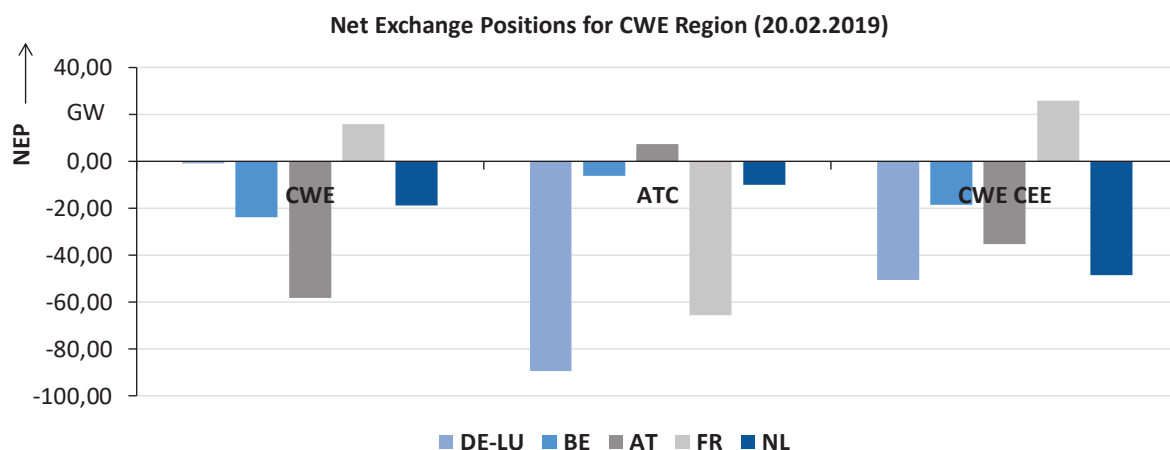


Figure 22: Net Exchange Positions for CWE Region (own figure)

4.3 Review and effects of more realistic modeling

In this chapter, the results of the exemplary studies are reviewed and checked according to their plausibility. Moreover, the required computation resources are analyzed.

4.3.1 Plausibility check

As the data on the power plant park is not complete, sufficient allocation of the capacities to certain agents is not given. This simplifies the problem and hinders to fully analyze strategic bidding with respect to large generation portfolios. Moreover, the investigations are highly dependent on the right parameterization as it was already mentioned. Therefore, a comparison with the observed values from the European electricity markets is only applicable with respect to the dimensions of the outputs.

The marginal costs of production are defined per technology and altered randomly for each plant at the initialization. This approach is unlikely to be suitable to simulate the plurality of the considered bidding zones correctly. In order to improve the model, the characteristics of the respective power plant parks of the different bidding zones should be. Regarding the learning algorithms, additional investigations should be considered. This is also valid for the investigations on the exchange positions. It should be stated, whether a trend can be recognized among all days regarding the net exchange positions of particular bidding zones. This, again, should be compared with the observed values in

order to check the results for plausibility. According to this, at first, the parameterization should be adjusted.

However, the first investigations reveal, that the model is capable to simulate the European electricity markets, although further extensions should be made. Especially, with respect to the implemented price prediction, which has been excluded for the investigations made above, the right parameterization needs to be found. This is necessary as the ANNs are trained by the observed prices.

4.3.2 Required computing power and memory of model

The different computation were run on the RWTH computation cluster. The maximally used memory and the runtime for each calculation is shown in Figure 23. Although expected differently, the investigations for both learning algorithms have the same runtime. However, tests showed that the runtime of the Erev & Roth algorithm is highly dependent on the set size of the markups.

