MSc thesis in Engineering and Policy Analysis

Simulating Bidding Behaviour on Offshore Wind Farm Tenders

Anna Noteboom

2022

SIMULATING BIDDING BEHAVIOUR ON OFFSHORE WIND FARM TENDERS

Master thesis submitted to Delft University of Technology
in partial fulfillment of the requirements for the degree of

Master of Science
in Engineering and Policy Analysis
Faculty of Technology, Policy and Management

by

Anna Noteboom

Student number: 4564979

To be defended in public on July 14 2022

Graduation committee

Chairperson:	Dr. Igor Nikolic, Section of Systems Engineering
First Supervisor	Dr. Yilin Huang, Section of Systems Engineering
Second Supervisor	Dr. Zenlin Roosenboom-Kwee, Section of Economics of Technology and Innovation
External supervisor:	Dr. Adam Eales, Shell International

Anna Noteboom: *Simulating Bidding Behaviour on Offshore Wind Farm Tenders* (2022)

Credits for the picture on the front page: Shell International (2022).

The work in this thesis was made at:

TU Delft TPM
Msc Engineering and Policy Analysis
Faculty of Technology, Policy & Management
Delft University of Technology

EXECUTIVE SUMMARY

Over the past decade, renewable power generation through wind power has increased significantly. Especially the installation of offshore wind energy is expected to skyrocket to a total of 2000 GW by 2050. The majority of rights to develop and operate offshore wind farms are allocated through tendering procedures. In tender procedures, interested parties issue a bid, which includes a subsidy price called strike price at which the party would be willing to accept to develop and operate the wind farm. Lower strike prices increase the chance of winning the tender.
In principle, this should lead to the cost-effective deployment of wind energy. However, current wind farm tender designs have been found to cause multiple undesirable results. Understanding the behaviour of the bidding parties that leads to these flaws will help policy makers improve the design of offshore wind farm tenders to counteract this.
Current modelling methods have failed to incorporate the influence of bounded rationality in the bidding procedure together with a realistic representation of the economic valuation of the tenders, which all bidding organisations conduct. This knowledge gap is addressed in this thesis with the main research question:

How can organisational bidding behaviour on a wind farm tender be captured in an agent based model, considering the economic value assessment of the tender by each organisation?

This main research method is the development of a coupled economic-agent-based model. The economic model is a valuation model that is provided by an industrial collaborator and represents a simplified yet realistic valuation of wind farm tenders.
The main research question is supported by the following sub-questions:

1. *What mechanisms drive organisational bidding behaviour?*
2. *How can the bidding on tenders be modelled to realistically represent organisational bidding behaviour?*
3. *How can the value assessment by bidding actors be considered in the modelling approach?*
4. *What is the validity of the model so that it realistically represents bidding behaviour on wind farm tenders?*
5. *What insights are created by the model into the bidding behaviour on wind farm tenders?*

The first sub-question is answered by a literature review on bounded rational behaviour. Next to the economic considerations that occur in bidding organisations, several biases have been found in the way organisations reason in situations where they have to invest in an asset.

The second sub-question is addressed through the development of an agent based model (ABM) that simulates to some extent the bounded rational decision making process of bidding into a tender. In the model, several agents consider a sequence of tenders. Agents are limited in resources which means they cannot invest in all good opportunities and have to prioritise. When prioritising, the agents consider their desire to achieve their profit target as well as their target in terms of total installed wind power capacity.

Agents can interact with a valuation model that is coupled to the ABM. Through this interaction, the agents formulate the expected value of the tenders. This perceived value formed the basis of the agents' bid on the tender. The interface between the ABM and the valuation model consists of the most influential input parameters of the valuation model, which were found through the conduct of a global sensitivity analysis. Tenders in the model differed in these parameters, and agents in the model could define their input parameters for the valuation model, based on their strategy. This interfacing between the ABM and the valuation part of the coupled model answers the third research sub-question.

Regarding sub-question four, the model has been validated through the method of face-validation with the industrial collaborator. The model logic and outcomes have been consulted and the results of the model traced back to its originating mechanism, which where realistic.

To answer sub-question five, experimentation with the model led to two main insights. First, model outcomes suggest that auctioning tenders in increasing order in terms of capacity could lead to a more polarised distribution of tender capacity per agent. This polarisation shifts to a leveling effect when auctioning tenders in decreasing order. A decreasing order of capacity where the difference in capacity between each tender is about 75 MW appears to level the distribution the most between the competing organisations. This can be interpreted as policy advice for governments to allocate a decreasing capacity to a sequence of offshore wind farm tenders as this can create the most competitive market for offshore wind capacity.
A second insight is a significant influence the budgets of competing organisations have on the chance for these organisation at winning specific tenders. The hypothesis that the total budget of the agents that compete for a sequence of tenders together with the variance in the distribution of the budgets would be the explaining factor for this varying chance of winning tenders was rejected. Translating this finding into a policy recommendation for commercial businesses is that it is important to consider the resources of the competition as this greatly impacts their bidding strategy and therefore the organisations chance of winning tenders.

Further investigation is necessary as the model presented in this thesis still omits behavioural complexities that can impact the resulting behaviour significantly. The most important recommendations for model expansions include the implementation of various assumptions of asset properties for the different organisations in the model, the inclusion of behaviour surrounding the formation of Joint Ventures, the inclusion of additional objectives for organisations regarding offshore wind, and lastly the inclusion of learning and adapting behaviour of the agents.
The work presented in this thesis is a proof of concept for using coupled modelling for socio-economic processes with a strategic component. The work contributed to the usage of model coupling in cross-disciplinary studies and encourages the research community to use coupled modelling for socio-economic processes in other domains as well.

ACKNOWLEDGEMENTS

This thesis concludes my time as a student of first the bachelor of Technology, Policy, and Management and now of the master Engineering and Policy Analysis. My time at the faculty of TPM has first sparked my interest and later nurtured my growing knowledge and skill in system thinking, simulation, and data science. This thesis shows what all this time has taught me and what I shall use as a foundation for my upcoming career.

I most certainly did not walk this path alone and I have many people to thank. Starting with my amazing supervisors from Shell, Adam, and Martina, thank you for all our meetings, words of insight, encouragement, and support. Your sharp eye, keen interest, and endless source of ideas are what made this thesis what it has become. Secondly, I would like to thank my supervisors from TPM, for your time and valuable feedback. Especially Yilin, not only for your supervision and feedback but also for our nice talks about houses and moving and life in general.

Then, when talking about foundation, thank you sweet parents for supporting me my whole life. You have been with me every step of the way, encouraging me to follow my heart and giving me the confidence, trust, and drive I needed to become the person I am today. You two shall always remain my biggest role models.

I would also like to thank my sweet boyfriend Sebas, who supported me from step one, pushed me to give it my all, gave me space when all I could think about was agents and tenders and was always there when I really really did not want to think about agents and tenders anymore. I am looking forward to all our future adventures.

Talking about people that kept me sane as a thesis writer, thank you to all my study buddies that worked alongside me in Stilteruimte A and when that was closed in Echo. In alphabetical order: Thank you Alma, Auriane, Job, Olivier, Otmar, Laurie, Lieke, Lotte, Martijn, Simone, Stephan, and Tim for the shared coffee breaks, lunches, and walks on campus. I know it is weird to thank products but thank you laptop stand Wouldstand for saving my posture. Thank you also sweet roommates for hanging out, sharing dinners and good times, and of course, listening to me going on and on about wind farms over the past 6 months. Lastly, thank you to all my awesome friends who made my life in Delft epic and amazing. Thank you Kroegploeg, EJD19, Forze friends, and Awesome EPA's. A very special shout out to the Potvissen, the friends I hope to have until the end of time, nobody swims like us.

After this big stream of thank yous, some details about my thesis time for all the nerds that love statistics as much as I do:

- It has been 145 days since the kick-off of my thesis.
- During this time, I biked 129.63 km to and from the office, and probably even more to and from the campus.
- I spent 54 hours spent in meetings, for which I produced a total of 382 slides, which means on average we discussed 7.07 slides per hour.
- In the development of the model that is presented in this thesis, I wrote 1292 lines to code, of which 339 were discarded again. The remaining code has been running for roughly 187 hours to produce 1.013 GB of raw output data.

I hope you enjoy reading my thesis.

Anna Noteboom
Delft, 2022

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

ABM Agent Based Model 5
CAPEX Capital expenditures 8
CfD Contract for Difference 10
DEVEX Development Expenditure 16
FIT Feed-in Tariff / Feed-in Premium 74
GC Gold Coin (fictitious currency) 8
GSA Global Sensitivity Analysis 19
GW Gigawatt 1
IRR Internal Rate of Return 10
JV Joint Venture 12
KDE Kernel Density Estimation 20
MDP Markov Decision Process 57
mln Million 42
MOD Money of Day 16
MSE Mean Squared Error 20
MW Megawatt 16
MWh Megawatt hour 16
OPEX Operating expenses 8
PPA Power Purchase Agreement 13
RT Real Terms 16
NPV Net Present Value 8

1 INTRODUCTION

This chapter introduces the problem that is addressed in this master thesis. Subsequently, the results of a literature review on the issue are presented, which leads to the identification of the knowledge gap and the research question that is addressed in this work.

1.1 PROBLEM FORMULATION

Why focus on offshore wind farm tenders?

In 2020, a record was broken: 93 Gigawatts (GWs) of wind power was installed in that year alone, 6.1 GW of which was installed as offshore wind (Lee and Zhao, 2021). The generation of wind power has been accelerating ever since it has become clear that renewable energy generation is paramount to reaching the Paris Agreement goals (United Nations, 2015). Especially the generation of offshore wind power is expected to rise massively, given the huge potential of this energy source. The International Renewable Energy Association (IRENA) foresees a total installation of 2000 GW of offshore wind by 2050 (IRENA, 2019). In 2020, the total offshore wind power capacity globally was 35.3 GWs (Lee and Zhao, 2021). Reaching the forecast of IRENA would therefore mean that on average, 65.6 GW of offshore wind has to be installed each year. Comparing this with the record of 6.1 GW in 2020, the challenge is clear.
With the rise of offshore wind energy production, the need for an efficient way to manage them arose. The vast majority of offshore wind parks are currently based in just six countries: the installed capacity in the United Kingdom, China, Germany, The Netherlands, Belgium, and Denmark combined make up 97.7% of the global installed capacity. The biggest growers are in this list as well, excluding Denmark, these five offshore wind giants installed 99.7% of the total installed offshore wind in 2021 (Lee and Zhao, 2021). The expectation, therefore, is that these countries shall make a significant contribution to the capacity installation that is needed to meet a total capacity of 2000 GW in 2050.
Apart from China, where virtually all generated offshore wind is state-owned, these countries use tenders to allocate future wind parks to an owner/operator (Iceberg, 2020; Cecchinato et al., 2021). This is why this thesis focuses on the process of tendering offshore wind.

Why are tenders used to allocate offshore wind capacity?

Wind farm tenders are a special type of auction where potential operators of a wind farm generate competing offers to gain the rights to develop and operate said wind farm at a certain location (The European Wind Energy Association, 2015). Policy around these tenders varies both over time and per area. For an overview of current tender designs, see Appendix A. When issuing tenders, policy makers have different objectives for these tenders, taken from a report by The European Wind Energy Association (2015), these include:

- Cost-effective deployment of wind energy that provides long-term support to investors.
- Assurance of security of supply

- Decentralisation of wind farm construction and operation.
- Reduce the negative impact on the local ecology.
- Short period between the allocation of the tender rights and the wind farm being operational.

Do auctions achieve their targets?

The question is if the designs of offshore wind farm tenders have reached their intended goals, or if the way competing parties bid on these tenders impedes progress. The European Wind Energy Association (2015) found a multitude of flaws in the current wind farm tender design. For instance:

- The financial component of a tender in most tenders is a bid for subsidy where the lowest subsidy bid wins. Flaws in tender designs can result in bids that are too low, due to investors wanting to be sure of winning the tender. With an unrealistic bid, the winner of the tender has a higher chance of delay or non-realisation of the tender, which counteracts the desire of policy makers to have the plant operational within a short period. A way to solve this flaw in the tender design could be to raise pre-qualification criteria and/or penalties for non-realisation. However, calibrating the height and content of these measures can be difficult as these measures also tend to drive up the expected support level, which makes the tender less cost-effective (Kreiss et al., 2017).
- Tender sites can be selected without regard for the environmental impact of the wind park.
- Investor uncertainty over the price can discourage investment and can drive up the bids for subsidy, resulting in a less cost-effective tender.
- Instances in which there was little or no competition counteract the cost-effectiveness of tenders.
- Small players can be discouraged from participating due to financial risks and complex tender procedures.

These flaws stand in the way of effective and efficient allocation of the rights to wind farms. Improving their policy and tender design therefore leads to a quicker and more effective road to the 2000 GW of offshore wind in 2050 that IRENA is aiming for and which is needed to ensure a sustainable planet for generations to come.

What can be done to improve tender designs?

Understanding the behaviour of the bidding parties that leads to these flaws will help policy makers improve the design of the tender to counteract this. Therefore, this master thesis is concerned with taking initial steps in modelling the process of bidding for wind farm tenders. The goal of the model is to provide policy makers insight into emergent behaviour resulting from multiple organisations bidding on wind farm tenders. This insight can then be used to improve the design of tenders that are issued by these policy makers.
The thesis shall be carried out in partnership with an industrial partner in the field. Insights from this organisation and their approach to the bidding process are an important addition to the resource pool of the thesis.

1.2 LITERATURE REVIEW

This section is concerned with demarcating the knowledge gap this thesis will address.

What is auction theory and why does it not capture organisational bidding behaviour?

Ever since tenders were invented as a means to fulfill a certain mandate for the best conditions, economists, public administration, and private companies have been interested in the way competitors decide on what to bid. Classical economic research was the first to investigate this issue when economic researchers came up with Auction Theory and Bidding Theory. Auction Theory is a subbranch of Game Theory that is applied to the way people optimise their bids during auctions (Milgrom et al., 1987). The theory is often used for designing auctions. Bidding theory is a subbranch of Decision Theory and describes a method for optimizing a single bid given sufficient data on previous bids from other agents (Friedman, 1956). There are several known issues with these theories due to their assumptions:

- The theory assumes the absence of bidder asymmetry, bidder risk aversion, and inertia (Rothkopf et al., 1990).
- Auction theory assumes costless and unlimited capacity of bidding parties to process information (Klemperer, 2002).
- The theory assumes rationality for all bidders and dismisses bounded rationality when agents act based on subjective information and information asymmetry (Hoogslag, 2014).

The assumption of bidding theory is especially problematic as rationality cannot be assumed in this case: bounded rationality has been established to be of significant impact on the choice behaviour of organisations (Radner, 1996). According to Zhu (2008), it is paramount that the aspect of bounded rationality is incorporated in modelling of auctions to make them sufficiently realistic to be used in the industry. Zhu urges to use more experimental and empirical data on real bidding behaviour to make the models more realistic. Applied to real-life cases, auction theory has also been proven to be inadequate for describing real-life behaviour. For instance, a study investigating the fixed-rate tenders of the European Central Bank found that the observed overbidding could not be explained by classic auction theory (Nautz and Oechssler, 2006).
Due to this apparent inability of game theory and auction theory to describe real human or organisational choice behaviour, this method is deemed insufficient to reach the intended goal of modelling bidding behaviour on wind farm tenders.

What bounded rational behaviour is observed in bidding behaviour?

The most influential forms of bounded rationality that drive organisational bidding behaviour are the following:

- The most obvious influence is the notion that it takes time and skill to gather, store, manipulate, and communicate information (Radner, 1996). As time and skill are resources that are often scarce in organisations, and it is simply impossible to know everything, organisations make decisions based on limited information. This uneven divide in information is called information asymmetry.
- After gathering information comes the interpretation of it. Here arises an additional uncertainty, Radner (1996) found that decision makers are notoriously bad at deducing the logical implications of its gathered information. This means that virtually all firms will interpret their information a little differently, which impacts their investment decisions. On top of that, Barber and

Odean (1999) found that though there are clear biases in information interpretation, there is a tendency by investors to be overconfident in the accuracy of their gathered information and their interpretation of it.

- 'Under promise and over-deliver' is a practice many organisations strive for but has been found to be irrational behaviour, exceeding one's promise is not appreciated more than simply keeping one's promise (Gneezy and Epley, 2014).
- Prospect theory states that it matters in what form the same choice is presented. This is called the isolation effect (Kahneman and Tversky, 2013). The theory states that choices involving sure gains lead to risk aversion and choices involving sure losses lead to risk-seeking. Applied to the case of decision making for bidding on wind farm tenders, how the different bidding options are presented to the decision maker influences the eventual bid. Related to this is the notion that risk aversion depends on previous outcomes, investors tend to take bigger risks if this could compensate for previous losses or after big successes Nofsinger (2017). Additionally, a study by Baker and Nofsinger (2002) found that there exists an irrational tendency to expect future successes when the agent experienced past successes.
- A study performed by Masini and Menichetti (2013) found several non-financial drivers to invest in renewable energy. One of them was that bounded rational a priori beliefs about the technical adequacy of renewable energy adequacy have a high influence on investment decisions, even if these beliefs are disproved. The same study found that the general attitude of the organisation towards renewable energy also influenced investment decisions, an attitude that is not always based on the actual profitability of the assets (Masini and Menichetti, 2013).

Addressing these known biases in organisations when modelling bidding behaviour could potentially give new insights to policy makers. This could help them in designing offshore wind tenders and potentially mitigate some of the flaws in tender design listed before.

Why use agent based modelling?

A different method that might be better equipped to capture real organisational choice behaviour is modelling and simulation. In 1991 already, Arthur was able to design artificial agents that replicate human behaviour in an economic setting using axioms and knowledge of human choice behaviour. Since, the modelling and simulation of economic bidding has developed significantly further. In 2005, Egemen and Mohamed proposed a reasoning model that delved deep into the decision-making process of contractors when bidding on a tender. The resulting framework for reaching a 'strategically' correct bid/no-bid and content of the bid showed important strategic considerations that classic economic theory overlooks but do play a significant role in the decision-making process. Other methods such as epistemic learning combined with behavioural reinforcement learning have been used successfully to represent the agent's choice in the tender market in a dynamic strategy choice model (Min and Mahmassani, 2007). Both methods assume that a certain game is repeatedly played by the same players, which is often the case in tenders. Even though the study was done specifically to model the freight service model, the authors argue that the methodology is fit to simulate any competitive situation entailing repeated decisions over time.
The above shows that different simulation paradigms are fit to capture organisational choice behaviour, in this thesis, the paradigm of Agent Based Modelling (ABM) shall be used. ABM is one of the most often used techniques to describe human behaviour in an auction setting. The paradigm revolves around autonomous, interacting agents (Macal and North, 2009). The approach has gained popularity

over the last 20 years as increasing computational capabilities make the technique viable for a wide range of applications. In the case of the tender market, Agent Based Model (ABM) has been used multiple times to simulate organisational bidding behaviour (Hailu and Schilizzi, 2004; Awwad et al., 2015; Kraan, 2019; Asgari, 2020). The ABM paradigm has been combined with direction learning and reinforcement learning to capture human trade-offs and behaviour in an auction environment (Hailu et al., 2010). Recently, the method has been successfully applied to simulate the specific case of bidding for wind tenders (Anatolitis and Welisch, 2017; Welisch, 2018, 2019; Welisch and Poudineh, 2020). The popularity and apparent success of diminishing the drawbacks of using auction theory to describe bidding behaviour have led to ABM being the core method for this proposed research.

Why is the economic value assessment of wind farm tenders by each bidder important to consider?

One important aspect of modelling realistic bidding behaviour is the agent's assessment of the value of the tender they bid on. In the previously mentioned ABM approaches of bidding on wind farm tenders, these values are generally described by sampling from a probability distribution, containing values that are deemed realistic. In reality, agents bidding for a tender make their own estimation of the value of a tender before making a bid. In the case of offshore wind farm tenders, value assessments are based on predictive economic models describing an expected electricity revenue and an estimation of investment and operational costs (Girard et al., 2013). Both deterministic and probabilistic models are used to predict the value of a given wind farm (Ioannou et al., 2020). Agents typically keep these models and the resulting perceived value of the wind farm private to have a perceived information advantage over their competitors. This leads to multiple assessments of the same tender, all based on different perspectives and assumptions made by the bidding parties. In this thesis, mathematical models that evaluate the value of a wind farm shall be referred to as valuation models. valuation models are a significantly more realistic representation of the perceived value of a wind farm tender by bidding agents than the rather simplistic representation in previously developed ABM's as described in the above section. In the overarching agent based model of the system, every agent can operate their own valuation model, each potentially with different assumptions and estimations. This architecture of a model within a model is referred to as nested modelling, which is a form of multisimulation. Multisimulation is defined as "a set of related approaches for addressing the challenges of problem situations that cannot be neatly captured within a single, unified representation of reality–for example, problems spanning multiple scales of time, space, and organization, as well as problems characterized by multiple valid conceptualizations of reality" (Bollinger et al., 2015). Utilising this nested multisimulation approach to more realistically represent agents bidding behaviour on wind farm tenders has not been done before and represents the knowledge gap of this thesis.

1.3 SYNTHESIS

To summarise, improving the policy on offshore wind farm tender is paramount for achieving the growth in offshore wind capacity that is needed to meet our climate goals. Understanding how organisations react to policy and how this affects their bidding behaviour can help policy makers in formulating new policies or adjusting existing policies. This new or improved policy could make the tendering process more effective and efficient.
Modelling this behaviour while considering the bounded rational behaviour of organisations can potentially aid this understanding, which is why it is important to conduct research in this field. This thesis aims to make the first step by investigating

if a coupled model consisting of an economic valuation model and an ABM could capture bidding behaviour in this setting.

1.4 RESEARCH QUESTION

The literature review and synthesis as stated above have led to the following research question: *How can organisational bidding behaviour on a wind farm tender be captured in an agent based model, considering the economic value assessment of the tender by each organisation?*

The main question can be broken down into five sub-questions:

1. What mechanisms drive organisational bidding behaviour?
2. How can the bidding on tenders be modelled to realistically represent organisational bidding behaviour?
3. How can the value assessment by bidding actors be considered in the modelling approach?
4. What is the validity of the model so that it realistically represents bidding behaviour on wind farm tenders?
5. What insights are created by the model into the bidding behaviour on wind farm tenders?

The five sub-questions are formulated to together form a logical flow to the answer to the main question. And though the questions were addressed chronologically over the time the thesis was conducted, they are not addressed chronologically in this report. The report is written to create a logical flow of information, which is why the first research question is already answered in section 1.2 of this chapter under the header 'What bounded rational behaviour is observed in bidding behaviour'. This section lists the most prominent mechanisms that drive organisational bidding behaviour.

1.5 STRUCTURE OF THE THESIS

In this research, the development and analysis of a coupled Economic-Agent Based model are described to answer the research question as stated above.
Chapter 2 introduces the notion of Agent Based Modelling and coupled modelling, and explains the added benefit and pitfalls of using this method for this research. The main elements and assumptions of the model are introduced here as well.
Chapter 3 describes and analyses the economic valuation model that the industrial partner has provided to simulate the assessments organisations actually perform to estimate the value of a wind farm tender. Here, the most influential inputs of the model are identified through a global sensitivity analysis. These inputs represent the interface between the Agent Based Model and the economic model.
Next, a simple version of the Agent Based Model is introduced in Chapter 4 to show the mechanism of the coupled model, build trust in the method and show how such a model can be analysed and its output interpreted.
Chapter 5 then builds on this simple model by adding complexity that reflects important bounded rational behaviour of organisations in auction settings. In these two chapters, the second, third, fourth, and fifth research questions are answered.
Finally, the research is concluded, its limitations noted and ideas for future research are posed in Chapter 6. Here, the overarching research question is answered.

2 METHODS

This chapter outlines the research methodology. Section 2.1 describes the general principle of Agent Based Modelling, its pros, cons, and considerations for this project. Section 2.2 describes the technique of model coupling, what its added value can be, and how the pitfalls of the technique shall be considered in this research. Section 2.3 presents the coupled modelling framework used, as well as the system boundaries. The conceptualisation in this section serves as a foundation for answering the second and third research questions.

2.1 AGENT BASED MODELLING

An Agent Based Model (ABM) is developed to understand the organisational bidding behaviour on wind farm tenders. ABM's strength is modelling autonomous, interacting agents (Macal and North, 2009). The model that is developed for this research captures the bounded rational process of an organisation formulating a bid on an offshore wind tender. In this process, the agents consider the other bidders, the tender scheme and conditions, their own financial situation, and general features related to world economics and politics such as inflation rates, and revenues achievable from selling green certificates. Limited information, assumptions, and biases on these aspects will prompt an agent to issue a specific bid in the tender. In a new tender round, the agent reevaluates its strategy based on the outcome of the previous tender and its expectations for future tenders. A conceptual model is developed to specify the algorithms and mechanism of the ABM. The ABM itself is implemented using the Python implementation of Agent Based Modelling called Mesa (Kazil et al., 2020). This package is chosen given its flexibility with regard to interfacing with the valuation model, which is an Excel-based model. Additionally, both the student and the company supervisor have experience with the Python language.

A limitation of using agent based models is that they typically require very specific data on the rules of agent behaviour, which often is not directly available. When such specific data was not available, assumptions were made, and/or reasonable proxies to the required data were used. These assumptions are documented clearly, as well as their implications on the validity of the model outcomes. It is worth noting that organisational behaviour can be complex and as of now it is impossible to fully replicate in a computer model. An asset to this research in this respect is the collaboration with an industrial partner, which can provide valuable insights into the decision making process of a real actor. A potential pitfall to consider is the assumption that all companies operate and approach decision making exactly like this organisation. Therefore, all assumptions and simplifications that are made shall be documented and communicated clearly.

2.2 THE CONNECTION OF THE VALUATION MODEL TO THE ABM

To capture the valuation of different offshore wind tenders by agents, the ABM is coupled to an economic model. This valuation model is a simplified but realistic model provided by the energy company. To protect the commercial sensitivity of the model, monetary values in the model are expressed in a fictitious currency, hereafter referred to as Gold Coin (fictitious currency) (GC). The approach of using a dummy version of an actual economic model is chosen for two reasons. The first is that this is a very realistic representation of real-life tenders as this type of model has been used for this specific purpose before. Secondly, using a model that is provided by the industry gave the researcher more time to focus on the focal point of this research: coupling the two models. The economic model is Excel based which can be coupled to the Python implementation of the ABM. The challenge in this phase was coupling the Excel based model to the Python model to establish useful multi-simulation. The agents in the model can interact with the economic model, assessing the perceived financial consequences of running with a certain strategy. Depending on the results of this assessment, the agent might iterate on its strategy. Approaching the problem using multi-modelling has made the approach more modular since the economic valuation model can be switched with a different version. The approach is more valid than historic modelling approaches to bidding behaviour because the approach resembles real decision making more than, for instance, sampling cost from a distribution, and more efficient since the economic valuation model can be reused (Nikolic et al., 2019). The development of a multi-model comes with several challenges as defined by Nikolic et al. 2019.
These challenges and their mitigation in this research are the following:

- Matching the ontologies of the model: In both the ABM as the economic valuation model, it is important that concepts, for instance, related to project economics (Operating expenses (OPEX), Capital expenditures (CAPEX), Net Present Value (NPV), Etc.) are defined and used in the same way.

- Multi-formalism alignment: Agent Based Models (ABMs) uses coupled state machines in a discrete time domain, this formalism has to be coupled with that of an economic model, where statements about the perceived value of a project are made using predictions of cash flows over the years. These two models need to interact meaningfully, especially when aligning their implementation of the time domain. In the method used for this research, economic predictions about a project are always conducted within a single tick in the ABM.

- Conflicting rationalities and abstractions: The challenge here is to align the intentions, perspectives, motives, and logic of both models. These should match the overarching model, to tell a coherent story. Given that the Excel model is already provided, the ABM is developed to match this investor's logic in the model. In this case, it is an advantage that the ABM was developed specifically for this research, which meant this matching was considered from the start.

- Scaling: The challenge of scaling the dimensions in both models did not pose large issues, given that the Excel model describes the economics of a single wind farm and the agents in the ABM use this model to assess a single wind farm.

- Model fidelity, resolution, accuracy and precision: The Excel model has a medium fidelity as it is a simpler representation of the full value assessment methodology of an energy company and it cannot be assumed that each company calculates expected value in this exact way. This simplification also leads to possible systematic errors in the model. The ABM simplifies strategic considerations to a comprehensive algorithm, which also lowers the fidelity of the model. The simplifications and assumptions are of a comparable scale and are both in disjunct fields. The model developed in this research aims to showcase possible behaviour in the setting of bidding on tenders, this is still very much possible given the limitations just stated. That being said, it is paramount that the assumptions and simplifications of reality are documented well and the modelling process is transparent.

- Variability, uncertainty, and noise (propagation): The Excel model has the option of incorporating uncertainty when the exact price or revenue of an aspect of the wind farm tender is unknown to the agent. In some of the agent strategies in the ABM, the Excel model run involves sampling, which makes the outcomes of the model variable. This variability is accounted for in the ABM by running the model multiple times and subsequently running statistical tests on the model outcomes to increase confidence in the model outcomes.

- Communicating and retaining meaning and intention: The meaning and intention of the Excel model are straightforward and well understood in this case. This is largely due to the simplicity of this model. The ABM is developed specifically for this research, which ensures the intention of the model aligns with the topic to investigate and the economic model. Meaning is added to the model when presenting and analysing the results of the model. Given that the model is developed by a single person with a single purpose, the risk of epistemic opacity (the meaning of the model is unclear) is limited.

- Analysis and Interpretation: Analysis and interpretation are relatively straightforward in the case of the Excel model, as it involves economic value and purely financial mechanisms. This means that the results of the model can be used straightforwardly in the ABM as well. The interpretation of the ABM results is more ambiguous and open for interpretation as it represents behaviour, which is a lot more subjective than finance. Therefore, it is very important to understand the underlying algorithms and logic of the agents in the model and the overarching model to understand what causes the results the model shows. This report helps in this regard by starting with a simple model setting to explain and interpret the model behaviour, before moving on to more complicated cases.

2.3 CONCEPTUALISATION OF THE MODEL STRUCTURE

In this section, the general structure and operation of the coupled model are explained. Agent based models consist of three elements: Environment, Agents, and the concept of time in the model (Van Dam et al., 2012). Subsections 2.3.1, 2.3.2, and 2.3.3 describe the environment the model operates in, what the agents in the model represent, and how the model deals with time. Subsection 2.4 describes at a high level what the main assumptions of the model are.

2.3.1 Environment

The environment represented in the model is a fictitious situation in which tenders are held. There is no exact geographical location tied to the model or specific agents linked to real-world actors that are simulated.

The tender rules are kept realistic but as simple as possible. A sweep of global wind farm tender designs and policies has been conducted, which is presented in Appendix A, which outlines the different types of tender policies in the world. For this research, the tender policy modelled is the German model as it existed in the past and currently exists for the 2022 tender in the German North Sea (Enerdata, 2022). The reason for this tender scheme is the simplicity of the tender rules. Every interested party issues one single blind bid that consists of the subsidy requirement for a set number of years of operation of the wind farm. The lowest subsidy bid wins, if multiple parties issue the same lowest bid, the winner is determined via a lottery. This tender scheme is called "the central model" (Enerdata, 2022). The support scheme for the tenders in the model is a two-sided Contract for Difference (CfD). In this support scheme, the bidder issues a price called a strike price. When operating the farm, the government that issued the tender will pay the difference between the strike price and the market price for the duration of the contract. When the market price is higher than the strike price, the operating party has to pay the government the difference (Welisch and Poudineh, 2020). This support scheme is different from the one currently used in Germany (one-sided CfD) and this is the tender scheme is a little simpler and is the one implemented in the valuation model as it is provided by the industrial collaborator of this thesis. A second simplification to the tender policy is the omission of 'the right to match' that exists in the central model. Germany allocates legal entry rights to projects that did not win in previous tenders, which they can use to match the winning bid of a current tender, snatching it from the original winner (Koch and Neumann, 2021). This rule is not included in the model presented in this thesis.

2.3.2 Agents

The agents in the system are energy companies that can bid on these tenders. As the system revolves specifically around offshore tenders and these tend to be significant in size, smaller parties such as energy communities are not considered an agent, as they would not have the resources to bid on such a tender. Public organisations are also omitted, as the organiser of the tender is typically a public organisation itself and public organisations typically realise wind projects outside the tender procedure.

The agents differ in the sense that they each have their own bidding strategy, and different attributes such as budgets and goals. These strategies interact with the valuation model, which shows the agent what the predicted economic return is of placing a certain bid. The agents interact with tenders, in the sense that they bid on them. A bid consists of a single strike price. Strike price refers to the subsidy rate at which the party is willing to develop and operate the wind farm. Bid and strike price are interchangeable in this case. These tenders can have different attributes such as the capacity of the wind farm and the maximum strike price that the agents are allowed to obtain in subsidy.

Figure 2.1 shows the relation between the different aspects of the model that are just mentioned in a UML Class diagram. The world class consists of tenders and agents. Agents can place bids on the tenders, which can differ in rounds (time the agent has to formulate its bid), capacity in MW, and maximum strike price in monetary value. The tender class determines which agent issued the lowest bid and conducts a lottery in case of multiple low bids. Agents use a strategy when considering what to bid, this strategy interacts with the valuation model that is coupled to the ABM. This model calculates the value of the tender under the agents' assumptions of the tender by calculating the Internal Rate of Return (IRR) and Net Present Value (NPV) of the project. The operation of the valuation model is explained in more detail in Chapter 3.

