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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 (tCO<sub>2e</sub>) 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 8

## AA strategies

### 8.1 Preliminaries

The adaptive-aggressive (AA) strategy has been developed by Vytelingum in his PD thesis [33] and then presented in [34]. The AA strategy combines estimation, modeling of aggressiveness, and short- and long-term learning.

An estimate of the equilibrium price at the close of trading time  $T$  is calculated as the weighted moving average of last  $N$  transaction prices  $p(t)$

$$\hat{p}^*(T) = \sum_{t=T-N+1}^T w(t)p(t) \quad (8.1)$$

$$w(t-1) = \rho w(t), \quad \sum_{t=T-N+1}^T w(t) = 1$$

where  $w(t)$  are weights, and  $0 < \rho < 1$ . From the above conditions it stems

$$w(T) = \frac{1 - \rho}{1 - \rho^N}$$

### 8.2 Trader

As before, the trader has its secret limit price  $\lambda$ . To simplify notation, we drop the subscript  $i$  denoting the trader. Two types of a trader are considered: an intra-marginal and an extra-marginal ones.

An *intra-marginal trader* has its limit price  $\lambda$  favorable for trading. That is, it can offer a better price than its estimate of the equilibrium price  $\hat{p}^*(T)$ . Thus, it holds:

$$\begin{aligned} \text{for an intra-marginal buyer} \quad & \lambda > \hat{p}^*(T), \\ \text{for an intra-marginal seller} \quad & \lambda < \hat{p}^*(T). \end{aligned}$$

An *extra-marginal trader* has its limit price unfavorable for trading, as it does not allow him to offer a better price than its estimate of the equilibrium price. It holds:

$$\begin{aligned} \text{for an extra-marginal buyer} \quad & \lambda < \hat{p}^*(T), \\ \text{for an extra-marginal seller} \quad & \lambda > \hat{p}^*(T). \end{aligned}$$

The notion of intra- or -extra-marginal trader depends on time, as the estimate of the equilibrium price changes during the auction.

### 8.3 Target price

The target price  $\tau$  of a trader depends on the type of a trader, as well as on some parameters, which are discussed in more details in the sequel. These parameters are the degree of aggressiveness  $r \in (-1, 1)$  and volatility parameter  $\theta \in [\theta_{\min}, \theta_{\max}]$ . Now, the target price is calculated as follows.

#### Intra-marginal traders

For an intra-marginal buyer

$$\tau(t) = \begin{cases} \hat{p}^*(t)(1 - \frac{e^{-r\theta} - 1}{e^\theta - 1}) & \text{if } -1 < r \leq 0 \\ \hat{p}^*(t) + (\lambda_b - \hat{p}^*(t))\frac{e^{-r\theta} - 1}{e^\theta - 1} & \text{if } 0 < r < 1 \end{cases} \quad (8.2)$$

where  $\lambda_b$  is a buyer limit price.

For an intra-marginal seller

$$\tau(t) = \begin{cases} \hat{p}^*(t) + (o_{ask, \max} - \hat{p}^*(t))\frac{e^{-r\theta} - 1}{e^\theta - 1} & \text{if } -1 < r \leq 0 \\ \lambda_s + (\hat{p}^*(t) - \lambda_s)(1 - \frac{e^{-r\theta} - 1}{e^\theta - 1}) & \text{if } 0 < r < 1 \end{cases} \quad (8.3)$$

where  $\lambda_s$  is a seller limit price and  $o_{ask, \max}$  is the maximum ask allowed in the market.

Exemplary curves showing dependence of the target price on  $r$  for two values of  $\theta = 2$  and  $\theta = -8$  for intra-marginal buyer and seller are depicted

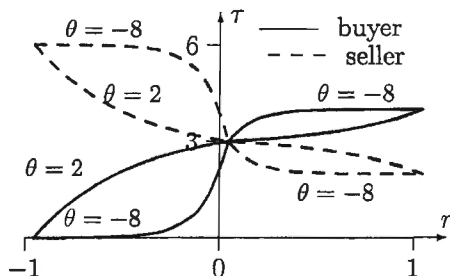


Figure 8.1: Dependence of the target price  $\tau$  on the degree of aggressiveness  $r$  for intra-marginal buyer and seller.

in Fig 8.1.

