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A Simulation Model for Studying the Influence of Algorithmic Trading and Vending Machines on the State of the Stock Market

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Abstract: This paper investigates the impact of algorithmic trading on the securities behavior in the stock market. To conduct the study and to identify this influence a computer simulation agent-based model of the stock exchange was developed. In a series of tests we study the effect of different combinations of trading algorithms on market behavior. The model consists of a kernel that performs basic functions and operations essential for the exchange, and an open set of trading algorithms. In this study, the model does not include margin trading, short positions, market makers, commissions, medium-and long-term trends. In the constructed model of algorithmic trading there is only one security studied. It is isolated from news factors, companies' reports, dividend payments, macroeconomic statistics, and also from other quotes, currency pairs, prices for raw materials.

Key words: algorithmic trading; vending machines; a simulation model of the stock market; market liquidity
JEL code: G23

1. Situation and Problem Definition

In the literature and in the Internet a variety of studies related to algorithmic trading is available. There are studies of algorithmic trading in the context of major transactions. In those studies methods of estimation of the market impact of large trades are described. Many studies have been devoted to the study of the effectiveness of specific trading algorithms and algorithmic trading in general (Sera C. M. & Sera C. E., 2013). At the same time, a significant share of market transactions are transactions carried out by trading robots—computer programs, used on the exchange and based on certain trading algorithms. Some studies show that errors and omissions in the design of trading algorithms and robots can cause a significant drop in the whole market (Marco Avellaneda, 2011). Regulators accused algorithmic trading in "rocking" the market (Palak Shah & Samie Modak, 2012). In contrast, this study analyzes the impact of robots and algorithmic trading on market behavior. At this moment in researches, studying various details of algorithmic trading, there is no or very little attention paid to this particular question.

2. The Object of the Study

This study has as its object financial markets. We consider only a special case—the stock market. In this study legal aspects are not so important; that is why saying market we will think about such a market where

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transactions are carried out with the securities by parties, directly or through an intermediary, outside the exchange, often with the conclusion of the traditional sales contract. Specificity of the research subject restricts the study with exchange market. In the stock market three main parties can be distinguished. They are the organizer of the trade, brokers and individuals. In addition to them managers, dealers and Central Banks also exist; but, their participation in the trade is not interesting and influential in this context and they are not studied in this research. According to the law “On the Securities Market” dated 22.04.1996 No 39-FZ, Russian Federation: individuals, or traders, cannot be admitted to the trading process directly. They can perform deals on the stock exchange only through authorized brokers.

3. Subject of the Study

Nowadays, financial markets are described from many angles: features of the functioning of the market, the history of the securities markets, the characteristics of the participants, macroeconomic and policy issues in relation to stock trading, the capitalization of the exchange, the infrastructure of the trades, the trading process, the principles of trade and the search for best practices, portfolio management, the issues associated with the analysis of securities, increased profitability and risk reduction, and much more (Downs J. & Goodman J. E., 1998; Rob Iati, 2009). However, there are a number of issues related to the stock exchange, which were beyond the attention of researchers. They include, for example, questions about the impact of endogenous, id est, internal factors on the state of the market. Endogenous factors include specifics of exchanges and market participants, especially the trafficking process, algorithmic trading influence etc. Exogenous factors may include macroeconomic, political and social factors as well as factors related to the business of the company, which shares are traded. Exogenous factors, as already was said previously, were studied better than the endogenous. As the subject of this study algorithmic trading in the stock exchange was chosen. In general, algorithmic trading is a formalized system of transactions in the financial markets, according to some algorithm, which is based on one or several trading strategies. Algorithmic trading can be studied from two different perspectives. First, it can be studied from the perspective of the construction of optimal algorithms and optimization of trading strategies that maximize profits and minimize risks and optimize other parameters of commerce (ZEW, Apr 21, 2011). Second, algorithmic trading can be studied from a position of influence that it has on the normal course of trading. Here, words “the normal course of trading” mean the course of trading that existed in the days before the wide use of algorithmic trading, or at least before its rapid spread. This study will focus exactly on the second approach.

