4th International Workshop
on Uncertainty in Atmospheric Emissions

7-9 October 2015, Krakow, Poland

PROCEEDINGS

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About the Workshop

The assessment of greenhouse gases and air pollutants (indirect GHGs) emitted to and removed from the atmosphere is high on the political and scientific agendas. Building on the UN climate process, the international community strives to address the long-term challenge of climate change collectively and comprehensively, and to take concrete and timely action that proves sustainable and robust in the future. Under the umbrella of the UN Framework Convention on Climate Change, mainly developed country parties to the Convention have, since the mid-1990s, published annual or periodic inventories of emissions and removals, and continued to do so after the Kyoto Protocol to the Convention ceased in 2012. Policymakers use these inventories to develop strategies and policies for emission reductions and to track the progress of those strategies and policies. Where formal commitments to limit emissions exist, regulatory agencies and corporations rely on emission inventories to establish compliance records.

However, as increasing international concern and cooperation aim at policy-oriented solutions to the climate change problem, a number of issues circulating around uncertainty have come to the fore, which were undervalued or left unmentioned at the time of the Kyoto Protocol but require adequate recognition under a workable and legislated successor agreement. Accounting and verification of emissions in space and time, compliance with emission reduction commitments, risk of exceeding future temperature targets, evaluating effects of mitigation versus adaptation versus intensity of induced impacts at home and elsewhere, and accounting of traded emission permits are to name but a few.

The *4th International Workshop on Uncertainty in Atmospheric Emissions* is jointly organized by the *Systems Research Institute of the Polish Academy of Sciences*, the Austrian-based *International Institute for Applied Systems Analysis*, and the *Lviv Polytechnic National University*. The 4th Uncertainty Workshop follows up and expands on the scope of the earlier Uncertainty Workshops – the *1st Workshop* in 2004 in Warsaw, Poland; the *2nd Workshop* in 2007 in Laxenburg, Austria; and the *3rd Workshop* in 2010 in Lviv, Ukraine.

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Multi-agent auction simulation of the GHG international emission permit trading

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Abstract

This short paper presents elements of a simulation environment for negotiation of prices in GHG emission permit trade and results of simulations of international trades performed by programmable agents. Several market mechanisms and strategies used by programmable agents are discussed and applied in simulations. The results show convergence of the trading schemes to the equilibrium, depending on the case that consists of the trading mechanism and the strategies used by the agents. The simulation can be used for estimation of equilibrium price at market designing stage. It can be also used for simulation of proposed markets for uncertain emission inventories, which is envisaged for further studies.

Keywords: Greenhouse gases, emission permit trading, computer simulation, multi-agent systems

1. Introduction

Although the trading of GHG emission permits has been introduced in the Kyoto Protocol more than a dozen years ago and some experience has been already gathered, the markets are still unpredictable, particularly in assessment of the equilibrium price. Good estimate of the equilibrium price would allow the market planner to better organize the market and plan its parameters. Ermoliev at al. [8] proposed simulation of a bilateral trade using multi-agent systems for assessing the equilibrium price. A programmable agent would be under control of a party taking part in the trade and would use discreet private information to bid in a process of automatic negotiation. This simulation approach differs from the game-theoretic simulations, like those presented in [2, 3].

Recently, estimates of marginal abatement curves obtained by using simulation tools were published, like those calculated in GAINS [26], EPPA [16], and using bottom-up modeling [1]. This enables simulations of trades among parties. In this paper a few market mechanisms are considered to simulate trade among 16 regions of the world. The cost curves were adopted from [16]. Results obtained by using different negotiation methods and different price formation strategies by programmable agents are compared and discussed. This paper develops the earlier approach by Nahorski at al. [18], where also a much smaller group of 5 parties was considered, by considering more market mechanisms and many other negotiation strategies. Multi-agent trade simulations could be also used for checking designed market schemes before they are practically implemented.

The simulation approach could be also used for markets for enterprises. The main obstacle is knowledge of marginal abatement curves in such markets.

Another difficulty in organizing the GHG emission permit markets is high diversity of emission accuracy bounds among the trading countries. There is a couple of approaches to cope with this problem, see e.g. [9, 14, 15, 18, 22, 27]. Simulation of these approaches by using multi-agent tools is envisage as continuation of the results presented in this paper.

2. The trading mechanisms used in simulations

A negotiation is a dialog between two or more parties, in order to resolve a conflict or to reach an agreement. A dialog is an exchange of communicates between two or more parties to reach their personal aim. The details of conducting the negotiation define most of the trading schemes. The automated agents negotiate parameters of the deal, as for example price, or conditions of delivery. The negotiation models can be divided into two categories: bilateral negotiations, which involve usually two parties (although multilateral negotiations are also possible), and auctions that by definition include multiple parties. There are many types of auctions which are in use, to mention the English Auction, the First-Price Sealed-Bid Auction, the Vickerey Auction, the Dutch Auction or Dutch Flower Auction, and the Continuous Double Auction. In the paper we consider the Dynamic Bilateral Negotiations and the following types of auctions: Continuous Double Auction, Sealed-Bid Auction, Sealed-Bid Reverse Auction, and Sealed-Bid Double Auction. For more detailed introduction to trade by programming agents see e.g. [12].

A market participant intending to buy a commodity (a buyer) places an offer; called a *bid*, together with the number of units and the price that the buyer is willing to pay for it. A participant intending to sell a unit of a commodity (a seller) places an offer; now called an *ask*, which includes the number of units and the price the seller wants. The market clears whenever the price of a bid is equal or greater than the price of the ask. The paired offers are removed from the market, and all other offers remain unchanged. The clearing price in every trade mechanism is set in the middle of the lowest accepted buying price (lowest accepted bid) and the highest accepted selling price (highest accepted ask). Every offer consists of the offered price and the offered number of permits.

