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ASSOCIATIVE MEMORY APPROACH TO MODELING STOCK MARKET TRADING PATTERNS

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The proposed research intends to use the ideas of stochastic Theory of Social Imitation (W. Weidlich, E. Calen and D. Shapiro, T. Vaga), and of the associative memory approach to modeling the dynamical structure of polarization relationships (S. Levkov and A. Makarenko) for modeling the stock market trading patterns. The method potentially will allow us to forecast the offer and demand dynamics of a particular security, and lead to modeling of the assets price behavior. Our approach is based on the attempt to utilize the principles of certain classes of neural networks to reveal and model the underlying structure of the real dynamical process. Also the models with internal structure of brokers are considered and results of computer experiments are discussed.

1. INTRODUCTION

Associative memory is one of the models used in Artificial Neural Networks (ANN) — field of research which has enjoyed a rapid expansion and increasing popularity among the financial analysts. This is a completely different from the conventional algorithmic model form of computation. Neural network consists of numerous elementary processors arranged in a network, each programmed to perform one identical simple processing task. Such technology allows ANN to simulate intelligence in pattern detection, association, and classification problem-solving.

Finance and economic problems solved by ANN fall into three categories [1] (1):

- Classification and prediction (analysis of bankruptcy, loan default, bond rating);
- Function approximation (valuation of assets from actual data, risk management);
- Time series forecasting (prediction of stocks, bonds, and other trading assets' prices).

It is generally recognized that Artificial Neural Systems (ANS) are most effectively applied to the problems of classification and clustering. The successful applications of neural networks include business failure prediction [1], credit scoring and credit performance forecasting, risk assessment of mortgage application, bond rating, financial and economic forecasting. The idea here is to formulate the task of a particular forecast as a classification problem: given a set of classes (for example, bankrupt and non-bankrupt, well-performing and poorly performing firms), and a set of input data vectors, the task is to assign each input data vector to one of the classes. The input vector components are usually the different financial ratios (like net sales / total assets for bankruptcy prediction) or different parameters (like confidence, growth, anticipated gains for the stock price performance prediction). The numerous ANNs solving classification problems differ basically in the neural network configuration, learning algorithms, and number, choice, and coding of input vector components. Usually, it is hard to compare different authors' approaches to a particular problem, since they optimize the network structure and input parameters in accordance with the training and test sets of historical financial data they have chosen, and this choice is pretty much arbitrary. Nevertheless, whatever ANN approach is implemented, it is generally performing better than the conventional forecasting techniques (discriminant analysis, regression methods, statistical techniques, etc.).

Among the other potential applications which merit further research, are: portfolio selection and diversification, simulation of market behavior, index construction, identification of explanatory economic factors, and other problems requiring massive parallel processing, fast retrieval of large amounts of information, and the ability to recognize patterns based on experience. Especially interesting financial problem, where an ANN is useful, is pricing and hedging derivative securities [2]. Here, the task of the neural network is to uncover (approximate) a value function describing the relationship between inputs and outputs. It can be done due to the universal approximation property of the learning network. Moreover, certain classes of ANN can approximate arbitrary well any continuous function on a compact domain, which means that there is always a choice for the network parameters that is better than any other possible choice [2].

Another promising and already quite developed area of ANN applications is time series forecasting. Time series are a special form of data where past values in the series may influence future values, depending on the presence of underlying deterministic forces [3]. A significant portion of real-time series is generated by nonlinear processes and besides, is highly contaminated by noise. Therefore, the task of ANN is to uncover the "true" relationship between variables using its learning ability. The idea here is to break the time series into the past and future sets. Then, the network is trained and learns on the past set of data and tested on the future set to see how well its forecast fits into the real data.

While a good deal of ANN applications has focused on the prediction of stock price dynamics, it has been noted that only moderate success has been achieved to date [4].

The reason for that, to our perception, is that one of the advantages of ANN - their ability to model non-linear processes with a few (if any) *a priori* assumptions about the nature of the generating process - becomes a disadvantage here. Forecasting (if ever possible) the time series behavior with a strong stochastic component without modeling the underlying dynamical system may well result in a failure or just a random success.

