Preface

This project has been an interesting journey. Many unexpected turns and explorations. I however feel that we have reached a point event though not the one planned.

Thanks go to my supervisor for interesting conversations and for giving me the freedom to work with my own approaches.

Also to my parents and other family members for support and endless Skype conversations.

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Abstract

Recently a new form of bids was introduced on the Swiss secondary control market. No clear methodology exists on how to strategically place bids in this market. In this project we propose a decision making guidelines for a market player.

The secondary control market in Switzerland is modeled with the means of agent based modeling. Agents are created that place bids on a market, get results of market clearing and then play out the rest of the time period, a week, according to their idea of prices on the spot market. There they optimize their profit while respecting the outcome of the bid on secondary control market.

This gives the agents rating of the bid placed. After some iterations a rating is present for many different bids resulting in agents placing bids according to their earlier experience.

First a simple market model, with one price bid per agent, is introduced that manages to show strategic behavior between the agents.

Next a more detailed model of the Swiss market is introduced. There, each agent can place a bid consisting of numerous pairs: price and amount. The market organizer can then choose by optimization which pairs he accepts.

This introduces some complications in learning which bids are best, especially since the possible combinations of pairs are immense. Many possible approaches were introduced of which one was tried out. The bids are structured by the use coefficients that the agents then optimize. This method, while theoretically sound, proved impractical since it requires many iterations.

Future approach suggested is to have more reasonable agents that evaluate each bid, understand what was good/bad about this certain bid. Afterwards they assign the rating to the characteristics of the bid rather than coefficients. Then bids are structured according to the optimum characteristics.
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Chapter 1

Introduction

Energy production and usage is becoming a more important factor in our world and it’s part will most likely only increase in the coming years. In the last few years the energy world has been moving from simply a production process to a more market influenced process. The sheer production of energy is now only the first step towards being profitable energy company. One has to master many and sometimes complicated market environments to optimize the profit.

The market is complicated and contains many different sectors. To begin with, the energy market sector itself has big selection of products: futures and spot market, to name two. And then other support market sectors like auxiliary services: primary, secondary control or tertiary control.

Another dimension of the market environment is the situation of the player within the market. One such example is when the market player in question has no influence on the market. He is a so called price taker. Then his approach is quite simple in theory. He sells as much as possible when the price high.

Another approach is needed when his actions influence the market. Then a more iterative approach is needed as his actions might change the prices. Those possible changes should be estimated and taken into account before taking a strategic action.

The secondary control market in Switzerland is a small, isolated market so there might be that market player can influence the prices. Therefore it is of interest to consider such strategic action. In addition a new form of bids were recently introduced by the market operator so no clear methodology exists yet for such strategy.

In this thesis focus is therefore put on this market and the aim is to come up with a decision making tool to help market players come up with bids.

In chapter 2 the basics of this market and the tools used are introduced. In chapter 3 a modeling approach is proposed, first for a simple market to show its effect and then on the current market to use for decisions. In
chapter 4 two case studies are introduced using the models. At last in chapter 5 results are discussed and improvements suggested.

\section*{1.1 Literature Overview}

Numerous studies have been done in the field of market power and on the secondary control market but not so many combining these two.

One common approach \cite{1} to the market power problems in a market with a common clearing price is to place quantity only offers, with zero prices. Then the bids are automatically accepted. The bid however shifts the supply curve and thus lowers market clearing price. So the optimization is about amount versus price. This approach however does not work in the secondary control market as each market player gets only paid according to his own bid and not a common clearing price.

Another approach is suggested in \cite{2} where duopoly is assumed and pricing is extracted using pure game theory. The market is modeled as a Carnot-game and the solution is computed in a way similar to dynamic modeling.

For complicated interaction agent based modeling is often used. There you have agents, for example market players, with predefined goals, for example to maximize their profit, have them interact and thus predict outcome. In \cite{3} it is used to predict the effect from battery powered fleet on network. While it is an unrelated field it covers the topic of agents with agenda.