2.1 Continuous Double Auction (CDA)

The Continuous Double Auction (CDA) is one of the market mechanisms frequently used in the stock market and also in their computer simulations. This type of market consists of three entities: the sellers, the buyers, and the market operator (the broker) that manages the trade: orders the bids and asks, and arranges transactions if prices of asks are lower or equal than prices of bids. The broker also records important market events and outstanding offers. The current lowest ask is called the outstanding ask, and the highest bid is called the outstanding bid, both these values are important during formulation of the offer price.

The buyers and sellers in the market are expected to behave rationally: their bids and asks should be profitable, and the ask-bid spread should be reduced in time to enable the market prices to evolve toward the equilibrium price.

There are variants of CDA markets, which depend on specifics of particular markets or traded goods. The CO_2 emission permits market also requires some modifications of the general schema. The most important is division of CDA trade into cycles. Market participants may give their offers simultaneously, but only one of each kind in one cycle. Having collected all offers, the cycle terminates. Only these transactions are executed which are profitable for both participants. Offers unused in one cycle could be valid in a limited number of cycles. But it is rather favorable to make a new offer in the consecutive cycle, taking into account new market events. Cycles in auctions are not identified with any real periods of time and time is not crucial in this kind of market. Surpluses and shortages from one cycle can be sold/bought in subsequent ones.

Due to changes of marginal prices of market participants caused by conducted transactions (see Fig. 3), limitations are imposed on the number of transferred permits in one transaction to avoid big perturbations of prices in consecutive cycles.

In another variant, the transactions are concluded immediately after an ask and a bit matches have been detected. Also this variant is considered in the simulations.

2.2 Dynamic Bilateral Transactions (DBT)

In the bilateral trading, agents split into pairs and a single negotiation process occurs inside any pair. The splitting process is performed randomly, it occurs after termination of the running negotiation process, and is repeated iteratively. Established pairs conduct bilateral contracts depending on their expected profits. Each negotiation process may lead to an agreement or not.

2.3 Sealed-bid Auction\Reverse Auction (SA\SRA)

In the sealed-bid auction mechanism there are two roles in the trade: the auction operator, and the bidders. The operator calls for the auction to sell/buy a number of permits, possibly specifying the minimum/maximum unit price. Responding, a bidder gives its preferred unit price. The operator collects all the bids, and selects the winning one, with the highest/lowest unit price. In the simulations, the operator role is chosen randomly among the agents, while the remaining are the bidders.

2.4 Sealed-bid Double Auction (SDA)

In the double auction there are three roles: buyers, sellers, and the operator. The operator calls for the auction, and the sellers put the asks, and the buyers put the bids. Single clearing uses a clearing price that is not greater than prices of accepted bids, and not lower than prices of accepted asks. The clearing can also consists of more than two offers. Then, the clearing price should be set to satisfy as many asks and bids as possible.

3. Strategies used in the simulations

Vytelingum et al. [25] 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. 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.

Strategies can be divided to those which use only current information and those which take into account also the history of the market states [17]. Among the former one there are the Frank or Truth Telling strategy, Pure Simple strategy, Kaplan strategy [23], Zero Intelligence strategy, and Preist and van Tol strategy [20].

Among the strategies that consider history, GD strategy proposed in [10] estimates so-called belief function from gathered information, which helps to form the proposed price. Other, complicated strategies with multi-level learning, are the Adaptive-Aggressive strategy and FL strategy [13]. The latter uses fuzzy logic reasoning. In this paper we use few chosen strategies described below.

3.1 Frank (F) or Truth Telling (TT) strategy

In the Frank strategy all agents bid according to its current marginal prices. As they do not behave strategically, the strategy is called Frank or Truth Telling.

In a similar simple strategy, described in [4] and called Pure Simple strategy, agents bid a constant 10% below the value of private evaluation. This strategy under the name Gamer was also played in the Santa Fe tournament [21], where it reached a similar, very low place to the TT and ZI strategies.

3.2 Zero-intelligence plus (ZIP) strategy

Zero intelligence (ZI) strategy was proposed by [11]. A ZI trader simply submits a random offer drawn from a uniform distribution.

Zero-intelligence plus (ZIP8) strategy, described in [5], bases on the auction history. 8 means the number of parameters passed to the strategy. It was later extended to 60 parameter strategy [6], which is however not discussed here. Every agent has the private price limit λ_i. For the seller it is the minimal value for which he is willing to sell one permission, and for the buyer it is the maximal value for which he is willing to buy one permission. At any time *t*, agent *i* calculates the price using its real-valued profit-margin μ_i(t).

$$p_i(t) = \lambda_i\,(1 + \mu_i(t)) \text{ – for sellers} \tag{1}$$

$$p_i(t) = \lambda_i\,(1 - \mu_i(t)) \text{ – for buyers} \tag{2}$$

The ZIP8 strategy assumes the constant recalculation of the real-valued profit margin. It is first drawn from the uniform distribution according to parameters:

$$\mu_i \sim U(\mu_{min}, \mu_{max})$$

In the course on the auction, the real-valued profit margin changes its value. To calculate it, the following is assumed. In the course of the auction, an agent can be either **greedy** or **careless**, and this property changes during the auction. A greedy agent wants to draw a largest possible profit from every transaction, neglecting the inherent risk. Careless agent is more aggressive and eager to enter into transaction, caring not so much about the profit.

An agent chooses at any time its behaviour (greedy or careless). It calculates its own possible offer from equations (1) – (2), and then checks the relation between calculated and the previous offer submitted to the market q_{j-1}. If the last offer has been rejected, an agent becomes careless, otherwise:

- if the agent is a seller and the last selling offer was greater than it had been calculated, it becomes greedy, otherwise it becomes careless,
- if the agent is buyer and the last buying was greater than it had been calculated, it becomes careless, otherwise it becomes greedy.