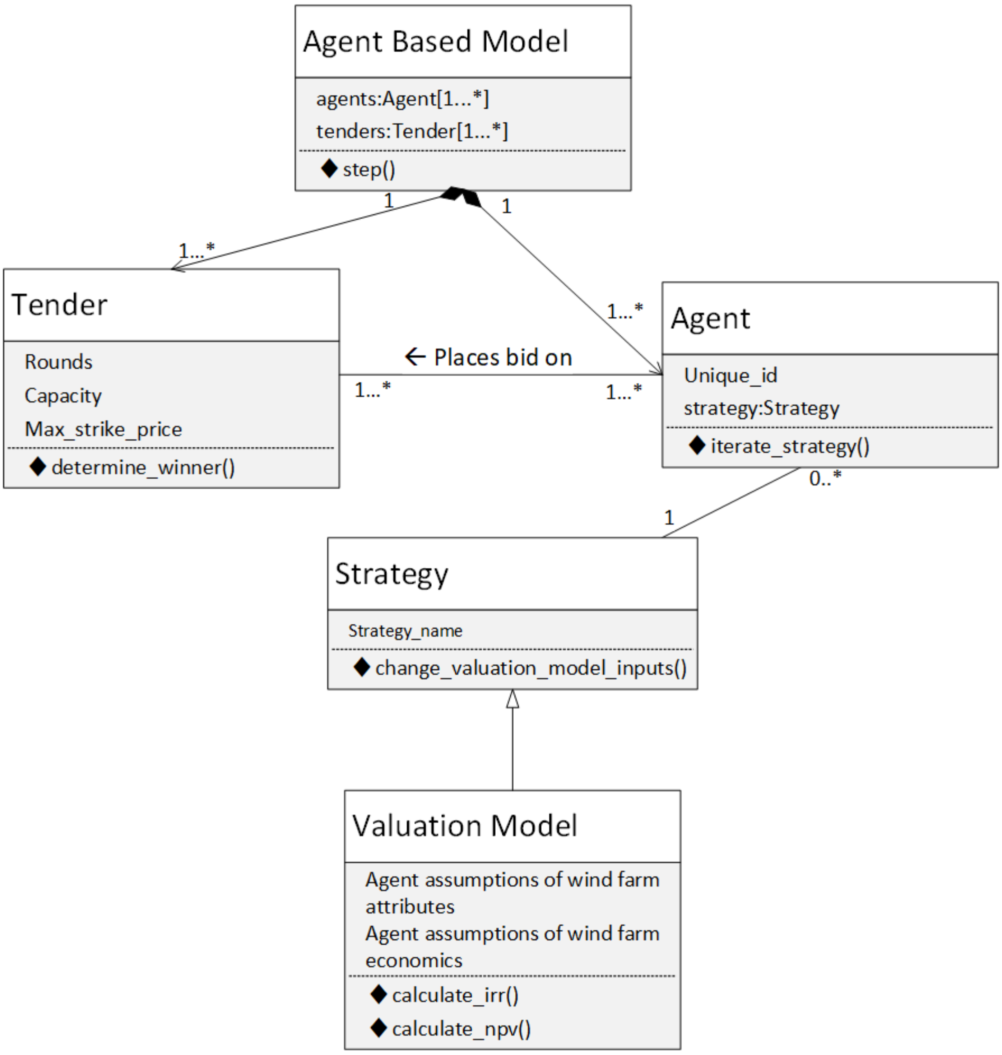


Figure 2.1: UML Class diagram of the Coupled model

2.3.3 Time

The goal of this research is to understand bidding behaviour on wind farm tenders. Offshore wind tenders can be announced less than a year in advance. A current example of this is the Dutch offshore wind tender in the North Sea, the rules of which were published in October 2021 and for which bids could be placed in April and May of 2022 (Rijksdienst voor Ondernemend Nederland, 2022). The wind farms auctioned here should be operational in 2026/2027. This typical time frame inspired the scope limitation to a time frame of the simple version of the model to one year. In the more elaborate version of the model (see Chapter 5), other, later tenders are considered as well to show the longer time of an organisations investment portfolio. However, the first tender that has to be considered, is tendered still within the year. Often in agent based models, time steps in the model represent a set duration of time. In the simple version of the model, this will be the case, every time step then represents a certain amount of time in which agents can strategise their bids. In the more elaborate version of the model, this duration is flexed to each time step representing the auctioning of a single tender. This change was necessary to explore different research questions.
In the model, agents do not interact with each other whilst performing a step, this means that the sequence of agents in each step is of no consequence so the scheduler used in the software to determine which agent goes when is also of no consequence. For reference, the agents are called in random order.

2.4 MAIN ASSUMPTIONS

A model is always an abstraction of reality, therefore it is important to report exactly how this abstraction is made and which assumptions about the world are made. In order of most influential to least influential, here listed are the main assumptions of the model:

When calculating the NPV and IRR of a tender, all agents assume the same values for capture price, imbalance cost, inflation, price of green certificates, tax-related values, and (only relevant for NPV), discount rates. For an explanation of these aspects in the valuation model, as well as the grounds on which is decided to keep these values fixed in the model, please refer to Chapter 3.
In reality, these assumptions differ as all agents have to gather and interpret their own information, which is one of the major aspects of bounded rationality (see section 1.2). This is expected to have a significant influence on the bidding behaviour of the agents and therefore on the robustness of the model. It is strongly advised to incorporate differentiation in model assumptions in a later version of the model before assuming the insights of the model as policy advice. The model interface with the valuation model already is fit for this addition, which would make this a relatively low-effort improvement to the model.

Agents do not form Joint Ventures (JVs) to reduce risk on tenders and increase the competitive strength of the organisations in the JV. In reality, organisations often join forces to increase their chances and benefits from a tender. To illustrate, in the 2022 tender Hollandse Kust in the North sea as many as four JVs issued a bid: Shell/Eneco, Ørsted/Total Energies, Vattenfall/BASF, and SSE Renewables/Brookfield all issued a bid (Algemeen Dagblad, 2022).
For this research, the extra complexity of organisations negotiating a JV and combining their resources is considered outside the scope due to time constraints. Once a JV is formed, it can be considered a single agent with the same behaviour as a single organisation, which makes the assumption reasonable within the scope of the model. However, that does assume that the formation of the JV and the decision making around the bid is a sequential process. In reality, these two processes go hand in hand, which could lead to substantially different behaviour.
The expectation is that the agents that succeed in the formation of a JV increase their competitiveness as the companies can combine their expertise and resources, which leads to different model dynamics. These dynamics are not trivial and potentially influence the robustness of the model. It is therefore strongly advised to incorporate this complexity in a future version of the model before assuming the insights of the model as policy advice.

Another aspect of bounded rationality is the influence of non-financial drivers in the decision to invest in offshore wind assets. For a full explanation of this bias, please refer to section 1.2. Bidding decisions are influenced by prejudices that exist in the organisations. This bias is considered not to have a significant influence on the model outcomes as it mainly affects the decision of whether to start investment in offshore wind, rather than the actual bid into the asset. The model is therefore considered robust to this assumption.

The only investment agents consider are wind farm tenders. This means that decisions for bidding on tenders are not influenced by third options. In reality, organisations often have a portfolio of (renewable) energy assets that they consider developing, which means that developments in these assets can influence their bidding behaviour on the wind farm tender. This influence can bias the bids of certain agents. However, it is not expected that this influence would change the model outcomes and the trends that result from the model as the influence can bias the bids in both directions and these are expected to balance. Therefore, the model is considered to be robust to this assumption.

Agents take the same amount of time to iterate their strategy. In reality, organisations have the option to allocate additional resources to the investigation of the option which means that they can iterate their strategy more often in the time before the auction. For instance, some organisations hire third parties to run the calculations or provide advice while others conduct the valuation in-house. This complexity is considered to be outside the scope of the model and all agents are assumed to be able to optimise their bids in the time that is given. The implication of the assumption is that there is a bit more randomness around the bids of the agents. This randomness is not expected to have a major influence on the trends that can be found in the model outcomes, which makes the model for this purpose robust to this assumption.

Agents do not consider concluding power price agreements to ensure a stable revenue stream after the subsidy period is over. This assumption is made after the assessment of the valuation model (see Chapter 3) pointed out that Power Purchase Agreements (PPAs) have a smaller impact on the outcome of the valuation model, compared to other variables. Still, it is not negligible and can influence the decision making of an organisation. The added complexity of PPAs, just like the added complexity of JVs, is the presence of negotiation to arrive at such an agreement. As the significance of the influence is limited, this assumption is not expected to influence the robustness of the model significantly.

These assumptions are valid for both versions of the model, which are explained in detail in the next two chapters. Additional assumptions that hold for these specific versions are listed in these chapters.

3 ANALYSIS OF THE VALUATION MODEL

This chapter explains and analyses the valuation model that was provided by the industrial collaborator to represent how companies evaluate the value of a wind farm tender. Understanding the operation of the model is paramount when incorporating it into the agent based model. Section 3.1 explains how the valuation model works. Then, when deciding how to interface between the agent base model and the valuation model, it is important to understand which input parameters in the valuation model have the biggest impact on its outcomes. Section 3.3 investigates this through a Global Sensitivity Analysis.

3.1 HOW THE MODEL WORKS

The valuation model is an Excel-based model that calculates the Risk Adjusted NPV of a project and the IRR. The Risk Adjusted NPV considers the cashflow over the lifetime of a project and calculates the difference between the present value of revenues and costs. Cash in the future is considered to be worth less than cash in the present, which is why a discount rate is used to reduce the value of cash over time. A risk adjusted NPV considers different discount rates for different revenue streams as they can differ in terms of risk. Lower risk revenues get a lower discount rate than higher risk revenues. The value of NPV can then be interpreted as a measure of the expected profitability of a project in Present Value.

The IRR represents the discount rate that the cashflow of a project would require to make the NPV be exactly 0. The reason investors often also consider this metric as an addition to NPV is that it gets rid of the size component of an asset. Smaller projects can still be a good investment in terms of IRR, even though they might bring in fewer returns over time.

The relation between NPV and IRR is given in equation 3.1. Do note that this relation holds for a non-risk adjusted NPV, which means it assumes a single discount rate for all revenue streams.

$$0 = NPV = \sum_{t=1}^{T} \frac{C_t}{(1+IRR)^t} - C_0 \tag{3.1}$$

where:

NPV = Net Present Value

IRR = Internal Rate of Return

C_t = Net cash inflow during period t

C_0 = Total initial investment cost

t = Number of time periods

Important Note: To preserve the confidentiality of the valuation model, the monetary inputs of the model are expressed in fictitious money (Gold Coins or GC). The values are in the same order of magnitude as Euros and US Dollars but there is no fixed conversion key to calculate the values back to actual currency values. This also

means that the conclusions that are made using this model should be interpreted as example behaviour and trends that can be observed, rather than looking at the specific monetary values.
The inputs the valuation model considers to calculate the costs, revenue streams, and eventually the NPV and IRR are the following:

- Capacity. This is a combination of the number of wind turbines and the wind turbine size and represents the total installed wind power in Megawatt (MW).
- CAPEX per MW. This is a representation of the capital cost related to developing one MW of wind farm capacity and is expressed in million GC in Real Terms (RT). 'Real terms' means it excludes the influence of inflation, which means the value stays constant to the value in the base year. The base year value can be calculated through equation 3.2.

$$V_0 = \frac{V_t}{(1+d)^{\Delta T}} \tag{3.2}$$

where:

V_0 = Value in base year

V_t = Value in year t

d = Discount rate

ΔT = Years between year t and base year

- Capture price assumption. This is the price assumption per produced power that the operator of a wind farm can get on average on the day-ahead market. The price is determined per year and is expressed in GC per Megawatt hour (MWh) RT when used as an input. In the model, this price is also mapped for the operational years of the tender, here the price represents the Money of Day (MOD) value. MOD means that the monetary value of the assumption matches the monetary value at that point in time, taking inflation into account.
- Corporation tax. This is the tax the operator of the wind farm has to pay for selling its power. Tax has to be paid for the value that the wind farm represents. As the wind farm ages, it wears out and the value goes down. The time between the development of the wind farm and the point in time that the value is assumed to be 0 GC is called depreciation years. In the model, depreciation years are fixed to 20 years, and the depreciation is assumed to follow a straight line.
- Decommissioning Cost. This represents the cost associated with decommissioning the wind farm after its operational years. The cost is expressed in million GC in base year value in RT.
- Development Expenditure (DEVEX). This represents the fixed development cost of the wind farm and is expressed in million GC in base year value RT.
- Dilution. This refers to the process where a company develops (part of) an asset and at a later stage sells (a part of) the operating asset to another party for a premium (Hubbard Jr, 1963). In this case, the asset is the wind farm. Developing the wind farm and selling a percentage of the shares afterward is a way to lower the risk for investors buying the diluted part of the wind farm. The risk is lowered as the risks related to the development have been removed. This means the diluted percentage of the assets can often be sold for a premium, which makes dilution a way to increase the profit of a project. In

this research, it is assumed that a party always develops the wind farm in its entirety and dilutes a percentage of the wind farm's assets directly after it has been built and is operational. The parameter 'Post-dilution company share' in the model refers to the percentage of assets that the developer of the wind farm keeps for himself to operate after construction. A second parameter that is varied in the model is the 'Price for operation', which refers to the premium that the developing party receives for the diluted part of the wind farm. A fixed transaction cost and a variable transaction cost per MW are also considered to be fixed in the valuation model.
All monetary values in this section are million GC in base year value RT.

- Discount rates. Different discount rates are assumed for revenues coming from subsidy volume, merchant revenues, and revenues coming from Power Purchase Agreements (PPAs) (the latter is explained later in this list). Merchant revenues pose a relatively high risk, which is why the discount rate is higher here, subsidy revenues and revenues from PPAs are considered to pose a lower risk.

- Green certificates. This is the assumed revenue per MWh due to the trade in green certificates that can be gained by producing sustainable power. It is expressed in GC MOD. The day in this case is the year the certificates are traded.

- Imbalance cost assumption. Transmission system operators have to balance the supply and demand of energy on the grid. These operators pose a cost to organisations that supply power that causes an imbalance. The cost for the organisation is equal to the cost the system operator has to make to restore the balance Willis (2016). In the model, this cost is fixed to be the assumed average that the wind farm operator has to pay per produced power for the imbalance it poses on the grid. The input is defined per year and expressed in GC per MWh in RT.

- Inflation. This is a percentage that is simplified in the model and assumed to be constant over the years.

- Operational years of the wind farm.

- OPEX. This represents the operational cost related to operating the wind farm. The cost is split into fixed cost and variable cost, expressed in million GC per MW per year.

- Power Purchase Agreement (PPA). PPAs are contracts between the operator of a wind farm and an electricity user. In this research, the PPAs are assumed to be of the 'as-produced' type, which means that the contract states the price (in GC per MWh) for which it will offtake a certain percentage of the production of the wind farm Brunnberg and Johnson (2019). As-produced also means that there is no obligation for a certain volume delivery or certain delivery profile. In the model, the contract takes effect the year that governmental subsidies have ceased and ends in the last year that the wind park is operational. Varied parameters are the percentage of produced electricity that falls under the PPA, and the PPA price.

- Subsidy. In this research, we investigate a two-sided CfD subsidy scheme. A two-sided CfD is a relatively simple scheme that is often used in wind farm tenders globally (Jansen et al., 2022). The agent that operates the wind farm gets a fixed price (Strike Price) for each unit of power it produces. When the agent sells its electricity on the day-ahead market and this yields a lower price than the Strike Price, the government that issued the tender pays the agent the difference. In case the market price is higher than the strike price, the agent has to pay the government the difference. In this research, the duration of the subsidy is fixed at 15 years, starting in the year that the wind farm becomes operational. The varied parameter is the strike price, which represents the bid of the agent. This price is expressed in GC per MWh.

- Yield. This relates to the electricity that is actually produced by the installed capacity in the wind farm and is expressed in percentages. Aspects that lower the yield are weather related (wind turbines can only generate electricity in a certain range of wind speeds), losses due to e.g. electrical resistance in the cabling and the turbine itself, wake effects, down-time for maintenance, and/or repairs, and annual degradation.

The model is peer reviewed within the industrial collaborator and deemed a simplified but realistic representation of models that are actually used in the business.

3.2 SIMPLIFICATIONS IN THE MODEL

The valuation model that is used in the coupled model is a simplification of what is really used in an organisation. This was done both to protect intellectual property and to keep the mechanisms of the model comprehensible for the purpose of the coupled model. However, it does influence the outcomes of the model. The main simplifications are listed below.

The valuation model by design does not take different taxation schemes and financial governmental policies into account. This is a consequence of using a fictitious currency and can have a significant influence on the valuation of a wind farm.

Capital cost (CAPEX) is in the valuation model presented as a single input, while in reality, this consists of sub-constituent parts such as costs related to the Balance of Plant [1], foundation, and the Wind Turbine Generator itself. This level of detail is not incorporated into the model and could potentially affect its outcomes.

The granularity of the model is set to a yearly basis. This means that for all the time series that represent revenue streams and cost streams, the cost and revenues are aggregated to years, whereas in reality monthly fluctuations are considered as well. These fluctuations can influence the eventual valuation.

The capture price assumption and revenue due to selling green certificates are considered a static value in the model where in reality, these follow the developments in the free market. As more renewable electricity penetrates onto the grid over the years, the assets could start experiencing cannibalization effects that are not considered in the valuation model.

Apart from the input values, the valuation model is considered to be the same for all agents in the model. Though asset appreciation is a relatively standardised field that is well understood by companies large enough to bid on wind farm tenders, it is expected that the level of detail of the model varies organisation to organisation.

Each of the above-stated simplifications is minor or intricate details that, according to the industrial collaborator, should not change the overall conclusions of the coupled model.

1 All infrastructural and facilities of a wind farm, excluding the turbine and its elements.

3.3 GLOBAL SENSITIVITY ANALYSIS OF THE VALUATION MODEL

In this section, the valuation model is analysed through a Global Sensitivity Analysis (GSA). Sensitivity analyses are conducted to assess what influence the inputs have on the outputs of a given model. The more the output changes as a result of an incremental change of an input parameter, the more sensitive the model is to that input. The advantage of GSA over classic sensitivity analysis techniques such as Monte Carlo, is that GSAs take interaction effects into account (Saltelli et al., 2019). Some inputs on their own have a limited influence on the output but in combination with another input, can have a significantly larger influence. Two dominant techniques to perform global sensitivity analyses are the Extra Trees algorithm and Sobol (Jaxa-Rozen and Kwakkel, 2018), both of which are implemented here using the Exploratory Modelling Workbench in Python in combination with the package SALib (Kwakkel, 2017; Herman and Usher, 2017).

Table 3.1 shows the input parameters that are assessed in the GSA together with the ranges that the parameters are varied over. The selection of parameters and ranges was done in consultation with the developer of the valuation model, the parameters are the ones that are likely to vary in reality and/or parameters that might be used by energy companies to adjust their bidding strategy. The ranges of the parameters represent all viable quantities these variables can assume.

Table 3.1: Input parameters for the global sensitivity analysis of the valuation model

Variable	Range	Unit
Capacity	[50-1000]	MW
CAPEX per MW	[1 – 3]	mln GC per MW
Decommissioning cost	[10-40]	mln GC
DEVEX	[0 – 100]	mln GC
Post-Dilution company share	[0-100]	Percentage
Price for operation	[0 – 5]	mln GC per MW
Gross yield	[25 – 75]	Percentage
OPEX variable	[0,0.01]	mln GC per MW per year
PPA offtake percentage	[0-100]	Percentage
PPA Price	[40-120]	GC per MWh
Strike price	[0-100]	GC per MWh

When plotting the outcome of the model for all GSA runs in terms of IRR and risk adjusted NPV, an hourglass shape appears. This is shown in figure 3.1. The figure shows all combinations of NPV and IRR, resulting from varying the variables listed in table 3.1 over their specified ranges. The zero-point in the figure for both NPV and IRR acts as a pivot point. This makes sense intuitively, as a project that is expected to make a loss will have per definition a negative NPV as well as a negative IRR and vice versa. Note that it becomes impossible to calculate an IRR for a project that has an NPV too far below zero. This is due to the nature of the equation for finding the IRR, which needs to find a solution for NPV = 0. In the model, when the IRR becomes so negative it could not be calculated, it reports a non-value. Later, in post-processing, these non-values are replaced with the lowest possible IRR the model has otherwise reported. This process means the outcomes are truncated on the left-hand side.

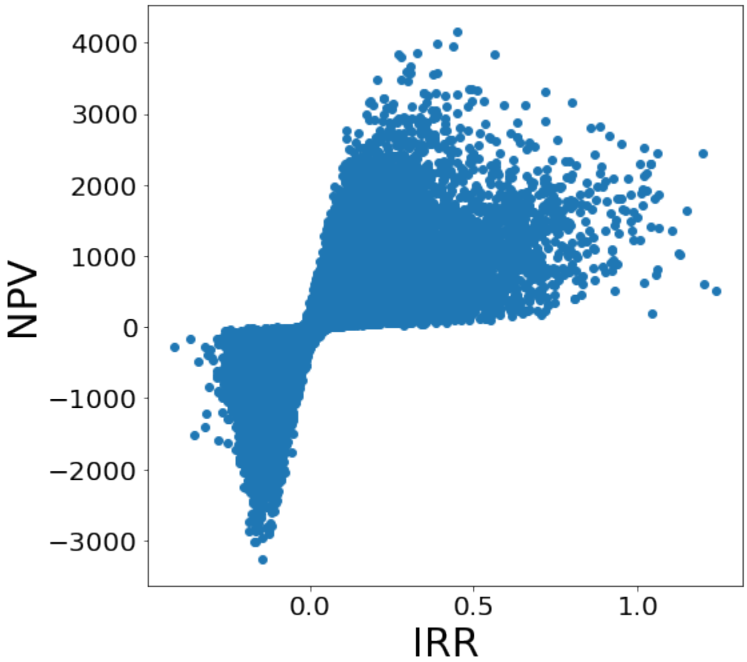


Figure 3.1: Output space of the valuation model in terms of IRR and NPV

3.3.1 Extra Trees GSA

Extra Trees is a machine learning-based method where an ensemble of extremely randomised decision trees are fitted on a data set (Geurts et al., 2006). These trees include decisions based on the features that are input in the model. Removing the decision rules that are based on such a feature increases the Mean Squared Error (MSE) of the prediction of the trees. The average increase in MSE over all trees for each of the features represents the influence that feature has on the outcomes of the model. The extra trees method performs relatively well on small sample sizes compared to other GSA techniques such as Morris or Sobol (Jaxa-Rozen and Kwakkel, 2018). This makes the technique a computationally light solution for finding the influence of the input of the valuation model with a limited set of runs. Several hyper parameters can be of influence on the outcome of the extra trees GSA. After changing the hyper parameters in this analysis and finding little difference in the outcomes, default values for these parameters are used as they are defined by the Python Package sklearn (Scikit-learn, 2022). The hyper parameter settings are as follows:

- The number of trees in the forest is 100.
- The splitting criterion in the trees is based on squared error.

The number of experiments that the GSA assesses to perform the analysis is 50.000 experiments, this number is chosen as after this number of experiments, the outcomes did not change significantly anymore.
The inputs for the experiments are combinations of the 11 parameters, each having a value in their range. To make sure these experiments cover the input space evenly, each input is sampled from a uniform distribution across the range of the parameter. A uniform distribution is important in this case to ensure the feature samples are not correlated, which would introduce a bias in the GSA. To show the method resulted in an evenly spaced output plot, the Gaussian Kernel Density Estimation (KDE) is plotted for each of the parameters in figure 3.2. KDE is a widely-used method that estimates the probability density function of a random variable (Scott, 2015). The figure shows that each parameter follows a uniform distribution over its range. The

rounded edges are a result of the KDE method, which allocates a probability to samples outside of the range, even though there are none in the samples. For the GSA, these samples cannot exist. The construction of a correlation matrix using the Pearson method also confirmed no correlation in the samples as no parameter pair in the matrix had a correlation coefficient greater than 0.0094 or smaller than -0.0088.

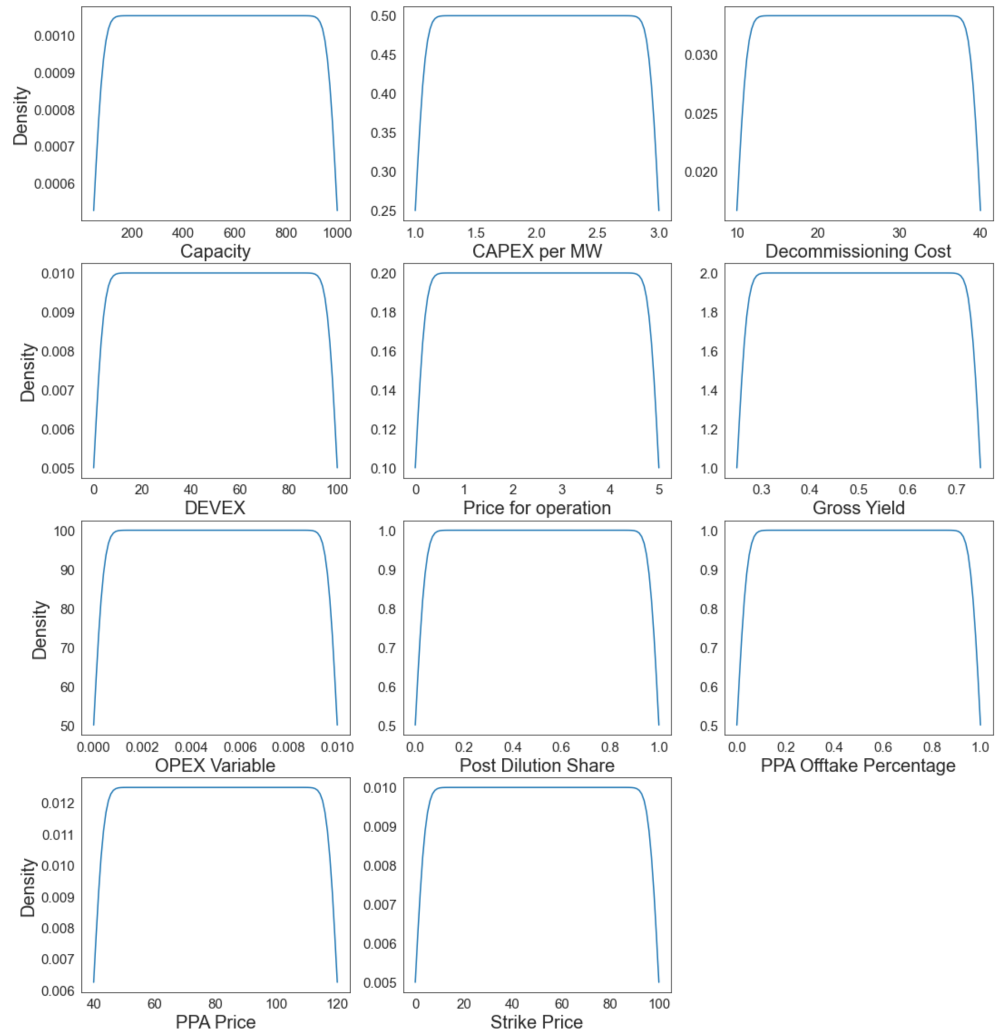


Figure 3.2: Gaussian kernel density estimations of parameter inputs for the Extra Trees GSA

Figure 3.3 shows the feature importance of each parameter on both outcomes of the model, as calculated by the extra trees algorithm. The y-axes in the figure (feature scores) show the relative average increase in the mean-squared error of the output prediction, associated with the removal of splitting criteria that relate to the parameter. The figure shows that overall, most input parameters that have a significant effect on NPV also have a significant effect on IRR and vice versa. This makes sense given the relation between the two, as explained in section 3.1 and equation 3.1. Two interesting deviations from this even influence are price for operation and capacity, both of which have a higher impact on NPV than on IRR. This has to do with the nature of IRR. One of the reasons why NPV becomes higher when the price for operation goes up is because dilution shifts the income closer in time, which makes it in terms of NPV worth more as the discounted value is then lower. IRR works differently as it calculates what discount rate is necessary to make NPV 0, which means this earlier revenue has a smaller effect on this metric. For capacity, the difference makes sense conceptually as well, as IRR gets rid of the size component in NPV, and capacity indicates the size of the wind farm.

For this analysis, it is assumed that inputs with a feature score of at least 0.05 on either IRR or NPV are considered to be significant. This means that when considering NPV there are six parameters of influence in the model; CAPEX per MW, Dilution price per MW, Gross Yield, Strike Price, Post-Dilution Share, and Capacity. For IRR, the first five of the list have a significant influence on the outcome.
To assess the reliability and stability of these outcomes, the analysis is performed on 100 different subsets of the data. Each subset consists of 50.000 random input sets, which are sampled with replacement. The range of different outcomes from these subsets determines the height of the error bars shown in figure 3.3. The error bars are relatively small, which supports the confidence in the conclusions of the algorithm.

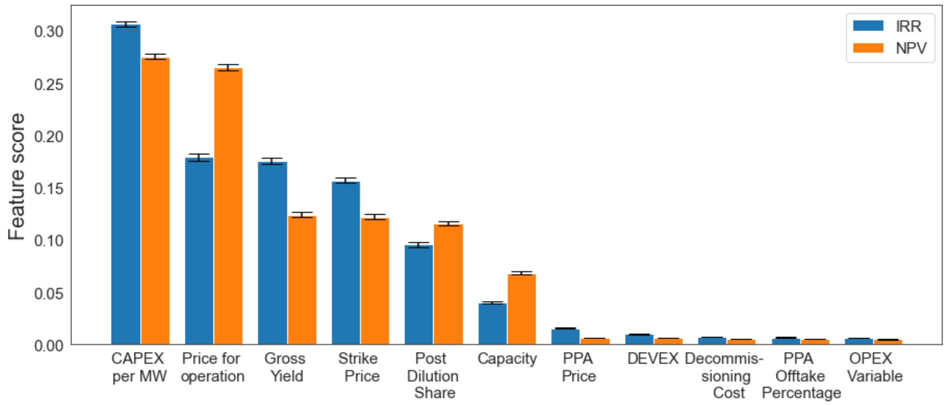


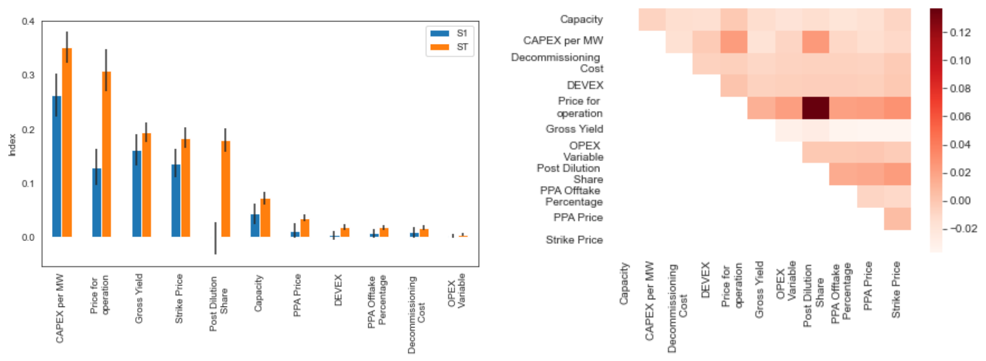
Figure 3.3: Feature importance for IRR and NPV

An aspect that the extra trees algorithm is unable to tell us is which parameters show interaction effects. The Sobol GSA is able to do this, which is why this GSA is performed as well. Additionally, if the results of the Sobol analysis match the ones of the extra trees algorithm, this acts as a validation of the conclusions of the extra trees analysis.

3.3.2 Sobol GSA

Sobol is a variance-based method that calculates the contribution to the total variance in the model output of each input in the model (Sobol, 2001). In Sobol, these inputs are referred to as factors. In the valuation model, these factors correspond to the input parameters. The contribution per factor in isolation is called the first-order effect (S1). Variance can also be added by interactions between the factor and other factors, the sum of variance that is added by all of these interactions is called the total order effect (ST) and is approximated analytically. The advantage of Sobol is that it can explicitly show second-order interaction effects, caused by two factors that together have a significant impact on the model outcome.
The analysis is performed using standard hyperparameter settings from the SALib implementation which means the number of resamples is set to 100 and the confidence interval level is 95%. The number of experiments that were run for the analysis is dictated by the algorithm to be 49152 experiments.