It is important to note that algorithmic trading can be used with two different purposes. First, algorithmic trading is used by speculative traders. Second, algorithmic trading is used to optimize large transactions (ZEW, Apr 21, 2011). The latter approach is used by the owners of large blocks of shares or institutional investors. It is necessary for them to ensure that the required number of shares is purchased or sold without great impact on prices. Naturally, the algorithms used in the first and second cases, are radically different. This study focuses on the first type of algorithmic trading. Further, the words “algorithmic trading” will mean just speculative, often high-frequency trading.

The share of algorithmic trading varies in different countries and at different markets. In the United States the proportion of high-frequency algorithmic trading is estimated to be 73% of the trading volume (PC Plus, issue 312, Oct 8, 2011). The size of the part of algorithmic trading in comparison with conventional trading affects the liquidity of a particular instrument, movement of prices, as well as the size of the fluctuations, id est, volatility.

Trading algorithm is based on trading strategies. Trading strategy is a set of rules which prescribe how to react to signals and which orders to form. Trade strategy generates signals based on indicators. Indicator is a mathematical calculation of market data (open or close prices, highest and lowest prices, trading volumes) that is used to present generally available market information in an easy for decision making form.

As an example of a popular indicator, it is possible to name indicators based on the function of the moving average. The moving average is a function which value at each point of definition is equal to the average value of the previous period with a certain width. The simplest trading algorithm based on a moving average uses channel of trade. The channel is formed by the moving average shifted up by some percent and down by some percent. Transactions are carried at the lower and upper boundaries of such a channel. There are many algorithms with one or more moving averages. The total number of different algorithms can hardly be ever calculated. Apart from market regulators there are other groups of interest that may benefit from the research. They are traders themselves, id est persons participating in the trade in the role of buyers and sellers. For them, the interest will be in a better understanding of the market and the factors influencing it. Of course, the well-chosen strategies and adjustment of the algorithm will have a stable income with minimal understanding of the market. However, one day such a strategy becomes ineffective. With this approach, the trader will not be able to find out the cause of the loss of the effectiveness of their strategies. The better the trader understands the market, the more it is likely that he would be able to adjust his strategy. That is why it is important to understand not only the principles of markets, but the causes and characteristics of market behavior. In addition, it is theoretically possible to identify some classes and groups of trading strategies and algorithms by their impact on the market and thus try to discern various behavioral patterns.

4. Description of the Model

For this study a computer model was developed. Computer simulation model of the stock exchange can be divided into two principal parts. The first part is the core of the model. It includes work exchanges, the performance of applications, support for different types of applications, asset management, configuration of the model. The second part includes an extensible set of trading algorithms. The core of the model together with the algorithms constitutes the model. The set of trading algorithms is extensible, due to the need to deal with the large number of different algorithms after the model had been designed several trading strategies were implemented. Several series of experiments with different combinations of strategies and different distributions of strategies were conducted. For this study it was decided to design an agent-based model. This decision was determined by a number of factors. First, agent-based approach for modeling the exchanges is widely spread. Second, the existing alternative approaches such as discrete simulation or system dynamics models are based on the apparatus of differential or difference equations, and the description of the behavior of traders using mathematical models is not possible, or the level of its complexity is beyond the scope of this study. Finally, the agent model is just appropriate in a given context. A large number of traders can be represented as agents in the model. Trading strategies define the behavior of each agent, as a set of rules by which the agents is involved in the trade. The structure of the model is shown in Figure 1.

In the center of the model there is a stock exchange, as the place where orders are received and queued, place where transactions are performed and recorded. Agents request market data on transactions made in the previous period from the exchange. The same data is requested by indicators which are calculated on the basis of this data.

Duplication stream of market data from the stock exchange is necessary for an improved management of agents for them to commit transactions. Trading strategies involve indicators on which basis they send trading signals. They use values, calculated with indicators and process them according to some algorithm. Strategies exist independently of the agents. Thus, several agents may use the same strategy, which corresponds with the real trading. Agents, guided by signals from their trading strategies generate and send orders to the queue where they are processed.