#### Extra-marginal traders

For an extra-marginal buyer

$$\tau(t) = \begin{cases} \lambda_b(1 - \frac{e^{-r\theta} - 1}{\theta\theta - 1}) & \text{if } -1 < r \leq 0 \\ \lambda_b & \text{if } 0 < r < 1 \end{cases} \quad (8.4)$$

For an extra-marginal seller

$$\tau(t) = \begin{cases} \lambda_s + (\alpha_{ask, \max} - \lambda_s) \frac{e^{-r\theta} - 1}{\theta\theta - 1} & \text{if } -1 < r \leq 0 \\ \lambda_s & \text{if } 0 < r < 1 \end{cases} \quad (8.5)$$

Exemplary curves showing dependence of the target price on  $r$  for two values of  $\theta = 2$  and  $\theta = -8$  for extra-marginal buyer and seller are depicted in Figure 8.2.

## 8.4 Degree of aggressiveness

A trader strategy depends on its aggressiveness in the market. An *aggressive* trader submits orders to improve its chance of transacting, i.e. orders that

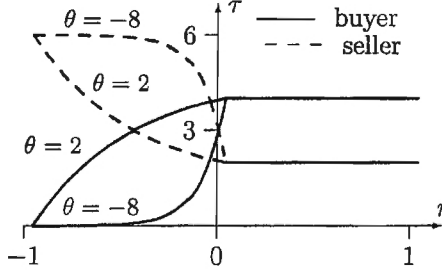


Figure 8.2: Dependence of the target price  $\tau$  on the degree of aggressiveness  $r$  for extra-marginal buyer and seller.

are better for trading partners than its estimate of the equilibrium price. A trader is *active*, if it submits orders equal to its estimate of the equilibrium price. A *passive* trader is inclined to win a more profitable transaction, so it submits orders worse for trading partners than its estimate of its equilibrium price.

We denote by  $r \in [-1, 1]$  a degree of aggressiveness of a trader. A completely passive trader has the value  $r = -1$ . It submits the bid at 0 as a buyer, and the ask at its limit  $\lambda_s$  as a seller. An active trader has the value  $r = 0$  and it submits the order equal to  $\hat{p}^*(t)$ . A completely aggressive trader has the value  $r = 1$ . It submits the bid at the limit price  $\lambda_b$  as a buyer and the ask 0 as a seller.

**Short-term learning.** The degree of aggressiveness is adapted according to the Widrow-Hoff rule, similar as used in the ZIP strategy. Thus, we have

$$r(t+1) = r(t) + \beta_1(\delta(t) - r(t)) \quad (8.6)$$

where  $0 < \beta_1 < 1$  is the learning rate, and  $\delta(t)$  is the current desired aggressiveness. The desired aggressiveness is calculated to possibly improve last shout, from the equation

$$\delta(t) = (1 \pm \zeta_r)r_{shout} \pm \zeta_a \quad (8.7)$$

where  $\zeta_r$  is the relative and  $\zeta_a$  the absolute change of  $\tau_{shout}$ . The value  $\tau_{shout}$  is the degree of aggressiveness that would form a price equal to last shout. It is taken into account and changed, if any of the following condition occurs:

**For a buyer**

If the last shout was followed by a transaction at price  $q(t-1)$ , and

if  $\tau(t-1) \geq q(t-1)$  then the buyer becomes more aggressive

( $\lambda_r$  and  $\lambda_a$  positive),

else the buyer becomes less aggressive ( $\lambda_r$  and  $\lambda_a$  negative).

If bid  $b$  was submitted and

if  $\tau(t-1) \leq b$  than the buyer becomes more aggressive.