As an attempt to model such an underlying dynamics, many publications have appeared recently regarding the applications of non-linear dynamics and chaos theory to the prediction of stock market behavior [5]. Most of the works in this field are either trying to apply directly the well-known facts from the dynamical chaos theory to the financial systems, or investigate the existence of dynamical chaos and its parameters in the financial time series.

As an example of applying the ANN related ideas (associative memory, in particular) to model the underlying dynamical structure of the financial markets, the work of Tonis Vaga can be cited [6]. This work is based on the theory of social imitation [7], and polarization phenomena in society [8], that go back to the famous Ising model — the model for ferromagnetism that describe the behavior of simple magnets. The Theory of Social Imitation extends it to the phenomenon of polarization of opinions in a variety of social groups. The assumption here is that individuals in a group behave similar to the molecules in a bar of iron. Under some conditions, the individuals' thinking becomes polarized, which means that they will act as a crowd and individual rational thinking will be replaced by a collective "group think" [8]. Such transitions from disorder to order and otherwise, share the same macroscopic characteristics, whether we deal with physical, biological, chemical, sociological, or financial system.

Unlike chaos theory, which seeks to forecast the stock prices time series in a deterministic (although dynamically chaotic) sense, the market hypothesis of Vaga based on the Ising model, give a method to analyze the transition from random walk behavior to periods of coherent price trends, and periods of chaotic fluctuations of market as a whole. However, the Theory of Social Imitation and Vaga's approaches give only a theoretical basis and are not intended for the forecasting of the actual trading dynamics or price movements, since it is essentially based on stationary state analysis of potential wells of distribution functions.

On the other hand, the attempts to construct a neural network-based mathematical model describing the underlying individualized dynamics of the social polarization phenomena have appeared recently in works of S. Levkov and A. Makarenko [9, 10, 11]. In those works, the analog of Ising model in the form of Hopfield associative memory network [12], was used to make the strategic forecast of geopolitical structures' (GPS) evolution and formation of blocks. The idea of the approach is to present the GPS as a network of elements characterized by the state variables describing the generalized power of a country and interconnection matrices describing the relationships between them. The reconstruction of interconnection matrices is based on historical patterns of inter-relations using a Hopfield Network Algorithm. The problem was considered of modeling the formation of bipolar and tripolar block structures depending on different initial conditions and parameters of interconnections. The key element is to construct the evolution law based upon the appropriate definition of energy of interconnections and of field of influence.

The proposed research intends to use the above mentioned ideas of stochastic Theory of Social Imitation (W. Weidlich, E. Calen and D. Shapiro, T. Vaga), and of the associative memory approach to modeling the dynamical structure of polarization relationships (S. Levkov and A. Makarenko) for modeling the stock market trading patterns. The method potentially will allow us to forecast the offer and demand dynamics of a particular security, and lead to modeling of the assets' price behavior. We would like to emphasize here, that in contrast to the existing ANN models, where the real process is considered as a "black box", and ANN is trained on the sets of input and output data to simulate the nonlinear relationship between them without actually revealing the nature and structure of the prototype process, our approach is based on the attempt to utilize the principles of the certain classes of neural networks to reveal and model the underlying structure of the real dynamical process.

2. JUSTIFICATION OF APPROACH.

2.1. Can the market be predicted?

There is still a big controversy regarding this matter. Some of the authors think that the market is non-predictable. Their popular expression is “You can’t beat the market”. Indeed, evidences and academic studies of professionally managed portfolios have shown that professional investors as a group not only fail to perform better than amateurs, but that it is even difficult to find individual portfolios which have achieved performance significantly better than neutral. The others are even more pessimistic and think that institutional investors will, over the long term, underperforms the market [13]. Nevertheless, the majority of institutional investors believe that they can outperform, and therefore predict, the market; otherwise they wouldn’t step into it. Besides, numerous financial analysts consider that making market forecasts does make sense (most of the endnote articles are devoted to forecasting one or other aspect of the market process).

