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Author(s)	Raghavendra, Srinivas; Paraschiv, Daniel; Vasiliu, Laurentiu
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A Framework for Testing Algorithmic Trading Strategies

Srinivas Raghavendra, Daniel Paraschiv and Laurentiu Vasiliu*

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Department of Economics
National University of Ireland, Galway

<http://www.economics.nuigalway.ie>

** Department of Economics National University of Ireland, Galway
CIMRU/DERI National University of Ireland, Galway*

Abstract

Algorithmic trading and artificial stock markets have generated huge interest not only among brokers and traders in the financial markets but also across various disciplines in the academia. The emergence of algorithmic trading has created a new environment where the classic way of trading requires new approaches. In order to understand the impact of such a trading process on the functioning of the market, new tools, theories and approaches need to be created. Thus artificial stock markets have emerged as simulation environments to test, understand and model the impact of algorithmic trading, where humans and software agents may compete on the same market. The purpose of this paper is to create a framework to test and analyse various trading strategies in a dedicated artificial environment.¹

Keywords: Artificial Stock Market, Double Auction, Back Testing, Algorithmic Trading, MACD

1. INTRODUCTION

Algorithmic trading and artificial stock markets have been in the last decade of high interest for business, IT research and academia. The emergence of algorithmic trading has created a new environment where the classic way of trading requires new approaches. High trading speed and automated algorithms have accelerated the trading process beyond human capabilities, moving brokers in a new area that can be called 'micro-second economics'. In order to tackle this, new tools theories and approaches need to be created. Thus artificial stock markets have emerged as simulation environments where to test, understand and model the already complex human behaviours and also to analyse the impact in the system of algorithmic trading where humans and software agents may compete on the same market. Considering this, the purpose of this paper is to create a framework to test and analyse various trading strategies in a dedicated artificial environment.

2. RELATED WORK

There exists a vast literature on the computer-simulated, artificial financial markets following the pioneering work done at the Santa Fe Institute. Some studies proposed artificial markets populated with heterogeneous agents endowed with learning and optimising capabilities with an aim to mimic the performance of the real world markets. These studies have concentrated on the behavioural side of the agents and worked out its implications for the overall market outcome. Other studies looked at various trading rules attributed to agent types and its implication for the market outcome. It is probably fair to say that the so called stylized facts of the financial markets have not yet been fully captured models in the genre. However, there is also another related strand of literature in this area, which studies the interaction between artificial agents and human agents and its implications for understanding the complexities of the financial market. The fundamental question in this literature is the following: How do artificial (software) agents influence the market behaviour of human agents and does the knowledge about software agents influence human behaviour and the market outcomes? Given the vastness of these two strands of literature, we will discuss a representative model from the first strand of literature and its relation to the present work, and briefly discuss some of the key findings of the second strand of literature and its relation to our future work.

In the paper by Raberto et al (2001) is presented an agent-based artificial financial market with heterogeneous agents who trade one single asset through a trading mechanism in order to study the process of price formation. The price-formation process of the market was built around a mechanism for matching demand and supply of market orders. In this market, agents are endowed with limited resources with the global-amount of cash in the economy in time-invariant. There are N agents and at each simulation step each agent issues a buy order with probability p_i or a sell order with probability $1-p_i$. The orders are generated in the following way: Suppose the i^{th} agent issues a sell order of quantity a_i^S at time $h+1$. The quantity of stocks offered for sale at time step $h+1$ is a random fraction of the quantity of stocks owned at time step h according to the rule: $a_i^S = [r_i A_i(h)]$ where r_i is a random number drawn from a uniform distribution in the interval $[0,1]$ and $A_i(h)$ is the amount of assets owned by the i^{th} agent at time h . In addition, a limit sell price s_i is associated to each sell order. The limit prices are computed by $s_i = (\frac{p(h)}{N_i(\mu, \sigma_i)})$ where $N_i(\mu, \sigma_i)$ is a random draw from a Gaussian distribution with $\mu = 1.01$ and a standard deviation is proportional to the historical volatility computed through the equation $\sigma_i = k\sigma(T_i)$ with k being a constant and $\sigma(T_i)$ is the standard deviation of log-price returns. The buy orders are generated in a fairly symmetrical way with respect to sell orders, where the buy order, c_i , at time $h+1$ is a random function of available cash at time h , i.e., $c_i = r_i C_i(h)$ with r_i being a random number drawn from a uniform distribution in the interval $[0,1]$ and $C_i(h)$ is the amount of cash with i^{th} agent. It is interesting to note that in this model the heterogeneous random behaviour arises from the fact that the random number r_i and $N_i(\mu, \sigma_i)$ are generated at each time step. The price formation process is set at the intersection of the demand and supply curves with the former is a decreasing step function of price and the latter is an increasing step function of price. The clearing price or equilibrium price is computed by the system at which the two functions cross.