**For a seller**

If the last shout was followed by a transaction at price  $q(t-1)$ , and

if  $\tau(t-1) \leq q(t-1)$  then the seller becomes more aggressive

( $\lambda_r$  and  $\lambda_a$  negative),

else the seller becomes more aggressive ( $\lambda_r$  and  $\lambda_a$  positive).

If ask  $a$  was submitted and

if  $\tau(t-1) \geq a$  than the seller becomes more aggressive.

## 8.5 Volatility parameter

An additional parameter  $\theta$  introduces dependence of the target price on price volatility  $\alpha$ , see (4.2). The desired value of this parameter  $\theta^*$  is determined from the equation

$$\theta^* = \theta_{\min} + (\theta_{\max} - \theta_{\min})(1 - \bar{\alpha}e^{\gamma(\bar{\alpha}-1)}) \quad (8.8)$$

where  $\theta_{\min}$  and  $\theta_{\max}$  are the minimal and the maximal value of updating  $\theta$ , respectively,  $\gamma$  is a coefficient that determines the shape of this function, and  $\bar{\alpha}$  is the normalized value of  $\alpha$ , i.e.

$$\bar{\alpha} = \frac{\alpha - \alpha_{\min}}{\alpha_{\max} - \alpha_{\min}}$$

**Long-term learning.** Also here the Widrow-Hoff rule is used to adapt the  $\theta$  parameter

$$\theta(t+1) = \theta(t) + \beta_2(\theta^* - \theta(t)) \quad (8.9)$$

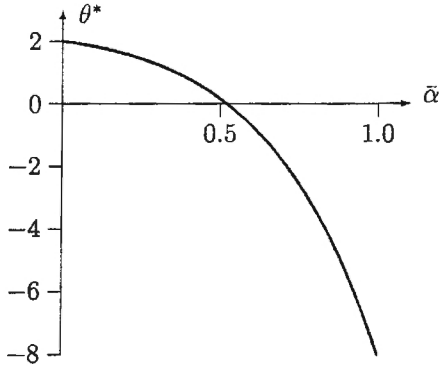


Figure 8.3: Dependence of  $\theta^*$  on  $\bar{\alpha}$ .

where  $0 < \beta_2 < 1$  is the learning rate. The desired value  $\theta^*$  is calculated from the following equation

$$\theta^* = \theta_{\min} + \frac{\theta_{\max} - \theta_{\min}}{1 - \bar{\alpha}e^{\gamma(\alpha-1)}} \quad (8.10)$$

Figure 8.3 presents dependence of  $\theta^*$  on  $\bar{\alpha}$ . Although it is not written explicitly,  $\theta^*$  depends on  $t$  through  $\alpha$ , see (4.2).

## 8.6 Price formation

Traders obey the following rules.

The buyer submits a bid only if its limit price is higher than the current bid  $o_{bid}$ . The seller submits an ask only if its limit price is lower than the current ask  $o_{ask}$ .

If the current ask is lower than or equal to the buyer's target price,  $o_{ask} \leq \tau$ , then the buyer accepts it. If the current bid is higher than or equal to the seller's target price,  $o_{bid} \geq \tau$ , then the seller accepts it.

If neither of the above conditions is satisfied, a trader submits an order according to the expressions given below. It is assumed that the auction consists of separated rounds. As at the beginning of auction, in the first round, a trader can not estimate the equilibrium price, its policy of announcing the order differs from that used later. Thus, the orders submitted are the following.

For a buyer

$$bid(t) = \begin{cases} o_{bid} + \frac{\min(\lambda_b, o_{ask}^+) - o_{bid}}{\eta} & \text{in the first round} \\ o_{bid} + \frac{\tau - o_{bid}}{\eta} & \text{otherwise} \end{cases} \quad (8.11)$$

where  $o_{ask}^+ = (1 + \zeta_r)o_{ask} + \zeta_a$  and  $1 \leq \eta < \infty$  is a constant.