The reason that forecasting methods make sometimes more, sometimes less correct predictions, lies, to our opinion, in the Coherent Market Hypothesis of T. Vaga [6]. According to it, the stock market has four major states: random-walk state, coherent bull market, coherent bear market, and chaotic market. The state of the market is controlled by the investor sentiment and the prevailing bias in economic fundamentals. The random-walk state, or efficient market, is characterized by low risk and, consequently, low reward. This is a period when investor sentiment is not conducive to “group think’ or crowd behavior. When economic fundamentals are positive (bullish) and investor sentiment is conducive to crowd behavior, the coherent bull market emerges. This is the safest, most rewarding state of the market. The coherent bear market is also characterized by low risk and high reward and is a result of the combination of negative (bearish) economic fundamentals and crowd behavior. The last major market state identified by Vaga, is a chaotic market. During this period, a high degree of polarization exists among the investors, but the economic fundamentals are neither positive nor negative, which results in the most dangerous market state with high risk and low reward.

Not going into further details of Vaga’s analysis, we can conclude that an opportunity to forecast the stock market behavior arises during the periods of coherent behavior. A similar approach can be applied also to a particular stock. The most interesting (yet more complex) problem in this case would be forecasting the transition periods from one market state to another.

2.2. Conventional theories of market forecasting.

Traditionally, two approaches to asset valuation and price prediction have been used - the “firm-foundation theory” and the “castle-in-the-air theory” [14]. The firm-foundation theorists believe that each investment instrument has its “intrinsic value” that depends on the present conditions and future prospects of the firm.

Consequently, an opportunity to make money arises when the market price falls below or rises above this firm foundation of intrinsic value. In contrast, the castle-in-the-air theorists concentrate on people's psychology. Analyzing how the crowd of investors is likely to behave in the future and how they tend to build their hopes into castles in the air under favorable market conditions, supposedly allows estimating what investment situations are most susceptible to public castle building and buy before the crowd.

Accordingly to these two views on the stock market, there are two opposite investing techniques - fundamental and technical analysis. Fundamental analysts believe the market to be 90% logical and 10% psychological. Therefore, they care little about the particular pattern of the past price movement, but rather seek to determine the proper value of the security. It is done by analyzing growth prospects, dividends payout, level of interest rates, and the degree of risk. Once the "true" value of the company is determined, the fundamentalist can start his game, since to his beliefs, the market will eventually reflect accurately the security's real worth. There are numerous examples when this theory fails and makes wrong predictions. Apparently, this approach underestimates the role of market and its participants in the mechanism of establishing the actual asset price.

In contrast, the technical analysis suggests that all the information about earnings, dividends, and the future performance of a company is already reflected in the company's past market prices. It presumes that the price chart and the trading volume are the only information needed for correct prediction. Essentially, the main technical analyst's task is to anticipate how the other investors will behave. Therefore, the true technical analyst doesn't even care to know what business or industry a company is in, as long as he can study its stock chart. There are also plenty of cases when this theory fails. This approach obviously neglects the role of information about firm fundamentals in the price formation and focuses mostly on market effects.

Evidently, those theories are two extremes. The price generically depends on the firm fundamentals but is determined on the market through the trading process. Therefore, the adequate models of the price dynamics should inevitably consider the market participants, their relationship, and their behavior.

2.3. The role of market structure and market relationships in price formation.

The financial theorists and practitioners are mostly uniform in determining who the market participants are. Basically, they divide them into the following categories [15]:

- Market makers or Specialists;
- Brokers;
- Uninformed traders (or Nice traders [16], or Noise traders [17]);
- Informed traders (or News traders [16], or Insiders [17]).

Some of the classifications, instead of informed and uninformed traders, include traders possessing special information, "liquidity-motivated" traders who have no special information but merely want to convert securities into cash or cash into securities, and traders acting on information which they believe has not yet fully discounted in the market price but which in fact has [18]. Another approach breaks them down into differentially informed traders and liquidity traders [19].

Trading takes place through the market makers and must pass through a broker. Such structure does not allow public to participate directly in the trading. Therefore, in order to understand the market mechanism, first, it is necessary to understand the relationship between market makers on one side and brokers representing their anonymous clients on the other. Moreover, as Jack Traynor (more known under the pseudonym Walter Bagehot) wrote in his famous and widely cited article "The Only Game in Town", "the market maker is a key to the stock market game". Technically, his role is to provide liquidity by stepping in and transacting whenever equal and opposite orders fail to arrive in the market at the same time. For this purpose, the market maker transacts with anyone who comes to the market. But still, any market maker has an ultimate goal of making a profit from his transactions. He always loses to informed traders; therefore the gains from the transactions with uninformed and liquidity-motivated traders must exceed these losses. Thus, the market maker can be thought as a channel through which money from uninformed and liquidity-motivated traders flow to insiders, since those who get information make the profit from the market makers, and the latter earn from the other traders who don't have it.