Figure 3.4 shows the outcome of the analysis for IRR. The lefthand figure shows the influence first-order effects and total order effects have on the model outcome in terms of IRR. For first-order effects, the y-axis represents the fraction of output variance that is reduced on average by fixing input x within its range. For total order effects, it represents the sum of all higher-order interaction effects (Jaxa-Rozen and Kwakkel, 2018). The bigger the difference between the right-hand bar and the left-hand bar, the bigger the influence of interaction effects with this parameter. The

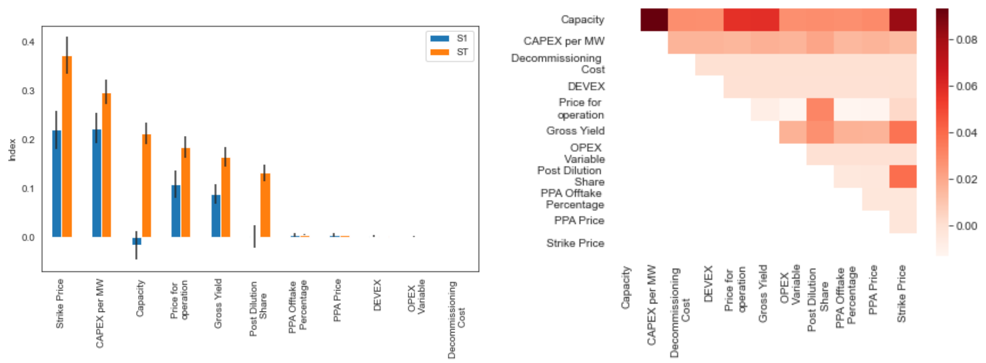


(a) Feature importance for IRR

(b) Second order interaction effects for IRR

Figure 3.4: Outcome of the SOBOL GSA for IRR

black vertical lines in each bar show the uncertainty range of that outcome. The figure shows the same five parameters to be the most influential in the model for IRR as the Extra Trees method: CAPEX per MW, the price for operation, gross yield, strike price, and post-dilution share show the highest ST in the figure. Additionally, the figure shows a big difference between S1 and ST for price for operation, and post-dilution share, indicating high interaction effects. The error bars in the figure are narrow, indicating a stable result.
Subfigure 3.4b shows the second-order interaction effects in the model, the darker the box, the larger the interaction effect between the parameter on the y-axis with the parameter on the x-axis. The figure shows that there are high interaction effects between Dilution price per MW, and Post-dilution share, which suggests that the high interaction effects of these two features stem from their interaction with each other.



(a) Feature importance for NPV

(b) Second order interaction effects for NPV

Figure 3.5: Outcome of the Sobol GSA for NPV

Figure 3.5 confirms the outcomes of the extra trees method as well. The bars indicating ST in the figure show the highest shows that Sobol analysis identified the same six influential input parameters on NPV as the Extra Trees analysis. Additionally, the analysis shows that interaction effects are the most pronounced for Capacity, and Post-dilution share. Subfigure 3.5b shows that mainly capacity has high second-order interaction effects, especially in combination with CAPEX per MW. Two interesting combinations of second-order effects came out of the Sobol GSA:

1. The interaction between Dilution price per MW and Post-dilution share, which influences IRR

2. The interaction between Capacity and CAPEX per MW, which influences NPV

These two effects are analysed further in the next section.

3.3.3 Direction of influence for dilution and capacity

Figure 3.6 shows the value of IRR for different combinations of Post-dilution share and Dilution price per MW. The heatmap shows that the Post-dilution share works as a form of accelerator that increases the impact that the dilution price has on IRR. If the return expectation of the asset during its operational years is lower than the price for operation the diluting party receives, the IRR goes up. The same goes vice versa, when the price for operation is lower than its expected return, the IRR for the diluting party goes down.

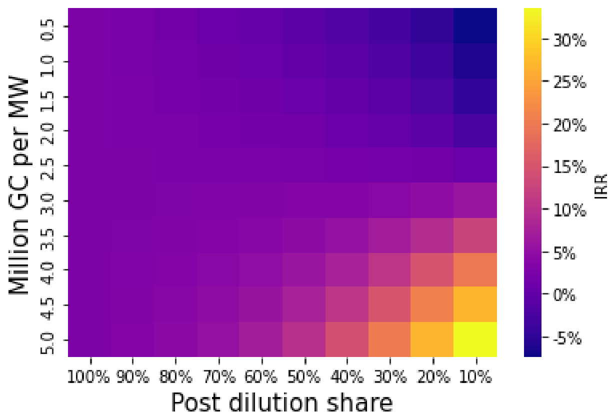


Figure 3.6: Heatmap of the impact of dilution parameters on IRR

To show the shape of this relation between the two dilution parameters, the IRR as a function of Dilution shares and price is plotted in figure 3.7. Here it can be seen that the relationship is nonlinear and the impact becomes stronger as the percentage of the farm that is sold increases. This result implies that if a company considers diluting and the negotiated price for operation is greater than its expected return, the larger part of the asset it can dilute, the higher its expected returns on the asset. This approach implies looking at renewable energy development more from a real estate point of view than from an energy production point of view.

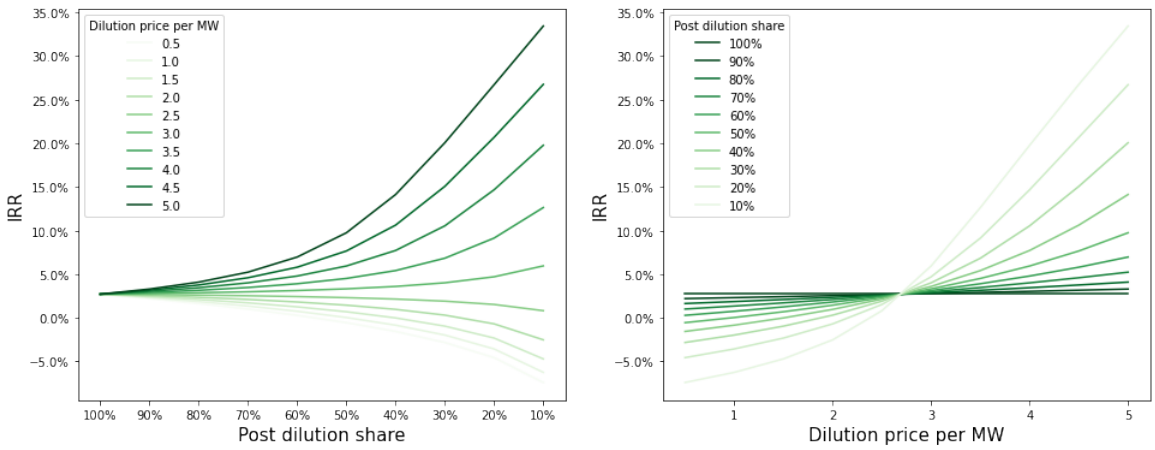


Figure 3.7: Line plot of the impact of dilution parameters on IRR

Figure 3.8 shows the relationship between CAPEX per MW, Capacity, and NPV. Here, a trend similar to the dilution heatmap appears: as the capacity of the wind farm increases, the influence of CAPEX per MW gets bigger. This can be explained when looking at the investment cost needed to build the wind farm. As capacity increases, more turbines have to be built, and if these turbines increase in cost, the total investment cost increases as well.

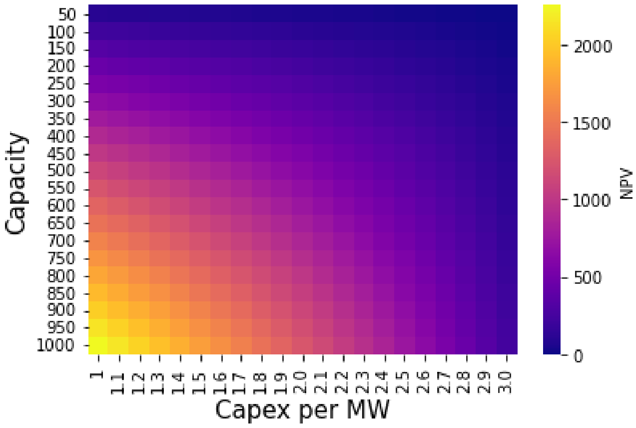


Figure 3.8: Heatmap of the effect of Capacity and CAPEX on NPV

The relationship between CAPEX, capacity and NPV is shown in figure 3.9. The relationship looks linear, calculating the derivative of all lines in the plot confirms that the data approaches a straight line. The biggest difference in dy for each line in the left-side figure is 0.47, on the right-side figure the biggest difference is 0.005.

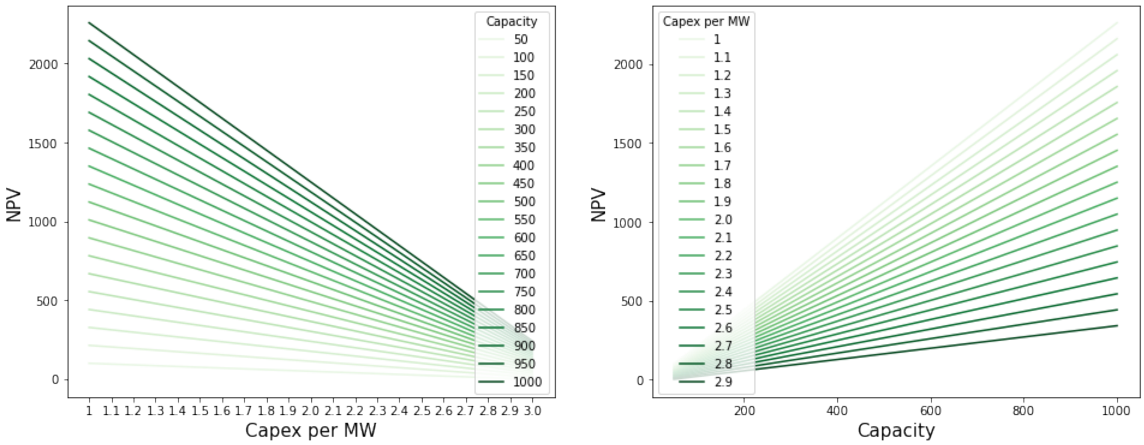


Figure 3.9: Line plot of the effect of Capacity and CAPEX on NPV

3.4 CONCLUSION FOR THIS RESEARCH

The analysis has shown that there are six influential parameters in the valuation model:

1. Strike Price
2. CAPEX per MW
3. Capacity
4. Dilution price per MW
5. Post-dilution share
6. Gross Yield

In the rest of this research, these six parameters are considered to be varied in the agent based model. This means that they can vary over the different tenders and that the bidding strategy of agents can include a variation in these parameters. Figure 3.10 gives a schematic overview of how the interface between the two models is defined. The influential parameters that were found in this analysis make up the 'Interface inputs', all other parameters shall remain constant at a reasonable value. This reasonable value is determined by the industrial collaborator that built the valuation model and is reported in Appendix B. Strike price is a special parameter in the coupled model, as this represents the bid that is issued in the tender. This shall be the output of an agent's strategy. Additionally, the GSA has found that Dilution share and price for operation together have a powerful influence on IRR and that Capacity and CAPEX together can impact NPV significantly.

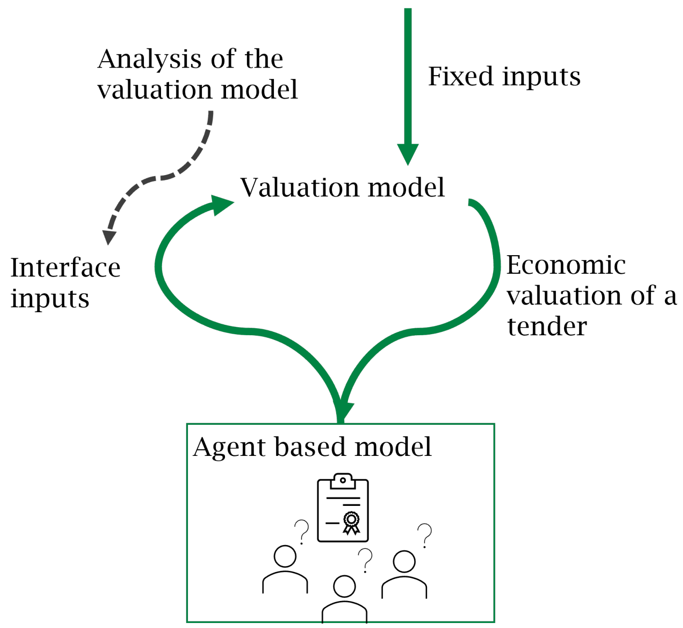


Figure 3.10: Schematic overview of the usage of the influential input parameters of the valuation model in the agent based model.

4 MODELLING A SINGLE TENDER WITH SIMPLE STRATEGIES

This chapter explains the integration of the valuation model with an agent based model in an environment where only one tender is auctioned and agents only apply simplistic strategies. Section 4.1 explains how the model is structured and what assumptions are made in the development. Subsequently, section C.1 verifies the correct implementation of the conceptualisation in the modelling software. Section 4.3 shows and analyses the outcomes of the experimentation with the model. Finally, section 4.4 concludes what the use is of the simple model and how this will serve as a base for the next chapter.

4.1 CONCEPTUALISATION OF SIMPLE STRATEGIES

This chapter and the simple version of the model presented in it serve as a basis and a benchmark for the final version of the coupled model. The model presented in this chapter assumes organisations consider a single tender and utilising relatively simple strategies when formulating their bid. The outcomes from the simple strategies can then be used as a benchmark for the more complex strategy in Chapter 5. Figure 4.1 is a modification to a subsection of the UML class diagram as presented in Chapter 2 in figure 2.1.

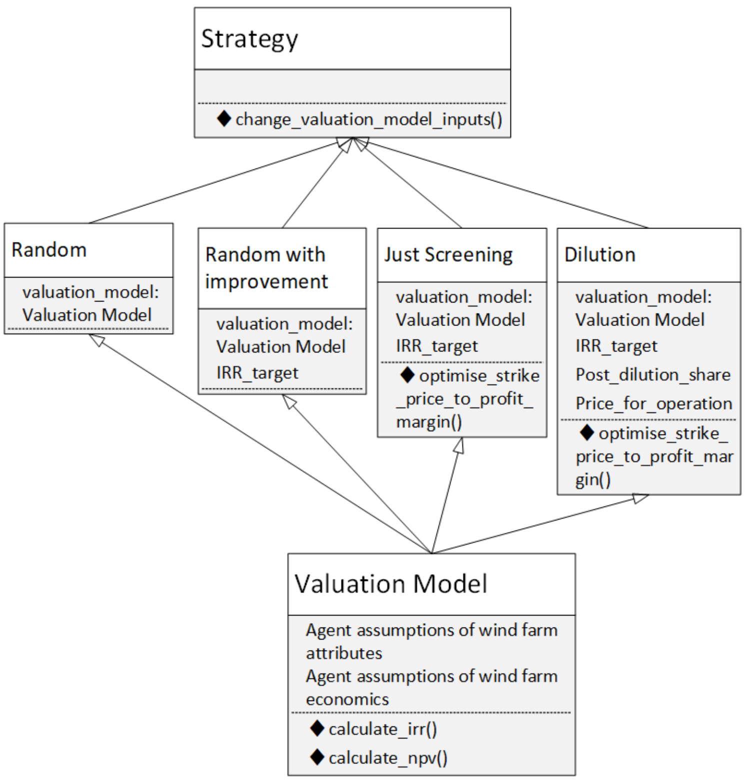


Figure 4.1: UML Class diagram of the simple agent strategies

The diagram shows that there are four sub-classes to the strategy class that every agent has. Each strategy interacts with the valuation model. Considering them left to right, the strategies increase in complexity in terms of parameters to consider and specific functions used to arrive at a bid. The next subsection explains the precise logic of each strategy. The simple model incorporates the notion that it takes time and resources to gather and interpret information, as was one of the key concepts of bounded rationality as explained in chapter 1. Time to acquire information is conceptualised in the form of rounds in which agents can iterate on their strategy. The general structure of a model run is visualised in figure 4.2 and works as follows: At the start, agents are created, and subsequently the first tender is initialised. Then, for as many rounds as the tender has, the agents in the model can iterate on their strategy. Once the auction date is reached, the winner is determined and the next tender is launched.

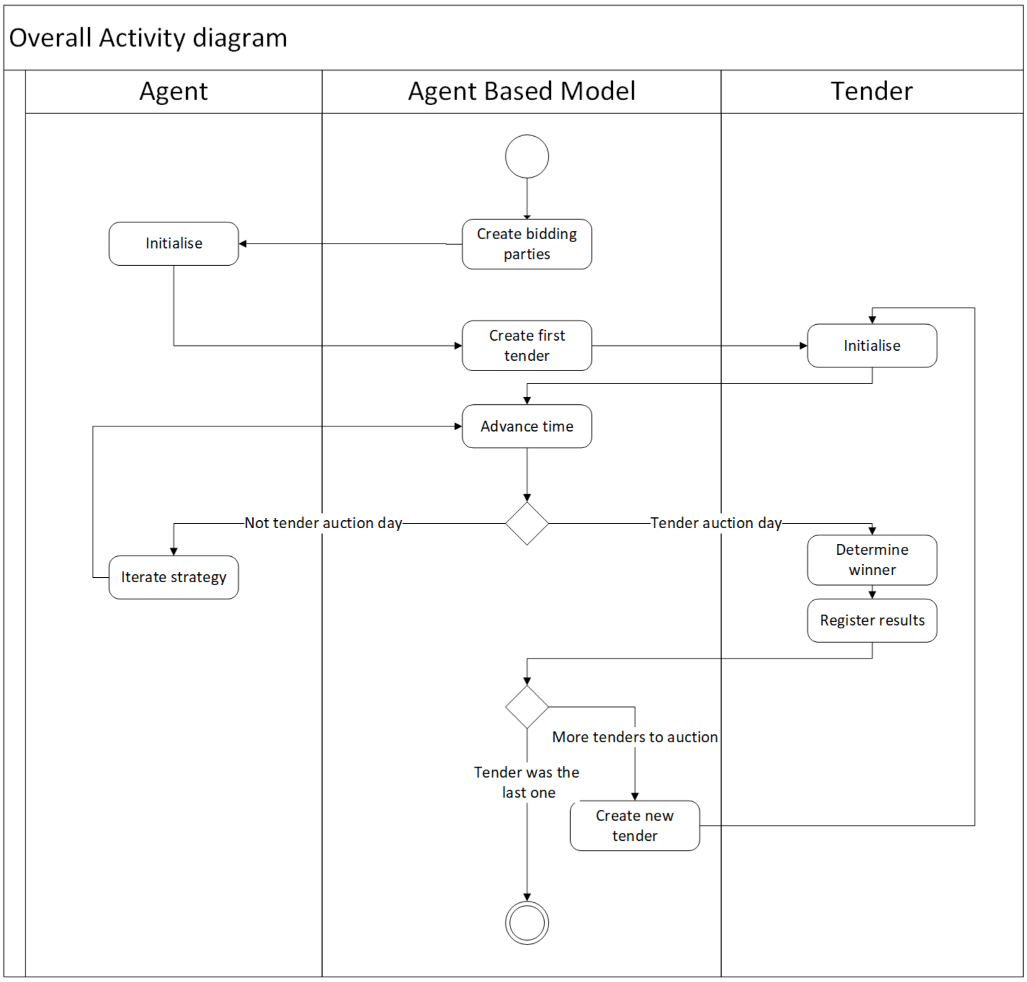


Figure 4.2: UML Activity Diagram of the high level logic of the single tender model

4.1.1 Logic of the simple strategies

The UML activity diagram in figure 4.3 shows the logic of a single step of the agents in the single tender world.
Tenders have two parameters:

- The amount of steps agents can take before the tender is auctioned.
- The maximum strike price agents are allowed to issue as a bid, expressed in Gold Coins per MWh.

Agents have five parameters:

- Their strategy, which is one of the following four: Random, Random with Improvement, Just Screening, and Dilution.
- Their IRR target, this is a parameter used by all strategies except Random.
- Dilution, this is a yes/no parameter that states whether dilution is turned on or off in the valuation model.
- Post-dilution share, in case dilution, is turned on, this parameter determines what percentage of the assets of the wind farm is sold after construction. For simplification, it is assumed that agents always start with a 100% share.
- Dilution price per MW, in case dilution is turned on, this parameter determines how much money the agent receives as a lump sum per MW of wind farm it dilutes.

Agents with a 'random' strategy sample uniformly a strike price between 0 and the maximum strike price of the tender. In this version of the model, the strike price is modelled as an integer, so bids can be precise to the single GC. The sampled strike price is directly the bid of agents with a 'random' strategy, so after the first step in the tender, the agent idles.
Agents with a 'random with improvement' strategy sample a random strike price between 0 and the maximum strike price each step. Subsequently, they assess whether this strike price brings them closer to their IRR target than the 'best guess' they had before. After the last step, their best guess at that time is their bid.
Agents with a 'just screening' strategy optimise their bid to land exactly at a strike price that according to the valuation model should result in a project with an IRR that matches their target. Optimisation is done using the Python implementation of the Golden-section search algorithm (Sci-Py, 2022a). The golden-section search algorithm is a robust method for finding the minimum of a certain, unknown, function that is widely used in computer science applications (Press et al., 2007). The function is relatively quick as the inputs and outputs are noncontinuous and an interval in which the inputs lie is defined as [0,maximum strike price of the tender].
Agents with a 'dilution' strategy arrive in the same way at their bid as just screening. Only after determining their bid, they change the input in the valuation model to turn on dilution, which gives a boost to the IRR and NPV of the tender.
Table 4.1 shows the values for all strategy parameters as they are defined for this chapter. A full list of model parameters is included in Appendix B.

Table 4.1: Input parameters for the simple strategies

Strategy	IRR Target	Dilution	Post-dilution share	Price for operation
Random		FALSE		
Random with improvement	5%	FALSE		
Just screening	5%	FALSE		
Dilution	5%	TRUE	50%	3.5 million GC per MW

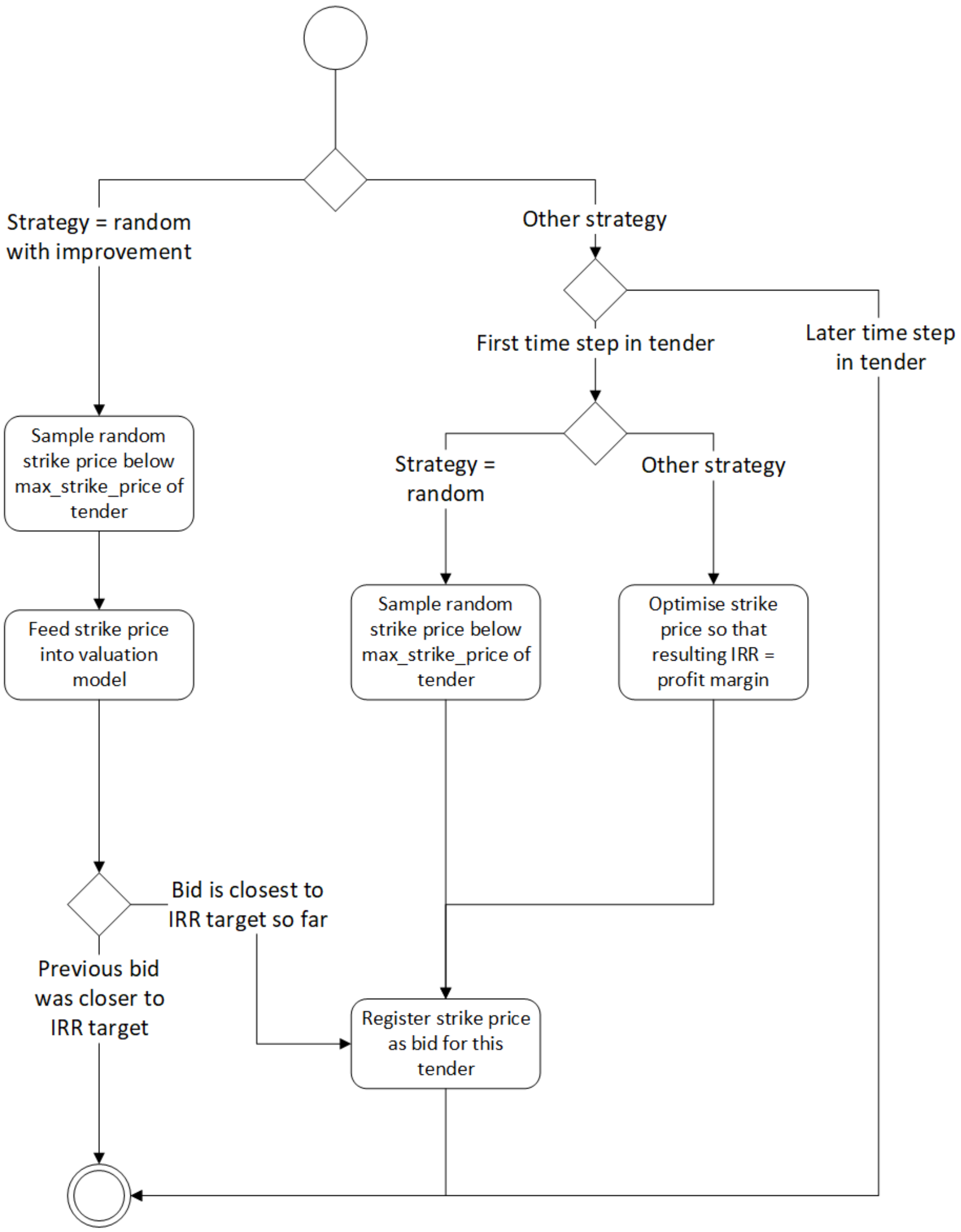


Figure 4.3: UML Activity diagram of the simple agent strategies

4.1.2 Assumptions

The general assumptions that are made in the model are explained in chapter 2.4. In this simple version of the model, additional assumptions apply. The most important assumptions are the following:

Agents assume the same economics for the tenders.
In reality, the economics can vary for instance according to the type of wind turbines the agents use, or development costs can be lower for agents that already have other wind parks and can have more experience as well as achieve operational and procurement synergies. Agents can also get better conditions on deals with other organisations or from a bank. A related topic is the aspect of bounded rationality where agents can disagree on aspects such as yield from the farm, maintenance cost, capture price for their produced power after the subsidy period, inflation, or prices

they can get for green certificates.

Agents do not consider any competition when deciding what to bid.
This assumption is made to really show the pure effects of simple strategies such as bidding randomly or approaching a target. In reality, organisations estimate what their competition will bid and will consider outbidding them, or, based on their estimation, decide it is not worth putting extra effort into bidding for this tender.

Agents only consider one tender at a time. Other tender options that might exist are not relevant for the bid the agent issues in the tender auction.

Agents do not learn or change their strategies over time. This is a consequence of simulating single tenders, which means agents only have a single chance to apply their chosen strategy and examine the results. The model was run for multiple replications purely for the statistical significance of the results. In reality, agents can learn from strategies they applied in the past and can change this strategy when they see it is not working well.

Agents are not limited by a budget when bidding on a tender, all bids between 0 and the maximum strike price of the tender can be issued by the agent.

These assumptions have a substantial impact on the behaviour of the agents in the model, which is why the results should not be interpreted as a representation of actual bidding. The goal of this chapter is to showcase the method of developing an ABM for this purpose and how to interpret its results. Also, keep in mind that these assumptions solely hold for the simple version of the model. In the next chapter, a more elaborate model is conceptualised and developed, which has different assumptions and simplifications. This more elaborate model is considered to be the product of this thesis, which is why the notion of the robustness of the model to the assumptions is not discussed in this chapter.

4.2 VERIFICATION

This section is concerned with assessing whether the algorithm as described in section 4.1.1 is implemented as intended.

4.2.1 Verification tests

The most straightforward way to do this is by looking at the resulting bids of the agents. As each agent only considers their own economics and not each other in their strategy, the bids can be assessed on their own.
Figure 4.4 shows the result of agents bidding on 2000 separate tenders. The top left shows the distribution of random bids, given that the agent should sample from a uniform distribution and the maximum strike price of all tenders is 100 GC, the algorithm seemed to have performed as intended. To test this hypothesis, a Kolmogorov-Smirnov test is performed to test whether this distribution is different from a uniform distribution between the same bounds based on a million samples. The Python implementation of the SciPy package is used for this Sci-Py (2022d). The p-value from the test is 0.60, which means the null hypothesis cannot be rejected, which supports the hypothesis that the distribution stems from a normal distribution.
The bottom two histograms show the result of just screening and dilution, both of which are deterministic strategies. In this specific configuration of the tender, a

strike price of 58 results in an IRR of exactly 5%, which was the IRR target of the agents. The figures show that the Golden-section search algorithm indeed land on this strike price each time.
Moving to random with improvement, the result of the algorithm should approach this optimum of 58 GC and indeed visually this seems to be the case. To test this, the SciPy implementation of the Shapiro-Wilktest for normality is performed on the samples Sci-Py (2022e). The test is performed on 2000 samples of this strategy and resulted in a test statistic of 0.99 with a p-value of 1.45e-29, which supports the hypothesis that the result approaches a normal distribution. The mean of the 2000 samples is 56.38, this is slightly lower than the optimum of 58. This is because 58 is a bit higher than the average of the sampling range ([0-100]).
Overall, the algorithm seems to work as intended. Additional verification tests are included in Appendix C.

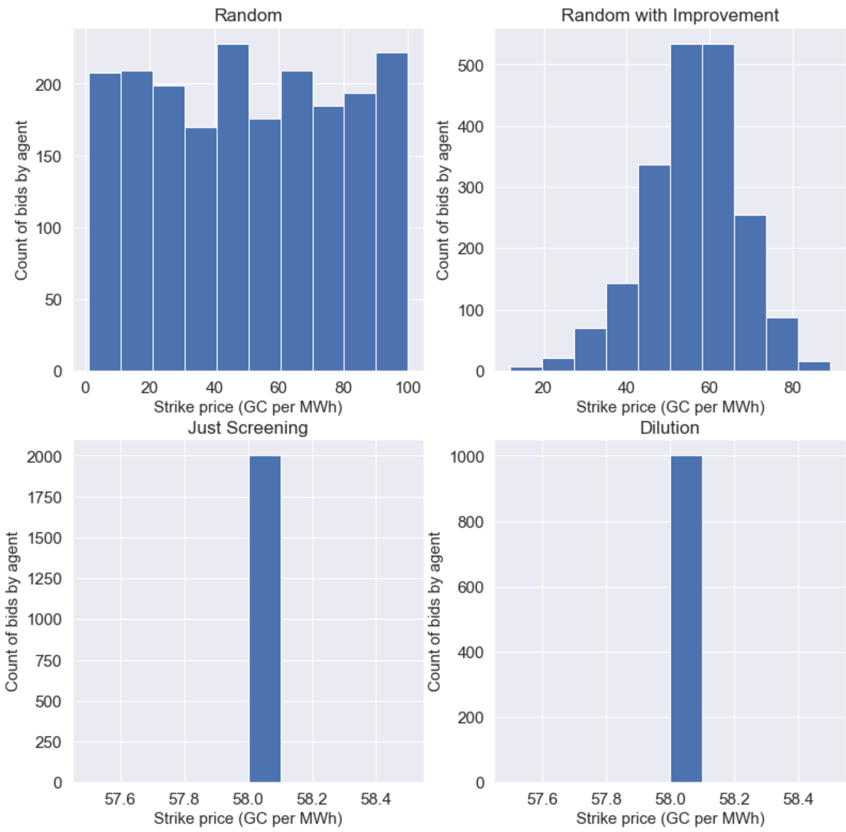


Figure 4.4: Distribution of bids for each simple strategy, based on 2000 samples of the strategies.

4.2.2 Assessing the convergence of the model runs

In the model, there are two places where stochasticity occurs. First, when agents with a 'random' or 'random with improvement' strategy formulate a bid, random numbers are generated between 0 and the maximum strike price of the tender. Second, when multiple agents issue a low bid, the winner is chosen through a lottery. This adds randomness to the model, which means the model has to be run sufficient times before the outcomes of the model are stable and reliable. The way to assess whether sufficient runs were performed in this research was the convergence of key model outputs. A model run is considered to be converged in the case that the 95% confidence interval on the mean of the output is smaller than a certain bandwidth which is defined per key outcome. Table 4.2 lists the key outputs that were considered. Appendix C includes the convergence plots of the outcomes. The fourth

key output, the winner's curse, converges slower than the other outputs, this stems from the fact that the winner's curse is only defined for runs where an agent wins a tender.
The mean of winner's curse and average bid are most uncertain for runs with agents that have a 'random' strategy, followed by runs with agents that include an agent with a 'random with improvement' strategy. For the other strategies, the bids of the agents are deterministic which means they do not vary. 2000 model runs per experiment were sufficient to meet these criteria for all outcomes, which is why all experiments with the model are run 2000 times.

Table 4.2: Outputs that were checked on convergence through a 95% confidence interval of the mean

Key output	Maximum band width	Unit
Success rate	0.5	% GC
IRR	0.5	%
Average bid	3	GC/MWh
winner's curse	3	GC/MWh

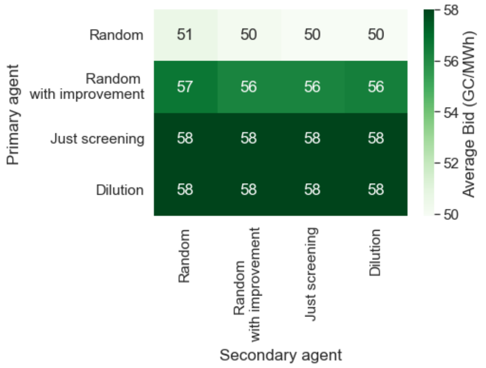
4.3 EXPERIMENTATION AND ANALYSIS

Experiments with the model are performed by creating set-ups where two agents bid on a single tender. This process is repeated 1000 times to arrive at statistically significant results for the strategies that involve random sampling (random and random with improvement). Tenders always allow for 5 steps by the agents before the tender is auctioned and the maximum strike price is always 100 GC per MWh. The parameters of the agents depend on the strategy that they apply, which is shown in table 4.1.
Metrics that are used to analyse these 1-on-1 games are the following:

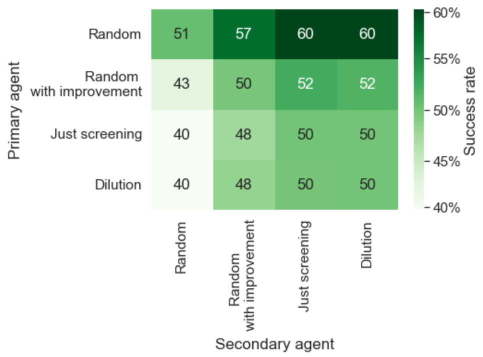
- Success rate: This is the percentage of tenders the agent wins using this strategy against another agent with a defined strategy.
- Average IRR: This is the average IRR the agents achieve over all tenders that they win.
- winner's curse: In this research, winner's curse is defined as the difference in strike price (in GC per MWh) between the winner of the bid and the runner-up for all tenders the agent has won. When entering an auction, the metric does not help the decision maker a lot to determine a winner as the winner's curse is only defined in hindsight. However, it does help to show what the effect is of the defined strategies in the long run so it is reported on in this research. Additionally, it is a metric that is often used in the field of auctioning to assess whether the strategy was efficient (Hahn and Seaman, 2010).