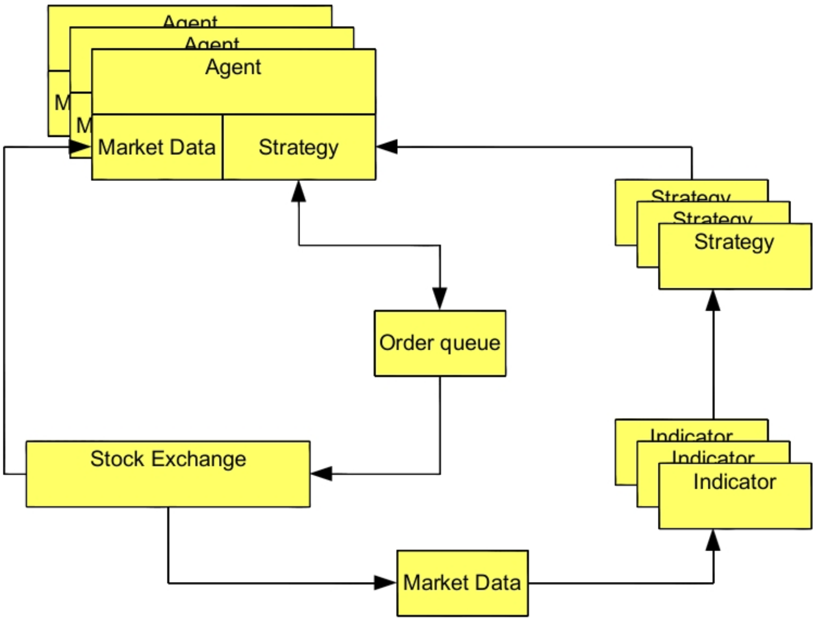

Figure 1 The Model

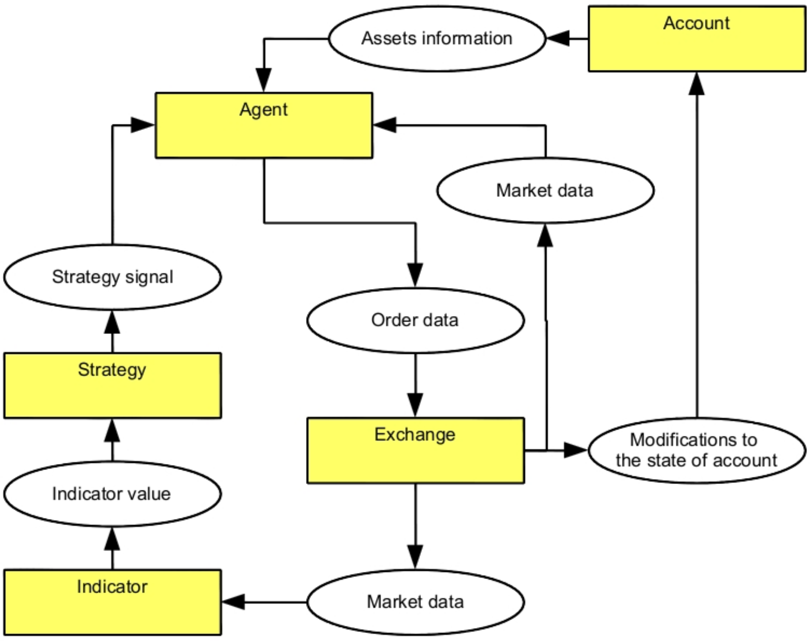

Figure 2 Data Flow in the Model

Figure 2 shows data flows in the model. Indicators request data on previous transactions from the exchange.

With this data values of the indicators are calculated. Strategies depending on the values of the indicators and their own parameters form trading signals that are, in fact, recommendations how to behave on the market, which orders to form, if any. Agents receive market data from the exchange, data about their assets and signals from their trading strategy. After processing the data in accordance with a certain algorithm, agent can generate an order for the purchase or sale of shares. Data on the order is sent to the stock exchange, where the order is created and placed in the queue. Exchange sends the data to change the account status of agents. Special unit is responsible for managing accounts.

