Gaming an Oligopoly

A Game Theoretic Computational Modeling Approach on the Dutch Secondary Reserve Capacity Market

Master Thesis

Reinier Witteveen

14 October, 2016

Abstract

This thesis is written in the context of a world in which renewable energy assumes an ever growing share within the Dutch electricity sector. Given the fluctuating output of renewable energy sources, the importance of the Dutch secondary reserve capacity market is expected to increase considerably in upcoming years. Its architecture, a monopsony in which the TSO seeks to reserve a predetermined quantity of reserve capacity from a limited set of producers, motivated to take a closer inspection on this market by capturing it in a game theoretic model. This study's main realization is the delivery of a proof of concept for a game theoretic model, capable to assist producers in optimizing bidding strategies. Furthermore, this research displayed the ability to apply the adopted research approach to investigate implications of different market designs. This feature is exemplified by the discovering of the declining price anomaly.

Keywords: Game theory, Oligopolistic competition, Strategic bidding, Policy analysis, Ancillary services market, Power market modeling, Declining price anomaly

Delft University of Technology

Gaming an Oligopoly

A Game-Theoretic Computational Modeling Approach on the Dutch Secondary Reserve Capacity Market

Author

Reinier Witteveen

reinierwitteveen@gmail.com

Education

Delft University of Technology

Faculty of Technology Policy and Management

Systems Engineering Policy Analysis and Management

Research domain: Energy & Industry

Graduation committee

Chair professor :	*Prof. dr. ir. Paulien Herder*	*Delft University of Technology*
First supervisor:	*Dr. ir. Scott Cunningham*	*Delft University of Technology*
Second supervisor:	*Dr. ir . Laurens de Vries*	*Delft University of Technology*
External supervisor:	*Drs. Vincent Erwig*	*Vattenfall*

TU Delft Delft University of Technology

Acknowledgments

This thesis is written as part of the Master’s degree Systems Engineering, Policy Analysis and Management at the Technical University of Delft.

I am very proud to conclude this important chapter of my life at this University. I would therefore like to thank every professor, employee and student whom I had the pleasure meeting during the last two years at this University.

On several instances since I started writing this thesis, I caught myself imagining this very moment; my final act as a student, writing the acknowledgements of my Master thesis.

Aside from a month-long hospitalization during my research, my final academic journey has been very pleasant. Various people along the way contributed to this gratifying experience and I owe them many thanks. So here we go.

I would like to begin to express my enormous gratitude to my first supervisor dr. ir. Scott Cunningham who has truly been a most helpful and accommodating supervisor. Throughout my research he has supported and challenged me, especially during our frequent brainstorm sessions. I am also very grateful for the way in which he provided me ample space to design and execute my research while helping me stay focused on the bigger picture. I am very thankful for that.

I would also like to thank dr. ir. Laurens de Vries who was particularly helpful in my quest for the right methodological approach, as well were his insights in the field of energy policy.

Prof. dr. ir. Paulien Herder is another person who merits my gratitude. She encouraged me to further advance my research and ultimately gave me the ‘Green Light” for graduating.

Within the field, Mr. Frank Nobel and Pim Glazenborg were of particular help, shedding light on the industry and helping me with my calculations respectively.

Vattenfall NL deserves my gratitude as well. All my co-workers there have been very supportive as I conducted my research project. Drs. Vincent Erwig was of notable importance. Even at the challenging times Vattenfall experiences, Vincent has always remained positive and supportive of my research. He has always been willing and patient enough to allow me plenty of his time, either to explain me something, or to brainstorm about creative ways to address a given problem. I owe him many thanks, as well for his role in the start of my professional career.

Reinier Witteveen,

Amsterdam, October 14th, 2016

Executive summary

This thesis is written in the context of a world in which renewable energy, guided by economic and political goals, assumes an ever growing share within the energy mix of the Dutch electricity sector. Given the fluctuating output of renewable energy sources, the importance of the reserve capacity auction and balancing energy market, is expected to increase considerably in upcoming years.

The architecture of the reserve capacity auction, *a monopsony in which a sole buyer* (TenneT) seeks to reserve *a predetermined quantity* of symmetrical (up- and downward) reserve capacity from *a limited set of producers*, motivated to take a closer inspection at the design of this market. Indeed, there is no reason to assume that the interests of the private entities, active in the secondary reserve capacity market, align with broader societal interests of efficient markets in which electricity is supplied at the marginal costs of production and perhaps a small premium.

By capturing the Dutch situation in a *game theoretic model*, reflecting the real-world behavior of three to four dominant producers in an oligopolistic market with a single buyer, this thesis sought to shed light on *the micro- and macro perspectives* of this market. The resulting main research question is therefore formulated:

To what extent and by which means can a game theoretic modeling approach support strategic decision making in the reserve capacity auction and how can this model be used to critically examine the design of this market?

From the micro perspective, the viewpoint of a single producer, active in the secondary reserve market seeking to optimally allocate its energy generating assets, this study sought to explore until what *extent* a model can inform producers in their strategic decision-making, and whether the bidding process can be 'game-ified'.

The first perspective is closely entwined with the second, the macro-perspective. From this perspective, this thesis examined the question until what *extent* the design of the market fosters efficient economical outcomes from a social welfare perspective.

This simultaneous investigation, on the reserve capacity auction from these two different perspectives resulted, in a research approach through which by *a combination of realistic market data and applied game theoretical concept*, the outcome of these auction could be predicted. The research goal was therefore formulated:

To investigate the strategic bidding problem of the reserve capacity auction by incorporating realistic market data for producers as input for a game theoretic computational auction model

It is established necessary to investigate which factors influence the behavior of producers (micro) and the market in general (macro). The first- and second research questions are therefore formulated:

"What are the specific characteristics of the balancing market?"

and:

"What factors influence decision makers in the reserve capacity auction?"

Answers to these questions are given in Chapter 2. In this chapter it is established that bidding strategies should be developed based on the *market structure* and *auction rules*. As a result, it is concluded that in order to have sufficient coherence with reality, an equilibrium model which aims to mimic real life behavior of the reserve capacity auction, should at least be able to incorporate the following most influencing factors; o*pportunity costs, earnings from activations, auction rules and previously accepted bids*.

This analysis concludes that the o*pportunity costs* can be approximated by unit commitment and dispatch models, while *earnings from activations* can be estimated by historical analysis of accepted bids in the balancing energy market. *Auction rules* are based on pay as bid with a fixed demand and *previously accepted bids* follow logically from previous auctions and can therefore readily be used in subsequent auction simulations.

The analysis in Chapter 2 uncovered *several potentials for inefficient conduct* by producers in the two related markets; balancing energy, reserve capacity. Firstly, in relation to the balancing energy market it is concluded that producers have a clear incentive to overbid their marginal costs in order to increase the market clearing price in times of higher imbalances. Secondly, in relation to the balancing energy market, it seems that the design of this market gives participants a clear incentive not to underbid each other's offer by too much as this might initiate a price war and would therefore destroy a great portion of the margin in future auctions.

The choice to select game theory as the main research methodology and the positioning of this research within the scientific literature is motivated in Chapter 3. The third research question is therefore formulated:

"Why a game theoretic modeling approach?"

This chapter concludes that in terms of *market structure* and *auction rules* the most important aspects are the composition of the market of a *single buyer* with *inelastic demand*, *oligopolistic sellers,* and the *pay as bid settlement scheme*. With regard to market power this has the effect of possibilities of market power abuse on the supply side and not on the demand side.

The insights drawn from the theoretical analysis, paved the way for the type of methodological approach that is undertaken in this study. Several approaches are investigated and a *game theoretic modeling approach* is found most suitable. The idea is that, game theory will predict a market equilibrium, as a result from the existence of human rationality and competitiveness in the auction.

From a micro- perspective on the market, the estimation of the market equilibrium offers producers great assistance in optimizing their bidding strategies. Applying this approach to the market also allows producers to predict what will happen to the market equilibrium if the circumstances change and help them to prepare for such an event. From a macro-, or public policy standpoint, the possibility to investigate where Equilibria might arise in different market designs and competitive environments promises rewarding results.

In a game theoretic model, market participants, are indicated as *players*, each with a finite or infinite number of *strategies* and associated *information* and *payoffs*. In the auction game, the players' payoff functions are calculated by subtracting their cost from their expected revenue.

Having positioned and motivated this study, this research proceeds to investigate how the market and methodology is rightfully conceptualized in a model. In Chapter 4 the fourth research question is therefore formulated:

"How can a game-theoretical approach be translated into practice?"

In Chapter 4 the research steps involved in the modeling process are elaborated and the design of the conceptual model is presented. The concepts and terminology of game theory are applied to a conceptual game in order to make clear how the methodology is implemented in this research. It is furthermore shown how the used data sources and results are verified and validated.

In Chapter 5, the results from the model experimentation are presented and implications of these results in relation to the main research question are drawn. The fifth and sixth research questions are therefore formulated:

"How can the results of the approach inform producers in their bidding strategies?"

and:

"What do the results of the approach reveal on the design of the reserve capacity market?"

In order to simulate the auction, the players need to be known. An analysis of the market´s architecture, set forth in Appendix A, concludes a market which, over the course of 2015, was dominated by three players; EON, RWE and Vattenfall. Furthermore, as, early 2015, ENGIE opened a new coal-biomass fired plant; this player´s entry in the market may add another player to the tripartite that currently dominates the market. To this background, the number of players is used as a variable between games.

The approach adopted required that the information at each player´s disposal has to be established. For this it is concluded that the payoff for each player can individually be defined by an approximation of the opportunity costs and earnings form activations. The results obtained from the model experimentations resulted in the following main insights.

A connection is seemingly found between the number of existing Nash Equilibria and the level of competition. It appears that lower number of Nash Equilibria point to stronger levels of competition and vice versa.

It is found that a split auction design results in a market equilibrium with lower rents for the producers, and consequentially lower procurement costs for TenneT. In the literature, this phenomenon is called the *declining price anomaly.* This study proposes that this anomaly can be attributed to the limited rationality of the players in the auction game and suggests that this result can be extrapolated to the real life behavior of the producers' strategists.

From the results of the experiments it is found that under some circumstances (i.e. demand levels and margin ranges), the cost difference between the producers is large enough to eliminate the possibility to compete by producers. These experiments revealed the fragile position of TenneT as a monopsonist with a fixed demand in an oligopoly.

[redacted]

Based on a linear trend, a price forecast was made for a simulated scenario where the demand for reserve capacity increased with 15 MW per year. This resulted in an accumulated cost increase of 200 million euro in 2016 with respect to the procurement costs observed in 2014.

A declining trend in the procurement cost for reserve capacity is observed in the last years. It seems that this decline has no relation with fuel prices and is more influenced by changes in the demand of reserve capacity. This observation, in combination with the results obtained from the model experimentations, seems to suggest that the market currently does not suffer from forms of collusive behavior.

The presumed entering of an additional producer in the market has a profound effect on the procurement costs for TenneT, as by the entering of this additional producer a decrease in procurement costs of approximately 33 percent is observed.

The predictive power of the model is only as strong as its capability to describe the system of interest. The value of the results, insights and conclusions as presented in Chapter 5 are therefore fully dependent to the extent in which the model concurs with reality. Therefore, in Chapter 6 this study's underlying assumptions and implications are explicitly discussed to make clear how to value the presented results and conclusions.

The increasing relevance of the Dutch reserve capacity market, in light of a growing share of renewable electricity, its intrinsic susceptibility to market failure and lack of academic understanding of the market, constituted the main driving forces behind the main research question of this study. This question is answered in Chapter 8 and is formulated:

To what extent and by which means can a game theoretic modeling approach support strategic decision making in the reserve capacity auction and how can this model be used to critically examine the design of this market?

With regard to the use of the word *extent* in the main research question, this study's main realization is the delivery of a *proof of concept for a game theoretic computational auction model,* as the results of this research have shown that the designed model is capable to predict where market Equilibria will presumably establish.

In relation the micro- perspective, the perspective on the bidding strategy of the individual producer, this result implies that using *game theoretic models can assist producers by forecasting the market clearing prices as a means to optimize their own bidding strategy*.

In relation to the macro perspective, the system-wide perspective of a public policymaker, a second realization of this research is the *displayed possibility to apply this research approach in order to investigate implications of different market designs*. This realization is perfectly exemplified by this studies finding that *the separation of the total volume over two auctions in which half is procured each time, resulted in an additional cost reducing effect*. Believed to be ascribed to the limited rational of producers' strategy makers.

At the end of Chapter 8, a number of areas for further research are appointed. These include methods to increase the functionality of the model and means to improve the accuracy of the predictions of the model. In this chapter, additional areas of further research with respect to the domain of public policy are also advised. These include approaches to expand the applicability of the model as well as specific recommendations with regard to the design of the reserve capacity market.

Table of Contents

List of Figures

List of Tables

List of Terms and Acronyms

APX: Amsterdam Power Exchange

ANCILLARY SERVICES: Variety of functions supporting the basic services of energy transportation

BASE LOAD: Plants are designated Base load based on their low cost of generation

BALANCE RESPONSIBILITY: Designated role for market parties with balancing responsibilities

BALANCING MECHANISM: Market instruments of TSO to ensure demand is equal to supply

BRP: Balancing Responsible Party

ENTSO-E: European Transmission System Operators for Electricity

E-PROGRAM: Energy program

EU: European union

FPSB: First-price sealed bid

FREQUENCY CONTROL: Regulating control of the oscillation recurrence of alternating current

GENCO: Generic term for a generation company

IMBALANCE SETTLEMENT: Remuneration scheme between BRPs and control power suppliers

IMBALANCE PRICE: Amount of remuneration paid by BRP's to control power suppliers

KW: Kilowatt

MARKET EQUILIBRIUM: Stable state of the market, reached by competition

MW: Megawatt

NASH EQUILIBRIUM: Stable state of conceptualized competitive environment

PEAK LOAD: Plants are designated peak load based on their high cost of generation

PR: Primary reserve

PAB: Pay-as-bid

PTU: Program time unit

RES-E: Renewable energy sources producing electricity

RESPONSE RATE: Rate at which control power reacts to load disturbances

RESERVE CAPCITY: Generating capacity controlled by the TSO to balance demand and supply

SR: Secondary reserve

SFE: Supply Function Equilibrium

SMP: System marginal price, also Uniform system price

TENNET: Dutch TSO

TR: Tertiary reserve

TSO: Transmission System Operator

VOM COSTS: Variable operations and maintenance costs

1. Liberalized reliability

1.1 Introduction

From the moment we wake up, until are heads hit the pillow at night. Virtually all aspects of our life are completely reliant on electricity. Electricity not only plays a big part in powering our daily lives at home, but it is also tremendously important for all the things that go on in the world around us. Assembly machines, conveyor belts, baking ovens, copying machines, printers, radio, television, email, internet, satellite, telephones, electronic roadwork signs, airports, trains, traffic lights. You name it. Our society is completely empowered by electricity.

Electricity is a commodity, and as such, tradable like any other. However, unlike conventional goods, electricity has some atypical properties. It is, for instance, transported from producers to consumers at approximately the speed of light, it cannot be stored with economic efficiency and its flow cannot be controlled deliberately. Such characteristics require a high level of coordination between actors and infrastructure components, thereby making the electricity market especially interesting for researchers in the field of systems engineering.

1.2 Affordable, reliable and sustainable

Towards the end of the 20th century, politicians throughout Europe grew disaffected with vertically integrated monopolies, as had existed throughout the century. Liberalizing other network industries, proved successful which, combined with the political climate, paved the way for a virtually complete liberalization of the European electricity system. Vertically integrated utilities have since been disassembled, whereas barriers to entry in the generation and supply of electricity were removed so as to foster competition within the electricity sector.

Liberalization of the European Union's (EU) electricity market was presented by the European Commission as a means towards reduced electricity prices, security of supply, improved efficiency and the development of an increased share of renewable electricity in the energy mix. These objectives perfectly capture the goals that are almost universally applicable for policy in the energy domain: *affordability*, *reliability* and *sustainability*. However, as is common with policy, a trade-off between goals typically ensues when they are applied to real world situations.

An example of such a trade-off is embodied in the case of 'the California electricity crisis which took place in the course of 2000 and 2001. The deregulation of the Californian electricity market, created an environment that enabled energy traders to create an artificial gap between the demand and supply of electricity. By taking power plants offline in days of peak demand, they were able to substantially increase electricity prices, an abuse of power that resulted in long term black outs and societal costs estimated at $40 to $45 billion (Weare, 2003).

When analyzing the functioning of electricity markets, this crisis stands out as exemplary of the risks entailed by allowing private entities to accumulate a disproportionate share of market power in deregulated electricity markets.

In 2014 EU leaders agreed on yet another framework for climate change and energy policies. This framework targets renewable power in the European market of at least 27% of the EU's energy consumption in 2030, with the underlying assumption that the share of renewable electricity will reach approximately 60 percent by the year 2060 (European Commission, 2014).

These sustainability goals, formulated to promote the renewable generation of electricity, will likely necessitate an increase in size and frequency of short-term adjustments in power flows as a result of the typically fluctuating output of these energy sources (Mott MacDonald, 2013). Thus, soon these targets, at least until some extent, may demonstrate that the pursuit of one policy goal tends to come at the expense of another; reliability.

In order to correct for these imbalances, created by an increasing share of renewable energy as part of the energy mix, frequency control and operating reserves become ever more important (Wen & David, 2000).

In a liberalized electricity market such as in the Netherlands this implies that, aside from the wholesale electricity market, additional marketplaces are required in which the compensation for the imbalances can be procured by the system operator. The '*secondary reserve capacity market'*, from now on '*reserve capacity market'*, is one such marketplace and accounts for the largest share of the total imbalance management in the Netherlands.

1.3 The reserve capacity auction

TenneT, the Dutch Transmission System Operator (TSO) procures reserve capacity in a quarterly- and yearly auction. In these auctions electricity producers submit pairs of quantity and price/unit ratios for which they are willing to keep a certain amount of production capacity available for the TSO to correct for imbalances. A producer may divide his capacity and submit multiple bids but, if called upon, he has to be able to deliver the summed capacity of his bids that were accepted by the TSO.

While the producers enjoy a degree of flexibility in setting the price and quantity of their bids, the demand of the TSO is predetermined and, due to ENTSO-E regulations, perfectly inelastic.[1] [2]

[1] ENTSO-E, the European Network of Transmission System Operators, represents 42 TSO's from 35 countries across Europe. This organization is established and given legal mandates by the EU's Third Legislative Package for the Internal Energy Market in 2009, which aims at further liberalizing the gas and electricity markets in the EU.

[2] To comply to ENTSO-E regulations, TenneT is required to have permanent availability of a predetermined volume of secondary control reserve.

The facts that the capacity is auctioned as a symmetrical product (producers are required to have both upward- and downward capacity on standby) in combination with the high response rate of the reserved capacity, imply that reserve power can only be provided by spinning reserves.[3] [4] As a result, base load power generating technologies, like coal and nuclear, have a large advantage over gas plants which are mostly running at peak hours.[5] Another important characteristic of the reserve capacity market is that reserve power can only be provided by plants that are able to quickly ramp-up/down and have a fast response time. Such a feat is technically complicated, and supplying plants require government certification (TenneT, 2015). These characteristics dictate that few electricity producers are able to compete within this market.

The results of the reserve capacity auction are not publicly available. In fact, TenneT only discloses the date and demand for the auction, which makes it very difficult for producers to gauge the strategies of the competition. However, other information, such as the fact that spinning reserves are expensive for non-base load plants, estimates of the technical capabilities of the portfolio of the competition, and publically available information on planned overhauls can perhaps also be used to gauge the strategies of the competition 'by proxy'.[6] In this light, the oligopolistic market structure (with a predetermined demand, few producers with approximately known capacities and an algorithmic market mechanism) merits economic analysis.

1.4 The strategic bidding problem

An electricity market is a system for carrying out purchases, through offers and bids. In the wholesale market, the TSO procures the energy and reserve capacity on behalf of the energy and reserve customers. The TSO aggregates the generation bids and clears the auction based on the producer's bids and the system requirements, such as load level, requested reserve. In this structure, the competition is driven by the competitive bidding of producers.

In order to increase the profit, energy producers have the challenging task to optimize their bids based on their cost of production and an estimated demand of the market. This is made complicated by the fact that there exist not one, but multiple interrelated electricity markets and network services auctions, for which producers can use their production capacity. Producers therefore have to optimize their production capacity on all markets simultaneously. This challenging

[3] *Response rate* is the speed in which an utility is able to adjust its load and is measured in MW/min.
[4] *Spinning reserves*, sometimes called operating reserve, is the generation capacity which is readily available for the TSO to adjust for imbalances. These units should therefore be operational, as the name might suggest.
[5] The difference in power production costs determine which type of plants are mostly running at base- or peak hours. Currently in the Netherlands (2016), coal fired plants have a cost advantage over gas fired plants and are therefore running base load hours.
[6] Power plants are designated *base load* based on their low cost generation, efficiency and safety at rated output power levels. Base load power plants do not change production to match power consumption demands since it is more economical to operate them at constant production levels.

task is often referred to as the strategic bidding problem in the literature. The restructuring of electricity markets has therefore introduced risk and uncertainty into a previously state-owned industrial sector.

In liberalized electricity markets, the maximization of profit for Generation Companies (GenCos) is now highly associated with optimizing bidding strategies (Prabavathi & Gnanadass, 2015). Optimizing bidding strategies in restructured electricity markets has become a complex task due to a manifold of influential factors (e.g. the development of fuel costs, demand and supply as well as the uncertain strategic behavior of competitors) and has engaged academics to research electricity markets from the perspective of the competitive electricity producer. Several modeling approaches have since then been proposed to generate strategic bidding strategies (Li, et al., 2011). However, literature, which is specifically dealing with modeling approaches for the reserve capacity auctions, is rather scarce.

Most articles examine the role of auctions in the wholesale electricity-, future, or balancing energy markets and consider the level of integration with the spot market as measure of efficiency. In contrast to the body of knowledge on these matters, the reserve capacity auction has hardly received academic attention. The sparse number of articles that do address this market differ greatly with respect to its assumptions on the functioning of the market and the situation in the Netherlands. Hence, the existing body of research is not applicable to the functioning of the Dutch reserve capacity markets.

For example: Wen & David (2000) address the reserve capacity auction by proposing an algorithmic model which can be used to optimize and coordinate bidding strategies for the balancing energy- and spot market. However, they assume linear cost functions and adopt a different settlement scheme than currently used in the Dutch electricity market. Rassenti, et al. (2003), and Federico & Rahman (2003) investigate the influence of different settlement regimes yet only consider the wholesale electricity auctions. While Swider & Weber (2007) model optimal bidding strategies with price uncertainty in the reserve power markets and use a 'pay-as bid' settlement scheme, they only consider a price-dependent probability of bid acceptance, and therefore fail to include potential collusive behavior by market participants and a discrete supply curve in their approach. Both are also inconsistencies with the Dutch reserve capacity market.

A considerable amount of research is devoted to the application of game theory in the study of strategic behavior in deregulated generation markets (e.g., see Petrov, et al., 2003; Gao, et al., 2007; and Kian & Cruz, 2005). Especially the game theoretical concept of the Nash Equilibrium has been useful in growing our understanding on the likely behavior of markets and rational electricity producers in oligopolistic electricity markets (Petrov, et al., 2003).

Game theory is defined as the study of mathematical model of conflict and cooperation between decision makers and can be used to analyze situations in which decisions made by so called players have an effect of the welfare of its competition. A game in the everyday sense can be described as a competitive activity in which players compete with each other according to a specific set of rules.

The illustration on the title page of this thesis is a hint towards the similarities between strategic interactions found in the game of chess as compared to the interactions found in oligopolistic markets. As, both in chess, as well as in oligopolistic markets, it is very unwise to develop strategies without considering the possible actions and reactions of your competition. This makes Game theory an attractive candidate to study the presumed oligopolistic reserve capacity market.

1.5 Motivation, aim and approach of this study

Many energy markets are intrinsically vulnerable to the abuse of market power, strikingly demonstrated by the Californian electricity crisis which illustrates that a well-designed market is paramount to achieve efficient outcomes from a social welfare perspective.[7] Minute flaws in the architecture of the electricity market, may already result in tens of millions or even billions of excess societal costs (Heim & Goetz, 2013).

Currently, the reserve capacity market has assumed a crucial role within the Dutch electricity market and, due to the projected increase in the share of intermittent (i.e. renewable) energy sources, its importance is expected to grow even further over the next decades. The characteristics of this auction make it seemingly appropriate for a game theoretic market modeling approach. However, given that, as of yet, little research has been devoted to this market segment, there is a clear gap in the academic understanding of the reserve capacity market in the Netherlands.

The increasing importance of the Dutch reserve capacity market, in light of a growing share of renewable energy, its intrinsic susceptibility to market failure and lack of academic understanding of the market therefore constitute the driving forces behind the main question of this research:

To what extent and by which means can a game theoretic modeling approach support strategic decision making in the reserve capacity auction and how can this model be used to critically examine the design of this market?

[7] The word efficiency has numerous connotations all depending on the perspective from which it is used. For example, in mechanical engineering the term is often used to indicate the ratio of useful work in relation to the input for certain processes, while in economics the application of the term in relation to markets often indicates the degree to which information is reflected in prices. Throughout this thesis, the term efficiency in relation to the reserve capacity market is used from the perspective of the consumer and indicates the degree in which market prices reflect the true value (or cost from a producer's perspective) of reserve capacity.

The California electricity crisis has shown that liberalization enabled market actors to exercise unhealthy levels of market power resulting in market manipulation, gaming and other inefficient conducts. Meanwhile, the reserve capacity market is growing in importance while energy policies are subject to rapid change. In this context, market actors can enjoy strategic advantages, possibly enabling market inefficiencies, necessitating a re-evaluation of the appropriateness of the reserve capacity market's architecture.

The goal of this research is therefore twofold. The first part of the question looks at the problem from a *micro perspective* and aims explicitly at **supporting strategic decision-making in the auction for producers**, which has an obvious economic value for participants that are currently active in this market. The second part of the question takes a macro perspective on the problem and is specifically directed towards **the architecture of the secondary reserve market as a whole** and will examine the system from the perspective of a public policymaker.

In order to answer the main research question, various sub questions need to be addressed across several chapters.

- Firstly, in Chapter 2, the architecture of the balancing market is examined, which is done through the following sub-question "*What are the specific characteristics of the balancing market?".*
- In the same chapter, the second sub-question "*What factors influence decision makers in the reserve capacity auction?"* is answered in order to shed light on how market participants inform their strategies. Connotations

Answering these first questions is pivotal, as the predictive power of the eventual analysis relies on the extent to which the model can grasp the architecture of the system with its actors.

- In Chapter 3, the third sub question: *"Why a game theoretic modeling approach?"*, will be answered to motivate the choice for this methodology and to elaborate the theoretical underpinnings of this study.
- Subsequently, in Chapter 4, the sub question: "*How can a game-theoretical approach be translated into practice?*" will be answered.
- In Chapter 5, the results from the model experimentation will be presented and implications of these results in relation to the main research question will be drawn by answering the questions: "*How can the results of the research approach inform producers in their bidding strategies*", and "*What do the results of the approach reveal on the design of the reserve capacity market?".*

Vattenfall, as a key player in the Dutch balancing energy market, is the point of departure for exploring these questions. The company's electricity production portfolio consists of several power plants of which some also provide city heating. The most common type of power plant of their portfolio is the gas steam plant. These plants are known to be very versatile but see difficult times at this moment due to low electricity prices, caused by cheap power from Germany, a failing EU emission trading scheme, increasing penetration of renewables and an overcapacity of installed production power. Another type of plant which Vattenfall operates is a coal plant which is currently a base load power generation source and is therefore almost always operational.

1.6 Scope of the research

In the previous section the motivation, aim and approach of this research are introduced. In this section the scope of this research is explained. A brief elaboration on some of the specific details of the research problem is however required first.

Adopting the socio-technical conceptualization as proposed by de Vries, et al. (2013), the electricity system can be seen as composed of a technical and an institutional layer, see Figure 1.

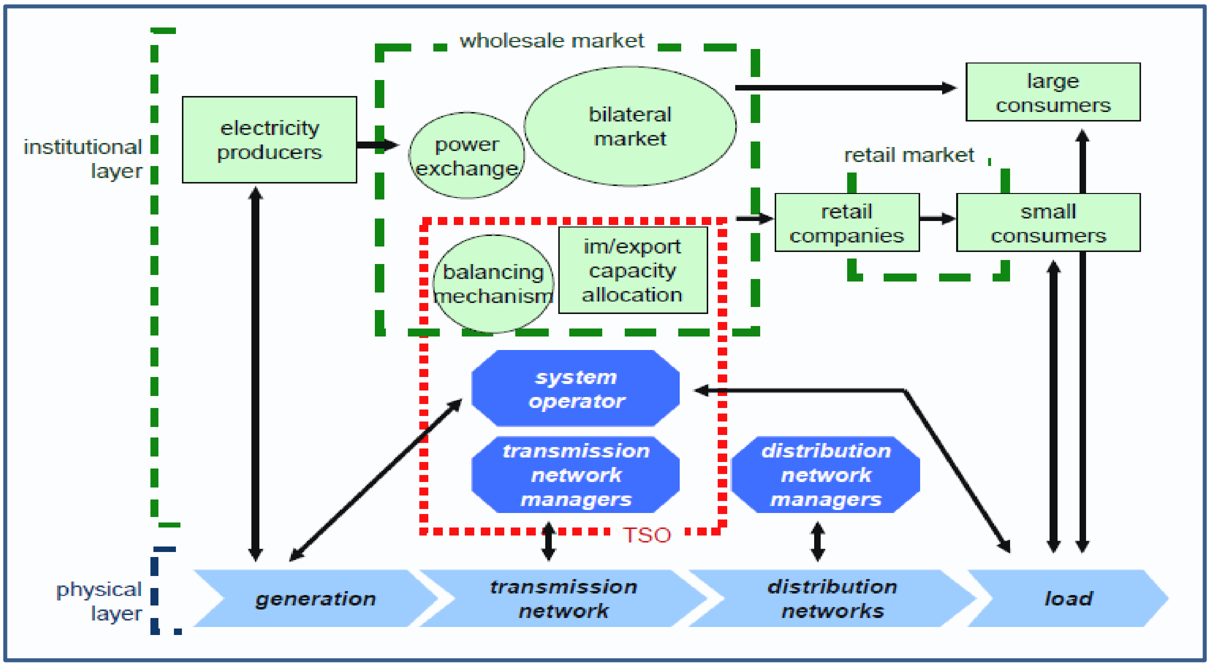

Figure 1 Diagram of electricity system (de Vries, et al., 2013).

The physical layer is best described as the technical infrastructure through which electricity finds its way from the electricity producers (referred to as producers in this thesis) to the power consuming equipment, or load, of the end users. The institutional layer of the electricity system is composed of the system operators, network managers, market participants and of the rules, responsibilities and market arrangements which govern their behavior.

In this figure the double pointed arrows are used to indicate which actors control which part of the physical system. The arrows with a single pointed arrow show the direction of the value chain of electricity. In the institutional layer of the electricity system it can be seen that producers and consumers meet in the wholesale market that actually consists of multiple related markets. These are: the bilateral market, in which electricity is directly sold by electricity producers to their customers, the power exchange, where electricity is traded for the next day on an hourly basis, and the *balancing mechanism*, which is composed of the rules and responsibilities for market participants, and ancillary service market places.[8]

The topic of this research is related to the balancing mechanism of the electricity system and therefore resides at the intersection of the wholesale market and system operation, as is indicated by the red box in Figure 1.

The balancing mechanism is composed of the rules, responsibilities and market arrangements which the TSO uses to maintain a physical balance between supply and demand. One of the major components of the balancing mechanism is the reserve capacity market, in which the TSO procures reserve capacity and energy to adjust for the imperfect market result of the wholesale market. This procurement process is subdivided into the *reserve capacity auction*, and the *balancing energy market*. In short, the reserve capacity auction is a tender in which balancing capacity is procured by the TSO and the balancing energy market is the marketplace in which pre-contracted electricity producers are mandated to place bids for balancing energy, corresponding to the volume which the TSO seeks to procure. This will be further explained in the next chapter.

The primary focus of this study is on reserve capacity auction and will not specifically analyze bidding strategies in the balancing energy market or any of the other markets. However, in relation to the strategic bidding problem for electricity producers it is not possible to investigate the auction as being completely separate.

The reason for this is that the choice to use part of the production capacity in one of the electricity markets – note the plurality – will come at a cost of not being able to use this capacity in the other markets – the so called *opportunity costs*. The strategic bidding problem therefore expands across the entire electricity market in which electricity producers attempt to economically optimize all their power plants, in all markets, simultaneously. However, this falls outside the scope of this intended research. As a means to overcome this issue, this study will attempt to approximate these opportunity costs by using a combination of market data and technical characteristics of participating utilities. The goal of this study therefore becomes:

To investigate the reserve capacity auction by incorporating realistic market data for producers as input for a game theoretic computational auction model.

[8] The term 'ancillary service' is used to refer to a variety of additional functions of the power grid that support the basic services of capacity generation, energy supply and delivery. These services are required to maintain grid stability and generally include, frequency control, spinning reserves and operating reserves.

1.7 Overview of thesis

This chapter has served to introduce and to engage the audience into the importance of the proposed research. In the next chapters the results of this study will be presented. This thesis is divided into three parts as illustrated in Figure 2.

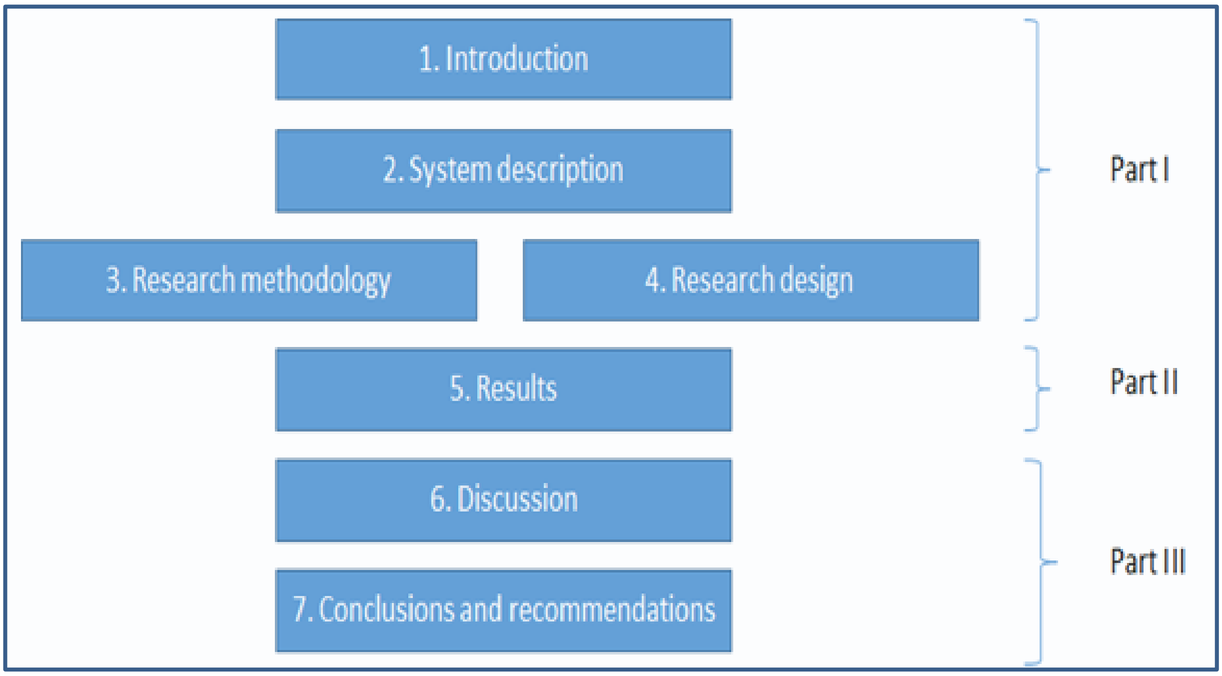

Figure 2 Structure of this thesis.

In the first part of this thesis, the context of the study is given shape. A first step is already made in this introduction, in which a background of the research problem, the targeted knowledge gaps, and adopted methodology has been introduced. In Chapter 2 the balancing mechanism will be further explained in order to establish the specific modeling environment for the economic analysis. This examination is followed by Chapter 3 in which the theoretical underpinnings of this study are elaborated, and the choice for a game theoretic methodology is substantiated. In Chapter 4 the research design is presented. This chapter will include a game-theoretical formal model, in order to quantitatively conceptualize and represent the strategic bidding problem and to clarify how the adopted methodology will be applied to the research problem.

The second part of this thesis contains the results of the model experimentation. These will be presented in Chapter 5. In this chapter the results will be analyzed and implications for the main research question will be drawn in terms of the strategic bidding problem for Vattenfall and in terms of policy implications in relation to the design of the market.

The third part of this thesis reflects upon the results of the preceding chapters and draws conclusions. Chapter 6 explicitly states and discusses the implications of the results, takes a critical look at these results. The study's main conclusions and recommendations are subsequently presented in Chapter 7.

2. System description

2.1 Introduction

In the previous chapter, an introduction to this thesis is presented in which the focus and scope of this study is described and several knowledge gaps identified. Moreover, this chapter introduced game theory as the research methodology for this study, which is to be further explained and motivated in chapters 3 and 4.

Game theoretic modeling is in essence the conceptualization of a competitive environment which outcome is controlled by both the strategic choices of rational decision makers and the rules which govern them. In order to model this competitive environment it is essential to have detailed information on the *decision problem*, as an inaccurate description of this problem is likely to result in major differences in market outcomes (Gao, et al., 2007).

In relation to the approach as adopted in this study, this means that it is necessary to give a clear description of the system of interest and all interrelated aspects entwined with the decision problem. This chapter will therefore commence by examining the architecture of the balancing market by answering the question "*What are the specific characteristics of the balancing market?"* and by shedding light on how decision makers inform their strategies by answering this chapter's second research question "*What factors influence decision makers in the reserve capacity auction?"*.

In reality, the number of relevant roles, parties and arrangements, related to the reserve capacity- and balancing energy market, are manifold. Several of these fall outside the scope of this research, yet in order to get a sufficient understanding of the decision problem, a number of these will be briefly touched upon.