Even though the results of the model seem to capture some of the stylized facts of fat tails and volatility clustering that we observe in real financial markets, limiting the model to only random or uninformed agents is too simplistic and there is a scope for generalising this model with different types of agents to test the robustness of the results. Subsequent development in the area has explored this issue using more sophisticated agent types and trading mechanisms to trace the stylized facts of the real financial markets that include Herding, Bubbles and Crashes. A comprehensive review of this field can be seen in Samanidou et al (2007). However, in terms of comparing various artificial agent models that generate various stylized facts of the financial markets, it is pertinent to develop an artificial agent environment that has

the capability of back-testing whereby it lends itself as a standard for comparing the empirical verifiability of this class of models. It is in this sense, the model presented here is a contribution to the literature of artificial agent models.

On the other hand, there is another strand of literature that focuses on the question of how artificial (software) agents influence the market behaviour of human traders by explicitly modelling the interaction between the two. This literature arose as a direct consequence of studies that questioned the role of algorithmic trading in big stock market crashes like the '87 crash. For example, Leland and Rubinstein (1988) and Varian (1998) have elucidated the role of artificial traders that followed price insensitive strategies such as portfolio insurance which might have contributed to the crash. As a representative study of this class Grossklags and Schmidt (2002) model introduces human agents to play with artificial agents with a passive arbitrage seeking strategy in a double auction experiment. They report the influence of information of the existence of artificial (software) agents on behaviour of human traders in the market. They conclude that the common knowledge on the presence of artificial arbitrageur agents has a significantly positive effect on human traders' ability to converge to equilibrium whereas in the alternative scenario of no-knowledge on the part of human traders of the presence of artificial arbitrageur agents leads to a lower efficient market outcome.

3. DEFINITIONS

Stock Definition

The stock is an instrument that signifies an *ownership position in a corporation*. It represents a claim on its proportional share in the corporation's assets and profits. Ownership in the company is determined by the number of shares a person owns divided by the total number of shares outstanding, see (Day Trading Term and Definition)

Stock Market Definition

A stock market is a place where stocks or other securities are bought and sold, see (Stock Exchange Definition). It is a place where it makes the connection between people that have wealth and people that know how to create wealth.

Algorithmic Trading

Algorithmic trading represents a trading system that utilizes computer programs for making transaction decisions in the financial markets. The programs implement algorithms that are based on certain investment strategies to determine size, price and timing of the orders.

4. BACK-TESTING

Back-testing is the process of optimizing a trading strategy using historical data and then seeing whether it has predictive validity on current data, see (Back-testing definition)

The historical data for each stock is loaded from yahoo finance website with the following query:

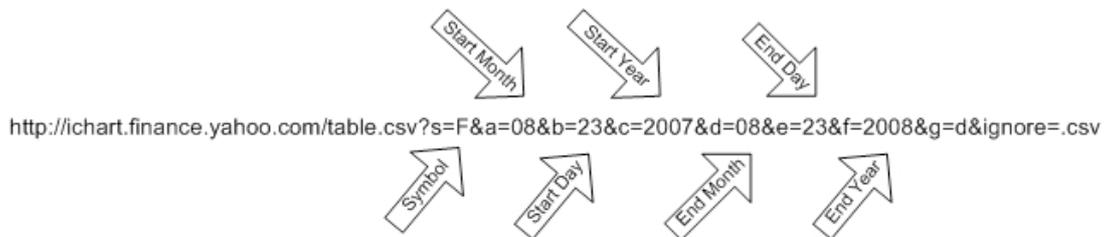


Fig. 1 HTTP Query for history of a stock.

The first parameter in the query is the symbol, which in this case represents Ford. The second parameter is the start month then start day, start year, end month, end day and end year. The result of the query is a CSV file of the following form:

```
Date,Open,High,Low,Close,Volume,Adj Close
2008-09-22,5.34,5.34,4.86,4.95,51322000,4.95
2008-09-19,5.66,5.70,5.15,5.29,91329800,5.29
2008-09-18,4.99,5.35,4.76,5.28,110364100,5.28
2008-09-17,5.00,5.04,4.63,4.94,122907200,4.94
2008-09-16,4.60,5.18,4.55,5.07,98797100,5.07
2008-09-15,4.61,5.07,4.50,4.74,103092600,4.74
```

Fig. 2 Result of the query for history of a stock

On the first line are the metadata and then on each line are the date, the open price, high, low and close price, volume and the adjusted close. The adjusted close is the closing price adjusted for dividends and splits.

In Back testing it is created past, current and future data from past history of a stock. In figure 3 a) is presented the evolution of a stock on a real stock market.

