DEVELOPMENT OF INTELLIGENT DECISION MAKING MODEL FOR STOCK MARKETS
INTELIĢENTA LĒMUMU PIEŅEMŠANAS MODEĻA IZSTRĀDE AKCIJU TIRGUS VAJADZĪBĀM

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Abstract. *This paper is focused on the development of intelligent decision making model which is based on the application of artificial neural networks (ANN) and swarm intelligence technologies. The proposed model is used to generate one-step forward investment decisions. The ANN are used to make the analysis of historical stock returns and to calculate one day forward possible profit, which could be get while following the model proposed decisions, concerning the purchase of the stocks. Subsequently the Particle Swarm Optimization (PSO) algorithm is applied in order to select the „global best" ANNs for the future investment decisions and to adapt the weights of other networks towards the weights of the best network. The experimental investigations were made considering different number of neural networks, moving time intervals and commission fees. The experimental results presented in the paper show that the application of our proposed methodology lets to achieve better results than the average of the market.*

Keywords: *Stock Markets, Artificial Intelligence, Artificial Neural Networks, Swarm Intelligence.*

Introduction

The continuing improvements of computer technologies, telecommunication services' grow make a big influence on the globalization of stock markets and more efficient its information processing tools are required. The complexity and „noisiness" of stock markets cause difficulties in making real time analysis of it and forecasting its changes in the future. Before, in stock markets the importance of decisions making was given to the stock market experts, as experts are able to provide rule and experience based solutions for well-defined systems. The situation is changing as the complexity of stock markets is growing. It was proved that having complex systems a collection of individuals often solves a problem better than an individual - even an expert [1]. Individuals acting within „a swarm" interact with each other in order to solve a global objective in a more efficient manner than a single individual could [4].

Recently, working with stock markets' prediction the bigger importance is given to the artificial intelligence tools then to the statistical once. It was proved by scientists, that the application of ANNs can give promising results in the stock markets prediction. The main objective of this paper is to develop the decision making model, based on the application of artificial intelligence tools: ANNs and swarm intelligence technologies (PSO).

The PSO is closely related to evolutionary computation and artificial life (A-life) in general [3]. The same as evolutionary programming it is highly dependent on stochastic processes. The optimizer which is used in the PSO algorithm, while making adjustment towards „local" and „global" best particles, is conceptually similar to the crossover operation used by genetic algorithms [5, 6]. As well PSO includes fitness function, which measures the closeness of the corresponding solution to the optimum. The same function is included in other paradigms of evolutionary computation. The main difference of PSO concept from the evolutionary computing is that PSO is the only evolutionary algorithm that does not incorporate survival of the fittest, which features the removal of some candidate population member [10].

The problem of stock markets forecasting was analyzed by many researchers in the past. Considerable efforts have been put into investigation of stock markets changes and creating its forecasting systems. But there are not so many examples of Swarm Intelligence applications. The swarm intelligence approach seems to be relatively new in the field of Computer Science. However, the published examples of swarm intelligence applications seem to be promising and

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give good results. In paper [7] there is proposed the forecasting methodology for the daily exchange rates of Japanese Yen against the US Dollar and of the US Dollar to the British Pound. The proposed forecasting methodology includes clustering technology, ANNs and evolutionary computing. In contrast to this paper we focus on the formation of recommendations while making investment decision in stocks' markets. As well we are working with a large data set that lets us to propose more stable investment decision system. In paper [2] the authors are focusing on adapting PSO to dynamic environments. This paper is more focused on the modifications of PSO algorithm, while our goal is to introduce the investment decision making methodology where PSO will be only one constituent of it.

First of all in the paper there is introduced the proposed decision making model. After, the presentation of experimental investigations is made and the main conclusions of the work are presented.

Proposed decision making model

The analysis and forecast of stock markets is stickler, because of its complexity and noisiness. Various economics activities and psychological factors affect the rise and fall of daily stock returns [8]. There is not enough to use conventional techniques to conduct the stock markets predictions, as its changes are influenced by stochastic human factors, non-linear, multivariable and temporal nature of stock price transitions. The use of artificial intelligence had made a big influence on the forecasting and investment decision making technologies and it was proved that the efficient results can be obtained. In this paper we are proposing a decision making model, which could be applied for stock trading processes. The scenario of proposed decision making model is presented in *Fig.1.*