The approach used in this thesis will be less deterministic. The problem is solved by trying out the actions of bids for SC certain week many times until agents have stopped learning and a 'best' approach is reached for each of them.
Chapter 2

Secondary Control and Agent Based Modeling

As stated earlier this thesis will focus on application of agent based modeling on the secondary control market in Switzerland. Here these two topics are introduced.

2.1 Agent Based Modeling

In the world there are many examples of complicated interaction between players, for example stock markets or drivers on a street. Often these interactions are too complicated to fully understand. One way of predicting outcome even though interactions are not really understood is to use agent based modeling (ABM).

In ABM a small model, called agent, is made of each player. In the case of the drivers on the street one agent would be one driver. This agent has a way to act, rate the outcome of his action and a goal to aim for. For example could a driver choose between different routes. The goals could include minimizing travel time or shortest route. Then these agents interact with each other according to rules, which are called the environment. For our driver the environment could be information about travel times for different routes.

In this way possible outcomes can be predicted based on the environment and the goals behind the agents’ decisions.

When an agent learns from the outcome of their earlier actions we talk about reinforced learning. There are many ways for this learning, differently elaborate, but as the learning task in this thesis is quite simple we will use a relatively simple method based on Q-learning.

Q-learning which was first brought forth by Watkins in 1989 [4] and is very useful to approach simple problems in a non changing environment. Next, some basics are introduced about Q-learning as it is used here.
First there are the states. The agent can be in one of different states. From each state an agent can perform one or more actions. At last we have the environment that gives feedback on a selected action performed from a state.

The state along with the action needs to be sufficient information to calculate the feedback from the environment.

The agent learns by having a matrix that keeps a record of rewards for each action done from a each state. This matrix is called the Q-matrix. The process normally goes so that a state is selected randomly and then an action from there is chosen by the agent. The reward is calculated and listed in the Q-matrix. When repeated the information in the Q-matrix is used to choose the best action from given state. Factors are used to define how much present rewards weighs against old Q-values. How fast new values overwrite the old. [5]

2.2 The Secondary Control Market in Switzerland

The market our agents will act in is the secondary control (SC) market in Switzerland. Secondary power is one of the regulating powers needed to run a power network. To supply a certain amount of SC one needs to be able to both ramp up and lower his production. Figure 2.1 shows how these obligations influence production. At each moment an agent can produce no more than maximum capacity minus SC obligations and never less SC obligation more than the minimum output a power plant can produce, the so called technical minimum.

The market operator is Swissgrid which issues information about how the auctions shall be held:

Each player places one or more bids and each bid contains pair of price and amount of SC offered. These bid-pairs can in theory be as many as wanted but the difference in amount must be at least 1 MW. From each bid Swissgrid can choose up to one pair. So within each bid a player only needs to be able to fulfill one pair at a time but if he places many bids he needs to be able to fulfill them all simultaneously. Swissgrid uses optimization and is free to choose any pairs while not taking more than one from each bid, thus it does not need to take the lowest priced pairs.

Each bid lasts for one week and during that time player needs to be able to increase or reduce his production by the amount of the bid taken within time frame listed in [6]. If the production is increased the player gets payed for that, spot price plus premium and if it is reduced then the agents needs to pay for that amount the spot price minus a premium. On top of price of needed energy they get for the preparedness remuneration, the price of the bid-pair.[7, 6] The bid price is therefore the price of this preparedness.

As for the size of the market there are over hundred plants that can
2.2. THE SECONDARY CONTROL MARKET IN SWITZERLAND

Figure 2.1: Explains the production margins one needs to respect when having SC obligations. Production amount is limited to the light blue area.

provide this service with combined capacity over 12 GW while the demand is $\pm 400$ MW. [8]
CHAPTER 2. SECONDARY CONTROL AND AGENT BASED MODELING
Chapter 3

Modeling Approaches

By combining the two concepts introduced in chapter 2 a model will be made. First one showing on a simple market the value of using strategic pricing and then another applying the same methodology to the current Swiss SC market. That more realistic model can be used as a tool for market players to decide bids for next week on the SC market. The models will in principle work as explained in figure 3.1.