Figure 4.5 shows the outcomes of the runs for all 1-on-1 games on these metrics as heat maps. The outcomes are presented as a heat map where the metric is shown through the colors in the grid. The two axes represent the two agents that are competing. At the top left of the figure, the average bid for each strategy in each game is shown. What this shows is the average from the distributions as shown in the verification section C.1. Conceptually, we know that the random strategy should result in an average bid of 50. For one game, the one shown on the top left where two random agents compete, there is a small deviation from this average. This is due to the sample size of 2000, which means the average can deviate a little. The same can be seen for random with improvement, the theoretical average is 56.4, in the experiment where it competes again a random agent, this

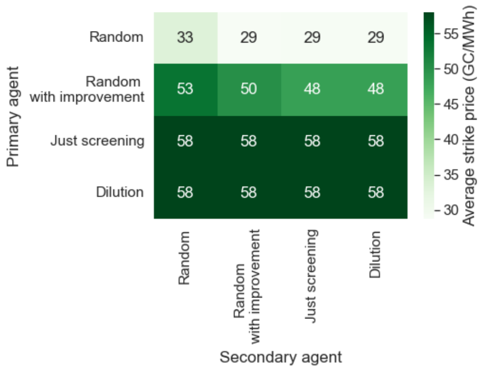
came up slightly higher. Overall, the plot shows stable results, where all agents have the same average bid, regardless of their competition. This is in line with the conceptualisation of this simple model. Subfigure 4.5b at the top right shows the success rate of each strategy pair when they play against one another. All strategies have an equal chance of winning when competing against an agent with the same strategy. Agents with a random strategy have a higher chance of winning over the other strategies. This is due to the different average bids, which are higher for the three other strategies. The 'dilution' strategy and the 'just screening' strategy result in the same optimal bid, which explains the 50/50 win chance between these two strategies.
Subfigure 4.5c, it can be seen that though the success rate of the random strategy tends to be higher than the others, the strike price it wins these tenders with is considerably lower. This also results in a lower average IRR, as shown in subfigure 4.5d. Here, it can also be concluded that the 'dilution' strategy reaches the highest average IRR in these model settings. This is because the strategy optimises for IRR and subsequently applies dilution to boost its expected returns.



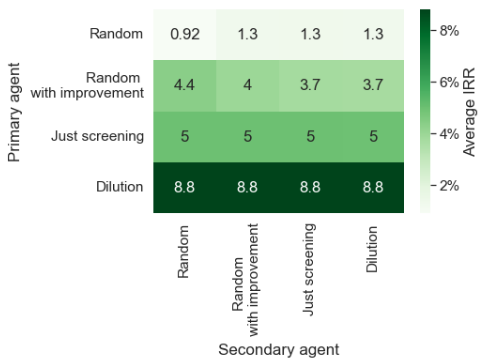
(a) Average bid of simple strategies when competing against one other agent



(b) Success rate of simple strategies when competing against one other agent



(c) Average strike price of simple strategies when competing against one other agent



(d) Average IRR of simple strategies when competing against one other agent

Figure 4.5: Outcome of 1000 runs for each combination of simple strategies in the single tender world

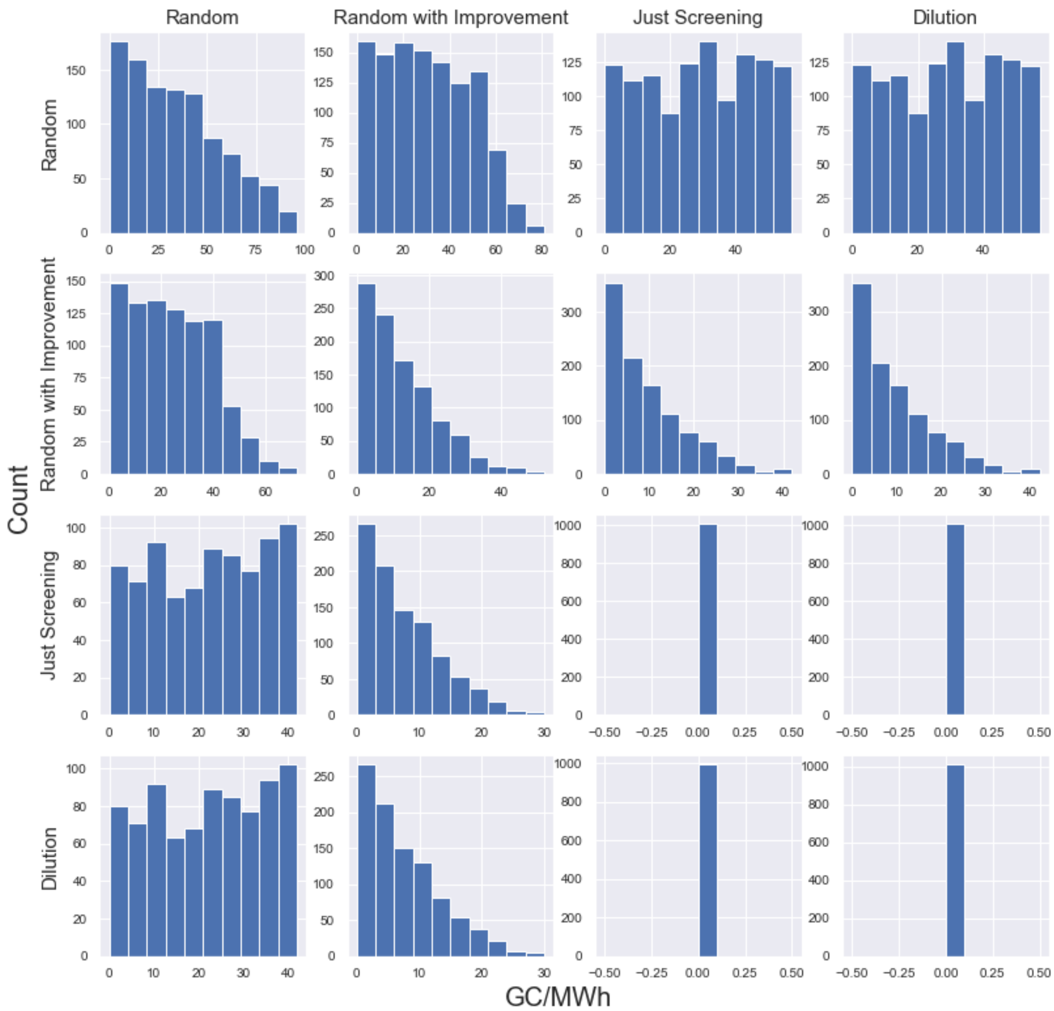


Figure 4.6: Distribution of winner's curse for the 1-on-1 games

Figure 4.6 shows the distributions of winner's curse for all 1-on-1 games. Just like in figure 4.5, the rows represent the primary agent for which the winner's curse is defined, the columns represent their competition (the secondary agent). The four figures in the right bottom show that the winner's curse is always 0 for two deterministic strategies playing against each other as they will always bid the same. Random with improvement has a chance of bidding lower than the optimal bid, but it tends to stay close to the optimum, which results in an exponential shape in the winner's curse. The 'random' strategy has an equal chance of bidding anywhere in the range, making it most prone to result in a high winner's curse. The distance between two random numbers in the same interval follows a triangular distribution, which explains the shape of the winner's curse between two 'random' strategies.
Overall, the distributions follow the theoretical distributions one should expect given the conceptualisation of the strategies. In the context of this research, utilising a 'random' strategy overall results in the highest winner's curse as it is prone to deviate from the competitors' bid. This makes this on average an inefficient strategy.

4.4 CONCLUSIONS FOR THIS RESEARCH

This chapter served as an introduction to the agent based method of considering bidding behaviour. The chapter has introduced the reader to the way the model works and it has shown that the conceptualisation of the basic structure of the model works as intended. Additionally, the heat maps of Success rate, Average IRR, and winner's curse showed how bidding behaviour and its consequences can be visualised and interpreted. From the analysis, it could be concluded that optimising one's bid is a sensible strategy that should lead to a significantly higher IRR of one's portfolio. Bid optimisation shall therefore form the basis of the more complex bidding strategy that is presented in the next chapter. Here, the model is expanded to allow agents to consider multiple sequential tenders, which allows for more complex and realistic bidding behaviour.

5 MODELLING SEQUENTIAL TENDERS

This chapter shows the expansion of the simple model of chapter 4 to include multiple tenders for the agents to consider. Section 5.1 explains the logic the agents follow to arrive at their bid and what assumptions and simplifications are made in the process of conceptualisation. Verification tests and their results are discussed in section 5.2 to build confidence in the implementation of the conceptualised model. Section 5.3 explains what experiments were performed with the model and what the outcomes were. The validation of the model and its outcomes are discussed in section 5.4. Conclusions that resulted from this are summarised in section 5.7 as well as their implications for organisations and policy makers.

5.1 CONCEPTUALISATION OF SEQUENTIAL TENDERS IN THE MODEL

The version of the model that is presented in this chapter is a more complex version of the model presented in the previous chapter. Factors that influence bidding behaviour in organisations, added in this version include:

- Budget constraints for the agents regarding investments. In the previous version, agents had an unlimited budget to compete in wind farm tenders. In reality, organisations allocate an investment budget to a certain portfolio, such as offshore wind. This capital allocation has to be published for stakeholders to see, which means the competition of the organisations can as well. Budgets are conceptualised in the model by giving each agent a quantity of Gold Coins that they can spend on the capital costs of wind farms.

- The consideration of future opportunities by the agents. In the previous version, agents only considered the tender that was being auctioned at that moment. In this version, agents consider other tenders in the pipeline when deciding what to bid. In the model, this consideration is conceptualised by allocating an 'importance' to each tender for each agent, this notion is further explained in the next section.

- Differentiation of goals of the agents regarding tenders. In the previous tender, the goal of the competing agents was solely to maximise their profit. In this version, a second goal of reaching a certain target in terms of the total installed capacity of wind power is added to the mix. These capacity goals are often announced publicly which makes them a separate objective from the basic goal of commercial companies to make a profit. Examples of this are Ørsted (2019) announcing their target to double their offshore wind capacity between 2015 and 2019 and Vattenfall, targeting 11 GW of offshore wind in Europe in 2025 (Eckert, 2019).
  To conceptualise these twofold goals, agents each have a generation target (in terms of installed capacity) and an economic target (in terms of NPV) that they want to achieve with the opportunities in the sequence of tenders. NPV represents the economic and not IRR as the size component of the expected revenue stream from their offshore wind assets is relevant for their target, not only the risk associated with the opportunities. To indicate the relative

importance of one target over the other, agents also have a parameter called **GenImp**. The parameter is defined between 0 and 1 where 1 means the agent solely strives to meet its generation target and 0 means the agent solely strives to meet its economic target. Values in between indicate the agent balancing both targets.

Figure 5.1 shows the general structure of the expanded model where agents consider a sequence of tenders. At the beginning of the run, the model creates a factorial design of all possible combinations of winning and losing tenders as they exist for the defined number of tenders in the run. Next, the agents are created. During their initialisation, the agents assess the factorial design and separate the combinations that are viable from the ones that are nonviable considering their budget and the investment cost of the tenders. To save computing time, the model discards all combinations from the factorial design that are nonviable for all agents in the model. Next, it is time to launch the first tender. The strategy the agents deploy in this version of the model consists of two phases. In the first phase, the agent considers what it would bid without understanding what its competition is. To do this, the agent adopts the Just Screening strategy, introduced in Chapter 4 where the agent has a certain target IRR and optimises its bid using the valuation model to reach this target. Subsequently, the agent estimates what its competition will bid and if necessary, it will adjust its bid accordingly. These two phases are further explained in the next section. After each agent has issued its bid, the winner of the tender is determined and the next tender in the sequence is initialised.

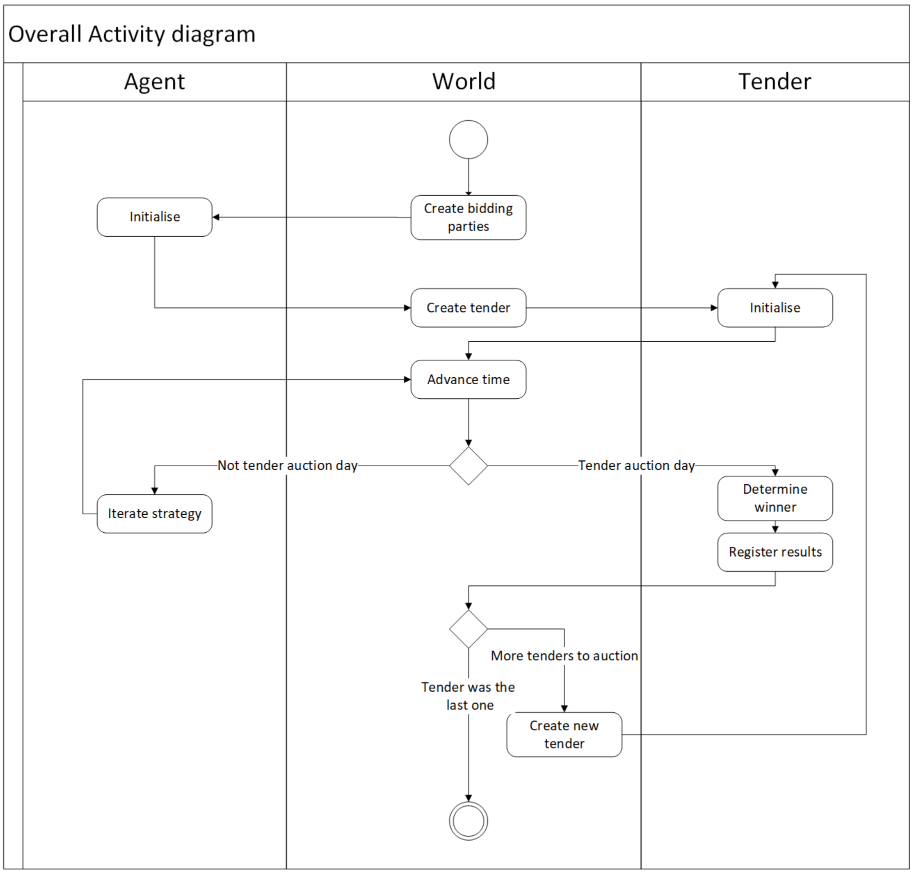


Figure 5.1: UML Activity diagram of the high level logic of the sequential tenders model

5.1.1 Logic of the agents

Figure 5.2 shows the three steps in which agents initialise. First, they consider their initial budget and determine for each tender set in the models factorial design if they can afford this combination of tenders. To do this, they consider the capacity of the wind farm (expressed in MW) and the CAPEX of the project (expressed in million GC/MW RT). The multiplication of the two represents the investment cost of the tender for the agent.
Secondly, the agent calculates how well each viable tender set performs in terms of generation. To do this, agents consider their generation target and the total generation that would be installed after achieving each combination of tenders that are considered viable. The score is then a value between 0 and 1 where 0 MW of generation resulting from the tender set gives a score of 0 and a score of 1 indicates the achievement of 1.1 times the generation target of the agent. The highest score is allocated to a higher value than the target to account for the agent's irrational desire to overdeliver on their promise (an investor bias explained in Chapter 1). Intermediate scores are defined through linear interpolation. An example of this is shown in figure 5.3. The graph shows what generation score corresponds to what achieved generation. Any additional generation after 1.1 times the target does not add any utility.

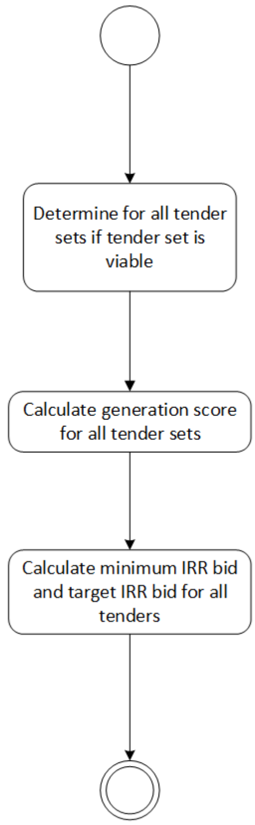


Figure 5.2: Initialisation process of agents

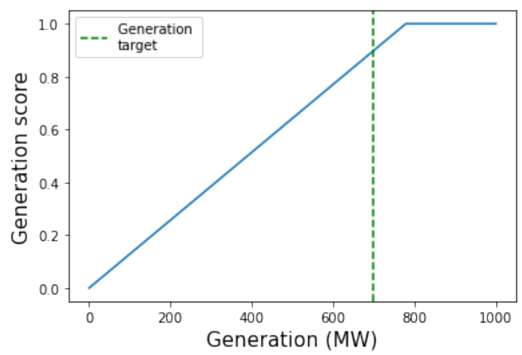
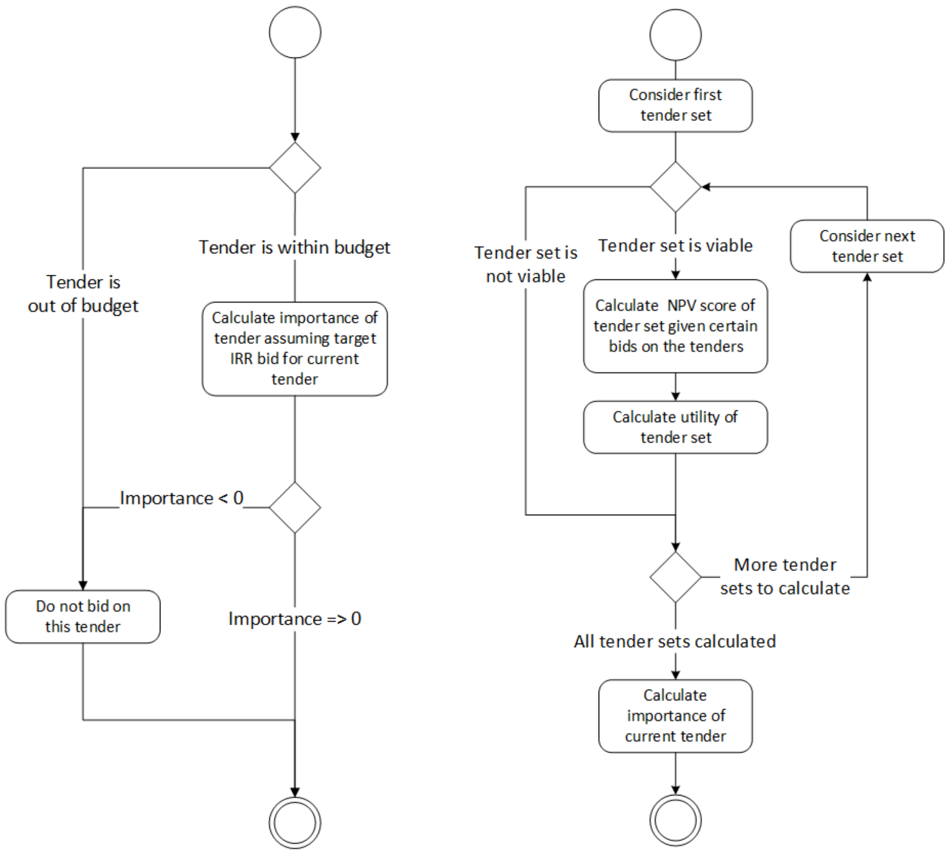


Figure 5.3: Example of the value of utility per generation capacity that is achieved.

As a last step in their initialisation, agents calculate two aspects for each individual upcoming tender, the minimum IRR bid and the target IRR bid. Agents use two parameters related to IRR for this; minimum IRR is the lowest IRR for which the agent would still be interested in a tender, and target IRR, which indicates the IRR the agent would like to get out of projects. In the last step of agent initialisation, the agent determines for each tender what subsidy strike price would result in the project having their minimum IRR and what price in their target IRR. This represents the range of bids the agent considers for each tender.



(a) Process of agents determining the importance of a tender without considering competition

(b) Process of agents calculating the importance of a specific tender

Figure 5.4: First strategy step of agents in the model

Figure 5.4 shows in detail how agents arrive at a bid for a tender. The left side figure (figure 5.4a) shows agents determine how important they find the upcoming tender auction considering the other tenders still to come. Importance is defined between -1 and 1 where positive numbers indicate agents finding this tender relatively important. How this importance is calculated is shown in figure 5.4b. For each viable tender set, the agent calculates how good that set scores in terms of NPV given that the upcoming tender would be won with the bid corresponding to the agents' target IRR. For previous tenders, the actual outcome of the tender is used and for future tenders, the agent assumes it would win the tender with the average of the tenders target IRR bid and the tenders minimum IRR bid. This limitation is further addressed in section 5.1.3. The NPV score is calculated in the same way as the score on generation (explained above). The score is defined between 0 and 1 where a maximum score of 1 is achieved when the tender set would realise 110% of the agents' target NPV.
Next, the NPV score is combined with the generation score that was calculated in the agents' initialisation to calculate the combined score of this tender for the agent. This combined score is referred to as 'utility' and is calculated through equation 5.1. In the utility function, tender sets that the agent cannot afford are not considered. Important to note here is that the utility of a tender set changes as the auctions progress. Winning a tender at a price different from the assumed one influences the utility of all sets that include this tender. Therefore, agents recalculate the utility of each possible tender set after each auction.

$$Utility_{Tenderset} = Gscore_{Tenderset} * GenImp_{agent} + NPVscore_{Tenderset} * (1 - GenImp_{agent}) \tag{5.1}$$

where:

$Gscore$ = Score on generation

$GenImp$ = Relative importance of the generation target over the NPV target

$NPVscore$ = Score on expected NPV

After calculating the utility of each viable tender set, the agent calculates the importance of the upcoming tender through equation 5.2. The importance is defined as the average utility the agent would achieve over all tender sets in which the current tender is won minus the average utility over all tender sets in which the tender is lost. This results in a score between the -1 and the 1 where a score > 0 indicates that the agent expects to gain more from winning this tender than from letting it pass.

$$Importance = \frac{\sum_{T_i \in tenders\ won} U_T}{\sum_{T_i \in tenders\ won} 1} - \frac{\sum_{T_i \notin tenders\ won} U_T}{\sum_{T_i \notin tenders\ won} 1} \tag{5.2}$$

where:

T = Tender set

i = Current tender in tender set

U = Utility

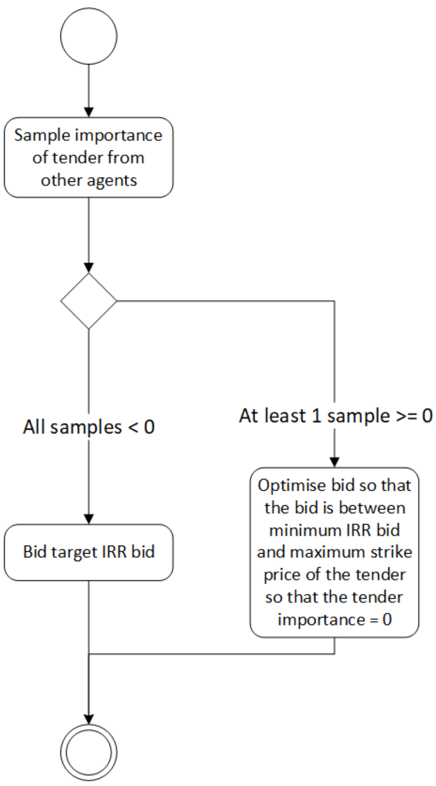


Figure 5.5: Process of agents considering adjusting their bid to account for expected competition

Figure 5.5 shows the second part of the agents strategy. First, the agent samples around the importance of the current tender of the other agents where it assumes the agent bids to achieve their target IRR for the tender. The importance is sampled uniformly in a specified range that is symmetrical around the true importance of the agent. The width of the range is a model parameter.

In case all the sampled importances come back negative, the agent assumes it is the only interested party in the tender and it will bid the strike price corresponding to achieve its target IRR for this tender. In case at least one sample comes back positive, the agent seeks the bid for which its minimum IRR is still achieved and the importance of the tender comes closest to 0. This bid represents the most competitive bid the agent is willing to issue.

An efficient method of finding the 0 point of a function is using root-finding algorithms (McMullen, 1985).

For this application, the root scalar function implementation in the Python package SciPy is used (Sci-Py, 2022c).

The method described in this section is one of many possible alternative formulations. After testing different formulations, this configuration was found to work well and generate intuitive results.

5.1.2 Model parameters

Table 5.1 shows the most important tender and agent parameters in the model, as well as their units and ranges. A full list of model parameters is included in Appendix B.

Table 5.1: Most important input parameters for the model

Parameter name	Range	Unit
Tender parameters		
Auction year	[2022,2032]	year
CAPEX per MW	[1-3]	Million GC / MW
Capacity	[50-1000]	MW
Maximum strike price	[0-150]	GC / MWh
Competitors importance uncertainty	[0,1]	-
Agent parameters		
Budget	[0,5000]	Million (mln) GC
Minimum IRR	[0,20]	%
Target IRR	[0,20]	%
NPV target	[0,1000]	Million GC
Generation target	[0,2500]	MW
GenImp	[0,1]	-

5.1.3 Assumptions

In order of most influential to least influential, the main assumptions of the model are the following:

In the model, the only objectives agents can have with acquiring wind farm tenders are the profit they expect to make on the wind farm and the total capacity (in MW) that they install. Other objectives could play a role as well, such as the desire to gain experience in a certain geographical area due to synergies with their other businesses or operations. Another could be the desire to use a specific technology that is required for that specific wind farm for a strategic advantage. This complexity is expected to create wild cards amongst the agents where sometimes a bid is lower than what is seen as reasonable. This can have a significant effect on the model outcomes and therefore has a significant influence on the robustness of the model.

Agents do not learn from past tender results nor change their strategy over time. In reality, agents rely heavily on their past experiences and even irrationally consider previous experiences to match future options (Baker and Nofsinger, 2002). This can potentially influence the model behaviour significantly by introducing path dependency for the agents, reinforcing strategies that worked out well for agents in previous auctions, and penalising strategies that were unsuccessful in the past of the agent. This could create more extreme bids in the model outcomes and potentially have a significant influence on the model robustness.

The model assumes all agents to reason the same way. This homology is not necessarily what is observed in reality. Organisations consist of employees that are all subject to their own bounded rationality and build on their own experiences. This assumption creates a consistency in the model that is likely not to exist in reality. The expectation is that this creates a bit more randomness in the model outcomes than currently depicted. However, this should not lead to significantly different results as the decision making process for offshore assets is typically conducted by a substantial team in an organisation, which introduces checks and balances in the decision making process, reducing the influence of this randomness.
That being said, the influence of groupthink in organisational decision making should not be underestimated. Groupthink refers to the desire of members of a group to conform to the consensus of the group, which prevents them from expressing their actual opinion (Janis, 2008). This could increase the randomness of the eventual bid decision again. Concluding, the assumption is expected to have a moderate influence on the robustness of the model.

Though dilution proved to be a profitable strategy in the simple model presented in Chapter 4, the option was removed in the final version of the model to reduce complexity. In reality, dilution is applied often to increase the returns on a wind farm project and could allow agents to regain resources from previously won tenders to acquire new ones. The influence of this assumption on the robustness of the model is limited, as dilution biases the bids in the model in the same direction, which means it has a limited influence on the trends that are found in the model outcomes.

Agents consider a static budget. As the tenders progress, the budget is not increased or decreased. In reality, budgets are flexible year on year, especially after previous successes. A study by Baker and Nofsinger (2002) found that there is even an irrational tendency to expect future successes that the agent has experienced in the past, which could mean that there is a higher chance of budget increases for a certain portfolio after a 'good deal' on a tender. Additionally, referring to the work of Nofsinger (2017), investors tend to take bigger risks to compensate for losses and after big successes, which would also mean that they could become more flexible in terms of what to spend on acquiring wind farm tenders. The robustness of the model is expected to be not very affected as the budget in organisations large enough to bid on offshore wind often is static in the short term and changes in the budget require time.

Agents always consider a specific set of tenders for which they can spend their budget and which they can use to meet their targets. As the tenders progress, no new tenders are added to this set. In reality, tenders are announced continuously and new prospects are investigated as they come in. For early tenders in the sequence, this should not influence the behaviour drastically. In later tenders, agents are expected to bid a bit less competitive than shown in this version of the model, as often the tender does not pose the last chance for the agents to win an offshore tender.
That being said, targets for organisations are set for a specific point in the future, which means that in that sense it would indeed be the last chance for the agents to reach their target. Therefore, the assumption is not expected to have a major influence on the robustness of the model.

When considering future tenders, the agent assumes it can win those tenders with a relatively high bid. In reality, agents can predict the outcome of future tenders based on different factors instead of simply taking the average between its target and its minimum bid. This can introduce a bit more variance in the agent's bids but is not expected to pose a significant influence on the robustness of the model.

When considering its bid, the agent does not consider that the predictions of the IRR or NPV in their valuation model are dependent on uncertain assumptions about the future. This is in line with the known investors bias where too much confidence is placed in the accuracy of the investors' information (Barber and Odean, 1999). Still, it is likely that organisations consider multiple scenarios for the future and consider adjusting their bid accordingly. This can create a bit more variance in the bids of the agents. However, compared to the influence of the other assumptions that introduce variance in agents' bids, the influence of this assumption on the model robustness is limited.

5.2 VERIFICATION

This section is concerned with assessing whether the algorithm as described in the previous sections is implemented as intended.

5.2.1 Story telling of an example run

Verification has been performed by carrying out a number of tests. Storytelling is verification method that can help the reader understand the logic of the model. We follow a 5 year run with yearly tenders, starting in 2022. All other model input is equal to the base case input of the model, which is listed in table 5.4.

Table 5.2: Storyline of an example run

Tender Number	Tender capacity	Target IRR bid	Minimum IRR bid	Agent 1	Agent 2	Agent 3	Agent 4
1	100 MW	93.6	64.5	64.5	64.5	64.5	93.6
2	300 MW	90.2	61.4	66.9	61.4	61.4	61.4
3	500 MW	89.5	60.8	71.1	73.4	60.8	73.4
4	700 MW	89.2	60.5	60.5	60.5	No Budget	60.5
5	900 MW	89	60.4	60.4	60.4	No Budget	No Budget
Outcomes							
			Generation achieved	1000	0	800	700
			Generation score	1	0	1	0.9
			NPV achieved	231.1	0	207.8	163.7
			NPV score	0.42	0	0.37	0.29
			Utility score	0.71	0	0.69	0.58

Table 5.2 shows the storyline of the tender. A cell that is hatched indicates the agent won the tender. Notice that the target IRR bid and minimum IRR bid vary as the tender capacity changes. This is due to economies of scale that make wind farms more profitable when they increase in capacity.
The first tender is not the most profitable of the bunch, all agents calculate its importance as 0.03. After sampling their estimate of the importance that the other agents assigned to this first tender, Agent 4 thinks it is the only interested agent in the tender. This means it thinks it can bid for its target IRR, so it issues a bid of 93.6 GC/MWh. The other agents suspect competition and calculate that even when bidding their minimum IRR bid, they expect to gain more with this tender than without it. All three agents decide to bid their minimum IRR bid. Through a lottery, Agent 1 gets the first tender. Having this first tender, the agent finds the next tender a bit less interesting, also because the first two tenders would take a big

bite out of its budget, preventing it from being able to afford the last two tenders. It calculates the tender would be worthwhile for a strike price of 66.9 GC/MWh. The other agents bid minimum IRR, and agent 3 wins the lottery.
The 500 MW tender is most interesting for agent 3 as it can combine it with its 300 MW that it has already won to achieve its generation target. The agent decides to bid minimum IRR. The other agents consider that winning this tender means that the last two tenders are out of the question and that total capacity does not get them anywhere near their NPV or generation target. They bid higher so agent 3 wins the third tender. This also means the agent has no more budget for the two remaining tenders so it does not bid on them. The fourth tender is interesting for all three remaining agents as there are only two tenders left and they are running out of options. They all bid minimum IRR, and agent 4 wins the lottery. This means also agent 4 does not have the budget for the final tender so it is a coin toss between agent 1 and agent 2. Agent 1 wins the final tender.
The final scores for the agents are shown in the bottom part of the table, it can be seen that agent 1, 3, and 4 met their generation target but given that agents 1 and 3 even went at least 10% over their target, they score maximum points for generation.
The storyline of the tender run shows the model runs as conceptualised. Additional verification tests showing the model outcomes correspond to the inputs and the model logic are presented in Appendix C. This Appendix also includes the profiling that has been performed on the code to make it run efficiently.