Agent calculates its interim offer according to the following equation:

$$\tau_j = R_i q_{j-1} + A_i$$

The parameter q_{j-1} is the previous offer submitted to the market, A_i and R_i are parameters that are drawn from the uniform distribution according to the following rules.

If the agent is careless:

$$A_i \sim U(1 - C_R, 1), \qquad R_i \sim U(-C_A, 0)$$

If the agent if greedy:

$$A_i \sim U(1, 1 + C_R), \qquad R_i \sim U(0, C_A)$$

where C_A and C_R are the parameters of the strategy.

Then, an agent calculates the interim profit margin:

$$d_j = 1 - \frac{\tau_j}{\lambda_j}$$

and subtracts the margin used in the previous negotiation round:

$$\delta_j = d_j - \mu_{j-1}$$

Next, the profit margin is modified using the Widrow-Hoff delta rule, that is the new margin is calculated as

$$\mu_j = \mu_{j-1} + \Delta_j$$

where Δ_j is calculated using the following rules with the learning rate β_i:

- if the agent is a seller:
  - if it is careless and $\delta_j \leq 0$ or it is greedy and $\delta_j > 0$, then:

    $$\Delta_j = \beta_i(d_j - \mu_{j-1})$$

  - if it is careless and $\delta_j > 0$ or it is greedy and $\delta_j \leq 0$, then:

    $$\Delta_j = \beta_i(\mu_{j-1} - d_j)$$

- if the agent is a buyer:
  - if it is careless and $\delta_j > 0$ or it is greedy and $\delta_j \leq 0$, then:

    $$\Delta_j = \beta_i(\mu_{j-1} - d_j)$$

  - if it is careless and $\delta_j \leq 0$ or it is greedy and $\delta_j > 0$, then:

    $$\Delta_j = \beta_i(d_j - \mu_{j-1})$$

The learning rate β_i is drawn from the uniform distribution:

$$\beta_i \sim U(\beta_{min}, \beta_{\max}).$$

Now, we can calculate the new profit margin:

$$\mu_j = \mu_{j-1} - 1 + \Gamma_j$$

where Γ_j is the updating parameter, calculated using the equation:

$$\Gamma_j = \gamma \Gamma_{j-1} + (1 - \gamma)\Delta_j$$

where γ is the profit margin momentum coefficient. It is set by drawing from the uniform distribution:

$$\gamma \sim U(\gamma_{min}, \gamma_{max})$$

3.3 Adaptive-aggressive (AA) strategy

The Adaptive-Aggressive strategy of price formulation has been presented in [24]. This is a rather complicated model of the price formulation, considering market events, marginal costs of contractors and estimates of the market equilibrium with elements of short- and long-term learning.

The market participants are divided into intra-marginal and extra-marginal traders, depending on their limit price (marginal costs) $\lambda_j(t)$ in moment t and its relation to an estimate of the market equilibrium price $\hat{p}^*(t)$, that is the moving average of last N transaction prices p_i.

$$\hat{p}^*(t) = \frac{\sum_{i=t-N}^{t} w_i p_i}{N}, \qquad \sum_{i=t-N+1}^{t} w_i = 1, \qquad w_{i-1} = \rho w_i, \qquad \rho = 0.9 \tag{3}$$

where:
p_i – transaction prices,
N – time horizon of the equilibrium estimation,
w_i – weights,
ρ - the forgetting factor (its value is set by the trading party).

Each of these groups is naturally divided into buyers and sellers (this allocation of participants changes during the market activity). Thus, four different causes of price formulation are distinguished:

- for an intra-marginal buyer $\lambda_j(t) > \hat{p}^*(t)$,
- for an intra-marginal seller $\lambda_j(t) < \hat{p}^*(t)$,
- for an extra-marginal buyer $\lambda_j(t) < \hat{p}^*(t)$,
- for an extra-marginal seller $\lambda_j(t) > \hat{p}^*(t)$.

So, the intra-marginal buyers and sellers are in good position for trading, while the extra-marginal ones in much worse. However, in the presented market functions of traders can be easily changed in consecutive iterations.

The price formation in the AA strategy requires a lot of information about the market, and the formulae used for bidding and asking are different for buyers and sellers:

- for a buyer

$$bid_j(t) = \begin{cases} o_{bid}(t) + \frac{\min(\lambda_j(t), o_{ask}^{+}) - o_{bid}(t)}{\eta} & \text{- the first round} \\ o_{bid}(t) + \frac{\tau_j(t) - o_{bid}(t)}{\eta} & \text{- other rounds} \end{cases} \tag{4}$$

$$o_{ask}^{+} = (1 + \zeta_r) o_{ask}(0) + \zeta_a, \qquad o_{ask}(0) = MAX_{ASK}$$

where:
MAX_{ASK} – the maximum price allowed on the market,
$\lambda_j(t)$ – the marginal (secret) price of the bidder,
$o_{bid}(t)$ – the current outstanding bid,
$\tau_j(t)$ – the target price (described later),
η – a correction factor, $1 \leq \eta \leq \infty$ (suggested value is 3),
ζ_a, ζ_r – modification factors (suggested values are 0.01 and 0.02, respectively).

- for a seller

$$ask_j(t) = \begin{cases} o_{ask}(t) + \frac{o_{ask}(t) - max(\lambda_j(t), o_{bid}^{\cdot})}{\eta} & \text{- the first round} \\ o_{ask}(t) - \frac{o_{ask}(t) - \tau_j(t)}{\eta} & \text{- other rounds} \end{cases} \quad (5)$$

$$o_{bid}^{\cdot} = (1 - \zeta_r)o_{bid}(0) - \zeta_a, o_{bid}(0) = 0$$

where $o_{ask}(t)$ is the current outstanding ask.