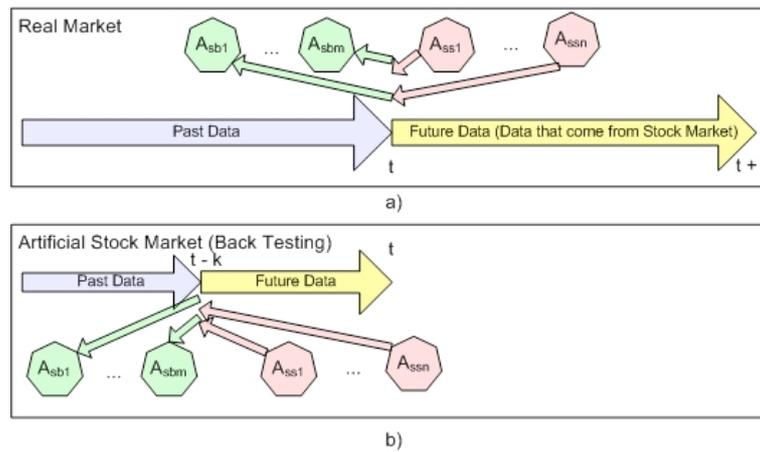


Fig. 3 Back testing time evolution

The current time is t . The past data are all data before time t . In reality all agents place orders at time t and the stock evolve based on the supply and demand of these agents, thus the future data is unknown. When somebody wants to test strategies he or she can do it fast using the past history as past and future data. In figure 3 b) is presented how the past data is divided in two parts as past data and future data. The data before time $t - k$ is past data and data after $t - k$ is future data. The current data is at time $t - k$. The agents do not know the future data, thus although this data is known the agents do not know this data. It is assumed that when the number of orders placed in back testing mode is much less than the number of orders placed on the real market then the orders do not influence the market. With back testing mode the algorithms of placing orders on the market can be tested in seconds instead of weeks or years of time that passes on a real market.

The algorithm used for back testing is:

1. We have the past market data for the time period $[0, T]$
2. At time 0, agents will take the opening price of time 0 and place orders. At the end of the trading day the data for that day, namely, the opening price, high, low and the closing price is stored in the history.
3. At time 1, agents will not only have the opening price of time 1, but also the opening price of time 0 stored in the history for placing their orders. Again, at the end of the trading day the data for that day, namely, the opening price, high, low and the closing price is stored in the history.
4. This loop will go on until we exhaust all the past market data.

The algorithm is also presented in the next figure

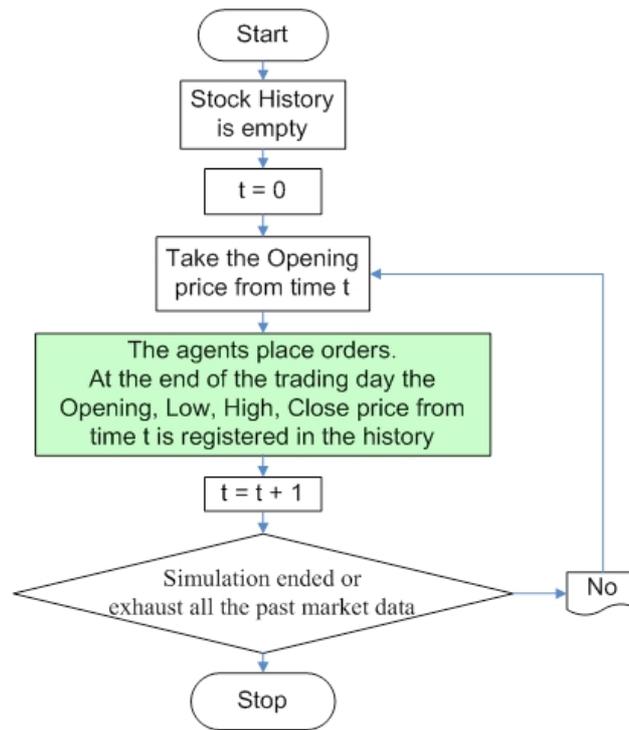


Fig.4 Back testing method.

5. DOUBLE AUCTION

In a double auction (Double Auction) stock market buyers and sellers place simultaneously buy and sell stock orders. Most of the stock markets use double auction systems. Examples of double auction stock markets are NYSE and AMEX. The price of a stock is given by supply and demand. For a stock if the total volume of buy shares is greater than the total volume of sell shares then the price of the stock is going up. If the volume of buy shares is less than the volume of sell shares then the price goes down.

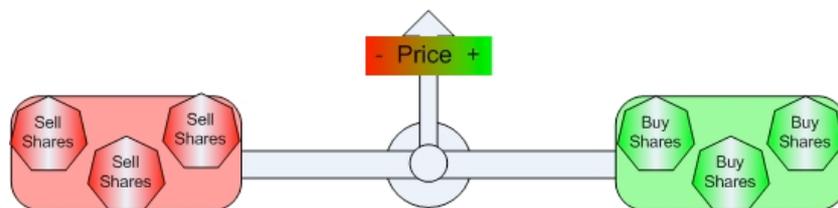


Fig.5 Double Auction seen as a balance of buy shares and sell shares

In figure 5 is presented a balance with the volume of buy shares and the volume of sell shares. In this example the market is at equilibrium, the volume of buy shares is almost equal with the volume of sell shares. When there are more sell shares, the price is decreased and sellers tend to remove the sell orders because their advantage is to sell high and the buyers

tend to place more buy orders because they want to buy cheap. When there are more buy orders the situation is reversed. In double auction system the price is changed to create equilibrium between supply and demand.