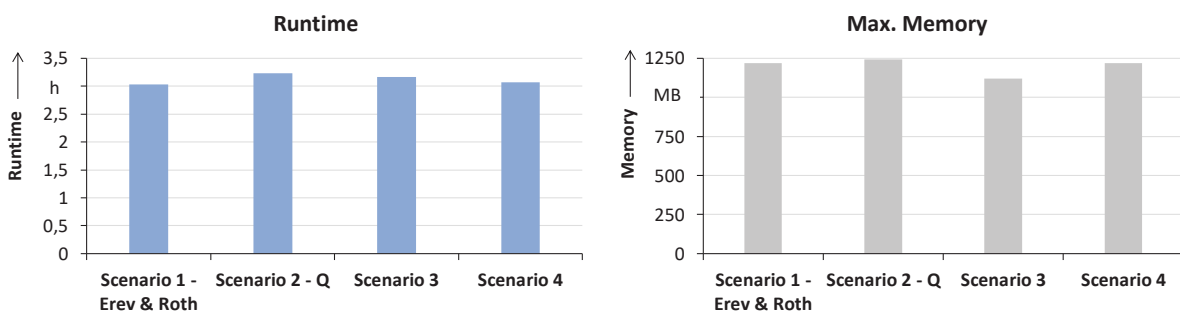


Figure 23: Runtime and Maximal Memory Used (own figure)

5 Conclusion and Outlook

The way towards fully coupled European electricity markets is barred by congestions between bidding zones. In this thesis an agent-based electricity market simulation model has been developed in order to analyze different approaches, that are in use to exploit the congestion economically. It is used to simulate different market coupling schemes in Europe as a whole. To be enabled to do so, two different learning algorithms have been implemented and compared with each other.

The learning algorithms show different preferred strategies. Whilst Q-learning results in strategies close to marginal bidding, the Erev & Roth learning results in smaller peaks. Moreover, the investigations on the different market coupling schemes indicate, that both ATC market coupling, as well as the extended flow-based approach, lead to increased overall net exchange compared to the CWE flow-based approach. This should be investigated in future investigations.

The developed model bears potential for re-shaping several aspects which have been simplified for the first development of the model. At first, on the market side, additional order types, such as block orders, can be implemented. Moreover, on the supply side, technical characteristics of the considered power plants should be implemented for the different technologies. For thermal power plants, in this context, load change rates and capacity limits can be introduced. Additionally, pumped hydro storage power plants can be added to the model in order to implement arbitrage trading. To do so, continuity equations need to be implemented in order to link two sequential time intervals. Moreover, the demand can be simulated more diverse by splitting the load into the demand of different agents. Also, the cumulated renewables can be split into several direct marketers as renewables are not traded by a single entity. Another opportunity is the introduction of additional learning algorithms as there are multiple machine learning algorithms that would benefit from the revolving character of day-ahead markets. Furthermore, balancing and intraday markets can be introduced. Regarding future investigations, the model can be used, to assess the impact of reshaping bidding zones according to internal congestions to implement market-based congestion management. Further investigations might also comprise the analysis of other bidding strategies beyond the concept of adding markups to the marginal costs.

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List of Figures

Figure 1: Market Clearing (own figure)	8
Figure 2: Load coverage according to different markets (according to [21])	12
Figure 3: Market Coupling (own figure)	17
Figure 4: Bidding zones of continental Europe (according to [33])	18
Figure 5: Market Coupling: Status Quo (according to [33])	20
Figure 6: Congested Market Coupling (own figure)	21
Figure 7: Nodal Capacity Allocation (according to [37])	24
Figure 8: ATC capacity allocation (according to [37]).....	28
Figure 9: Flow-based Capacity Allocation (according to [37])	30
Figure 10: Marginal and Average PTDF strategy (according to [44])	32
Figure 11: Topology of an Artificial Neural Network (own figure).....	53
Figure 12: Model Topology (own figure).....	58
Figure 13: ANN topology for price estimation (own figure)	60
Figure 14: Schemes of implemented learning algorithms (own figure)	64
Figure 15: Parameterization (according to [64, 65])	68
Figure 16: Installed Capacity of Conventional Power Plants in CWE Region(according to [33])	69
Figure 17: Basic coupling scenario (according to [33])	70
Figure 18: Day-Ahead Market Prices from 18.02.2019 until 24.02.2019 (own figure)	71
Figure 19: Choice of Strategy (own figure)	72
Figure 20: Additional Market Coupling Scenarios (according to [33])	73
Figure 21: Overall Net Exchange Position (own figure)	74
Figure 22: Net Exchange Positions for CWE Region (own figure)	75
Figure 23: Runtime and Maximal Memory Used (own figure)	76

List of Tables

Table 1: Parameterization Erev-Roth Reinforcement Learning	71
Table 2: Parameterization Q-Learning	72