The target prices $\tau_j(t)$ are different for all four categories:

- for an intra-marginal buyer

$$\tau_j(t) = \begin{cases} \hat{p}^*(t)\left(1 - \frac{\exp(-r\theta)-1}{\exp(\theta)-1}\right) & \text{- for } -1 < r \leqslant 0 \\ \hat{p}^*(t) + \frac{(\lambda_j(t) - \hat{p}^*(t)) * \exp(r\theta) - 1}{\exp(\theta)-1} & \text{- for } 0 < r < 1 \end{cases} \quad (6)$$

- for an intra-marginal seller

$$\tau_j(t) = \begin{cases} \hat{p}^*(t) + \left(MAX_{ASK} - \hat{p}^*(t)\right)\frac{\exp(-r\theta)-1}{\exp(\theta)-1} & \text{- for } -1 < r \leqslant 0 \\ \lambda_j(t) + \left(\hat{p}^*(t) - \lambda_j(t)\right)\left(1 - \frac{\exp(r\theta)-1}{\exp(\theta)-1}\right) & \text{- for } 0 < r < 1 \end{cases} \quad (7)$$

- for an extra-marginal buyer

$$\tau_j(t) = \begin{cases} \lambda_j(t)\left(1 - \frac{\exp(-r\theta)-1}{\exp(\theta)-1}\right) & \text{- for } -1 < r \leqslant 0 \\ \lambda_j(t) & \text{- for } 0 < r < 1 \end{cases} \quad (8)$$

- for an extra-marginal seller

$$\tau_j(t) = \begin{cases} \lambda_j(t) + \left(MAX_{ASK} - \lambda_j\right)\frac{\exp(-r\theta)-1}{\exp(\theta)-1} & \text{- for } -1 < r \leqslant 0 \\ \lambda_j(t) & \text{- for } 0 < r < 1 \end{cases} \quad (9)$$

The aggressiveness of the trader is an element of the short-time learning strategy and is controlled by the parameter $r \in [-1,1]$. A trader with the value r close to -1 is called a **completely passive**. It tries to buy at price near 0 and sell at price near MAX_{ASK} (with the maximum profit). A trader, for which $r = 0$ is called **active**. It tries to buy and sell at price close to $\hat{p}^*(t)$ (with a moderate profit). At last the trader with r close to 1 is called a **completely aggressive** and tries to buy and sell at its price $\lambda_j(t)$ (without profit).

The degree of aggressiveness is controlled using the Widroff-Hoff rule:

$$r_j(t+1) = r_j(t) + \beta_1(\delta_j(t) - r_j(t)) \quad (10)$$

$$\delta_j(t) = (1 \pm \zeta_r)r_{j_{shout}} \pm \zeta_a \quad (11)$$

where:

β_1 – random variable with a uniform distribution on the interval [0.2, 0.6],

$r_{j_{shout}}$ – a value of r_j at the currently last bid,

$\delta_j(t)$- is obtained according to following rules:

if there was no transaction at time $t-1$, $\delta_j(t)$ is determined as follows:

for purchase:

if $\tau_j(t-1) \leq bid_j(t-1)$, then $\delta_j(t) = (1 + \zeta_r)r_{j_{shout}} + \zeta_a$

-that means an increased aggressiveness of the buyer at the auction,

for sale:

if $\tau_j(t-1) \geq ask_j(t-1)$, then $\delta_j(t) = (1+\zeta_r)r_{j_{shout}} + \zeta_a$

- that means an increased aggressiveness of the seller at the auction,

if there was a transaction at time $t-1$, then:

for purchase:

if in the session $t-1$ the buyer j bought emissions for the price $q_j(t-1)$, then:

if $\tau_j(t-1) \geq q_j(t-1)$, then $\delta_j(t) = (1-\zeta_r)r_{j_{shout}} - \zeta_a$

- that means a decreased aggressiveness of the buyer at the auction.

otherwise $\delta_j(t) = (1+\zeta_r)r_{j_{shout}} + \zeta_a$

- that means an increased aggressiveness the buyer at the auction,

for sale:

if in session $t-1$ the seller j sold emissions for the price $q_j(t-1)$, then:

if $\tau_j(t-1) \leq q_j(t-1)$, then $\delta_j(t) = (1-\zeta_r)r_{j_{shout}} - \zeta_a$

- that means a decreased aggressiveness of the seller at the auction,

otherwise $\delta_j(t) = (1+\zeta_r)r_{j_{shout}} + \zeta_a$

- that means an increased aggressiveness of the seller at the auction.

Suggested values are $\zeta_a = 0.01$, $\zeta_r = 0.02$.

Similarly the long-term learning rule also uses the Widroff-Hoff rule to update the value of θ:

$$\theta(t+1) = \theta(t) + \beta_2(\theta^*(\bar{\alpha}(t)) - \theta(t)) \tag{12}$$

$$\theta^*(\bar{\alpha}(t)) = (\theta_{max} - \theta_{min})(1 - \bar{\alpha}(t)\exp(\gamma(\bar{\alpha}(t) - 1))) + \theta_{min} \tag{13}$$

$$\bar{\alpha}(t) = (\alpha(t) - \alpha_{min})/(\alpha_{max} - \alpha_{min}) \tag{14}$$

$$\alpha(t) = \frac{\sqrt{\frac{1}{N}\sum_{i=t-N+1}^{t}(p_i - \widehat{p^*}(t))}}{\widehat{p^*}(t)} \tag{15}$$

where:

$\alpha_{min}, \alpha_{max}$ – minimal and maximal value of factor α,

$\theta_{min}, \theta_{max}$ – given minimal and maximal values of parameter θ (suggested values -2 and 8, respectively).

γ – the function shaping factor (suggested value 2).

4. Simulations

4.1. Simulation system

The mathematical formulation of the market and organization of simulation was analogous to that described in [18] and is not repeated here. The differences are presented below.