Instead of relatively continuous transaction processing in a real exchange, where transactions are received near simultaneously, in this model transactions are performed in steps and orders are formed by turns. At the beginning of each step (iteration) agents check their strategies and send orders. At the end of each step those applications that can be executed are executed. Figure 3 is a diagram of the basic process.

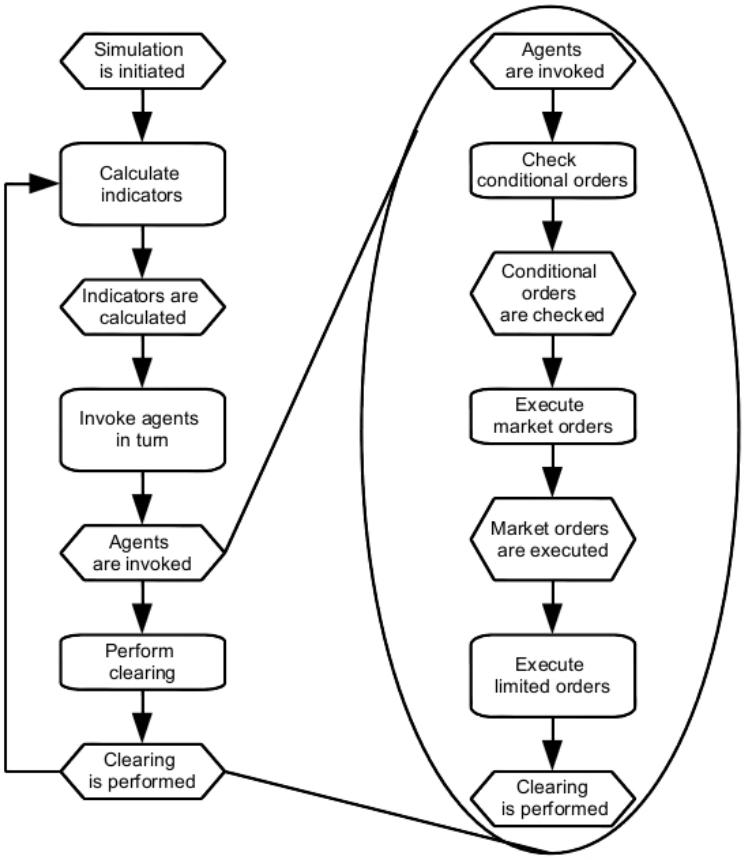

Figure 3 EPC-Diagram of Main Process

This process includes all the events in the model, from the start of the experiment and to the end of the last iteration of the trade cycle. At the beginning of each iteration the values of the indicators are calculated. Then, in turn, agents are invoked and they perform some actions referred to below. After all agents are interviewed, the process of clearing is performed, that is, execution of orders, transfer of ownership between the accounts of agents, debiting and crediting of funds. On this chart we can see details of the clearing process. In this model, the clearing operation involves execution of proper orders possible for execution, charge-off and enrollment. If special condition occurred, the conditional order is submitted to the queue, either as a market or as a limit order according to its original type. After verification of conditional orders, market orders are executed. These orders have priority and performed first. Then limit orders are checked and performed. After the clearing is performed next iteration of the simulation is started. The number of iterations is determined at the beginning of simulation, that is, before the experiment is started. At each iteration, agents are invoked one after another.