2.2 The balancing mechanism

In the Netherlands, TenneT, the Dutch TSO, is responsible for maintaining a continuous balance between electricity production and consumption and hence for correcting the frequent situation in which gapes between the two arise. The 'balancing mechanism' is defined as '*the institutional arrangement that establishes market-based balancing'.*

It consists of the following three elements:

1. Balance responsibility
2. Imbalance settlement
3. Reserve capacity

Participants in the Dutch electricity market can freely decide with whom they trade electricity. By trading, producers and consumers enter into contractual agreements that stipulate the quantity and price of the power they are buying and selling. In practice, the agreed quantities will differ from what these participants actually produce or consume. These discrepancies must be settled so no power shortages or surpluses occur. For this TenneT uses a system of *Balance responsibility* which defines the role of the so-called '*Balance Responsible Parties'* (BRPs).

BRPs are all market parties that have the responsibility for balancing their portfolio of generation and consumption connections. As such, these BRPs have the obligation to submit an energy program, or E-Program, one day prior to the day of delivery. The E-Program contains the planned electricity production and consumption per hour.

In the *imbalance settlement* process, the BRPs are penalized with an '*imbalance price*' for deviation from this E-program, which gives them an incentive to balance their production portfolio.

Reserve capacity is classified in three different ancillary service products with regard to their activation and response time; *Primary Reserve* (PR), *Secondary Reserve* (SR) and *Tertiary Reserve* (TR). These products are called in sequence in response to disturbances, as can be seen in Figure 3.

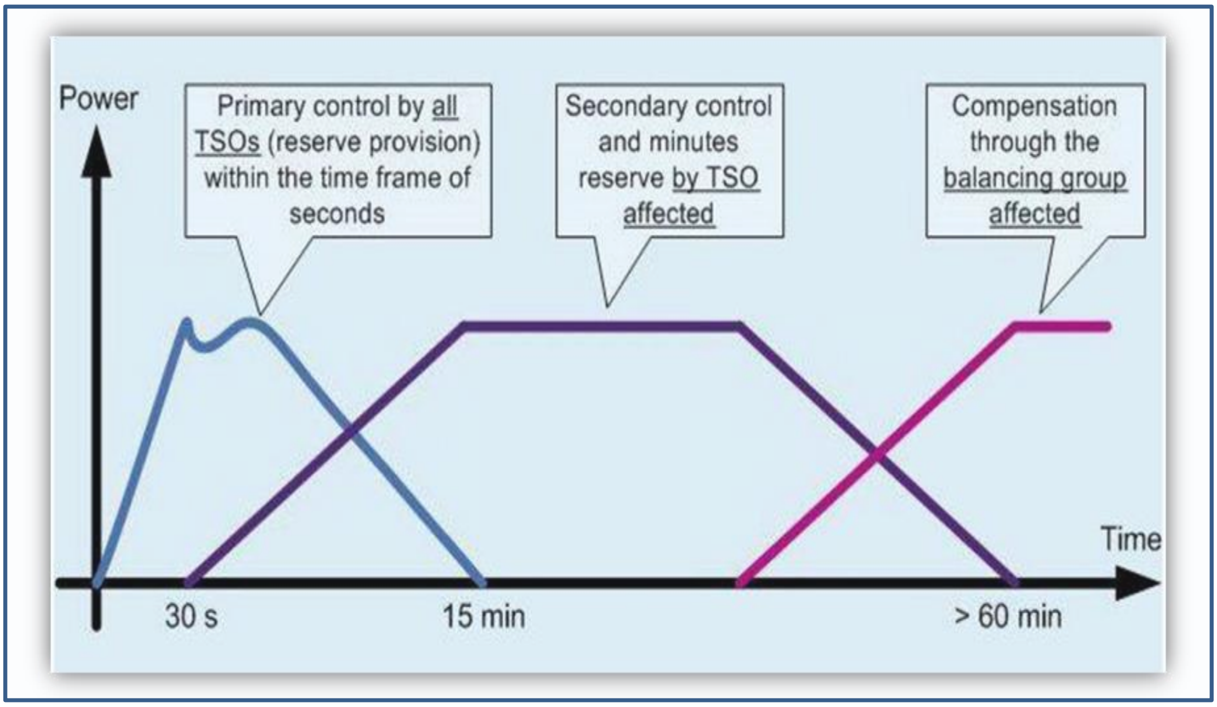

Figure 3 Activation sequence of control reserves (Amprion, 2012).

The activation of these products follows the principle of hierarchical substitution. PR is automatically triggered within seconds throughout the entire European region when deviations from the optimal system frequency of 50 HZ are in excess of tolerable limits.[9] PR thus restores frequency immediately and is subsequently substituted and complemented by SR after a maximum of 30 seconds. SR is also an automatically activated 'regulating power product' intended to replace the use of activated PR

[9] The system frequency is the rate of recurrence of oscillations of alternating current (AC). In continental Europe the standard for this frequency is 50 Hz with tolerable limits between 47.5 and 51.5 Hz. In case of a loss of load the system frequency is immediately affected. Serious frequency disruptions can initiate a black-out.

capacity within 15 minutes. In the case of persistent system failures TR is activated, thereby releasing PR and SR capacities and making them available again for further imbalances.

For clarity, if not specifically indicated, the usage of the term *reserve capacity market* refers to the *secondary reserve capacity market* throughout this study and this research will focus on this market segment in the subsequent sections of this thesis.

2.3 The reserve capacity market

The market for reserve capacity is two-staged. In the first step, reserve capacity is procured, in the second step balancing energy is delivered, or activated. A distinction is therefore made between two components of the reserve capacity market; ***the reserve capacity auction***, a tender in which capacity is procured by TenneT, and ***the balancing energy market,*** in which this reserved capacity is subsequently activated.

Remuneration is therefore given to market participants both for keeping part of their capacity available as well as for the energy which is delivered if the capacity is activated. This aspect of the market is important to consider as in the Dutch electricity market most of the capacity which is used as a balancing resource is pre-contracted and producers therefore do not have a choice but rather an obligation to bid in this market.[10]

As said previously, the first step of the two-staged balancing market starts with the procurement of capacity by the TSO in the reserve capacity auction. In the Netherlands this is done by TenneT who contracts reserve power in a separate market which is organized as a web-based procurement auction. Participating in this auction requires energy plants to meet high technical standards which they have to prove in so-called ‘prequalification procedures’ (TenneT, 2011).

As a result of these requirements, only few types of plants are licensed to use their capacity to provide reserve power. On top of the difficulty in meeting the technical qualifications, undergoing the prequalification procedure for the auction is costly and time consuming, lasting for up to a year. Given said circumstances, it is hypothesized that in 2015, the reserve capacity market was dominated by *three major players*. In Appendix A, a detailed analysis can be found which should serve as proof to this statement.

The auction is therefore best described as an *oligopolistic market*, a market typified by its relative lack of competitiveness and susceptibility to market to problems arising from market power.

As of 2016, the demand for reserve capacity (340MW, 2016) is procured in separate batches, in two auctions, each handling the procurement of half of the required volume. The reason for this

[10] Most is used here as in addition to the contracted market parties, all technically qualified producers can also bid voluntarily into the balancing energy market. As these producers are not pre-contracted they only receive remuneration if called corresponding to the imbalance price.

new approach is explained as to foster competition by reducing the barriers to entry in this market through increasing the flexibility of the contracts (Nobel, 2016).

The reasoning goes that contracts that are awarded for smaller periods have a lower risk as compared to contracts which extends longer periods. The reduced risk related to the granting of contracts should therefore reduce barriers to entry in the market, allowing other producers to participate in the auction. This is further explained in Box 1.

Box 1 Reducing barriers to entry by decreasing contract risks.

Consider the following example:

Initially a producer who is lacking a power plant with low marginal costs (such as a coal fired plant), had to guarantee the availability of spinning reserves for an entire year. Given the volatility of electricity prices and the absence of a power plant running at marginal costs, the producer would perhaps find it too risky to enter this market. If, however, the frequency is raised to shorter periods, the producer may choose to enter if he is confident enough that his forecasting models are correct in predicting a profitable contract.

Another important aspect of this market is that the sizing of reserve capacities is calculated on the basis of shortfall probability. Consequently, in order to ensure a sufficient level of security of supply, the European TSO's have the legal requirement to contract a pre-determined amount of reserve capacity in the reserve capacity auctions, regardless of the price. *The demand in these auctions is therefore perfectly inelastic.*

The second step of the balancing market proceeds with the *activation* of the pre-contracted market parties. This is done in the balancing energy market. The organization of this market is as follows. All contracted market parties are obliged to always bid at least the contracted capacity into the balancing energy market at an energy price of their choice, within certain ranges.

In a well-functioning market, the price which is paid for reserve capacity should reflect the *opportunity costs* and the energy prices from the activated capacity in the balancing energy market should mirror the actual costs of generation.

Now that the rules, responsibilities and market structure of the reserve capacity market have been established, it is possible to examine the bidding problem from the perspective of the producers' decision makers who determine the bidding strategy. This is done in the subsequent section.

2.4 Bidding strategy

In the previous analysis, the balancing mechanism and associated market structure were described. This section implicitly identified some of the drivers behind the strategic decision making process. The purpose of the following analysis is to name and explain these drivers explicitly. This will be done according to a decision making influence diagram as illustrated in Figure 4.

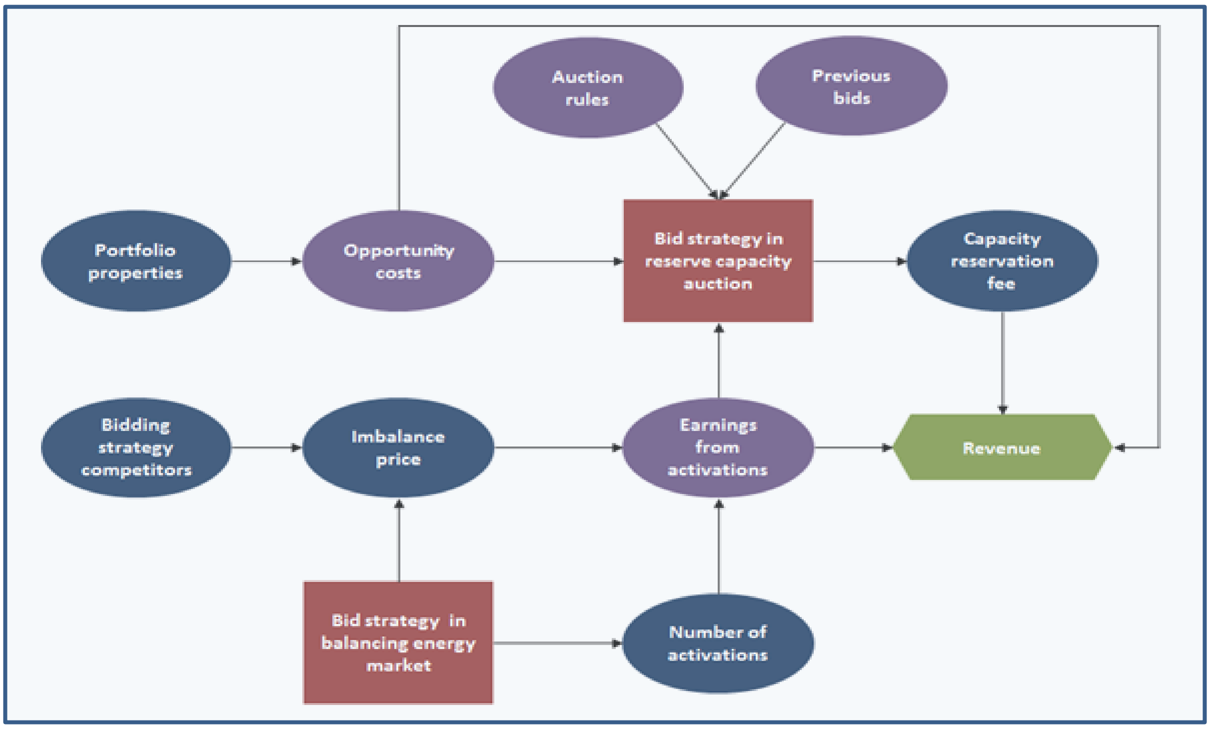

Figure 4 Influence diagram of strategic decision making in reserve capacity auction and balancing energy market.

In reality the number of factors and complex interrelations, determining the effectiveness of a given strategy, by and large exceeds the factors displayed in Figure 4.

While excluding some factors and including others may seem arbitrary, the purpose of this analysis is not to perfectly describe the functioning of the two markets. Rather it seeks to provide a simplified visual representation of the decision making process in order to establish a thorough understanding of the *decision problem*. In reality it can be assumed that decision makers also lack a complete understanding of the decision problem through their bounded rationality. The overview as presented in Figure 4, should therefore be sufficient.

In this illustration, the color green is used to indicate the goal of decision makers, which is to generate a profit. The color purple is used to show which factors directly influence decision makers while preparing their bid strategy in the two market components. Indicated in blue are the secondary influencing factors and, shown in red, are the two bid strategy aspects of this market.

The bid strategy for the reserve capacity auction is therefore determined by four factors: *Opportunity costs*, expected *earnings from activations*, *auction rules* and information about *previously accepted bids.*

Opportunity costs

The cost of providing reserve capacity for producers is mainly determined by the opportunity costs that are "incurred" by keeping capacity part loaded and not being able to sell the reserved capacity in other parts of the wholesale electricity market.

In the introduction it was stated that the wholesale electricity market actually consists of multiple related markets. These markets can be distinguished by the difference in trading period for electricity supply, and as such, are subdivided into the *Future-, Day-ahead-* and the *Intraday* electricity market.[11] In relation to the estimation of the opportunity costs, this means that in reality the *market opportunities* in all these market should be taken into account. However, the Day-ahead market accounts for the largest volume of traded electricity, amounting to approximately 50 percent of total trade in the Netherlands (APX, 2014). Therefore, this market is used as comparison to determine the opportunity costs of reserve provision.

There are two situations in which opportunity costs arise from the provision of reserve power. These situations are illustrated in Figure 5.

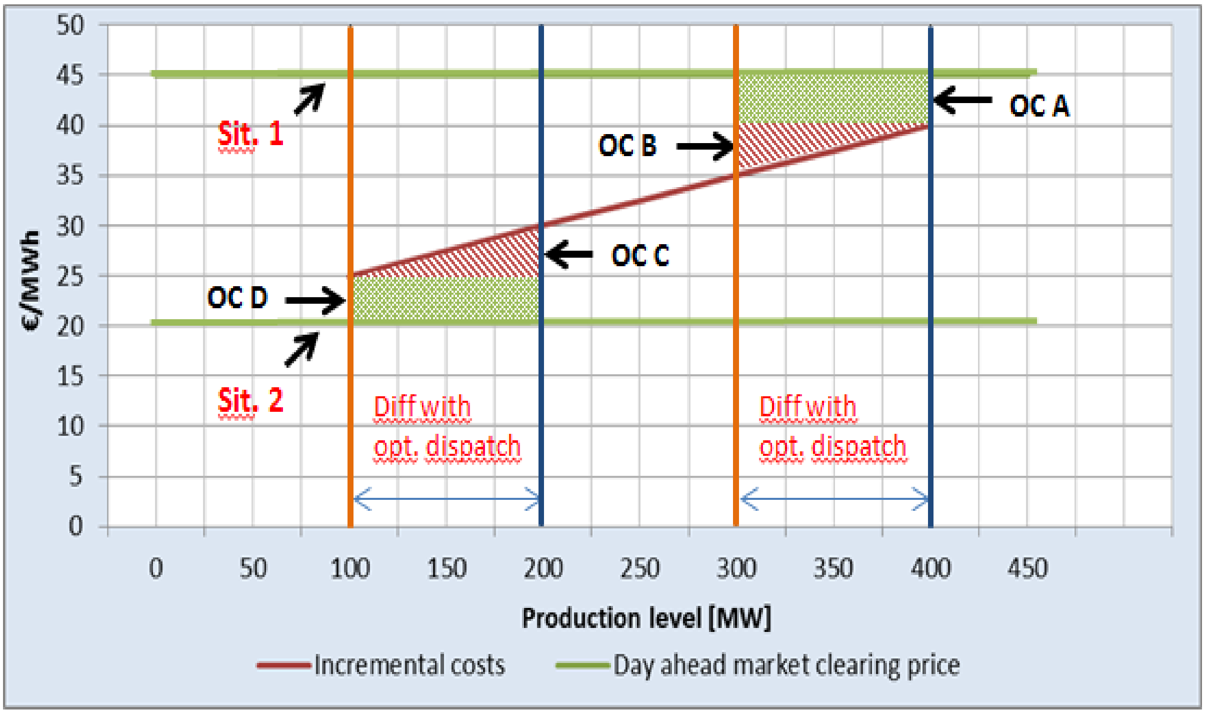

Figure 5 Opportunity costs arising from sub-optimal dispatch by the provision of reserve capacity. In the figure two situations are illustrated where opportunity costs (OC) arise by difference in cost between the sub-optimal dispatch (depicted by the orange line) and optimal dispatch (depicted by the blue line).

In the first situation, the Day-ahead market is profitable for a generator, as the producer's incremental costs are below the Day-ahead market clearing price. In this situation opportunity costs

[11] Electricity prices in the spot market are highly variable. This exposes both generators and retailers to significant risks. In order to reduce the impact of these risks market participants can hedge against this risk by closing long-term contracts in the *Futures market*. As the names might suggest, in the *Day-ahead market* electricity contracts are traded for physical delivery during the next day, while in the *Intraday market* electricity contracts are traded the same day as delivery.

arise by revenue losses from not being able to use the full capacity in the Day-ahead market. This source of opportunity costs is depicted by the rectangular green portion, designated OC A.

The second source of opportunity costs arise in the opposite situation; when the electricity market price is lower than the producer's incremental costs, the provision of operating reserves then entails selling a minimum load at a price lower than its variable cost of production. This implies opportunity costs emanating from plants that are actually forced to make a loss. This portion of opportunity costs is depicted by the rectangular green portion, designated OC D.

Another source of opportunity costs is applicable in both circumstances and is due to the fact that the efficiency of a power plant is decreased if it is forced to run on a partial load. Depicted by the triangular red portions, designated OC B and OC C. In Box 2, an explanatory calculation of these costs is presented based on the previously described situations.

As a result, only marginal plants – production units with a variable production cost equivalent to the Day-ahead market clearing price – do not have these two sources of opportunity costs. Simply speaking, reserve provision is provided most economically by the plants closest to the expected Day-ahead market clearing price. This means that at different times of the day (i.e. various Day-ahead market clearing prices) different units are more suitable for reserve capacity provision (Just, 2010).

Box 2 Opportunity costs calculation.

Based on the two illustrated situations of Figure 5, the Opportunity Costs (OC) can be calculated. This is done by calculating the difference in revenue in relation to the Day-ahead market clearing price (DAP) between the Optimal Dispatch (OD) and Sub-Optimal Dispatch (SOD). This therefore also includes the effect of a SUD on the incremental cost (IC).

Situation 1: Day-ahead market is profitable for GenCo

$$\boldsymbol{OC\ A} = [DAP - IC(OD)] \times [OD - SOD] \quad \textbf{(1)}$$
$$\rightarrow \boldsymbol{OC\ A} = [45 - 40] \times [400 - 300] = \mathit{500\ €/h}$$

$$\boldsymbol{OC\ B} = 0.5 \times [IC(OD) - IC(SOD)] \times [OD - SOD] \quad \textbf{(2)}$$
$$\rightarrow \boldsymbol{OC\ B} = 0.5 \times [40 - 35] \times [400 - 300] = \mathit{250\ €/h}$$

$$\boldsymbol{Total\ costs} = OC\ A + OC\ B = 500 + 250 = 750€/h$$

Situation 2: Day-ahead market is not profitable for GenCo

$$\boldsymbol{OC\ C} = 0.5 \times [IC(OD) - IC(SOD)] \times [OD - SOD] \quad \textbf{(3)}$$
$$\rightarrow \boldsymbol{OC\ C} = 0.5 \times [30 - 25] \times [200 - 100] = \mathit{250\ €/h}$$

$$\boldsymbol{OC\ D} = [IC\ (OD) - DAP] \times [\ OD - SOD] \quad \textbf{(4)}$$
$$\rightarrow \boldsymbol{OC\ D} = [20 - 25] \times [100 - 200] = \mathit{500\ €/h}$$

$$\boldsymbol{Total\ costs} = OC\ C + OC\ D = 500 + 250 = 750€/h$$

Electricity producers approximate the opportunity costs by using a combination of unit commitment and dispatch models. A unit commitment model is used first to optimize the production portfolio by selecting the generating units to be in service for a particular scheduling period. In these models the optimization problem is formulated such that the committed units must satisfy the system load and reserve requirements at minimum operating costs, subject to a selection of constraints. Once it is established which units are operational, economic dispatch models are used to determine the optimal allocation of the load demand between the operational units while satisfying the power balance equations and unit production limits (Soliman & Mantawy, 2011). [12]

In these models the *portfolio properties*, such as startup costs, efficiencies, minimum and maximum load of the production portfolio, as well as the expected *market circumstances*, such as the forecasted – and volatile – Day-ahead market-, fuel- and CO^2 certificate- prices, are incorporated.

The opportunity cost for a given contract is estimated by comparing the dispatch of the production portfolio with- and without a reserve contract. The change in cost between the two scenarios is roughly equal to the Day-ahead market clearing price minus the producer's incremental production cost, multiplied by the volume of the reserve contract (Hummon, et al., 2013).

Reserve capacity contracts either cover a quarter- or an entire year. The optimization models should therefore also cover these long extending periods of time to estimate the opportunity costs for a given contract. This also means that the estimates of opportunity costs are often just very rough approximations. The reason for this is that the output of the optimization model is very much dependent on the input of the forecasted market circumstances, which by themselves are already very challenging to estimate – especially over such long periods of time. In Figure 6 an example of an opportunity cost curve for different sized contracts is presented.

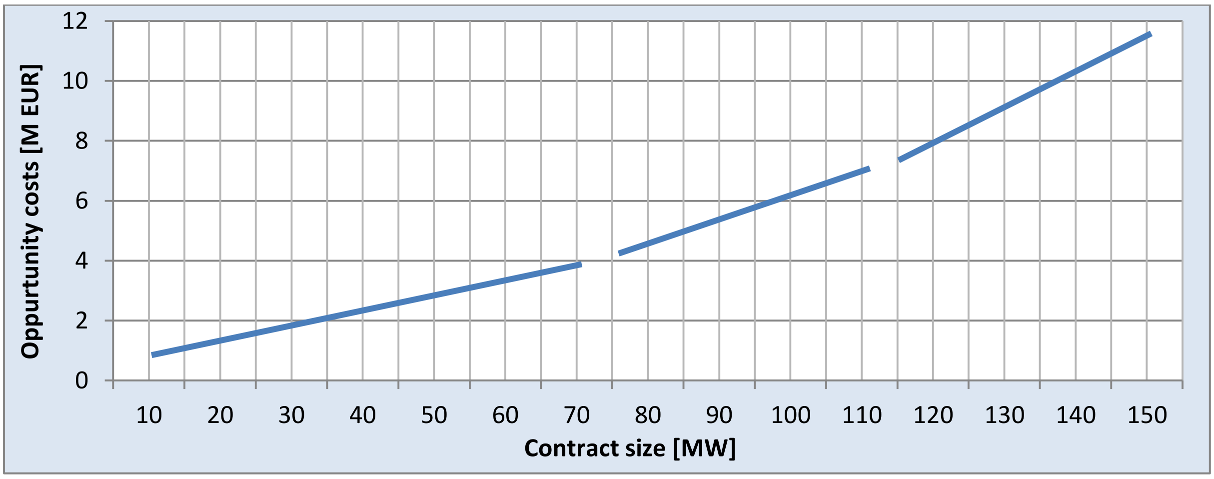

Figure 6 Opportunity costs curve with piece wise linear slopes.

The most important aspect to note from the cost curve of Figure 6 is that it is composed of piecewise linear slopes. The position and number of the piece wise linear slopes varies per production portfolio. However, all opportunity cost calculations should in theory look something similar to this. The reason for this is that differences in the slope of the cost curve can only arise from variations in the incremental cost of production between units at various levels for reserve provision (Kirschen &

[12] Unit commitment problems are formulated as mixed-integer linear programs and economic dispatch problems are formulated as a linear programs.

Strbac, 2004). From this it follows that the opportunity cost function will be composed of separate piece-wise linear sections for different segments of the bid slope.

The rules of the contract oblige market participants to provide the contracted reserve volume upon demand. The penalties for failure of meeting the contract are severe. For this reason, the calculated scenarios should also entail the possibility of an unforeseen outage as a means to incorporate this risk in the opportunity costs.

Aside from opportunity costs, other sources of costs, such as variable operations and maintenance costs (VOM) related to readiness, staffing costs, gas scheduling and reservation costs, can also be related to the provision of reserve power (California ISO Corporation, 2014).

Earnings from activations

In the beginning of this chapter the concept of activation was briefly touched upon. Simply put, activation is the triggering of a reserve capacity contract. Holders of reserve capacity contracts are contractually bound to offer, at a minimum, the contracted capacity into the balancing energy market at an energy price they can choose (within certain ranges). All energy bids are then sorted in a so called '*bid price ladder*' in which bids with the lowest energy price are called in first, proceeding to more expensive bids until sufficient balancing resources have been deployed. In Figure 7 an example of a bid price ladder and imbalance price system is presented.

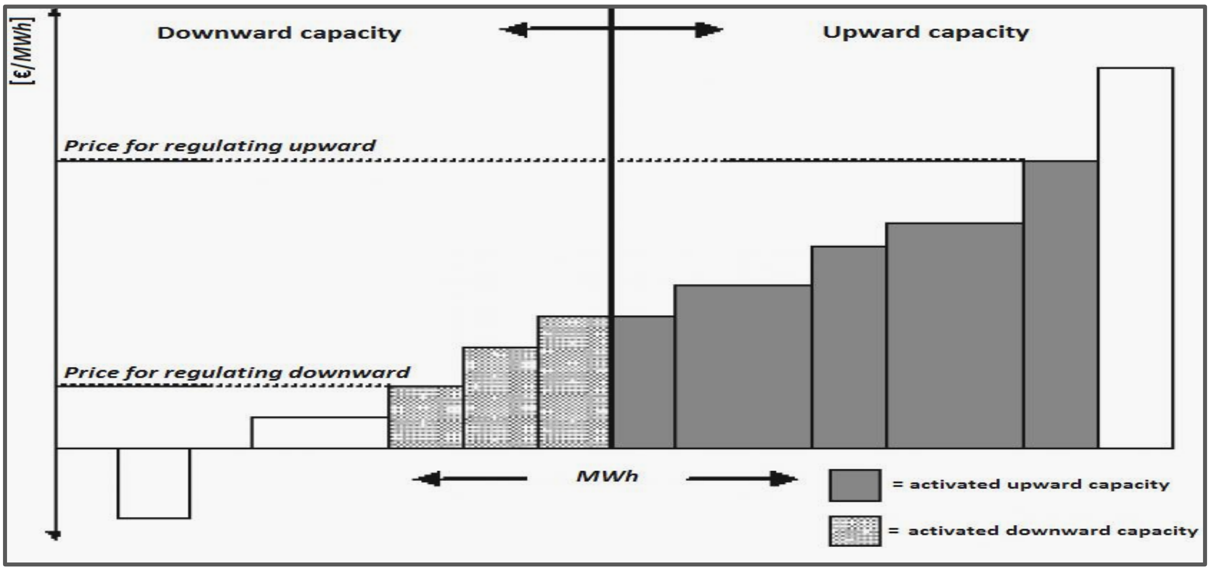

Figure 7 Bid price ladder for the determination of the imbalance price, adapted from TenneT (2004). Each of these blocks represent one of the bids of a producer. The price which all producers receive for the bids correspond to the lowest and highest activated capacity block for downward- and upward capacity respectively, the so called market price setter.

The settlement scheme in this market is based on uniform prices. This means that amount of remuneration in this market is dependent on the highest accepted bid which becomes the *market price setter*, thus determining the price each producer receives for their share of activated capacity.

A reserve capacity contract may be divided into separate bids, as long as the aggregate of these bids equals the volume of the awarded contract. In terms of the *bid strategy in the balancing* *energy market* this allows for some room to play, as producers face the choice to either submit their bids around marginal price levels to ensure a high frequency of activations, or to submit their bids at considerably higher prices to increase the settlement price in times of higher imbalances.

Consequently, if all producers in this market decide to offer the total of their bids at the marginal price of their production units, the profit generated in this market will never be higher than the difference between the lowest- and highest variable cost unit which is activated. However, if one or more of the producers decides to considerably increase the bid price of some of their bids, then the market clearing price would be higher at times of high imbalances when the most expensive bids are also activated. In short, the choice becomes; higher number of activations with lower average prices, or lower number of activations with higher average prices. This therefore represents a clear prisoner's dilemma for decision makers in this market. This dilemma is further described in Box 3.

Box 3 Prisoner's dilemma in reserve capacity market

The prisoner's dilemma is a text book example of a game analyzed in game theory which demonstrates why two completely "rational" individuals might choose not cooperate, even if it appears that it is in their best interests to do so.

Consider the following three possible scenarios:

1) *All producers cooperate (i.e. offering the same share of their bids at higher prices).*
   - ➢ *Average prices would increase and the number of activations would not decrease for each producer; hence everybody would be better off.*
2) *Some of the producers cooperate and some do not (free riders).*
   - ➢ *The producers who did not cooperate are better off than those who did, since those who did not cooperate will enjoy having a higher share of activations and would also benefit from the higher average prices, while the cooperation strategy here leads to lower activations.*
3) *No producer chooses to cooperate.*
   - ➢ *Everybody is clearly worse off since the average prices paid to each producer would never be higher than the producer with the highest variable cost.*

This description leads to the 2-player payoff matrix displayed in Table 1.

Table 1 Payoff table for reserve energy bids

GenCo 1 ↓ / GenCo 2 →	*Cooperate*	*Defect*
Cooperate	+ / +	- - - / + +
Defect	+ + / - - -	- - /- -

Earnings from activations are perhaps even more difficult to approximate as compared to the estimation of the opportunity costs. The reason for this is that the amount of profit generated in the balancing energy market depends on both the frequency and the size of imbalances (both of which are very difficult to predict), as well as on the strategies of the competition, the strategy employed by the producer itself, and finally how TenneT chooses to deploy the reserved capacity.

Calculating the expected profit from the balancing energy market is therefore very complex and a systematic approach to estimate this source of revenue is yet to be developed. However, in practice, an approximation to this revenue stream can be made based on the analysis of historical data. In Figure 8, an example of such an analysis can be found.

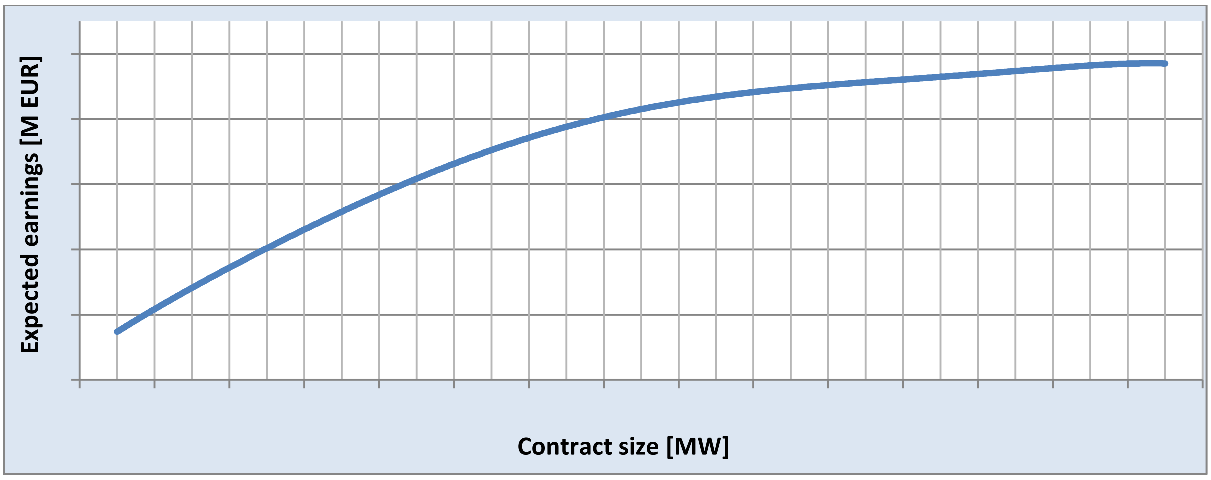

Figure 8 Curve representing the expected earnings from activations.

The most important thing to note from Figure 8 is that the earnings from activations decrease as the contract awarded in reserve capacity auction becomes larger (i.e. size in terms of Megawatts). Earnings from activations therefore tend to monotonically decrease to a limit as the contract sizes become larger. This is explained by the fact that the first capacity blocks get activated more frequently than the last capacity blocks – as the market is more frequently a little bit imbalanced than greatly imbalanced. The first capacity offers therefore contribute more to the generation of revenue than the sections to the far left and right of Figure 8. It can furthermore be assumed that this same logic holds for all producers and will show a similar shape.

Auction rules

The reserve capacity auction is organized as a web-based procurement auction and is settled on a First-Price Sealed Bid (FPSB) regime. It is a single buyer market, or monopsony, taking place once every year and once every quarter.[13] Each offer consists of multiple discrete bids which have a capacity- and a price component (single-part) and is offered in discrete steps of 5 MW. TenneT awards as many bids (multi-unit) as required to cover demand. Bids are selected solely on the basis of their capacity prices, as the actual utilization of reserves, or activations, is unknown ex ante due to the stochastic nature of imbalances (TenneT, 2011). Every producer can submit several bids by splitting up his available capacity. Finally, as it is a FPSB auction and nothing is disclosed about the contract details, none of the producers have information on the other producer's bid strategies.

[13] The frequency of this auction is currently in a transition phase from annually to quarterly. Currently, 340 MW SR capacity is procured by TenneT. Half of this volume was auctioned in 2015, the remaining 170 MW is auctioned each quarter.

Previously accepted bids

Analyzing *Previously accepted bids* from preceding auctions can also be effective for decision makers as it tells them how effective an earlier adopted strategy has been. However, as no information about contract details is disclosed, it only reveals what single bid was too expensive to be accepted.

Decision makers, nonetheless, may still use this information to decide to lower the bids that weren't accepted in the previous auction. However, doing so may bring about a price war, in which the competition reduces its prices in subsequent auctions, ultimately destroying part of the margin for every participant. This therefore presents another example of a prisoner's dilemma, as each participant is able to create more profit if he unilaterally decides to undercut the prices of the competition, yet everybody is worse off if all decide to undercut each other's prices. See Box 4 for a more detailed description of this dilemma.

Box 4 Prisoner's dilemma in reserve capacity auction

Consider the following three possible scenarios:

1) *All producers cooperate (i.e. not undercutting each other's bids to keep prices high).*
   - *No price war will be initiated and profitable margins can be maintained for each active participant; hence everybody is better off.*
2) *Some of the producers cooperate and some do not.*
   - *The producers who did not cooperate are better off than those who did, since those who did not cooperate will obtain a higher share of the market, while the cooperation strategy here leads to lower market share.*
3) *No producer chooses to cooperate (i.e. all producers are trying to undercut each other's bids to obtain higher market share).*
   - *A price war will be initiated and everybody is clearly worse off as the average prices of reserve contracts which are paid to each producer will gradually decrease.*

Aside from this dilemma for decision makers, this factor not only pertains to the bid strategy based on previously accepted bids, but also to the contract size of previously accepted bids. As half of the required reserve capacity is auctioned every quarter, while the other half is auctioned every year, this means that decision makers have to take the previously awarded contract volumes into account when making bids. Simply for the reason that an existing contract limits producers in terms of attainable contract sizes and opportunity costs for reserve provision. This also holds for contracted primary- and tertiary reserve as the also limit the capacities for providing this service.

2.5 The perspective of the Dutch TSO

This section serves to reveal the perspective of TenneT in relation to the market design choices is has made for the secondary reserve capacity market. This interview was held with Frank Nobel, an employee of TenneT who has been involved in the design of the reserve capacity markets since the beginning of the energy liberalization. A selection of this interview is found in Box 5.

Box 5 Portions of interview held with Frank Nobel (F), an employee of TenneT who has been involved in the design of the reserve capacity market since the beginning of the energy liberalization. Interview was held on the 16th of August 2016.

In the Netherlands, SR remuneration is given to participants for both the capacity as well as for the delivered energy. TenneT envisions an Energy only market. Why then this market design?

F: After the decoupling of the GenCos from the organization Samenwerkende Electriciteits-production companies (SEP), it became a requirement to all participating TSO's to purchase a predetermined amount of regulating power. TenneT started with a system in which all GenCos were obliged to have a certain amount of reserve capacity available and if necessary to deliver balancing energy from this reserved capacity. However, this did not work because the GenCos did not comply with the agreements. Therefore, TenneT eventually opted to pre-contract the capacity while also allowing non-contracted parties to place bids in the balancing energy market.

The tender is characterized by a very low level of transparency. This in contrast to many existing initiatives that advocate a higher level of transparency in the electricity market. Why is so little information disclosed in this market?

F: In the early years of liberalization, the market was composed of a small number of large GenCos. In this market, TenneT had the role of a monopsonist with a fixed and predetermined demand in an oligopoly. The combination of these characteristics therefore limits TenneT in its transparency, as TenneT aims to reduce the risk of having to face with a market failure (not being able to secure predetermined levels of reserve capacity).

The properties associated with the delivery of this product determine that not every type of producer will be active in this market. TenneT is therefore dependent on a few large GenCos for this service. Suppose one or more of these parties chooses not to participate in the auction. What if not enough reserve capacity is offered in the auction? And how can TenneT prevent ever coming in a position where it has to accept any price asked for reserve capacity?

F: This would indicate a market failure and TenneT will have to renegotiate with GenCos in order to secure sufficient reserve capacity. It is not possible to rule out this possibility and in case of abnormally high bids TenneT still has to renegotiate with participating GenCos.

With a bit of sun or wind, large flows of renewable electricity are transported from Germany into our country. The downside of this is the deteriorating effect it has on the current overcapacity. This feeds the debate on the need to compensate GenCos for keeping capacity available, for instance by means of a so called capacity market. Do you see a future for a capacity market?