To organize simulations, the maximal and minimal prices for the parties are needed. The maximal price can be taken as a reasonably high arbitrary value. The minimal value is, however, bound by the shadow price of the party. The shadow price is the derivative of the marginal abatement cost curve at the current emission value. The marginal abatement cost curves for reducing the emission of greenhouse gases have been developed on the basis of the data for 2010 published by [16] and its online supplementary documentation. Originally they were calculated using version 4 of the

MIT EPPA model [19]. To use them in the computer simulations, the cost curves were approximated by polynomials fitted by using the regression method. The data were given for 16 countries and regions in the world: USA, Canada (CAN), Japan (JPN), European Union (EUR), Australia and New Zealand (ANZ), Eastern Europe (EET), Former Soviet Union (FSU), India (IND), China (CHN), Indonesia (IDZ), East Asia (ASI), Mexico (MEX), Central and South America (LAM), Middle East (MES), Africa (AFR), Rest of World (ROW).

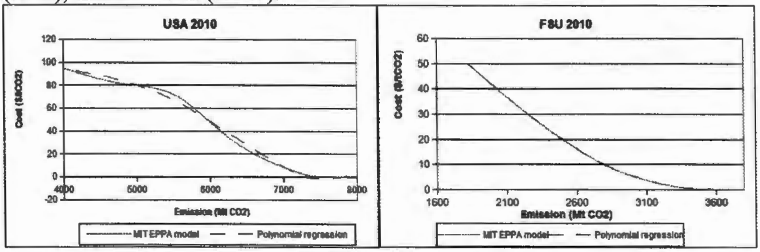
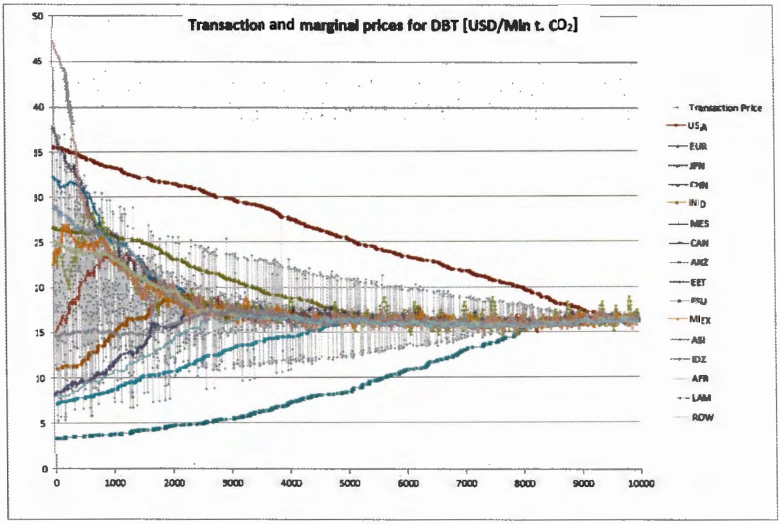
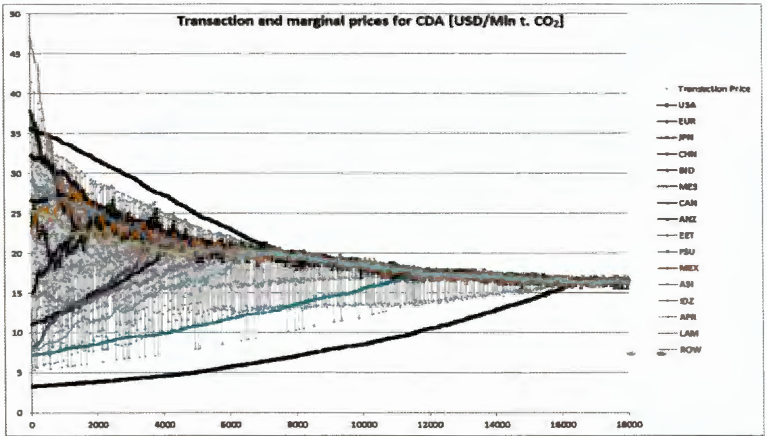


Figure 1. Exemplary cost curves and their approximations for USA and FSU in 2010.

Sample plots for the USA and FSU are shown in Figure 1. The approximated curve almost perfectly fits the original curve for FSU, while for USA the polynomial function is of too low order to fit the original data exactly. But for computational purposes this error is admissible.