For a seller

$$ask(t) = \begin{cases} o_{ask} - \frac{\max(\lambda_s, o_{bid}^-) - o_{ask}}{\eta} & \text{in the first round} \\ o_{ask} + \frac{\tau - o_{ask}}{\eta} & \text{otherwise} \end{cases} \quad (8.12)$$

where  $o_{bid}^- = (1 - \zeta_r)o_{bid} - \zeta_a$ .

In [34] the following values of constants required in the method have been used:

$$\eta = 3$$

$$\zeta_a = 0.01, \zeta_r = 0.02$$

$$\gamma = 2$$

$\beta_1$  and  $\beta_2$  drawn from the uniform distribution on the interval [0.2, 0.6]





# 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  $\text{CO}_2$  from a power plant may be few percents, while that of  $\text{N}_2\text{O}$  from agricultural activities may be close to 100%. Thus, a risk for traders to really reach the imposed emission level is much different when buying 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 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.

# Bibliography

- [1] K. Cai, J. Niu, and S. Parsons. Using evolutionary game-theory to analyse the performance of trading strategies in a continuous double auction market. In *Adaptive Agents and Multi-Agent Systems III. Adaptation and Multi-Agent Learning*, pages 44–59, 2007.
- [2] D. Cliff. Minimal-intelligence agents for bargaining behaviors in market-based environments. Technical report, School of Cognitive and Computing Sciences, University of Sussex, 1997.
- [3] D. Cliff. Zip60: Further explorations in the evolutionary design of online auction market mechanisms. Technical report, School of Cognitive and Computing Sciences, University of Sussex, 2005.
- [4] E. Drabik. Wykorzystanie reguł aukcyjnych do handlu energią w polsce. *Przegląd statystyczny*, 57(4):70–88, 2010.
- [5] Y. Ermoliev, M. Michalevich, and A. Nentjes. Markets for tradeable emission and ambient permits: A dynamic approach. *Environmental & Resource Economics*, 15(1):39–56, January 2000.
- [6] T. Ermolieva, Y. Ermoliev, G. Fischer, M. Jonas, and M. Makowski. Cost effective and environmentally safe emission trading under uncertainty. *Lecture Notes in Economics and Mathematical Systems*, 633(2):79–99, 2010.
- [7] T. Ermolieva, Y. Ermoliev, M. Jonas, G. Fischer, M. Makowski, F. Wagner, and W. Winiwater. A model for robust emission trading under uncertainties. *3rd International Workshop on Uncertainty in Greenhouse Gas Inventories*, pages 57–64, September 2010.

- [8] D.P. Friedman and J. Rust. *The Double Auction Market, Institutions, Theories, and Evidence: Proceedings of the Workshop on Double Auction Markets, Held June, 1991 in Santa Fe, New Mexico*. Proceedings Volume, Santa Fe Institute Studies in the Scienc. Basic Books, 1993.
- [9] S. Gjerstad and J. Dickhaut. *Price Formation in Double Auctions*. Computer science/mathematics. IBM T.J. Watson Research Center, 2000.
- [10] O. Godal, Y. Ermoliev, G. Klaassen, and M. Obersteiner. Carbon trading with imperfectly observable emissions. *Environmental & Resource Economics*, 25(2):151–169, June 2003.
- [11] D. K. Gode and S. Sunder. Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. *Journal of Political Economy*, 101(1):119–137, 1993.
- [12] M. He, N. R. Jennings, and H. Leung. On agent-mediated electronic commerce. *IEEE Transactions on Knowledge and Data Engineering*, 15:985–1003, 2003.
- [13] M. He, N. R. Jennings, and H. Leung. On agent-mediated electronic commerce. *IEEE Trans on Knowledge and Data Engineering*, 15(4):985–1003, 2003.
- [14] M. He, H. Leung, and N. R. Jennings. A fuzzy-logic based bidding strategy for autonomous agents in continuous double auctions. *IEEE Transactions on Knowledge and Data Engineering*, 15:1345–1363, 2003.
- [15] Ch. Hood. Reviewing existing and proposed emissions trading systems information paper, November 2010.
- [16] G. Klaassen, A. Nentjes, and M. Smith. Testing the dynamic theory of emissions trading: Experimental evidence for global carbon trading. Technical Report IR-01-063, International Institute for Applied Systems Analysis, November 2001.
- [17] F. Lopes, M. Wooldridge, and A. Q. Novais. Negotiation among autonomous computational agents: principles, analysis and challenges. *Artif. Intell. Rev.*, 29(1):1–44, March 2008.