F: TenneT is against the introduction of a capacity market. TenneT sees a capacity market as a policy instrument that serves to compensate for the negative effects caused by other policy instruments (such as renewable energy subsidy schemes). Furthermore, TenneT has the vision that further development towards an energy-only market is the most desirable. This vision arises from the liberalist character of TenneT, aiming for a market in which supply and demand prevail. In this market there is no place for remuneration for capacity without a clear demand for this service. Price peaks should be sufficient to secure sufficient levels of capacity

2.6 Conclusion

In order to get a clear understanding of the decision problem in the reserve capacity auction, this chapter has served to find answers to the questions: "*What are the specific characteristics of the balancing market?*" and "*What factors influence decision makers in the reserve capacity auction?*". The analyses supporting these answers have resulted in the following main conclusions.

The architecture surrounding the reserve capacity market can be characterized as an *oligopoly*, a market typified by its relative lack of competitiveness and susceptibility to market to problems arising from market power. Another important aspect of this market is that the sizing of reserve capacities is calculated on the basis of shortfall probability. Consequently, TenneT has the legal requirement to contract a pre-determined amount of capacity in the reserve capacity auctions and *demand in these auctions is therefore perfectly inelastic*.

Considering the number of factors and complex relations involved in the bidding strategy in the balancing energy market and reserve capacity auction it can be concluded that arriving at an effective strategy is not a sinecure. Finding the *most optimal* strategy is impossible and can, at best, be approached by using models. The strength of these models depends upon the amount of available information and the model's underlying assumptions.

Several important aspects that guide the decision makers' strategies were identified and it was established that the simulation model will have to be able to incorporate the most important influencing factors; *Opportunity costs, Earnings from activations, Auction rules and Previously accepted bids*.

The calculation of the opportunity costs can be approximated by unit commitment models while earnings from activations can be estimated by a historical analysis of accepted bids in the balancing energy market. These two factors are thus the input of the model for each producer. The rules of the auction should furthermore be incorporated in the model in such a way that the bids are accepted in the same fashion as would be in the actual auction.

The preceding analysis has also uncovered a strong potential for inefficient conduct in the two related markets. Firstly, in relation to the balancing energy market it is concluded that producers have a clear incentive to overbid their marginal costs in order to increase the market clearing price in times of higher imbalances. Secondly, in relation to the reserve capacity auction, it appears that the design of this market gives participants an incentive not to underbid each other's offer by too much as this might initiate a price war, thereby destroying a great portion of the margin for future auctions. This could mean that this part of the market is susceptible to collusive behavior.

In the following chapter, the theoretical background underpinning this study will be further elaborated and the choice for the selected approach will be further substantiated.

3. Methodology

3.1 Introduction

The main research question is to investigate how and to what extend a game-theoretic modeling approach can assist strategic decision making in the reserve capacity auction. A first step to address this issue has been taken in the previous chapters in which the specific characteristics of the decision problem are described. This chapter will serve to answer the question: *"Why a game theoretic modeling approach?"*. This will be done by first describing the theoretical background underlying this study after which the methodological approach as adopted in this research will be motivated.

3.2 Auction theory

An auction market can be considered as a trading institution where buyers and sellers can readily meet to maximize their trade gains (Sheblé, 1999). However, a more encompassing definition is given by McAfee & McMillan (1986), who define an auction as a *"market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from market participants*". Auction theory is then the applied branch of economics which deals with how people act in auction markets and investigates the properties of these markets. Many different auction designs have been developed and typical studies surrounding this topic are mostly centered on the efficiency of a given auction design, optimal and equilibrium bidding strategies, and revenue comparison (Krishna, 2010).

Auction theory has been crucial in developing our understanding of price formation and negotiations in which both the buyer and seller are actively involved in determining the price (Krishna, 2010). Especially in the field of the theory of optimal auctions and monopoly pricing as well as in supporting the development of models of *oligopolistic pricing* (Klemperer, 2004). This last notion of oligopolistic pricing specifically applies to the current research problem and indicate a clear position for this study within the literature.

3.3 Auction rules, bidding protocol and market structure

According to Li, et al. (2011), bidding strategies should be developed based on the *auction rules*, *bidding protocol* and *market structure*. Therefore, before such an approach can be taken, it is necessary to explore these aspects in greater detail in order establish the specific details of the modeling environment.

Liberalization changed the Dutch electricity system from a vertically integrated setting to a deregulated and competitive environment. This means that participants are concerned with profit maximization rather than system-wide cost minimization (Hossein, et al., 2007).

As a result, market characteristics, such as the price elasticity of demand and the level of competition within this market, have important implications for the behavior of market participants and hence, the outcome of the auction. Price elasticity of demand is a measure used in economics to show the relationship between price and quantity demanded. Specifically, it provides a precise calculation of the effect of change in price on quantity demanded.

In the reserve capacity auction, the roles of buyer and seller are reversed. Unlike with a regular auction, in which buyers compete to obtain a good or service by offering increasingly higher prices, in the reserve capacity auction TenneT acts as the buyer and the producers compete with their capacity offers. This means that prices are expected to decrease as an effect of competition.

An additional characteristic is that the auction is structured as a single buyer market, or ´monopsony´. A monopsony can lead to situations where the buyer has market power but only if the buyer has the flexibility to change the amount he wishes to purchase to affect prices. For example, if TenneT could purchase a lower amount of capacity contracts, consistent with its valuation of guaranteeing a security of supply, then TenneT could drive down the price for all capacity contracts purchased. However, it is accepted that in a single buyer market, a buyer with completely inelastic demand cannot exercise monopsony power (Borenstein, et al., 1999).

The demand of the TSO in the reserve capacity auction, perfectly inelastic due to legal requirements, renders it vulnerable to abuses of power from the supply side. Meeting a fixed demand, independent of price, is therefore problematic from a market power perspective, as even relatively small amounts of inelastic demand can result in substantial market power to producers.

In 2015, the reserve capacity market in the Netherlands was dominated by three major players (Appendix A provides information in support of this statement). The level of competition is thus best described as an oligopoly. An oligopoly is a market form in which a market or industry is dominated by a small number of sellers which all, independently and non-cooperatively, compete to maximize their profit. Oligopolies can result in various forms of collusion which reduce competition and can often lead to higher prices for consumers as firms may employ restrictive trade practices in much the same way as in a monopoly (Niyato & Hossain, 2008).

This market structure therefore has implications for the strategic behavior of market participants as it is more likely that each participant is aware of and acts upon the actions of the others. Producers in the reserve capacity auction can therefore optimize their bidding strategies by taking the expected responses of the other market participants into account. Consider Box 6.

Box 6 Gaming opportunities in the reserve capacity auction.

In accordance with article 4(1) of Council Regulation (EC) No 1227/2011, all producers in the ENTSO-E area are obligated to disclose insider information. Knowledge about the amount of available capacity are examples of insider information and producers therefore are restricted to trade before the market has been informed by any changes in plant availability. In relation to the possibility of gaming in the reserve capacity auction, now consider the following situation:

Imagine a producer knows in advance that in the next quarter there will be a considerable reduction in the plants which are usually responsible for a portion of the provision of reserve capacity. As the demand of TenneT is perfectly inelastic, this producer may then relate this information to an increase in average procurement cost by TenneT and may therefore decide to increase its own bid, increasing the procurement cost even further.

Another important characteristic of the reserve capacity auction is that contracts are awarded by means of a sealed first-price (FPSB) auction. Sealed bid means that all bidders simultaneously submit bids and none of the bidders has any information about the bids of any other participant. First-price indicates that the lowest bidders receive the price they submitted as they are selected first. FPSB are commonly used as a tendering methodology for procurement by companies and organizations, particularly for government contracts and auctions for mining leases (McAfee & McMillan, 1987).

An often discussed aspect of regulating market design is whether to use a pay-as-bid (PAB) pricing auction design, in which each bidder is remunerated according to their own individual bid price, or to adopt a system marginal price (SMP), in which each producer optimally bids its output at cost as the price they receive is exogenous to their bid.[14]

In a PAB auction the expected profits are the product of the probability of a bid being accepted and of the mark-up on cost associated with this bid. Bidders are therefore faced with a trade-off between the profitability and the probability of producing. The reason for this is that higher bids reduce the likelihood of being called to produce, but also increase the mark-up over cost earned if the bid is accepted. PAB auctions are therefore often used as a method to reduce windfall profits of low cost producers (Frontier Economics, 2011). However, as a PAB auction does not create incentives for bids tied to marginal costs, it is unlikely that bids represent their true costs, as bidders adapt the bid to their expected level of the market price (Federico & Rahman, 2003).

Bidding the true value for a bid in a PAB auction is therefore not an effective strategy as is the case with uniform pricing.[15] The reason for this is that if players bid their true value, they receive a payoff of zero if they lose, but also a payoff of zero if they would win, since they'll get paid exactly

[14] The exception to this rule is when a bidder suspects its bid to be price-setting. In that case a bidder has an incentive to overbid his marginal costs.

[15] By true value in this sentence, the total amount of gain of the accepted bid is meant. Bidding the true value in this sense therefore means that there is nothing to gain. However, bidding above the true value doesn't necessarily means that a profit can be made, as contracts may also be necessary for business continuity.

what the bid was worth to them. As a result, the optimal way for players to bid in a reverse first-price auction is to "shade" their bid slightly upward, so that if they win you will get a positive payoff.

Determining how much players should shade their bid involves balancing a trade-off between two opposing forces: if one bids too close to the true value, the payoff will be modest but chances are bigger that the bid is accepted. If one were to place a bid that is well above the true value, the possible payoff will be high, yet the chances of the bid being accepted would be slimmer. Finding the optimal trade-off between these two factors is a complex problem that depends on knowledge of the other bidders and their distribution of possible values.

Instead of having incentives tied to marginal costs as in SMP, in a PAB auction bidders are stimulated to guess the market clearing price. This introduces randomness to the bids of producers which is caused by differences in forecasts of the market price (Tierney, et al., 2008). As a result, the producer with the lowest bids may not reflect the producer with the lowest marginal costs. This therefore has a clear consequence for overall system efficiency and social welfare.

Other inefficiencies in a PAB auction arise from the cost of forecasting itself which (in theory) is not required in a SMP auction. In addition to this, a clear advantage is given to big producers as compared to smaller producers. The reason for this is that big producers have a larger amount of financial resources at their disposal to improve their forecasting quality and these producers are also able to distribute these costs over a bigger organization (Heim & Goetz, 2013).

Furthermore, as decision makers are faced with questions such as "*What is the competition going to bid?*" and: "*How much margin should we take?*" there is a high degree of uncertainty is involved in PAB auctions which discourages competition and investments. These combined aspects create considerable barriers to entry for smaller producers which in itself is also a market inefficiency and therefore negatively affects the social welfare.

On the positive side, some studies have shown that a PAB auction suffers less from short term price volatility, as price changes due to unexpected shifts in market conditions – ranging from weather conditions to unscheduled plant outages – are smaller in a PAB auction, therefore resulting in a lower price volatility (e.g., see Mount, 2001; and Rassenti, et al., 2003).

Another argument in support of PAB auctions is that the ability of producers to exercise market power is lower in PAB- than in SMP auctions. The reason for this is that in SMP auctions only the bids that are most likely to set the market clearing price have to be increased and therefore only those bids face the risk of not being accepted. In contrast to this, in PAB auctions all the bids have to be increased and therefore all bids face the risk of not being accepted. This therefore reduces the incentive to exercise their market power, see for example (Federico & Rahman, 2003).

In summary, even though academics present convincing arguments that exercise of market power is lower in PAB auctions, all of these studies are focused on the wholesale electricity market and do not involve similar market structures as in the market under investigation. It thus remains to be clarified if and until what extent PAB auctions encourage efforts of producers to exercise their market power in the reserve capacity auctions, typified by an inelastic demand of a single buyer and an oligopolistic market structure.

3.4 Modeling approaches

The restructuring of electricity markets has engaged academics to research the strategic bidding problem for the competitive electricity producer and several modeling approaches have since been proposed to generate strategic bidding strategies.

For the purpose of this study, the classification of bidding strategy analysis, as proposed by Li, et al. (2011), is adopted. As such, the modeling literature can be classified into four different groups of optimization models: 1) Single GenCo optimization models, 2) Game theory based models 3) Agent-based models, and 4) Hybrid or other models, as depicted in Figure 9.

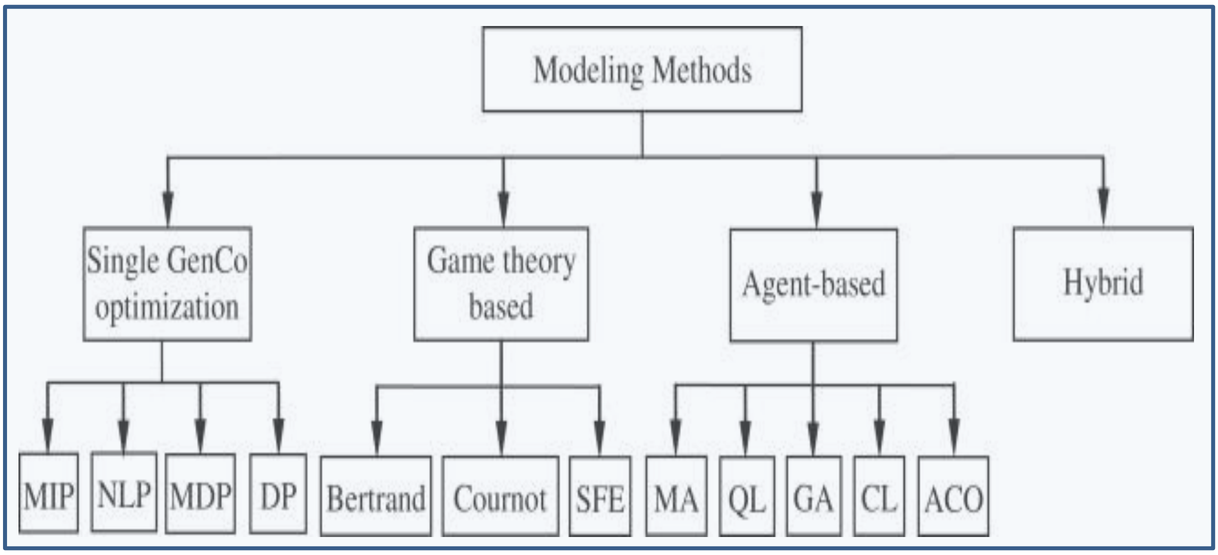

Figure 9 Modeling methods for optimizing bidding strategies in the electricity market, from (Li, et al., 2011).

In Figure 9 it can be seen that each modeling approach can further be divided into smaller subgroups according to model formulation and solution algorithms. The single GenCo optimization models include various different mathematical programming methods such as Mixed Integer Programming, Nonlinear Programming, and Dynamic Programming.

Game theory models can be sub-divided by the different competition rules that are assumed; Bertrand competition, Cournot competition, Supply Function Equilibrium (SFE), but also include some other recently proposed competition rules. Agent-based models can be classified with respect to different learning algorithms such as model-based adaptation algorithm, genetic algorithms, Q-Learning, computational learning, Ant Colony Optimization (Li, et al., 2011).

The analysis in Chapter 2 has shown that the outcome of the reserve capacity auction is specifically determined by the combined influence of strategic decisions of all producers. This means that, for the purpose of addressing the problem of optimizing the bidding strategy in the reserve capacity auction, the single GenCo optimization model is not very effective, as this approach is solely focused on a single producer while simplifying other influencing factors.

Agent-based models, in contrast, are capable to include more complex influencing factors and are specifically effective by mimicking human behaviors to arrive at optimal bidding strategies (Gao & Sheble, 2010). In these models, each agent arrives at an optimal bidding strategy by learning from past experiences obtained from the direct interaction with the environment (Li, et al., 2011). However, although interesting results on the behavior of the market may be obtained from this approach, these models are less effective in determining what strategy is most effective for an individual producer. This approach is therefore also not very effective.

Game theory models, also equilibrium models, address the situation by investigating the strategic interactions of multiple players and subsequently by analyzing the economic Equilibria of the system. Auctions are one of the most useful test-beds for game theory as its rules are often better defined than in other markets (Durlauf & Blume, 2008).

In an oligopoly producers are not only affected by their own strategic decisions, but also greatly by the strategic decisions of the competition. Game theory is therefore very useful in these type of situations, as it is specifically created to model circumstances in which each actor should consider how others might respond to that action, before deciding on a course of action for themselves. The examples of the prisoner's dilemma of the previous chapter also illustrate that cooperation is difficult to maintain for oligopolists, even in circumstances when cooperating is mutually beneficial and legal. This means that a tool which predicts the best course of action, without having knowledge about the moves of the competitors, can be very beneficial for producers.

A game-theoretical approach therefore seems most promising to address the main research question, as it wields the right tools to model the complex strategic environment of the market, allowing for an analysis of the bidding problem from both a single producer- as well as from a system level perspective.

3.5 Game theory

In his book: "*Game Theory-Analysis of Conflict* ", Robert Myerson describes game theory as the study of mathematical models of conflict and cooperation between intelligent rational decision makers. This means that game theory deals with decision situations in which rational participants have conflicting objectives (Morinec & Villaseca, 2008). This definition is very applicable to the behavior of market participants as, in general, each has the goal of maximizing profit. In a game theoretic model, market participants, are indicated as *players*, each with a finite or infinite number of *strategies* and associated *payoff*. In a game involving a market, such as the reserve capacity auction, a player's profit can be viewed as his payoff and is calculated by subtracting his cost from his revenue.

In game theory players are assumed to behave rationally in these sense that they will choose the strategy which, based on available information, offers the best chance of maximizing profit regardless of the competitors´ strategies. The goal of game theory is to mathematically deduce which actions each players of a game should take to secure the best outcomes for themselves. The objective of game theorists is then to locate the ´Nash Equilibrium´. This solution is not necessarily the most efficient, as is with a Pareto optimal solution, but simply an equilibrium that will logically result from each rational player individually pursuing his optimal strategy.

The Nash Equilibrium, named after mathematician and economic Nobel Laureate, John Nash, is a concept of game theory and is widely regarded as one of the most important utilizations of Game Theory. In his famous paper, John Nash proved that for every finite game there exists an equilibrium which can be calculated (Nash, 1950).[16]

The location of the Nash Equilibrium is at a strategy coordinate (a strategy, or set of strategies for each player) in which any unilateral change in strategy of each of the participants, will not result in an incremental improvement to either of the players (see Appendix G for a visual representation of a strategy coordinate system). As a result, the Nash Equilibrium is situated at the point where no player has an incentive to deviate from his strategy after considering an opponent's choice. If a set of strategies with this property exists, that strategy coordinate and corresponding payoffs is called the Nash Equilibrium (Myerson, 1997).

Two types of Nash Equilibria exist. *Pure strategy* Nash Equilibria are found when all players are playing pure strategies, while *Mixed strategy* Equilibria are found when at least one player is playing a mixed strategy.[17][18] If all players´ strategies and payoff functions are known, it possible to determine the location of the Nash Equilibrium. Simply reveal each player's strategy to the other players and notate *the best response* to each of the players' actions. If, as subsequently considered for each individual, a set of strategies exist where each action taken by others result in the same action taken by the individual, the existence of a Nash Equilibrium is proven.

At the core of the theory, the Nash Equilibrium, is a model of human rationality and behavior. As long as individual players have full understanding of the rules of the game and those rules are

[16] A *finite game* is a game with a definite beginning and ending, fixed rules and boundaries. Played for the purpose of winning and thereby ending the game.

[17] A *pure strategy game* provides a complete description of what actions each play player will take during a game. In specific, it defines the action a player will take for any situation he could face.

[18] A *mixed strategy game* includes the assignment of a probability to each pure strategy. This allows for a player to randomly select a pure strategy. As probabilities are continuous, infinitely many mixed strategies are available to players.

static then the outcome can be predicted. The reason for this is that the Nash Equilibrium is self-enforcing; once players are at a Nash Equilibrium they have nothing to gain by moving because they will be worse off. The most famous examples of a prediction made by game theory is called the prisoners dilemma, previously touched upon in Chapter 2. The dilemma suggests that if a conflict of interest between individual players and the combined group of players exist, the most likely scenario is that the individual players will defect from the optimal group strategy.

The combination of the rules of the auction, the payoff functions and strategies of the producers therefore determine the outcome of the auction. Game theory predicts that this outcome can be calculated. This means that in order to arrive at an optimal solution to the set of strategies it is necessary to investigate which kind of equilibrium the market may arrive at, given the inherent characteristics of the producers (David & Wen, 2000).

In the equilibrium state, every producer should bid in accordance with the results of the equilibrium solution as this is the *best response* to its competitors. Oligopoly equilibrium analysis, provides a tool to this end (David & Wen, 2000). Several oligopoly equilibrium models are available that explicitly model the strategic behavior of producers. The most prominent of these being *the Cournot Model, the Bertrand Model* and *the Supply Function Equilibrium Model (SFE).*

The analysis of bidding in auction markets relies on assumptions regarding firm behavior. Carefully selecting the type of equilibrium model is therefore essential as these differ greatly in their underlying assumptions of market behavior and therefore on the eventual equilibrium state solution. For example: the Cournot Model works with the assumption that producers decide on their supply quantities, assuming that rivals will not alter their outputs. The price is then determined solely by the quantity strategies of the producers and the demand curve (David & Wen, 2000). This is a major difference with the Bertrand model, in which it is assumed that producers offer a single price and there are no capacity constraints. However, both of these models assume price elasticity of demand and are therefore not well-equipped to simulate the market behavior of the reserve capacity auction.

Considering the market characteristics, the SFE models appears to be appropriate to analyze and simulate market behavior within the Dutch secondary reserve capacity auction. The reason for this is that the SFE model offers a compelling model of competitive behavior with multiple producers in which the existence of the Nash Equilibrium not requires the demand to be elastic (Rudkevich, 2005). Instead, the behavior of producers is simulated by means of supply functions. So rather than price-quantity pairs, the residual demand, faced by each player, creates elasticity and could result in a sensible equilibrium outcome even if the demand is non-responsive to price (Rudkevich, 2005).

However, although the assumption of price elasticity of demand may be relaxed in SFE, other assumptions that is contained within this model such as with regard to the strategic variables (e.g., possibilities to collude, price, quantity), capacity constraints, number of players, etc., which differ largely from the characteristics which define the reserve capacity auction (i.e. monopsony with perfectly inelastic demand, oligopoly, limited capacity, piece wise linear cost-, and logarithmic payoff functions, multi-unit-, pay as bid settlement regime, limited freedom to enter, no freedom to exit for TSO, heterogeneous product due to time, space and generation details, etc.) determine that this study holds that any comparison between any of the existing competition models and the reserve capacity auction is impossible.

This study will therefore approach this problem by creating an alternative competition model that adopts an entirely different set of assumptions with regard to the rationality of decision makers and the functioning of the market.

3.6 Conclusion

The purpose of this chapter was to present the theoretical background underpinning this study and to give arguments that supports the choice for the adopted research methodology by answering the question: *"Why a game theoretic modeling approach?".*

Beginning with the theory in support of this thesis, it was found that the results of this study could especially be valuable in the theoretic field of oligopolistic pricing, which indicates a clear position for this research within the academic literature.

It was furthermore established that auction rules and market structure largely inform bidding strategies of market participants. Studying the various effects of different auction rules and market structures is therefore an important step for the modeling approach this study has taken.

In terms of market structure, the most important aspect guiding the behavior of market participants is the market´s architecture with a single buyer and inelastic demand, a small number of producers that are enjoying relatively high degrees of market power. The market´s architecture renders it vulnerable to the abuse of market power on the supply side.

In terms of auction rules, the type of settlement scheme appears to be crucial in informing the market behavior of producers. In a PAB auction, the expected profits are the product of the probability of a bid being accepted and the mark-up on costs associated with this bid. Bidders are faced with a trade-off between the profitability and the probability of selling, while in SMP, bidding incentives are tied to marginal costs. PAB auctions are therefore often used as a method to reduce windfall profits of low cost producers as compared to SMP as bidding protocol. With respect to the effect these rules can have on market power it is yet unclear whether PAB auctions do in fact invite efforts of producers to exercise their market power in the reserve capacity auctions with the previously discussed market structure.

The insights drawn from the theoretical analysis, motivated the choice for the type methodological approach that this study should take. Several approaches have been investigated of which a game theoretic modeling approach was found most suitable, as it possesses the tools to model the complex strategic environment of the market and allows for an analysis of the bidding problem from both a single producer- as well as from a system-wide perspective.

The idea is that on a system wide perspective, game theory should predict a stable market equilibrium, as a result from the existence of human rationality and competitiveness in the auction. However if in reality this equilibrium is found elsewhere then this could be proof for an imperfect market or the presence of collusive behavior.

From an individual producers perspective the Nash Equilibrium reveals a great deal on how he should bid in the market, what his expected market share is and that of the other players. Approaching this market with the use of a game theoretic model could also predict what would happen to this equilibrium if the market circumstances would change which would allow this producers to prepare himself for such an event.

A game theoretic equilibrium model capable of mimicking the behavior of the decision makers could therefore be used to analyze the strategy of a player against the possible strategies of the competition and can therefore support the strategic decision making of Vattenfall. However, in order to calculate associated payoffs of the competition it will also be necessary to estimate the cost and most likely strategies of these players. In the next chapter the research design will be presented in order to specify how game theory will be applied to the research problem of this study.

4. Research design

4.1 Introduction

The previous chapter provided the methodological underpinnings of this research while this chapter seeks to demonstrate how said methodology can be applied to address this thesis´ main question. In doing so, the question:, "*How can a game-theoretical modeling approach be translated into practice?",* will be answered.

In this chapter the main question is implicitly answered by elaborating on the research steps. This will be done by first describing the different modeling stages that this research has entailed, whereafter the concepts and terminology of game theory is explained. From this understanding, a conceptual model for the auction simulation is presented and the computational model specified.

4.2 Modeling stages

While models can be helpful tools for addressing real world problems, they remain but an abstraction of reality, thus will never fully grasp the intricacies of real life situations. The process of modeling this research is best illustrated in the modeling cycle of Figure 10.

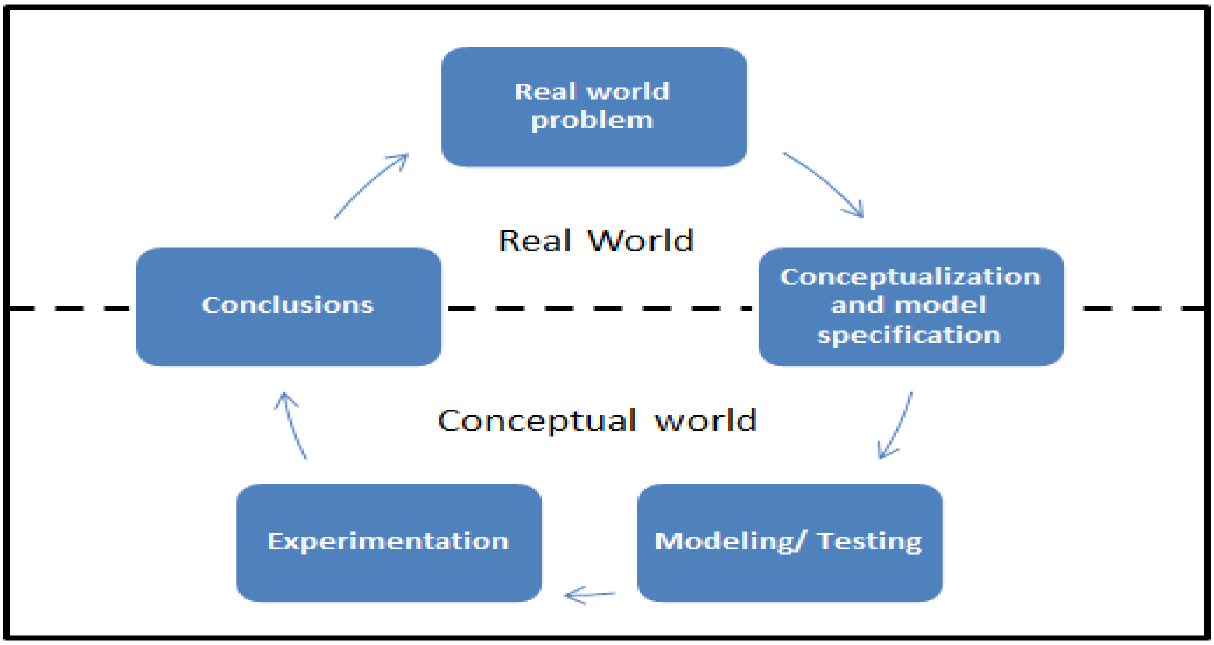

Figure 10 Modeling cycle of this study represented by an iterative effort between the real world observation and the conceptual abstraction of this reality.

This research departed from the observation of a *Real world problem: "*strategic bidding in a market which design may invoke collusive behavior", it seeks to analyze with various research questions.

Having elaborated the specific characteristics of the research problem it has become possible to conceptualize the problem in a model. In the previous chapter, the methodological choice for a *game theoretic modeling approach* was substantiated while the type of model and the tools to address the issue were discussed.

Several studies utilizing game theory for the analysis and optimization of bidding strategies in the electricity market exist. However, their overall focus on the Day-ahead market make them of little value for a separate analysis on the reserve capacity auction, as the factors determining the effectiveness of a strategy in this market spread across multiple segments of the wholesale market.

Consequently, the market is best studied from both the micro perspective of a single producer and the system wide perspective of the market in its entirety. To this end, this study adopts a game-theoretical approach in which assumptions about the utility functions of participants – composed of the expected opportunity cost and expected earnings from activations, as well as on the monetary value of the bid itself – were incorporated.

In the approach adopted, the opportunity costs and expected utilities were calculated over the year 2015, combining the technical characteristics of the participating power plants, the fuel and APX prices at that time, as well as the historical generation data per generation unit (as published by ENTSO-E).[19]. An explanation of this method and the results it generated, can be found in Appendix B.

Whereas the approach opted for in this research, lacks the predictive power of a "unit commitment model", it succeeds in revealing the relative position of each player in 2015, Equally, it allows conclusions to be deduced pertaining to the forthcoming years.[20] A system wide perspective on the auction can be attained by comparing the calculated Nash Equilibrium of 2015 with the actual results of the market in that year. Such allows approximations to be made regarding the efficiency of the market and the behavior of its participants.

The problem this research entails therefore involves an actual analysis of the reserve capacity market. This means that further specification of the model and the required data sources is required in order to answer the question: *How can the strategic decision making be improved?*

This involves a data collection step in which answers to the following questions are given:

- *Who are the players?*
- *What is their information?*
- *What are their strategies?*
- *How is their payoff defined?*
- *What are the rules of the game*

[19] The ENTSO-E data contains the generation data for all the electricity production units within the ENTSO-E control area with an installed generation capacity of over 50 MW. By comparing the 2015 data to the fuel and APX prices at that time, an optimal dispatch can be calculated. The hypothesis is that deviations from this optimal dispatch of participating producers is caused by opportunity costs and can therefore be calculated with this approach.

Upon answering these questions, said elements can be captured in a model. Modeling the reserve capacity auction, involved a testing phase in which the input of the model was verified by experts in the field of optimization and modeling from Vattenfall. As the goal of this research is to support the actual decision making of participants in the reserve capacity auction, the quality of the model´s output relies on the data it is being ´fed´.

A subsequent step in the creation and testing of this research´s model was the experimentation process. In this phase several model experimentations were run, utilizing various input scenarios. In this step, the following questions were investigated:

- *How can players influence the outcome of the auction in order to serve their self-interest?*
- *How can does their potential influence affect the outcome of the auction?*

In the next section a correct definition of the application of game theory and related concepts are given as a first step before arriving at the eventual model itself.

4.3 Game theory: Concepts and terminology

Game theory is the process of modeling the strategic interaction between two or more players in a situation containing a set of rules and outcomes. A game, in this sense, is defined as any set of circumstances whose result is dependent on the actions of two of more decision makers. It consist of the following elements that will have to be established in each game:

- *Players:* Collection of strategic decision makers within the context of the game;
- *Information Set:* The information available to each player at a given point in the game;
- *Strategy set:* Collection of possible moves (decisions, actions, plays, moves...) that each player can choose to make in each of his possible information states;
- *Payoff:* The payoff which a player receives from arriving at a particular outcome by adopting a certain strategy. Often the payoff is measured by a utility function.
- *Rules:* Procedure that determines how the strategic choices of all players collectively conclude the possible outcomes of the game

The primary goal of game theoretic modeling is to find the Nash Equilibrium. This is achieved by deducing a set of strategies for each player that, when employed, preclude the player from profiting by unilaterally deviating from the chosen strategy. Game theory holds that finding the Nash Equilibrium of a game, allows for a prediction of how actual human decision makers will behave when faced with situations analogous to the game, provided certain assumptions regarding their behavior are valid (e.g. players behave rationally, aiming to maximize their payoffs).

4.4 Game theoretical formal modeling in a(u)ction

In this section a formal description of a game, representing the reserve capacity auction, will be presented. In this game a single buyer seeks to purchase a fixed number *Q* of identical units from one or more of *N* potential sellers (bidders), each with a different production capacity. The number *N* of sellers is known, and these sellers each have undisclosed values *T* for each unit. The auction rules are based on a FPSB settlement scheme which is correctly viewed as a multi-unit generalization of the first price auction (Ausubel, 2008).

Sellers *simultaneously* submit their (multiple) bids, while considering the value of their expected profit for each unit. The buyer accordingly makes allocation and payment. The bids which are offered at the auction consist of a capacity- *C* and a price- component *P*. This bid is offered in discrete steps of *j'th* units. As it is a first price auction (FPA) the lowest bids are accepted for allocation. Hence, a formal description of this game is given as presented in Box 7.

Box 7 Game theoretical formal description of the auction game

In relation to the sellers. Number of sellers: n = 1, 2, . . . , N. Each seller has the following characteristics: For every *n'th* seller a set of actions $X_n(C,P) = \sum_{j=1}^{J} C_n^j, P_n^j$, *s.t* $\sum_{j=1}^{J} C_n^j \leq prod.capacity$; a set of types T_n of which the value $t_n \in T_n$ is the private information that player *n* has; a utility function $u_n: T_n \times X_1 \times, \dots, \times X_n \rightarrow \mathbb{R}$, where $u_n(t_n, x_1, \dots, x_n)$ is the utility achieved by seller *n* if his private value type is t_n , and the actions taken by all sellers is $x_1, \dots, x_n$. The strategy of the *n'th* seller is then described by the function $s_i: T_i \rightarrow X_i$; and sellers have the goal to $max\ s_i: T_i \rightarrow X_i(P)$.

In relation to the buyer. A single buyer *b = 1*. This buyer has the following characteristics: a single set of actions for this buyer: $X_b(C,P) \sum_{n=1}^{N} \sum_{j=1}^{J} C_n^j, P_n^j$, *s.t* $\sum_{n=1}^{N} \sum_{j=1}^{J} C_{n}^{j}, = Q$; an information set T_b; and utility function: $u_b: T_b \times X_1 \times, \dots, \times X_n \rightarrow \mathbb{R}$; and the buyer has the goal to $min\ s_b: T_b \rightarrow X_b(P)$.

For the sake of simplicity, consider that the players of this game consist of two bidders*: Genco1* and *Genco2*; and one buyer: *TenneT*. Assume that Q = 20 MW and bids are offered in discrete steps of 5 MW. Each of the bidders has three actions to choose from x_1, x_2, x_3, which correspond to either bidding: *low; medium; or high*. In Table 2, the resulting mix of strategy combinations can be found.

Table 2 Strategy profiles. First entry corresponds to the strategy of Genco1, second entry corresponds to the strategy of Genco2.

	Genco1		
Genco2	*l, l*	*l, m*	*l, h*
	m, l	*m, m*	*m, h*
	h, l	*h, m*	*h, h*

TenneT has only one option available; to buy the volume Q. The goal of the strategy for Genco1 and Genco2 is to maximize their utility: $max\ u_n = \sum_{j=5}^{15} P_j - C_j$, with $j = (5, 10, 15, 20)$. Where u_n is the profit of the accepted bid, calculated as a factor of P (the accepted bid price) minus the costs C associated with performance of the size j of the contract. The opposite holds for TenneT which has the goal to minimize the total procurement cost by: $min\ P\ = \sum_{n=1}^{2} \sum_{j=5}^{15} C_n^j,\ P_n^j, s.t.\ C = Q = 15.$

In order to illustrate how the Nash Equilibrium can be found in this example we can quantify the utilities associated with all possible combinations of actions. Let us assume that GenCo1 and GenCo2, each have the same cost for providing different sized contracts and these costs are lower than the demanded price of the offered bids. As the Nash Equilibrium is calculated based on the relative difference between utilities, these costs can then be ignored when calculating the utilities.

The distribution of the total volume Q between the Genco1 and Genco2 in this example is completely based on the relative difference of their bids (i.e. the difference of bids with respect to Genco1,Genco2→ l, l = 0; l, m = 1; l, h =2, while m, l= -1 and h, l = -2). If the difference between bids is zero, each player receives half of the volume Q, in this game this therefore equals 10 MW. If the difference between bids is +1 for Genco1 against -1 for Genco2, then Genco1 gets 75 percent of the contract and Genco2 is awarded 25 percent of the contract, 15 and 5 respectively. If the difference between bids is +2 for Genco1 against -2 for Genco2 then the total volume of 20 MW is awarded to Genco1 while Genco2 receives nothing. This leads to the distribution of contract as seen in Table 3.

Table 3 Distribution of the size of awarded contract.

	Genco1		
Genco2	*10, 10*	*15, 5*	*20, 0*
	5, 15	*10, 10*	*15, 5*
	0, 20	*5, 15*	*10, 10*

However, Table 3 only tells half the story, as the utility is calculated based on both the volume of the awarded contract and of the profitability of that contract. If we were to assume that the profitability (and therefore utility value), of a contract equals the size of the contract multiplied by the margin which is gained from this contract, the margins correspond to the bids as following: low bid= 1, medium bid= 1.5 and high bid = 2. This leads to the heuristic payout matrix as illustrated in Table 4.

Table 4 Heuristic payout table of the auction, the first two columns represent the adopted strategy profile of both players and the third and fourth table represents the utilities associated with that strategy profile. Best responses have been indicated in bold.