5.2.2 Assessing the convergence of the model runs

In the model, there are two places where stochasticity occurs. First, when multiple agents issue a low bid, the winner is chosen through a lottery. Secondly, when estimating the competition, agents sample the importance of other agents. This adds randomness to the model, which means the model has to be run sufficient times before the outcomes of the model are stable and reliable. For this research, each experiment is run 500 times. More iterations were unfeasible due to time and computational constraints in the scope of this research.
The way to assess the convergence of key model outputs is by calculating the 95% confidence interval around the mean of the output. Table 5.3 lists the key outputs that were considered together with the maximum interval that was observed throughout the runs.
The first outcome is relatively well converged, given the fact that a typical total subsidy in a run lies in the realm of 150000 million GC so percentage-wise, the bandwidth is only 0.7%. The second output 'Percentage of tenders distributions landing on a specific outcome' refers to the limited options on dividing five tenders over four agents. A distribution where two agents win two tenders, one agent wins one tender and one agent wins no tenders is a typical outcome. Checking how often this distribution occurs is considered a key output. The third output seems converged as the maximum bandwidth is only 0.1 percent. This is unlike the fourth and fifth output, which still have a significant bandwidth. When considering the outcomes of these outputs in the experiments, this confidence interval has to be kept in mind. The fifth output 'Percentage of times agent number 2 wins tender number 2' is chosen as a key output as it exemplifies the convergence of agents winning specific tenders.
Appendix C includes the convergence plots of the outcomes.

Table 5.3: Outputs that were checked on convergence through a 95% confidence interval of the mean

Key output	Maximum band width	Unit
Total subsidy handed out	1000	Million GC
Percentage of tender distributions being 2-2-1-0	2	%
Total achieved utility per agent	0.1	-
Average bid per agent	3	GC/MWh
Percentage of times agent number 2 wins tender number 2	7.5	%

5.3 EXPERIMENTATION AND ANALYSIS

The goal of experimentation with the model is to find emergent behaviour, this is done by initially running experiments in an exploratory fashion to find parameter changes that cause notable emergent behaviour. To keep the number of experiments in this phase manageable, experimentation was done by varying parameters 1-by-1 from a base case. The base case was defined through a combination of calibration and consultation of the developer of the valuation model to identify 'average settings'. Six parameters that had to be calibrated were the Tender CAPEX per MW, Tender Capacity, Minimum IRR, Target IRR, NPV targets, and Generation target. Those were calibrated to assure that agents needed to win two standard tenders with an average IRR bid to assure a utility of 1. This calibration is explained further in Appendix B. In the base case, five tenders are auctioned over four agents. The tender parameter settings of the base case are shown in table 5.4.
In this thesis, we shall focus on two parameters that showed interesting behaviour which gave cause to further exploration: Tender capacity variation and agent budgets. This is presented in the following two sections.

Table 5.4: Model parameter settings for the base case

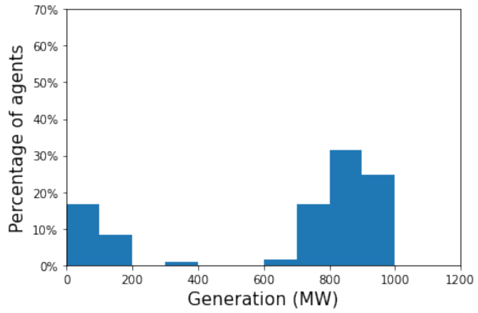
Parameter name	Value	Unit
Tender parameters		
Auction year	2022,2023,2024,2025,2026	Year
CAPEX per MW	2	Million GC / MW
Capacity	500	MW
Maximum strike price	120	GC / MWh
Competitors importance uncertainty	0.2	-
Agent parameters		
Budget	2000	Million GC
Minimum IRR	4	%
Target IRR	8	%
NPV target	500	Million GC
Generation target	700	MW
GenImp	0.5	-

5.3.1 Model behaviour for variable tender capacity

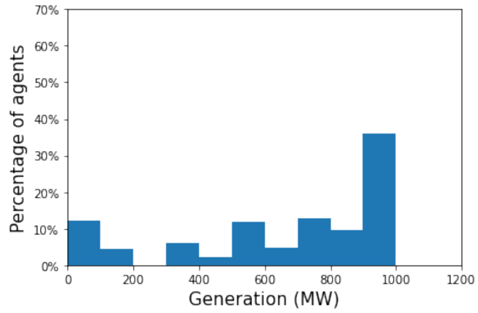
When varying capacity together with the sequence of capacity in the exploratory experiments, interesting model behaviour occurred. To isolate these effects, the total sum of capacity over the five tenders was kept the same as the base case, only the tender capacity was increased or decreased by the same quantity every tender. How large this quantity is defined by a metric called steepness. Steepness can be captured by dividing the capacity of the first tender by the capacity of the last tender, as shown in equation 5.3. To keep the scale of increasing tenders the same as the decreasing tenders, the log base 10 is added to the equation.

$$Steepness = \log 10(\frac{Capacity_{First\ tender}}{Capacity_{Last\ tender}}) \tag{5.3}$$

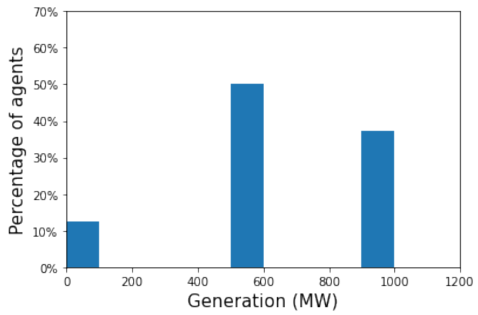
Figure 5.6 shows the impact of two experiments with a steepness of -0.954 (figure



(a) Increasing capacity over the tenders with a steepness of -0.954



(b) Decreasing capacity over the tenders with a steepness of 0.954



(c) Static capacity over the tenders. All tenders have a 500 MW capacity, Steepness is 0.

Figure 5.6: Distribution of tenders per agent

5.6a) and 0.954 (figure 5.6b) compared to the basecase (figure 5.6c) on the distribution of generation capacity that the agent can achieve with the tenders they win.
In the base case, an agent can win zero, one, or two tenders before its budget runs out, this is reflected in the three bars in the plot. In the base case run, about half the agents on average win one tender, about 40% win two tenders and the remaining agents win no tenders at all.
What can be derived from the top two figures is that in the model, increasing the capacity over the tenders results in higher polarisation in terms of how much capacity each agent achieves over the run compared to the same set of tenders when they are tendered in decreasing order. To prove the distributions are significantly different from each other, a Kolmogorov-Smirnof test was performed for each distribution pair. The Kolmogorov-Smirnof test is a non-parametric test that tests the goodness of fit of a given set of data to a given distribution (Berger and Zhou, 2014).

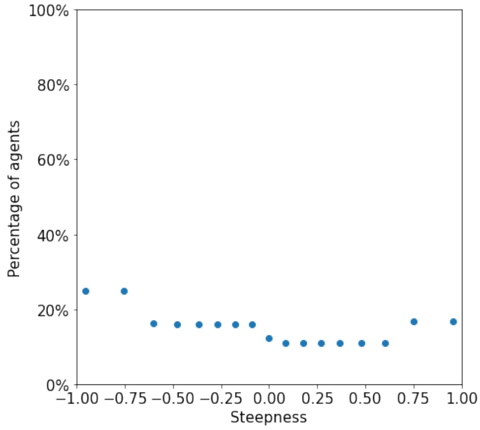
Essentially, it tests whether two distributions are identical or not. The following two hypotheses apply:
H0: The distributions are identical
H1: The distributions are not identical

P-value for steepness -0.954 - base case: 7.85e-121
P-value for steepness 0.954 - base case: 4.08e-59
P-value for steepness -0.954 - steepness 0.954: 1.28e-18
All P-values are below 0.05. Therefore, the H0 for all three distribution pairs can be rejected and the statement made that the three distributions shown in figure 5.6 are significantly different.

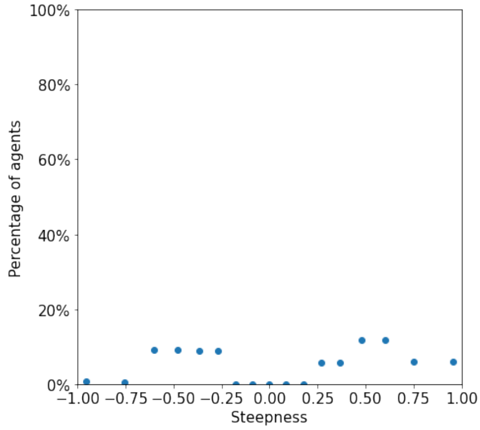
Table 5.5: Storyline of run with steepness 0.954

Tender nr	Tender capacity	Target IRR bid	Minimum IRR bid	Agent 1	Agent 2	Agent 3	Agent 4
1	900 MW	89	60.4	60.4	60.4	60.4	60.4
2	700 MW	89.2	60.5	60.5	No Budget	60.5	60.5
3	500 MW	89.5	60.8	No Budget	No Budget	60.8	60.8
4	300 MW	90.2	61.4	61.4	No Budget	61.4	61.4
5	100 MW	93.6	64.5	64.5	64.5	64.5	64.5
Outcomes							
			Generation achieved	700	900	600	300
			Generation score	0.9	1	0.77	0.39
			NPV achieved	184.1	251.1	151.4	72.7
			NPV score	0.33	0.45	0.27	0.13
			Utility score	0.62	0.73	0.52	0.26

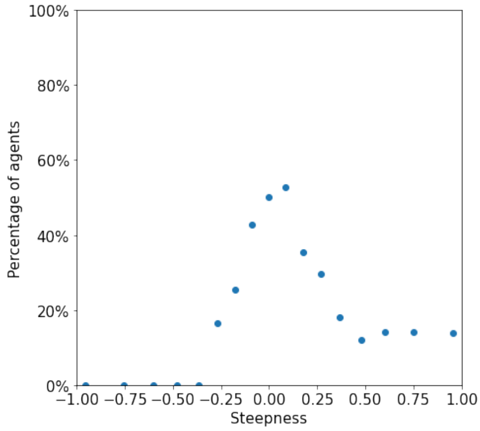
Table 5.5 shows an example run of a 0.954 steepness run. Comparing this with the example run of the -0.954 run in figure 5.2 which shows the 0.954 run can help us understand the behaviour that leads to the different capacity distributions shown in figure 5.6. The major differentiating behaviour that can be observed from the tables is that in table 5.2, the agent that lands the 300 MW tender automatically wins the subsequent 500 MW tender as it is the only agent willing to bid its minimum IRR for the 500 MW tender. This creates polarisation because it means there will always be an agent with 800 MW generation at the end of the run, which is not the case in table 5.5. Here, three agents are competing for the 300 MW tender after the 500 MW tender has passed.
This behaviour could mark a significant find in the model as it could mean that the order in which tenders are auctioned can have an effect on the distribution of tender capacity in the market.
With the significantly different distributions in generation for the -0.954 and 0.954 cases, the question arises whether the steepness of the increasing or decreasing capacity makes a difference in the generation distribution. To investigate this, the steepness was varied in the experimentation.
The 0.954 and -0.954 cases that were shown above are taken as the extreme values. 14 additional experiments were run with intermediate steepness. The capacities per tender that were used as input values for the experiments are documented in Appendix B.



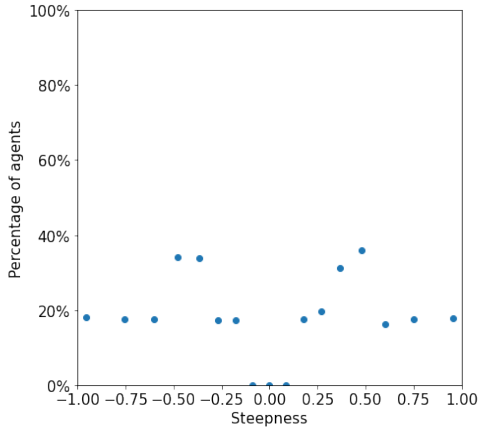
(a) <200 MW



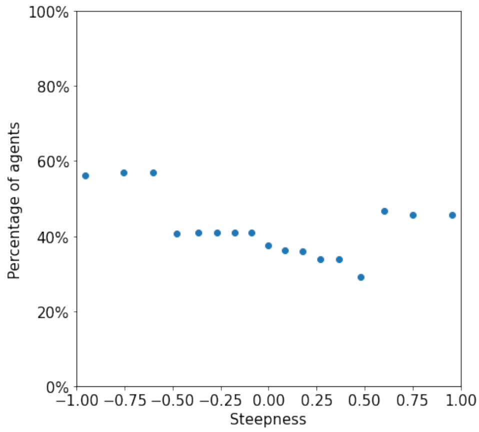
(b) 200-400 MW



(c) 400 - 600 MW



(d) 600 - 800 MW



(e) >800 MW

Figure 5.7: The effect of steepness on percentages of agents in the model securing a certain wind farm capacity.

Figure 5.7 shows the difference in the percentage of agents in the run securing a total capacity within a certain bandwidth. The total capacity that can be achieved by an agent in this setup is 1000 MW as the CAPEX per MW is 2 million GC per MW for all tenders and all agents have a 2000 mln GC budget. The differences between the experiments can be explained through the same kind of logic explaining the difference between the -0.954 and the 0.954 runs, where the budget constraint leads to different importances allocated by the agents to the tenders. The changes in importance show path dependency, which means that what happened in the past, matters for what will happen in the future (Buchanan, 2001).

Figure 5.7a shows that most agents are left with a generation lower than 200 MW at the end of the run when the steepness is between -1 and -0.75. After that, 7.5% of agents can secure this low amount of generation for all experiments where the capacity increased over the runs. Interestingly, the number of agents securing less than 200 MW increases when the steepness of decreasing capacity tenders rises above 0.6.

A similar kind of trend can be found at the upper limit of the spectrum in the >800 MW of the spectrum, shown in figure 5.7e. The trend suggests that high polarisation, characterised by a high percentage of agents securing either a high capacity or low capacity, most often occurs when tenders increase in size significantly. The least polarisation seems to happen in moderately decreasing tender capacity, in the region of 0.5 steepness. Here, the percentage of agents with a capacity of > 800 MW and the percentage of agents with a capacity of <200 is low. This is an interesting find, as it could point to a steepness where low capacity per organisation is minimal, which could be an objective for policy makers.
Figures 5.7b, 5.7c, and 5.7d do not show a linear trend either but rather regions in steepness where this level of capacity secured by the agents occurs more often. For instance, this region seems to lie at moderately increasing and moderately decreasing capacity for securing 200-400 MW of capacity.
Appendix D shows the storyline of typical runs from the experiments showing a steepness of -0.477 and 0.477. These experiments illustrate the logic of moderately increasing or decreasing tender capacities.

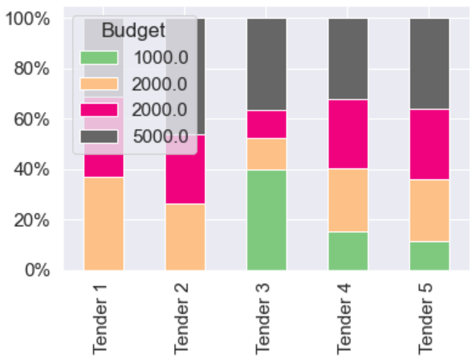
Though the results are fascinating and could point to real behaviour, it is important to realise that the behaviour stems from the logic the agents are given in the model. Additional experiments will therefore need to be performed before concluding. This is the subject of future work. The initial results, however, look very promising to form the basis of policy advice regarding the timing and size of tenders: Tendering offshore wind power in moderately decreasing steps of capacity can help level the capacity per organisation that competes for the tenders.
This is an important find for policy makers who are looking to ensure the available wind capacity is not concentrated in a small number of organisations. A more equal distribution could mean the power supply is less dependent on a small number of organisations, which helps the security of supply and reduces the market power of these organisations.
Interestingly, auctioning tenders in decreasing capacity is not what for instance the Dutch government has done in the past and plans to do in the future. All offshore tenders between 2020 and 2027 have been of equal size (700 MW) and the ones planned for after that are larger (1000 MW) (Government of the Netherlands, 2020).

5.3.2 Model behaviour for variable agent budgets

When varying agent budgets in the exploratory experiments, one aspect of the model outputs seemed especially impacted by the changes. The chance of winning each specific tender in the sequence varied significantly when changing the standard budget of agents from 2000 (enough to win 2 standard tenders) to a combination of 1000,2000,3000,4000, and 5000. Figure 5.8 shows this for two example runs and the base case for comparison. Conceptually, the base case should show an equal chance for each agent for each tender, however, as the 95% confidence interval of the mean of winning specific tenders lies at around 7.5%, there is still some variation to be seen in the graph. This means that when interpreting the other graphs, it has to be considered that some random variation still exists. Still, figure 5.8a and 5.8b look very different from the base case so it is worth investigating what causes the differences. Table 5.6 shows the storyline of the experiment shown in figure 5.8b.

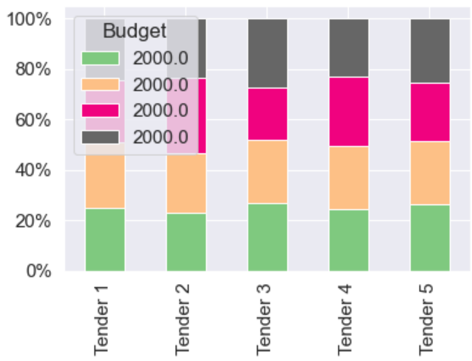
Overall, the logic for this experiment is that agents with budget for only 1 tender bid higher than minimum IRR IRR until tender 3. This causes the 0% chance of winning the first two tenders, shown in figure 5.8b. After the second tender, these agents bid minimum IRR until they secure a tender and have to stop bidding due to their spent budget. This is why the chance of winning the third tender is larger for these agents than the chance of winning tenders number four and five.

The agent with a budget for 2 tenders bids competitively to secure their first tender quickly, then waits until the fourth tender to bid minimum IRR again. This explains the dip in the chance to win the second tender after the first, and the further dip after the second. The agent with a 4000 million GC budget virtually always bids minimum IRR, only if it wins the first four tenders, it will opt out for the last one.



(a) Experiment with varying budgets

(b) Experiment with two low budgets and two higher, different budgets



(c) Base case where all agent have the same budget

Figure 5.8: Chance at winning each tender in the run

Table 5.6: Story line of an exploratory run with agents with different budgets

Tender Number	Target IRR bid	Minimum IRR bid	Agent with 1000 budget	Agent with 1000 budget	Agent with 2000 budget	Agent with 4000 budget
1			64.9	64.9	60.8	60.8
2			63.2	63.2	65.3	60.8
3			60.8	60.8	63	60.8
4			60.8	No budget	60.8	60.8
5	89.5	60.8	60.8	No budget	60.8	60.8
	Outcomes					
		Generation achieved	500	500	500	1000
		Generation score	0.64	0.64	0.64	1
		NPV achieved	112	126	141.5	252.2
		NPV score	0.2	0.23	0.25	0.45
		Utility score	0.42	0.43	0.45	0.73

The previous example showed that the apparent simple change of giving agents different resources results in complex model behaviour. The question then arises whether the chance of winning a certain tender depends on the combined budget of the agents, indicating how competitive the market is. Secondly, the chance of winning tenders could depend on how much the budgets differ between the agents. To test this, the following two parameters are defined:

- Total budget over the agents. This parameter is varied over the range of [8000 - 20000 million GC]. The lower bound of 8000 is chosen as this allows agents to land two tenders. Lower than that, the competition quickly goes down, which is not deemed a realistic environment for offshore wind farm tenders. At 20000 all agents have a budget of 5000, allowing them to pay for all five tenders, which means they have an unlimited budget for this setup.
- Variance between budgets. This parameter can range between 0, where all agents have the same budget, and 4, where there is a steep divide between agents with a very low, and agents with a very high budget. Variance is calculated through equation 5.4.

$$Variance = \frac{\sum(x - \bar{x})}{N} \tag{5.4}$$

where:

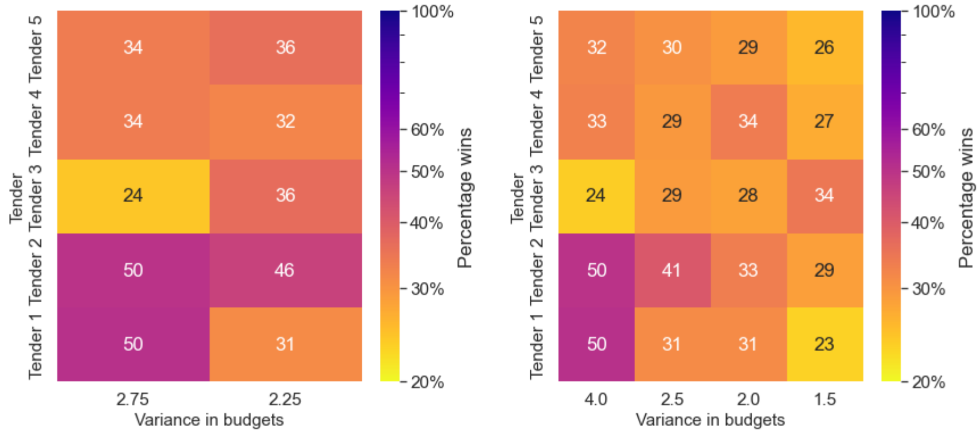
x = Budget of an agent

$\bar{x}$ = Mean of budgets of all agents

N = Number of agents

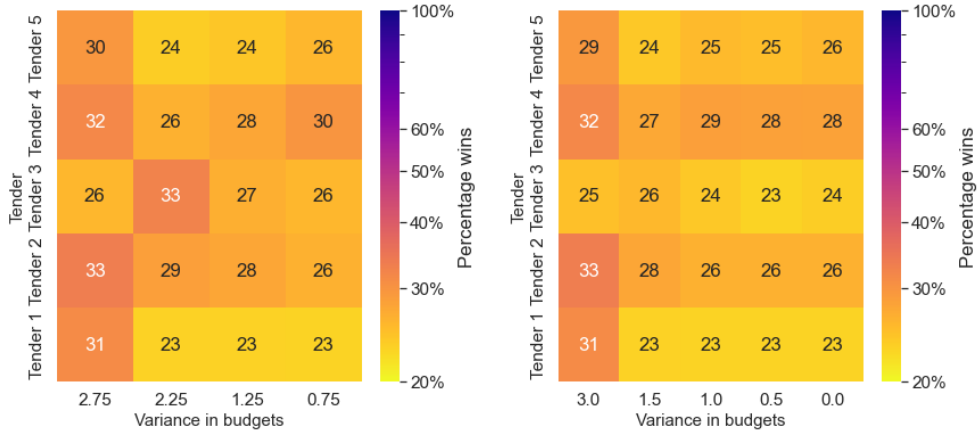
Agents never have a budget lower than 1000 and never a budget higher than 5000. The lower bound is to ensure that agents can always compete in at least one tender. The upper bound is the budget necessary for investing in all five tenders. As agents cannot share resources, the allocation of the budget is always done in steps of 1000. 35 Experiments are run for all possible budget distributions given the budget step size for a total budget of 8000, 10000, 12000, 14000, 16000, 18000, and 20000. The exact budgets that were allocated to each agent in the experiments are documented in Appendix B.

When considering the experiments from the perspective of an agent with only budget for one tender, a larger trend occurs due to the relatively deterministic behaviour of these agents. The agents stand no chance in the first two tenders but then have a relatively good chance at winning the third and a decreasing chance at winning the fourth and fifth tender. This behaviour is in line with the observed behaviour shown in table 5.6 and stands for all experiments performed here. The outcomes could point to a part in the model logic where the emergent behaviour of the agents is rather simplistic. Future work is necessary to iterate on the model logic in this part of the model.



(a) Total budget: 10000 million GC

(b) Total budget: 12000 million GC



(c) Total budget: 14000 million GC

(d) Total budget: 16000 million GC

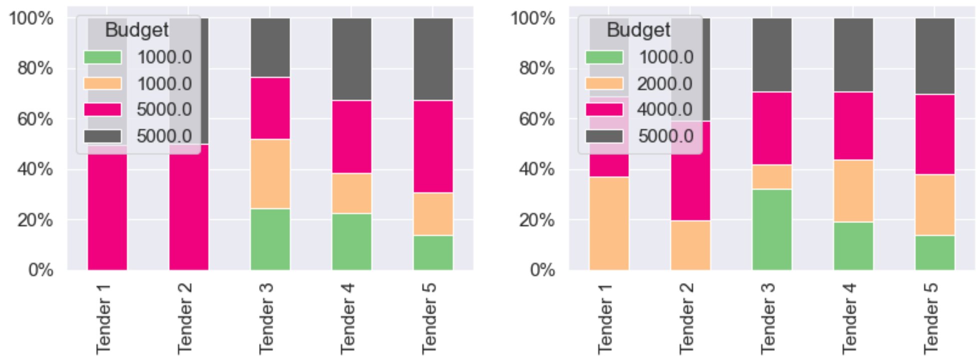
Figure 5.9: Chance at winning each tender from the perspective of a 5000 million GC budget agent.

When considering the experiment outcomes from the perspective of an agent with an unlimited budget, interesting trends occur. Figure 5.9 shows for all experiments with a total budget between 10000 and 16000 million GC budget what the winning chance is for each tender and different variances in budget. The runs with a total budget of 8000, 18000 or 20000 million GC were omitted from view as they did not show a difference in variance whatsoever.
The colors in the figure are mapped on a logarithmic scale to also show the difference in the low chance regions. Because there are only a limited number of budget distributions over the agents, not all total budget and budget variance combinations are possible, which is why the variance on the x-axes differs between the subplots.
The plots show that there seems to be a trend where in high variance cases, agents with a limitless (5000) budget have a higher chance of winning the first two tenders. After the first two, the difference in chance becomes a lot smaller and the chance of winning seems to be very case-dependent for tender numbers three, four, and five. When considering the figures, keep in mind that the 95% confidence interval

of agents winning specific tenders is around 7.5% which means that differences of only a few percent can be coincidental. However, the difference between 50% win chance in the first two tenders when the total budget is 12000 million GC and the budget variance is 4 is significant compared to the other variances shown in figure 5.9b.
To investigate what model behaviour causes this trend, two experiments are investigated further:

1. The experiment where agents have a total budget of 12000 mln GC and the budget variance is 4

2. The experiment where agents have a total budget of 12000 mln GC and the budget variance is 2.5



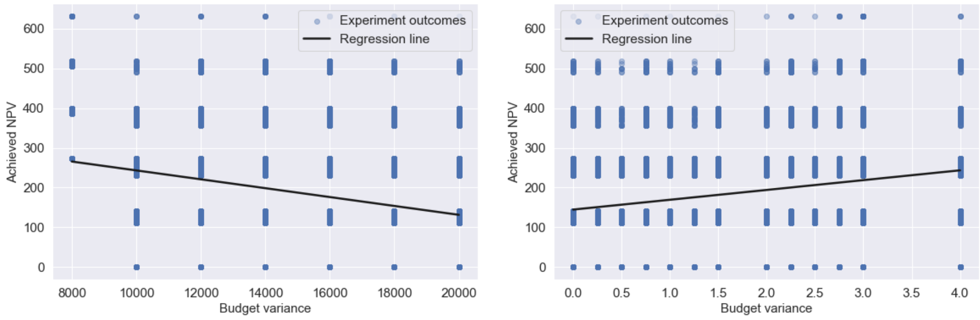
(a) Total budget: 12000 budget variance: 4

(b) Total budget: 12000 budget variance: 2.5

Figure 5.10: Chance at winning each tender from the perspective of a 5000 million GC budget agent.

Figure 5.10 shows the chance at winning each tender for all agents in these two experiments. Figure 5.10a shows that the reason why agents with an unlimited budget win 50% of the first two tenders when the budget variance is 4 is that two of its competitors have a budget enough for only one tender. This causes them to not bid into the first two tenders, which means it will be a coin toss between the two 5000 million GC budget agents. When the variance is 2.5, there is only one agent that does not compete for the first two tenders, which makes the chance of winning the first two lower for the 5000 million GC budget agents.
The trend that higher variance in budget results in a higher chance for agents with an unlimited budget at winning tenders stems from logic as described above. In general, the conclusion that agents with a high budget have a higher chance of winning tenders when their competition has a relatively low budget is an intuitive one.
When considering the chance of winning each tender from the perspective of agents with a budget of 2000, 3000, or 4000 mln GC, similar trends could be found as the one described for agents with a 5000 million GC budget. The trend does become less pronounced as the budget of the agent is lower. Appendix D shows the results for these agents.
Overall, it can be concluded that there does exist a trend in the chance of winning specific tenders when varying total budget and budget variance. Especially from the perspective of an agent with a limitless budget, it could be seen that there is a higher chance of winning early tenders when the variance in budgets is high.

When looking at the effect budget variance and total budget have on the achieved NPV of an agent with a limitless budget, trends can be found as well.



(a) Impact of total budget variation

(b) Impact of budget variance variation

Figure 5.11: Impact of total budget and budget variance on NPV of an agent with unlimited budget

Figure 5.11 shows for an agent with unlimited budget what its achieved NPV is for all budget experiments. Through the data points, a least-squares regression line is fitted.

Figure 5.11a shows that there is a negative trend between a higher total budget and the achieved NPV of the agent with an unlimited budget. This makes sense intuitively as the other agents have more resources to compete for more tenders as the total budget increases. The Pearson correlation between the two variables is -0.26 with a P-value of 1.91e-250, which makes the correlation statistically significant.

Figure 5.11b shows a positive trend between the variance between budgets and the achieved NPV of the agent with an unlimited budget. This can be explained through the fact that with higher variance, more agents have a significantly lower budget than the unlimited budget agent, which makes them a smaller competition. The Pearson correlation between the two variables is 0.22, with a P-value of 4.87e-179, which makes the correlation statistically significant. Concluding, an agent with an unlimited budget in the model generally achieves a higher NPV when the budget variance is high and the total budget is low.

For agents with a budget of 4000 million GC or 3000 million GC a similar trend can be found, though the trend becomes less steep, indicating that the budget of the competition makes less of a difference for these agents. For agents with a budget of 2000 million GC or 1000 million GC, there was still a negative trend between total budget and achieved NPV. The trend between budget variance and achieved NPV was negative as well, which is the opposite trend of all higher budget agents. This makes sense intuitively as well, as a lower variance in the case of low-budget agents means that there are fewer agents with a very high budget, which means less competition. All trends were found to be statistically significant. Appendix D shows the correlations for these agents with a budget between 1000 million GC and 4000 million GC.

Lastly, the winner's curse is considered for the budget experiments. Given the fact that in these experiments, all agents had the same IRR, this meant that agents that wanted a tender badly enough to bid minimum IRR had a fair chance to win it.

This caused the winner's curse to only occur in very low total budget cases with high variance. Appendix D elaborates on this finding.

5.4 VALIDATION

Validity in the context of the agent based model in this research entails the question if the model that is built is sufficient to answer the research question. In other words: "did we build the right thing?" (Van Dam et al., 2012).

To assess this question, face validation is conducted through expert consultation.

This research is conducted in collaboration with an industrial partner that has bid on offshore wind tenders in the past and is doing so still. The conceptualisation and analysis of the results have been performed in consultation with this partner, ensuring that how bidding behaviour is described in the model is a realistic enough abstraction of the actual process in the organisation. The results from the outcomes of simple runs were intuitive, both to the modeller and to the consulted experts.
The outcomes from all model experiments could be traced back to the behaviour that caused it but still showed emergent behaviour that was not considered straightforward or expected from the start. An important example of this is the influence of sequence when tendering wind farms with different capacities.
As the purpose of the model was to gain insight into emergent behaviour in the bidding process, this supports the statement that the developed model is valid and fit for its purpose.

5.5 RECOMMENDATIONS FOR FURTHER PARAMETER ANALYSIS

The analysis that is performed to find model behaviour in this chapter is exploratory and far from exhaustive. Here listed are ideas to dive deeper into experimentation with the model parameters to discover additional trends and behaviour in future research.

The first recommendation in this respect is to run additional iterations of the experiments presented in this thesis. Due to computational constraints, the experiments with the sequential tender model are run 500 times, which led to relatively large confidence intervals on the mean of the key outputs as defined in section C.2. Narrower confidence intervals due to a higher number of iterations would increase the confidence of the conclusions that are made with the model output.

The input parameters that were chosen in the univariate experimentation do not cover all possible combinations of the parameters in their range. This was done to keep the number of experiments limited in this first phase of experiments but can mean that interesting behaviour gets overlooked. Some parameters were not varied from tender to tender. This assumption could be relaxed. Additionally, the uncertainty can be increased even more to see where it would start to have an effect. Given that there are multiple agents and multiple tenders in each run, many parameters can assume different values, which means there are many opportunities to run additional univariate experiments here. Appendix B lists all parameters in the model with their ranges, as well as the experimental design that is used in this thesis.

A model parameter that has not been considered in any of the experiments is the influence of the number of agents and the number of tenders that are considered in a run. These parameters can have a significant influence on model behaviour. The ratio between the two can indicate the level of competition for the tenders, which can be contrasted with the influence of other parameters that influence the level of competition such as the targets of the agents, the capacity of the tenders, the cost of the tenders, and the budget of the agents.

Model parameters that have been considered fixed in the experiments performed for this research are the inputs of the valuation model per agent. The experiments include runs where the valuation model inputs CAPEX per MW or wind farm capacity is varied per tender. However, these values can differ per agent as they can assume the usage of a different type of wind turbine or have different assumptions about its cost. Technological progression of turbines, the balance of plant, and foundations can influence the values of these parameters also over time. Additionally, agents can have different assumptions about other valuation model parameters such as Gross Yield, or, if dilution is applied in the experiments, dilution price per MW and post-dilution share.