- [18] H. Mizuta and Y. Yamagata. Agent-based simulation and greenhouse gas emissions trading. In *Winter Simulation Conference*, pages 535–540, 2001.
- [19] Z. Nahorski and J. Horabik. Compliance and emission trading rules for asymmetric emission uncertainty estimates. *Climatic Change*, 103:303–325, 2010. 10.1007/s10584-010-9916-4.
- [20] Z. Nahorski, J. Horabik, and M. Jonas. Compliance and emissions trading under the kyoto protocol: Rules for uncertain inventories. *Water, Air and Soil Pollution: Focus*, 7(4-5):539–558, September 2007.
- [21] Z. Nahorski and W. Radziszewska. Price formation strategies of programmable agents in continuous double auctions. In M. Bustowicz and K. Malinowski, editors, *Advances in Control Theory and Automation*, pages 181–194. Komitet Automatyki PAN, Oficyna Wyd. Politechniki Białostockiej, 2012.
- [22] Z. Nahorski, J. Stańczak, and P. Pałka. Multi-agent approach to simulation of the greenhouse gases emission permits market. *3rd International Workshop on Uncertainty in Greenhouse Gas Inventories*, pages 183–194, September 2010.
- [23] S. Phelps, S. Parsons, and P. Mcburney. Automated trading agents verses virtual humans: An evolutionary game-theoretic comparison of two double-auction market designs, 2004.
- [24] E. J. Pinker, A. Seidmann, and Y. Vakrat. Managing online auctions: Current business and research issues. *Management Science*, 49:2003, 2003.
- [25] Ch. Preist and M. van Tol. Adaptive agents in a persistent shout double auction. Technical Report HPL-2003-242, Hewlett-Packard, December 2003.
- [26] W. Radziszewska. Auction-based market for ghg permits. Technical Report RB/16/2011, IBS PAN, 2011.
- [27] J. Rust, J. H. Miller, and R. Palmer. Behavior of trading automata in a computerized double auction market. *The Double Auction Market: Institutions, Theories, and Evidence*, pages 155–198, 1991.

- [28] J. Rust, J. H. Miller, and R. Palmer. Characterizing effective trading strategies: Insights from a computerized double auction tournament. *Journal of Economic Dynamics and Control*, 18(1):61 – 96, 1994. <ce:title>Special Issue on Computer Science and Economics</ce:title>.
- [29] V. Smith. An experimental study of comparative market behavior. *Journal of Political Economy*, 70:111–137, 1962.
- [30] D.T. Spreng, T. Flüeler, D.L. Goldblatt, and J. Minsch. *Tackling Long-Term Global Energy Problems: The Contribution of Social Science*. Environment and Policy Series. Springer London, Limited, 2011.
- [31] J. Stańczak. Application of an evolutionary algorithm to simulation of the co2 emission permits market with purchase prices. *Operations Research and Decisions*, 4:94–108, 2009.
- [32] J. Stańczak and P. Bartoszczuk. Co2 emission trading model with trading prices. *Climatic Change*, 103:291–301, 2010.
- [33] P. Vytelingum. *The Structure and Behaviour of the Continuous Double Auction*. PhD thesis, University of Southampton, December 2006.
- [34] P. Vytelingum, D. Cliff, and N. R. Jennings. Strategic bidding in continuous double auctions. *Artificial Intelligence Journal*, 172(14):1700–1729, 2008.
- [35] P. Vytelingum, R.K. Dash, M. He, and N. R. Jennings. A framework for designing strategies for trading agents. In *IJCAI Workshop on Trading Agent Design and Analysis*, pages 7–13, 2005.