Transaction and marginal prices for CDA [USD/Mln t. CO_2]
Transaction Price
USA
EUR
JPN
CHN
IND
MES
CAN
ANZ
EET
FSU
MEX
ASI
IDZ
AFR
LAM
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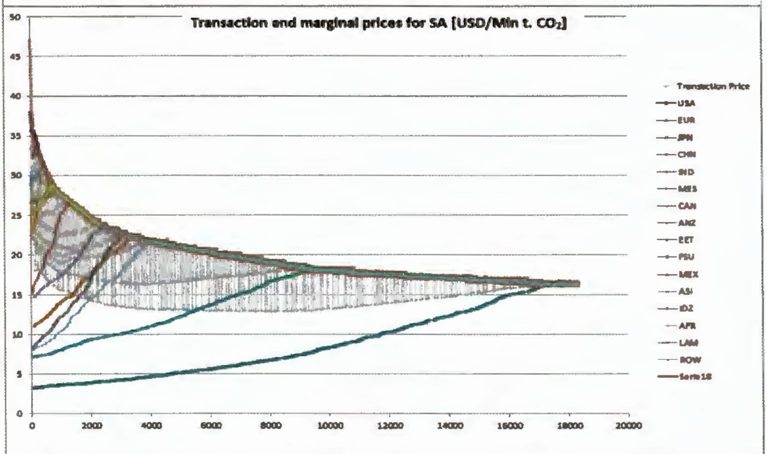
Transaction and marginal prices for SA [USD/Mln t. CO_2]
Transaction Price
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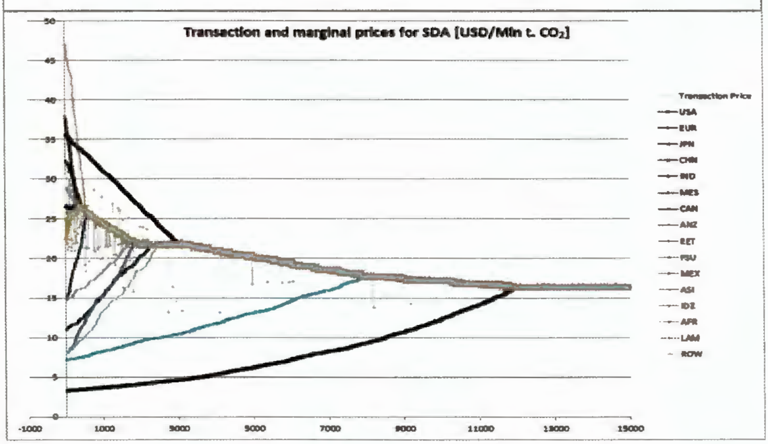
Transaction and marginal prices for SDA [USD/Mln t. CO_2]
Transaction Price
USA
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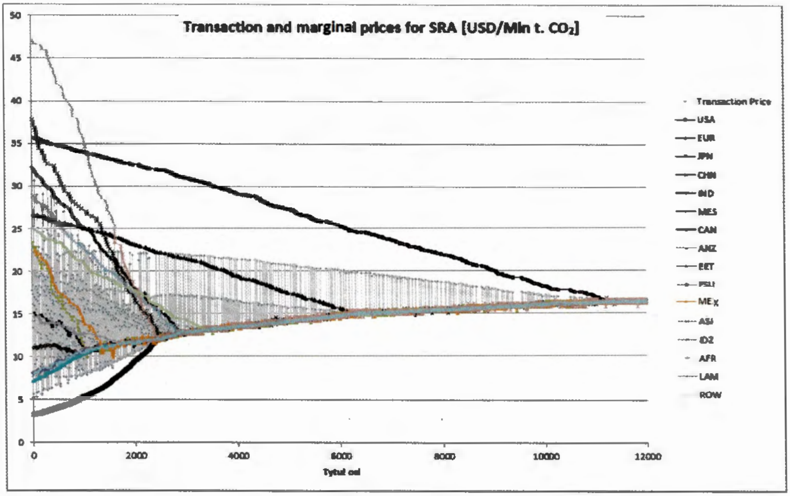
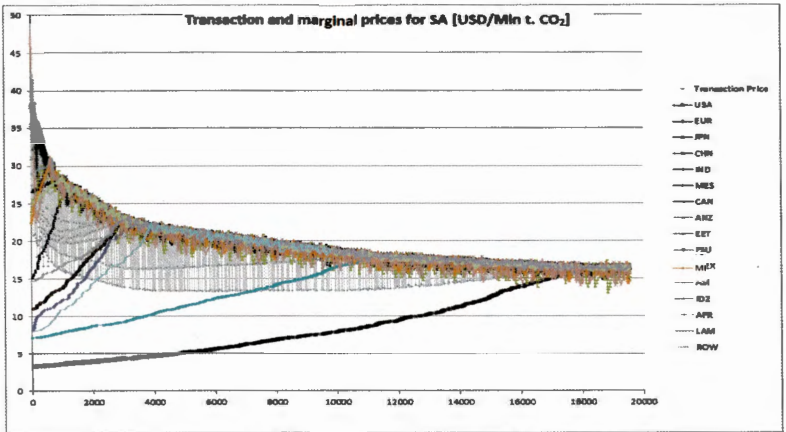


Figure 2 Trajectory of marginal and transaction prices in consecutive contracts, in [USD/MtC/y] for different trading mechanisms. In consecutive panels from the top: SA, DBT, SDA, CDA, SRA. Every party uses Frank strategy.

There are evident differences in parties trajectories for different cases that are connected with the random elements of the strategies. However, the following features can be observed for the Frank and ZIP strategies:

- For Continuous Double Auction and Dynamic Bilateral Trade, the plots of transaction prices are most spread out; the reason is high randomness of strategies used by parties which are concluding contracts, as in both mechanisms the decision of contract is made with less knowledge as compared with other auctions.
- For the Sealed-bid Auction the contracts are concluded one after the other by decreasing prices.
- For the Sealed-bid Reverse Auction, the contracts are concluded one after the other by increasing prices.
- For the Sealed-bid Double Auction, the plot of transaction prices is most condensed, as the contracts are concluded by choosing the most attractive offer among more than two competing ones.
- For the Frank strategy the plots of marginal prices are smoother than for the other strategies, what comes from the fact, that the parties do not use random strategies.
- In every simulation, the prices converge to a value about 16.4 [USD/MT CO2]