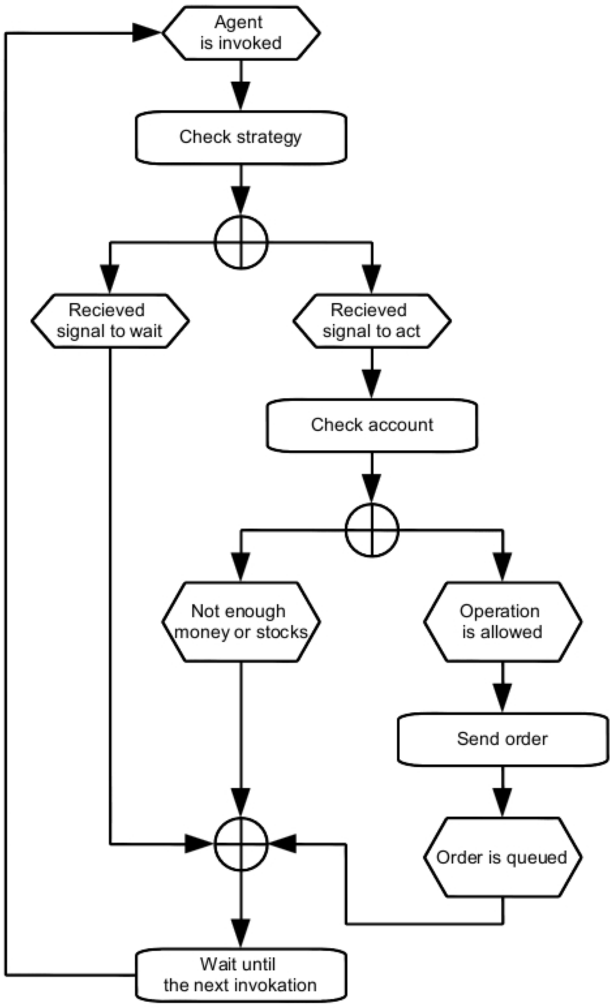

Figure 4 EPC-Diagram of Agent's Actions

Actions of an invoked agent are shown in Figure 4. After an invocation from the main process agent checks his strategy. The strategy requests the latest value of the indicator, which was calculated at the beginning of this iteration of the main process. If the strategy sends a signal to the agent to perform a transaction, the agent checks the status of his account. If strategy sends a signal to wait, agent proceeds to state of waiting for the next call in the following iterations. If account limits allow transaction, agent forms an order and sends it to the stock exchange, where it is added to the queue of orders. Otherwise, the agent waits. After an order is placed on the exchange agent finally proceeds to wait.

As a programming language for the implementation of this model programming language JAVA was chosen. As a development environment was chosen Eclipse Indigo. The argument in favor of the environment might be its relative lightweight in comparison with Net Beans. Eclipse framework is open source software that can be called an advantage for the research project. Program architecture is divided into two blocks, presented in Figure 5.

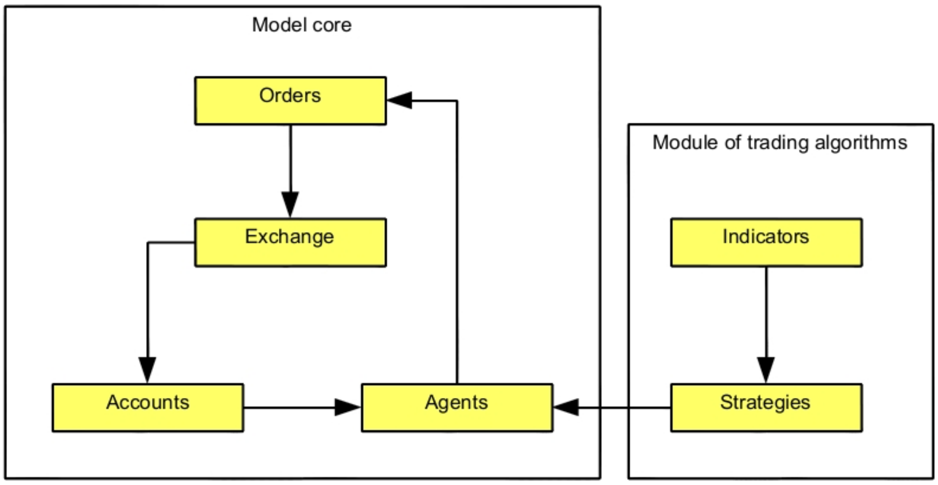

Figure 5 Software Modules Architecture

The first part of the computer model is the core of the model. The second part of the model can be called trading algorithms. The core of the model includes all the logic of order processing, clearing and account management. The center of the core is the exchange itself, which places orders in the queue, removes orders, manages queue, maintenances history of transactions. Since the exchange interaction of agents is applying for. The model supports all the main types of conditional and unconditional orders, that is why it is important to mention application sub-module as part of the core model. Accounts of agents and all logic of account management, including reservation of assets and assets transition from one account to another are also included in the core. Completion of the development model is the completion of the core model. That is why it does not require extensive modifications after it is developed.