6. MODEL FRAMEWORK: ARTIFICIAL STOCK MARKET WITH ALGORITHMIC TRADING

The framework of the artificial stock market is presented in figure 6. The artificial stock market can be in one of the two modes: double auction or back testing. Using algorithmic trading the agents place buy or sell orders on the artificial stock market. The artificial stock market makes the connection between buy orders and sell orders of the same stock. In the software it was implemented a client server architecture using sockets in which the artificial stock market is the server and the agents are the clients.

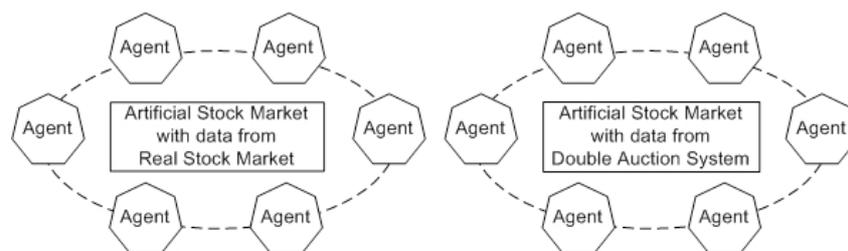


Fig. 6 The framework of the artificial environment

In order to test the artificial stock market and the algorithmic trading on this market, there were implemented six types of agents: agents that place random orders, a human agent for a user to be able to place buy/sell limit or market orders, a market maker agent and 3 types of strategic agents which have 3 templates of strategies.

The algorithm of the Artificial Stock Market is:

1. while (market is open) do
2. IF time to apply tick passed THEN
3. Change all Stocks Price with a tick
4. Process Orders for a cycle
5. IF a day has passed THEN
6. Change time period to all stocks

In the software of the artificial stock market are four queues: one for buy at market price orders, one for buy at limit price orders, one for sell at market price orders and another one for sell at limit price orders. An order from an agent is placed in one of these queues. When in the queue with limit price are orders that satisfy the limit condition then the orders are processed repeatedly one from market orders queue and one from limit orders queue.

The aim of a double auction system is to maximize the number of shares processed, see (Demarchi et. Al.). To do so the price of each stock is changed every 100ms with a tick, at step 3. The formula of the new price for each stock is:

$$Price_{new} = \begin{cases} Price_{old} + Tick & IF \ V_B - V_S > 10 \\ Price_{old} - Tick & IF \ V_S - V_B > 10 \\ Price_{old} & otherwise \end{cases}$$

Where V_B is the total volume of buy shares form orders from the queues with buy at market price and buy at limit price of the stock with price P; V_S is the total volume of sell shares from orders from queues with sell at market price and sell at limit price of the same stock.

There were implemented two types of tick. One type of tick is with a fixed value of 0.005 and another type of tick is with a dynamic value give by the following formula:

$$Tick_{Dynamic} = \frac{1}{1000} \times Price_{old} + \frac{|V_S - V_B|}{V_S + V_B}$$

At step 4, at most 1000 shares from buy and sell queues are matched for each stock. The queues with the limit orders are sorted by limit price and timing when the order was placed. If there are orders in the queues with limit price that satisfy the limit criteria then the processed orders are repeatedly one from the queue with the market price and one from the queue with the limit price. Shares from the same order can be processed with different prices and the final price of the shares is given by the volume weighted average price formula (Kim), that is:

$$Price = \frac{\sum noOfShares \text{ Pr ocessed} \times \text{ Pr ocessed Price}}{TotalSahresInOrder}$$

When a day has passed (step 6) the current data is added to a list of old data in case of double auction mode or real data are loaded from database and added to this list of old data in case of back testing mode. For these tests the real data were downloaded from Yahoo Finance, being the historical data from 1st of March 2005 to 24th of March 2008 for ten companies: Microsoft, Yahoo, IBM, Google, Apple, Sony, General Motors, Ford, Honda Motor and NISSAN.

7. AGENT TYPES

Using algorithmic trading agents have knowledge to buy, hold or sell stocks. The tested and analyzed classes of agents are random agents, human agents and strategic agents.