Transaction and marginal prices for SA [USD/Mln t. CO2]
Transaction Price
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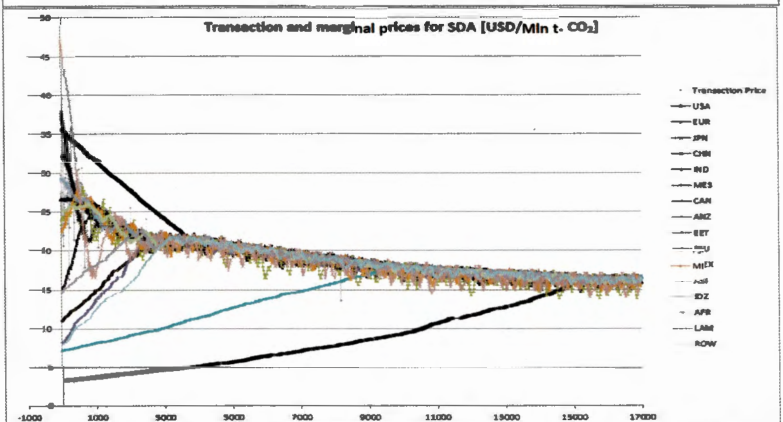
Transaction and marginal prices for SDA [USD/Mln t. CO2]
Transaction Price
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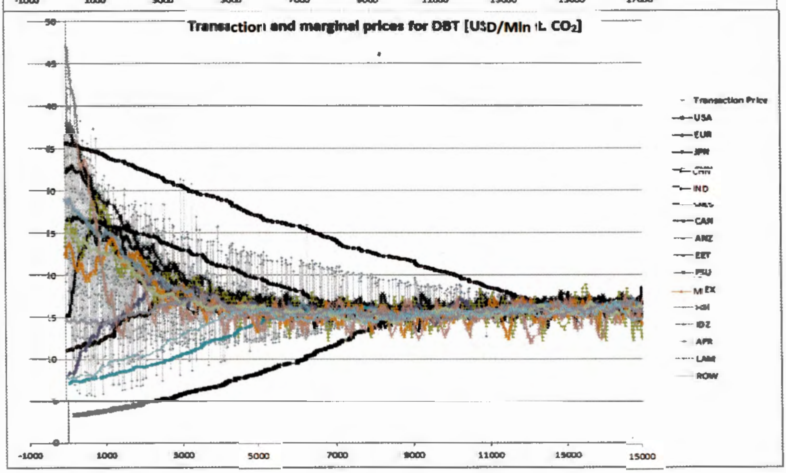
Transaction and marginal prices for DBT [USD/Mln t. CO2]
Transaction Price
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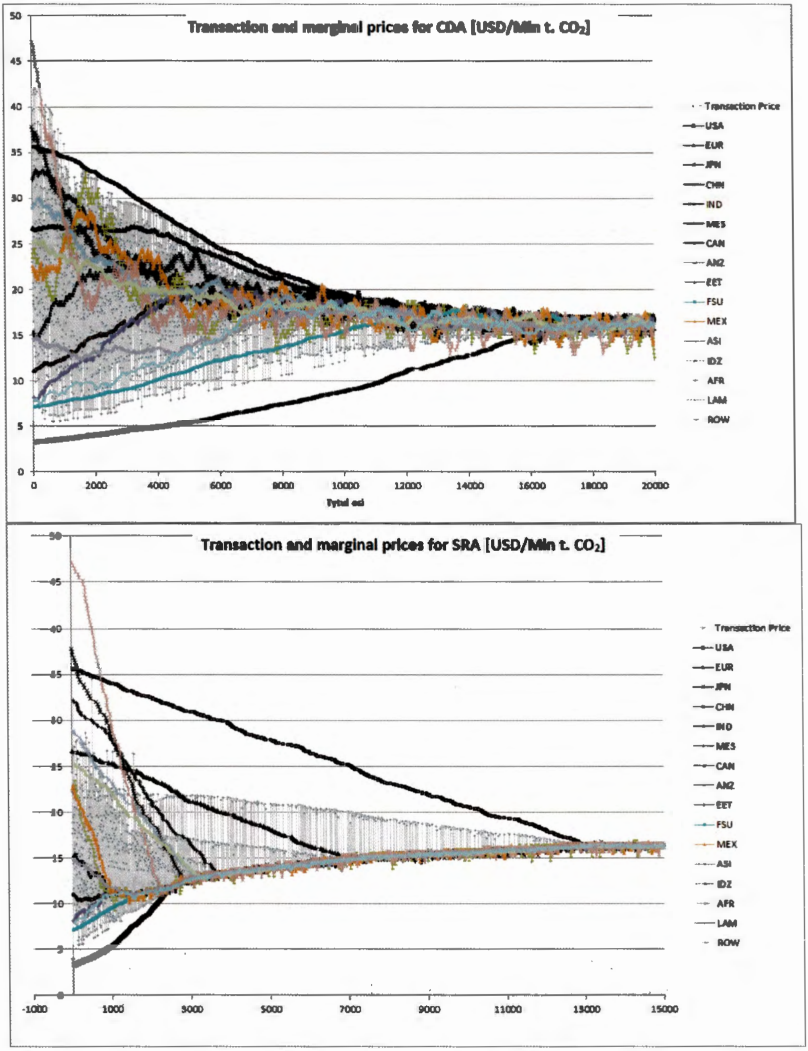


Figure 3 Trajectory of marginal and transaction prices in consecutive contracts, in [USD/MtC/y], for different trading mechanisms. In consecutive panels from the top : SA, DBT, SDA, CDA, SRA. Every party uses ZIP strategy.

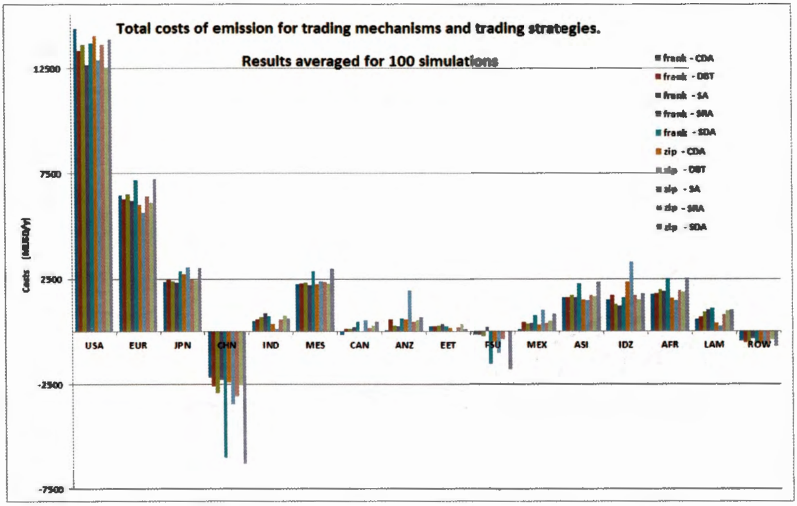


Figure 4. Total averaged costs of emission for trading mechanisms and trading strategies.