The second part of the module constitutes trading algorithms. It contains all the logic associated with the processing of market data and the formation of trading signals to buy, sell or hold. This module consists of trading strategies and indicators. The connection between the module and the kernel is through trading strategies and agents that use them to determine their behavior.

5. The Studied Strategy

At this moment three strategies and one important indicator are implemented.

(1) Intelligent Investor strategy implements a strategy of intelligent investor. The essence of the strategy is to buy shares when they are sold at a discount to fair price. Here, discount is a relative discount, in percentages. Fair price is an estimated by every investor value of the stocks. On the stock exchange fair price is based on the financial performance of the related company. In this model a fair price is included artificially, it is installed before the experiment. Since all strategies, using historical data, repeats the history, the history should be created by other strategies. That is why it was important to implement this strategy, to make the model of the market more realistic. Intelligent investor strategy does not use any indicators.

Table 1 shows the values of parameters, used for the intelligent investor strategy. The lower limit is set at the level of fair price. Fair price is calculated artificially on the basis of historical data. The upper boundary is defined at low levels without any specific reasoning, taking into account the discount. These values of parameters are chosen to smoothly continue trading on historical data, to avoid serious fluctuations in prices at the beginning of the experiment.

Table 1 Intelligent Investor Strategy Parameters Values

Parameter	Distribution	Range
Number of agents with intelligent investor Strategy	No	500
Quantity of money per agent	Uniform	10000-1000000
Number of stocks per agent	Uniform	100-50000
Discount	Uniform	10-25%
Fair price	Uniform	32-45

(2) The other two strategies are based on the moving average indicator. One of the two strategies uses only one moving average. This strategy is implemented in the class IndicatorMA. Shares are bought when moving average crosses price taken with discount, if at that moment ma was higher than price. Shares are sold when moving average crosses price taken with added percentage, if at that moment ma was lover then price. Sales are possible only if the position has been previously opened.

Table 2 Simple MA Strategy Parameters Values

Parameter	Distribution	Range
Moving average period	No	10-120, war 5
Number of agents for each ma period	Uniform	100
Quantity of money per agent	Uniform	1000-5000000
Number of stocks per agent	Uniform	10-10000
Lower price	Uniform	0.1-1%
Upper price	Uniform	0-0.1%

Table 2 shows the parameters of a moving average strategy (InvestorMA). The period of the moving average is the width of the window or the calculation basis or the range of data used to calculate it. The upper limit determines price at which stocks should be sold. This limit is taken as a percentage of the value of the moving average, making thus the margin.

(3) At this moment last implemented strategy is a class MAInvestorSeveral. It uses several indicators of moving averages. When the moving average with the smallest period crosses above moving average with the second lowest period, and the other moving averages are not decreasing, the strategy sends a signal to purchase shares. The sell signal is generated when the moving average with the smallest period crosses above moving average with the second smallest period. The function of moving average shows a certain trend with the duration equal to the value of the period of this moving average. The idea of the strategy is to buy shares when the short-term trend is beginning to overtake the medium-term and long-term trends shows an increase. According to the strategy shares should be sold, when short-term trend crosses above the medium-term trend.

Table 3 Crossing MAs Parameters Values

Parameter	Distribution	Range
Moving average periods	No	20, 40, 100
Number of agents for each period	No	100
Quantity of money per agent	Uniform	1000-5000000
Number of stocks per agent	Uniform	100-10000
Discount	Uniform	0.01-5%
Width of local period	No	80

Table 3 shows the parameters of the strategy crossing moving averages (MAInvestorSeveral). The strategy uses three moving averages with periods of 20, 40 and 100. , The width of local period means the local number of transactions (ticks) that are counted for the current moment. This option is needed to calculate the local minimum and maximum prices, because there is no use in absolute minimum and maximum values. These values are calculated for the implementation of stop-losses and take-profits. Any strategy can be provided with these conditional actions, but in this research stop-losses and take-profits are tested only on the agents, that use crossing moving averages strategy.