There will be agents that place bids on the market. After that the market operator decides on the best bids and sends results back to the agents. Next each agent then simulates the week on the spot market, optimizing his profit while still respecting the obligations due to SC bid. Profit is calculated, agents learn and repeat the process.

To increase transparency we exclude pumping from the modeling.

Figure 3.1: Shows different steps in the modeling of the SC market.

3.1 Strategic Behaviour in a Simple Market

Here we introduce a simplified market. It does not reflect the current market situation in Switzerland but it contains the characteristics sufficient to show
room for strategy and the benefits of strategic bidding.

### 3.1.1 Market Configuration

The market works in such a way that the market operator declares an amount needed for secondary control during the next week. Each agent places one bid consisting of amount and price. The market operator accepts the lowest bids to reach the needed amount. If the market clearing bid is not needed fully the market operator only takes the part of it that is needed.

Should the agents not place enough bids to cover the secondary control demand then the market operator provides the needed amount via other means but charges for that amount the highest placed bid, dividing the cost between agents. This was a fairly realistic solution to insure that bids were not overly high and also to make sure a market clearing was reached in every iteration.

### 3.1.2 Agent Profit

After the market operator has returned its results we calculate the profit for each agent resulting from that bid. Taking into account remuneration from the secondary control as well as payments from the spot market: both when the agent is forced to run because of his commitment by SC (see chapter 2.2) and when the spot market is good and he wants to sell energy.

Even though the water is free the agent could profit from it later. Therefore an assumed price of the water spent during the week is subtracted. That is done by the help of water value (WV) which represents expected possible future profit from the water. In the end we subtract penalties.

$$P = \sum_{h=1}^{168} b \cdot SC - pen + \begin{cases} \left( p_{spot, h} - WV \right) \cdot (cap - SC) & \text{if } spot > WV \\ \left( p_{spot, h} - WV \right) \cdot (min + SC) & \text{if } spot < WV \end{cases}$$

In equation 3.1 we see how the profit $P$ is calculated. It is summed over each hour of the week: $b$ being the price of bid and $SC$ the SC amount accepted by grid operator. Penalties are subtracted and then if spot market is feasible maximum amount (according to figure 2.1) is sold and WV of spent water subtracted. If spot market is not feasible then minimum amount (according to figure 2.1) is sold and WV of spent water subtracted.

As can be seen here above we make two simplifications. We assume that the request for secondary control is symmetrical and balances out. We also neglect the 20% premium on requests to use the SC agents obliged to provide.
3.1. STRATEGIC BEHAVIOUR IN A SIMPLE MARKET

3.1.3 Learning Agents

To keep track of learning a matrix, called $Q$, is used where each price bid has a rating. As the aim for agents is to maximize their profit the rating of each bid was chosen to be the expected profit from that bid. At each iteration the values of $Q$ change according to the formula:

$$Q_n(b) = \begin{cases} 
\alpha * Q_{n-1}(b) + (1 - \alpha) * P, & \text{if } Q_{n-1}(b) > 0, \\
P, & \text{if } Q_{n-1}(b) = 0.
\end{cases} \quad (3.2)$$

Where $Q_n(b)$ represents the value of $Q$ for bid $b$ after $n$ iterations and $P$ represents the profit from bid $b$ in iteration $n$. The $\alpha$ is a constant defining the weight of new $Q$ values vs. current values.  

3.1.4 Bidding Agents

With the method introduced in chapter 3.1.3 the agents gain information about how much profit certain bid gave in past iterations. To close the circle they need to use this information to improve next bids. The bids need to be based on the knowledge while also allow for some improvement or experimenting.