Analysing the averaged costs after 100 simulations we can note the following:

- USA mainly purchases the permits, so the difference among particular mechanisms is not significant; the lower costs can be observed for Sealed-bid Reverse Auctions (for both strategies), and for Dynamic Bilateral Trade with ZIP strategy.

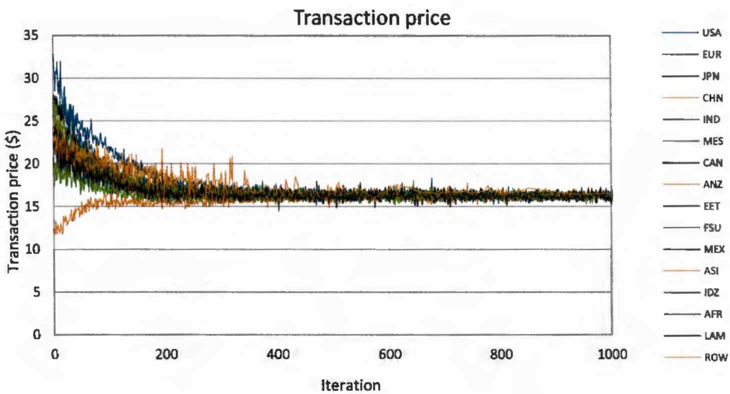
- In turn, China (CHN) mostly sells the permits and benefits from the trade. The mechanisms that are most favourable for CHN is the Sealed-bid Double Auction.

- The same situation is for FSU, where this party benefits bet from the Sealed-bid Double Auctions, while for other mechanisms it benefits only marginally or even loses.

- EUR, ASI, AFR, and MES are the permits buyers, and similarly to CHN the best for them mechanism is the Sealed-bid Double Auction.

- For IND and LAM the lowest costs are for Continuous Double Auction and Dynamic Bilateral Trade with ZIP strategy.

The most interesting feature of the AA strategy for CDA is much shorter time of convergence of the transaction and marginal prices to the equilibrium. While the Frank strategy needed 1000-1600 iterations for convergence and ZIP strategy 1300-1600 iterations, the convergence for the AA strategy required about 300 iterations for transaction prices and about 500 iterations for the marginal prices. This is caused by very complicated strategy trying to elaborate as good offer as possible. The much shorter negotiations are an important feature for applications, where agent representing real parties negotiate.



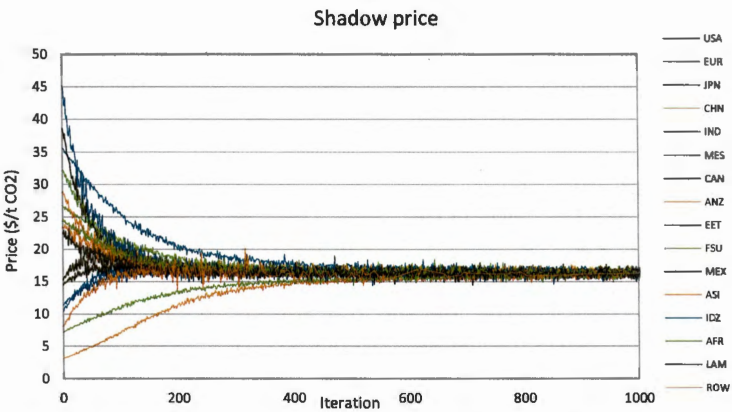


Figure 5. Averaged (100 iterations) values of transaction prices (upper panel) and shadow prices (lower panel) for 16 countries and regions for the Continuous Double Auction and AA strategy.

5. Conclusions

This paper presents the basic parts of a computer environment for simulation of emission permit trade using multi-agent framework. As far, different trading mechanisms, like bilateral trade and few types of auctions, and strategies which can be used by programmable agents, were reviewed, coded as computer subroutines, and described in the text. The results of simulated trade are presented. The case considered is a trade of GHG emission permits between 16 countries and regions of the world. The marginal costs for these parties were taken from [19].

Different simulated cases, each of which consists of a chosen pair of a trade mechanism and a strategy, showed differences in details, but similar general behaviour concerning convergence to the equilibrium and relative final total costs of the trading parties.

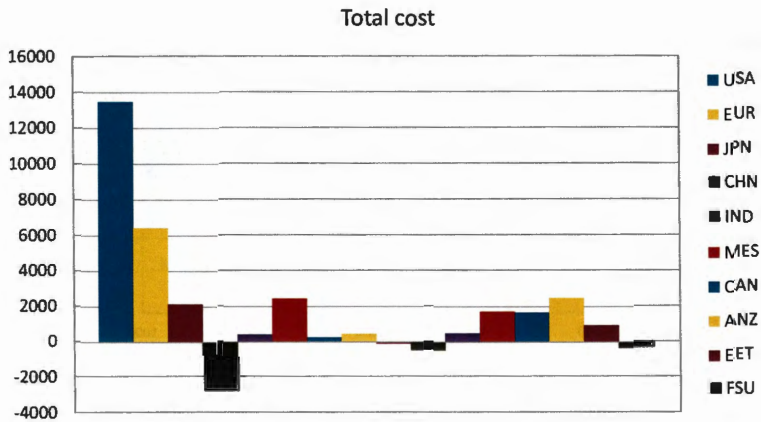


Figure 6. Averaged (100 iterations) values of total costs of CO_2 emission reduction for 16 countries and regions for the Continuous Double Auction and AA strategy.

The proposed simulation can be developed for estimating the equilibrium price in a designed market by implementing a simulated game, in which a programmable agent situated and operated by a playing party can use its secret information on marginal costs to take part in the game. Results of such a game would help to better design the market rules, not only by getting better information on the equilibrium price, but also on possible malfunctioning of the market.

The elaborated environment can be also developed for simulation of proposed markets for uncertain emissions. This kind of markets has not exist until now and can show unexpected features. The simulated experiments of such markets can demonstrate their strong and weak sides.

Acknowledgement

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