Univariate experiments overlook interaction effects, which is why in the analysis of the valuation model, a Global Sensitivity Analysis (GSA) was performed to find the real influence of model parameters. The same analysis could be performed for the coupled model. This would give a more reliable overview of which parameters in the model really influence bidding behaviour and what interaction effects exist in the model. A challenge in doing this is the number of runs that are necessary to perform such an analysis. Secondly, the model aims to showcase bidding behaviour that is more complex than what can be predicted using economic models or ABMs alone. Capturing what indicates such behaviour in model outputs in such a way that it is usable in a GSA can be a major challenge.

Alternatively to a GSA, reinforcement learning techniques such as Q-learning could potentially be applied to efficiently find areas in the model parameter space that affect model output. Reinforcement learning and specifically Q-learning has already been applied successfully to train stock market trading systems, proving that the method can be applied in the socio-economic field (Moody and Saffell, 1998). Using the method would involve the model being transformed to a Markov Decision Process (MDP)[1] that rewards significant changes to certain model output compared to the base case output. Similar to the challenges that arise when applying GSA to the model, it must be noted that it can be a challenge to exchange the human interpretation of model output with a definition that is precise enough to work in a MDP as this involves quantifying what makes an outcome 'interesting'.

Additional focused experiments from the perspective of government policy could be performed where tender parameters are varied to find bidding behaviour as a consequence of different tender policies. In this research, this has been done through the experiment where different tender capacities are placed in different orders. The same could be done with other tender conditions such as a fixed turbine selection influencing the CAPEX, capacity, and OPEX of a wind farm, different tax schemes, subsidy mechanisms, or rules regarding dilution and/or PPAs. Presenting the bidding behaviour as a consequence of such policy decisions can be a start for policy makers to optimise their tender policy to reach certain objectives they have with wind farm tenders. Eventually, this could lead to a tool where policy makers can optimise their tender policy based on their objectives. A qualitative version of such a tool called Auction designer already exists as a part of the EU-funded AURES project and can be found on their website: http://aures2project.eu/auction-designer/.

Lastly, experiments mimicking the conditions of historic tenders could be performed as a way of validating the model outcomes. Should the model show similar behaviour given these conditions, the other outcomes of the model can be considered more valid as well. This validation method is called historic replay (Van Dam et al., 2012).

1 A Markov Decision Process is a mathematical model of sequential decisions and a dynamic optimization method that is used in reinforcement learning techniques (Shi, 2021).

5.6 RECOMMENDATIONS FOR MODEL EXPANSION

The model presented in this thesis is an abstraction of real tender situations. Simplifications were made to develop a model that was able to show complex behaviour. Expanding the model on these areas of simplifications could allow the model to show more complex and realistic behaviour. Here listed are the most prominent areas in the model where interesting behaviour can be expected.

An assumption that has been made in the model is that JVs are not considered in the model while in reality, these are a common occurrence. A consequence of including JVs is that the model should include logic to allow for negotiation between agents in the model. This can be a complex endeavor but ABM is well fitted for such uses, as demonstrated in a study by Baarslag (2014), where negotiation processes were modelled in an ABM.
In the valuation model, power prices and expected revenue streams from green certificates are assumed to be certain over the lifetime of a wind farm. In reality, future prices are uncertain and can merely be predicted. The coupled model can be extended in such a way that agents can have an estimation of future prices on which they base their bids. Afterward, this can be contrasted with the actual price which becomes known after the tender procedure and potential price differences can affect the agent when they bid on a new tender. This incorporates an important aspect of bounded rationality where it is impossible to know everything and organisations have to consider their uncertainty.

In the current version of the model, agents do not employ dilution as a means to both increase their expected IRR on a tender and to recycle budget from previous tenders to acquire new ones. This process of building a wind farm and then selling (a part of) it with a profit margin is common behaviour in the field and modelling this can add interesting and relevant behaviour to the model. In the model, it could even be included that agents cannot only sell parts of their wind farm but can also acquire them in the same way. Agents could then negotiate the purchase of wind farms from other agents to meet their targets. This again requires the addition of negotiation logic in the ABM.

Another interesting expansion of the current model logic could be to allow agents to actively learn from past results. Organisations continuously learn from past experiences and this biases them in their future actions. This is a known bias that has also been touched upon in the literature review in Chapter 1 but has not been included yet in the model.

Moving away from GC space to actual currency could increase the validity of the model. As mentioned in the research reflection, modelling monetary value in a fictitious currency with a simplified tax scheme impacts the outcomes of the valuation model. Implementing the financial governmental policy of actual countries and including their actual currency would be a big step towards the validity of the model outputs as values instead of only their trends and behaviour.

Tying into dividing agent predictions from actual results is the possibility to include weather fluctuations that can affect the production of assets. Weather can influence the yield of a wind farm and is very location dependent. Including this effect on the actual revenues, agents get from their assets can show different results for agents acquiring tenders centered in a certain geographical area and agents diversifying to be more robust against these weather fluctuations. This lack of robustness has been shown to cause problems for wind farm operators in the past. For example, SSE, a large energy company that owns wind farms mostly off the coast of the UK and

Ireland saw its production from renewable assets drop by 32% between the start of April 2021 and the end of September 2021 when wind speeds were lower than expected in that area (Stevens, 2021).

The lifespan of currently operating wind farms lies at around 20 to 25 years (Phillips, 2022). During that time, macroeconomic developments can impact the operation, cost, and revenue streams of wind farms. For instance, if the infrastructure of the farm gets sabotaged, or an energy crisis drives up the power price, this has a significant impact that often is not considered during the bidding process. Other developments include the closing of a large international deal, agreement, or socio-economic trends that influence demand in certain geographical areas. Modelling these uncertainties can showcase the robustness and resilience of bidding strategies when agents are building their wind farm portfolio.

Also on the topic of agent behaviour is the investigation into the predictability of agent strategies. With enough data, a model could potentially be fitted to agent behaviour to infer the strategy they are using. This model could be used by other agents to form a better idea or expectation of the next move of their competition. Mind you that the model needed to reliably fit such a model is extensive and in reality, it would be next to impossible to acquire such data in sufficient quantities. Especially so since the situation and rules of the game are subject to constant change, as well as the strategy of organisations that bid into tenders.

5.7 CONCLUSIONS FOR THIS RESEARCH

This chapter showed the development and results of the agent based model designed to show emergent behaviour for bidding behaviour on wind farm tenders. With the conceptualisation of the agent based model, the second and third research question as posed in Chapter 1 is answered, respectively "How can bidding on tenders be modelled to realistically represent organisational bidding behaviour" and "How can the value assessment by bidding actors be considered in the modelling approach?". An important note here is that the method and abstraction as presented in this chapter and this research, in general, is only one interpretation of the system. To validate the model outcomes, a second ABM for the same purpose could be developed. If this model would show the same behaviour in experimentation, the model is more likely to show valid results. This immediately leads to the answer to the fourth research question: "What is the validity of the model so that it realistically represents bidding behaviour on wind farm tenders?". In this research, validation is performed through face validation through expert consultation. Though this is only one of many methods to validate a model, the results are promising and the model seems to be fit for its purpose.
The final research question is "What insights are created by the model into the bidding behaviour on wind farm tenders?". To answer this question, preliminary univariate experimentation has been performed, as well as an investigation into the influence of capacity differences and budget differences. The results show interesting emergent behaviour. The outcomes suggest that increasing the capacity of tenders over a sequence of tenders could lead to a higher polarisation of tender capacity owned by bidding organisations after the auctions, compared to a decreasing order. The results suggest that a moderately decreasing order of capacity could lead to the most level distribution of capacity over the competing organisations. This is an important finding for policy makers who are looking to ensure the available wind capacity is not concentrated in a small number of organisations. A more equal distribution could mean the power supply is less dependent on a small num-

ber of organisations, which helps the security of supply and reduces the market power of these organisations.
Additionally, the results of experiments with different budgets for the bidding organisations suggest that the distribution of resources over the bidding organisations has a significant impact on their chance at both winning specific tenders in the sequence as the total NPV they achieve overall tenders. This is an insight that is interesting from a business perspective as it shows the influence the budget of the competition has on the chance of winning.
The trends shown by the model show potential for informing policy regarding the design of offshore wind farm tenders, as well as policy for organisations looking to strategise their bids on offshore wind farm tenders. Further research is necessary to extract solid policy advice from the results.

6 CONCLUSION

This final Chapter gives an overview of the outcomes of the research conducted for this thesis. Section 6.1 provides answers to the research questions posed in Chapter 1, section 6.2 reflects on the conduct of the research and recommends directions for future research. Finally section 6.3 argues what the added value of this work is for society and for the academic field.

6.1 ANSWERS TO THE RESEARCH QUESTIONS

This research aimed to find whether a coupled economic-agent based model could capture complex bidding behaviour on offshore wind farm tenders. Specifically, the goal of the thesis was to answer its main research question: *"How can organisational bidding behaviour on a wind farm tender be captured in an agent based model, considering the economic value assessment of the tender by each organisation"*.
The question is answered through the development of a coupled model consisting of an ABM and an economic value assessment model. Following are the answers to the five sub-questions that are defined to answer the main research question.

What mechanisms drive organisational bidding behaviour?

Through a literature study, it has been found that organisational bidding behaviour is driven by a combination of rational and bounded rational behaviour. Rational behaviour can for a large part be captured by the economic considerations captured in the economic part of the ABM. There are a number of bounded rational behaviours exhibited in the process of offshore wind farm tendering. Previous methods used to capture this process, such as auction theory, ignored these but agent based modelling has been found fit to capture these complex behaviours.

How can the bidding on tenders be modelled to realistically represent organisational bidding behaviour?

The conceptualisation of the coupled model is done in consultation with an industrial partner that bids on wind farm tenders itself. The partner also provided a simplified version of an economic valuation model used to assess the economic value of a tender, which formed the basis of the agents' strategy in the final version of the model. The valuation method in the model is a standard economic approach to value assessment and represents an important part of the rational behaviour by the agents in the model. The agent based part of the model incorporates the notion of information asymmetry in the sense that agents can have different assumptions about an asset and base their bids on these assumptions. Additionally, the model incorporates the bias to under promise and over-deliver by adding an incentive for the agents to keep bidding, even when their targets have been met.

How can the value assessment by bidding actors be considered in the modelling approach?

The interface between the ABM and the valuation model consist of the most influential input parameters of the valuation model, which were found through the conduct of a global sensitivity analysis. Six influential input parameters were iden-

tified: Strike Price, CAPEX per MW, Capacity, Dilution price per MW, Post-dilution share, and Gross Yield. Please refer to Chapter 3 for an explanation of these concepts. Tenders in the model differed in the input parameters, and agents in the model could define their input parameters for the valuation model, based on their assumptions and strategy. The bids of the agents were based on the output of the valuation model.
The technical implementation of the coupled model was done through an ABM implemented in Python and an economic model that was provided as an Excel file. As Excel is the industry standard for valuation models, this format was kept.

What is the validity of the model so that it realistically represents bidding behaviour on wind farm tenders?

In the context of agent based modelling, validation revolves around the question if the model that was developed is suitable for its purpose (Van Dam et al., 2012). The validity of the model presented in this thesis is assessed through face validation through expert consultation. The logic of the model was deemed a valid abstraction of organisational decision making in the context of bidding on wind farm tenders. Additionally, the outcomes of the model could be traced back to logically follow this conceptualisation while still showing interesting and unexpected emergent behaviour. This lead to the conclusion that the model has the potential to be fit to provide insight into complex bidding behaviour in this context.

What insights are created by the model into the bidding behaviour on wind farm tenders?

Analysis of the outcomes from experimentation with the model led to the finding that the sequence of different capacity tenders can influence the distribution of tenders over the agents. Model outcomes suggest that auctioning tenders in order of increasing capacity could lead to a higher polarisation of total wind farm capacity over the bidding parties than auctioning tenders in order of decreasing capacity. Decreasing capacity even seemed to level the capacity compared to the base case where all tenders had equal capacity. This could mean that policy makers that seek a more competitive or less concentrated market, could consider tendering their assets from high capacity to low capacity.
Additionally, analysis of the model outcomes from an agents perspective resulted in the insight that success in winning tenders very much depends on not only the budget of the agent itself but also on the distribution of budget over the other competing agents. Results suggest that agents with a relatively high budget stand a higher chance at winning early tenders when their competition shows a high variance in budget and combined have a relatively low budget.
The hypothesis that the chance at winning a certain tender can be explained fully by the total budget over the competing agents combined with the variance in the budget has been rejected. The chance at winning often varied substantially per case. These insights are important for bidding parties looking to improve their chances at winning a certain tender, or deciding what budget to allocate to their wind power portfolio. The results from this analysis show the impact of budget allocation is very case dependent, which means it is advised to bidding parties to analyse specific expected budget allocations using the logic presented in this work and potentially adjust their bidding strategy accordingly. Given that capital allocations are publicly announced in companies' public financial disclosures, this knowledge could prove very useful for business planning purposes.

6.2 LIMITATIONS AND FUTURE WORK

This section lists the aspects that were not considered to be inside the scope of this research but could add valuable contributions to the work presented here. The list is prioritised. The future work recommendations that can contribute the most to future insights are discussed first.

When calculating the NPV and IRR of a tender, all organisations in the current model assume the same values for capture price, imbalance cost, inflation, price of green certificates, tax-related values, and (only relevant for NPV), discount rates.
In reality, these assumptions differ as all agents have to gather and interpret their information, which is one of the major aspects of bounded rationality. This is expected to have a significant influence on the bidding behaviour of the agents and therefore on the robustness of the model. For future work, it is strongly advised to build onto the simulation model to incorporate differentiation in these assumptions. This would add confidence in the outcomes of the model, which builds confidence in the policy recommendations that are made based on these outcomes. It is advised to start with this specific addition as the model interface with the valuation model already is fit for different tender assumptions, which makes this a relatively low effort improvement to the model.

Organisations in the model do not form Joint Ventures (JVs) (JV) to reduce risk on tenders and increase the competitive strength of the organisations in the JV. In reality, organisations often join forces to increase their chances and benefits from a tender. To illustrate, in the 2022 tender Hollandse Kust in the North sea as many as four JVs issued a bid: Shell/Eneco, Ørsted/Total Energies, Vattenfall/BASF, and SSE Renewables/Brookfield all issued a bid (Algemeen Dagblad, 2022).
For this research, the extra complexity of organisations negotiating a JV and combining their resources was left outside the scope due to time constraints. Once a JV is formed, it can be considered a single agent with the same behaviour as a single organisation, which makes the assumption reasonable within the scope of the model. However, that does assume that the formation of the JV and the decision making around the bid is a sequential process. In reality, these two processes go hand in hand, which could lead to substantially different behaviour.
The expectation is that the agents that succeed in the formation of a JV increase their competitiveness as the companies can combine their expertise and resources, which leads to different model dynamics. These dynamics are not trivial and can influence the robustness of the model. It is therefore strongly advised to incorporate this complexity in a future version of the model before assuming the insights of the model as policy advice.

In the model, the only objectives agents can have with acquiring wind farm tenders are the profit they expect to make on the wind farm and the total capacity (in MW) that they install. Other objectives could play a role as well, such as the desire to gain experience in a certain geographical area due to synergies with their other businesses or operations. Another could be the desire to use a specific technology that is required for that specific wind farm for a strategic advantage. This complexity is expected to create wild cards amongst the agents where sometimes a bid is lower than what is seen as reasonable. This can have a significant effect on the model outcomes and therefore has a significant influence on the robustness of the model. It might be possible to gain insight into strategies from organisations using data from past tenders. However, given the changing nature of policy design and priorities of organisations, caution is advised when considering an attempt to strategies from organisations.

A final important aspect agents disregard in the model is learning from past tender results and as a result, potentially changing their strategy over time. In reality, agents rely heavily on their past experiences and even irrationally consider previous experiences to match future options (Baker and Nofsinger, 2002). This can influence the model behaviour significantly by introducing path dependency for the agents, reinforcing strategies that worked out well for agents in previous auctions, and penalising strategies that were unsuccessful in the past of the agent. This could create more extreme bids in the model outcomes and can have a significant influence on the model's robustness.

The current model only includes the tender policy of the German central model while many tenders operate under different policies. Including these types of policies in the model would greatly improve the applicability of the model results to real-world situations. The most important aspect of tender policy that most offshore tender policies include but the German central model does not consider is the inclusion of a qualitative aspect to the bid. This qualitative aspect refers to a plan that each bidder has to include in its bid, stating how it will design, develop, and/or operate the wind farm. A challenge in this respect is modelling these plans, and how they are made and appreciated in the selection of the winner. ABM has been used before to simulate innovation processes and qualitative change, which means this technique is believed fit to add the qualitative aspect to the tender process in the model (Pyka and Grebel, 2006).

In the current application of the model, the outcomes of certain model input parameter configurations are merely presented and analysed. Going a step further could be to optimise these parameters for governments and/or competing organisations. For governments, the tendering policies can be optimised using the model to reach the objectives of policy makers. Having this structure could even allow for the facilitation of developing new types of policies and tender rules.
From the perspective of the organisations, agent strategies in the model can be optimised in situations where the other agents in the model behave a certain way. The optimised strategy could give the organisations a competitive edge in real tenders.
Optimisation in the model can be done through multi-scenario Many Objective Robust Decision Making (MORDM). Multi-scenario MORDM is a decision making framework combined with a search algorithm that is based on machine learning techniques (Bartholomew and Kwakkel, 2020). The technique has been found to consider robustness and optimality in different scenarios well and to do so at reasonable computational costs.
Using this technique to optimise policy for either governments or energy companies would be a great step forward in the direction of using the model and the technique of coupled modelling in the support of policy making. This way the model could serve as a tool to efficiently search for candidate policies that are expected to work well in many scenarios.

A finding that is presented in this thesis is that auctioning tenders in increasing capacity causes the agents in the model to polarise in terms of the capacity they own at the end of the run. This behaviour where auctioning in increasing value or size could also be found in other tendering or auctioning situations. For instance, auctioning for public transport rights or retail rights in a certain area, or auctioning valuable goods such as art or classic cars. Modelling and analysing these systems could show whether this behaviour could be universal or limited to specific domains. Would the behaviour be found in multiple domains, the applicability of policy advice stemming from the model could be increased significantly with this finding.

6.3 CONTRIBUTIONS AND POLICY RECOMMENDATIONS

The work presented in this thesis marks an important step toward using coupled modelling to simulate bidding behaviour on offshore tenders. Organisational bidding behaviour lies on the edge of technology and behavioural science which is an active field of research. The active academic debate revolves around the question of what the best way is to simulate this type of complex behaviour. This thesis contributes to this debate by showcasing a promising method of simulation. The state-of-the-art agent based modelling (ABM) technique is expanded by combining it with a realistic economic valuation as an innovative way to capture the complex field of offshore wind farm tendering. The complexity of the field stems from different perspectives that highly impact bidding behaviour in the field of offshore tenders. These perspectives include the economics of assets, which is captured by the valuation model, and political and organisational reasoning, which is subject to bounded rationality that is captured in the ABM. Coupling these two types of models allowed for simulation of the intersection between these perspectives.

This thesis has performed a careful sensitivity analysis on the valuation model to find its influential parameters, developed a coupled model by designing an ABM and connecting it to the valuation model, and conducted exploratory experimentation with the coupled model. The result is a proof of concept for using coupled modelling for socio-economic processes with a strategic component. The work contributed to the usage of model coupling in cross-disciplinary studies and encourages the research community to use coupled modelling for socio-economic processes in other domains as well.

A more specific contribution of this work is the finding that the sequence of tenders with varying capacity could have a substantial impact on the distribution of capacity over the competing organisations. The results show that auctioning tenders in decreasing order of capacity levels this distribution, meaning that there are more businesses capable of producing a significant amount of offshore wind capacity. The interpretation of this behaviour is that auctioning offshore wind farm tenders in decreasing order of capacity could help in creating a more competitive market in the field of offshore wind.

For the business competing for offshore wind, a more competitive market would mean that they have to stay very sharp and innovate effectively to keep their competitive edge. For the consumer, a more competitive market could lead to lower energy prices as there are more energy producers to offer sustainability. For the government, operating at the boundary of society and economy, a more competitive market would mean a more robust supply of energy to their country. More organisations that are capable to produce a significant amount of electricity for the country means that the country is less reliant on a single party, which is considered desirable. Therefore, a policy recommendation for governments that design wind farm tenders is to place the tenders in increasing order of capacity.

The significance of this finding also means it is important to investigate this behaviour further. Further investigation is necessary as the model presented in this thesis still omits behavioural complexities that can impact the resulting behaviour significantly. The most important recommendations for model expansions in this respect are described in section 6.2 and include the implementation of various assumptions of asset properties for the different organisations in the model, the inclusion of behaviour surrounding the formation of Joint Ventures, the inclusion of additional objectives for organisations regarding offshore wind, and lastly the inclusion of learning and adapting behaviour of the agents.

If these complexities are added to the model, the model is deemed to capture sufficiently the bidding behaviour of organisations on offshore wind tenders. This would also mean that recommendations from behaviour found in model experimentation can be used as a basis for policy advice for both governments and organisations.

Sufficiently complexities in this context still means the coupled model only captures the exact tender design and situation that is conceptualised in Chapter 2. Most state-of-the-art tender designs for offshore wind globally are more complex as they include not only a financial subsidy bid but also a qualitative aspect. Therefore it is strongly advised to include complexities in behaviour related to the development of this qualitative bid and their appreciation in the selection process of the winner.

Ultimately, when the model is ready and captures all that has been stated in this section, the biggest step towards using the model and the technique of coupled modelling in the support of policy making would be to add an optimisation step. Optimising the policy would allow policy makers to efficiently generate candidate policies that are expected to perform well on their objectives in many scenarios. These policies would then help achieve our goals as a society to expand offshore wind generation globally and ultimately our goal to live on a sustainable planet.

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A OVERVIEW OF TENDER DESIGNS

This appendix summarises the analysis of different tender designs that are used or have been used in offshore wind globally.

Considering offshore wind tender policy over the years in different countries, three major classifying factors were found that divided the tender policies. Figure A.1 shows this classification.

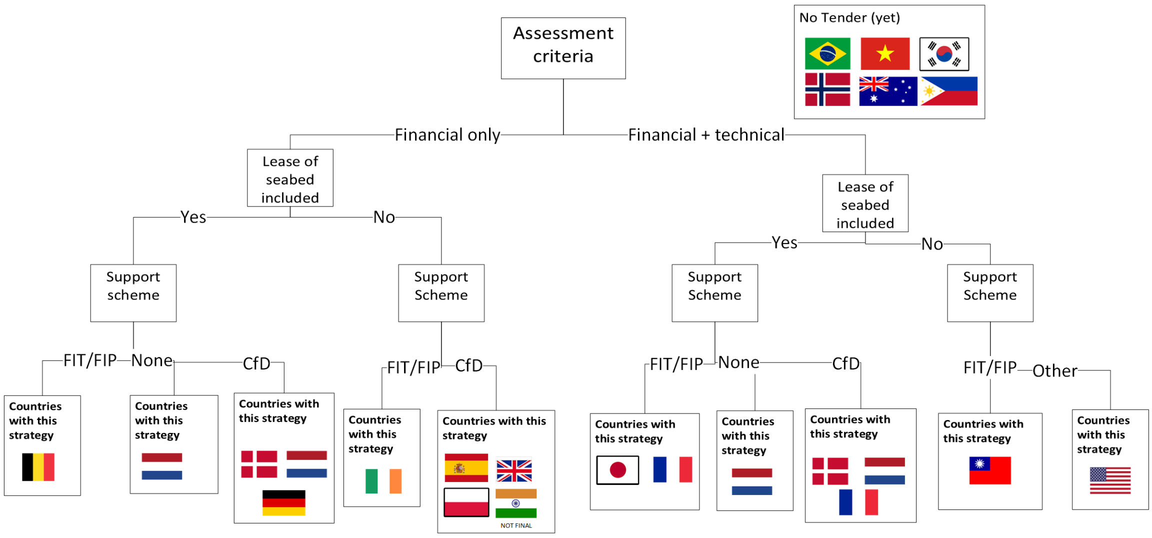


Figure A.1: Overview of global offshore wind farm tender designs

The first dividing aspect is the assessment criteria. Tenders used today in Germany, as well as tenders issued in previous years in The Netherlands, Denmark, Belgium, Ireland, Spain, Poland and the United Kingdom, were price-based auctions (The European Wind Energy Association, 2015; Commissie voor de Regulering van de Elektriciteit en het Gas, 2018; Council of European Energy Regulators, 2020). Price-based options mean that the winner of the tender is based purely on a financial basis. Typically, tenders include a subsidy scheme and in financial only tenders, the organisation that bids the lowest subsidy to operate the wind farm for, wins the tender.

The other option opposed to financial only schemes is to include a plan for the design or management of the wind farm. This can have different topics. For instance, two recent tenders near the Dutch shore had different focus areas. For the one area, the bidding parties had to include a plan on how to integrate the energy systems related to the wind farm in their bid (Ministerie van Economische Zaken en Klimaat, 2022b). For the other area, the parties had to show how they would consider the ecology of the wind farm area in their development and operation of the wind farm (Ministerie van Economische Zaken en Klimaat, 2022a). Countries that use these tender policies where the bid is a combination of the price-based bid and the content of the plan on how to develop and operate the wind farm include The Netherlands, Denmark, Japan, France, the United States and Taiwan (Barthélemy et al., 2020; International Renewable Energy Agency, 2021; Huang and

Bowler, 2021).

A second dividing factor between different tender policies is whether the lease of the seabed is included in the tender or if organisations have to go through a different procedure to gain the right to use the seabed. In the United States for instance, the lease of the seabed is governed by the separate states and often a separate auction is held to hand out these rights. This was done for example for the lease of several areas off the coast of Rhode Island and Massachussetts (Bureau of Ocean Energy Management, 2020). Another example is the United Kingdom, where the offshore wind farm tenders are governed by the British government but the lease of the seabed is governed by the Crown Estate through a separate procedure (The Gas and Electricity Markets Authority, 2015; The Crown Estate, 2022).

The third dividing factor in tender policy is the type of support scheme that is used to support the operation of the wind farm. Two main types are found:

- Feed-in Tariff / Feed-in Premium (FIT): In this support scheme, the generator obtains a fixed amount of subsidy over each MWh it produces under the scheme (Held et al., 2014). This support scheme is one of the most widely adopted support schemes.
- Contract for Difference CfD: In this support scheme, the bidder issues a price called a strike price. When operating the farm, the government that signed the contract with the organisation will pay the difference between the strike price and the market price for the duration of the contract. There is a distinction between a one-sided CfD, where only the government has to pay when the market price is lower than the strike price. In a two-sided CfD, the organisation that signed the contract also has to pay the government the difference in the occurrence that the market price is higher than the strike price (Welisch and Poudineh, 2020).

Figure A.2 is taken from a paper by Jansen et al. (2022) and shows which support scheme has been used for offshore wind over the years and per country. The figure shows that FITs and CfDs are the most common support mechanisms, especially for wind farms that will be auctioned in the near future.

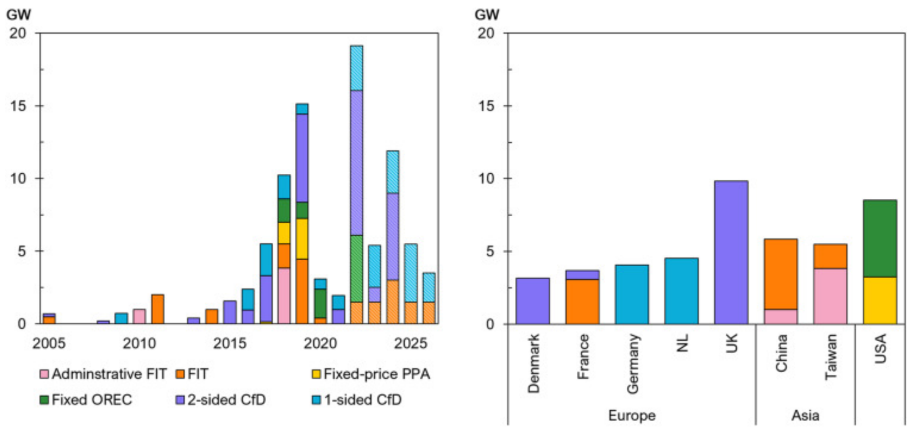


Figure A.2: Overview of offshore wind from auctions by support scheme. The left-side figure shows the capacity over time, the right side per continent and country. The figure is taken from Jansen et al. (2022).

There also exist tenders that offer no support scheme whatsoever. An example of this are the two areas off the Dutch coast that were mentioned before (Ministerie van Economische Zaken en Klimaat, 2022a,b). Here, organisations winning the tender can gain revenue from the tenders through selling the power on the free market, signing Power Purchase Agreements (PPAs), and/or diluting (a part of) the wind farm after construction.

At the top right of figure A.1, six country flags are shown that cannot be classified in the tree yet as. These countries have announced to start offshore wind tenders in the near future but have not published their offshore wind farm tender policy as of yet.

For this research, the policy to allocate tenders is chosen as a basis for the simulation model; the central model that is currently used for the 2022 tender in the German North Sea (Enerdata, 2022). When competing for the tender, an interested party must issue one single blind bid that consists of the subsidy requirement for a set number of years of operation of the wind farm. The lowest subsidy bid wins, if multiple parties issue the same lowest bid, the winner is determined via a lottery. This tender scheme is called "the central model" (Enerdata, 2022). The support scheme for the tenders in the model is a two-sided CfD. This support scheme is different from the one currently used in Germany, which uses a one-sided CfD, this is decided as this is the tender scheme is what is implemented in the valuation model as it is provided by the industrial partner of this thesis.

B MODEL PARAMETERS

This appendix lists all model parameters that were defined for running the experiments with the model. Section B.1 gives an overview of all parameters in both the valuation model and the ABM. Section B.2 shows what parameter values were used to run the experiments on the simple version of the model. Finally, section B.3 does the same for the sequential tenders version of the model.

B.1 PARAMETERS

This section lists all input parameters that are used in both models that make up the coupled model in this thesis. Table B.1 is a copy of the table shown in the main text in chapter 3 and is reported here as well for completeness.

Table B.1: Input parameters for valuation model

Variable	Range	Unit
Capacity	[50-1000]	MW
CAPEX per MW	[1 – 3]	mln GC per MW
Decommissioning cost	[10-40]	mln GC
DEVEX	[0 – 100]	mln GC
Pre-dilution company share	[0-100]	Percentage
Post-dilution company share	[0-100]	Percentage
Price for operation	[0 – 5]	mln GC per MW
Gross yield	[25 – 75]	Percentage
OPEX variable	[0,0.01]	mln GC per MW per year
PPA offtake percentage	[0-100]	Percentage
PPA Price	[40-120]	GC per MWh
Strike price	[0-100]	GC per MWh

All input parameters including their allowed range in the ABM are documented in table B.2. An additional constraint when defining the model parameters for a run is that Pre-dilution share must always be larger than post-dilution share and that Target IRR must always be large than Minimum IRR. If this condition is not met, the model shall throw an error.

Table B.2: Model parameters

Parameter	Range	Unit
Model parameters		
Number of tenders	[1,∞]	Tender
Number of agents	[1,∞]	Agent
Seed	[1,∞]	-
Tender parameters		
Auction year	[0,∞]	year
Capacity	[50,1000]	MW
CAPEX per MW	[0-1]	mln GC/ MW
Competitors importance uncertainty	[0,1]	-
Agent parameters		
Budget	[0,∞]	mln GC
Dilution	True/False	-
Pre-dilution Company Share	[0,100]	%
Post-dilution Company Share	[0,100]	%
Price for operation	[0,∞]	mln GC/MWh
Generation target	[0,∞]	MW
Relative importance of generation target	[0,1]	-
NPV target	[0,∞]	mln GC
Strategy	[Random, Random with improvement, Just Screening, Dilution]	-
Target IRR	[0,∞]	%
Minimum IRR	[0,∞]	%

B.2 SIMPLE MODEL EXPERIMENTS

This section lists the input parameters that were used in the experimentation performed for Chapter 4. Table B.3 shows the model parameters that were not changed during any of the experiments. The number of tenders and number of agents follow from the nature of the experiments being 1-on-1 games. The tender parameters were fixed to realistic values in consultation with the industrial collaborator that developed the model. As can be seen from the agent parameters, it is assumed that agents cannot share tenders they win, which implicates that the pre-dilution company share must be 100%.

Table 4.1 is a copy of the table that is presented in chapter 4 and is added here for completeness. The table shows the agent parameters that correspond to an agent using a certain strategy. What strategy each agent adopts in the model experiments is listed in table B.5.

Table B.3: Fixed parameter input for the simple model experiments

Parameter	Value	Unit
Model parameters		
Number of tenders	1	Tender
Number of agents	2	Agent
Seed	123	-
Tender parameters		
Auction year	2022	year
Capacity	500	MW
CAPEX per MW	1.75	mln GC/ MW
Competitors importance uncertainty	-	-
DEVEX	25	mln GC
Decommissioning cost	20	mln GC
Gross Yield	50	%
OPEX	0.025	mln GC/MW/Year
Agent parameters		
Budget	-	mln GC
Pre-dilution Company Share	100	%
Generation target	-	MW
Relative importance of generation target	-	-
NPV target	-	mln GC
Target IRR	5	%
Minimum IRR	-	%

Table B.4: Input parameters for the simple strategies

Strategy	IRR Target	Dilution	Post-dilution company share	Price for operation
Random		FALSE		
Random with improvement	5%	FALSE		
Just screening	5%	FALSE		
Dilution	5%	TRUE	50%	3.5 million GC per MW

Table B.5: Experimental design simple tenders

Experiment number	Strategy primary agent	Strategy secondary agent
1	Random	Random
2	Random	Random with improvement
3	Random	Just Screening
4	Random	Dilution
5	Random with improvement	Random with improvement
6	Random with improvement	Just Screening
7	Random with improvement	Dilution
8	Just Screening	Just Screening
9	Just Screening	Dilution
10	Dilution	Dilution

B.3 SEQUENTIAL TENDERS MODEL EXPERIMENTS

This section lists the input parameters that were used in the experimentation performed for Chapter 5. To construct the base case parameters, the model was calibrated, this is reported on in this section first.