This is reached by bids with the form:

$$b_{n+1} = \mathcal{N}(\beta, \varsigma) \quad (3.3)$$

Where $b_{n+1}$ is the bid in iteration $n+1$, the $\beta$ is the bid with the best rating in $Q$ after $n$ iterations and $\varsigma$ is a coefficient describing the willingness of the agent to try new bids. Finally $\mathcal{N}$ is the normal distribution with mean $\beta$ and variance $\varsigma$.

To allow the agents to experiment even more, every 100 iterations they place a completely random bid, independent from the knowledge they possess.

3.1.5 Break-even Price for Comparison

To compare the price suggested by the model a reference price is needed. To do that secondary control bid is observed as a loss of possibilities to act in future. As can be seen in figure 3.2 there are basically two choices the agents are giving up. When the spot price is good they can not produce the maximum as they want since we need to leave the margin.

---

1The reason why the approach to change $Q_n(b)$ is based on the value of $Q_n(b)$ is because the original value of $Q_n(b)$ is 0. So if this approach is not used then the rating of bid $b$ is largely based on how often the bid $b$ has been tried. That is how well the original zero has been overwritten. Therefore the first try for a certain price has full weight and then is overwritten slowly. When choosing the number of iterations this has to be taken into account by having many iterations after stability is reached.
CHAPTER 3. MODELING APPROACHES

Figure 3.2: Explains the production margins one needs to respect when having SC obligations. Production amount is limited to the light blue area. SC obligations result in less flexibility on the spot market - resulting in losses. Green arrows refer to good market conditions and red to unfavorable spot market.

However when the spot price is bad the other obligation comes into play. They need to keep on producing the technical minimum and secondary control amount and sell on the market even though they loose from it.

If it is assumed that the agent has a hourly price forward curve (HPFC) for next week he should be able to calculate the cost of these obligations. Of course a rational agent should put some kind of risk premium on top of this marginal price but we assume an agent that trusts his HPFC very well.

By this method we can find for each SC capacity a minimum price an agent should bid on the SC market. In a competitive market this should be the bid from an agent.

3.2 Application to Current Market

As stated in section 2.2 the current secondary control market is not so simple. Here it is modeled more closely but with the same method as used in the simple model.

Each bid can now consist of many pairs, amount and price, of whom only one can be taken. Also each bid-pair can only be taken or rejected, not taken partially. For simplicity of modeling each agent can just place one bid.
3.2. APPLICATION TO CURRENT MARKET

3.2.1 The Market Configuration

The market configuration becomes a little more complicated as Swissgrid, the market operator, performs an optimization to get the lowest cost of fulfilling SC demand. Let’s look at how the optimization is performed. From each of the agents the market operator receives a bid, the bid is list of pairs, amount and price as can be seen in equation 3.4. In the first column are the prices in CHF/MW and the second column we have amount of SC in MW.

\[
P = \begin{pmatrix}
p_1 & a_1 \\
p_2 & a_2 \\
\vdots & \vdots \\
p_i & a_i \\
\vdots & \vdots \\
p_I & a_I \\
\end{pmatrix}
\] (3.4)

The market operator chooses the pairs that result in the lowest overall cost while respecting two criteria. First of all the demand of SC amount needs to be fulfilled and second, only one pair can be taken per bid.

To solve this optimization we use Binary Integer Optimization with a branch and bound approach. A more detailed description of how it was used for the solution can be seen in appendix A.

After the optimization the market operator sends information about accepted bids to the agents.

3.2.2 Agent Profit

When the agents get information about which bid-pairs were taken they use that information to calculate the profit. That is done in the same way as described in 3.1.2 apart from the fact that no penalties are to consider in this market.

3.2.3 Agent Learning

As done in chapter 3.1.3 the information about the rating of the bid is stored in a matrix called \( Q \) again the profit is used as rating since that is what the agents strive to maximize.