Action Genco1	Action Genco2	Utility Genco1	Utility Genco2
l	*l*	**10**	**10**
l	*m*	**15**	7.5
l	*h*	20	0
m	*l*	7.5	**15**
m	*m*	**15**	**15**
m	*h*	**22.5**	10
h	*l*	0	20
h	*m*	10	**22.5**
h	*h*	20	20

Now that the utilities associated with each strategy set is calculated it becomes possible to locate the Nash Equilibrium. This is done by finding all the best responses of a player while taking the other players' strategies as given. The Nash Equilibrium is found at the strategy set corresponding to both players' best response with respect to each other's strategies. The point where both player selected his best response to the other player's best response corresponds to the Nash Equilibrium. If multiple of such points exist we speak of Nash Equilibria.

In Table 4, the best responses have been indicated in *bold.* We find two responses which are equally good if Genco1 or 2 plays strategy *l or m.* As a result, we find more than one Nash Equilibrium in this payoff matrix. Relying on the correctness of this game´s representation, it can be concluded that decision makers of Genco1 and Genco2 arrive at the Equilibria found at strategy coordinates *l, l*; or *m, m*. More specifically, in relation to the strategic bidding problem, these results would reveal that both Genco1 and 2 would be better off to adopt their *m* strategy as this delivers the highest payoff. However, an even higher payoff can be achieved if both players were to cooperate and submit high bids in this auction. Going back to our discussion at the end of Chapter 2, this example therefore clearly illustrates how this market is inherently susceptible to inefficient conduct, which perhaps is even stimulated by the market´s architecture, as the value of the bid not only affects whether and how much each player wins, but also how much each player might lose the next auction if he chooses to undercut each other's offers.

4.5 Conceptualization and model specification

The hypothetical auction game of the previous section served to show in what manner the concept of game theory is applied in this study. This section seeks to apply this concept to the actual bidding problem and will therefore detail the functioning of the model, its inputs of the model and explain the reasoning and argumentations behind the assumptions of the model.

In Figure 4 of Chapter 2, it was shown that the bidding strategy in the reserve capacity auction is affected by a great number of interdependent factors. However, in terms of economic analysis it is simply not practical to include all factors. This conclusion can also be expanded to how market participants decide on their strategy. This has led to the development of the following conceptual description of the game theoretic computational auction model, as is illustrated in Figure 11.

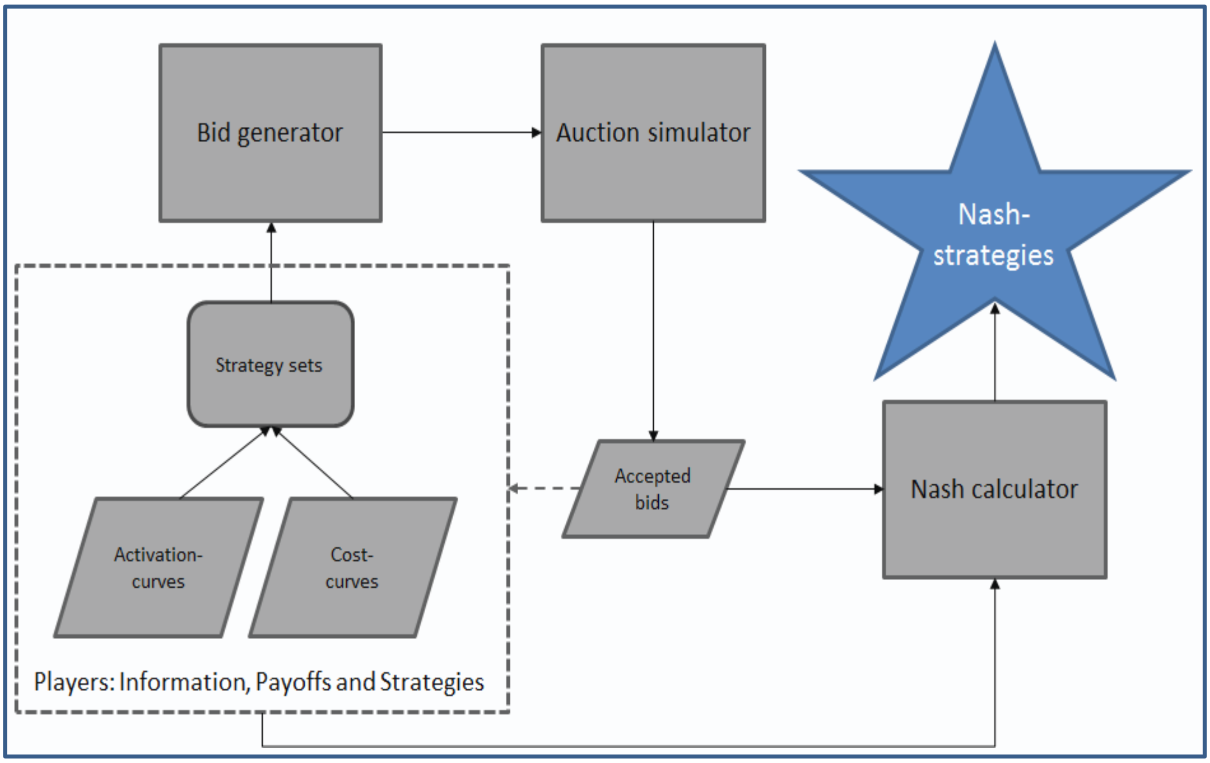

Figure 11 Conceptual description of the game theoretic computational auction model

In the conceptual auction game, it is assumed that players determine their bid based on respectively*:* their 1) *Activation curve*; 2) *Cost curve* and 3) *Strategy. The activation curve* is the expected profit from activated capacity. *The cost curve* is determined by the opportunity costs which are incurred from failing to use this capacity in the spot- or futures market. The strategy can then be defined as the margin players desire for their bids. *Accepted bids* from the previous auction inform the player with regard to the opportunity costs and earnings from activation by winning a new contract. The combination of the inputs of players and strategies can therefore be used to calculate the payoff vector to each combination of strategies. The bids are in the form of quantity and price quotations and specify how much the players are willing to sell and at what price. The quantity steps are in discrete steps of 5 MW.

This leads to the mathematical description of the players' payoff functions , as seen in Eq.5.

$$\pi_e = B_i + A_i - O_i \tag{5}$$

Where,

- π_e is the expected profit (payoff)
- B_i is the bid price of the *i'th* accepted bid
- A_i is the expected Activation earnings of the *i'th* accepted bid
- O_i is the expected Opportunity of the *i'th* accepted bid

The shape of the earnings from activation curve (monotonically increasing to a limit as the contract sizes become larger, see Figure 8 in Chapter 2), determines that the payoff of each succeeding bid is not linearly increasing, even if the bid price is kept at a constant margin. Furthermore, as the earnings from activations already compensate for a considerable amount of the opportunity costs, it may be beneficial for producers to bid lower than their respective opportunity costs. In addition to this, it may also be advantageous for producers to select different margins for several portions of the bid curve in order to adjust their margins in line with the cost competitiveness at different sections of the bid curve.

As it is unknown how producers currently generate their bids, the following two type of games have therefore been developed:

1. *Game with bid curves based on piece wise linear cost curves;*
2. *Game with simple bid curves*

In the first game each player can determine a separate margin for each section of cost curve. This thereby acknowledges the fact that the incremental profit generated by activations decreases, as the awarded contract size become larger. This representation of the auction would be accurate if the assumption: *Decision makers are not indifferent towards the risks involved in being - or not being - awarded different sized contracts*, is valid. Making a distinction between different sections of the bid curve allows producers to take full benefit of the possibility to adjust their margins based on their relative cost competitiveness for various contract sizes.

In the second game it is assumed that each player determines the margin they wish to have on top of the cost level for each contract size. This thereby ignores the fact that the incremental profit generated by activations decreases the larger a contract – in terms of MW volume – becomes, see Figure 8 in Chapter 2 for an illustration of this. This representation of the auction is therefore applicable when the following assumption holds true: *Decision makers are indifferent towards the risks involved in being - or not being - awarded different sized contracts.*

The process of calculating the Nash Equilibrium from the results of the first and second game is exactly the same and therefore only differ in the manner in which the strategies are formed. The stepwise procedure, as implemented in the game theoretic computational auction model is explained in detail on the next page.

1. A strategy set of 27 bid offers are generated.
    a. In the first game: The strategy set of each player is generated based on a selection of three margins (M_j) for three different sections of the cost curve. This results in 3^3 or 27 strategies, see Eq.6.

$$\left(\sum_{i=1}^{1st\ section} -O_i + \sum_{j=1}^{3} M_j\right) + \left(\sum_{i=1st\ section}^{2nd\ section} -O_i + \sum_{j=1}^{3} M_j\right) + \left(\sum_{i=2nd\ section}^{3rd\ section} -O_i + \sum_{j=1}^{3} M_j\right) \tag{6}$$

$$with, \quad (e.g.\ M_j = 20j - 20\ \left[\frac{EUR}{kW}\right])$$

    b. In the second game: The strategy set of each player is generated based on a selection of 27 margins on top of the positive slope of the cost curve. This results in 27^1 or 27 strategies, see Eq. 7.

$$\sum_{i=1}^{max\ capacity} -O_i + \sum_{j=1}^{27} M_j \quad with, \quad (e.g.\ M_j = 2j + 40\ \left[\frac{EUR}{kW}\right]) \tag{7}$$

2. The strategy set of each player is combined, with *N* players this leads to 27^N combinations.
3. The 27^Ncombinations are processed in a market clearing model, which returns:
    a. The awarded contract volume for each player
    b. The price of the accepted bid for each player.
    c. The chosen strategy for each player.
    d. The total cost for the TSO.
4. In order to establish for each player the respective payoffs of each of the 27^N market clearings, the cost and earnings from activations are added to the *i'th* accepted bid and the payoffs are stored in a database. Along with the details a→d of the previous step.
5. An extensive search algorithm is then used that runs through the database in order to determine for each player, the best response (i.e. highest payoff) to each combination of strategies chosen by the other players. These are then stored in a list.
6. A second extensive search algorithm is used that compares the best responses of each player to look for a match. In a game in which the number of players, n = 1, 2, . . . , N, this is programmed as follows:
    i. Return all matching best responses of player 1 and 2 and store in list1_2.
    ii. Return all matching best responses of player 3 with list1_2 and store in list1_2_3.
    iii. Continue until player *N*.
7. The Nash Equilibrium is located if there exitst a match between the last player and the list which contains the matches of all previously analyzed previous players.

4.6 Data collection

In the previous section it was explained that the payoff is dependent on both the adopted strategy as well as on the activation- and cost curve, as can be seen in Figure 11. While the strategy set can be regarded as a model variable that can easily be adjusted, the activation- and cost curve of all players should be calculated separately as these are required as input for the model. In this section the methodological approach for acquiring these two data sources will be explained as well as the necessary verification and validation steps.

The earnings from activation curve

In Chapter 2 it was stated that estimating the expected profit of activations is very complex and no systematic approach to this end has yet been developed. The reason why developing such a systematic approach is so problematic has to do with the unpredictability of the size and frequency of imbalances, along with many uncertainties regarding the bidding strategies of both contracted as voluntary bidders. However, as the earnings from activations curve has been fairly stable in the last few years, an historical analysis can be used to approximate this source of revenue.

The opportunity cost curve

On the 14th of June 2013 the EU regulation no 543/2013 was accepted in which the minimum common set of data relating to generation, transportation and consumption of electricity to be made available to market participants were laid down. As of the 5th of January 2015, ENTSO-E started to publish actual generation data per generation unit. This data contains the generation data for all the electricity production units within the ENTSO-E control area with a generation capacity of over 50 MW and can be used to estimate the opportunity costs for providing reserve power. This method is briefly described in this section. A more thorough explanation is given in Appendix B.

1. Make a selection of market parties that participate in the auction, see Appendix A.
2. Combine ENTSO-E data of participating parties into separate portfolios (e.g. see Table 5).

Table 5 Original dispatch of portion of ENTSO-E data. Based on portfolio of RWE.

DATE	HOURS	Amer 8	Amer 9	Moerdijk 1	Moerdijk 2	Swentibold 1	Eemshaven A
05/01/2015	00:00 - 01:00	410	576	170	0	111	766
05/01/2015	01:00 - 02:00	361	509	169	28	109	770
05/01/2015	02:00 - 03:00	357	428	180	60	112	635
05/01/2015	03:00 - 04:00	357	423	161	90	103	598

3. Determine the optimal dispatch by comparing the incremental cost of each unit at each hour with the APX prices (e.g. see Table 6).[21]

[21] The incremental costs are calculated based on the technical characteristics of each plant and the current fuel prices. See Appendix B for a more detailed explanation.

Table 6 Optimal dispatch of portion of ENTSO-E data. Based on portfolio of RWE.

DATE	HOURS	Amer 8	Amer 9	Moerdijk 1	Moerdijk 2	Swentibold 1	Eemshaven A
05/01/2015	00:00 - 01:00	590	590	95	0	80	800
05/01/2015	01:00 - 02:00	590	590	95	430	80	800
05/01/2015	02:00 - 03:00	590	590	95	200	80	800
05/01/2015	03:00 - 04:00	590	590	95	200	80	800

4. Calculate up- and downward oppurtunity costs
    a. Upward oppurtunity cost:
        i. If any of the plants available in the portfolio is running at minimum load then the upward oppurtunity cost is zero.
        ii. If none of the plants available in the portfolio is running at minimum load then the upward oppurtunity cost is calculated by multiplying the contract size by the available unit with the highest incremental cost.
    b. Downward oppurtunity costs:
        i. If any of the plants available in the portfolio is running at maximum load then the downward oppurtunity cost is zero.
        ii. If none of the plants available in the portfolio is running at minimum load then the downward oppurtunity cost is calculated by multiplying the contract size by the available unit with the lowest incremental cost.
5. The total oppurtunity costs for 2015 are then calculated by sumurizing the up- and downward oppurtunity costs over the entire year. Steps 4 and 5 should be repeated for each contract size (e.g. 5, 10, … 180 MW).

Following step 1 to 5 will lead to entirely linear cost curves. However, as was concluded in Chapter 2, these cost curves are not linear due to the fact that each unit has a limited capacity for providing reserve power. In order to calculate the piece wise linear cost curves the following additional steps need to be taken:

6. For each unit determine the maximal capacity for providing reserve power, see Eq 7.

$$Capacity_{reserve} = \frac{P_{max} - P_{min}}{2} \tag{7}$$

7. Proceed with step 1 to 5 for each contract level but this time remove a unit if the capacity for providing reserve power exceeds the contract size.
8. Continue until the maximal capcity for providing reserve power of the portfolios has been reached.

Again, for a more detailed explanation this study refers to Appendix B.

4.7 Verification, validation and resources

In the next sections the process of verification of the data sources and modeling approach will be explained. Followed by an description of how the results found in the model experimentations can be validated and which resources this study has used to these ends.

Verification

The research project was performed at Vattenfall. This organization has numerous experts in the field of optimization, modeling and power systems. This has allowed this study to verify the research steps, which have previously been discussed, and its results.

Furthermore, as this study required an analysis of the technical characteristics (such as efficiencies, minimum- and maximum capacities) of power plants, and since this information is not readily available, the power engineers have been used to verify the correctness of these characteristics. See Table 15 in Appendix B for an overview of these technical characteristics.

Verification is an essential step in the modeling process this study has undertaken, as the goal of this research is to support the actual decision making in the reserve capacity auction and the quality of the results of the model depend heavily on its inputs.

Validation

It is very challenging to validate the model as TenneT does currently not disclose anything with respect to participating producers, contract sizes and historical bid offers. However, two other sources can be used to verify the accuracy of the results found from model experimentations. Firstly, the ENTSO-E data can be used to investigate who the participating producers were and what their respective contracts sizes have been in the year 2015, see Appendix A.

Secondly, this study has been able to acquire the costs [EUR/kW] which have been occurred by TenneT in order to procure sufficient levels of reserve power over the last 10 years. This can therefore be used to validate if the cost levels found at the Nash Equilibrium are comparable to the actual cost levels in 2015.

Research tools and resources

The nature and complexity of the problem requires a great deal of computational force and solving can therefore not be done by hand. A computer program which can easily process vast amounts of data is therefore required. The proposed games have therefore been programmed in python and Gurobi was used as an all-purpose optimization solver. [22] [23]

[22] Python is a widely used high-level, general-purpose, interpreted, dynamic programming language.

[23] The Gurobi Optimizer is a commercial optimization solver for linear programming (LP), quadratic programming (QP), quadratically constrained programming (QCP), mixed integer linear programming (MILP), mixed-integer quadratic programming (MIQP), and mixed-integer quadratically constrained programming (MIQCP).

The choice to limit the number of strategies for each player to 27 has to do with the fact that the number of possible combinations increase with a power of 27 over the number of players, while the processing time increases even with a greater factor, as can be seen in Figure 12.

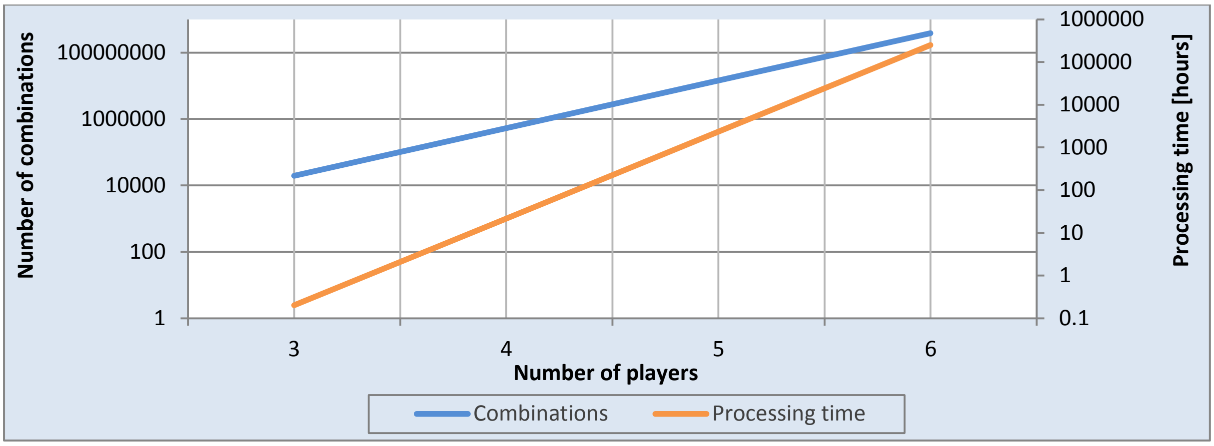

Figure 12 Strategy combinations and computational processing time

From the graph it can be seen that with 27 strategies and three players, the number of combinations is already well in the ten thousands while the processing time is still within limits. However, at four players the number of combinations reaches hundreds of thousands. At this point the processing time approaches resource limits. This means that for three players there is sufficient time for quite some model experimentation but for four players a smaller selection of experimentations can be run.

Aside from modeling the problem more efficiently, the processing time can also be reduced by eliminating ineffective strategies and thereby only considering strategic dominance.[24] However, this possibility has not been researched in this study and is therefore a suggestion for future research.

Research flow diagram

The envisioned design of this research leads to the main project steps as depicted in Figure 13.

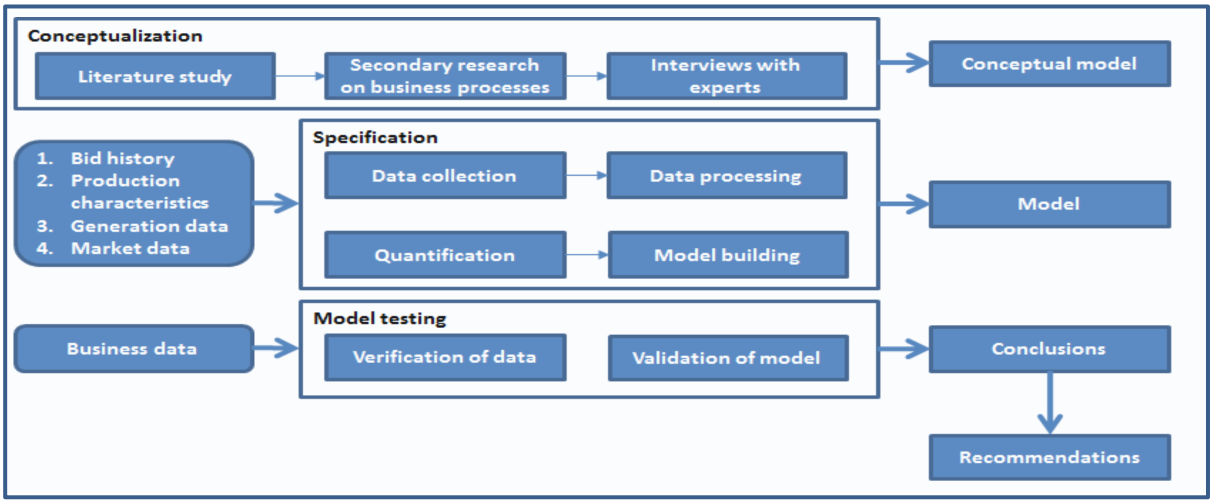

Figure 13 Research flow diagram

[24] In game theory, the term strategic dominance is used to indicate strategies which are more effective than another strategy for that player, no matter which strategies the other player(s) use.

4.8 Possible implications of results with respect to the market design

This study has approached the research problem from both a practical- and a theoretical perspective on the reserve capacity market. In practical terms, by incorporating actual data sources and in theoretical terms by using game theory to predict at what point the market will be in equilibrium. Therefore, the games and resulting conceptual models, which have been proposed in the preceding sections, are only meaningful if the coherence between the model and the real-life situation is preserved. However, if this assumption is correct then the approach as proposed in this study allows for interesting insights to be obtained, which can be used to question the suitability of the design of the market. These are as follows.

Firstly, as of the time of writing, no other study was found in the academic literature which adopts an extensive search algorithm to find the Nash Equilibria in a similar approach as in this research. Therefore, the first and foremost implication of the results found in this study could be the delivery of a *proof of concept* that confirms the feasibility of the proposed method.

Secondly, if the results of this study indicate that it is in fact possible to *forecast the market equilibrium* to a sufficient degree of accuracy, it could mean that a similar approach to this market (and other comparable markets), may be *useful for regulatory agencies* (e.g. regulatory agencies could use such Equilibria models to test whether markets suffers from forms of collusive behavior, to experiment with different market designs and to investigate the effect of demand changes on procurement costs).

Thirdly, the Nash Equilibrium also tells us something about the *rent* which is taken by the producers and the resulting costs which are incurred by TenneT. If the rent is high, then the structure of the market perhaps does not create sufficient *incentives for competition*.

Fourthly, by comparing the total procurement cost of TenneT in 2015, with the procurement costs found at Nash Equilibrium in the model experimentations, it can perhaps be determined whether the market is *vulnerable to collusive behavior*.

Fifthly, the point at which the market reaches an equilibrium can tell us something about the *competitiveness within the market*. Are the contracts evenly divided or do some producers clearly have an advantage over other producers in terms of market share.

Finally, the fact that an auction is such a simple and well-defined economic environment, means that it is relatively simple to test what the effects are when certain modifications are made to this market. To this end, this study will investigate what the influence is of the recently implemented demand division between two separate auctions. By comparing the effect of this changed auction design with the former design it may be possible to discover unexpected, additional effects.

4.9 Possible implications of results for the strategic bidding problem

The Equilibria found in the auction game is to some degree quite arbitrary in terms of different information settings (complete information is not realistic) and perfect rationality (e.g. maximize profit or market share). In the academic literature, the study on the strategic bidding problem is therefore mostly focused on the theoretical analysis of market behavior, the macro perspective, but rarely specifically concentrated on optimizing bidding strategies for individual producers, the micro perspective (Gao, et al., 2007).

In contrast to the general usage of game theory within the domain of economic analysis of electricity markets, this study aims to demonstrate that game theory can in fact also be used to inform the bidding strategy of individual producers.

However, this should be done with great care as small errors in data input may already generate large errors which may render the results useless to this end. Therefore, it is necessary to validate the results first before any conclusions should be drawn. If sufficient coherence between the results of the model and the real-life situation is preserved, then this study offers some very interesting insights in terms of the micro perspective of the individual producer as well.

For example, if the cost which TenneT has incurred from procuring reserve capacity in 2015, approximate the points at which the Nash Equilibrium is found in the model experiments it could be tentatively concluded the actual market is in balance. This would mean that it could pay off for producers to develop unit commitment and dispatch models that are able to simulate the opportunity costs of the competition, and to use these forecasted costs as inputs for game theoretic models that will predict the points at which the market will reach an equilibrium. This will allow for the following insights: 1) How much share each producer has*,* 2) What to expect from future rents taken in this market*,* and 3) In what range the bids should be placed (e.g. a producer should not bid far greater than the average total procurement cost if he wants a share). These insights are extremely valuable for producers.

4.10 Summary

This chapter has served to elaborate on the design of this research seeking to answer the question "*How can a game-theoretical approach be translated into practice".* This question is implicitly answered by elaborating on the research steps which have been taken. First the modeling process is explained. Subsequently, the concepts and terminology of game theory are applied to a conceptual game in order to make clear how the chosen methodology is applied in this research. From this understanding the conceptual description and logic of the two types of games is presented and the methodology, data collection process, verification research steps are explained. In the following Chapter the results of this study are presented.

5. Results

5.1 Introduction

The first part of this thesis served to set the context of this research and to demonstrate the knowledge gaps and methodological approach to address the research problem. This chapter constitutes the second part of this thesis and represents the crux of this study in which the results emanating from the model experimentations will be analyzed and implications to the main research question will be drawn by answering the questions: *"How can the results of the approach inform producers in their bidding strategies?"* and, "*What do the results of the approach reveal on the design of the reserve capacity market?"*.

This chapter will commence by presenting the results of the player analysis upon which the results from the model experimentations are set forth. After this, this chapter will proceed by giving a more detailed description of the two different analyzed game types and will subsequently present the results of the model experimentations of these game forms. The chapter closes by summarizing the main conclusions based on the results derived of the model experimentations.

5.2 Players

So as to simulate the auction, the players need to be known. An analysis of the market´s architecture, set forth in Appendix A, implies a market which, over the course of 2015, was dominated by three players; EON, RWE and Vattenfall.

As, early 2015, ENGIE opened a new coal-biomass fired plant with a capacity of 736 MW, this player´s entry in the market may add another player to the tripartite that currently dominates the market. To this background, the following four types of experiments were opted for.

1. 3 player games with EON, RWE and Vattenfall based on:
   1.1. Games with bids based on piece wise sections of cost curve
   1.2. Games with bids based on cost curve
2. 4 player games with EON, RWE, Vattenfall and ENGIE based on:
   2.1. Games with bids based on piece wise sections of cost curve
   2.2. Games with bids based on cost curve

All participants of the auction are referred to as ´players´. Compliant with this auction game´s set up, TenneT, is also referred to as a player, albeit assuming the role of auctioneer rather than a strategically operating player seeking payoff maximization. This results in the following participants and division of roles in the game.

- EON: Rational seller
- RWE: Rational seller
- Vattenfall: Rational seller
- ENGIE: Rational seller
- TenneT: Rational buyer

The objective function of the rational sellers is maximum utility. This means that the Nash Equilibrium is found by going through all responses to a given combination of strategies of the competitors and to look for the best responses to that combination. By comparing all best responses and corresponding strategy combinations the Nash Equilibrium can be located.

The objective function of the rational buyer is also based on maximum utility which, in the buyer´s case, corresponds to minimum procurement costs and the settlement while awarding bids according to the pay-as-bid and set up.

5.3 Strategies activation- and cost curve

Having identified the game´s players, the information at each player´s disposal has to be established, in order to define their payoff functions. The auction is based on a pay as bid settlement scheme, meaning that players´ information is limited to their own *strategy set*, *activation*- and *cost curve*. The *strategy set* contains a range of *bids* so that in the auction games the payoff for each increment of awarded contract volume is defined as the aggregate of the *awarded bid*, *activation curve* and the *opportunity cost curve* (see Eq. 5).

In games 1.1 and 2.1 bids are generated by utilizing the same logic; the strategy sets are composed of 27 strategies and three margins are taken in consideration by each producer. As these three margins can differ between three different sections of the bid slope, this adds up to 27 strategies per producer (see also Eq.6). In Table 17 in Appendix C, an heuristic overview can be found in which each strategy for this game type is clarified.

The sets of strategies in games 1.2 and 2.2 are generated by a different logic. In this game the strategy sets also contain 27 strategies, yet this time this set is generated based on the negative of the cost curve plus a twenty-seven-fold linear series between a minimum and maximum margin (see Eq.7). The eventual bids then equals the adopted strategy (margin) + the negative of the cost curve.

Considering the technical characteristics of the participating producers portfolios, this study holds the assumption that the earnings from activations curve of each producer should have a similar size and position. The reason for this is that all participating producers provide reserve power with similar gas and coal fired power plants. As a result, the cost for providing this service should be comparable between the producers. Differences in this curve can however definitely arise if a producer chooses to adopt a different bidding strategy in this market, see section 2.4 in Chapter 2 for a more thorough discussion on this. Adopting this assumption allows for a generalization of the activation earnings over each producer. In Figure 14 an approximation of the activation curve is presented as averaged in [EUR/kW].

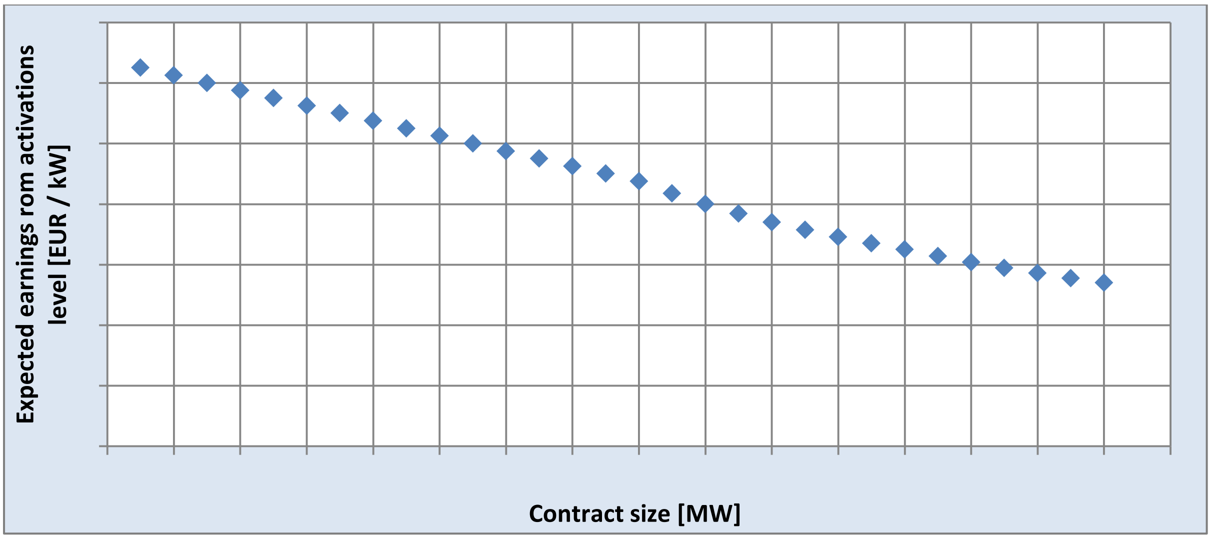

Figure 14 Estimation of expected earnings from activations based on an historical analysis. Total expected earnings from activations are found by multiplying the contract size with expected earnings from activations level.

An important characteristic of the expected earnings by activations curve is that the **marginal profit decreases incrementally as the contract becomes larger**. This means that in smaller contracts this source of revenue contributes more to the total profit than in larger contracts. It can furthermore be inferred that this source of revenue accounts for a **considerable source of revenue for producers** when compared to the opportunity cost curves displayed in Figure 15.

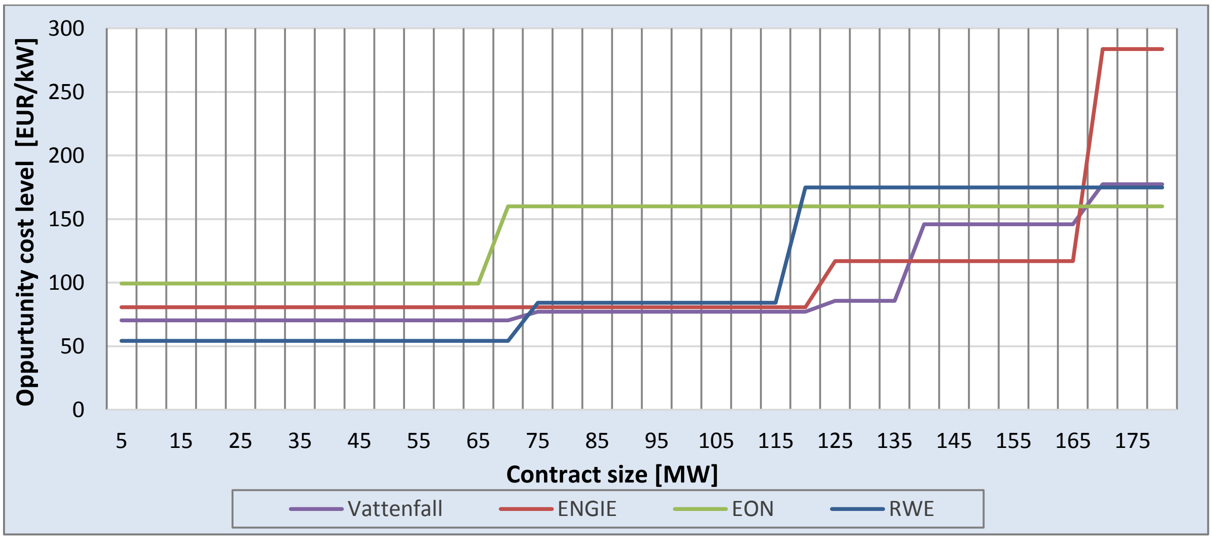

Figure 15 Opportunity cost levels for different sized contracts. Total opportunity costs are calculated by multiplying the contract size with the opportunity cost level.

In order to clearly visualize the cost differences amongst producers, the results of the opportunity cost calculation were presented in terms of relative cost-levels instead of total opportunity costs. By multiplying the contract size with the opportunity cost level, the piece wise linear character of the opportunity cost curve can be deduced.

The results of the opportunity cost calculation, underpinning the analysis as depicted in Figure 15, confirm the assumption of piece wise linear cost curves raised in Chapter 2. From this figure, it can furthermore be seen that there is a **clear difference between players in terms of their cost-competitiveness**. Notably, some producers are more competitive for small contracts (e.g. Vattenfall and RWE; <70 MW), whereas other producers are more competitive for larger contracts (e.g. EON; >165). This implies that **it can pay off for producers to adopt different strategies for different sections of the bid slope**. This can considerably impact how contracts are divided.

Having defined the strategies and the activation- and opportunity- cost curves, the payoff and bids can be calculated. However, the way in which the payoffs and bids are defined, differ between the two game forms. This will be explained in the next two sections.

5.4 Games with bids based on piece wise sections of cost curve

In this section an explanation will be given with respect to the way in which players generate their bids by adding a margin on top of the cost curve in which a distinction is made between piece wise sections of their individual cost curve. This representation of the auction would be accurate provided that producers are *not indifferent with respect to the risks (and benefits) involved in having a small contract as compared to a larger contract*.

Differentiating between sections on the bid curve allows *producers to fully seize the opportunity to adjust their margins in line with their relative cost competitiveness for various contract sizes*. Such differentiation is reflected in Table 7, which demonstrates how the total bid ladder is split amongst players in terms of margin selection. In other words the table delineates the intervals, with respect to contract sizes, where producers can differentiate in margin selection.

Table 7 Intervals for margin selection

Player	First section	Second section	Third section
EON	5-65 MW	70-125 MW	130-180 MW
RWE	5-70 MW	75-115 MW	120-180 MW
Vattenfall	5-70 MW	75-135 MW	140-180 MW
ENGIE	5-120 MW	125-165 MW	170-180 MW

In Table 17 of Appendix C, an heuristic table can be found reflecting the margin level corresponding to each strategy. A representation of the bids and payoff function of this game form can be found in Figure 16.

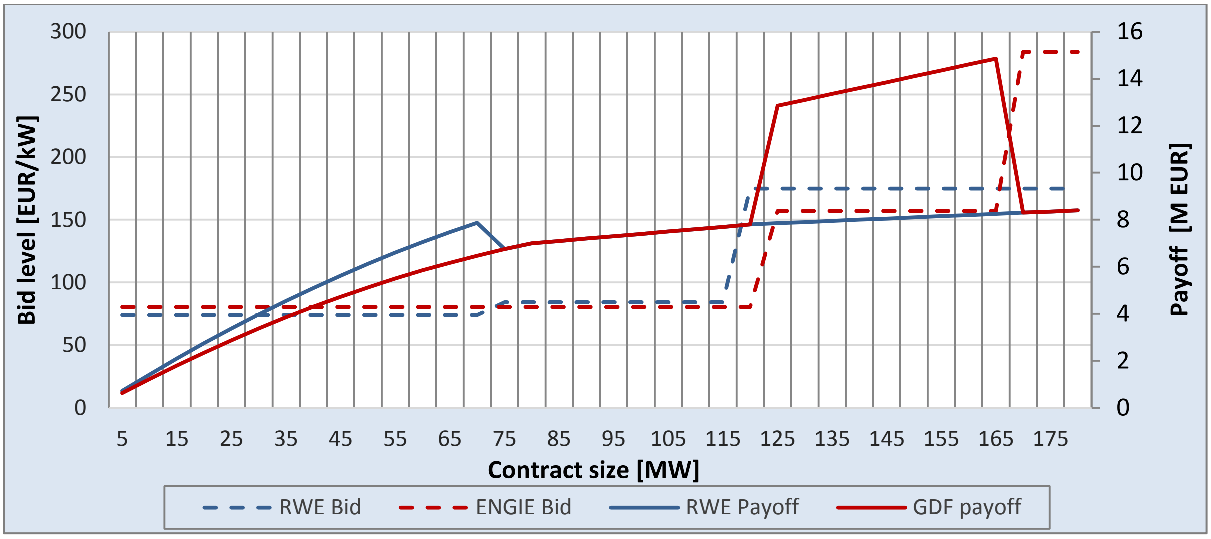

Figure 16 Payoff- and bid level in games with bids based on piece wise distinction of cost curve. Bid-levels (left) and payoff (right) are depicted in relation to different contract sizes. RWE adopts strategy 10 and ENGIE strategy 7.