Indicator moving average is calculated for each iteration of the model. It sums determined number of the latest values of prices and divides the sum by the number of values equal to the period of the moving average. This simple indicator is very popular.

(4) Another experiments used the principle of provocation. An additional agent with relatively big assets on his account was implemented. This agent does not use any strategies, and posts very large orders on the market at defined moments. The experiment was carried out with orders for sale, as well as with orders for purchase of shares. Orders for sale were posted at low prices, orders for purchase-at high prices.

6. The Research Results

A series of experiments was conducted. It consisted of simulations with different values of parameters. From all the simulations it is possible to point out two most typical.

(1) Experiments have shown that all the significant price fluctuations were caused by agents that used the intelligent investor strategy. They purchased and sold in accordance with their own vision of a fair price. Those agents, who used short-term moving average strategies only supported the movement, without serious improvements to it. From the graph it is clear that after considerable hesitation market comes to a sustainable position faster than linear function. Equilibrium was formed at approximately the level of the average price based on historical data. The experiment conducted showed that the market equilibrium for a given distribution strategies was stable even after significant forced deviations from this equilibrium price. Results of the experiment are presented on Figure 6.

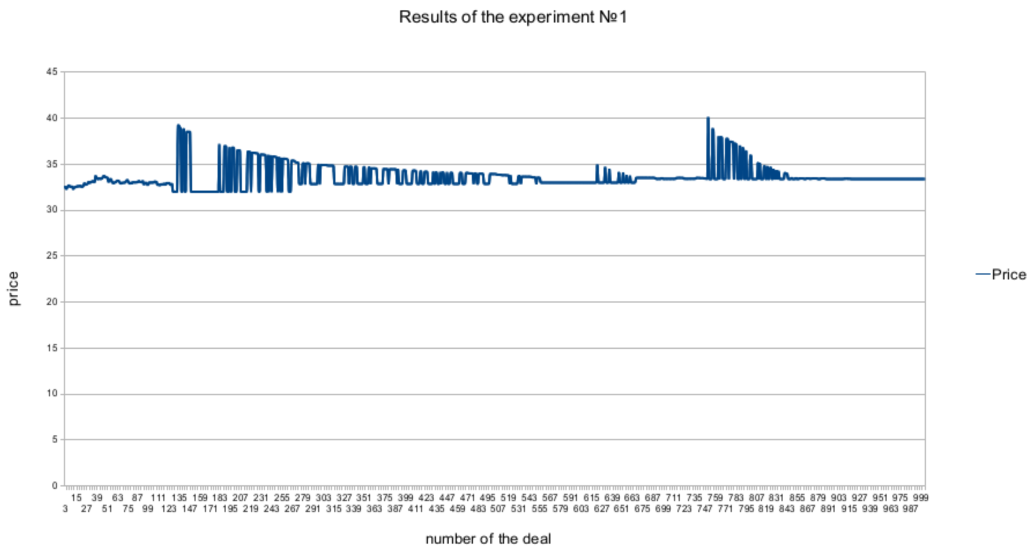

Figure 6 Experiment with the Strategy of "The Intelligent Investor"

(2) Figure 7 shows the results of an experiment which used the same values, but agents using intelligent investor strategy were excluded. The results of this experiment are substantially different from the previous results. First, liquidity is decreased. Both experiments used 15 iterations. If in the previous experiment there were 1002 transactions (with regard to the real prehistory data counting 126 ticks) in this experiment there were only 357 transactions. Less more than three times. Taken into consideration that the average amount of assets agents with the intelligent investor strategy possess were less, and their number was 5 times smaller than the number of other agents, such a significant reduction in liquidity cannot be explained only on the basis of that difference in quantity. Obviously, strategy type is responsible for the most part of the reduction in liquidity.