The difference here is that instead of only the price of bid placed, more information is needed to describe a bid. The bid is now a list of pairs and many different factors decide why a certain pair was accepted. For example: the reason for a certain bid-pair to be taken is not only the presence of that bid-pair but also the absence of lower priced pairs. Thus the environment of the pair matters. Since it is not clear which factors are important the rating is connected to the bid as a whole, not just the bid-pair that was taken.
Since there are really many ways of composing such bid some kind of simplification is needed.

The method of choice was to have a number of independent coefficients, \( B = (b_1, b_2, \ldots, b_m) \) that described the bid and connect the profit to those coefficients. So for a certain combination of coefficients a certain rating is stored in a similar way done in the simple model.

\[
Q_n(B) = \begin{cases} 
\alpha * Q_{n-1}(B) + (1 - \alpha) * P, & \text{if } Q_{n-1}(B) > 0. \\
P, & \text{if } Q_{n-1}(B) = 0.
\end{cases}
\] (3.5)

Here \( Q_n(B) \) represents the the value of \( Q \) for bid with coefficients \( B \) after \( n \) iterations and \( P \) represents the profit from bid \( b \) in iteration \( n \). The \( \alpha \) is a constant defining the weight of new \( Q \) values vs. current values.

### 3.2.4 Agent Bidding

Now one has to decide how to translate these coefficients into bids.

One approach would be to decide that relationship between price and amount is according to some function and have the coefficients adjust that function. Another would be to decide some strategies for bids and use the coefficients to choose between them. Both of these approaches mean that one needs to think about the strategies and the input strategies chosen affect and restrict the outcome.

The final decision on the use of the coefficients was the following:

\[
P_i = P_{i-1} + f_P(i, B)
\] (3.6)

\[
A_i = A_{i-1} + f_A(i, B)
\] (3.7)

Where \( P \) and \( A \) are one column in the bid each. \( P \) representing price and \( A \) representing amount. \( P_i \) and \( A_i \) represent price and amount in pair number \( i \). The functions \( f_P(i, B) \) and \( f_A(i, B) \) decide the difference between price and amount in pairs \( i \) and \( i + 1 \) respectively. They are governed by the coefficients in \( B \).

Now the task of the agents is to pick the coefficients in \( B \). The two first are the price and amount of first pair in a bid and then how the next represent how the price develops and the last two how the amount develops. More coefficients can be introduced as needed.

This solution was chosen because it offers a really direct control of the bids by not so much information stored in \( Q \). The functions that map from coefficients to bids can be freely chosen and need to be decided based on trial and error.
3.2. APPLICATION TO CURRENT MARKET

New coefficients can be introduced so the model precision and flexibility is scalable. Some coefficients could even function only on some of the bid-pairs. Some could decide between 2 or more functions to be used. One could even use $i$ as an input to the function.\(^2\)

So by correct choice of function the agents can get freedom to come up with almost any bids they want.

\(^2\)The choice of the right equations is a hard task and needs a little bit of attention, they should be chosen so that the agents get as much freedom as possible to shape bid-pairs. Also as new coefficients are introduced the model needs more iterations.
Chapter 4

Numeric Results

4.1 Strategic Behavior in a Simple Market

Here the goal is to use the simple model presented in chapter 3.1 bring forth strategic behavior between the agents. An environment with 5 agents was used. Then an overview can be kept over all agents while still having enough agents to bring forth interaction and competition. All had their own realistic capacities in the SC market and different water values, these values can be seen in table 4.1. SC demand of 200 MW was used, half the current demand in Switzerland. That is normal since we have fewer agents. Spot prices were from September 2011, like the WV. 10,000 iterations were performed, that was decided after trial and error. That is enough to have agents reach equilibrium while still taking limited time to perform.