Another aspect that makes the market even more complicated is the broker - market maker relationship. Since the market maker's spread between bid and asked price mainly depends on the difference between his losses to informed traders and gains from the others, he will readily reduce it if the broker reveals that his client trades, for example, just for liquidity purposes. Better execution of orders means more clients for the broker. On the other hand, in order to make such relationship work, the broker also has to reveal when his client is informed, which will definitely lead to the poorer execution of his order. Thus, the broker faces the dilemma: whether to tell the specialist when his client is a news trader and perhaps, lose him, or conceal this fact and get poorer execution for all the other clients' orders. Since uninformed and liquidity-motivated traders are in absolute majority in the stock market, the broker has an incentive to reveal the informed traders. However, if informed traders were always identified, they would be forced out of the market; because the market maker would set such a spread that the advantage an informed trader has might disappear. Nevertheless, news traders *are* in the stock market, which means that they are not always correctly identified either because the broker makes mistakes, or because the broker chooses randomizing strategy when sharing the information with the market maker.

This picture of the stock market, being simplified, shows nevertheless, that the way the market participants interact with each other, their beliefs and disbeliefs, credibility and trustworthiness have considerable impact on the price formation.

2.4. Possibilities for modeling.

The above analysis shows that a possibility of forecasting the market behavior may exist at least for some periods of market dynamics and for particular securities. The adequate models of the price dynamics should inevitably include the market participants, their relationship, and their behavior. The interaction of market participants, their beliefs and credibility have significant influence on the market trends. The combination of methods of stochastic theory of social imitation (W. Weidlich, E. Calen and D. Shapiro, T. Vaga), and of the associative memory approach to modeling the dynamical structure of polarization relationships (S. Levkov and A. Makarenko) represent a solid foundation for developing the model of the stock market trading patterns that would allow to forecast the offer and demand dynamics of a particular security, and lead to modeling of the assets' price behavior.

3. THE MODELING CONCEPT

3.1. General ideas

We present here briefly the core idea of the approach and the rough draft of the model that we are going to develop in the research. The proposed model does not pretend to be full and is intended only to demonstrate the basic ideas presented here.

Assumptions.

In order to make easier understanding of the method and to simplify the initial formulas, we consider the idealized market of one security. The trade consists of discrete steps, at which the actual transactions take place. Within each step we identify the sub steps, which describe the dynamic bidding and asking or decision-making processes for every individual. The market consists of N homogeneous participants (in future developments the homogeneous assumption obviously should be removed).

With every trader we associate the state variable $s_i \in S = \{0, \pm 1, \pm 2, \ldots$ $\ldots, \pm M_i\}$**,** where s_i represents the number of shares that trader i is planning to buy (if $s_i > 0$) or to sell (if $s_i < 0$), and M_i is the maximum allowed trading volume, which represents the number of shares trader i_{is} able to buy.

With every pair of traders i and j we associate the variable $c_{ij} \in \mathbf{R}$ — the integral value of reputation that trader j has from the point of view of trader i. This value measures the degree of how well informed; trader j is in the eyes of the trader i. The large positive values of c_{ij} mean that, in the opinion of trader i, trader j is an informed (news, insider) trader, the values close to zero can mean that the trader j is an uninformed (noise, nice) or liquidity trader, while the negative values mean that the trader j is either insider who trades against the information he has in order to hide himself, or a trader who is likely to be wrong in his judgment. The reputation variables c_{ij} form a matrix

$$C = \{c_{ij}\}_{i,j=1,\ldots,N} . \tag{1}$$

that we call the matrix of reputation. The approach c_{ij} valuation will be discussed later at the end of this section.