Figure 16 compares the division of the bid ladder for ENGIE and RWE, respectively, with the way their bids are supplied and utility functions are defined. The figure shows that, in this example, RWE has adopted a strategy in which it increases the bid in the first section (as seen from the higher payoff function between 0-65MW), while ENGIE has chosen a strategy in which the margin is increased in the second section of the bid ladder (as seen from the higher payoff function between 125-165MW). The missing blue section of the payoff curve (between 75- 120 MW) is situated at the bid interval where both players have selected the same margin and therefore overlap.

The strategies in the example of Figure 16 were not randomly selected but were chosen to show how this game design **allows for players to benefit from the differences in cost competitiveness across different sections of the bid slope**. For example, ENGIE can choose a higher margin in the first section yet still underbids RWE in this segment of the bid curve. This, however, is not possible in the second section in which RWE can opt to increase its bid while still being less expensive than ENGIE. This discretionary power therefore allows players for more flexibility and is therefore interesting to analyze.

5.5 Games with bids based on cost curve

In this section, an explanation will be given with respect to the way bids are generated from margins with respect to the cost curve. These bids take an entirely different form as compared to the previously described bid curves.

This representation of the auction, therefore applies when *players refrain from differentiating between the size of contracts in their strategic decision making*. This applies if producers are *indifferent with respect to the risks involved having a small contract as supposed to a large contract*. In Figure 17 a representation of the bids and payoff function can be seen.

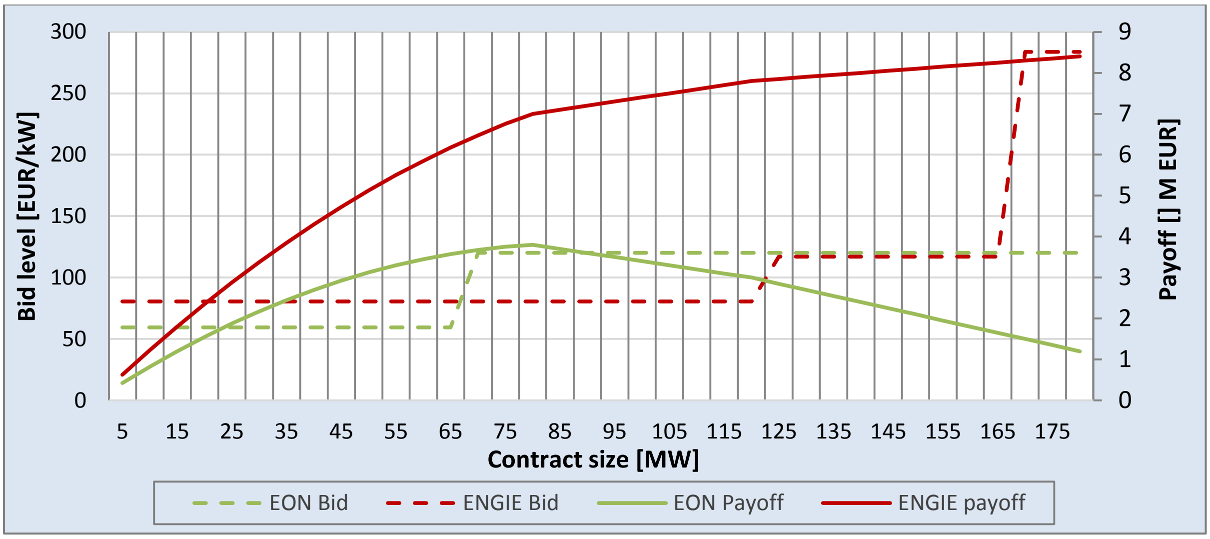

Figure 17 Payoff- and bid level curve in games with bids without piece wise distinction on cost curve. Bid-levels (left) and payoff (right) are depicted in relation to different contract sizes. EON adopts the strategy of a negative margin of 40 EUR/kW, while ENGIE selects the strategy of zero margin. With these strategies the optimal contract for EON is 80 MW, while there is no optimal contract size for ENGIE as the payoff function does not approach a maximum.

The example of a payoff- and bid level curve, as presented in Figure 17, shows that the shape of the payoff curve remains constant while the position of the slope varies between the two different adopted strategies. The is due to the fact that in this representation of the auction game the payoff curve is determined by the activation curve plus *and* minus (at negative margins) the margin which is taken (as can be deduced from Eq.7 in the previous chapter).

In this game form, players can choose to lower their bids below their opportunity costs in an attempt to underbid their competitors. Although this lowers the payoff function for that particular player, it increases the chances for that player to be awarded a larger share of the total volume. In the example of Figure 17, EON adopts a negative margin of 40 EUR/kW with respect to his opportunity costs, and is therefore underbidding ENGIE for the first 65 MW. This may be beneficial as the payoff curve is still positive for each level of contract size and it increases the chance for EON to be awarded a contract that is ultimately profitable.

5.6 Real life auction results

When analyzing the results, it is important to establish what to look for. In the sections 4.9 and 4.10 in the previous chapter a number of possible implications of the results generated by the model experimentations were discussed. In these sections it was argued that most of these *implications only hold any real world applicability, if coherence between the results of the model and the real-life situation is preserved*. For this purpose, the results of the model experimentations are validated with the total actual annual procurement costs of TenneT depicted in Figure 18, as this enables a comparison between the model results and the real life auction results.

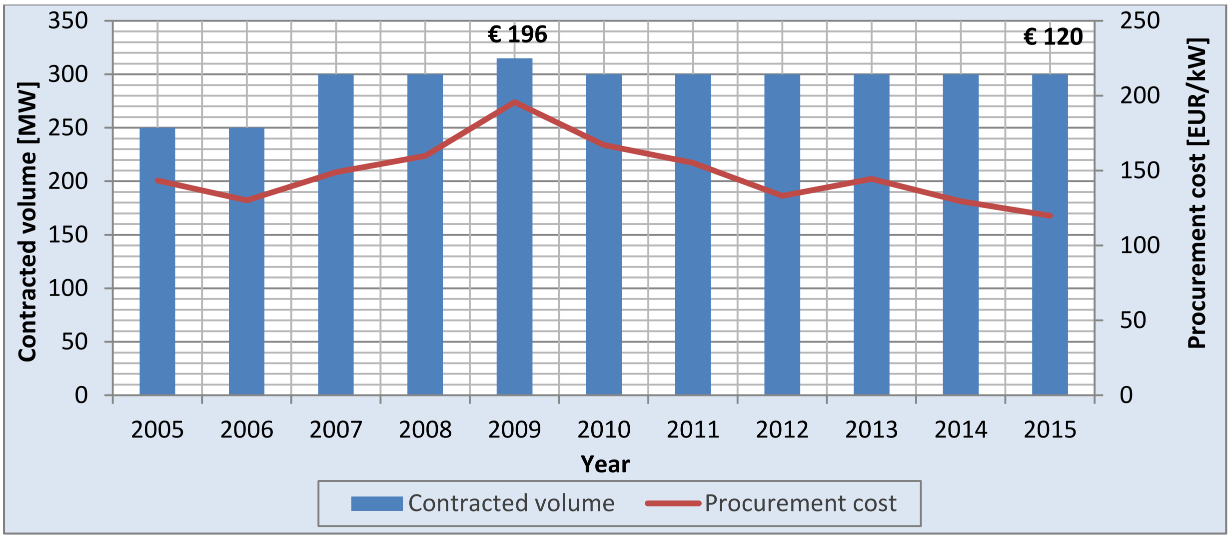

Figure 18 Average annual procurement cost and contracted volume. The contracted volume (left) is compared to the procurement cost (right).

This information enables a comparison between the model results and the real life auction results. From Figure 18 it can be observed that the total procurement costs over the last ten years has steadily decreased from 196 €/kW in 2009 down to 120 €/kW per kW in 2015. It therefore seems that the procurement costs is showing a declining trend. To be precisely, in 2015 the procurement costs were 119.79 (reference to validate results from model experimentations). When comparing these results with the analysis of Figure 19, it can furthermore be observed that the *years in which the contracted volume had increased compared to the previous year, often coincided with a large increase in procurement costs, while no correlation is found between the development of natural gas or coal prices in the same period*. It therefore seems that the procurement cost is more affected by the demand as compared to the effects of fuel prices.

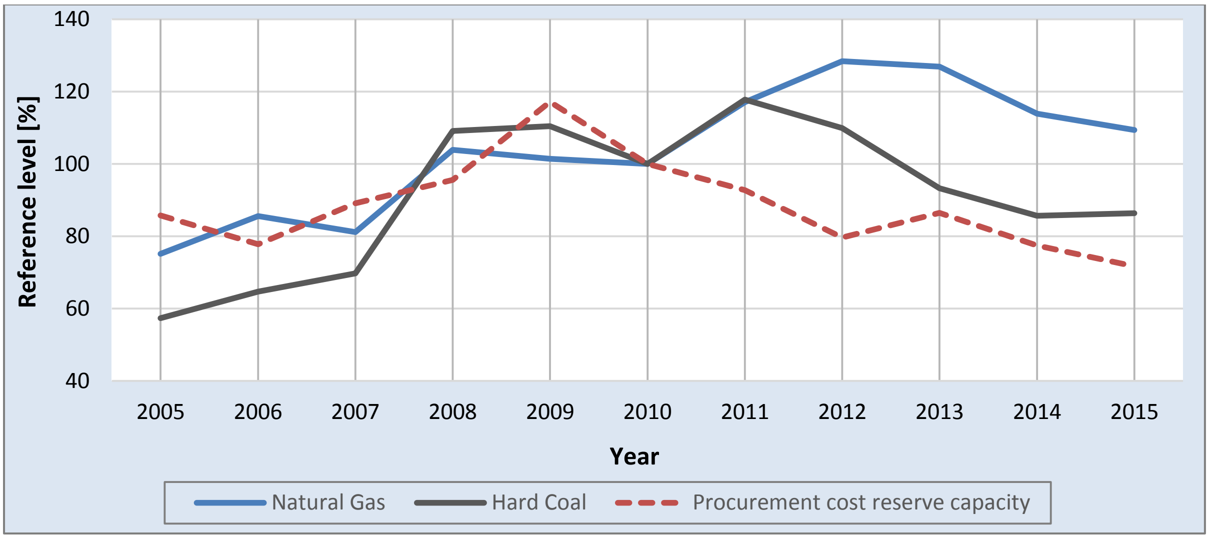

Figure 19 Development of Natural Gas and Hard Coal prices in comparison to the development of the average annual procurement cost of reserve capacity. Observe that no correlation can be seen between the development of fuel- and procurement cost in the last decade (reference level 2010 = 100%).

5.7 Model experiments

This section showcases the results of the model experimentation, separately for each of the two types of games. Due to very large number of possible strategy combinations (19683 in three player games; 531441 combinations in 4 player games) this study analyzes the model´s results mainly from a macro perspective on the market.

Processing a model of a 3-player game takes approximately fifteen minutes, whilst processing a 4-player game amounts up to over 20 hours of computational time. Therefore, a choice was made to conduct a limited number of experiments with carefully selected model parameters.

Three player games with bids based on piece wise sections of cost curve

In this section the main outcomes of the analyses from the model experimentations of the three player games with bids based on piece wise sections if the cost curve are presented. For a more extensive overview of the results of this game´s variant and specific model input parameters this study refers to tables 18 through 23 in Appendix D.

Given that this study´s purpose is to examine the reserve capacity auction by finding coherence between the actual market outcome and the output of the model, a number of preliminary experiments were first run to validate the output of the model. These experiments established at which parameters (i.e. the selection of margins for each producer) the procurement costs found at the Nash Equilibrium approached the actual market outcome of 2015. The results of these experiments can be seen in Figure 20.

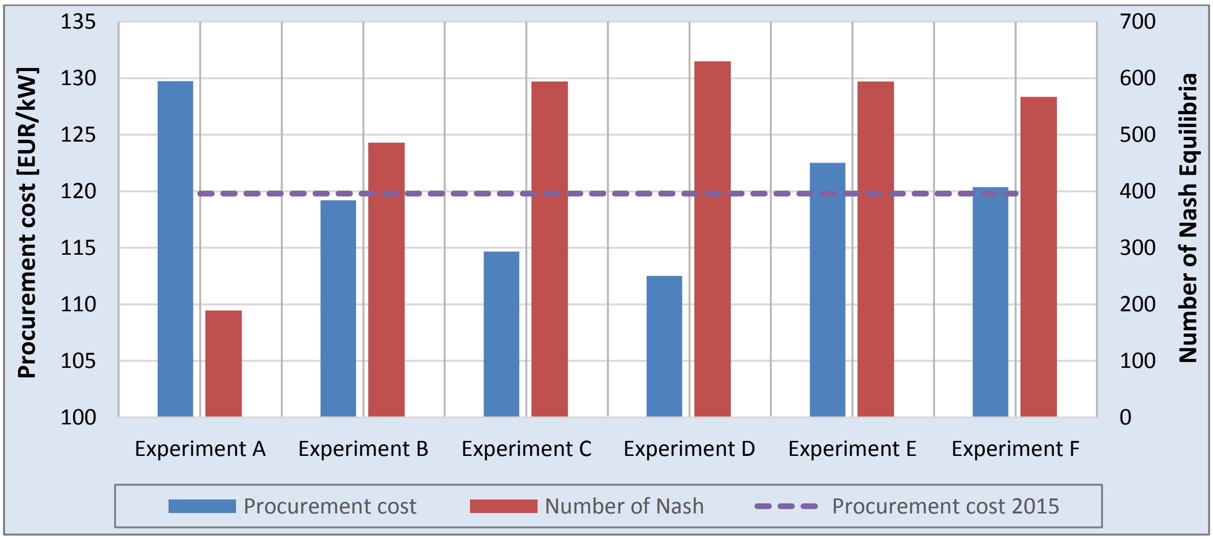

Figure 20 Validating the results of model experimentations. Indicated by the purple dotted line are the actual procurement cost of 2015 (left) which is compared to the number of Nash Equilibria found in these experiments (right).

Figure 20 shows that the Nash Equilibrium closely approached the actual procurement costs of 2015 throughout all experiments. Even in Experiment A, whose outcome most strongly deviates, is still located within reasonable limits of the 2015 procurement costs. If an actual market equilibrium were to exist and the models underlying assumptions are correctly estimated, this result implies that the input data for the model was chosen correctly. As the model is capable in gauging the actual procurements costs, this therefore implicates a **proof of concept of the game theoretic computational auction model** that confirms the feasibility of the proposed research method**.**

A second conclusion that can be drawn from these results is that the outcome of this game is *unlikely to result in finding merely one Nash Equilibrium*. A more plausible outcome is the finding of multiple ´Nash Equilibria´, at least three in most scenarios. This result can be traced back to the logic in which bids are supplied to the auction simulator. As each player has the option to set the margin of their bid separately for each section of their bid ladder while the awarded contract will always be in *one* of these sections, the outcome of the auction is often indifferent to the choice of margins for the other sections (e.g. in Appendix C compare strategies 4-6, 13-15, 22-24 for a contract that is located in the 2nd section of the bid curve). This does not imply that the outcome is always indifferent as else there would be at least 729 Nash Equilibria (9x9x9), which is not observed.

However, by carefully comparing the individual strategies of which the Nash Equilibria is composed, it was found that, in some experiments, producers in fact do enjoy only *limited discretion in choosing the margins for each individual section*, as changing the margin of one section completely changes the outcome of the auction. As the number of Nash Equilibria is limited by the number of possible best responses of each producer, this could indicate that *fewer Nash Equilibria are found when analyzing markets where the level of competition is higher.*

Considering the simulated procurement costs along with the Nash Equilibria of each experiment, the parameters for the strategy selection of Experiment A and B were used for further analysis of this game with varying the demand for reserve capacity.

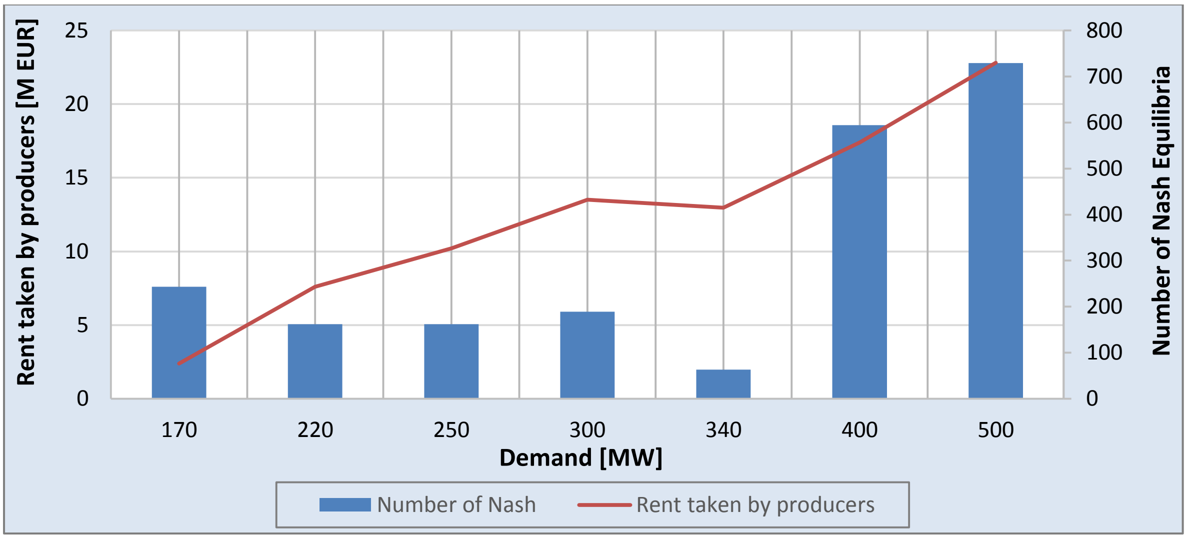

Figure 21 Results of experiments A. Rent taken by producers (left) and number of Nash Equilibria (right) found in these experiments in relation to different levels of demand for reserve capacity.

The results in Figure 21 pertain to the experiments A. In this graph, the rent taken by producers (i.e. their profit) is compared with the number of Nash Equilibria that are found in each of the experiments (i.e. with the same parameters for margins as chosen in Experiment A but with varying demand). The graph suggest a connection between the increase in rent and the number of Nash Equilibria. With the exception of the slope of the rent curve found on 170 MW, all other experiments seem to indicate that the lower the number of Nash Equilibria, the smaller the increase in rent for producers and vice versa. The same results were found in an identical analysis of the results of experiments B as presented in Figure 22.

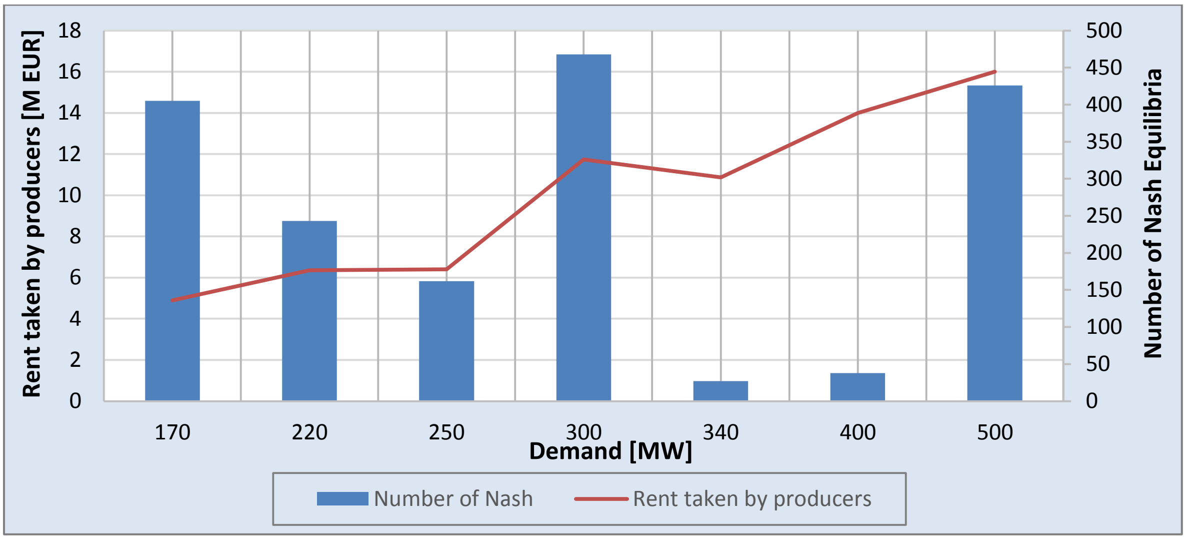

Figure 22 Results of experiments B. Rent taken by producers (left) and number of Nash Equilibria (right) found in these experiments in relation to different levels of demand for reserve capacity.

Although sparse number of experiments prevents making any firm conclusions, the results correspond to the notion that **fewer Nash Equilibria indicate a higher level of competition**.

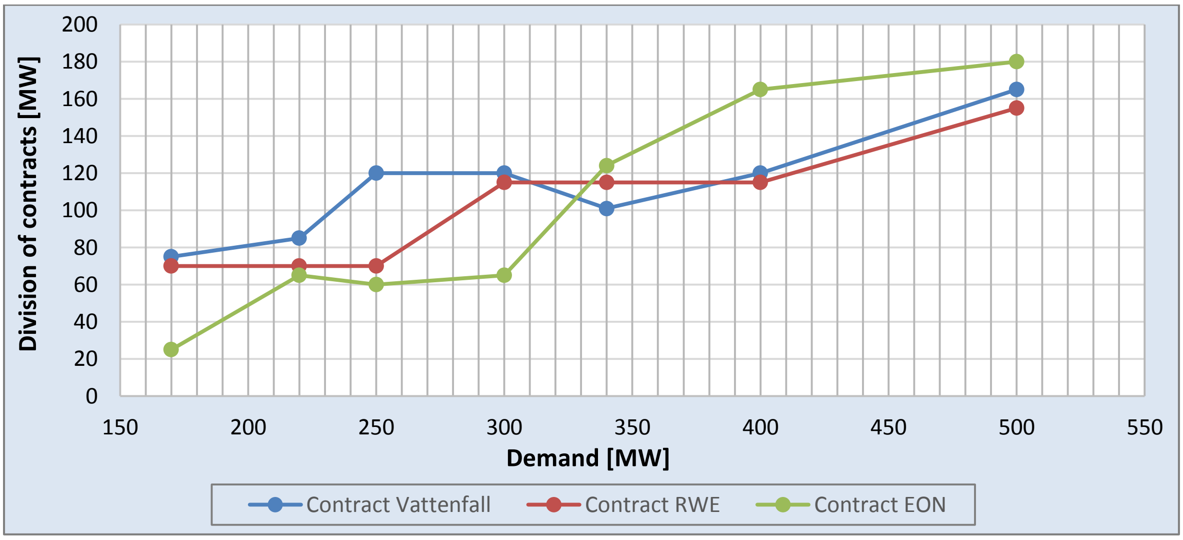

Figure 23 Results of experiment A. Division of contracts in relation to different levels of demand of reserve capacity.

Further indications in support of this statement can be found in Figure 23. In this figure the results of awarded contracts are compared with the aggregate demand within the auction simulation. The figure shows that a demand of 340 MW, is the point where the difference in market shares between the producers differ most profoundly. Comparing the awarded contracts with the cost function for each player (as can be seen in Figure 15), it can be seen that at a demand of 340 MW, EON suddenly becomes more competitive in terms of its costs, thus acquiring a larger market share.

Increasing the demand can also negatively impact the competitiveness of an individual producer. This can be seen by comparing the contract of Vattenfall at a demand of 300 MW and at a demand of 340 MW. Interestingly enough not only the relative market share of Vattenfall decreases between these demands but the absolute contract volume decreases as well. The reason for this is that at 350 MW, the aggregate of costs for Vattenfall overtook the aggregate of costs for EON and at this point EON starts to become more cost competitive than Vattenfall.

As of 2016, the demand for reserve capacity (340MW) is procured in separate batches, in two auctions, each handling the procurement of half of the required volume. The underlying reason for this decision is to increase competition by reducing the barriers to entry in this market (see section 2.3 in Chapter 2 for a discussion on the policy considerations supporting this decision).

Aside from the removal of barriers to entry, the splitting of the procurement may also have additional effects. To test if such additional effects can be demonstrated, the experiment to auction 340 MW was repeated and separated in two separate tenders. The outcome of these experiments were subsequently compared to the regular auction in which the total amount is procured in one tender. The results of these experiments are illustrated in Figure 24.

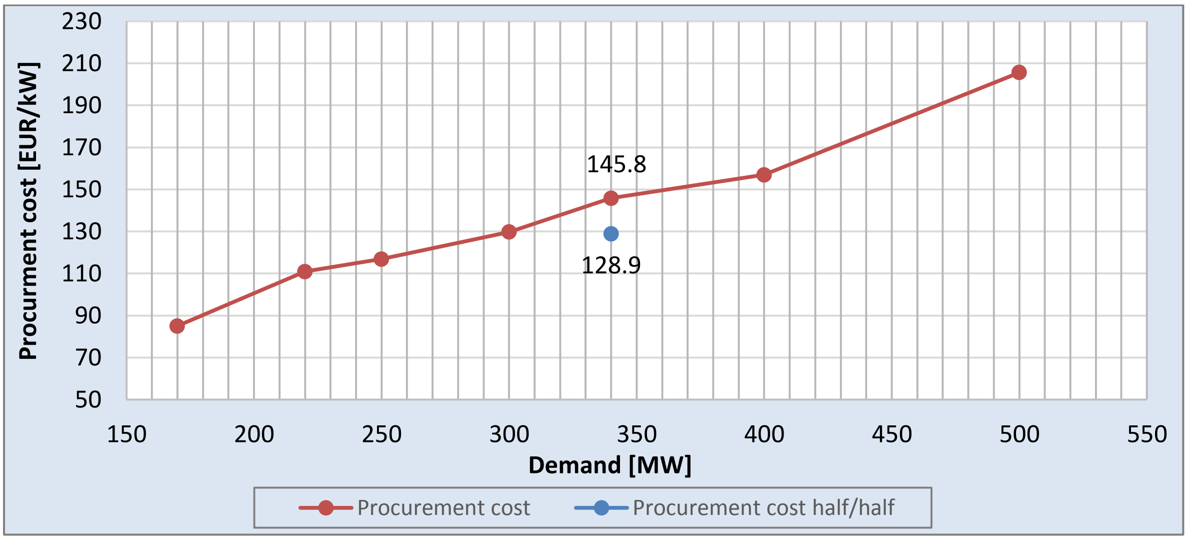

Figure 24 Results of experiment A: Procurement cost with respect of different levels of demand of reserve capacity. Indicated by the blue dot is the result which is found when the total volume of 340 MW is divided over two auctions.

In Figure 24 it can be seen that the **split auction experiment has resulted in a market equilibrium with lower procurement costs as compared to the single auction experiment**. As the division of contracts are the same in the outcome of both experiments, this means that the payoff function of each producer has not changed with respect to the earnings from activations- and opportunity costs. As a result, **in the double auction experiment an equilibrium is established with lower rents for**

producers as compared to the single auction experiment. The same evidence is found in an identical analysis of experiments B, see Figure 25.

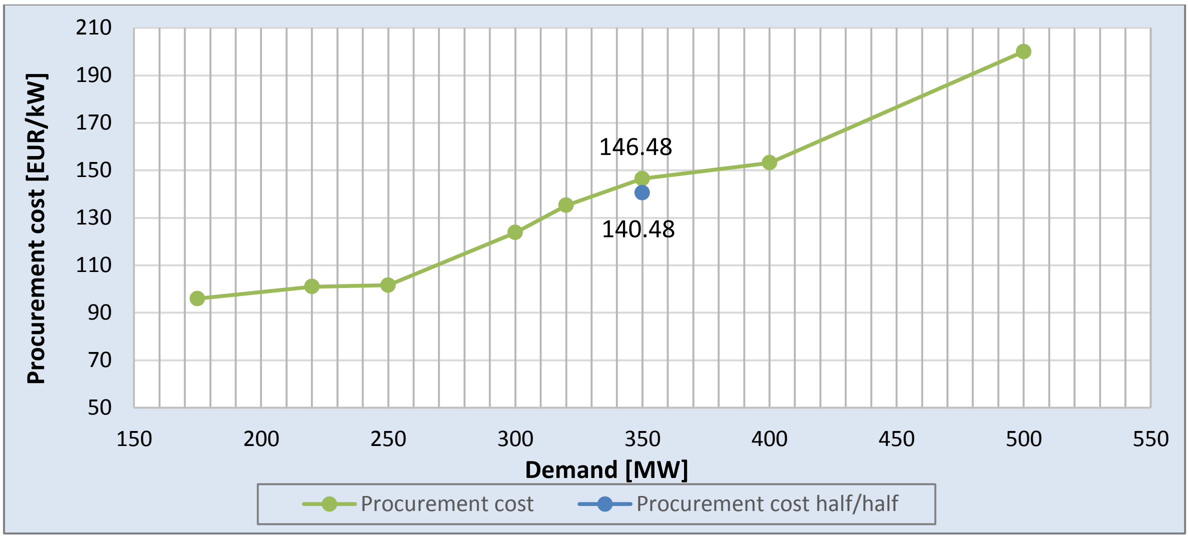

Figure 25 Results of experiment B: Procurement cost with respect to the demand for reserve capacity. Indicated by the blue dot is the result which is found when the total volume of 350 MW is divided over two auctions.

The change in auction design from single to sequential auctions has thereby not been offset by the change in behavior of the producers as was expected (i.e. the effect of reduced available capacity in second auction is offset by the decrease in demand). In the literature this effect is called the ***declining price anomaly***. Several attempts to resolve this abnormality have been made, each with its own explanations and underlying assumption with regard to the real world phenomenon (e.g. McAfee & Vincent (1993), postulate that this effect stems from risk aversion of the producers, Jeitschko (1999) claims that this phenomenon is caused by uncertain supply and demand in succeeding auctions, while Black & de Meza (1992) argue that the price anomaly is non-existent).

However, none of the explanations given in these studies seem applicable to justify the effect as found in the previously discussed experiments and all concern markets with widely differing characteristics and assumptions with regard to the behavior of the participants. This study therefore proposes a different explanation for obtaining this result.

Given this study´s context and the models underlying assumptions, this study proposes that this outcome points to the *limited rationale of the producers***.** It could be tentatively concluded that the reason why the market is cleared at a lower price in two separate auctions is that in a sequential auction, producers optimize their strategy, for each auction, based on a smaller volume without considering the value of the future auctions. This presumed cause will **allow producers to submit more competitive bids in two sequential auctions as compared to a single auction**.

This line of thought can be extended to the limited rationale in which the producers´ decision makers that submit bids and decide on their intricacies currently address this bidding problem.

When producers initiate in the auction while being fully aware of the current value of the auction, and those of future auctions, you would expect to see no difference in auction results between the two experiments. However, in the auction game it is assumed that producers do not have *information* on the financial opportunities of future auctions. As a result, the players of this game cannot value both auctions simultaneously. Furthermore, in the auction game the value of each bid is determined by the bid itself, as well as on the monotonically decreasing marginal earnings from activations. Consequently, producers will **bid more aggressively in the aggregate of two auctions**, as in separate auctions the demand is more scarce and the share of expected earnings from activations therefore relatively higher.

Highly volatile fuel and electricity prices makes it problematic for producers to consider future auctions in their strategy. This study therefore proposes that this assumption correctly describes the manner in which each producer currently addresses the bidding problem of this auction. This means that the results of these experiments can be extended to the real life behavior of producers (i.e. producer's value each auction independently). This implies that, aside from seeking to increase the competition within this market by making the product more flexible (thus removing barriers to entry), this new policy may have the **additional benefit for TenneT of decreasing procurement costs**, caused by the previously described delimitation of the bidding problem for producers.

With respect to the bidding strategy from an individual producer's perspective, this also means that it can be very valuable to estimate the opportunity cost of the competition and to approximate the previously division of contracts of the previous auction. This information can then be used to optimize the bids by using market equilibrium models. This could diminish the cost reduction, described earlier, which is indicative of the value of such models for producers.

Having now established some aspects about the apparent functioning of the model and resulting implications for the actual market, it is also interesting *to investigate to what extent the model may be used for forecasting purposes in relation to the expected increase of reserve capacity.*

The take up of renewable energy sources (RES) in the Netherlands, has so far been suboptimal as compared with neighboring countries. However, due to an attractive renewable energy investment climate, RES are steadily assuming a greater share within the mix for electricity production in the Netherlands and the Dutch now belong amongst the top ranked in the category for annual RES investments per capita (REN21, 2015).

The importance of a well-functioning electricity market is evident, as argued in the introduction of this thesis. Policies, seeking to further this aim, sometimes result in undesired and unpredictable outcomes. The pursuit of a more renewable electricity system entails an increased requirement for power flow adjustments, which are expected to grow in size and in frequency, and therewith the necessity to correct for imbalances by instruments such as reserve capacity.

Based on the linear trend found in the results of the experiments, a price forecast is made for various demand levels in order to simulate the societal cost of increasing the share of RES in relation to the procurement of reserve capacity. The results of this analysis is presented in Figure 26.

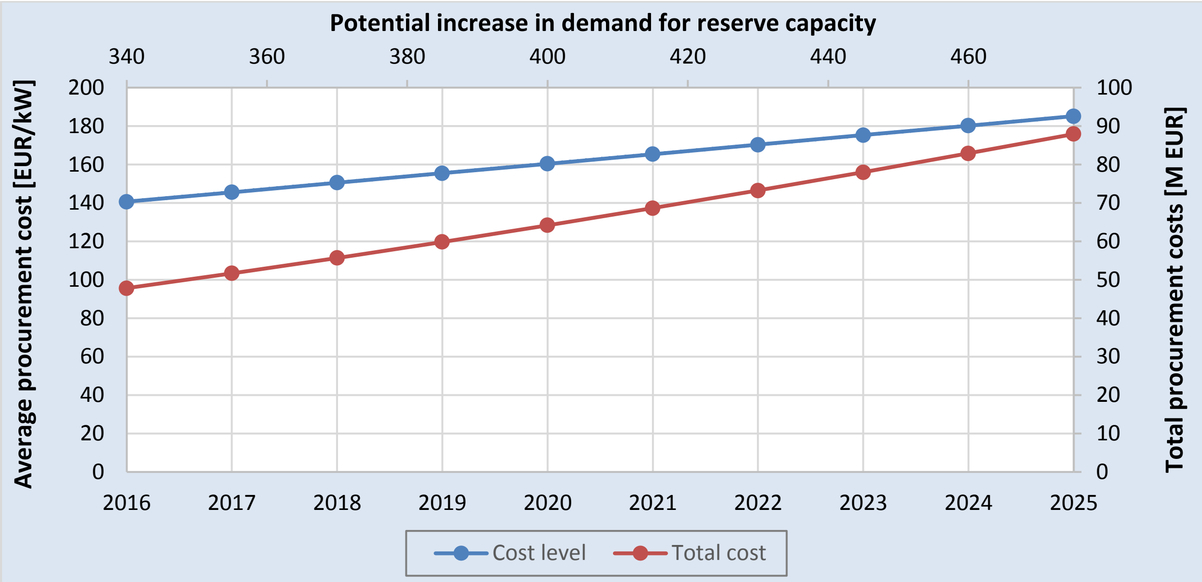

Figure 26 Forecasted price increase for the procurement of reserve capacity. The average annual procurement costs (left) and total procurement costs (right) are depicted in relation to a yearly (below) potential increase in demand for reserve capacity (above). In this scenario the demand for reserve capacity increases with 15 MW per year.

Supposedly this increase in RES will force TenneT to increase their demand for reserve capacity of 15 MW per year, while it can be assumed that the market is currently in equilibrium (with the model correctly in forecasting the movement of this equilibrium). The model then predicts that the **increase in the demand for reserve capacity results in a growth of 40 Million EURO annual procurement costs, with an aggregate of nearly 200 Million in less than 10 years**.

In the previously discussed game, the assumption was held that: "*Producers seize the opportunity to adjust their margins in line with their relative cost competitiveness for various contract sizes*". However, this representation of the auction might be inaccurate. Therefore, in the next section, the model experimentation results of a different type of game will be discussed, which contains the opposite assumption: "*Producers refrain from adjusting their margins for different sized contracts*". This will allow this study to examine whether different results are obtained when a different strategy protocol is tested.

Three player games with bids based on cost curve

The results of model experimentation of this section regard the games in which players choose their bids without making a distinction between different sections of the bid slope in setting the margin.

The results of these experiments and the related model parameters can be found in tables 24 until 31 in Appendix E.

The outcome of these experiments were entirely different from the results of the previous game and in this game form *the most interesting finding actually came by not obtaining any result*.

Quite a number of these experiments resulted in finding not even a single Nash Equilibrium. Not in any of the 19683 strategy coordinates. Whilst in the other experiments - and without exception - only a single Nash Equilibrium was found and located at the strategy coordinate where each player chooses their highest margin (i.e. bid its highest bid).

Not finding a Nash Equilibrium indicates that for that given set of model parameters there exist no point where any of the players have an incentive to choose a different strategy from his pure set of strategies after considering all the opponent's strategy selections.

Fortunately this does not disprove Nash's theorem, as Nash himself had demonstrated that only if we allow mixed strategies, then every game with a finite number of players with a finitely many pure strategies should at least have one Nash Equilibrium. *This result therefore merely shows that the Nash Equilibrium in these experiments are not located in pure strategy coordinates but are found in mixed strategies* (see section 3.5 for an discussion on these types of Equilibria).

Considering that locating the Nash Equilibrium in mixed strategies is not part of the intended scope of the research this is not further investigated. A suggestion for future research is to search for mixed strategy Equilibria by altering the algorithm (e.g. by including the COMPASS model). [25]

Experiments which did result in locating the Nash Equilibrium, all had in common that the Nash Equilibrium was situated at the strategy coordinate where all players selected the strategy which corresponds to bidding their possible highest bid (see Appendix G for a representation of this coordinate). This could imply that the design of the market does not promote efficiency as the expected market outcome is situated at a point which is very costly from the TenneT's perspective.