1) Random Agents: They are useful to have buy and sell orders on the market. They make the stock price to go up and down and on average the stock price is at equilibrium. They place, for each stock, buy orders with probability p and sell orders with probability $1-p$. In our case we chose p to be 0.5. They place orders with quantity of shares uniform distributed between Q_{min} and Q_{max} . After a uniform distributed, between R_{min} and R_{max} , random number of placing orders they check the total volume of buy orders and sell orders and they place an order that makes the number of buy shares equal with the number of sell shares. When random agents are activated it is generated for each agent random numbers for Q_{min} , Q_{max} , R_{min} and R_{max} . Q_{min} and Q_{max} are uniform distributed between 0 and 500, R_{min} is 10 and R_{max} is uniform distributed between 10 and 30.

2) Human Agents & Market Makers agent: Anybody can place an order manually using a human agent. The orders can be limit orders or market orders. The strategic agents always buy shares first and then sell what they bought. Thus somebody has to place shares in the double auction system. The human agent can place buy or sell orders for each company or for all companies at once. With human agent we place shares on the market in order the strategic agents to buy them. In real stock markets the market makers make sure that shares are available for buy orders. Optionally we can start an agent called Market Makers Agent that at each few days automatically makes sure that buy volume and sell volume (demand and supply) are almost balanced.

3) Strategic Agents: These agents implement a rule of the form:
IF condition THEN buy/sell stock(s)

There are going to be used three types of strategic agents. The rules of these types of agents are presented using candlestick charts. The candlestick charts formation are presented in figure 7

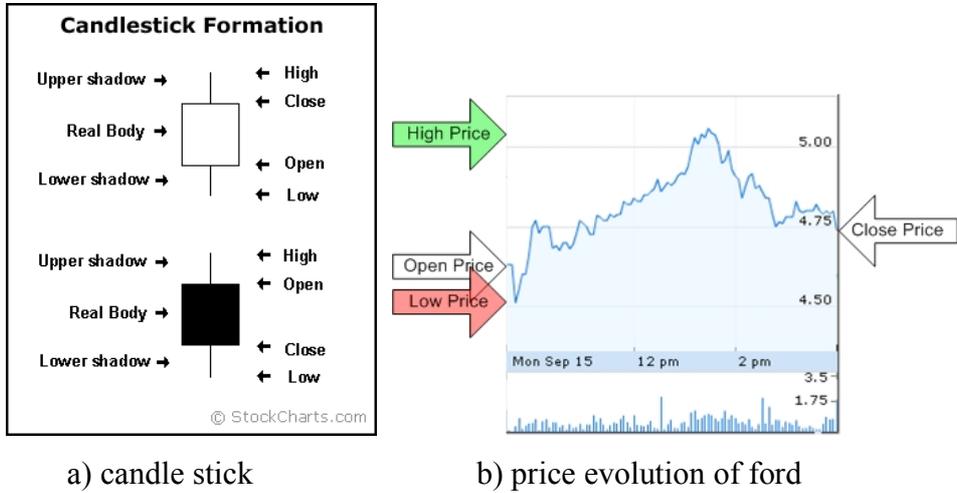


Fig. 7 Candle stick formation

In figure 7 b) is presented the price evolution of Ford for one day. There are arrows for opening price that is the first price in that day, lower price that is the lowest price in that day, higher price that is the highest price in that day and the closing price that is the last price in that day. The formation of a candle stick is based on open price, low price, high price and close price. In figure 7 a) is presented the candle stick formation. When the closing price is higher than the opening price, the chart is white or green and when the closing price is lower than the opening price, the chart is black or red.

a) Rule 1 Agent type: This type of agent implements the rule:

IF the agent has stock X in portfolio AND Y is not in portfolio AND X is above UpThreshold AND Y is below DownThreshold in NoOfDays THEN sell stock X and buy Y with money from stock X.

With this rule the agent sells with a profit a stock that he or she bought previously and buy a stock that fall with a given percentage in a given number of days in the hope that this bought stock will rise in value. In figure 8 a) and b) is presented an example with this rule. In this example stock X is Yahoo and stock Y is Sony. It is supposed that Yahoo stock is in portfolio and Sony stock is not in portfolio. In figure 8 a), the blue dot represents the moment when the stock was bought. When the Yahoo stock price rose at least Up Threshold then it is time for

this stock to be sold. The program searches the whole stocks that are not in portfolio and extracts the one with the highest fall in a no of days (NoOfDays). Let's say that the stock with the highest fall is Sony. If also Sony has the fall higher than the down threshold then the condition is met and Yahoo is sold and with the wealth from Yahoo Sony shares are bought.



a) stock X from rule 1



b) Stock Y from rule 1

Fig. 8 The evolution of stocks X and Y from Rule 1

When the agents of this type are activated initially they buy randomly 3 stocks of 500 shares each and they have assigned the parameters UpThreshold, DownThreshold and NoOfDays. The tests were with 98 agents of this type with the parameters being combinations of the form: no of days 5 and 10, up threshold and down threshold 1%,4%,7%,10%,13%,25% and 50%.

b) Rule 2 Agent type: This type of agent implements the rule:

IF the agent has stock X in portfolio AND X is above UpThreshold OR X is below DownThreshold THEN sell stock X and buy Y that is not in portfolio and has the highest fall in NoOfDays, with money from stock X.