As one of the basic characteristics of the system we introduce the concept of a vector field of influence

$$F = \{ f_i \}_{i=1,\ldots,N} : f_i = \sum_j c_{ij} \frac{s_j}{M_j}, \;\; c_{ii} = 0 \tag{2}$$

where f_i means the integral influence of opinions of all other participants on i trader. The intuition behind this formula is the following. The ratio $\frac{s_j}{M_j}$ represents the trading intentions of participant j at the current step. It shows the number of shares trader j is planning to buy or sell as a percentage of what his actual buying or selling power is. The product $c_{ij} \times \frac{s_j}{M_j}$ is the information about intentions of trader j filtered through the matrix of reputation. Thus, the sum (2) represents all the available to trader i information about the actions of other participants, and since it is filtered through the matrix of reputation, it is meaningful and trustworthy to him. We would like to note here, that all the other information, trader i might have, is already incorporated in his initial intentions to buy or sell s_i.

Obviously, the best strategy for rational individual will be to adjust his own initial intentions to the filtered information about others. Speaking formally, we say that every participant is associated with the information utility function, which he is trying to maximize during the decision-making process. It is done by correlating the trading decision of individual i with the corresponding value of the field of influence f_i.

Thus, we may formulate the evolution equation describing the trading dynamics:

$$s_i(t+1) = \begin{cases} s_i + 1, & \text{if } \; f_i(t) > 0 \; \text{ and } \; s_i(t) < M_i, \\ s_i - 1, & \text{if } \; f_i(t) < 0 \; \text{ and } \; s_i(t) > -M_i, \\ s_i & \text{otherwise.} \end{cases} \tag{3}$$

The initial conditions for this dynamic equation are the intentions of each individual to buy or sell at the beginning of the trading step. They are formed under the influence of the sources outside the system, and represent the trader's forecast of how well the particular stock will be doing.

Given the initial conditions for s_i and known values of influence matrix, we may calculate the dynamics of the trading patterns. Such dynamics is expected to be beneficial for each trader, since it leads to the maximal utilization of the filtered, and therefore useful, information available to him.

Obviously, the system consists of protagonists with different and frequently antagonistic goals. Thus, the actions beneficial for a particular participant do not necessarily benefit the others. Moreover, each trader acts from his own interests and generally, if somebody wins, someone loses. However, all these egoistic individuals comprise the system we consider. Therefore, from the system point of view the question is, whether the defined above dynamics of every trader leads to a meaningful evolution of the whole system, or is this just a disordered, chaotic motion? The answer can be found using the analogy with the physical systems.

As the variable summarizing the evolution of the system, we introduce the concept of energy E, which characterizes the impact all the traders have had on each other in making their buying/selling decisions:

$$E = -\sum_i f_i s_i \ .$$

Thus, at any given point in time, energy E characterizes the state of the market. Naturally, we are interested in the evolution of the trading patterns leading to a state that has the property of stability. By analogy with the physical systems, we will call the state of the system stable if the energy E has a local minimum in this point. As we will see, the system will tend to minimize its energy during the evolution process. To show this, we will first formulate and prove the following statement.

Statement 1. Under the law of evolution (3) the system evolves to a local minimum of energy E.

After energy reaches the local minimum, due to (A1) any change of the state of the system will increase the energy, which is impossible because of (A2). Thus, $s_i(t+1) = s_i(t) \quad \forall i$, and the system will retain its stable state until some external forces are applied. Such stable state can be thought as an equilibrium, at which trading takes place and shares change their hands. It simply means that all the participants have reached their decisions having maximized their own information utility functions. Since we are assuming that all the external information the participants might have is represented by their initial intentions, trading occurs. Thus, maximization of individuals' information utility functions leads to the minimum of energy of the system and, therefore, to its coordinated movement during the decision-making step.

The next trading step begins with the new initial conditions, which contain the new information traders have been able to obtain.

The reputation matrix in the described above model remains invariable during the bidding/asking or decision-making steps. Obviously, it should change at each trading step, since traders analyze their own performance as well as the performance of other participants and market as a whole. Therefore, each individual might assign different coefficients to the corresponding elements of the matrix of reputation, which will be enforced at the next trading step.

Thus, the reputation matrix plays one of the major roles in the proposed model, and the applicability of the model depends, to a great extent, on the correctness and accuracy of the reputation coefficients. The numeric values for the entries of the matrix of reputation are not readily available. However, one of the advantages of the given approach is that it uses already proved and experimentally tested algorithms for the identification of the matrix C via the prior observations of the trading patterns. This algorithm has the form of the well-known rule from the pattern recognition theory of associative memory models [12]. Its brief idea can be outlined as follows.