In figure 4.1 it can be seen how many times out of 10,000 each agent won a bid on the market. One can see that there is a drastic difference between the agents. And that there are three kinds of agents. Two are almost never the winners, two almost always and one somewhere in between. To understand this behavior it is good to look at figure 4.2 which shows the rating of different price bids for different agents. Here three types of agents can also be seen. Lets try to understand.

<table>
<thead>
<tr>
<th>nr.</th>
<th>Agent</th>
<th>Water value</th>
<th>Tech. min.</th>
<th>SC bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Mattmark, 80% full</td>
<td>7 CHF/MW</td>
<td>8 MW</td>
<td>80 MW</td>
</tr>
<tr>
<td>2.</td>
<td>Mattmark, 40% full</td>
<td>34 CHF/MW</td>
<td>8 MW</td>
<td>80 MW</td>
</tr>
<tr>
<td>3.</td>
<td>Mattmark, 100% full</td>
<td>3 CHF/MW</td>
<td>8 MW</td>
<td>80 MW</td>
</tr>
<tr>
<td>4.</td>
<td>Cleuson-Dixence, 80% full</td>
<td>78 CHF/MW</td>
<td>50 MW</td>
<td>500 MW</td>
</tr>
<tr>
<td>5.</td>
<td>Cleuson-Dixence, 100% full</td>
<td>67 CHF/MW</td>
<td>50 MW</td>
<td>500 MW</td>
</tr>
</tbody>
</table>
CHAPTER 4. NUMERIC RESULTS

Figure 4.1: Simple market: Graph show how many times each agent won the bid. One can see that agents 1, 3 and 4 are not really participating. The price they would need to profit from SC market is too high for them to win any bids.

First there are agents 2 and 5 who find optimum SC market price to maximize their profit without losing the bids. They want to participate. In figure 4.2 optimum prices can be seen, the bids with the highest rating. Interesting is to see that they are higher than the marginal price.

Secondly there are two agents, number 1 and 3, which have really low marginal costs. They do not want to restrict their production. Therefore they want to bid high enough so their bids are not taken. Then they can turbine full time at full capacity.

At last there is one agent, number 4, that has such high WV that the spot price does not cover that. He wants to stop participating in the spot market so that he can turn off his turbines. In other words he does not want to be forced to produce the technical minimum and is therefore not aiming at profit but to avoid losses. He ends up bidding price above his marginal price resulting in occasional win.  

When looking at figure 4.3 one can see how the bids develop over time.

---

1After looking at figure 4.2 one might ask why bids above the break even price still result in negative profit for agent 4. That is because the break even price assumes that full SC bid is taken by market. If a bid is only partially taken the technical minimum is divided by a smaller number of sold SC MW. The remuneration is only partially the remuneration expected from the break even price.
Here it can be seen that the iterations are plenty enough. After iteration 100 we have fairly stable bids. The fluctuation however is because of the exploration of the agents.

After looking at these results one can see two interesting things. First the actions can be understood and explained and secondly for agents 2 and 5 there is difference between the marginal price and recommended bidding price.

That suggests that the model reflects the reality and it adds to agents profit. When that has been showed one can with confidence move on to application to the current market environment.
Figure 4.2: Simple market: Blue line shows the rating of different priced bids. Red line shows break even price as mentioned in 3.1.5. The fluctuating at high bids result from those bids not being feasible and therefore the agent does not try them out often. Due to total randomness he tries them out a few times, resulting in some showing profit while others still show 0 which is the preset value of rating.
4.1. STRATEGIC BEHAVIOR IN A SIMPLE MARKET

Figure 4.3: Simple market: Blue line shows how agents bids develop over iterations. Red line shows break even price as mentioned in 3.1.5. Here it can be seen that the bids converge.
4.2 Current Bid Market

As shown in chapter 2.2 the SC market in Switzerland is more complicated than the modeling in 3.1. To look at this more complicated market the method described in chapter 3.2 is used.