This rule is an exit rule for stock X, the stock X is sold in case of an increase in price with a threshold or a decrease in price with another threshold. With the wealth from stock X another stock Y is bought. This stock Y has the highest fall in a given number of days and it is between the stocks that are not in portfolio,. It is desired that Y will increase in price because it already decreased in price. Recursively the same rule is going to be applied for Y.



a) Stock X from rule 2



b) Stock Y from rule 2

Fig. 9 The evolution of stocks X and Y from Rule 2

In figure 9 a) and b) is presented an example with this rule. Yahoo is the stock X and Sony is the stock Y. Yahoo is in portfolio and Sony is not in portfolio. If Yahoo goes up or down with given threshold then it is time for Yahoo to be sold. In this case the yahoo reaches the down threshold, thus it will be sold with loss wealth. When Yahoo reaches a threshold the condition is met and it is searched the stock that it is not in portfolio and has the highest fall in no of days, let's say that the found stock is Sony. The yahoo shares are sold and with the wealth from Yahoo shares Sony shares are bought.

Like in case of rule 1, when the agents of this type are activated each agent buys 3 stocks of 500 shares and they have the same values for UpThreshold, DownThreshold and NoOfDays.

c) MACD Agent type: This type of agent implements the rule:

IF X is in portfolio AND the histogram changed from positive to negative THEN sell X;
IF X is not in portfolio AND the histogram changed from negative to positive THEN buy X.

MACD (Moving Average Convergence Divergence), see (MACD), is a method to identify a trend for a stock. The formulas for MACD are:

$MACD = EMA[D2] \text{ of price} - EMA[D1] \text{ of price}$

$signal = EMA[D3] \text{ of MACD}$

$histogram = MACD - signal$, where EMA is the exponential moving average, see (EMA) with the give number of days (D_i), and $D1 > D2 > D3$

When the histogram is positive it is an up trend and when the histogram is negative it is a down trend. These agents consider a buy signal when the histogram changes from negative to positive and a sell signal when the histogram changes from positive to negative. In case of a buy signal the agent buys 500 shares and in case of a sell signal the agent sells the 500 shares.



Fig. 10 MACD rule

In figure 10 is presented an example of MACD rule on Sony stock. The green lines represent when to buy and the red lines represent when to sell. Initially at the beginning of April 500 shares are bought. Then on around 12 of May these shares are sold for a profit. Soon new shares are bought because the histogram (the blue graph) just changed from negative to positive. On 27th May the shares are sold without any profit or lose. At the beginning of June new shares are bought and on 10 of June these shares are sold with wealth lose.

The tests were with 121 MACD agents in back testing mode and 8 MACD agents in double auction mode. The number of days are $D3 = i$, $D2 = D3 + j$ and $D1 = D2 + k$, where i is 3,6,9 and 12, j is 2,4,6,8 and 10 and k is 10,15,20,25,30 and 35 for the case of 121 Agents and i is 4 and 8, j is 3 and 9 and k is 10 and 26 for the case of 8 agents. The default values for MACD are $D3 = 9$, $D2 = 12$ and $D3 = 26$ and these values are also added in the case of 121 MACD agents.

8. RESULTS AND DISCUSSION

To analyze the behavior of the artificial stock market an index was created, which is the arithmetic average of all 10 stocks, and for each stock and index are candlestick charts, a chart with logarithmic return and a chart with the distribution of return. The charts were implemented using JFreeChart which has a lot of java open source charts. Also for each stock

are statistical indicators like excess demand, current price, price change, current volume, average volume, number of orders processed and the total number of days. To see all indicators see figures 11 and 12.

The statistics that are seen for each agent are initial wealth (money), current wealth, portfolio wealth, the percentage of profit or loss, no of bought orders, no of sold orders, no of bought shares and no of sold shares for each stock and per total. All agents are sorted by profit and loss in order to see the agents that have the highest profit and the agents with the highest loss.

Random agents and human agent

The random agents, also known as uninformed agents, are useful to guarantee a volume of shares on the artificial stock market for both modes back testing and double auction. They place buy and sell orders without checking the price and in average the number of sold shares are equal with the number of bought shares. Usually their profit is negative. Sometimes it happen that 20% of these agents to have significant profit when the stocks follow a positive trend, but the profit is not for long time.

If only these agents are active, in double auction mode, then the stocks follow a sinusoidal move and the average of each stock and the average of the index is usually equal with the initial value. When the human agent is also active and we place a buy order with the volume equal with half of the average daily volume then a positive trend follow for the respective stocks. If we place a sell order with a significant number of shares then a negative trend follows. This shows that when in reality somebody places an order with a huge amount of shares, this is going to cause a trend in the stock price.