Suppose we have recorded information about trading patterns Z_k, $k=1,\dots,K$, where $Z_k=\{s_i\}$ at the time moment k, K is the number of observations, $i=1,\dots,N$, N — number of traders. Then the matrix of reputation C can be evaluated as

$$C=\{c_{ij}\},\ c_{ij}=\sum_k \frac{s_{ik}}{M_i}\times\frac{s_{jk}}{M_j},\ c_{ii}=0\,. \tag{4}$$

3.2. Accounting the internal structures of market participants

The next step in development of proposed models is to account the internal structure of agents (we named such agents as 'intellectual').

Let us consider the idealized market as the collection of N intellectual agents. We will consider the process with discrete time steps. Each agent should to do decision (change of state) at each time step in dependence of all agents' states [20].

Agent's state is described by the variable $S_i(t)\in S=\{0,\pm 1,\pm 2,\dots,\pm M_i\}$, which corresponds to the amount of the recourse (information, materials and so on), which may be gain (if $S_i(t)<0$) or collect (if $S_i(t)>0$) by i individual (agent). Here M_i is the maximal volume of its resource (its potential). Interaction of individuals in organization is described by influence matrix $C=\{c_{ij}\}$, $j=1,\dots,N$, $c_{ij}\in[0,1]$ where c_{ij} — influence coefficient of j individual on i. The influence matrix $\mathbf{C}$ may reflect the authority power in organization. In simplest model we take $C_{ij}=0$, $i=1,\dots,N$.

So the collection $Q^R(t)=\left(\{S_l^R(t)\},\{C_{lj}^R\}\right),\ i,j=1,\dots,N$ represents the real state at moment t. Let us consider also $Q^i(t)=\left(\{S_l^i(t)\},\{C_{lj}^i\}\right),\ i,j,l=1,\dots,N$ as ideal pattern of situation from the i agent point of view. Then we can calculate the difference between real and ideal patterns of situation:

$$D_i(t)=\left\|Q^i(t)-Q^R(t)\right\|. \tag{5}$$

We suppose that the dynamics of i agent depends on the difference $D_i(t)$ and on the mean influence field by other agents. We accept the influence field $G(t)=\{g_i(t)\}$, $i=1,\dots,N$ as:

$$g_i(t)=\sum_{j=1}^N C_{ij}^R\,\frac{S_j^R(t)}{M_j}\,. \tag{6}$$

The term $\dfrac{S_j^R(t)}{M_j}$ $\dfrac{S_j^R(t)}{M_j}$ in (6) corresponds to the activity of j agent at the moment t. The term $C_{ij}^R\,\dfrac{S_j^R(t)}{M_j}$ corresponds to activity with reputation accounting.

In general case the dynamical law for agent takes the form (F some law for agent's reaction, named frequently activation function):

$$S_i^R(t+1) = F(v_i(t)), \tag{7}$$

where the argument $v_i(t)$ may takes the form:

a) Multiplicative

$$v_i(t) = \alpha(D_i(t))g_i(t), \tag{8}$$

where for example $\alpha(D_i(t)) = e^{-kD_i(t)}$. In simplest evident variant we may take:

$$D_i(t) = \sum_{j=1}^{N} \left| S_j^i(t) - S_j^R(t) \right|; \tag{9}$$

b) additive $v_i(t) = g_i(t) + f_i(D_i(t))$, where $f_i(D_i(t))$ — some influence function. The simplest example is:

$$f(D_i(t)) = \sum_{j=1}^{N} C_{ij}^R \frac{(S_j^R S_j^i)}{M_j}. \tag{10}$$

In this model vector $v_i(t)$ represent the understanding by i agent on the tendencies in market: If $v_i(t) > 0$, then the tendency is to increase the recourse, if $v_i(t) \approx 0$, then the stability is the main tendency, if $v_i(t) < 0$, then the tendency is to reduce the resources.

One of the most usable forms of activation function F in such type models are:

$$S_i^R(t+1) = \begin{cases} S_i^R(t)+1 & \text{if } v_i(t) > \dfrac{\|G(t)\| \left|S_i^R\right|}{M_i} \text{ and } S_i^R(t) < M_i, \\ S_i^R(t)-1 & \text{if } v_i(t) > \dfrac{\|G(t)\| \left|S_i^R\right|}{M_i} \text{ and } S_i^R(t) > -M_i, \\ 0 & \text{othervise,} \end{cases} \tag{11}$$

where

$$\|G(t)\| = \frac{\sqrt{\sum_{i=1}^{N} g_i^2(t)}}{N}. \tag{12}$$

Remark that very interesting development of proposed models consist in introduction time dependence of connections by some dynamical laws. Of course the models described here correspond to the constant bonds.