The agents are the same as earlier and can be seen in table 4.1. The secondary control demand is again 200 MW. As each extra pair in the bid adds to optimization time the number of pairs in each bid is limited to 10. As it turns out no bids resulted in 10 pairs so this limitation was not restricting the freedom of the agents in any way.

The coefficients are chosen to be 4 to reduce computing time: 2 are dedicated for the starting price and amount and the next 2 to describe the development of the pairs. The Q matrix is also limited in size. Therefore only 6 different input prices can be chosen: 10-60 CHF/MW and 30 different input amounts: 50-1500 MW. The other coefficients have range of -10 to 10.

As earlier stated two coefficients describe starting amount and price while the other describe the pair development, the functions in equations 3.6 and 3.7 become:

\[ P_i = P_{i-1} + f_P(i, B) = P_{i-1} + e^{b_3} \]  \hspace{1cm} (4.1)

\[ A_i = A_{i-1} + f_A(i, B) = A_{i-1} + b_4 \]  \hspace{1cm} (4.2)

With the limited size of Q the translation from Q values to \( b_1, \ldots, b_4 \) need to be adjusted so that the agents stay within their bounds. Thus we make sure that simplifications are only effecting precision not the outcome.

But even with those serious size restrictions the size of Q is quite large. By comparing possible inputs and iterations from chapter 4.1 it is possible to guess the iterations needed.\(^2\) This comes up with roughly 100,000 iterations needed which takes half a day to run.

After introducing only 2 more coefficients\(^3\) over 28 million iterations are needed and calculations could take over a month. Especially since each element needs to be tried often to reduce the effect of randomness. This introduces trouble which will handicap this method a lot.

After 100,000 iterations we come to a result. Here the rating is to complicated to depict in figure so only the optimum bid is shown for each agent. In figure 4.5 we see the optimum bids. Note that not only the slope between the points is relevant but only the distance between them.

In figure 4.4 we see how often each of the agents had a winning pair. We see that this is more distributed than in the simple model.

With only 100,000 iterations these bids need to taken with a word of caution. The agents have most likely not reached equilibrium and they’ve

\(^2\)This is a lower estimate. It is highly likely that even more iterations are needed as here the interactions are more complicated.

\(^3\)Introducing 2 more coefficients at least is needed to give agents acceptable freedom to act. Current model with 4 coefficients is highly restricted.
only tried out limited amount of the combinations. Secondly the agents are somewhat restricted in their behavior. However this should show that the method comes up with bids.

Figure 4.4: Realistic market: Shows how often each agent won a bid out of the 100,000 iterations.
Figure 4.5: Realistic market: Points show the optimum bids for the different agents. Not only the slopes are interesting but only the distance between points.
Chapter 5

Conclusion and Outlook

This project has looked into the secondary control market in Switzerland. The use of agent based modeling was tried out in order to predict good bids when modeling agents in a market.

First a simple market was constructed and five agents were made compete and define optimum price-bid to place. The results do not depict the SC market as the market was quite different but considerable amount of strategic actions were realized. One could understand the actions the agents performed. Thus it was shown that this approach could be feasible.

Next a more realistic market was assumed. There each bid consists of many price-amount pairs and the task was to define the optimum pair composition. This task is more complicated as many combinations are possible. An approach was chosen where coefficients were used to map the combinations of pairs and then the optimum coefficients chosen.

As mentioned earlier there are many possible combinations of pairs so many iterations are needed, even for a simplified case. Output was produced but it is hardly useful as agents were highly restricted in their actions.

Even with iterations that are many enough it is hard to assign cause for profit. If one profits from an assortment of pairs in a bid. To find the factor in the bid that caused a good outcome is hard. It might differ from case to case. Sometimes being the price, sometimes the right amount and sometimes the distribution of bids.

At this stage and with these approaches the results are not useful for the current market and will not be useful until number of iterations needed is reduced. That can be done by more intelligent agents. That intelligence can come in two forms.