In reality there are also taxes and we considered the taxes included in the bid ask spread, which is the money that goes to the artificial stock market.

Random Agents, Human agent and the agents with rule 1 and rule 2

There were four main simulations with different types of agents and different modes, as presented in table 1 and table 2. The first two simulations are with random agents, human agent and the agents with rule 1 and rule 2. In table 1 are presented the results in double auction mode and in table 2 are presented the results in back testing mode.

Table 1 The profit and lose of agents from different types of agents in double auction mode

Double Auction			
Random Agents, Human agent and the agents with rule 1 and rule 2 (150 days)			
Winner:	Rule 1 , Profit: 10.42%		
	Rule 2, Profit: 8.49%		
Loser	Rule 2, Loss: 4.15%		
Random Agents, Human agent, rule 1 (R1) and rule 2 (R2) agents and MACD (M) agents			
	250 days	500 days	750 days
Winner:	R1: 11.8%	R2: 19.1%	R2: 35.2%
	R2: 9.2%	R1: 13%	R1:16.8%
	M: 3.99%	M: 1.62%	M: - 0.37%
Loser:	R2: - 2.9%	M: -5.2%	M: - 8.26%

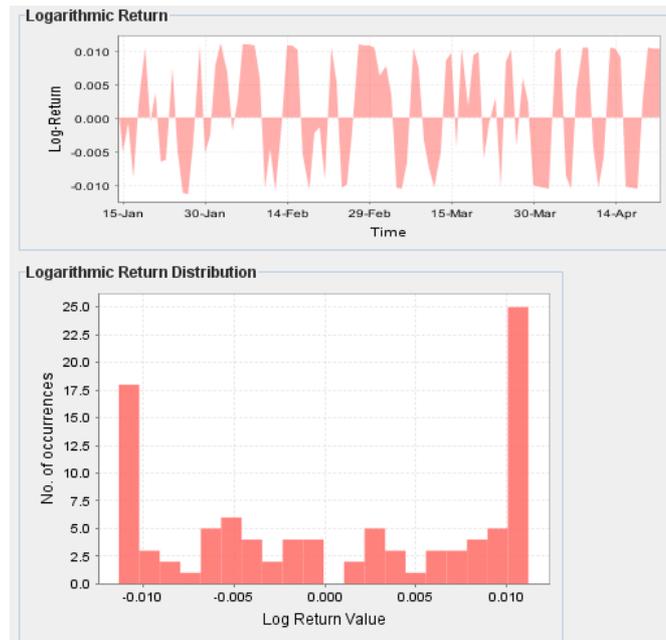
Table 2 The profit and lose of agents from different types of agents in back testing mode

Back Testing			
Random Agents, Human agent and the agents with rule 1 and rule 2 (150 days)			
Winner:	Rule 1 , Profit: 11.17%		
	Rule 2, Profit: 7.3%		
Loser	Rule 2, Loss: 3.13%		
Random Agents, Human agent, rule 1 (R1) and rule 2 (R2) agents and MACD (M) agents			
	250 days	500 days	750 days
Winner:	R1 : 15.2%	R1 :23.8%	R1 : 26%
	R2: 11.4%	R2: 21.4%	M: 22.6%
	M: 11.01%	M: 15.19%	R2: 13.5%
Loser:	R2: -4.4%	R2: - 8.37%	R2: - 8.6%

In order to test the behavior of these agents we start 10 random agents, 98 rule 1 agents and 98 rule 2 agents as presented in section 7. The agents of type rule 1 and rule 2 initially buy a total of 29400 shares of each stock. To make these shares available, with the human agent were manually placed a sell order with this amount of shares for all stocks. If we do not make available these shares then an up trend is going to be created as presented in the behavior of random agents and human agent.



a) The stock chart



b) Logarithmic return and logarithmic return distribution

Fig. 11 Simulation in double auction mode

In Figure 11 a) is presented the evolution of a stock in double auction mode with random agents, rules agents and human agent. This chart shows the evolution of the stock price and of the volume in the last 30 days. In figure 12 a) is presented the evolution of the google stock in back-testing mode. In Figures 11 b) and 12 b) are presented the logarithmic return and the distribution of this return for the last 100 days. The formula for logarithmic return is $\text{Log Return} = \ln(\text{close price}) - \ln(\text{close price of previous day})$ Using these agents the distribution of

return is bimodal for most of the stocks in double auction mode. Usually in back testing mode the distribution of logarithmic return is a normal distribution.

