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Negotiation strategies of programmable agents in Continuous Double Auctions

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Chapter 1

Introduction

Auctions as a method of selling and buying goods have a long history, initially there were only ascending auctions with simple rules (now known as English auctions) but with time a variety of types of auctions has emerged. Now, auctions have become a very popular method of trading popularized by on-line auctions as Ebay or Allegro (a big Polish auction platform).

According to definition made by McAfee and McMillan in 1987: "an auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants".

A special type of auctions, maybe not the most popular in an on-line internet auctions but interesting from point of view of computer simulation, are so called *double auctions*. In double auctions, there are multiple buyers and sellers on the market that place their offer simultaneously.

In this work we review strategies of agents participating in a double auction. There are a lot of different categories of strategies: some consider history, others are reacting on the last placed bid or apply learning algorithms. Some strategies, as ZI, GD, and AA, have been already reviewed in an earlier publication of the present authors [21]. They are repeated here to make a possibly full compendium of strategies proposed in the literature.

The practical context of this research is the double auction for trading emissions of pollutants. Emission, in this context, is the short name for "permission to emit a unit of greenhouse gas"; its unit is either one tonne of carbon dioxide or the mass of another greenhouse gas which is recalculated to so-called carbon dioxide equivalent (tCO2e) emissions. This is expressed in units like Certified Emission Reductions (CERs) or carbon credits. This concept was introduced in the Kyoto Protocol, which entered into force in

16 February 2005, obliging countries that ratified it to limit their greenhouse gases (GHG) emissions below the levels of 1990.

The protocol introduced so called "flexible" market-based mechanisms (Emission Trading, Joint Implementation and Clean Development), which are meant to achieve the common reduction target with minimal costs, without knowledge of the parties cost functions. The emission trading market is still not mature and it is still under the process of adjusting the rules and protocols to make it efficient and resistant to collapsing. The Chicago Climate Exchange market ceased operations in 2010 because the legislation was refused by the US Senate and companies were no longer interested in trading this commodity.

There are different schemes developed for this type of market. In report [26], the English auction trading scheme for emission permit trading was considered. In the present work the double auction mechanism for emission trading is defined, as it is a very popular method of creating efficient markets.

This work summarizes the most well known strategies, that present the evolution of automated negotiation strategies: from simple and intuitive approaches as ZI, PS and ZIP, to more forecasting like GD and adapting as AA strategy. None of the general issues of on-line auctions are discussed here. An interested reader is referred to recent reviews of these matters [12, 17, 24].

The structure of the paper is as follows. In chapter 2 the current state of research on the Continuous Double Auction, emission trading and agent strategies are shortly reviewed. In the following chapter the concept of negotiations and different ways of trading is described. In chapter 4 some informations on double auction are presented. Chapter 5 discusses the formal model of the auction double market used in this paper. The following chapters contain the description of the existing strategies for participants in the continuous double auction, they are divided to strategies using only current information, GD strategies, AA strategies and FL-strategy, that uses fuzzy rules to determine the value of next shout. The general architecture of the implemented software is located in the chapter 10, followed by description of its implementation. In chapter 11 some preliminary results are presented. Conclusions summarizes the whole report. Also future works are sketched there.

Chapter 6

Strategies using only current information

6.1 Information Knowledge Behavioral Model

Vytelingum et al. describes in [35] a framework for designing strategies for trading agents. They define a strategy of an agent as a set of atomic actions (that the agent can do), which were chosen based on the history of the market states and on the agent states[1]. A transition to the new state of the market is made by transition function that depends on the previous market state, the history of market states, agents strategies and external inputs.

In a real situation it is very unlikely that an agent has information about all historic states of the market and especially about all parameters of the market. That is why real strategies are operating with limited number of variables, considering limited computational and sensory resources. To deal with these limitations Vytelingum et al. propose a framework that divides strategy into three layers:

1. **Information Layer.** The agent gathers information from its environment and from it own state, information consists of raw data that can be perceived by the sensors.

2. **Knowledge Layer.** The agent processes the collected information and creates a knowledge base about market and agent state.

[1]The state of an agent is a collection of variables describing its resources and private preferences, see (5.2).

3. **Behavioral Layer.** The agent decides which set of actions to take based on the knowledge it has.

6.2 Truth-Telling (TT) strategy

That is the most basic strategy, which is not efficient in a market with multiple strategies, but it is good as a baseline for evaluation of other strategies.

Agents following this strategy are always shouting their private evaluation of the price of the good that is on the market: their limit price augmented by the expected profit. This strategy is simple and efficient if all agent use it. It works well in English auctions and Vickrey auction.

6.3 Pure Simple (PS) strategy

Like the TT it is a very simple strategy, described in [1], where agents bid a constant 10% below the value of private evaluation. This strategy under the name *Gamer* was played in the Santa Fe tournament [28], where it reached a similar, very low, place to the TT and ZI strategies. The weak point of this strategy is the constant 10% underbidding.