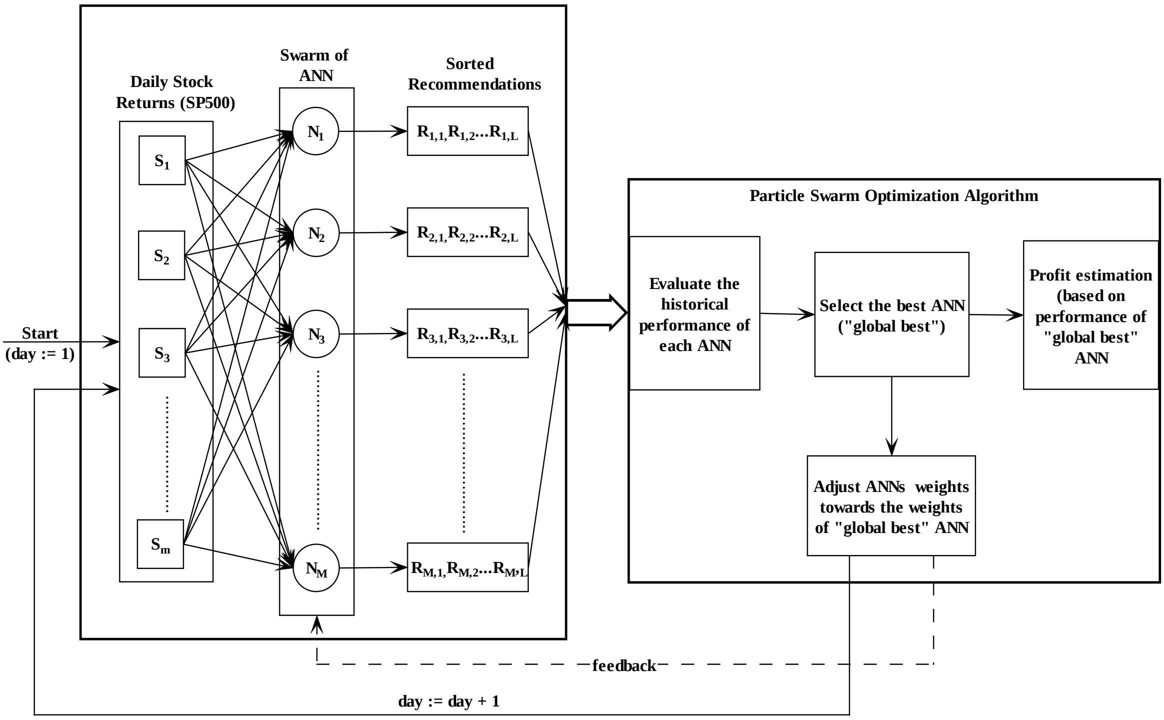

Fig. 1. **Scenario of decision making model**

The introduced decision making scenario (Fig. 1) presents a realization of the model, which is made every day and its result is one day forward decision (buy, sell and hold). The scenario could be described in several stages:

1. At first, the data set of 350 stocks (from S&P500 group) is formed. This data set includes the information about daily stock returns for the time period of 12 years (01/Oct/91-01/Oct/03).

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2. The data set is passed to the ANNs. The net result is a linear combination of each of the weighted input vectors.

$$x = \sum w_j p_j \tag{1}$$

Here w_j represents the weights, and p_j - the changes of stocks price.

The ANNs' weights are initialized randomly at the beginning of the procedure according to the formula:

$$w = rand(n,k) - 0.5 \tag{2}$$

Where n is randomly initializes weights of ANNs and k corresponds with the number of used ANNs. The random numbers are kept relatively small.

3. Further, for each day, and each stock the recommendations are calculated using different number of ANNs. The net result is passed to the hyperbolic tangent function and the recommendations for the stocks' trading are calculated according to the below presented formula:

$$R = \frac{2}{1+e^{-x}} - 1 \tag{3}$$

The recommendations (R) represent the relative rank of investment attraction to each stock in the interval *[-1,1]*. The values *-1, 0* and *+1* represent recommendations: sell, hold and buy respectively.

4. After the recommendations are calculated, all the stocks are sorted (according to these recommendations) in the descending order.
5. From the sorted list of stocks, three stocks with the highest recommendation are selected.
6. Further, the decision concerning the stock returns is made, according to the chosen stocks' returns and applying sliding windows.
7. Before the next iteration of the model the training of ANN is made. For the training of ANN there is applied PSO algorithm (see Fig.1). The training of all ANNs is made through the adjustment of ANNs weights towards the weights of "global best" ANN on a current day.

For experimental investigations we were considering two different kinds of ANN (see Fig. 2 and Fig. 3): single layer ANN (linear case) and two layers ANN (non-linear case).

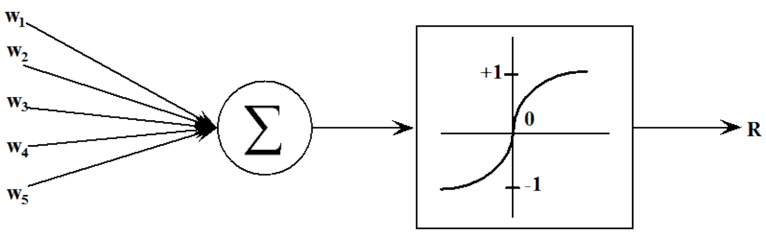

Fig. 2. **Single layer ANN**

While applying single layer ANN we are checking what results can be achieved while having the simplest cased of the decision making model. The non-linear case of ANN lets to check if the more advanced case of decision making model is correlated with the improvements of the results.