4. RESEARCH TASKS AND PROBLEMS TO BE SOLVED

Proposed approach allows developing the software and trying to understand some properties of market. Here we describe some examples of computer experiments with the models (5)–(12) which accounting the internal structure of brokers and non-constant in time reputation of brokers.

The horizontal axe corresponds to the steps of trading. The vertical axe represents the intentions of different traders. The left picture correspond to stabilization of intentions of traders. The right-side picture corresponds to the case of market with changeable bonds (reputations) during trading.

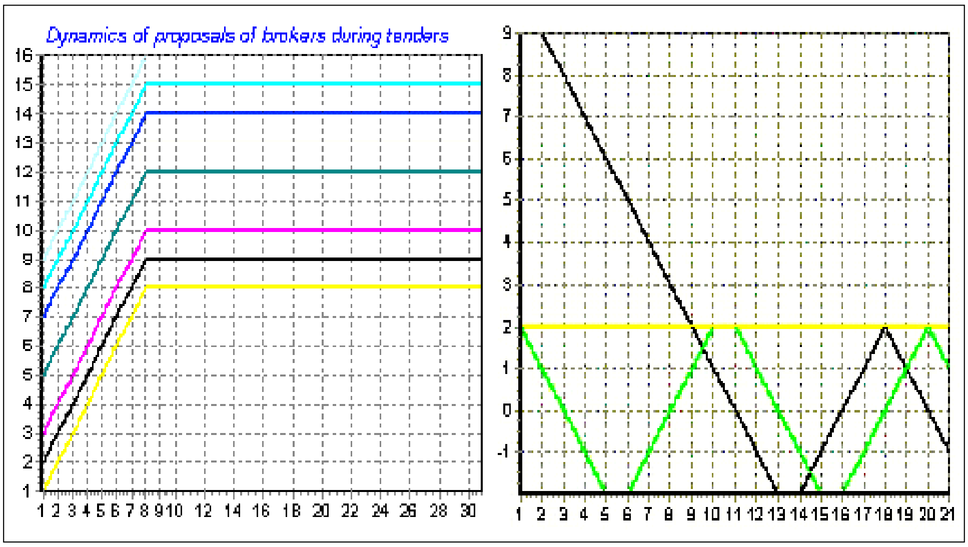

Fig. 1. Modeling the market trading

The right picture illustrates the possibilities of oscillations of the market. The oscillations are intrinsic for market with asymmetrically informed brokers. Moreover the market with mostly asymmetrically informed brokers may have chaotic behavior. Other very interesting phenomenon is the possibilities of sudden changes of stable trading patterns of market evolution in the case of variable reputation of traders. It may correspond to real phenomena in the market. Also it may correlate with phenomena of punctuated equilibrium in biology.

Of course till now our computational investigations are model with artificial date and further investigations will be interesting. But just now some prospective issues may be discussed.

First of all proposed internal representation may be considered as some correlate to ontology of market participant. Also it may be interesting for considering classical problem of reputation. At second the approach reminiscent usual multi-agent approach. The description of trader remember agent with special representation of the internal and external worlds by network structure. Also the prospective feature in the approach is the associative memory in proposed models.

5. CONCLUSION

Thus in proposed paper we consider the approach for market modeling which implement some properties of real market. The main distinctive features are the accounting of internal properties of traders. As the authors envisage, the modeling principles, described in section 3 can lead to the formulation and solution of the following problems:

1. Development of models of trading patterns for the specific markets.
2. Enhancement of the models of trading patterns with price formation models and developing the price forecast methods.
3. Numerical simulation of specific markets.
4. Establishing of the asset price dynamics through the offer/demand-price relationship.

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From the Editorial Board: the article corresponds completely to submitted manuscript.

Dear Serjeza, Happy New Year with best regard from I and Kolja. Big privet vsem Ire,Yure and Tanya Barzilovich.

Your Alla/