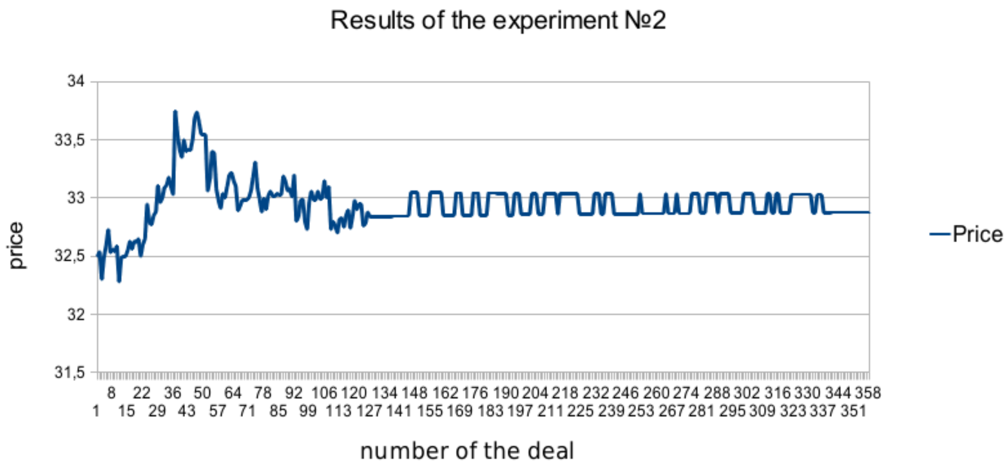

Figure 7　Experiment with Moving Averages Strategies

In addition to the reduction in liquidity in the experiment conducted a reduction in volatility can be noticed. Despite the sharp price fluctuations, these fluctuations are smaller than those that have been shown by historical data and the previous experiment. The characteristic feature of this experiment is that the price fluctuates about the same level. This fact can be explained by the fact that this group of strategies is based on market data from historical deals. Since these data is shared by all agents in the model (and it is also true regarding real exchange), it becomes obvious that strategies from this group provide stabilization of the market price at the point near to the level of equal demand and supply.

(3) Experiments have shown that this provocative agent has no significant impact on the market. This can be explained by the fact that the model has no strategy of using market signals to form the current state of supply and demand. This condition reflects the so-called “exchange glass”, which shows the current balance of supply and demand on the market of the instrument. Therefore, other agents are not aware of the balance of supply and demand. Even when the experiment is carried out within the framework of provocation, which consists in flooding large orders with non-market prices, the market in any way does not respond. The market is not interested in current orders in the market; it is interested only in historic deals, which have been really performed.

(4) If the market has a significant amount (in terms of capital at their disposal) of agents using different combinations of moving averages as a trading strategy, market will seek to ensure that it imposes on the majority—that is, to the average of the market. The group of strategies consisted of moving averages helps to establish the equilibrium price equal to the average price of the longest (with the largest period) moving averages. Under long period moving averages such moving averages are understood, which are calculated on the basis of a

large number of values. The price will be approximately equal to the longest running average, because traders who use these indicators will for the longest time demand shares at higher prices, or offer shares at lower prices. Members of long moving average strategies group will tend to trade at prices different from the average price. This will continue until the market is equal at some average level for all participants. Gradually, the market will come to equilibrium. In a series of experiments it was shown that the price values returns to their stable level quickly, faster than a linear function.

(5) It can be assumed on the basis of experiments conducted, that the role of trading robots (or bots) is to ensure that they increase market volatility. If the market falls, the robots can support that drop. If the market grows, the bots will support the growth, strengthening it. On their own trading robots are neutral with respect to price movements. On the contrary, they keep prices at a stable level. Therefore, if market fluctuates, these fluctuations are not created by robots, no, robots do not create them. They can only amplify fluctuations caused by non-algorithmic trading, or very specific algorithmic trading. These assumptions follow from the fact that a large part of trading strategies uses transaction history to generate trading signals.

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