However, taking a closer look at these results a different conclusion may also be drawn. The fact that in some experiments, with a certain set of parameters, no Nash were found whilst in others the most inefficient Nash Equilibrium was found, indicate a different possible type of market failure**.**

In the experiments where no Nash were found it is apparently always possible for players to benefit (i.e. increasing their profit) by unilaterally changing his strategy. The actual Nash Equilibrium in these experiments would then be found by taking the probabilities of choosing a particular strategy for each player into account. Not finding any Nash, in this game designed for locating pure

[25] The compass model is an implementation of a linear complementary program and is be able to find Nash Equilibrium in games with continuous strategies and should therefore also be able to find the Nash equilibrium in mixed strategies.

strategies, therefore indicate that the Nash Equilibrium resides somewhere in between – but not exactly on- the least- and most efficient outcome from a public welfare perspective.

The experiments where the Nash Equilibrium was found exactly on the least efficient outcome (i.e. where all players bid their highest bid), from the perspective of TenneT, points to a severe **weakness in the current design of the market**. It was found that finding the Nash in these experiments had to do with the fact that in some circumstances *producers can benefit very profitable from the single buyer position with predetermined demand of TenneT, whilst each producer only has a limited available capacity to offer.*

In the event that no single player has sufficient capacity to offer to fulfill demand completely while at the same time the difference in the cost for providing reserve capacity is large enough between the producers so that there is no possibility to underbid each other in order to obtain a greater contract and still obtain a higher profit, then it is in the best interest of each player to bid its maximum bid. These results therefore clearly indicate the **fragile position of TenneT as a monopsonist in an oligopolistic market structure.**

Obtaining this outcome means that the results from the experiments cannot be analyzed in the same manner as in the previously discussed game, as the market clearing results by themselves (i.e. without Nash Equilibria) reveal nothing about the market and effectiveness of a given strategy.

However, considering each players profit function, the results from these experiments can be used to investigate the amount of rent which each producer currently takes from this market.

So, as with the previously described game, this study again sought out to find a coherence between the model output and the actual market outcome of 2015. As a result, number of preliminary experiments have been carried out with different parameters for margins while keeping the demand fixed at 300 MW. In Figure 27 the results from these experiments can be found.

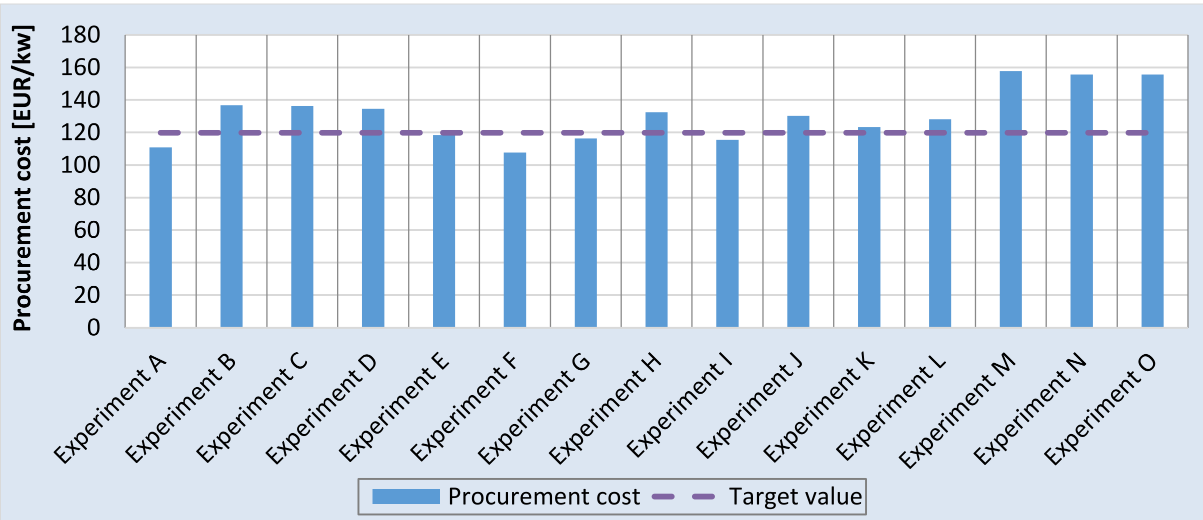

Figure 27 Validating the results of model experimentations. Indicated by the purple dotted line are the actual procurement cost of 2015.

By comparing the total actual procurement cost in 2015 with the results from these experimentations, it can be seen that with the model parameters as used in Experiment E (i.e. selection of margins for the producers), the result for total procurement cost approaches the actual procurement costs found in 2015 most accurately. By combining the results of this experiment, with the activation- and opportunity cost functions of each producer, *it is possible to establish the total amount of rent taken in this market and compare these figures to the total costs of the producers and TenneT*. The outcome of this analysis is presented in Figure 28.

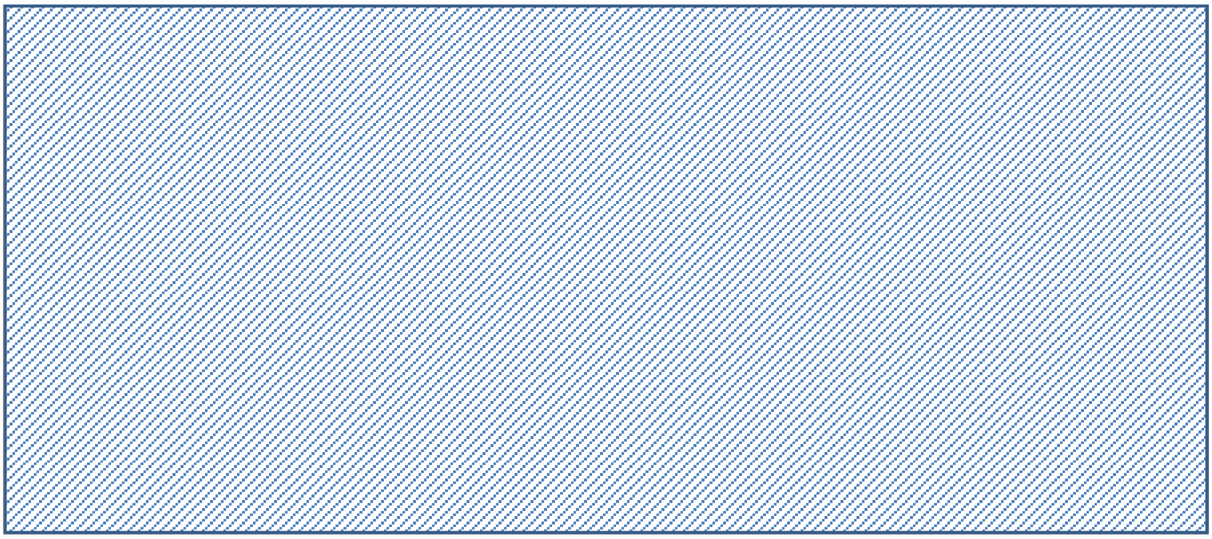

Figure 28 Results of Experiment E. Comparison of the total procurement cost of TenneT and total rent taken by producers. The procurement cost of TenneT is composed of the aggregate of the opportunity costs and margins on the accepted bids from producers. The rent taken by producers is composed of the margins on the accepted bids and earnings from activations.

Obviously, the total cost of procurement should equal the accumulation of the opportunity costs plus the added rent, or margin, of the producers. The total amount of rent taken by producers is composed of the margin taken on the accepted bids and the additional rent acquired from the activation earnings in the balancing energy market. [redacted]

In a liberalized electricity market, the cost of providing this service should in theory be compared to the *consumer's willingness to pay* for having a certain degree of reliability. However, the pricing of this service is very difficult as it involves placing a value on the reliability of the grid while consumers do not readily reveal this value and may also individually place different values on grid reliability. Through network tariffs, the provision of reserve capacity is therefore treated as a public good by TenneT**.** Consequently, it is not possible to make firm statements on whether the incurred costs and rents taken within this market are currently too high**.**

As was stated in the beginning of this chapter, it is believed that an additional producer may enter the market as of the beginning of this year. It is therefore interesting to test how the results would change in this new market structure. The results of these experiments are given in the next sections.

Four player games with bids based on piece wise sections of cost curve

The results of the model experimentations in this section consider 4 player games in which players can choose their strategy (i.e. set their margin) by differing between different sections of the bid. The crude data of these experiments and related model parameters are found in tables 32 and 33 of Appendix F.

A very limited selection of experiments of this game form is executed as conducting one experiment amounts up to 24 hours of processing time. This selection is based on the 2016 demand for reserve capacity (340 MW) and the suspicion on the participation of the previously discussed players: *EON, RWE, Vattenfall and ENGIE*. The selection of model parameters (i.e. selection of margins) has been in accordance with the previously calibrated experiment B of the three player games with bids based on piece wise section of cost curve. The results of this experiments are presented in Figure 29.

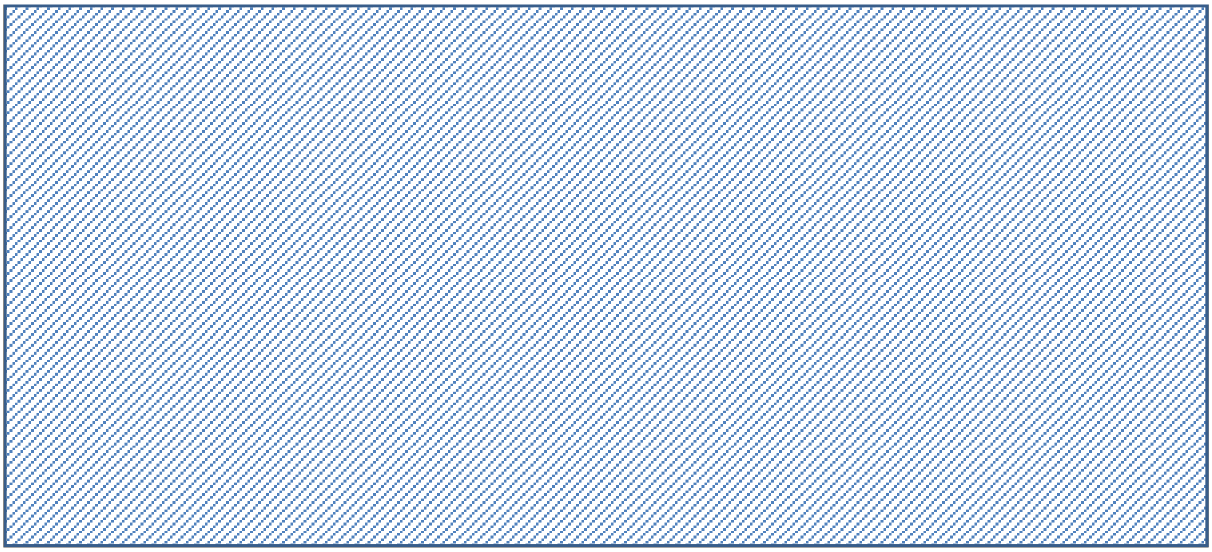

Figure 29 Results of Experiments A1, A2 and A0a. Procurement cost of TenneT and rent taken by producers as compared between the a single auction- and split auction market design. A clear difference in procurement cost and total rent can be noted between the two market designs. Aside from the decrease of the margin taken by producers in the split auction as compared to single auction, a slight change can also be observed between the total costs of producers (single vs. split). This is due to a different division of contracts found at the Nash Equilibrium of these experiments.

From the figure a number of conclusions can de deduced. Firstly, the entering of an additional producer to the market has a profound effect on the procurement cost for the TenneT. Whereas in experiment B, with three players, the procurement cost for TenneT averaged 146 EUR/kW, the entering of an additional producer lowered the procurement cost to approximately 98 EUR/kW. A decrease of approximately 33 percent, which accumulates to over approximately 16 million euros a year. This thereby clearly shows how much there is to gain (and lose) with respect to the amount of competition in this market.

In relation to the bidding problem from the perspective of an individual producer (micro-perspective), this result also reveals the **great potential value of game theoretic models in oligopolistic markets for individual producers**. Being able to predict at what point (i.e. market clearing price) the market will reach an equilibrium, would allow producers to optimize their bids in accordance with the expected change of the average bids. This therefore increases the chances of optimal bids being accepted and would therefore increase the profits made in this market.

In these experiments the effect of splitting the total volume between two auction is furthermore investigated. The results again clearly demonstrate a similar effect as compared to the three player games, **procurement costs of TenneT and rent taken by producers both decrease in the split auction market design.** The reason for this effect is thought to be exactly the same as for the previously described three player games and can be related to the limited rationale of each producer. By making the problem smaller, producers are more capable of optimizing their bids strategies, thereby making them more competitive and reducing the total amount of rent which is taken and consequential incurred costs for TenneT.

Four player games with bids based on cost curve

The same results were found as compared to the game in this form with three players. The conclusions which were made in the three player games are therefore identical to those made on four player games.

5.8 Conclusion

In sections 4.9 and 4.10, possible implications of the proposed research were discussed. From the analyses of the players, the market and the results from the model experimentations, several conclusions are drawn and multiple insights obtained. From this improved perspective it is now possible establish the ultimate implications that have resulted from the adopted research approach.

The results obtained in this chapter actually entailed several different analyses, therefore the main results are first presented in relation to each individual analysis, whereafter implications of these analyses will be drawn in order to answer this chapter's research questions.

Regarding the results from the player analysis

The analysis of the market´s architecture implied a market which is currently dominated by three or four players; EON, RWE and Vattenfall ENGIE. Regarding their expected earnings it is found that the incremental expected earnings from activations is monotonically decreasing as contracts become larger. It is furthermore concluded that this source of revenue should be comparable for each of the producers. In relation to the producers' opportunity cost curves, a clear difference in cost competitiveness for different sized contracts is seen and it therefore appears that it can pay off for producers to adopt different strategies for different sections of the bid slope.

Regarding the analysis of the real life auction results

A declining trend in the procurement cost for reserve capacity is observed in the last couple of years. However, it seems that this decline has no relation with fuel prices but is more influenced by changes to the demand of reserve capacity.

Regarding general results from the model experimentations

Results of the experiments seem to indicate that the market does not show signals of being affected by severe forms of collusive behavior, as the Nash Equilibria found in all experiments approaches the actual market equilibia. This thereby implicates a proof of concept of the computational game theoretic auction model and confirms the feasibility of the proposed research method of this study.

This study has therefore shown that a similar approach, as taken in this research, may also be valuable for regulatory agencies (e.g. as a method for testing different auction designs, possible forms of collusive behavior or other market failures). The same conclusion may also be drawn with respect to the value this approach may have for producers (e.g. using game theoretic models to optimize bidding strategies by estimating market clearing prices).

Regarding the results obtained in the experiments where producers can differentiate in setting their margins in separate sections of the bid curve

The first insight obtained is that this game type will certainly result in finding multiple Nash Equilibria. By comparing the amount of best responses and taken rent of each player in the different experiments, it was found that, as the number of Nash Equilibria is limited by the number of possible best responses of each producer, there exist fewer Nash Equilibria at demand levels where the competition between the producers is higher. This is attributed to the fact that in experiments with high number of Nash Equilibria, at least one of the players has a large discretion in selecting its best response to the combination of the strategies chosen by the competition. As a result finding a large number of Nash Equilibria therefore indicates a bigger difference with respect to cost-competitiveness as compared to finding a small number of Nash Equilibria.

From the analysis of the results in which the new design of the auction is tested (i.e. demand of reserve capacity divided over sequential auctions), it was found that aside from removing barriers to entry, the separation of the total volume over two auctions may result in an additional cost reducing effect. This experimentation result is ascribed to the bounded rationality of the players as in the auction game these players are not able to consider the value of future auctions. This therefore results in more competitive bids as compared to in a single auction. This study proposes that this result can be extrapolated to the real life behavior of the producers' strategists, as these are also not capable in including both auctions in their value system when submitting bids and therefore also consider each auction independently.

Regarding the results obtained in the experiments where producers cannot differentiate in setting their margins between separate sections of the bid curve

The most interesting finding from these results actually came from not locating a Nash Equilibrium in most experiments. This result showed that in these experiments, the Nash Equilibrium was not situated in pure strategy Equilibria but rather in mixed strategy Equilibria.

In the experiments which did result in finding a Nash Equilibrium, the equilibrium resided at the strategy coordinate where each player had chosen its maximum margin. It was found that in some circumstances (i.e. demand levels and margin ranges), the cost difference between producer's was large enough so that there was no possibility to underbid each other in order to obtain a greater contract and still obtain a higher profit. These experiments therefore revealed the fragile position of TenneT as a monopsonist in an oligopoly with a predetermined demand.

By comparing the expected earnings from activations earnings, costs and contract fees of each producer it was found that the reserve capacity market, with a current margin of approximately 125 percent, is very attractive in financial terms. In relation to the subsequent costs which are incurred by the Dutch consumers, this study however concludes that it is not possible to make informed conclusions on whether these profits and costs are currently too high, as consumers are not able to reveal how much they are actually willing to pay for having reserve capacity available.

Based on a linear trend found in the experiments a price forecast is made for various demand levels. In a simulated scenario where the demand for reserve capacity increases with 15 MW per year, an accumulated cost increase of 200 million euros is found in 2014 as compared to 2016.

Regarding the difference in results between 3 and 4 player games

The entering of an additional producer to the market has a profound effect on the procurement cost for the TenneT. Whereas with three players the procurement cost for TenneT averaged 145.8 EUR/kW, the entering of an additional producer lowered the procurement cost to 97.9 EUR/kW. A decrease of approximately 33 percent. This accumulates to over approximately 16 Million a year.

This result thereby clearly shows how much there is to gain (and lose) with respect to the amount of competition in this market. Again this also show how valuable an economic analysis of the competition can be for individual producers. As without such an analysis, producers may bid in accordance with preceding adopted strategies and thereby ignoring this effect. This would deem their strategy much less profitable.

The effect of splitting the total volume between two auction in four player games again clearly demonstrated a similar effect as compared to the three player games; Total procurement cost and rent decreases.

Implications to chapter's research questions

In contrast to the common usage of game theory within the domain of economic analysis of electricity markets, this study has aimed to demonstrate that game theory can also be applied to inform the bidding strategy of individual producers. To this end, this research has targeted the research problem by answering the research question: *"How can a game theoretic modeling approach support strategic decision making in the reserve capacity auction?".*

The large number of interdependent strategy combinations, determine that it is problematic to examine individual bidding strategies in the approach adopted by this study. However, the results of the experiments appear to confirm that the model is capable of accurately forecasting the market clearing price. This result therefore serves as a proof of concept that demonstrates that the adopted research approach is in fact feasible.

The possibility of being able to accurately forecast the market clearing prices is of high value for producers, as an accurate estimation of the market clearing price will greatly assist producers to optimize their bidding strategies. A similar approach, as taken in this research, could also be of value for regulatory agencies (e.g. a method for testing auction designs and forms of collusive behavior).

A far more common usage of game theory is to analyze markets from a macro perspective on the market. This viewpoint has also been adopted in this study by shedding light upon the second research question of this chapter: "*What do the results of the game theoretic modeling approach reveal about the design of the reserve capacity auction?".*

This perspective on the market has revealed a great number of insights previously discussed. Having analyzed numerous experiments, this study concludes that this approach has resulted in the following main insights.

It is possible to simulate the market outcome in the approach adopted by this study. This result shows that the approach of this study may also be useful for regulatory agencies to test whether markets suffer from collusive behavior.

Aside from removing barriers to entry by increasing the flexibility of the auction, the separation of the total volume over two auctions, may have an additional cost reducing effect. This study proposes that these results may be extrapolated to the real life behavior of strategists.

The results found in several experiments showed how vulnerable the position of TenneT is. It was furthermore found that the reserve capacity market, with a total accumulative margin of 125 percent, is currently very attractive for producers in financial terms.

6. Discussion

6.1 Introduction

The first part of this thesis served to define the context, scope, theoretical underpinnings and research approach of this study. The second part of this thesis presented the results emanating from the research approach of this study. This chapter constitutes the beginning of the third and final part of this thesis and aims to provide reflections on the game theoretic computational modeling approach and the implications drawn from its results.

In the beginning of this thesis it is stated that the predictive power of a model is only as strong as its capability to describe the system of interest. The reason for this is that a model is merely a conceptualization of reality and therefore in essence always an incorrect representation of this reality. The main research question was therefore formulated:

To what extent and by which means can a game theoretic modeling approach support strategic decision making in the reserve capacity auction and how can this model be used to critically examine the design of this market?

The goal of this study is therefore to investigate to what *extent* a game theoretic modeling approach can be used to address the said research question. This therefore pre-acknowledges that a perfect representation of reality is in fact impossible.

In order to represent and analyze the real world problem, a combination of theoretical- and practical research methods were used to design a game theoretic modeled abstraction of this reality. Theoretical, in terms of the mathematical tools of game theory that, under the assumption of perfect rationality and a correctly defined decision problem, predicts where players will establish an equilibrium. Practical, in terms of the applied research methods, used to define the decision problems and competitive settings (i.e. model parameters such as players' payoff functions, rules, information etc.). In other words, practical techniques established the economics of the game, while game theory guided the actions of the players by giving them a rationale to act upon.

In order to make the problem manageable this study relied on a considerable number of assumptions. These assumptions can be grouped in belonging either to the *assumptions underlying the economics of the model* (i.e. the decision problems) or belonging to the *assumptions underpinning the rationality of the decision makers*. As these assumptions will inevitably be incorrect, it is important to discuss these assumptions explicitly in order to reflect upon the results obtained in this study. This will be done in two separate sections in which first the establishment of the model parameters – the economics - will be critically examined and secondly a reflection will be given upon the manner in which the outcome of games correctly represents real life behavior.

6.2 Reflection upon the abstraction of the economics

Economics is a very broad concept, the usage here refers to all aspects that determine the effectiveness of a given bidding strategy in the reserve capacity auction. In this thesis game theoretic modeling is explained as the conceptualization of a competitive environment and, if players are acting perfectly rational, a correct representation of this environment depends on how accurate the *decision problem* is defined.

The existence of a *decision* actually presupposes the possibility of multiple choices, while the presumed *problem* implies that a different choice may result in more or less beneficial outcome. In order to correctly represent the decision problem, it is therefore important to establish what the options are for decision makers and how each decision should be valued.

In competitive markets, it can be assumed that a decision is mainly valued in terms of its profitability and this study concluded that in the reserve capacity market the profitability of a reserve contract is mainly determined by three financial elements; *expected earnings from activations*, *forecasted opportunity costs*, and the *selection of strategies* (i.e. margin of bids).

With regard to the *forecasted earnings from activations,* this study assumed that the shape and size of this curve is likely to be the same for each producer. However, it may very well be that there is a difference between the shape of these curves, as each producer has slightly different portfolio characteristics and resulting marginal cost functions. Furthermore, each producer may also adopt a different bidding strategy in this market. The possible effect this may have, is explained in Chapter 2, illustrated by the concept of the prisoner's dilemma.

Electricity is an unusual product, aside from its deviating technical characteristics its economics also differs greatly from other commodities. The price for which it sells, for example, depends on a wide range of variables such as the weather (temperature, wind speed, precipitation, etc.), the intensity of commercial and non- commercial activities, fuel prices, etcetera. As a result, forecasting the price of electricity is very similar as compared to predicting something like the weather. While predicting if, where, and at what time it will rain tomorrow is one thing, it is another thing to predict how the weather will be in half a year from now. However, in order to calculate the costs associated with a given reserve capacity contract, this is exactly what is required of producers. This is not an easy task, as Niels Bohr has phrased it quite intelligibly:

"Prediction is very difficult, especially about the future"

Opportunity costs are normally forecasted by a combination of unit commitment- and dispatch models, as was explained in Chapter 2. These models require very specific information such as start costs (fixed start- and start fuel costs), variable operating and maintenance costs, minimum and maximum capacity, efficiency curve, as well as connections and obligations to possible heat networks and industries. The models used for this purpose are very complex and difficult to design and this study therefore approximated the opportunity costs by using a different approach.

The main idea behind using the ENTSO-E generating data for this purpose, is that the problem could be made much more simple once it is established which generating units are scheduled to be in service during a particular period (the unit commitment). Not only does this eliminate the need for complex optimization models, it also reduces the requirement of having information on very specific details of production portfolio's.

Having established the unit commitment, the opportunity costs for a given contract was estimated. This is done by comparing the dispatch of a portfolio with- and without a reserve contract. The change in cost between these scenarios is roughly equal to the Day-ahead market clearing price minus the producer's variable production cost multiplied by the reserve contract.

However, this meant that publically unavailable information regarding efficiency curve's and minimum- and maximum capacities had to be obtained. Although, through the process of continuous refinement, this study is confident that the estimates regarding the technical characteristics of the production portfolios have been estimated to a sufficiently accurate degree, that allowed this study to make certain statements with respect to cost-differences, these estimates are still just approximations. Minor errors in these approximations can have a major effect on the outcome of this analysis. The opportunity cost calculations, as presented in this study, should therefore be viewed from this perspective.

Furthermore, while this approach allowed to make a distinction between the units providing upward reserve and the units providing downward reserve (e.g. 80 MW contract→ Unit A: 80 MW downward; Unit B: 80 MW upward), it did not involve splitting individual upward- and downward reserve provision between units (e.g. Unit A: 50 MW downward; Unit B: 30 MW downward; Unit C: 60 upward; Unit D: 20 MW upward). So, even though there is always a single unit on which it is most economically efficient to provide reserve capacity, if the size of a contract exceeds the capacity for providing reserve capacity, it can be less costly to divide the reserve provision between units. Not including this possibility may therefore have resulted in an overestimation of the opportunity costs, especially for larger contracts.

The capacity, ability or capability to provide reserve capacity is another aspect for which certain assumptions have been adopted. This capacity is estimated by subtracting the maximum- with the minimum production capacity and dividing this volume by two. However, the actual capacity for reserve provision of a given producer is also influenced by a number of other factors. For instance, the provision of additional ancillary services, such as primary- and tertiary reserve capacity contracts, as well as other network responsibilities, such as heat obligations and other relevant connections with industries, have a considerable impact on the capability to provide reserve capacity, as well as on the cost to provide this service. Not including these aspects may therefore have a considerable influence on the correctness of the results obtained from this analysis.

Furthermore, in the auction model the reserve provision capacity of each player is limited to 180 MW. This design choice was deemed necessary as increasing the size of this capability greatly increased the processing time of the model. In reality some producers do have a larger ability to provide this service and the rules of the auction allow for a maximum share of 2/3 of the total auctioned volume, adding up to 227 MW for an auction in which 340 MW is procured. This assumption is therefore clearly incorrect. However, this does not necessary imply that erroneous results were obtained. This is due to the large difference in cost levels between small and large contracts of individual producers and consequential unlikeliness of any of the producers to be awarded a contract exceeding 180 MW.

Another important limitation of this approach is that the opportunity costs only refer to the costs which were incurred over the year 2015. This places limits on the predictive powers of the model, as different market circumstances (i.e. fuel price, supply and demand) may result in different outcomes for each production portfolio. However, as the opportunity costs are calculated based on the difference between the incremental costs and the day ahead market clearing price, multiplied by the contract volume, this effect could also be very limited. This is explained as follows.

The Day-ahead market clearing price (through which by comparison the opportunity costs are calculated) is mainly influenced by supply, demand and fuel prices. However, averaged over long periods of time, supply and demand does not change rapidly. Furthermore, fuel prices have a comparable effect on the average incremental costs of units, as well as on the Day-ahead market clearing price. Therefore, the effect of changing fuel prices is somewhat canceled by the simultaneous effect it has on the incremental costs and Day-ahead market clearing price. Evidence to support this statement is found by comparing the procurement cost for reserve capacity of TenneT with the fuel prices of the last decade.

Obviously, *the selection of strategies* for each of the players also influences the outcome of the auction model. In this study, the selection of these strategies were validated by comparing the outcome of the model's simulated procurement costs with the actual procurement costs of TenneT. For this validation process to be correct, this study had to rely on a number of assumptions.

First of all, this validation process supposes that only a single combination of strategies could result in the found procurement costs. However, it is very well possible that multiple combination of strategies will give similar results. Without having additional information to validate the results of the model experimentations, it is not possible to decide which selection of strategies is more likely than others. This therefore imposes serve limits to the reliability of the results' validation.

Furthermore, the assumption, that the selection of strategies can be validated in this manner, is also only correctly taken when the assumption that the opportunity cost curve is accurately approximated is also correct and vice versa. As, by validating the results in this manner, it is not possible to distinct between correctly approximated costs, or correctly chosen selection of strategies (i.e. margins). This therefore places severe limits on the accuracy of the model's validation.

Aside from the practical assumptions to concern the payoff function of each producer, the strength of the model also crucially relies on the premise of certain theoretical arguments about the functioning of markets and the behavior of its participants. These will therefore be discussed in the next section.

6.3 Reflection upon the abstraction of rationality

Oligopolistic markets have very dissimilar characteristics as compared to more competitive markets. Unlike in the more competitive market, in which firms of smaller size have limited effect on the behavior of its competitors, the behavior of an oligopolist does have a powerful and consequential effect on the profitability of its competitors. The process of decision making in an oligopolistic market is therefore much more *comparable to a game of chess* as compared to the strategic decision making in more competitive markets, as oligopolists are inter-dependent on each other's strategic decisions. Therefore, organizations in oligopolistic markets are always (or should always), considering the behavior of their competitors while making their own economic decisions.

In order to understand the behavior of oligopolist, game theory can be used as a mathematical tool to predict the outcome of these markets under various conditions.

Many economic competition models have been developed that describe the manner in which market participants interact within a market (e.g. the Cournot, Bertrand and kinked demand curve model). These models all contain their own specific assumptions such as with regard to price elasticity of demand, strategic variables (e.g., possibilities to collude, price, quantity), capacity constraints, number of possible players, etc. These assumptions about the organization and functioning of markets all widely differ from the characteristics defining the reserve capacity auction (i.e. monopsony, perfectly inelastic demand, oligopoly with limited capacity, piece wise linear cost-, and logarithmic payoff functions, a multi-unit-, pay as bid settlement regime, limited freedom to enter, no freedom to exit, heterogeneous product due to time, space and generation details) that this study holds that any comparison between these economic models and the reserve capacity auction is impossible.

As of yet, no comparable competition model exists and this study therefore relied on the correct representation of the decision problem and the *rationality* that guides their decisions. For this purpose, a different model with an entirely different set of assumptions with regard to firm behavior and interaction of the participants was developed. These assumption are classified with regards to the behavior of the producers in terms of their *Rationality; Information* and*; Capabilities*.

With respect to the ***Rationality***, it is assumed that the players are *profit maximizing agents*, *indifferent towards market share* and have a *single auction time horizon.* The combination of these assumptions eliminate certain moves for the players that are actually possible for producers.

Furthermore, although producers are presumably rightfully described as profit maximizing agents, they may opt different strategies as to attain their profits. For example, the combined effect of the assumptions of indifference towards market share and limited time horizon, eliminates the possibility of collusive behavior and price wars. This therefore puts obvious limits as to what can and cannot be concluded from the results. This should also be seen in light of the presumed intrinsic susceptibility to market failure and collusive behavior of this market.

In order to investigate if different results would be obtained when players value different sized contract differently, two separate games were developed. In one game it was assumed that producers value different sized contracts differently, whereas in the other game players valued different sized contracts equally.

This study holds that the representation of the rationality of strategy makers in the real word is more accurately captured in the first- as compared to the second game. The reason for this can be related to the shape of the activation curve in which the marginal profit decreases incrementally as contracts become larger. Furthermore, as the financial risks are greater for larger contracts as compared to smaller contracts, you would also expect producers to want to be compensated for this risk by asking an additional premium for larger contracts.

It is furthermore assumed that the players' ***Information*** is limited with respect to four factors that decide the profitability of each strategy. These are; *earnings from activations*, *opportunity costs, previously accepted bids and the selection of strategies*. In reality the number of complex relations that determine the effectiveness of a given strategy is numerous. Ignoring these factors could therefore represent an oversimplification of reality and perhaps deem the results less valuable. However, for reasons ascribed to the limited rationality of decision makers, it can perhaps be assumed that strategy makers are also not capable to include all factors in their attempt to optimize bidding strategies. Nevertheless, the inclusion of some factors which have been ignored or assumed constant may have changed the outcome of this study.

In terms of the ***Capabilities***, it is assumed in the game that each producer has a *restricted and identical capacity*. Producers can therefore only obtain a maximum market share as relative to this capacity and to the total demand in the market. Although this assumption is incorrect, it was found that, due to major differences in cost levels between low capacity and high capacity contracts, this assumption would not affect the result. This assumption was implemented, as this reduced the computational time for the model considerably.

6.4 Implications of assumptions

The representation of the auction relied on a combination of assumptions with regard to the economics and rationality of the decision makers. Consequently, the extent to which these assumptions correctly describe the real world determine how to value this study's results.

The sheer number of variables determine that it is problematic to make statements with regard to the sensitivity of each of the individual variables on the results. However, with regard to the outcome of the experiments, it can be deduced that the opportunity cost function is most influential and this calculation should therefore be given priority for further investigation.

7. Conclusions & recommendations

7.1 Introduction

This chapter concludes this thesis by recapitulating the main results and insights obtained. This chapter will commence by restating the main research objective in order to evaluate this study's realizations. After this the research questions will be individually revisited. At the end of this chapter, the aggregated insights are merged and implications to the main research question are drawn.

7.2 Research objective

This thesis is written in the context of a world in which renewable energy, guided by economic and political goals, assumes an ever growing share of the energy mix within the Dutch electricity market. Given the fluctuating output of renewable energy sources, an intrinsic feature, the importance of the reserve capacity auction, is expected to increase considerably in upcoming years.

The architecture of the reserve capacity auction, a monopsony in which a sole buyer (TenneT) seeks to reserve a predetermined quantity of symmetrical (up- and downward) reserve capacity from a limited set of producers, motivate to take a closer inspection at the design of this market. Indeed, there is no reason to assume that the interests of the private entities active in this secondary reserve capacity market, align with broader societal interests of efficient markets in which electricity is supplied at the marginal costs of production and perhaps a small premium.

The specific characteristics of the reserve capacity auction, determined Game theory to be the most suitable candidate as this study's main research methodology. By capturing the Dutch situation in a game theoretic model, reflecting the real-world behavior of three to four dominant producers in an oligopolistic market with a single buyer, this thesis sought to shed light on the micro- and macro perspectives of this market.

From the micro perspective, the viewpoint of a single producer active in the reserve capacity auction seeking to optimally allocate its energy generating assets, this study sought to explore until what extent a model can inform the producers' strategy makers in their bidding process.

The first perspective is closely entwined with the second, the macro-perspective. From this perspective, this thesis examined the question until what extent the design of the market fosters efficient economical outcomes from a public welfare perspective.

This twofold perspective on the reserve capacity auction, resulted in a research approach through which by a combination of realistic market data and applied game theoretical concepts, the outcome of the auction could be predicted. The research goal was therefore formulated:

To investigate the reserve capacity auction by incorporating realistic market data for producers as input for a game theoretic computational auction model.

7.3 Answers to the research questions

The main goal of Game Theory is to analyze optimal decision making in the presence of strategic interaction among players. Game theoretic modeling is therefore in essence the conceptualization of a decision problem in a competitive environment. In relation to the approach as adopted by this study this meant that it is necessary to give a clear description of this problem. This resulted in formulating the first and second research question of this thesis as following:

"What are the specific characteristics of the balancing market?"

and:

"What factors influence decision makers in the reserve capacity auction?"

These questions are answered in Chapter 2 in which it was established that bidding strategies should be developed based on o*pportunity costs, earnings from activations, auction rules and previously accepted bids*.

This analysis concluded that the o*pportunity costs* can be approximated by unit commitment and dispatch models, while *earnings from activations* can be estimated by historical analysis of accepted bids in the balancing energy market. *Auction rules* are based on pay as bid with a fixed demand and *previously accepted bids* follow logically from previous auctions and can therefore readily be used in subsequent auction simulations.

The analysis in Chapter 2 also uncovered several potentials for inefficient conduct by producers. Firstly, in relation to the balancing energy market it is concluded that producers have a clear incentive to overbid their marginal costs in order to increase the market clearing price in times of higher imbalances. Secondly, in relation to the reserve capacity auction, it seems that the design of this market gives participants an incentive not to underbid each other's offer by too much, as this might initiate a price war. This implicates that these markets are susceptible to collusive behavior.

In order to motivate the choice for selecting game theory as the methodology for this research and to position this study within the scientific literature the third research question, which is answered in Chapter 3, is formulated:

"Why a game theoretic modeling approach?"

Chapter 3 established that the *market structure* and *auction rules* have a defining effect on the way bidding strategies are formed. In terms of the *market structure* the most important aspects are found to be that the market is composed of a single buyer with inelastic demand, and oligopolistic sellers. With regard to market power this has the effect that there is a possibility for abuse of market power on the supply side and not on the demand side. In terms of *auction rules* the type of settlement scheme was found to be crucial in shaping strategic behavior of producers. In a pay as bid settlement scheme bidders are faced with a trade-off between the profitability and the probability of selling their products.

The insights drawn from the theoretical analysis determined a game theoretic modeling approach most suitable as it possesses the tools to model the complex strategic environment of the market and allows for an analysis of the bidding problem from both a single producer- as well as from a system level perspective.

The idea is that, from an individual producer, or micro-, perspective the Nash Equilibrium reveals a great deal on how he should bid in the market, what his expected market share is and those of the other players. While, from a macro- perspective, game theory predicts a stable market equilibrium which reveals a great deal on human rationality and competitiveness within the auction.

Having positioned and motivated this study, this research sought to investigate how the market and methodology can be conceptualized in a model. In Chapter 4 the following research question is therefore answered.

“*How can a game-theoretical approach be translated into practice?*”

Chapter 4 presents the design of the conceptual game theoretic computational auction model and elaborates on the involved modeling steps.

In this chapter, it was established that the results obtained by the adopted research approach are only meaningful, if sufficient coherence between the model and the real-life situation is preserved. It was found that the model’s output can be validated with the actual procurement costs incurred by TenneT. If sufficient coherence is established, this study’s research approach offers interesting results in terms of the macro- and micro- perspectives on the market.