In double auction mode an agent of rule 1 having up threshold 1% and down threshold 7% in 10 days has proved to have the highest profit, 10.42%, in 150 days, see also “Rule 1” agent in table 1. In this case it means that it is good to sell the stock from portfolio with the highest profit and buy stocks with a fall of at least 7% in the last 10 days. On the second place was an agent of rule 1 type with 4% up threshold and 4% down threshold in the last 10 days with a profit of 9.7%. On the third place was an agent of rule 2 type with up threshold 50% and down threshold 1% with a new buy of a stock that has the highest fall in the last 10 days, having a profit of 8.49%, see also “Rule 2” agent in table 1. From 196 agents of type rule 1 and rule 2 only 9 agents had lost money. The highest loss was for the agents of type rule 2 with up and down thresholds of 1% for 10 and 5 days, with lose of 4.15% and 3.79%. In table 1 is seen the rule 2 agent with a lose of 4.15%. On the third place was a rule 2 agent with a loss of only 0.51% which had 10% up threshold and 4% down threshold with new buys of the stocks with the highest fall in the last 10 days.



a) the stock chart



b) Logarithmic return and logarithmic return distribution

Fig. 12 Simulation in back testing mode

In the back testing mode, after 150 days, the first three places were of agents of type rule 1. The first one had 11.17% profit as seen also in table 2, the second one had 10.94% profit and the third one had 9% profit. The parameters were up threshold 25%, down threshold 10% and 10 days for the first agent, up threshold 50%, down threshold 4% and 5 days for the second agent and up threshold 25%, down threshold 7% and 5 days for the third agent. The fourth one was of rule 2 agent with a profit of 7.30% having the parameters 10% for up and down threshold and 10 days. These agents can be seen in table 2. In this mode 54 agents from 196 agents of rule 1 and rule 2 type had a loss, with the highest loss 3.13%, of rule 2.

Random Agents, Human agent, rule 1 and rule 2 agents and MACD agents

There has been run simulation with these agents in double auction mode and back testing mode for 750 virtual days. In double auction mode there were 10 random agents, one human agent, 196 rule 1 and rule 2 agents and 8 MACD agents. There was noticed that MACD agents detect trends and if in the market are many agents that use MACD then they create trends. With 121 MACD agents in double auction mode the whole market went up or down in case of a small up trend or small down trend. They create mass buying in case of a small up trend and mass selling in case of a small down trend. In the simulation with 8 MACD agents we created equilibrium between buy orders and sell orders using the human agent and then the index was almost constant on the period of simulation. The distribution of return was

bimodal for most of the stocks, like in figure 11. After 250 days on the first and second place was an agent of rule 1 type and on the third place was an agent of rule 2, with profits 11.82%, 9.88% and 9.20% respectively. The first MACD agent was on the 18th place with a profit of 3.99%. From the 8 MACD agents only 2 had lost 2.60% and 3% of their money. After 500 days rule 2 and rule 1 agents were on the first places. The MACD did worse than after 250 days. After 750 days Rule 2 was on the first place with 35% profit and rule 1 was on the 5th place with 16% profit. In this case all MACD agents had lost money. In table 1 are presented these agents where R1 means the agent with rule 1, R2 means the agent with rule 2 and M is the MACD agent.

In the simulation with back testing mode there were used the same agents except for MACD that were 121 agents because this time they do not influence the market. For most of the stocks the logarithmic return had a Gaussian distribution. In this mode all MACD agents did not lose money. Rule 1 was also on top in this mode. After 250 days the agent with the highest profit was of rule 1 and it had 15.2% profit. On the fourth place was an agent with rule 2 having 11.38% profit and on the 6th place was an MACD agent with profit 11%. After 500 days an agent with rule 1 had 23% profit, an agent with rule 2 had 21.82% and an MACD agent had 15.19% profit. After 750 days an agent with rule 1 had 26% profit, an MACD agent had 22.62% profit and an agent with rule 2 had only 13% profit. In this mode 85% of the agents with rules had a profit and only 15% lost money most of them having 1% loss. All MACD agents had a profit. In table 2 are presented the agents with the top profit and the ones with the highest loss.

9. CONCLUSIONS

The human agent described in the artificial market can represent a group of traders. There had been observed during experiments in double auction mode that when the human agent places a buy order with a high volume (more than 50% daily volume) of shares then an up trend is created. If the human agent places a sell order with a high volume of shares then a down trend is created.

Although rule 1 looks very similar with rule 2 (as presented in section 7, 3) a) and b)), it has been proved experimentally that rule 1 is better than rule 2 in most of the cases and rule 2 is better than rule 1 in a down market.

MACD method is suited to detect a trend. In double auction mode if there are many MACD agents then they create trends in which the market goes up for small up trends, and for small down trends they create mass selling which produces down trends.

MACD has been proved to be useful in back testing mode and it was not so useful in double auction mode. This showed that MACD is not useful for traders that place big orders and influence the market, it is useful for small orders that do not influence the market.

More types of agents can be created and tested. There can be created agents that chose their strategies based on index as some strategies are better suited than others when the index goes up or down. There can be created agents that forecast the prices of stocks. Other technical indicators can be automated, e.g. momentum indicators, William's and so on, see (Algorithmic trading indicators).

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