B.3.1 Calibration of base case parameters

The sequential model includes a two-fold objective for agents; agents want to achieve a certain generation target and an NPV target as well. The fundamental difference between the two objectives is that generation targets are achieved regardless of the strike price the tender is achieved with, NPV on the other hand relies heavily on the strike price.

For the base case, the objective was to calibrate the two targets so that winning a standard tender for an average price results in the same utility gain for NPV as for generation. In this case, an average price is defined as the mean between the minimum IRR bid and the target IRR bid of an agent.

Figure B.1 shows how this turns out for a situation with four tenders where the NPV target is 500 mln GC and the generation target is 700 MW. On the x-axis, the combination of tenders won or lost is shown as a tuple where 1 indicates a tender won and 0 indicates a tender lost. The y-axis shows the performance of winning this set of tenders on the different targets and utility, which is an overall shore of performance. In the base case, generation and NPV are equally important targets, which means the data in the utility graph on the top left is the mean of the two bottom graphs. The two targets are calibrated in such a way that the score on generation on average aligns with the score on NPV, as can be seen when comparing the bottom two graphs.

The analysis has lead to the decision to fix the NPV target at 500 mln GC and the generation target at 700 MW.

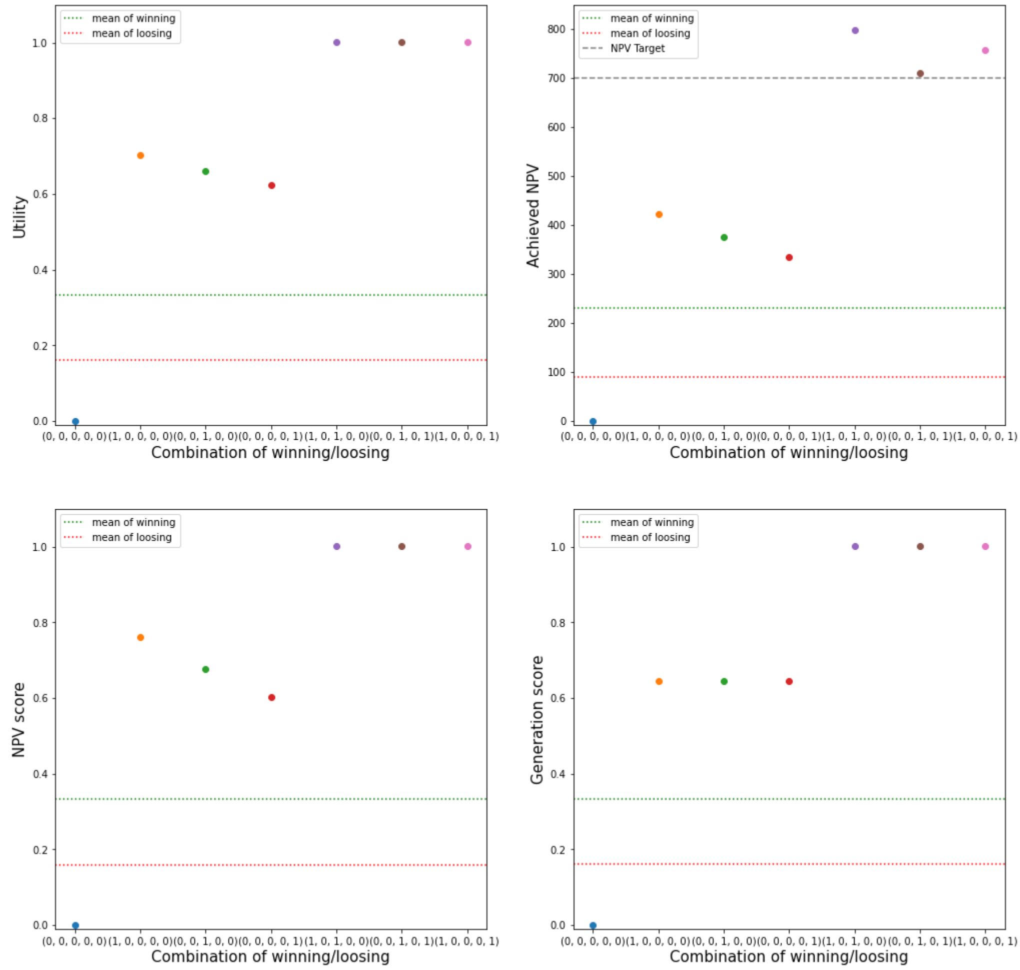


Figure B.1: Calibration of the input parameters to the importance function. Example shown is for a 75.2 GC/MWh bid on the first out of four tenders and results in an importance of 0.1582

Table B.6 shows the input parameters that remain fixed throughout all experiments with the sequential tenders model. The analysis as described above means that an agents target is met when winning two standard tenders for an average price. To simulate a realistic setting where competition is high, all experiments are run where this cannot be achieved by all agents, there are only five tenders to divide over four agents. The tender parameters in the experiments are fixed in consultation with the industrial partner to create realistic values for IRR and NPV in the experiments.

Table B.6: Fixed parameter input for the sequential tenders model experiments

Parameter	Value	Unit
Model parameters		
Number of tenders	5	Tender
Number of agents	4	Agent
Seed	123	-
Tender parameters		
DEVEX	10	mln GC
Decommissioning cost	20	mln GC
Gross Yield	50	%
OPEX	0.025	mln GC/MW/Year

Table B.7 shows the full list of base case input parameters for the experiments. Tenders happen every year and have a capacity of 500 MW. Agents have a generation target of 700 MW, an NPV target of 500 GC per MW, and find both targets equally important. The reasoning behind this is described previously in this section. All agents apply the Just Screening strategy that is defined in Chapter 4 to determine their bid. They strive for an IRR of 8% but will settle for 4% if they find the tender important enough.

Table B.7: Base case input parameters sequential tenders model

Parameter	Value	Unit
Tender parameters		
Auction year	T1: 2022 T2: 2023 T3: 2024 T4: 2025 T5: 2026	year
Capacity	T1-T5: 500	MW
CAPEX per MW	T1-T5: 2	mln GC/ MW
Competitors importance uncertainty	T1-T5: 0.2	-
Agent parameters		
Budget	A1-A4: 2000	mln GC
Generation target	A1-A4: 700	MW
Relative importance of generation target	A1-A4: 0.5	-
NPV target	A1-A4: 500	mln GC
Strategy	A1-A4: Just Screening	-
Target IRR	A1-A4: 8%	%
Minimum IRR	A1-A4: 4%	%

B.3.2 Experimental design of univariate experiments

Table B.8 shows the experiments that were performed for the exploratory univariate experiments as described in Chapter 5. The experiments go over the parameters in table B.7 and chance only one of the parameters to see what the effect is on the model outcomes. One exception is experiment number 13, where target NPV and generation importance are changed simultaneously. This is done because the NPV and generation targets are calibrated to result in roughly the same utility for average tenders. To really see the effect of a different generation importance, the target NPV was varied here as well to see agents making a trade off between fewer tenders, resulting in a lower total capacity with a higher return or a higher total capacity with lower returns.
Capacity and budget appear multiple times in the table. This is done to show both the effect of lowering/increasing the capacity/budget in the whole run, and the effect of varying the parameter over the tenders/agents.

Table B.8: Experimental design 1-on-1 experiments sequential tenders model

Experiment number	Changed parameter	Parameter values
1	Base case	
Changes in tender parameters		
2	Auction year	T1: 2022 T2: 2024 T3: 2026 T4: 2028 T5: 2030
3	Capex per MW	T1: 1 T2: 1.5 T3: 2 T4: 2.5 T5: 3
4	Capex per MW	T1: 3 T2: 2.5 T3: 2 T4: 1.5 T5: 1
5	Capacity	T1-T5: 250
6	Capacity	T1: 100 T2: 300 T3: 500 T4: 700 T5: 900
7	Capacity	T1: 900 T2: 700 T3: 500 T4: 300 T5: 100
8	Competitors importance uncertainty	T1-T5: 0.4
Changes in agent parameters		
9	Minimum IRR	A1: 3 A2: 3.5 A3: 4 A4: 4.5
10	Target IRR	A1: 7 A2: 7.5 A3: 8 A4: 8.5
11	Target NPV	A1: 400 A2: 400 A3: 600 A4: 600
12	Target generation	A1: 600 A2: 600 A3: 800 A4: 800
13	Target NPV + generation importance	A1: 400 & 0 A2: 400 & 0 A3: 600 & 0 A4: 600 & 0
14	Budget	A1-A4: 3000
15	Budget	A1-A4: 1000
16	Budget	A1: 1000 A2: 2000 A3: 3000 A4: 4000

B.3.3 Experimental design of capacity runs

Table B.9 shows the additional experiments that were run to investigate the effect of the sequence and steepness of tender capacity variance. The experiments correspond to the analysis shown in Section 5.3.1 of Chapter 5. The steepness that is calculated from the five columns showing capacity per tender is reported in the final column. Steepness is calculated through equation B.1.

$$Steepness = \log 10(\frac{Capacity_{First\ tender}}{Capacity_{Last\ tender}}) \tag{B.1}$$

Table B.9: Experimental design capacity experiments

Experiment number	Cap T1	Cap T2	Cap T3	Cap T4	Cap T5	Steepness
17	900	**700**	500	300	100	0.954
18	850	675	500	325	150	0.753
19	800	650	500	350	200	0.602
20	750	625	500	375	250	0.477
21	700	600	500	400	300	0.368
22	650	575	500	425	350	0.269
23	600	550	500	450	400	0.176
24	550	525	500	475	450	0.087
25	500	500	500	500	500	0.000
26	100	300	500	700	900	-0.954
27	150	325	500	675	850	-0.753
28	200	350	500	650	800	-0.602
29	250	375	500	625	750	-0.477
30	300	400	500	600	700	-0.368
31	350	425	500	575	650	-0.269
32	400	450	500	550	600	-0.176
33	450	475	500	525	550	-0.087

B.3.4 Experimental design of budget runs

Table B.10 shows the additional experiments that were run to investigate the effect of assigning different budgets to the four agents in the model. The experiments correspond to the analysis shown in Section 5.3.2 of Chapter 5. The budget per agent is shown in the first four columns in the table. All budgets in the table are expressed in million GC. The sequence does not matter in this case, as all agents bid into the tender simultaneously. The sum of the budgets over all agents is reported in the second to last column. The variance between the budgets of the four agents is shown in the final column. The table shows all possible combinations of budgets for agents for the given sums of budgets. A constraint here is that agents only get budgets in steps of 1000 mln GC as this is the investment cost needed for a standard tender and tenders cannot be shared.

Table B.10: Experimental design budget experiments

Experiment number	Budget A1	Budget A2	Budget A3	Budget A4	Total budget	Budget Variance
34	1000	**1000**	1000	5000	8000	3
35	1000	1000	2000	4000	8000	1.5
36	1000	1000	3000	3000	8000	1
37	1000	2000	2000	3000	8000	0.5
38	2000	2000	2000	2000	8000	0
39	1000	1000	3000	5000	10000	2.75
40	1000	1000	4000	4000	10000	2.25
41	1000	2000	2000	5000	10000	2.25
42	1000	2000	3000	4000	10000	1.25
43	1000	3000	3000	3000	10000	0.75
44	2000	2000	2000	4000	10000	0.75
45	2000	2000	3000	3000	10000	0.25
46	1000	1000	5000	5000	12000	4
47	1000	2000	4000	5000	12000	2.5
48	1000	3000	3000	5000	12000	2
49	1000	3000	4000	4000	12000	1.5
50	2000	2000	3000	5000	12000	1.5
51	2000	2000	4000	4000	12000	1
52	2000	3000	3000	4000	12000	0.5
53	3000	3000	3000	3000	12000	0
54	1000	3000	5000	5000	14000	2.75
55	1000	4000	4000	5000	14000	2.25
56	2000	2000	5000	5000	14000	2.25
57	2000	3000	4000	5000	14000	1.25
58	2000	4000	4000	4000	14000	0.75
59	3000	3000	3000	5000	14000	0.75
60	3000	3000	4000	4000	14000	0.25
61	1000	5000	5000	5000	16000	3
62	2000	4000	5000	5000	16000	1.5
63	3000	3000	5000	5000	16000	1
64	3000	4000	4000	5000	16000	0.5
65	4000	4000	4000	4000	16000	0
66	3000	5000	5000	5000	18000	0.75
67	4000	4000	5000	5000	18000	0.25
68	5000	5000	5000	5000	20000	0

C VERIFICATION AND CODE OPTIMALISATION

This appendix reports on the verification tests that are performed to verify the model algorithms as described in the thesis work as intended. Verification of the simple version of the model as presented in Chapter 4 is described in section C.1. The verification of the sequential model as presented in Chapter 5 is described in section C.2. Additionally, section C.3 reports on the code profiling that has been performed to find what processes in the model took the most computational power and what processes have been made more efficient as a consequence of that.

C.1 SIMPLE MODEL

This section describes the verification of the model implementation, as well as the verification of the model convergence.

C.1.1 Verification tests

The simple model is verified through comparing a few key processes with known correct output. Secondly, agents in the model are followed throughout a run to track whether its behaviour are in line with the logic of the model. Finally, extremely high and low inputs are tried to find the ranges in which the model works as intended.

Key processes that were verified are the following:

- When multiple agents issue a bid, the tender assigns the agent that bids the lowest strike price as the winner.
- In case multiple agents issue the same lowest bid, the winner is chosen at random, no bias occurs in this process.
- The optimisation of strike price lands on the same strike price as manual optimisation in the valuation model.
- The Golden Ratio algorithm that is used to optimise the strike price for the just screening and dilution strategy follows the expected iterations,

After these tests of separate procedures in the model, the model was run for one tender in which four agents with the four respective strategies compete. The agents were tracked to find whether they follow the expected steps to arrive at their bid. The result of this tracking is shown in figure C.1 and verifies the agents act and reason as intended. The just screening and dilution strategy agents follow the same logic to arrive at their bid because dilution is only applied after the calculation of the bid.

```
model = Tender_Model(nr_of_tenders=1,nr_of_agents=4,sequential = False,
                     verification = True,
                     input_parameters_directory = 'Input_Parameters.xlsx',
                     valuation_model_directory = 'Valuation_Model.xlsb',
                     valinputs = valu_inputs, aucinputs = auct_inputs,
                     excel_input = exc_input, seed = 123)
while model.run_finished == False:
    model.step()
```

```
Agent 1.0 with strategy random is initialised
Agent 2.0 with strategy random_w_impr is initialised
Agent 3.0 with strategy just_screening is initialised
Agent 4.0 with strategy dilution is initialised
Agent 1.0  starts its step function
Agent  1.0  samples random bid  7
Agent 2.0  starts its step function
Agent  2.0  samples random bid  34 . Corresponding irr: 0.021
Agent  2.0  samples random bid  11 . Corresponding irr: -0.005
Agent  2.0  finds  34 still the best bid so far
Agent  2.0  samples random bid  98 . Corresponding irr: 0.117
Agent  2.0  finds  34 still the best bid so far
Agent  2.0  samples random bid  52 . Corresponding irr: 0.042
Agent  2.0  finds bid is an improvement on  34 and accepts 52 as new preliminar
y bid
Agent  2.0  samples random bid  34 . Corresponding irr: 0.021
Agent  2.0  finds  52 still the best bid so far
Agent 3.0  starts its step function
Agent  3.0  starts bid optimisation
Agent  3.0  tries strike price  0.0 with corresponding irr  -0.015
Agent  3.0  tries strike price  1.0 with corresponding irr  -0.014
Agent  3.0  tries strike price  2.62 with corresponding irr  -0.013
Agent  3.0  tries strike price  5.24 with corresponding irr  -0.01
Agent  3.0  tries strike price  9.47 with corresponding irr  -0.006
Agent  3.0  tries strike price  16.33 with corresponding irr  0.001
Agent  3.0  tries strike price  27.42 with corresponding irr  0.014
Agent  3.0  tries strike price  45.36 with corresponding irr  0.034
Agent  3.0  tries strike price  180.15 with corresponding irr  0.321
Agent  3.0  tries strike price  45.36 with corresponding irr  0.034
Agent  3.0  tries strike price  96.84 with corresponding irr  0.115
Agent  3.0  tries strike price  38.51 with corresponding irr  0.026
Agent  3.0  tries strike price  65.03 with corresponding irr  0.06
Agent  3.0  tries strike price  77.18 with corresponding irr  0.079
Agent  3.0  tries strike price  57.51 with corresponding irr  0.049
Agent  3.0  tries strike price  52.87 with corresponding irr  0.043
Agent  3.0  tries strike price  60.38 with corresponding irr  0.053
Agent  3.0  tries strike price  55.74 with corresponding irr  0.047
Agent  3.0  tries strike price  58.61 with corresponding irr  0.051
Agent  3.0  tries strike price  56.84 with corresponding irr  0.048
Agent  3.0  tries strike price  57.93 with corresponding irr  0.05
Agent  3.0  tries strike price  58.19 with corresponding irr  0.05
Agent  3.0  tries strike price  57.77 with corresponding irr  0.05
Agent  3.0  tries strike price  58.03 with corresponding irr  0.05
Agent  3.0  tries strike price  58.09 with corresponding irr  0.05
Agent  3.0  tries strike price  57.99 with corresponding irr  0.05
Agent  3.0  tries strike price  58.06 with corresponding irr  0.05
Agent 4.0  starts its step function
Agent  4.0  starts bid optimisation
Agent  4.0  tries strike price  0.0 with corresponding irr  -0.015
Agent  4.0  tries strike price  1.0 with corresponding irr  -0.014
Agent  4.0  tries strike price  2.62 with corresponding irr  -0.013
Agent  4.0  tries strike price  5.24 with corresponding irr  -0.01
Agent  4.0  tries strike price  9.47 with corresponding irr  -0.006
Agent  4.0  tries strike price  16.33 with corresponding irr  0.001
Agent  4.0  tries strike price  27.42 with corresponding irr  0.014
Agent  4.0  tries strike price  45.36 with corresponding irr  0.034
Agent  4.0  tries strike price  180.15 with corresponding irr  0.321
Agent  4.0  tries strike price  45.36 with corresponding irr  0.034
Agent  4.0  tries strike price  96.84 with corresponding irr  0.115
Agent  4.0  tries strike price  38.51 with corresponding irr  0.026
Agent  4.0  tries strike price  65.03 with corresponding irr  0.06
Agent  4.0  tries strike price  77.18 with corresponding irr  0.079
Agent  4.0  tries strike price  57.51 with corresponding irr  0.049
Agent  4.0  tries strike price  52.87 with corresponding irr  0.043
Agent  4.0  tries strike price  60.38 with corresponding irr  0.053
Agent  4.0  tries strike price  55.74 with corresponding irr  0.047
Agent  4.0  tries strike price  58.61 with corresponding irr  0.051
Agent  4.0  tries strike price  56.84 with corresponding irr  0.048
Agent  4.0  tries strike price  57.93 with corresponding irr  0.05
Agent  4.0  tries strike price  58.19 with corresponding irr  0.05
Agent  4.0  tries strike price  57.77 with corresponding irr  0.05
Agent  4.0  tries strike price  58.03 with corresponding irr  0.05
Agent  4.0  tries strike price  58.09 with corresponding irr  0.05
Agent  4.0  tries strike price  57.99 with corresponding irr  0.05
Agent  4.0  tries strike price  58.06 with corresponding irr  0.05
Agent 1 bids 7
Agent 2 bids 52
Agent 3 bids 58
Agent 4 bids 58
Winning agent: 1.0 who bid 7
```

Figure C.1: Verification of agent strategy procedures

The final verification method that was used to test the model is testing the model behaviour after entering extremely high or extremely low inputs as its parameters. One limit was found in the model: When IRR drops below -14%, the valuation model is unable to calculate it. This is a limitation of Excel where too low IRRs are not accepted. When using the model, this shall rarely occur as this means the project is very unattractive for actors. For reference, under standard model parameters (refer to Appendix B to know what those parameters are), the strike price has to be ¡-426 for this phenomenon to occur. In this case, the projects NPV would be -11268 million GC.

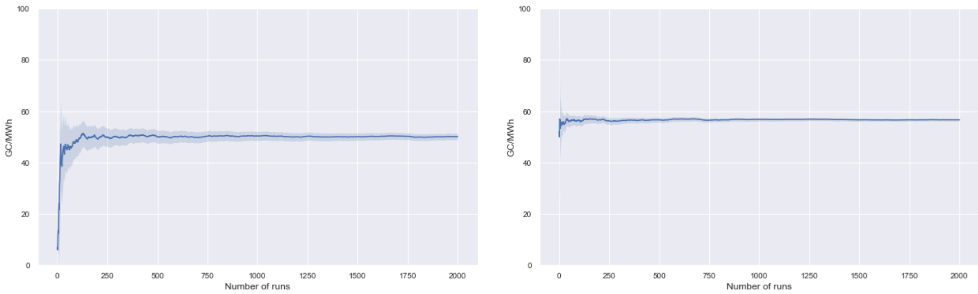
C.1.2 Assessing the convergence of the model runs

Key model outputs were identified to assess whether enough runs have been performed to be able to say the outcomes of the experiments performed with the simple model were stable. For each of these outputs, the maximum 95% confidence interval was calculated for all experiments. Table C.1 shows these outputs, together with this maximum confidence interval.

Table C.1: Outputs that were checked on convergence through a 95% confidence interval of the mean

Key output	Maximum bandwidth	Unit
Success rate	0.5	% GC
IRR	0.5	%
Average bid	3	GC/MWh
Winners curse	3	GC/MWh

The most random activities that occur in the model stem from the random and random with improvement strategies as their bid differs when tender parameters remain fixed. This is why the convergence of a run where a random agent competes with a random with improvement agent for a single tender is plotted in the figures of this section. Plots C.2 to C.5 cover all key outputs for this experiment as defined in table C.1. The line in the plot represents the progressing mean of the output, the shaded area around the line shows the 95% confidence interval of this mean.
Additionally, tables C.2 to C.5 show the 95% confidence interval as it exists for 2000 runs for all experiments with the simple model. The experiments cover 1-on-1 experiments between agents with varying strategies, in the tables, the rows represent the agent strategy from which perspective the key outputs confidence interval is defined. When two agents with the same strategy compete against each other, the output of the first agent is used, as this is also the way it is processed in the analysis of the experiments, as presented in Chapter 4 and Appendix D.



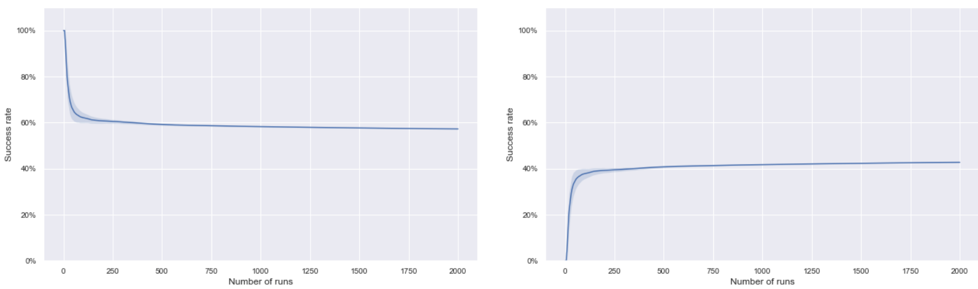
(a) Random strategy

(b) Random with improvement strategy

Figure C.2: Progression of convergence of the average bid over the runs for a 1-on-1 game between a random strategy and a random with improvement strategy

Table C.2: 95 % confidence intervals of the average bid in each experiment

Primary agent	Random	2.5729	2.5725	2.5634	2.5634
	Random with improvement	0.9799	1.0145	0.9789	0.9790
	Just Screening	-	-	-	-
	Dilution	-	-	-	-
		Random	Random with improvement	Just Screening	Dilution
		Secondary agent			



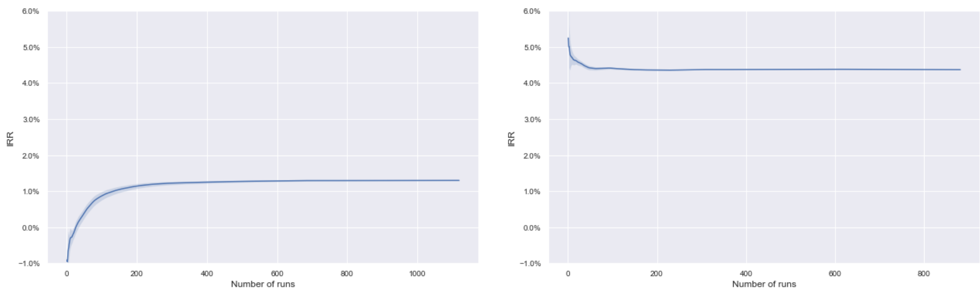
(a) Random strategy

(b) Random with improvement strategy

Figure C.3: Progression of convergence of the success rate over the runs for a 1-on-1 game between a random strategy and a random with improvement strategy

Table C.3: 95 % confidence intervals of the success rate in each experiment

Primary agent	Random	0.0016	0.0026	0.0031	0.0031
	Random with improvement	0.0026	0.0027	0.0029	0.0029
	Just Screening	0.0031	0.0029	0.0018	0.0018
	Dilution	0.0031	0.0029	0.0018	0.0033
		Random	Random with improvement	Just Screening	Dilution
		Secondary agent			

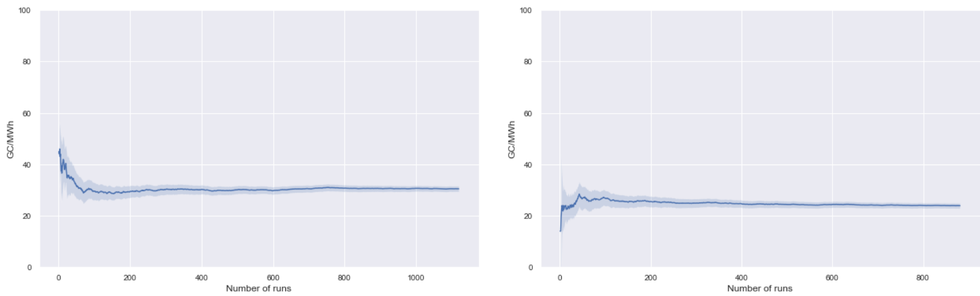


(a) Random strategy (b) Random with improvement strategy

Figure C.4: Progression of convergence of the average IRR over the runs for a 1-on-1 game between a random strategy and a random with improvement strategy

Table C.4: 95 % confidence intervals of the average IRR in each experiment

Primary agent	Random	0.00023	0.00027	0.00017	0.00017
	Random with improvement	0.00008	0.00016	0.00007	0.00006
	Just Screening	0.00000	0.00000	0.00000	0.00000
	Dilution	0.00000	0.00000	0.00000	0.00000
		Random	Random with improvement	Just Screening	Dilution
		Secondary agent			



(a) Random strategy (b) Random with improvement strategy

Figure C.5: Progression of convergence of the winners curse over the runs for a 1-on-1 game between a random strategy and a random with improvement strategy

Table C.5: 95 % confidence intervals of the winners curse in each experiment

Primary agent	Random	2.9373	2.1535	1.8932	1.8932
	Random with improvement	2.0141	1.2574	1.0160	1.0221
	Just Screening	1.6972	0.7549	-	-
	Dilution	1.6972	0.7509	-	-
		Random	Random with improvement	Just Screening	Dilution
		Secondary agent			

C.2 SEQUENTIAL MODEL

This section describes the verification of the model implementation of the sequential tenders version of the model, as well as the verification of the model convergence.

C.2.1 Verification tests

The sequential tender model is verified through comparing a few key processes with known correct output. Secondly, the reasoning of the agents in the base case of the model is followed throughout a run to track whether their behaviour is in line with the logic of the model.

Key processes that were verified are the following:

- The calculation of the scores on generation and NPV of a tender set is implemented correctly. Manual recalculation of these scores was done to determine this.
- The calculation of the utility of a tender set is implemented correctly. Manual recalculation of the utility was done to determine this.
- The calculation of the importance of a tender is implemented correctly. Manual recalculation of the importance was done to determine this.
- The root finding algorithm that is used to find the strike price at which the importance of a tender is exactly 0 for the agents follows the expected iterations,

After these tests of separate procedures in the model, the model was run for one tender in which four agents compete for five sequential tenders. The parameters of the agents and the tenders are fixed at the base case value. Appendix B shows what these values are exactly. The agents were tracked to find whether they follow the expected steps to arrive at their bid. The result of this tracking is shown in figure C.6 and verifies the agents act and reason as intended. Agents find calculate their importance, calculate their bid accordingly and cease bidding as soon as they reach their budget limit.

```
model = Tender_Model(nr_of_tenders=5,nr_of_agents=4,sequential = True,
                     verification = True,
                     input_parameters_directory = 'Input_Parameters.xlsx',
                     valuation_model_directory = 'Valuation_Model.xlsb',
                     valinputs = valu_inputs, aucinputs = auct_inputs,
                     excel_input = exc_input, seed = 125)
while model.run_finished == False:
    model.step()
```

```
Agent  1.0  thinks the most interested party has an importance of  0.32
Minimum IRR bid ( 60.8 ) already makes Tender 1 important for Agent 1.0
Agent  2.0  thinks the most interested party has an importance of  0.25
Minimum IRR bid ( 60.8 ) already makes Tender 1 important for Agent 2.0
Agent  3.0  thinks the most interested party has an importance of  0.2
Minimum IRR bid ( 60.8 ) already makes Tender 1 important for Agent 3.0
Agent  4.0  thinks the most interested party has an importance of  0.24
Minimum IRR bid ( 60.8 ) already makes Tender 1 important for Agent 4.0
Agent 1 bids 60.8
Agent 2 bids 60.8
Agent 3 bids 60.8
Agent 4 bids 60.8
Winning agent: 4.0 who bid 60.8
Agent  1.0  thinks the most interested party has an importance of  0.32
Minimum IRR bid ( 60.8 ) already makes Tender 2 important for Agent 1.0
Agent  2.0  thinks the most interested party has an importance of  0.21
Minimum IRR bid ( 60.8 ) already makes Tender 2 important for Agent 2.0
Agent  3.0  thinks the most interested party has an importance of  0.39
Minimum IRR bid ( 60.8 ) already makes Tender 2 important for Agent 3.0
Agent  4.0  thinks the most interested party has an importance of  0.26
Agent  4.0  starts finding its 0 importance bid, minimum IRR bid is  60.8 targe
t IRR bid is  89.5
Outcome for bidlist [60.8, 60.8, 75.2, 75.2, 75.2] with position 1 has outcome
65.3
Agent 1 bids 60.8
Agent 2 bids 60.8
Agent 3 bids 60.8
Agent 4 bids 65.3
Winning agent: 3.0 who bid 60.8
Agent  1.0  thinks the most interested party has an importance of  0.38
Minimum IRR bid ( 60.8 ) already makes Tender 3 important for Agent 1.0
Agent  2.0  thinks the most interested party has an importance of  0.3
Minimum IRR bid ( 60.8 ) already makes Tender 3 important for Agent 2.0
Agent  3.0  thinks the most interested party has an importance of  0.36
Agent  3.0  starts finding its 0 importance bid, minimum IRR bid is  60.8 targe
t IRR bid is  89.5
Outcome for bidlist [None, 60.8, 60.8, 75.2, 75.2] with position 2 has outcome
63.0
Agent  4.0  thinks the most interested party has an importance of  0.33
Agent  4.0  starts finding its 0 importance bid, minimum IRR bid is  60.8 targe
t IRR bid is  89.5
Outcome for bidlist [60.8, None, 60.8, 75.2, 75.2] with position 2 has outcome
63.0
Agent 1 bids 60.8
Agent 2 bids 60.8
Agent 3 bids 63.0
Agent 4 bids 63.0
Winning agent: 2.0 who bid 60.8
Agent  1.0  thinks the most interested party has an importance of  0.28
Minimum IRR bid ( 60.8 ) already makes Tender 4 important for Agent 1.0
Agent  2.0  thinks the most interested party has an importance of  0.38
Minimum IRR bid ( 60.8 ) already makes Tender 4 important for Agent 2.0
Agent  3.0  thinks the most interested party has an importance of  0.44
Minimum IRR bid ( 60.8 ) already makes Tender 4 important for Agent 3.0
Agent  4.0  thinks the most interested party has an importance of  0.7
Minimum IRR bid ( 60.8 ) already makes Tender 4 important for Agent 4.0
Agent 1 bids 60.8
Agent 2 bids 60.8
Agent 3 bids 60.8
Agent 4 bids 60.8
Winning agent: 3.0 who bid 60.8
Agent 3.0 does not have budget for Tender 5
Agent  1.0  thinks the most interested party has an importance of  0.56
Minimum IRR bid ( 60.8 ) already makes Tender 5 important for Agent 1.0
Agent  2.0  thinks the most interested party has an importance of  0.72
Minimum IRR bid ( 60.8 ) already makes Tender 5 important for Agent 2.0
Agent  4.0  thinks the most interested party has an importance of  0.46
Minimum IRR bid ( 60.8 ) already makes Tender 5 important for Agent 4.0
Agent 1 bids 60.8
Agent 2 bids 60.8
Agent 3 Does not bid
Agent 4 bids 60.8
Winning agent: 4.0 who bid 60.8
All tenders have been conducted, model run is finished
```

Figure C.6: Verification of agent behaviour in the base case of the sequential model

C.2.2 Assessing the convergence of the model runs

Key model outputs were identified to assess whether enough runs have been performed to be able to say the outcomes of the experiments performed with the simple model were stable. For each of these outputs and for each experiment, a maximum 95% confidence interval of its mean was calculated. Table C.6 shows these outputs, together with their maximum confidence interval found in any experiment.