At the end of Chapter 4, possible implications of the proposed research are discussed. From the analyses of the players, the market and the results from the model experimentations, several conclusions are drawn and multiple insights obtained. From this improved perspective it became possible to establish the ultimate implications that have resulted from the adopted research approach. The results of this study represents the crux of this study and are presented in Chapter 5.

In contrast to the common usage of game theory within the domain of economic analysis of electricity markets, this study has aimed to demonstrate that game theory can also be applied to inform the bidding strategy of individual producers. To this end, this research has targeted the research problem by answering this chapter’s first research question:

“How can the results of the approach inform producers in their bidding strategies?”

The large number of interdependent strategy combinations, determine that it is problematic to examine individual bidding strategies in the approach adopted by this study. However, the results of the experiments appear to confirm that the model is capable of accurately forecasting the market clearing price. This result therefore serves as a proof of concept that demonstrates that the adopted research approach is in fact feasible.

The possibility of being able to accurately forecast the market clearing prices is of high value for producers, as an accurate estimation of the market clearing price will greatly assist producers to optimize their bidding strategies. A similar approach, as taken in this research, could also be of value for regulatory agencies (e.g. a method for testing auction designs and forms of collusive behavior).

A far more common usage of game theory is to analyze markets from a macro perspective on the market. This viewpoint has also been adopted in this study by shedding light upon the second research question of this chapter:

"What do the results of the approach reveal on the design of the reserve capacity market?"

In experiments where producers differentiate in setting their margins in separate sections of their bid, a connection is seemingly found between the number of existing Nash Equilibria and the level of competition. It appears that lower number of existing Nash Equilibria points to stronger levels of competition (and vice versa). However, further research is needed to confirm this relation.

From the analysis of the results in which the new design of the auction is tested (i.e. demand of reserve capacity divided over two sequential auctions), it was found that a split auction design results in a market equilibrium with lower rents for the producers, and consequentially lower procurement costs for TenneT. This means that aside from increasing competition by lowering barriers to entry, the separation of the demand over two auctions may have an additional cost reducing effect.

In the literature this observation is called the *declining price anomaly*. This study proposes that this anomaly can be attributed to the limited rationality of the players of the auction game and suggests that this result can be extrapolated to the real life behavior of the producers' strategists.

In relation to the games where players could not make a distinction between sections of the bid slope in their strategy, it was found that the Nash Equilibrium in these games is sometimes not situated in pure strategy Equilibria but exist in mixed strategy Equilibria.

In experiments that did result in finding a Nash Equilibrium, the equilibrium resided at the strategy coordinate where each player had chosen its maximum margin. It was found that in some circumstances (i.e. demand levels and margin ranges), the cost difference between producer's was large enough so that there was no possibility to underbid each other in order to obtain a greater contract and still obtain a higher profit. These experiments therefore revealed the fragile position of TenneT as a monopsonist in an oligopoly with a predetermined demand.

[redacted]

Increasing the share of RES can have a large effect on the procurement cost of reserve capacity. Based on a linear trend, a price forecast was made for a simulated scenario where the demand for reserve capacity increased with 15 MW per year. This resulted in an accumulated cost increase of 200 million euro in 2016 with respect to 2014 procurement cost level.

A declining trend in the procurement cost for reserve capacity is observed in the last years. It seems that this decline has no relation with fuel prices and is more influenced by changes in the demand of reserve capacity. This observation, in combination with the experimentation results obtained, seem to suggest that the market currently does not suffer from forms of collusive behavior.

The presumed entering of an additional producer in the market has a profound effect on the procurement cost for the TenneT, as the entering of an additional producer decreased the procurement with approximately 33 percent. This demonstrates how much there is to gain (and lose) with respect to the amount of competition in this market.

Again, this result also shows how valuable a game theoretic equilibrium model can be for individual producers. As without such an analysis, producers may bid in accordance with preceding adopted strategies, thereby ignoring this effect, deeming their strategy far less effective.

7.4 Conclusion to main research question

The increasing relevance of the Dutch reserve capacity market, in light of a growing share of renewable electricity, its intrinsic susceptibility to market failure and lack of academic understanding of the market constituted the main driving forces behind the main question of this research:

To what extent and by which means can a game theoretic modeling approach support strategic decision making in the reserve capacity auction and how can this model be used to critically examine the design of this market?

With regard to the use of the word *extent* in the main research question, this study's main realization is the delivery of a proof of concept for a game theoretic computational auction model.

Results of this research have shown that the designed model is capable to predict where market Equilibria might establish.

In relation the micro- perspective, the perspective on the bidding strategy of the individual producer, this result implies that using game theoretic model can assist producers by forecasting the market clearing prices as a means to optimize their own bidding strategy.

In relation to the macro perspective, the system-wide perspective of a public policymaker, a second realization of this research is the displayed possibility to apply this research approach in order to investigate implications of different market designs. This realization is perfectly exemplified by this studies finding that the separation of the total volume over two auctions in which half is procured each time, resulted in an additional cost reducing effect. Believed to be ascribed to the limited rational of producers' strategy makers.

7.5 Areas for future research

Many results have been obtained in this study. However the implications drawn from these results can greatly be advanced by further research as more attention is required on several of these. The main following areas for further research have therefore been appointed.

With regard to the current functionality of the game theoretic computational auction model, this study proposes to alter the model by including an algorithm that removes ineffective strategies. This will reduce the solution space and allow for more experiments and strategies to be tested. A second suggestion with regard to the model's current features is to include the possibility to look for mixed strategy Equilibria. For example by implementing COMPASS in the logic of the model.

In an oligopolistic market, such as the Dutch reserve capacity auction, it is essential to inform bidding strategies with possible moves of the competition. In terms of the applicability of the model in this market, this study therefore advices producers to increase their efforts in cost forecasting of the competition as it can greatly assist in optimizing their bidding strategies.

This same area for future research is also advised to the public policy makers within the domain of the reserve capacity markets and other markets with similar characteristics. Results of this study have demonstrated a number of possible features but promises a lot more.

In particular the usage of game theoretic models to discover signs of collusive behavior, to investigate impact of different market design choices, and effect of increasing the number of participants, can be very rewarding for policy makers in domains similar to the researched market.

In terms of specific recommendations with regard to the design of the reserve capacity market this study has found that a major reduction in costs can be attained by increasing the number of market participants. It was furthermore found that the nature of the reserve capacity contract in its current form imposes great barriers to entry for several producers.

Increasing the flexibility of the contracts, such as by the currently tested reduced duration of contracts is therefore a step in the right direction. Other possibilities, such as dividing the demand over sequential auctions (N.B. the observed declining price anomaly), and further increasing the flexibility by allowing asymmetrical contracts (separate upward- and downward capacity contracts), may also help to increase competition in this market.

A final area of suggested further research involves the discovery of a presumed connection between the number of existing Nash Equilibria and level of competition, as further research is needed to confirm this relation. As a final suggestion this study suggest that the discovery of the declining price anomaly deserves more scientific attention, as this cost reducing effect may be applicable in other markets, it offers great potential from a social welfare perspective.

Bibliography

Amprion, 2012. *Procurement of control power and energy in Germany,* Dortmund, Germany: s.n.

APX, 2014. *Power NL - Yearly Overview 2014,* Amsterdam: APX B.V..

Ausubel, L. M., 2008. Auction Theory for the New Economy. In: S. N. Durlauf & L. E. Blume, eds. *Auctions: Theory for the New Palgrave, 2nd Edition.* s.l.:Palgrave Macmillan, pp. 123-161.

Borenstein, S., Bushnell, J. & Wolak, F., 1999. Diagnosing Market Power in California's Deregulated Wholesale Electricity Market. *Competition Policy center,* 1(1), pp. 1-39.

California ISO Corporation, 2014. *The Role of Separate Capacity Offers in Spot Capacity Reserve Markets,* California: CAISO.

David, A. K. & Wen, F., 2000. *Market Power in Generation Markets.* Hong Kong, Proceedings of the 5th International Conference on Advances in Power System Control, Operation and Management.

de Vries, L. J., Correljé, A. F. & Knops, P. A., 2013. *Electricity - Market design and policy choices.* s.l.:Technical University of Delft.

Durlauf, S. N. & Blume, L. E., 2008. Auctions: Theory. In: *The New Palgrave Dictionary of Economics.* s.l.:Palgrave Macmillan.

ENTSO-E, 2013. *Network Code on Load-Frequency Control and Reserves,* Brussels: ACER.

European Commission, 2014. *European Commission Cimate Action,* s.l.: Luxembourg: Publications Office of the European Union.

Federico, G. & Rahman, D., 2003. Bidding in an electricity pay-as-bid auction. *Journal of Regulatory Economics,* 24(2), pp. 175-211.

Frontier Economics, 2011. *Qualitative assessment of balancing market design for the Netherlands,* London: s.n.

Gao, C., Bompard, E., Napoli, R. & Wan, Q., 2007. *Bidding strategy with forecast technology based on support vector machine in Electricity Market.* Lisbon, Portugal, Applications of Physics in Financial Analysis 6th International Conference 4.

Gao, F. & Sheble, G. B., 2010. Electricity market equilibrium model with resource constraint and transmission congestion. *Electric Power Systems Research,* 80(1), pp. 9-18.

Heim, S. & Goetz, G., 2013. Do pay-as-bid auctions favor collusion? - Evidence from Germany's market for reserve power. *ZEW - Centre for European Economic Research Discussion Paper No. 35.*

Hossein, H., Hossein, S. & Ashkan, R. K., 2007. Gaming Analysis in Joint Energy and Spinning Reserve Markets. *IEEE TRANSACTIONS ON POWER SYSTEMS,* 22(4), pp. 2074-2084.

Hummon, M. et al., 2013. *Fundamental Drivers of the Cost and Price of Operating Reserves,* Denver, Colorado: National Renewable Energy Laboratory (NREL).

Just, S., 2010. *Appropriate Contract Durations in the German Markets for On-line Reserve Capacity,* Duisburg, Germany: Chair for Management Sciences and Energy Economics University of Duisburg-Essen.

Kian, A. & Cruz, J., 2005. Bidding strategies in dynamic electricity markets. *Decision Support Systems,* 1(1), pp. 543-551.

Kirby, B. & Hirst, E., 1996. Unbundling Electricity Ancillary Services. *IEEE Power Engineering Review,* pp. 5-6.

Kirschen, D. & Strbac, G., 2004. *Fundamentals of Power System Economics.* 1st ed. West Sussex, England: John Wiley & Sons.

Klemperer, P., 2004. *Auctions: Theory and Practice.* s.l.:Princeton University Press.

Krishna, V., 2010. *Auction Theory.* London: Elsevier Academic Press publications.

Li, G., Shi, J. & Qu, X., 2011. Modeling methods for GenCo bidding strategy optimization in the liberalized electricity spot market–A state-of-the-art review. *Energy,* 36(8), pp. 4686-4700.

McAfee, P. R. & McMillan, J., 1987. Auctions and Bidding. *Journal of Economic Literature,* 25(2), pp. 699-738.

Morinec, A. G. & Villaseca, E., 2008. *Optimal Generator Bidding Strategies for Power and Ancillary Services Using Game Theory.* Calgary, US, 40th North American Power Symposium.

Mott MacDonald, 2013. *Impact Assessment on European Electricity Balancing Market,* Brighton, United Kingdom: s.n.

Mount, T., 2001. Market Power and Price Volatility in Restructured Markets for Electricity. *Decision Support System,* Volume 30, pp. 311-325.

Myerson, R. B., 1997. *Game Theory Analysis of Conflict.* 1st ed. Cambridge: Harvard University Press.

Nash, J. F., 1950. Equilibrium points in n-person games. *PNAS. Proceedings of the National Academy of Sciences of the USA,* 36(1), pp. 48-49.

Nissan, N., Roughgarden, T., Tardos, É. & Vazirani, V. V., 2007. *Algorithmic Game Theory.* 1 ed. Cambridge: Cambridge University Press.

Niyato, D. & Hossain, E., 2008. Competitive Pricing for Spectrum Sharing in Cognitive Radio Networks: Dynamic Game, Inefficiency of Nash Equilibrium, and Collusion. *IEEE Journal on Selected Areas in Communications,* 26(1), pp. 192-202.

Nobel, F., 2016. *Interview with Frank Nobel on design choices for reserve capacity market* [Interview] (16 August 2016).

Petrov, K., Scarsi, G. & Veen, van der, W., 2003. *Modeling strategic bidding behavior in power markets.* The Hague, Research Symposium European Electricity Markets.

Prabavathi, M. & Gnanadass, R., 2015. Energy bidding strategies for restructured electricity market. *International Journal of Electrical Power & Energy Systems,* 64(2), pp. 956-966.

Rassenti, S., Smith, V. & Wilson, B., 2003. *Controlling Market Power and Price Spikes in Electricity Networks: Demand Side-Bidding.* s.l., the Proceedings of the National Academy of Sciences.

REN21, 2015. *Renewable 2015 Global Status Report,* s.l.: Renweable Energy Policy Nework for the 21st Century.

Rudkevich, A., 2005. On the Supply Function Equilibrium and its Applications in Electricity Markets. *Decision Support Systems,* Volume 3, pp. 409-425.

Sheblé, G. B., 1999. *Computational Auction Mechanisms for Restructured Power Industry Operation.* 1st ed. New York: Kluwer Academic Publishers.

Soliman, A. & Mantawy, A., 2011. Economic Dispatch (ED) and Unit Commitment Problems (UCP): Formulation and Solution Algorithms. In: *Modern Optimization Techniques with Applications in Electric Power Systems.* New York: Springer, pp. 185-297.

Tennet, 2004. *Transparantie voor onbalans,* The Hague: s.n.

TenneT, 2011. *Productinformatie regelvermogen,* Arnhem: TenneT TSO B.V..

TenneT, 2015. *www.tennet.eu.* [Online]
Available at:
http://www.tennet.eu/nl/fileadmin/downloads/Customers/News/2015/Energie_en_Vermogen_Martijn_Ophuis_Klanten_dag_26_mei_2015.pdf
[Accessed 2 February 2016].

Tierney, S. F., Schatzki, T. D. & Mukerji, R., 2008. *Uniform-Pricing versus Pay-as-Bid in Wholesale Electricity Markets: Does it Make a Difference?,* s.l.: Analysis Group.

Weare, C., 2003. *The California electricity crisis: causes and policy options,* s.l.: Public Policy Institute of California.

Wen, F. & David, A. K., 2000. *Coordination of Bidding Strategies in Energy and Spinning Reserve Markets for Competitive Suppliers Using a Genetic Algorithm.* s.l., Power Engineering Society Summer Meeting, IEEE.

Appendices

A: Market analysis

On the 14th of June 2013 the EU regulation no 543/2013 was accepted in which the minimum common set of data relating to generation, transportation and consumption of electricity to be made available to producers were laid down. As of the 5th of January 2015, in accordance with this regulation, ENTSO-E started to publish actual generation data per generation unit. This data contains the generation data for all the electricity production units within the ENTSO-E control area with an installed generation capacity of over 50 MW.

This data could prove to be very valuable for both system operators, as it allows for better control and monitoring, as well as for electricity producers as these might use this data in to improve their forecast of the electricity price and to determine their market share and power position within the electricity markets. For the purpose of this study this data set can in theory for example also be used to examine *which producers are active in the reserve capacity market*. This study even suspects that a fairly *good estimation of the distribution of contract sizes* can be approached by analyzing this data. Both of which represents information which is currently not disclosed by the TSO.

This analysis is therefore separated in two distinct parts to investigate previously discussed unknowns and its approach and results will be presented in the next section.

Participating producers

In order to establish which electricity producers are taking part in the reserve capacity auction this this study has adopted the following methodology:

Market analysis: Investigating which production unit belongs to which producer and subsequently grouping the ENTSO-E production data per producer, see Table 8 for a sample of this data[26].

Table 8 Sample of ENTSO-E data as grouped for the electricity company EON. Values represent the average production per hour of the individual power plants. Indicated in bold are the night time hours as used in the following analysis.

DATE	HOURS	Maasvlakte 1	Maasvlakte 2	Maasvlakte 3	RoCa 3	EDH
05/01/2015	00:00 - 01:00	298	295	0	115	49
05/01/2015	**01:00 - 02:00**	250	248	0	110	91
05/01/2015	**02:00 - 03:00**	227	226	0	110	99
05/01/2015	**03:00 - 04:00**	220	220	0	106	99
05/01/2015	**04:00 - 05:00**	261	259	0	95	89
05/01/2015	05:00 - 06:00	328	325	0	100	99

[26] There are over a hundred companies which own power plants in the Netherlands. This analysis has limited itself to select only seven parties which are the most likely candidates for reserve capacity contracts.

Checking for spinning reserve: Contracted parties have an obligation to always be able to provide reserve power. Producers which did not have spinning reserves operational at all times in 2015 can therefore be ruled out as being active in this market. Analyzing the ENTSO-E data at times of low electricity prices (generally between 1 am and 5 am). This analysis is presented in Table 9.

Table 9 Results of spinning reserve analysis during night time between 1 and 5 am. This represent a total number of 1460 hours investigated. Delta therefore had nearly 10 days without spinning reserves operational in 2015.

Electricity producers	Hours/percentage without spinning reserve	Conclusion
1. Delta	39 hours →2.67%	Uncertain
2. Eneco	671 hours →45.96%	No contract
3. EON	0 hours →0.00%	Very likely
4. EPZ	36 hours →2.47%	Uncertain
5. ENGIE	52 hours → 3.56%	Uncertain
6. RWE	0 hours →0.00%	Very likely
7. Vattenfall	0 hours →0.00%	Very likely

Cleaning up data: Daily power output of power plants is generally composed of a large share of powering up- at high electricity prices and powering down patterns– or shutting down altogether – at times of low electricity prices. These powering up- and down patterns severely pollute the data with regard to the purpose of this study and therefore need to be removed. In order for this the analysis is only based on hours with generally high prices (between 10 am and 16 pm) and in hours with generally low prices (between 1 and 5 am). The reason for this is that in these hours it is reasonable to expect that the power plants will be operational at a steady level. Changes in output are then more likely to be caused by other market obligations such as reserve capacity.

Regression analysis: Analyze if there is a strong correlation between changes in power production of individual power plants, as well as the total hourly average portfolio power output, and changes of the amount of activated reserve power. See Table 10 for a sample of this analysis and see Table 11 for the results of this analysis.

Table 10 Sample of regression analysis performed on the portfolio of EON. Depicted below the power plants is the delta of the hourly production [MWh]. Comparing both the individual plants as the total portfolio with the activated reserve allows to discover the correlation of power output behavior and activated reserve.

DATE	HOURS	Msvlkt 1	Msvlkt 2	Msvlkt 3	RoCa 3	EDH	Total portfolio	Delta activated reserve
01/11/2015	01:00 - 02:00	0	0	-208	0	49	-208	3.47
01/11/2015	02:00 - 03:00	-13	-17	-141	0	91	-171	-96.25
01/11/2015	03:00 - 04:00	11	15	-77	0	99	-51	108.18
01/11/2015	04:00 - 05:00	4	5	-44	0	99	-35	43.53

Table 11 Results of Spearman correlation analysis between production behavior and activated reserve capacity. A distinction is made to consider all units with a correlation of less than 0.2 as inactive in the reserve capacity market.

1. Delta	DAY	NIGHT	DAY/NIGHT	Active?
ELSTA	0.13	0.02	0.11	N
Sloecentrale unit 10	0.19	0.09	0.17	N
Sloecentrale unit 20	0.20	0.11	0.18	N
Total portfolio	0.21	0.04	0.18	N
2. Eneco	DAY	NIGHT	DAY/NIGHT	Active?
Lage Weide 6	-0.04	-0.04	-0.04	N
Enecogen	33.00	0.05	26.41	Y
Centrale Merwedekanaal	0.01	0.01	0.01	N
Total Portfolio	0.19	0.12	0.18	N
3. EON	DAY	NIGHT	DAY/NIGHT	Active?
Maasvlakte 1	0.46	0.28	0.42	Y
Maasvlakte 2	0.45	0.26	0.41	Y
Maasvlakte 3	-0.01	0.04	0.00	N
RoCa 3	0.31	0.24	0.29	Y
EDH	0.05	-0.02	0.03	N
Total Portfolio	0.32	0.25	0.30	Y
4. EPZ	DAY	NIGHT	DAY/NIGHT	Active?
Borssele 12	0.01	0.00	0.01	N
Borssele 30	0.01	-0.04	0.00	N
Total Portfolio	0.01	-0.01	0.01	N
5. ENGIE	DAY	NIGHT	DAY/NIGHT	Active?
Eemscentrale (EC3)	0.12	-0.02	0.09	N
Eemscentrale (EC4)	0.13	0.03	0.11	N
Eemscentrale (EC5)	0.16	-0.03	0.12	N
Eemscentrale (EC6)	0.10	-0.03	0.08	N
Eemscentrale (EC7)	0.26	0.11	0.23	Y
Maxima Centrale (FL4)	0.23	0.17	0.22	Y
Maxima Centrale (FL5)	0.26	0.09	0.23	Y
Centrale Gelderland (CG13)	0.00	-0.01	0.00	N
MVL380 Centrale Rotterdam 1	0.03	0.01	0.02	N
Total Portfolio	0.22	0.06	0.18	N
6. RWE	DAY	NIGHT	DAY/NIGHT	Active?
Westereems 2	0.01	-0.02	0.00	N
Amer 8	0.23	0.09	0.20	Y
Amer 9	0.25	0.28	0.25	Y
Moerdijk 1	0.44	0.33	0.42	Y
Moerdijk 2	0.23	0.07	0.20	Y
Swentibold 1	0.37	0.33	0.36	Y
Eemshaven A	-0.02	-0.01	-0.01	N
Eemshaven B	0.03	-0.01	0.02	N
Total Portfolio	0.35	0.15	0.32	Y
7. Vattenfall	DAY	NIGHT	DAY/NIGHT	Active?
Diemen 33	0.23	0.08	0.20	Y
Diemen 34	0.23	0.19	0.22	Y
Eemshaven 10	0.39	0.05	0.32	Y
Eemshaven 20	0.26	0.00	0.21	Y
Eemshaven 30	0.25	0.02	0.20	Y
Hemweg 8	0.38	0.52	0.40	Y
Hemweg 9	0.35	0.23	0.32	Y
IJmond	-0.02	-0.06	-0.03	N
Velsen 24	-0.07	-0.10	-0.07	N
Velsen 25	-0.05	-0.14	-0.07	N
Offshore Windpark Egmond aan Zee	-0.03	-0.04	-0.03	N
Prinses Alexia Windpark	-0.04	-0.04	-0.04	N
Total Portfolio	0.33	0.27	0.31	Y

Conclusion: Participating producers

Before presenting the conclusions it is necessary to explain how the results should be interpreted.

First of all, in the first step of the previous analysis a choice was made to only consider a few parties in this analysis as these are the most likely candidates for having a contract. This has to do with a number of factors such as the number of plants which producers have in their possession, the capacity of these plants and type of plants. Furthermore, although some producers are registered as separate companies, quite a few of the smaller producers are partly owned by other larger producers. Engie, for example, formerly known as Electralabel, is now fully owned by ENGIE, while other alliances also exist between smaller parties. Whilst by themselves some of these parties are too small to partake in the auction, their alliance may in fact allow them to participate.

Secondly, it should be noted that although large differences were found between the portfolios in spinning reserves analysis, these were not sufficient to immediately rule out some of the producers as eligible for having a contract. The reason for this has to do with the fact that this year was the first year in which producers had the obligation to submit their production output, as a result it is therefore important to consider the possibility of missing data. On the 1st of January in 2016 for instance, it seems that each producer has coincidently forgotten to send out their data, or that someone at ENTSO-E was perhaps a little less sharp after celebrated new year's eve the previous night.

Thirdly, it is very important to know how to interpret the correlation analysis. Correlation is a statistical method used to assess a possible linear association between two continuous variables. It is simple both to calculate and to interpret. A couple of important aspects need to be considered for this. First of all, a choice was made to use the Spearman analysis as opposed to the more commonly used Pearson correlation. The reason for this is that although a linear relation is suspected between the delta of the power output and the delta of the activated reserve power variables, it is uncertain whether the data is normally distributed. The spearman correlation coefficient is calculated as following. For a sample of size n, the n raw scores of the $\Delta\text{Power Output},\ \Delta\text{ Activated reserve power};\ \text{X}_{\text{i,}}\text{Y}_{\text{i}}$ are converted to ranks $\text{rg }\Delta\text{Power Output}, \text{rg }\Delta\text{ Activated reserve power};\ \text{rg X}_{\text{i,}}, \text{rg Y}_{\text{i}}$ and r_{s} is calculated as:

$$r_s = \rho_{rgX,rgy} = \frac{cov\ (rg_x\ , rg_Y)}{\sigma_{rgX}\ \sigma_{rgY}}\ (EQ.4)$$

Where

- r_s is the Spearman coefficent
- ρ denotes the usual Pearson correlation coefficient, but applied to the rank variables.
- $cov\ (rg_x\ , rg_Y)$ is the covariance of the rank variables.
- $\sigma_{rgX}\ and\ \ \sigma_{rgY}$ are the standard deviations of the rank variables.

Misuse of correlation is very common among researchers it is therefore important to consider how the results of the analysis should be valued. In Table 12 a rule of thumb for interpreting the results can be found.

Table 12 Rule of Thumb for Interpreting the size of a correlation coefficient.

Size of correlation coefficient	General interpretation
.80 to 1.00 (−.80 to −1.00)	Very high positive (negative)
.60 to .80 (−.60 to −.80)	High positive (negative)
.40 to .60 (−.40 to −.60)	Moderate positive (negative)
.20 to .40 (−.20 to −.40)	Low positive (negative)
.00 to .20 (.00 to −.20)	Very Weak or no correlation

When examining tables 11 and 12 it can be seen that just a few plants score a high enough correlation to be interpreted as merely moderately positively correlated. Just a few more score sufficient to be graded as low positively correlated and what is left fall within the category of very weak or no correlation. However, as there is a clear difference between the correlation of the wind parks (e.g. Prinses Alexia Windpark; Offshore Windpark Egmond aan Zee and Lage Weide 6), of which it is known that these are currently not actively providing regulating reserve, and coal plants (e.g. Moerdijk 1; Maasvlakte 1 and Hemweg 8), of which it is suspected that these do provide regulating reserve, it is obvious that a clear difference can be found from analyzing these results.

The reason why such low correlation scores are found has to do with the fact that changes in power output are for a large portion caused by other contract- and market responsibilities as well as still present powering up- and down- patterns. More importantly the low height of the correlation can be assigned to the difference in the measurement interval between the two variables – ENTSO-E data is published per hour, while activated reserve power is published every 15 minutes. In order to compare the variables, it is therefore necessary to average the activation data per hour. As it is not uncommon to have both upward- and downward reserve activation in a single hour, this averaging has as a consequence that the correlation would also generally be lower. Considering this fact, it is therefore not surprising that low correlations are found and portfolios with correlations of 0.2 are sufficient to be interpreted as a possible candidate for a reserve capacity contract.

In conclusion, from the analysis as presented in this section, this study estimates that in 2015 there were three producers which had a contract for reserve power provision. These were **EON**, **RWE** and **Vattenfall**. Although a high correlation between the delta of the activated reserve power and the delta of the power output of the portfolios of ENGIE, Eneco and Delta, these producers are not likely to have a contract. The reason for this is that these producers have a too high percentage of no available spinning reserves throughout 2015. The correlation found within these portfolios are presumable caused by voluntary reserve provision. This statement is furthermore reinforced by the relative larger difference between the correlation during day and night time of these portfolios.

Market share of producers

Establishing whether a producer takes part in the reserve capacity market is one thing. It is however a lot more difficult to investigate what the share of individual producers is in this market in terms of contract size. For this you have to be somewhat more creative. This innovative though process has brought this study to investigate this issue with the following methodology:

Cleaning up data: In order to paint a clearer picture, it is also necessary to clean the ENTSO-E data for this analysis as well. However, aside from cleaning the data by removing the powering up- and down patterns, a slightly different approach is needed for this analysis as well. In this step a distinction is made to 1) *analyze behavior at times of high APX prices* and 2*) analyze behavior at low APX prices*. The reason for this has to do with the fact that at times of high electricity prices it can be economically more favorable to provide regulating power with a gas plant than with a coal plant. Therefore, you would expect that during day time (between 10 am and 16 pm) contracted parties would supply regulating reserve with their gas plants and during night (between 1 and 5 am) with their coal plants. Furthermore, as it is possible for producers to divide their regulating reserve provision responsibilities amongst their various power plants, you would expect a cloudier image from analyzing day time hours than during night, as during night gas plants are often not operational during off peak hours.

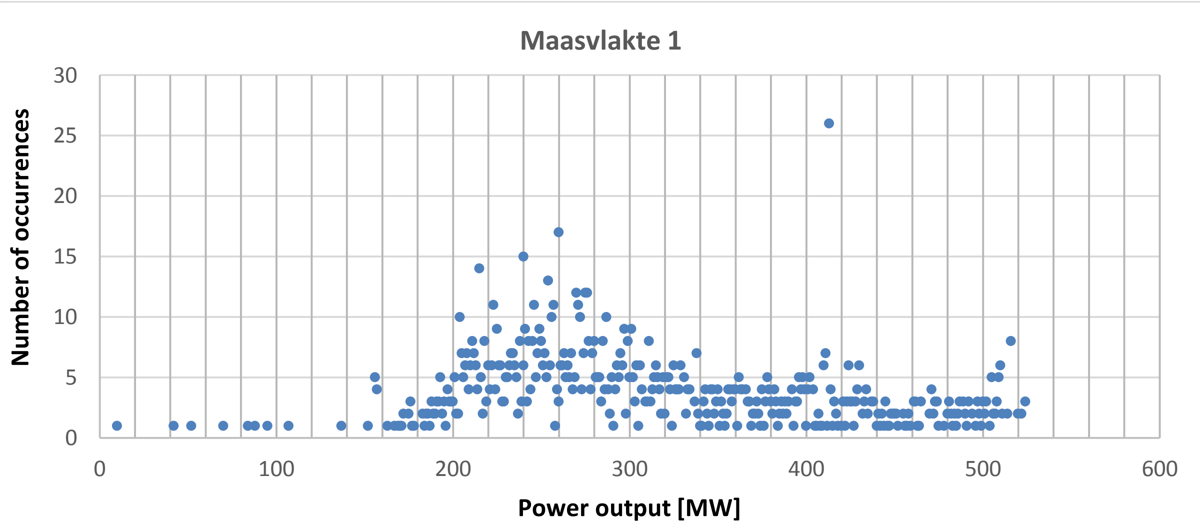

Figure 30 Scatterplot of number of occurrences of power output levels. In this Figure it can be seen that the power output levels seem to oscillate both upwards and downwards around the point of 260 MW.

Ranking the power output: By ranking each output level of the individual power plants by the number of occurrences, it becomes possible to discover whether patterns for providing regulating control exist, see for example the difference between Figure 30 and Figure 31. From Figure 30 a clear bandwidth pattern can be discovered around 240 MW while in Figure 31 such a pattern is clearly not present.

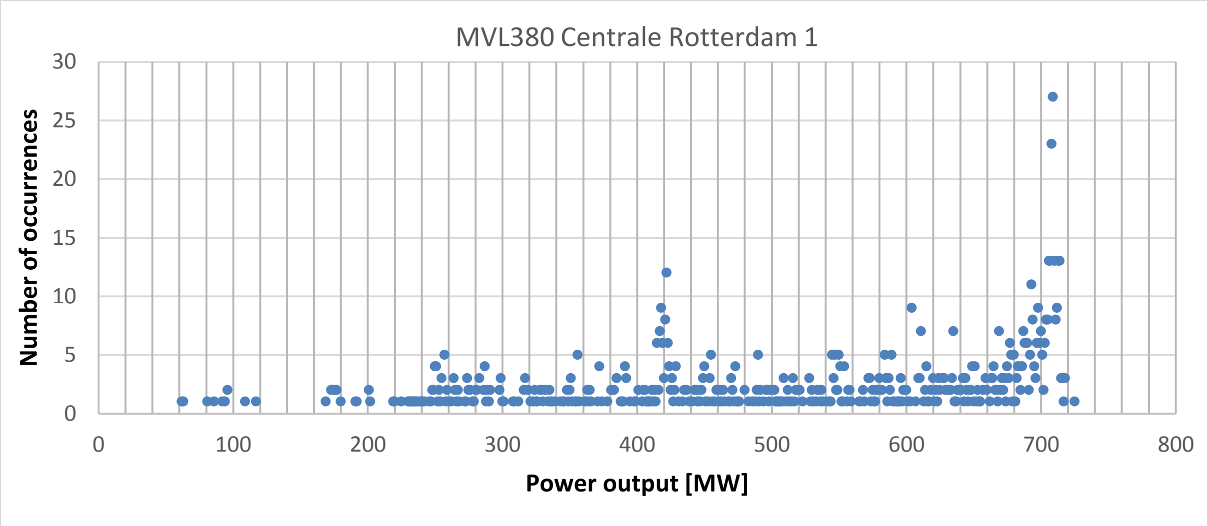

Figure 31 Scatterplot of number of occurrences of power output levels. In this figure it is not possible to indicate a point at which power output levels seem to oscillate.

Determining contract size: Having enumerated the number of occurrences of each power output level and having plotted this data on scatterplots, it now becomes possible to estimate what the contract sizes are of the participating producers. The results of this analysis can be found in figures 32 through 34 and have been summarized in Table 13.

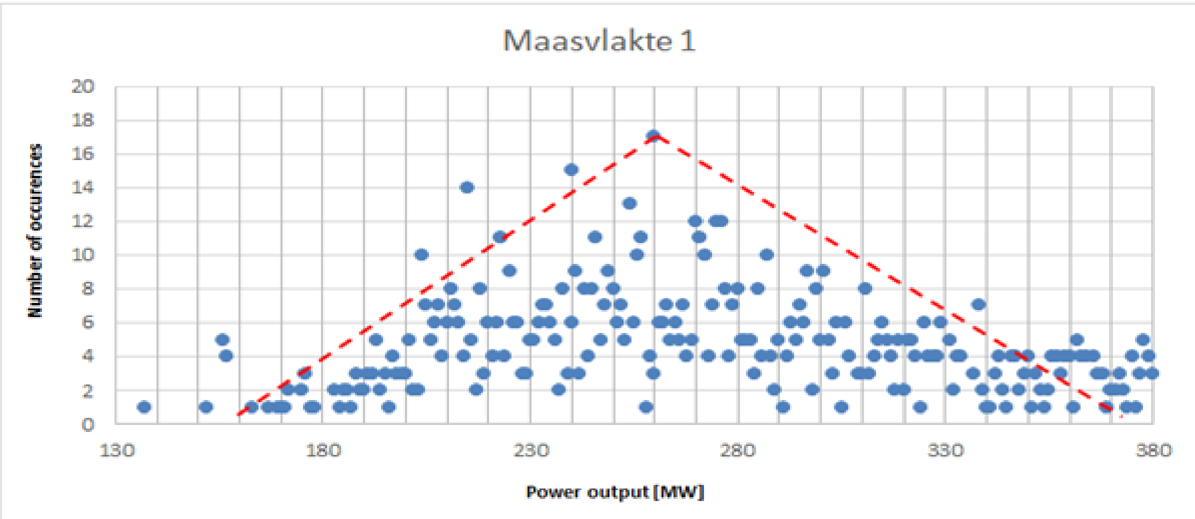

Figure 32 Scatterplot of number of occurrences of power output level taken zoomed in on point of oscillation. The section which is enclosed in the red dotted line signifies the estimated size of the contract multiplied by two. As a result the estimated contract of EON is 105 MW ($\frac{370-160}{2}$).

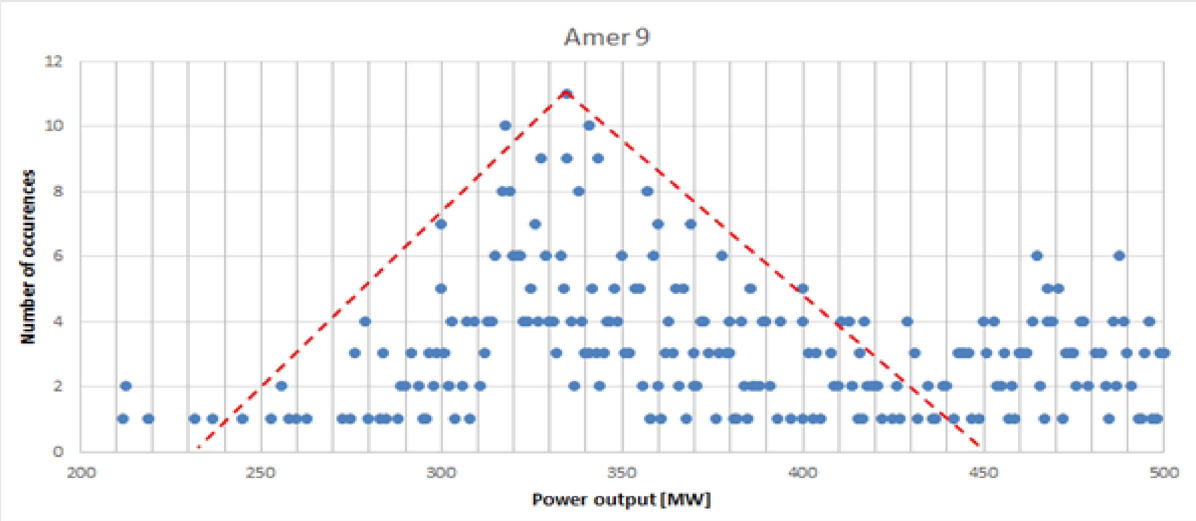

Figure 33 Scatterplot of number of occurrences of power output level taken zoomed in on point of oscillation. The section which is enclosed in the red dotted line signifies the estimated size of the contract multiplied by two. As a result the estimated contract of RWE is 110 $(\frac{450-230}{2})$.