This strategy, like TT, can be treated as a point of reference to strategies with more sophisticated adjustment of profit factor.

6.4 Kaplan strategy

This strategy is called also the *sniping* strategy [33]. It is a reactive strategy, which focuses only on exploiting the other strategies. It performed so well that it won the Double Auction Tournament in 1990 (in Santa Fe Institute, [27]). In [28] the Kaplan strategy is characterized as a simple, nonadaptive, nonpredictive, nonstochastic, and nonoptimizing. It uses very limited information about the state of the market: current outstanding bid and ask, number of units of goods to sell and the remaining time of the auction. The algorithm allows the other agents to do the negotiating part and places an offer only if: the best ask was cheaper than the one in previous time period, or if the bid-ask spread was small enough and the expected profit is still within the defined borders or when the time for the auction is just about to end. It exploits the situation when the price is close to equilibrium (the bid-ask spread is small enough) and the fact that other players made mistakes and placed offers at an unfavorable price. Because the Kaplan strategy does not make bidding mistakes, it outperformed other strategies during the tournament.

A problem with this strategy is that, if all agents use it, there is no bidding at all. Agents using the Kaplan strategy wait till the end of the session until someone starts bidding or asking.

6.5 ZI strategies

6.5.1 Zero intelligence (ZI) strategy

Zero intelligence strategy has been proposed by Gode and Sunder [11]. A ZI trader simply submits a random offer drawn from a uniform distribution in the ranges given in (4.3). Despite its simplicity, Gode and Sunder [11] claimed on the basis of simulation that ZI traders are highly efficient.

6.5.2 Zero intelligence plus (ZIP) strategy

Cliff and Bruten [2] argued that the results obtained by Gode and Sunder were due to symmetries in the demand and supply in the case considered in simulations. They proposed a more advanced strategy, called zero intelligence plus strategy.

To derive the ZIP strategy they used the Widrow-Hoff delta rule. According to it, the trader shout price in the time $t+1$ is established as the sum of the trader shout price in time t and a value $\Delta_i(t)$, i.e. $p_i(t+1) = p_i(t) + \Delta_i(t)$. Thus, from (4.3) we get

$$p_i(t) + \Delta_i(t) = \lambda_i(1 + \mu_i(t+1)) \tag{6.1}$$

According to the Widrow-Hoff rule the value of $\Delta_i(t)$ is theoretically set as

$$\Delta_i(t) = \beta_i(\tau_i(t) - p_i(t)) \tag{6.2}$$

where β_i is a learning rate and $\tau_i(t)$ is a target price set randomly according to the equation

$$\tau_i(t) = R_i(t)q(t) + A_i(t) \tag{6.3}$$

In (6.3) $q(t)$ is the price of the current last shout in the auction. $R_i(t)$ and $A_i(t)$ are drawn randomly. It holds: $R_i(t) \geq 1$ and $A_i(t) \geq 0$ when $\tau_i(t)$ is to be increased, and $R_i(t) \leq 1$ and $A_i(t) \leq 0$ when $\tau_i(t)$ is to be decreased.

To avoid quick changes of $\Delta_i(t)$, its value is smoothed using the equation

$$\Gamma_i(t) = \gamma_i \Gamma_i(t-1) + (1-\gamma_i)\Delta_i(t-1) \tag{6.4}$$

with $0 \leq \gamma_i \leq 1$. Thus, inserting $\Gamma_i(t)$ in (6.1) we can obtain the desirable profit

$$\mu_i(t+1) = \frac{p_i(t) + \Gamma_i(t)}{\lambda_i} - 1$$

which allows us to calculate the shout in time $t+1$ according to (4.3).

In the above algorithm each of the following 3 parameters for each trader: initial profit $\mu_i(0)$, learning rate β_i, smoothing factor γ_i, is drawn randomly from a uniform distribution over the ranges: $[\mu_{\min}, \mu_{\min}+\mu_\Delta]$, $[\beta_{\min}, \beta_{\min}+\beta_\Delta]$, $[\gamma_{\min}, \gamma_{\min}+\gamma_\Delta]$. This requires setting of 6 parameters for interval ends. Moreover, two additional parameters are required, that is c_r defining an interval for $R_i(t)$, either $[1, 1+c_r]$ or $[1-c_r, 1]$, and c_a defining an interval for $A_i(t)$, either $[0, c_a]$ or $[-c_a, 0]$, where the former intervals are taken when $\tau_i(t)$ is to be increased, and the latter intervals when $\tau_i(t)$ is to be decreased. This makes 8 parameters to be set altogether. That is why in later papers this algorithm has been called ZIP8. These parameters were initially guessed by humans. Later on the parameters were determined using a genetic algorithm.