Table C.6: Outputs that were checked on convergence through a 95% confidence interval of the mean

Key output	Maximum bandwidth	Unit
Total subsidy handed out	1000	Million GC
Percentage of tender distributions being 2-2-1-0	2	%
Total achieved utility per agent	0.1	-
Average bid per agent	3	GC/MWh
Percentage of times agent number 2 wins tender number 2	7.5	%

Figures C.7 to C.11 show the progression of the mean of the key outputs as determined in table C.6 as well as the 95% confidence interval around that mean. Experiment 11 was chosen as an example case to show in the plots as this is one of the few where the total subsidy handed out is prone to significant fluctuations so this was actually one of the experiments that required the most runs to converge. The input parameter that correspond to experiment 11 can be found in Appendix B.

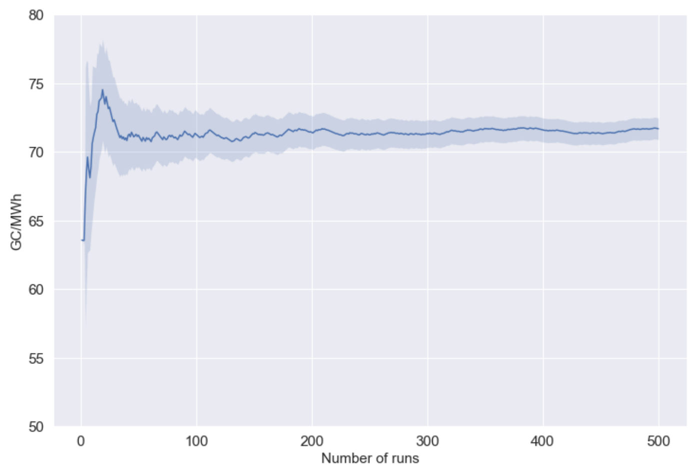


Figure C.7: Progression of convergence of the average bid of an agent over the runs for sequential experiment 11

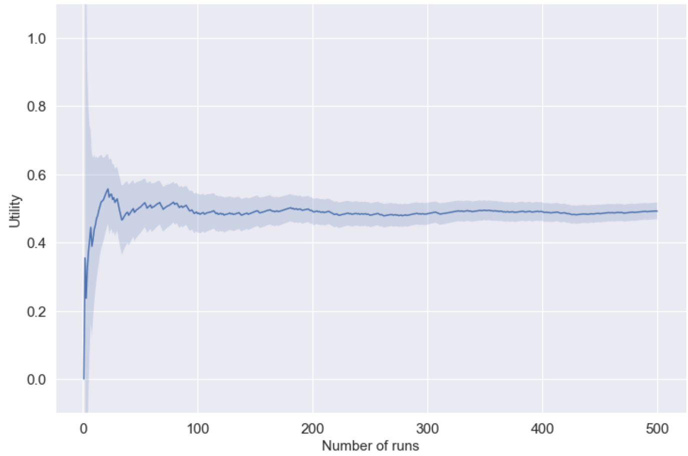


Figure C.8: Progression of convergence of the total utility achieved by an agent over the runs for sequential experiment 11

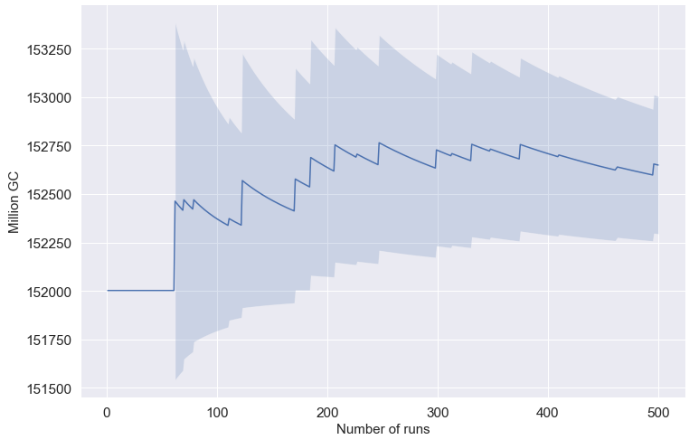


Figure C.9: Progression of convergence of the total subsidy handed out during a run over the runs for sequential experiment 11

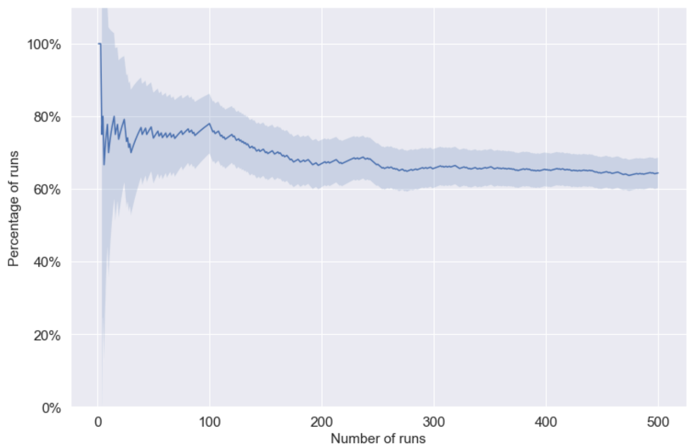


Figure C.10: Progression of convergence of the percentage of times the distribution of tenders per agent was 2-2-1 in sequential experiment 11

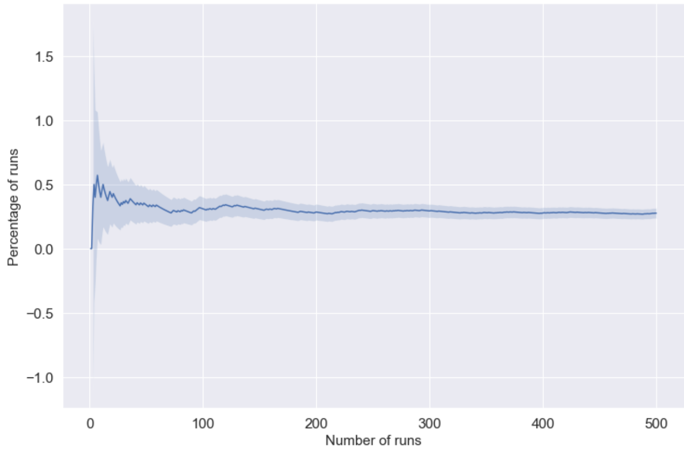


Figure C.11: Progression of convergence of the percentage of times agent number 2 wins tender number 2 in sequential experiment 11

C.3 CODE PROFILING

Profiling of the simulation model code is performed to ensure the efficiency of computational power needed to run experiments. The built-in Python module cProfile is used to conduct the analysis. The bottle necks that were found and the way they were handled is listed here:

- The valuation model is implemented in Excel. In an early version of the model, agents looking to interact with the model opened and closed the model for each interaction. This opening and closing took the majority of the run time, which is why the adaptation was made to open the model once at the beginning of the run and only close it after all runs had been performed.

- Agents optimising their bids used to construct a look-up table with strike prices that would lead to a certain IRR or importance of a tender. This method approached a brute force method of trying out all possibilities and took a considerable amount of computational time. This lead to the usage of the optimisation algorithms. For the simple model, the standard Python SciPy package solutions 'minimize' was used initially, which uses the BFGS algorithm to minimize a function Sci-Py (2022b). The BFGS algorithm in Scipy (Sci-Py, 2022b). The BFGS algorithm is a variation on gradient descent algorithms which is widely used in machine learning to efficiently minimize a unknown, nonlinear function (Kochenderfer and Wheeler, 2019). This, however, still took a considerable amount of time and given that the function used non-continuous input and the algorithm solves it as if it is continuous. This makes it take more iterations than necessary to find the solution. Consequently, the Golden-section search algorithm was chosen to succeed the BFGS algorithm Sci-Py (2022a). For the sequential tenders model, the standard root finding algorithm 'root_scalar' from the SciPy package worked well Sci-Py (2022c).

- Code profiling indicated that the calculations of the bids for the minimum IRR bid and the target IRR bid in the sequential model took a considerable amount of computational power. To save on this, a large dictionary was created at the beginning of each experiment that mapped these bids for each combination of tender parameters and agent parameters that occurred. Experiments consist of a considerable amount of runs. Plus, often experiments consist of multiple agents with the same input parameters which meant pulling the values from the dictionary saved substantial run time.

- Considering all tender sets when calculating the importance of the tender at hand cost the agents in the sequential tender model a considerable amount of time. To save on this, unfeasible tender sets that no agent is able to consider due to budget constraints are removed from consideration right at the beginning of the run.

D ADDITIONAL OUTCOMES FROM EXPERIMENTATION WITH THE SEQUENTIAL MODEL

This appendix adds supporting results to the findings presented in Chapter 5.

D.1 STORYLINE OF CAPACITY VARIANCE RUNS

In this section, storylines of typical runs from the capacity variance runs with a steepness of 0.477 and -0.477 are shown. Through the storylines, the logic and path dependency that these experiments follow becomes clear. The storylines are a supplement to the ones with steepness 0.954 and -0.954 that are already explained in the main text of Chapter 5.

Table D.1 shows the typical storyline of a steepness 0.477 run. The logic is very similar to the logic that can be found in in 0.954 run. The winner of the first tender does not bid until the last tender due to budget constraints. The second tender is won by any of the remaining agent, which then also opts out for the third tender. This third tender is won by any of the two remaining agents.
Tender number four goes to any agent that did not win the first tender. If the agent with no tenders yet wins it, the last tender goes to any of the four agents, if the agent that already won tender number 2 or 3 wins, that agent will opt out for the last tender due to budget constraints.

Table D.1: Storyline of run with steepness 0.477

Tender number	Tender capacity	Target IRR	Minimum IRR	Agent 1	Agent 2	Agent 3	Agent 4
1	750 MW	89.2	60.5	60.5	60.5	60.5	60.5
2	625 MW	89.3	60.6	60.6	No Budget	60.6	60.6
3	500 MW	89.5	60.8	No Budget	No Budget	60.8	60.8
4	375 MW	89.8	61.1	61.1	No Budget	61.1	61.1
5	250 MW	90.5	61.7	61.7	61.7	61.7	61.7
Outcomes							
Generation achieved				625	750	750	375
Generation score				0.8	0.96	0.95	0.48
NPV achieved				165.3	210	183.6	90
NPV score				0.3	0.38	0.33	0.16
Utility score				0.55	0.67	0.65	0.32

Table D.2 shows a typical run with steepness -0.477. Here too, any of the agents win the first tender by bidding their minimum IRR. The winner does not find the second tender interesting as it would restrict it from bidding on any other tenders and this tender is not enough to meet its NPV target not its generation target. The other three agents bid minimum IRR and one of them wins. The one that wins is the only one that thinks the next tender is its highest priority as for it, it is the only tender left that it has budget for. The other agents are not prepared to bid their minimum IRR for this tender, which means the agent that wins tender number 2 always wins tender number 3 as well.

Next it will stop bidding as its budget has run out. The other agents bid minimum IRR, the winner opts out of the last tender, which goes to one of the two remaining agents.

Table D.2: Storyline of run with steepness -0.477

Tender number	**Tender capacity**	**Target IRR**	**Minimum IRR**	**Agent 1**	**Agent 2**	**Agent 3**	**Agent 4**
1	250 MW	90.5	61.7	61.7	61.7	61.7	61.7
2	375 MW	89.8	61.1	61.1	Negative importance	61.1	61.1
3	500 MW	89.5	60.8	60.8	62.5	69.9	69.9
4	625 MW	89.3	60.6	No Budget	60.6	60.6	60.6
5	750 MW	89.2	60.5	No Budget	60.5	60.5	No Budget
Outcomes							
Generation achieved				875	250	750	625
Generation score				1	0.32	0.96	0.8
NPV achieved				227.2	72.9	166.3	147
NPV score				0.41	0.13	0.3	0.26
Utility score				0.7	0.23	0.63	0.53

D.2 IMPACT OF BUDGET VARIANCE AND TOTAL BUDGET ON THE CHANCE TO WIN SPECIFIC TENDERS

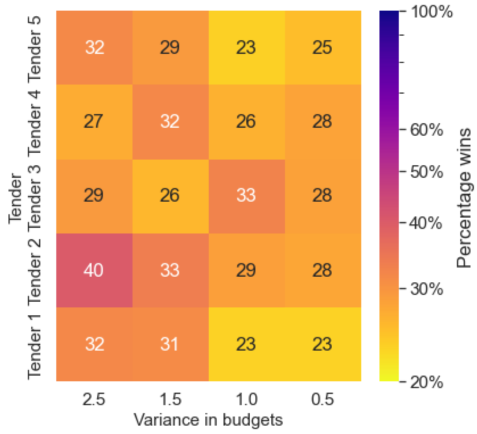
Figure D.1 shows for an agent with a 4000 million GC budget what its chances are at winning each tender for varying total budget and budget variance. The plots for a total budget of 8000 million GC and 18000 million GC are omitted as there is only one budget distribution possible where an agent with a 4000 million GC budget occurs in these cases.

Figure D.1a shows that the 4000 million GC budget agent has an advantage in the first two tenders when the total budget is low. As the total budget increases, this effect becomes less pronounced until in figure D.1d there is no significant difference at all.

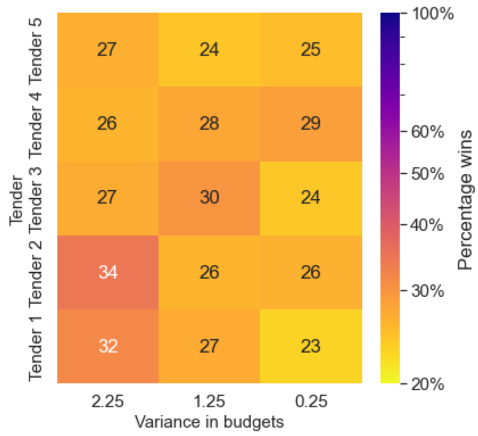
Figures D.2, D.3, and D.4 show the results for agents with a budget of respectively 3000, 2000, and 1000 million GC. Similar trends as found in figure D.1 can be found, though they become less pronounced as the budget becomes lower.

In figure D.4 it can be seen that agents with budget for only one tender do not bid their minimum IRR on the first two tenders and therefore never wind these.

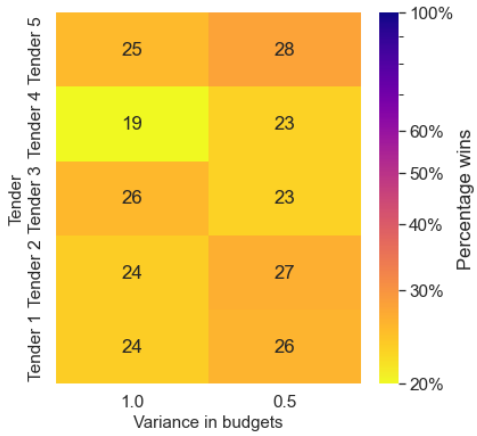
(a) Total budget: 10000 million GC



(b) Total budget: 12000 million GC

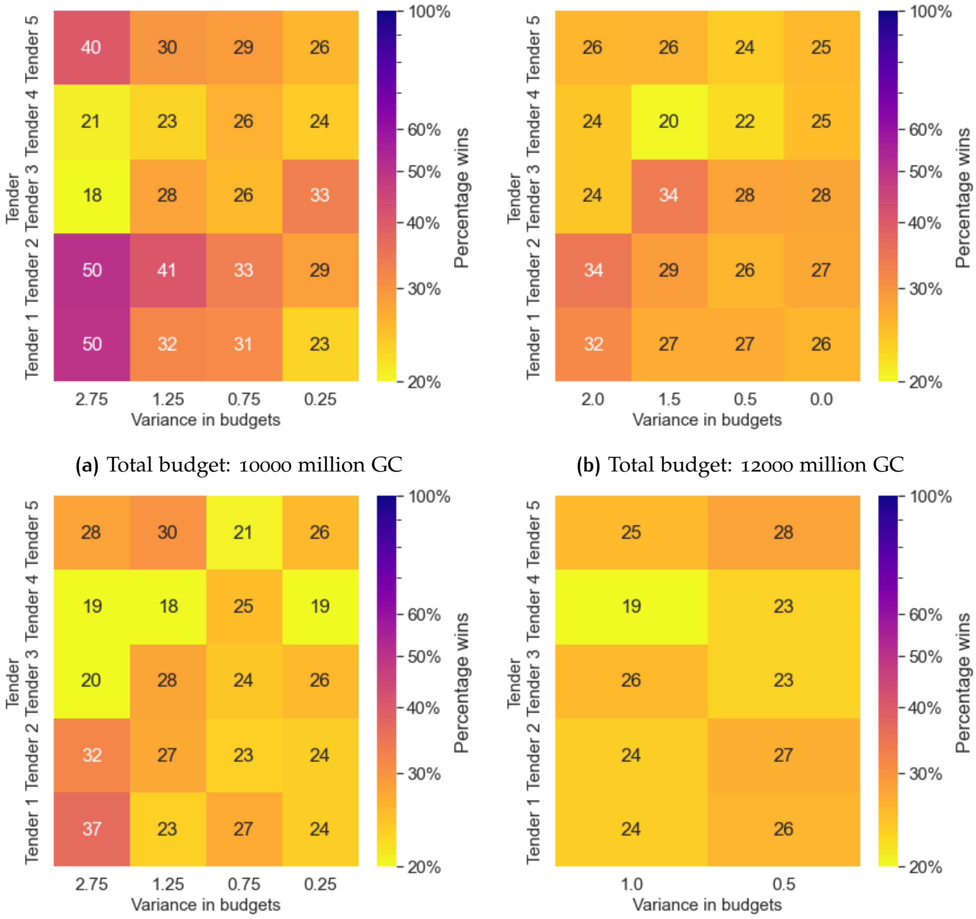


(c) Total budget: 14000 million GC



(d) Total budget: 16000 million GC

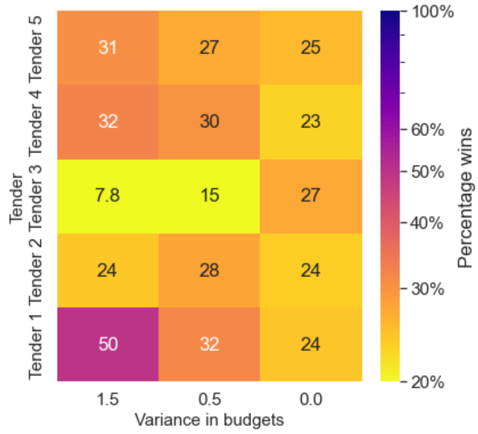
Figure D.1: Chance at winning each tender from the perspective of a 4000 million GC budget agent.



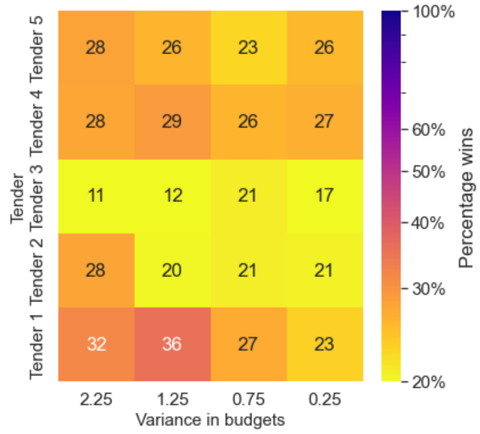
(a) Total budget: 10000 million GC **(b)** Total budget: 12000 million GC

(c) Total budget: 14000 million GC **(d)** Total budget: 16000 million GC

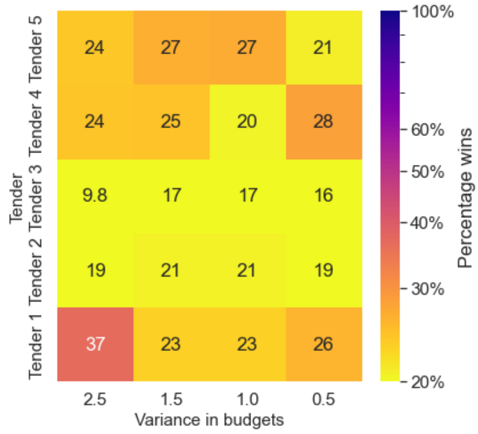
Figure D.2: Chance at winning each tender from the perspective of a 3000 million GC budget agent.



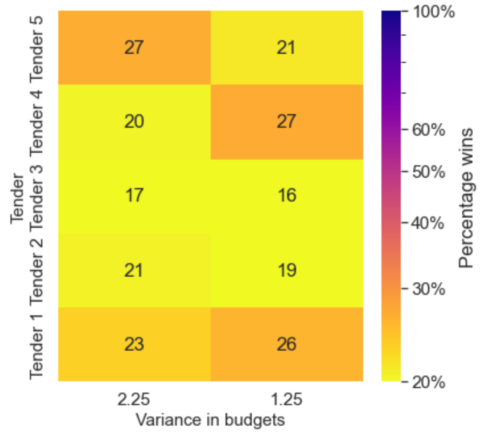
(a) Total budget: 8000 million GC



(b) Total budget: 10000 million GC

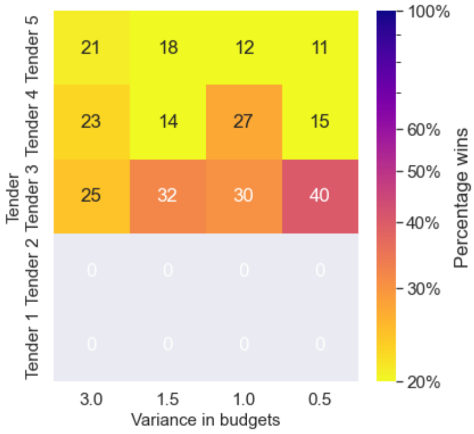


(c) Total budget: 12000 million GC

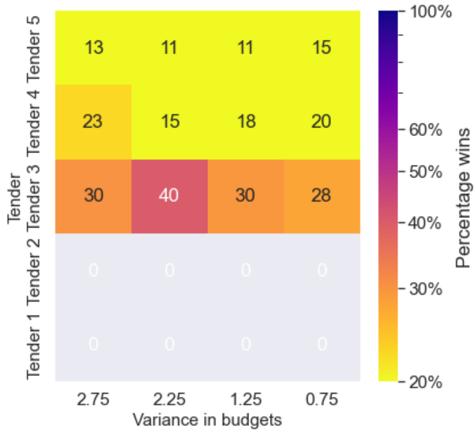


(d) Total budget: 14000 million GC

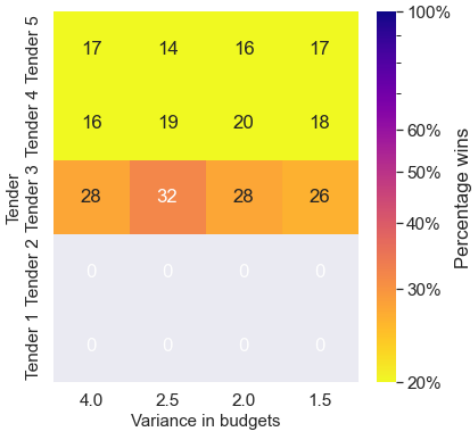
Figure D.3: Chance at winning each tender from the perspective of a 2000 million GC budget agent.



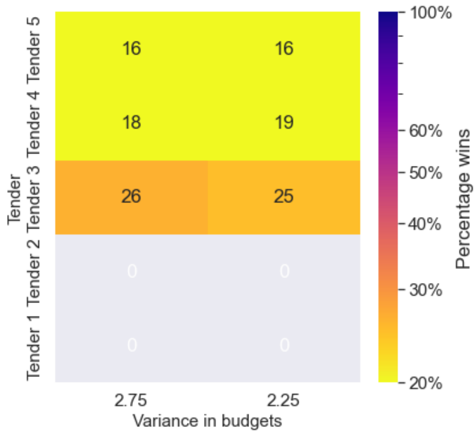
(a) Total budget: 8000 million GC



(b) Total budget: 10000 million GC



(c) Total budget: 12000 million GC

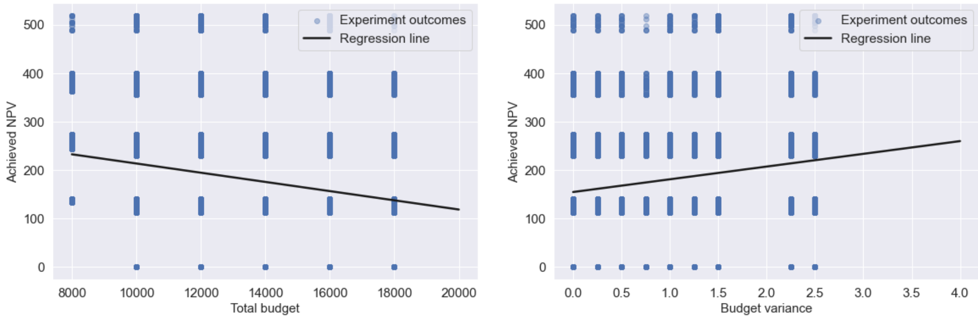


(d) Total budget: 14000 million GC

Figure D.4: Chance at winning each tender from the perspective of a 1000 million GC budget agent.

D.3 IMPACT OF BUDGET VARIANCE AND TOTAL BUDGET ON AGENT NPV

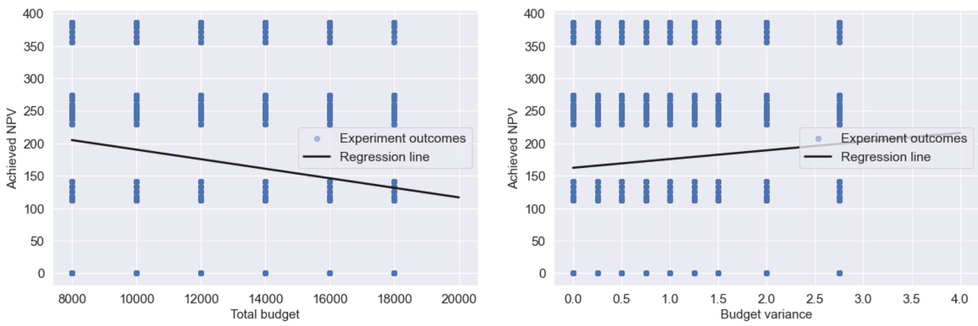
The figures in this section supplement the findings in Chapter 5 that total budget and budget variance influences the NPV of the competing agents.
Figure D.5a shows NPV for an increasing total budget from the perspective of an agent that has a budget of 4000 million GC. The regression line through the scatter plot shows that as the total budget increases, the achieved NPV of this agent tends to go down. The Pearson correlation between the two variables is -0.26 with a P-value of 1.91e-250, which makes the correlation statistically significant.
When looking at NPV for increasing variance, the trend is up. This trend is significant too, with a Pearson correlation of 0.22, with a P-value of 4.87e-179.
The trend is a bit less steep than the trend for agents with a 5000 million GC budget but it follows the same direction.



(a) Impact of total budget variation (b) Impact of budget variance variation

Figure D.5: Impact of total budget and budget variance on NPV of an agent with a 4000 million GC budget

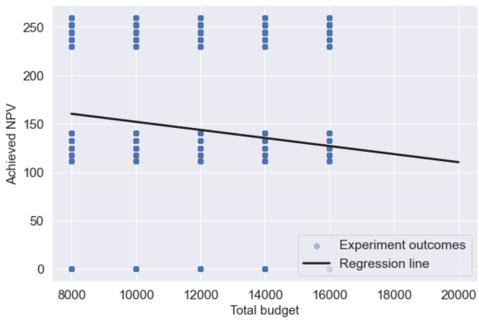
Figure D.6 shows the same graphs for an agent with a budget of 3000 million GC. The conclusions are the same as for the 4000 million GC agent, the only difference being that the trend on variance is a little less steep again. Both trends are significant:
Pearson correlation -0.16, significance: 8.34e-92 for the trend in figure D.6a.
Pearson correlation 0.087, significance: 3.17e-27 for the trend in figure D.6b.



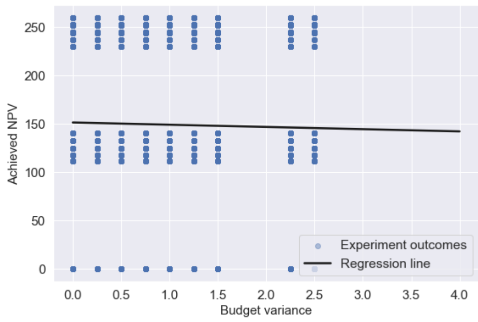
(a) Impact of total budget variation (b) Impact of budget variance variation

Figure D.6: Impact of total budget and budget variance on NPV of an agent with a 3000 million GC budget

Figure D.7 shows the same graphs for an agent with a budget of respectively 2000 million GC and 1000 million GC. Interestingly, the trend for variance has now flipped, indicating that for these low budget agents, it is beneficial to have low budget variance. Importance to note though is that the trend is very minimal, which can be seen by the trends in figure D.7b and D.7b being near horizontal.
Pearson correlations showing the trends are significant are the following: Pearson correlation -0.02, significance: 0.02 for the trend in figure D.7a.
Pearson correlation -0.11, significance: 9.31e-36 for the trend in figure D.7b.
Pearson correlation -0.02, significance: 0.02 for the trend in figure D.8a.
Pearson correlation -0.06, significance: 1.15e-10 for the trend in figure D.8b.

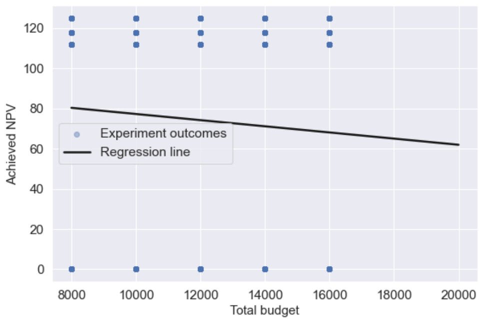


(a) Impact of total budget variation

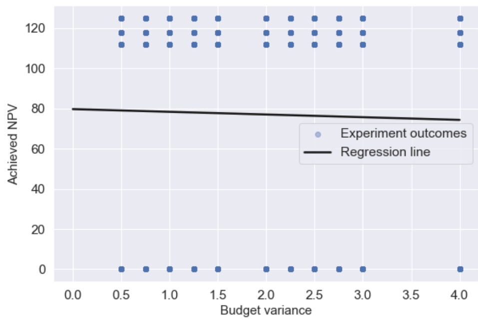


(b) Impact of budget variance variation

Figure D.7: Impact of total budget and budget variance on NPV of an agent with a 2000 million GC budget



(a) Impact of total budget variation



(b) Impact of budget variance variation

Figure D.8: Impact of total budget and budget variance on NPV of an agent with a 1000 million GC budget

D.4 WINNERS CURSE WHEN VARYING BUDGET VARIANCE AND TOTAL BUDGET

Figure D.9 shows the distribution of winners curse for two runs where the budget variance was high and the total budget was low. These are the only instances where winners curse occurs. For the situation where there is one agent with a 5000 million GC budget and three with a 1000 million GC budget, winners curse occurs during the auction of the first two tenders. The agents with budget for only one tender are not willing to bid their minimum bid, which means the agent with enough budget for all five tenders bids too low for these tenders. The second tender is already a bit more important to the 1 tender budget agents, which is why they bid a little more competitive, which explains the two different values for winners curse in figure D.9a.
Figure D.9b shows similar behaviour, only here, winners curse only occurs when the first tender is won by the 2000 million GC budget agent, which makes it bid less competitive for the second one.
All other experiments where budget was varied, there were always at least two agents bidding minimum IRR, making the winners curse always 0.

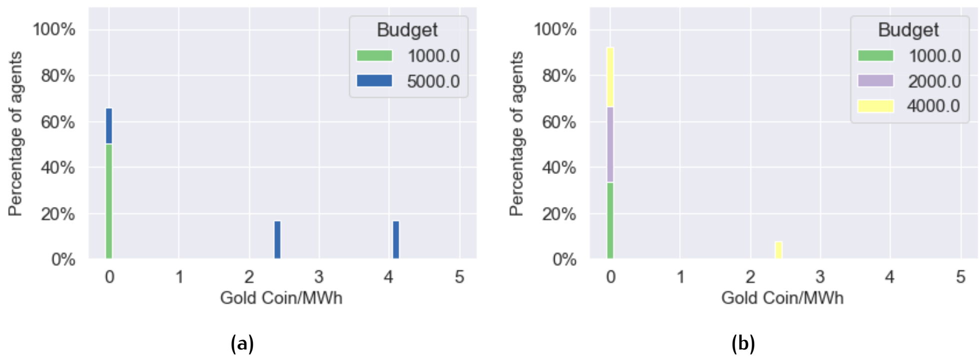


Figure D.9: Winners curse

COLOPHON

This document was typeset using LaTeX. The document layout was generated using the arsclassica package by Lorenzo Pantieri, which is an adaption of the original classicthesis package from André Miede.