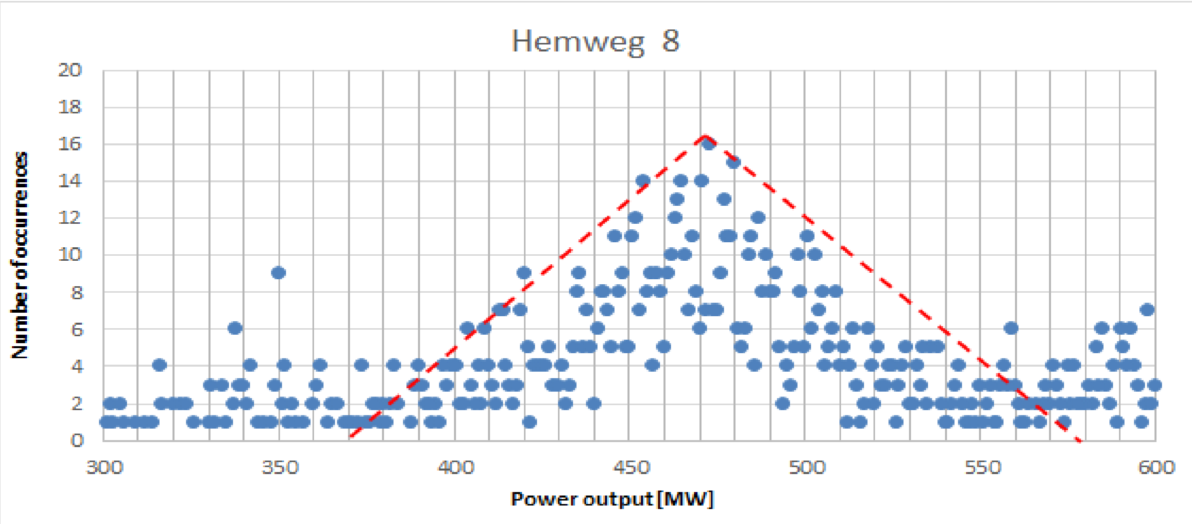

Figure 34 Scatterplot of number of occurrences of power output level taken zoomed in on point of oscillation. The section which is enclosed in the red dotted line signifies the estimated size of the contract multiplied by two. As a result the estimated contract of Vattenfall is 105 MW $(\frac{580-370}{2})$.

A.2.1 Conclusion: Market share of producers

It is obviously a little bit more difficult to establish what the share of each electricity producers is as compared to which producer is participates in the market. However, when examining all scatterplots, a clear oscillation pattern emerges but only with parties of which it is concluded that these presumably have a contract.

In 2015 TenneT procured 300 MW. Considering the results as presented in Table 13 it can be seen that the summarized volume of the contract sizes adds up to 320 MW. This is therefore not possible. However, this overestimated volume can be attributed to additional voluntary regulating power provision. The market share results of Table 13 should therefore be regarded as relatively to the market share of all parties.

Table 13 Summary of the results of market share analysis. Total volume which was auctioned in 2015 equaled 300MW. Relative market share is calculated by dividing the estimated contract size by the summarized total estimated estimate.

Producer	Active plants	Estimated contract size	Relative market share
EON	• Maasvlakte 1 • Maasvlakte 2 • Roca 3	105	33%
RWE	• Amer 8 • Amer 9 • Moerdijk 1 • Moerdijk 2 • Swentibold	110	34%
Vattenfall	• Diemen 33 • Diemen 34 • Eemshaven 10 • Eemshaven 20 • Eemshaven 30 • Hemweg 8 • Hemweg 9	105	33%

In order to establish the amount of competition in a market the Herfindahl-Hirschman index (HHI), is used. HHI is a commonly accepted measure of market concentration. The HHI is calculated by squaring the market share of each firm competing in the market and then summing the resulting numbers (see Eq.8).

$$HHI = \sum_{i=1}^{N} s_i^2 \tag{8}$$

Where

- s_i is the market share of firm I in the market
- N indicates the numer of firms

An HHI index of 10000 is a true monopoly, whilst an index of 1000 is considered a perfectly competitive market. Using the relative market shares as percentages found in Table 13 leads to a HHI market concentration of 3335. This indicates a very concentrated market and is generally considered as an oligopolistic market.

B: Calculating opportunity costs

The cost of providing reserve capacity for producers is mainly determined by the *Opportunity costs* of keeping capacity part loaded and not being able to sell the reserved capacity in other parts of the wholesale capacity market. As this study means to incorporate realistic data in the auction simulator, this means that in order to calculate the payoffs associated with the strategies of the participating producers, these opportunity costs have to be calculated.

Electricity producers approximate the opportunity costs by using optimization models which incorporates the following main portfolio properties and forecasted market circumstances:

- Min/max capacity
- Start costs
    - Start fuel cost
        - Fuel price
        - Fuel type
    - Fixed start cost
- Stop costs
- Operational cost
    - Fuel cost
        - Efficiency
        - Fuel price
    - CO_2 cost
        - Type of fuel
        - CO_2 factor
        - CO_2 certificate price
    - Variable Operation and Maintenance (VOM) cost

In this manner the opportunity costs for a given contract is estimated by examining the commitment and dispatch of a the production portfolio with and without a reserve contract. The change in production cost between the two scenarios is then roughly equal to the spot market price minus the producer's incremental production cost multiplied by the reserve amount provided by the producer (Hummon, et al., 2013).

As a first step it is therefore necessary to establish which units are estimated to be profitable. This is done in unit commitment models which determine the unit commitment based on the technical and financial characteristics of each unit and the forecasted fuel and electricity prices. However, the technical and financial characteristics of power plants is considered to be very confidential information and are therefore not publically available. This approach is therefore a bit problematic for the purpose of this study. Fortunately, the unit commitment has already been established in 2015 and is readily available in the ENTSO-E data, see Table 14 for a sample of this data. This thereby circumvents the necessity to have all information regarding the financial and technical characteristics of each unit.

Table 14 Sample of ENTSO-E generation data as taken on the portfolio of ENGIE

DATE	HOURS	EC3	EC4	EC5	EC6	EC7	FL4	FL5	MVL380
22/11/2015	20:00 - 21:00	0	379	370	338	340	0	396	0
22/11/2015	21:00 - 22:00	0	355	355	329	318	0	382	0
22/11/2015	22:00 - 23:00	0	318	245	306	281	0	362	0
22/11/2015	23:00 - 00:00	0	350	366	325	3	0	386	0
23/11/2015	00:00 - 01:00	0	27	286	257	2	0	166	95
23/11/2015	01:00 - 02:00	0	0	266	196	1	0	0	250
23/11/2015	02:00 - 03:00	0	0	117	189	0	0	0	372
23/11/2015	03:00 - 04:00	0	0	0	235	0	1	0	454
23/11/2015	04:00 - 05:00	0	0	0	168	0	52	0	491
23/11/2015	05:00 - 06:00	0	14	61	208	54	159	56	496
23/11/2015	06:00 - 07:00	0	192	190	203	188	206	216	588
23/11/2015	07:00 - 08:00	0	288	313	278	293	306	318	711

Having established which units are running in 2015 it is then only necessary to establish the most optimal dispatch for each unit. The optimal dispatch is established by comparing *the incremental production costs* of the units which were operational with the spot market price at that time. The incremental production costs are determined by the following characteristics of each unit:

- Min/max capacity
- Fuel cost
  - Efficiency
  - Fuel price
- CO_2 cost
  - CO_2 factor
  - CO_2 price

The minimal and maximal capacity of each unit can be found by analyzing the data to look for production patterns at specific market conditions. In this process the following logic is applied:

- Minimal capacity
  - ➢ Analyze ENTSO-E data to discover patterns where a unit is running at a lower than optimal load with a high number of occurences. Investigate patterns and apply rule of thumb that minimal capacity is $\pm \frac{Capacity_{max}}{3}$.
- Maximal capacity
  - ➢ Analyze ENTSO-E data to find maximal output of power plants. Adjust maximal capacity for weather influences.

Determining the efficiency of each unit is a little more complicated. The reason for this is that the efficiency of a unit is greatly determined by the load under which it operates. It is therefore not so much a single efficiency but rather an efficiency curve.

At maximal load a gas fired plant averagely runs over 12 percent more efficient as compared to running at minimal load and for coal fired plants this difference averages somewhere around 6 percent (source). For the sake of keeping it manageable this study has simplified the problem by assuming that the efficiency follows a linear path between the efficiency found at minimal load and that which is found at maximum load. The minimum and maximum efficiency have been established and refined by a combination of the following applied logic and approaches.

- Reverse engineer the efficiencies of each unit by analyzing ENTSO-E data
- Compare plant with unknown effciencies with plants with known efficiencies
- Counsel with experts and professionals
- Investigate publications for information regarding the plants efficiency
- Compare with simular plants of a certain age

The two previously discussed approaches have resulted in Table 15 in which the technical characteristics have been depicted.

Table 15 Technical characteristics of power plants active in reserve provision market (as established in Appendix A). Units of Vattenfall have been left out intentionally with regard to confidentiality.

Unit	Fuel	Year of construction	Min load	Max load	Efficiency at min load	Efficiency at max load
EC3	GAS (IGCC)	1996	140	383	0,4100023	0,5300023
EC4	GAS (IGCC)	1996	140	383	0,4100023	0,5300023
EC5	GAS (IGCC)	1996	140	383	0,4100023	0,5300023
EC6	GAS (IGCC)	1997	140	383	0,4100023	0,5300023
EC7	GAS (IGCC)	1997	140	383	0,4100023	0,5300023
FL4	GAS (IGCC)	2010	120	452	0,4823743	0.5850031
FL5	GAS (IGCC)	2010	120	452	0,4823743	0.5850031
MVL380	COAL/80%Biomass	2015	200	735	0,4150021	0,4650021
Msvlkt 1	COAL	1989	150	520	0,3500007	0,4000007
Msvlkt 2	COAL	1988	150	520	0,3500007	0,4000007
Msvlkt 3	COAL	2015	400	1000	0,4050072	0,4650072
RoCa 3	GAS (IGCC)	1997	80	218	0,3730409	0,4941228
Amer 8	COAL	1981	180	590	0,3250031	0.3690033
Amer 9	COAL	1994	190	590	0,3767597	0,4236348
Moerdijk 1	GAS (IGCC)	1998	95	220	0,3730409	0,4941228
Moerdijk 2	GAS (IGCC)	2012	200	430	0,4923743	0,5972720
Swentibold 1	GAS (IGCC)	1999	80	220	0,3640076	0,4840076
Eemshaven A	COAL /Biomass	2015	200	800	0,4000022	0,4500022
Eemshaven B	COAL /Biomass	2016	200	800	0,4000022	0, 4500022
Diemen 33	GAS (IGCC)	[redacted]				
Diemen 34	GAS (IGCC)					
Eemshaven 10	GAS (IGCC)					
Hemweg 8	COAL					
Hemweg 9	GAS (IGCC)					

It now becomes possible to calculate the incremental production cost of each unit. This is calculated by the formula:

$$Incremental\ cost\ = \frac{\left(\frac{Load_{max}}{Eff_{min}} \times Fuel\ price\right) - \left(\frac{Load_{min}}{Eff_{min}} \times Fuel\ price\right)}{Load_{max} -\ \ Min\ cap} \tag{9}$$

The incremental cost of production is dependent on the fuel price, as can be seen from Eq.9. This means that incremental costs have to be calculated for each day of the year as the fuel market are generally cleared on a daily basis.

Having calculated the incremental production cost of each unit it now becomes possible to establish the optimal dispatch for each unit throughout the year 2015. This is simply done by comparing the APX price with the incremental cost of each operational unit. If the incremental cost is lower than the APX price, then the plants are profitable and should be running on full power. If the incremental costs are higher than the APX price, then the plants are running at a loss and should be operating at the minimal load. The optimal dispatch of each portfolio throughout 2015 can therefore be established by doing this for each unit and for each hour of the year, In Table 16 a sample of the optimal dispatch of the sample of the original dispatch of Table 15 can be found.

Table 16 Optimal dispatch as taken on the sampled generation data of Table 15

DATE	HOURS	EC3	EC4	EC5	EC6	EC7	FL4	FL5	MVL380
22/11/2015	20:00 - 21:00	0	383	383	383	383	0	452	0
22/11/2015	21:00 - 22:00	0	383	383	383	383	0	452	0
22/11/2015	22:00 - 23:00	0	140	140	140	140	0	120	0
22/11/2015	23:00 - 00:00	0	140	140	140	0	0	120	0
23/11/2015	00:00 - 01:00	0	140	140	140	0	0	120	735
23/11/2015	01:00 - 02:00	0	0	140	140	0	0	0	735
23/11/2015	02:00 - 03:00	0	0	140	140	0	0	0	735
23/11/2015	03:00 - 04:00	0	0	0	383	0	0	0	735
23/11/2015	04:00 - 05:00	0	0	0	140	0	120	0	735
23/11/2015	05:00 - 06:00	0	140	140	140	140	120	120	735
23/11/2015	06:00 - 07:00	0	383	383	383	383	452	452	735
23/11/2015	07:00 - 08:00	0	383	383	383	383	452	452	735

It now becomes possible to calculate the opportunity costs. This is done according to the logic:

1. Calculate up- and downward oppurtunity costs
   a. Upward oppurtunity cost:
      i. If any of the plants available in the portfolio is running at minimal load then the upward oppurtunity cost is zero.
      ii. If none of the plants available in the portfolio is running at minimal load then the upward oppurtunity cost is calculated by multiplying the contract size by the available unit with the highest incremental cost.
   b. Downward oppurtunity costs:
      i. If any of the plants available in the portfolio is running at maximal load then the downward oppurtunity cost is zero.

ii. If none of the plants available in the portfolio is running at minimal load then the downward oppurtunity cost is calculated by multiplying the contract size by the available unit with the lowest incremental cost.

2. The total oppurtunity costs for 2015 are then calculated by sumurizing the up- and downward oppurtunity costs over the entire year. Steps 4 and 5 should be repeated for each contract size (e.g. 5, 10, … 180 MW).

Following step 1 and 2 will lead to entirely linear cost curves. However, these cost curves are generally not linear due to the fact that each unit has a limited capacity for providing reserve power. In order to calculate the piece wise linear cost curves the following additional steps need to be taken:

3. For each unit determine the maximal capacity for providing reserve power, see Eq. 10.

$$Capacity_{reserve} = \frac{P_{max} - P_{min}}{2} \tag{10}$$

4. Proceed with step 1 and 2 for each contract level but this time remove a unit if the capacity for providing reserve power exceeds the contract size.
5. Continue until the maximal capcity for providing reserve power of the portfolios has been reached.

Following steps 1 to 5 it can be deduced that for each hour there are four possibilities:

1. Only downward oppurtunity costs
2. Only upward oppurtunity costs
3. No oppurtunity costs
4. Both upward and downward oppurtunity costs

The first possibility arises when the spot market is profitable for a unit, which is to say that the unit's incremental cost is below the electricity spot price. The opportunity costs then arise from revenue losses caused by being forced to run at a lower load and thereby not being able to use the full capacity in the spot market.

The third source of opportunity costs arise in the opposite case, when the electricity market price is lower than the unit's incremental cost. This means that the unit is making a loss and the provision of operating reserves than entails the cost of having to run at higher than minimal load. This means that the opportunity cost then emanates from plants that are actually forced to make an even greater loss.

The third case is only possible when the APX price is in-between the incremental cost of some of the operational plants within the portfolio. The reason for this is that upward reserve may than freely be provided by a plant which is already running at a minimal load, while downward reserve can be provided without costs by plants which are running at maximal load. Having both plants available which are running at minimum- and at maximum load means that no costly changes have to be made with respect to the optimal dispatch.

In the fourth and last scenario the costs are incurred on both sides. This is only possible if the possibility to provide reserve power is limited by a plant. This can be in all directions. The resulting opportunity cost levels are presented in Figure 35.

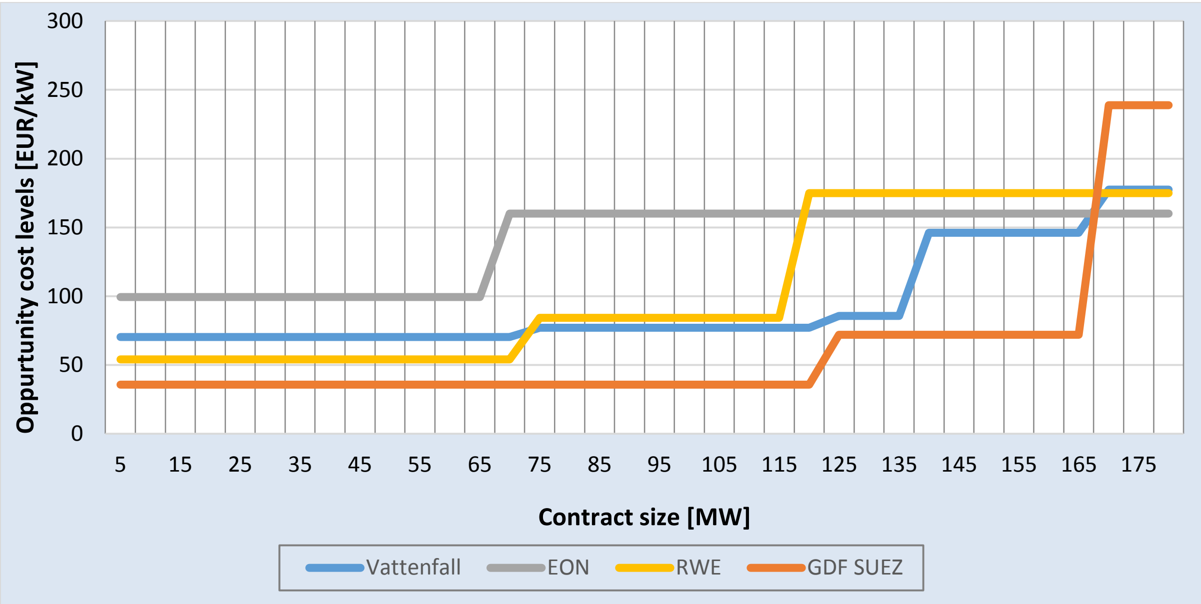

Figure 35 Opportunity cost levels for different sized contracts. Total opportunity costs are calculated by multiplying the contract size with the opportunity cost level.

C: Strategy sets

Table 17 Heuristic lookup table of the strategies in 3P- games with piece wise distinction.

Strategies	1st section	2nd section	3rd section
1	low	low	low
2	low	low	medium
3	low	low	high
4	low	medium	low
5	low	medium	medium
6	low	medium	high
7	low	high	low
8	low	high	medium
9	low	high	high
10	medium	low	low
11	medium	low	medium
12	medium	low	high
13	medium	medium	low
14	medium	medium	medium
15	medium	medium	high
16	medium	high	low
17	medium	high	medium
18	medium	high	high
19	high	low	low
20	high	low	medium
21	high	low	high
22	high	medium	low
23	high	medium	medium
24	high	medium	high
25	high	high	low
26	high	high	medium
27	high	high	high

D: Experimentation results: 3P- games with piece wise distinction

Table 18 Results of experiments A-F.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. A	129.75	120	115	65	14542857	12299999	7474999	25405458	38924504	13519046	35194046
Exp. B	119.22	120	115	65	12600000	11588888	8774999	25405458	35764513	10359055	32034055
Exp. C	114.68	120	115	65	11400000	11149999	8124999	25405458	34405456	8999998	30674998
Exp. D	112.52	120	115	65	11400000	11149999	7474999	25405458	33755456	8349998	30024998
Exp. E	122.52	120	115	65	12600000	12299999	8124999	25405458	36755456	11349998	33024998
Exp. F	120.35	120	115	65	12600000	12299999	7474999	25405458	36105456	10699998	32374998

Table 19 Parameters of experiments A-F.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. A	300	20	60	20	60	-20	20
Exp. B	300	0	40	0	40	0	40
Exp. C	300	0	30	0	30	0	30
Exp. D	300	0	30	0	30	-10	20
Exp. E	300	10	40	10	40	0	30
Exp. F	300	10	40	10	40	-10	20

Table 20 Results of experiments A. Indicated by the asterisks are the experiments in which the total demand is divided over two separate auctions.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. A1	85.0514	75	70	25	8250000	7874999	2374999	12058738	14458736	2399998	18499998
Exp. A2	110.937	85	70	65	10500000	10674999	6174999	16806110	24406108	7599998	27349998
Exp. A3	116.837	120	70	60	12600000	10674999	7049999	19009161	29209159	10199998	30324998
Exp. A4	129.748	120	115	65	14542857	12299999	7474999	25405458	38924504	13519046	35194046
Exp. A5	145.823	101	115	124	14923810	12299999	7933332	36617059	49579908	12962848	35862848
Exp. A6	156.914	120	115	165	15000000	14599999	11549999	45365705	62765703	17399998	41149998
Exp. A7	205.656	165	155	180	18150000	17449999	11999999	80027834	102827833	22799999	47599999
Exp. A0a*	172.761	55	45	70	4450000	3024999	5824999	17511426	29369439	11858013	28558013
Exp. A0b*	128.906	130	115	95	12700000	10899998	8199998	36040330	43828175	7787845	30687845

Table 21 Parameters of experiments A. Indicated by the asterisks are the experiments in which the total demand is divided over two separate auctions.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. A1	170	20	60	20	60	-20	20
Exp. A2	220	20	60	20	60	-20	20
Exp. A3	250	20	60	20	60	-20	20
Exp. A4	300	20	60	20	60	-20	20
Exp. A5	340	20	60	20	60	-20	20
Exp. A6	400	20	60	20	60	-20	20
Exp. A7	500	20	60	20	60	-20	20
Exp. A0a*	170	20	60	20	60	-20	20
Exp. A0b*	340	20	60	20	60	-20	20

Table 22 Results of experiments B. Indicated by the asterisks are the experiments in which the total demand is divided over two separate auctions.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. B1	95.93	105	70	0	9600000	9274999	0	11888103	16788101	4899998	18874998
Exp. B2	101.00	108	70	42	10300000	9274999	5441666	15864034	22220176	6356142	24631142
Exp. B3	101.64	120	70	60	10200000	9274999	7049999	19009161	25409159	6399998	26524998
Exp. B4	123.80	120	115	65	12600000	12034614	8774999	25405458	37140071	11734613	33409613
Exp. B5	135.23	128	115	77	13016667	11277777	9063888	32409273	43272214	10862941	33162941
Exp. B6	146.48	135	115	100	13350000	12299999	11399999	37269466	51269464	13999998	37049998
Exp. B7	153.19	135	115	150	13350000	12299999	14099999	45275871	61275869	15999998	39749998
Exp. B8	200.06	165	155	180	14850000	14349999	15599999	80027834	100027833	19999999	44799999
Exp. B0a*	185.04	30	45	100	1650000	2849999	11399999	20557391	32381362	11823971	27323971
Exp. B0b*	140.48	135	115	100	11250000	12124998	11399999	37269466	49169463	11899997	34949997

Table 23 Parameters of experiments B. Indicated by the asterisks are the experiments in which the total demand is divided over two separate auctions.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. B1	175	0	40	0	40	0	40
Exp. B2	220	0	40	0	40	0	40
Exp. B3	250	0	40	0	40	0	40
Exp. B4	300	0	40	0	40	0	40
Exp. B5	320	0	40	0	40	0	40
Exp. B6	350	0	40	0	40	0	40
Exp. B7	400	0	40	0	40	0	40
Exp. B8	500	0	40	0	40	0	40
Exp. B0a*	175	0	40	0	40	0	40
Exp. B0b*	350	0	40	0	40	0	40

E: Experimentation results: 3P- games without piece wise distinction

Table 24 Results of experiments A-Q.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. A	110.685	120	115	65	10920000	10689999	7864999	25405458.02	33205456	7799998	29474998
Exp. B	136.685	120	115	65	14040000	13679999	9554999	25405458.02	41005456	15599998	37274998
Exp. C	136.252	120	115	65	14040000	13679999	9424999	25405458.02	40875456	15469998	37144998
Exp. D	134.518	120	115	65	14040000	13679999	8904999	25405458.02	40355456	14949998	36624998
Exp. E	118.518	120	115	65	12120000	11839999	7864999	25405458.02	35555456	10149998	31824998
Exp. F	107.652	120	115	65	10920000	10689999	6954999	25405458.02	32295456	6889998	28564998
Exp. G	116.351	120	115	65	12120000	11839999	7214999	25405458.02	34905456	9499998	31174998
Exp. H	132.352	120	115	65	14040000	13679999	8254999	25405458.02	39705456	14299998	35974998
Exp. I	115.485	120	115	65	12120000	11839999	6954999	25405458.02	34645456	9239998	30914998
Exp. J	130.185	120	115	65	14040000	13679999	7604999	25405458.02	39055456	13649998	35324998
Exp. K	123.318	120	115	65	13320000	12989999	6954999	25405458.02	36995456	11589998	33264998
Exp. L	128.018	120	115	65	14040000	13679999	6954999	25405458.02	38405456	12999998	34674998
Exp. M	157.685	120	115	65	18120000	17589999	7864999	25405458.02	47305456	21899998	43574998
Exp. N	155.518	120	115	65	18120000	17589999	7214999	25405458.02	46655456	21249998	42924998
Exp. O	155.518	120	115	65	18120000	17589999	7214999	25405458.02	46655456	21249998	42924998
Exp. P	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. Q	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash

Table 25 Parameters of experiments A-Q.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. A	300	0	26	0	26	0	26
Exp. B	300	0	52	0	52	0	52
Exp. C	300	0	52	0	52	-54	50
Exp. D	300	0	52	0	52	-10	42
Exp. E	300	10	36	10	36	0	26
Exp. F	300	0	26	0	26	-40	12
Exp. G	300	10	36	10	36	-10	16
Exp. H	300	0	52	0	52	-20	32
Exp. I	300	10	36	10	36	-40	12
Exp. J	300	0	52	0	52	-30	22
Exp. K	300	20	46	20	46	-40	12
Exp. L	300	0	52	0	52	-40	12
Exp. M	300	60	86	50	86	0	26
Exp. N	300	60	86	60	86	-10	16
Exp. O	300	60	86	60	86	-10	16
Exp. P	300	60	86	60	86	-10	16
Exp. Q	300	80	106	80	106	0	26

Table 26 Result of experiments A.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. A1	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A2	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A3	119	120	115	65	12120000	11840000	7865000	25405458	35555456	10149998	31825000
Exp. A4	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A5	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A6	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A7	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A8	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A9	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A10	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. A11	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash

Table 27 Parameters of experiments A.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. A1	170	0	26	0	26	0	26
Exp. A2	240	0	26	0	26	0	26
Exp. A3	300	0	26	0	26	0	26
Exp. A4	305	0	26	0	26	0	26
Exp. A5	310	0	26	0	26	0	26
Exp. A6	315	0	26	0	26	0	26
Exp. A7	340	0	26	0	26	0	26
Exp. A8	380	0	26	0	26	0	26
Exp. A9	390	0	26	0	26	0	26
Exp. A10	440	0	26	0	26	0	26
Exp. A11	520	0	26	0	26	0	26

Table 28 Results of experiments B.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. B1	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B2	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B3	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B4	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B5	136.68	120.00	115.00	65	14040000	13680000	9555000	25405458	41005456	15599998	37275000
Exp. B6	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B7	139.81	135.00	115.00	60	14970000	13680000	8970000	27220554	43340552	16119998	37620000
Exp. B8	139.99	135.00	115.00	65	14970000	13680000	9555000	27717545	44097543	16379998	38205000
Exp. B9	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B10	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B11	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B12	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B13	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. B14	162.06	135.00	115.00	125	14970000	13680000	14350000	41272669	60772667	19499998	43000000
Exp. B15	162.72	135.00	115.00	130	14970000	13680000	14660000	42073309	61833307	19759998	43310000
Exp. B16	163.99	135.00	115.00	140	14970000	13680000	15280000	43674590	63954588	20279998	43930000
Exp. B17	165.19	135.00	115.00	150	14970000	13680000	15900000	45275871	66075869	20799998	44550000
Exp. B18	167.42	135.00	115.00	170	14970000	13680000	17140000	48478433	70318431	21839998	45790000
Exp. B19	187.00	165.00	115.00	160	16830000	13680000	16520000	59400533	82280532	22879999	47030000
Exp. B20	212.63	165.00	175.00	180	16830000	17450000	17760000	83526159	110566158	27039999	52040000

Table 29 Parameters of experiments B.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. B1	170	0	52	0	52	0	52
Exp. B2	240	0	52	0	52	0	52
Exp. B3	260	0	52	0	52	0	52
Exp. B4	280	0	52	0	52	0	52
Exp. B5	300	0	52	0	52	0	52
Exp. B6	305	0	52	0	52	0	52
Exp. B7	310	0	52	0	52	0	52
Exp. B8	315	0	52	0	52	0	52
Exp. B9	320	0	52	0	52	0	52
Exp. B10	330	0	52	0	52	0	52
Exp. B11	340	0	52	0	52	0	52
Exp. B12	360	0	52	0	52	0	52
Exp. B13	370	0	52	0	52	0	52
Exp. B14	375	0	52	0	52	0	52
Exp. B15	380	0	52	0	52	0	52
Exp. B16	390	0	52	0	52	0	52
Exp. B17	400	0	52	0	52	0	52
Exp. B18	420	0	52	0	52	0	52
Exp. B19	440	0	52	0	52	0	52
Exp. B20	520	0	52	0	52	0	52

Table 30 Results of experiments G.

Exp. name	Cost [EUR/kW]	Contr Vf [MW]	Contr RWE [MW]	Contr EON [MW]	Payoff Vf	Payoff RWE	Payoff EON	Total cost producers	Total cost TSO	Rent taken by producers	Rent incl. activation
Exp. G1	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G2	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G3	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G4	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G5	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G6	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G7	107.40	120	70	65	12120000	8995000	7215000	-19506152	-27386150	7879998	28330000
Exp. G8	111.62	125	70	65	12350000	8995000	7215000	-20961249	-29021247	8059998	28560000
Exp. G9	111.99	135	70	65	12810000	8995000	7215000	-21818240	-30238237	8419997	29020000
Exp. G10	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G11	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G12	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash	No nash
Exp. G13	116.22	120	105	65	12120000	11280000	7215000	-24563086	-33703084	9139998	30615000
Exp. G14	116.29	120	110	65	12120000	11560000	7215000	-24984272	-34304270	9319998	30895000
Exp. G15	116.35	120	115	65	12120000	11840000	7215000	-25405458	-34905456	9499998	31175000
Exp. G16	119.84	130	115	65	12580000	11840000	7215000	-27289050	-37149048	9859998	31635000
Exp. G17	134.99	120	115	105	12120000	11840000	9180000	-35758019	-45898018	10139999	33140000
Exp. G18	139.32	120	115	145	12120000	11840000	10370000	-42163143	-52943141	10779998	34330000
Exp. G19	143.33	135	115	170	12810000	11840000	11020000	-48478433	-60198431	11719998	35670000
Exp. G20	164.27	165	115	180	14190000	11840000	11280000	-62603095	-75563094	12959999	37310000
Exp. G21	172.78	135	165	180	12810000	14190000	11280000	-69253615	-82933614	13679999	38280000
Exp. G22	188.86	165	155	180	14190000	13730000	11280000	-80027834	-94427833	14399999	39200000
Exp. G23	189.29	165	165	180	14190000	14190000	11280000	-81776997	-96536996	14759999	39660000
Exp. G24	189.70	165	175	180	14190000	14650000	11280000	-83526159	-98646158	15119999	40120000
Exp. G0a	271.18	45	95	115	2070000	5195000	4065000	-29581448	-69150843	39569395	26605000
Exp. G0b	189.29	165	165	180.00	14190000	14190000	11280000	-49087601	-96536996	14759999	39660000

Table 31 Parameters of experiments G.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE [low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]
Exp. G1	170	10	36	10	36	-10	16
Exp. G2	175	10	36	10	36	-10	16
Exp. G3	180	10	36	10	36	-10	16
Exp. G4	220	10	36	10	36	-10	16
Exp. G5	240	10	36	10	36	-10	16
Exp. G6	250	10	36	10	36	-10	16
Exp. G7	255	10	36	10	36	-10	16
Exp. G8	260	10	36	10	36	-10	16
Exp. G9	270	10	36	10	36	-10	16
Exp. G10	275	10	36	10	36	-10	16
Exp. G11	280	10	36	10	36	-10	16
Exp. G12	285	10	36	10	36	-10	16
Exp. G13	290	10	36	10	36	-10	16
Exp. G14	295	10	36	10	36	-10	16
Exp. G15	300	10	36	10	36	-10	16
Exp. G16	310	10	36	10	36	-10	16
Exp. G17	340	10	36	10	36	-10	16
Exp. G18	380	10	36	10	36	-10	16
Exp. G19	420	10	36	10	36	-10	16
Exp. G20	460	10	36	10	36	-10	16
Exp. G21	480	10	36	10	36	-10	16
Exp. G22	500	10	36	10	36	-10	16
Exp. G23	510	10	36	10	36	-10	16
Exp. G24	520	10	36	10	36	-10	16
Exp. G0a	255	10	36	10	36	-10	16
Exp. G0b	510	10	36	10	36	-10	16

F : Experimentation results: 4P- games with piece wise distinction

Table 32 Results of experiments A. Indicated by the asterisks are the experiments in which the total demand is divided over two separate auctions.

Exp. name	Numb Nash	Cost [EUR/kW]	Distribution of contracts				Distribution of Payoffs			
			Vf	RWE	EON	ENGIE	Vf	RWE	EON	ENGIE
A1	13122	75.90	100	70	0	0	7400000	7874999	0	0
A2	1458	97.81	120	70	65	85	10200000	9274999	6174999	8800000
A0a*	10935	111.97	25	0	65	80	1450000	0	6174999	10199999
A0b*		93.93	125	70	65	80	8850000	7874999	6174999	10199999

Table 33 Parameters of experiments A. Indicated by the asterisks are the experiments in which the total demand is divided over two separate auctions.

Exp. name	Demand	Bidrange Vf [low]	Bidrange Vf [high]	Bidrange RWE[low]	Bidrange RWE [high]	Bidrange EON [low]	Bidrange EON [high]	Bidrange ENGIE [low]	Bidrange ENGIE [high]
A1	170	0	40	0	40	0	40	0	40
A2	340	0	40	0	40	0	40	0	40
A0a*	170	0	40	0	40	0	40	0	40
A0b*	340	0	40	0	40	0	40	0	40

G: strategy coordinate system

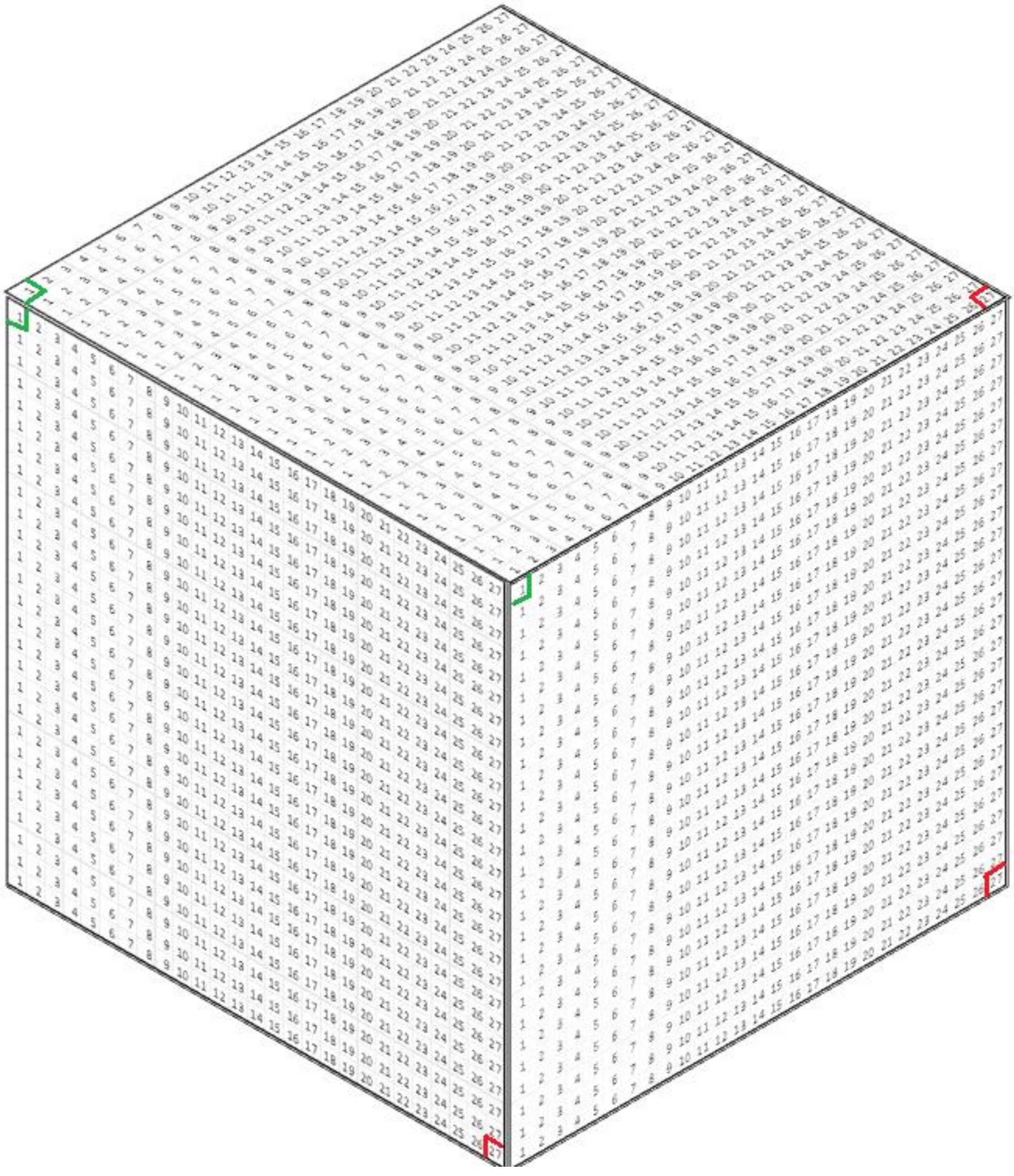

Figure 36 Strategy coordinate system of the 3 player game. Each of the players have a strategy set composed of 27 different strategies. The total amount of possible combinations of strategies therefore equals 27^3, or 19683 coordinates, represented by the volume of this 3D matrix. In relation to the auction game, the combination of strategies that together represent the strategy coordinate which is most efficient from a socio welfare perspective (green), and least efficient coordinate from a social welfare perspective (red), can be seen.