The first form would be to have more intelligent search. Instead of trying out coefficients normally distributed agents would decide in an informed way which combination to try out next. Many ways are existing for this improvement as this is a common problem with all kinds of agent based models.
The second form of intelligence would be to include more understanding of the characteristics of the bids. So instead of having the agent think "I placed this bid and got this profit" he should think "I placed this kind of bid on the market and got this profit." Then the agent would come up with bids that involve these characteristics. This intelligence is less explored and would be more specific to this problem.

Overall I think the project suggest that the simple approach is unfit for giving meaningful advice for decision makers. However if one is willing to continue with the method down the route suggested then it might become a useful tool.
Appendix A

Optimization for Market Operator in Matlab

In this appendix the approach for preparing the bid data for optimization in Matlab is described. Following information is taken in from the bidding algorithm. The price/MW matrix:

\[
P = \begin{pmatrix}
p_{1,1} & p_{1,2} & \cdots & p_{1,A} \\
p_{2,1} & p_{2,2} & \cdots & p_{2,A} \\
\vdots & \vdots & \ddots & \vdots \\
p_{I,1} & p_{I,2} & \cdots & p_{I,A}
\end{pmatrix}
\] (A.1)

and then the amount matrix:

\[
B = \begin{pmatrix}
a_{1,1} & a_{1,2} & \cdots & a_{1,A} \\
a_{2,1} & a_{2,2} & \cdots & a_{2,A} \\
\vdots & \vdots & \ddots & \vdots \\
a_{I,1} & a_{I,2} & \cdots & a_{I,A}
\end{pmatrix}
\] (A.2)

Where A is the number of agents, I the number of pairs in each bid. Next we introduce a reshape function \( \Gamma \) that reshapes a vector so that for example the vector B becomes:

\[\Gamma(B) = (a_{1,1} \ a_{1,2} \ \cdots \ a_{1,A} \ a_{2,1} \ a_{2,2} \ \cdots \ a_{I,1} \ a_{I,2} \ \cdots \ a_{I,A})\] (A.3)

We also introduce a new shape of the decision vector:

\[X = (x_{1,1} \ x_{1,2} \ \cdots \ x_{1,A} \ x_{2,1} \ x_{2,2} \ \cdots \ x_{I,1} \ x_{I,2} \ \cdots \ x_{I,A})\] (A.4)

Regarding the restrictions the maximization problem is subject to we have two kinds of them. Firstly we have the restriction that the sum of bids taken needs to reach SC. That can be shown:

\[X^\top \Gamma(-B) \leq -SC\] (A.5)
and second we have the restriction that only one bid-pair can be taken from each agent. That we can represent as follows. For each agent, \( a \), we introduce a restriction in the form of a matrix \( \text{Rest}_a \) the size of the matrix \( B \) with all elements 0 except in column \( a \) where all elements are 1. For each of these matrices the following must hold:

\[
X' \Gamma (\text{Rest}_a) \leq 1 \quad (A.6)
\]

To store those restrictions we introduce the matrix \( A \):

\[
A = \begin{pmatrix}
\Gamma(-B) \\
\Gamma(\text{Rest}_1) \\
\vdots \\
\Gamma(\text{Rest}_A)
\end{pmatrix} \quad (A.7)
\]

and

\[
V = \begin{pmatrix}
-S C \\
1 \\
\vdots \\
1
\end{pmatrix} \quad (A.8)
\]

Now we have all we need for creating the optimization restrictions:

\[
X' A \leq V \quad (A.9)
\]

Returning to the optimization problem it boils down to:

\[
\text{minimize } X' (\Gamma(C)) \text{ subject to: } X' A \leq V, x \text{ binary} \quad (A.10)
\]

where \( C \) is the matrix resulting from peace wise multiplication of \( B \) and \( P \) so it contains the overall price of each pair from all of the agents.
Bibliography