In the paper [3] the ZIP algorithm has been further extended. First of all, the values c_a and c_r are drawn from the random distributions on the intervals $[c_{a,\min}, c_{a,\min}+c_{a,\Delta}]$ and $[c_{r,\min}, c_{r,\min}+c_{r,\Delta}]$. This makes 4 additional parameters instead of 2 in ZIP8. That is, 10 parameters is necessary to characterize a trader. Further, these sets of 10 parameters have become depend on different market circumstances. Six circumstances or cases has been considered:

1. a seller raises its profit margin;
2. a seller lowers its profit margin after last order, which was a bid;
3. a seller lowers its profit margin after last order, which was an ask;
4. a buyer raises its profit margin;
5. a buyer raises its profit margin after last order, which was a bid;

6. a buyer raises its quote margin after last order, which was an ask.

Altogether, these makes 60 parameters describing a trader. These version has been called ZIP60. Results of simulations presented in [3] showed that ZIP60 is 12-14% more efficient than ZIP8, according to (4.1), and is 6-12% less volatile, according to (4.2). The range of improvement depended on initialization of an genetic algorithm.

6.6 Preist and van Tol strategy

It is a strategy designed by Chris Preist and Maarten van Tol, based on the ZIP strategy, but with a simplified heuristics. It was described in [25] as a strategy for persistent shout double auction where agents achieve equilibrium faster than ZIP agents and are more robust to the changes of learning rate.

This strategy assumes that agents know the bids and asks submitted on the market and the last price on the market $price(t_k)$. Each agent has a profit margin that is modified according to currently submitted offers. The modification is always toward the assumed equilibrium point that lays somewhere between outstanding bid and ask. The algorithm first determines the new value of the profit margin, then the learning rule determines how much the profit margin is altered.

Defining δ as a random value, small in comparison to outstanding bid and ask, the target price $\tau_i(t)$ is determined as follows (it is a same value as defined in ZIP strategy):

For buyers:
If $ask(t_k) > bid(t_k)$ then
$\tau = bid(t_k) + \delta$
If $ask(t_k) \leq bid(t_k)$ then
$\tau = ask(t_k) - \delta$

For sellers:
If $ask(t_k) > bid(t_k)$ then
$\tau = ask(t_k) - \delta$
If $ask(t_k) \leq bid(t_k)$ then
$\tau = bid(t_k) + \delta$

The buyers are only placing bids and sellers are only placing asks, target value is set using bid or ask depending on the comparison with outstanding values. If the last ask has smaller value than the outstanding bid (or last bid has greater value than the outstanding ask) it is still assumed that the equilibrium lays somewhere between last offer and the outstanding value. When the transaction occurs ($ask(t_k) > bid(t_k)$) then participants assume that the equilibrium price is very close to the current market price and try to reach the deal as quickly as possible.

Similar to the ZIP strategy, the δ is determined as follows:

If $\tau = bid(t_k) + \delta$: then

$$\delta = r_1 bid(t_k) + r_2$$

If $\tau = ask(t_k) - \delta$: then

$$\delta = r_1 ask(t_k) + r_2$$

where r_1 and r_2 are independent random variables distributed in the range $[0, 0.2]$.

The algorithm lowers the bid of the agent by adjusting the target value if no trading takes place. It increases the price otherwise, to make a bigger profit.

An agent tries to reach the target value at a rate determinded by learning rule, which is the Widrow-Hoff rule with momentum. It is defined by two parameters: learning rate β to determine the speed and the momentum γ that counteracts oscillations. The new valuation of the commodity is computed as follows:

$$p(t+1) = \gamma p(t) + (1-\gamma)\beta(\tau(t) - p(t))$$

The values of the learning rate and the momentum suggested by authors are equal to 0.3 and 0.05, respectively.

Chapter 12

Conclusions

Emission permits are a new commodity that can have a very uncertain volume. Moreover, uncertainties for different types of greenhouse gases differ considerably. For example, uncertainty of emission of CO_2 from a power plant may be few percents, while that of N_2O from agricultural activities may be close to 100%. Thus, a risk for traders to realy reach the imposed emission level is much different when buing one or another emissions. Trading under such conditions requires new rules, but also provides a unique base to develop new strategies that are able to fulfill the requirements. Before it will be possible to include uncertainties in the agents behavior, the market scheme has to be designed and tested.

Given the tool as the *multi-agent system*, it is possible to design a market that is be simple, dynamic and that allows participants to adjust their desired profit and the time of placing an offer. The continuous double auction chosen in the report has simple rules and does not impose limitations on neither the number of participants nor their strategies.

The aim of the present report is to go through the most well-known strategies for this type of market, to classify them and to summarize their properties. The existing strategies can be divided into few groups: simple and reactive strategies (e.g. TT, ZI, ZIP); strategies that are using historical data to predict the prices (e.g. GD) and strategies that are exploiting features of agents and market configuration (e.g. Kaplan, AA). Most of the strategies (except for the very simple ones) result in the market price converging to equilibrium price and generally in most participants reaching profit.

The next step is to create agents that will dynamically adjust or even change their strategies depending on the situation on the market. After that, specific features of the emission market will be added to check how agents behave. Limit price will become a function of traded permits and participants would have to consider the level of uncertainty of the traded permit.

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