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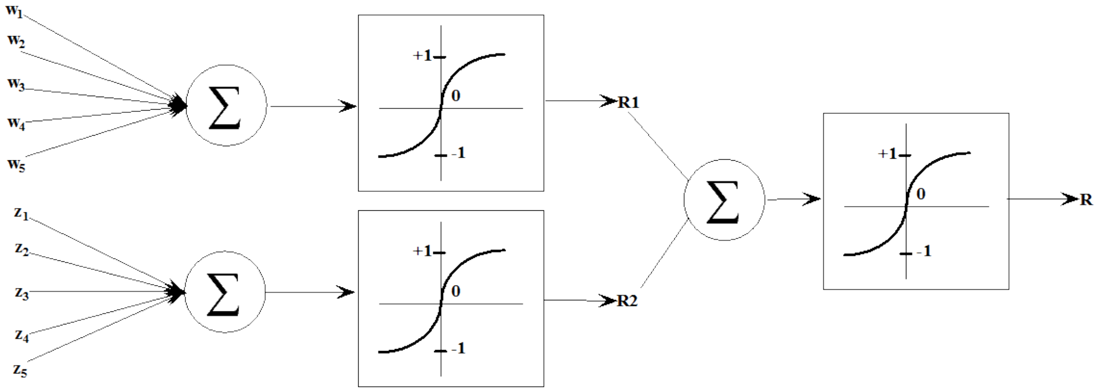

Fig. 3. **Two layers ANN**

As it was mentioned before, the expected return is calculated using the idea of sliding window. An example of sliding windows is presented in Fig.4.

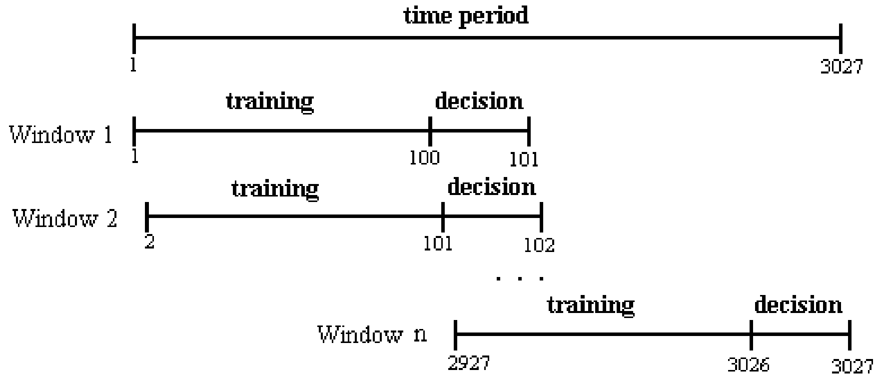

Fig. 4. **Sliding window**

As it can be seen from the Fig. 4, the sliding window is divided into two parts: training and decision making. In the training part there are selected the particles with the best performance (the highest total profit for the selected sliding window) and the „worst" particles are trained towards the behavior or these selected „global best" particles. It is important to mention, that the data, which was used for the calculation of recommendations it is not further used for the training of ANNs (it becomes out sample data).

Experimental investigation

The realization of the proposed decision making model was made using MATLAB software package. The experimental investigations were divided into three parts:

1. The first part was focused on the selection of sliding window size and number of ANNs (the detailed experimental investigation is presented in article [11])
2. The second part of experimental investigations focuses on the analysis of learning rate (see article [11]).
3. The third part was dedicated for the evaluation of decision making model (linear and non-linear cases).

All the experimental investigation were run according to the above presented scenario (see Fig. 1) and were focused on the estimation of possible returns, which could be got while applying our proposed decision making model. In all the cases the expected returns were calculated considering transaction fees that are unavoidable in the stock markets. The analysis of the commission fees of different e-brokers showed that the commission fee in real trading process is usually between 0.15 % - 0.3 %. For example, such transition fees are provided by the company of Interactive Brokers [9]. Having bigger selling and buying volumes this fee could be even

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smaller - 0.1 %. Based on that for the further investigations we are considering the commission fee which is equal to 0.15 %. We are making an assumption that each day we are paying 0.15 % of commission fee for buying new stocks. The value got on the last investigated trading day is considered as the profit. The profit is calculated as a sum of stock returns (%):

$$P_{end} = \sum_{t=2}^{P_{end}} P_{t+1} \tag{4}$$

Where:

$$P_{t+1} = \frac{K_{t+1} - K_t}{K_t} * 100\% \tag{5}$$

Here P_{t+1} represents the profit at time period $t+1$. If at the moment t there were bought stocks for the price K_t, when the price of these stocks after some time period (year, month etc.) will be K_{t+1} and the profit (%) will be equal to the value of P_{t+1}.

In all experimental investigation the training of ANNs was made through the adjustment of ANNs weights towards the weights of ``global best'' ANN. For the adjustment of the weights there was chosen the learning rate of 0.05. Such value was selected based on the experimental results which are presented in the article [11]. As well it is important to mention, that for all experimental investigation, the sliding window of 100 days was used. The results of experimental investigations are presented in Fig. 5.

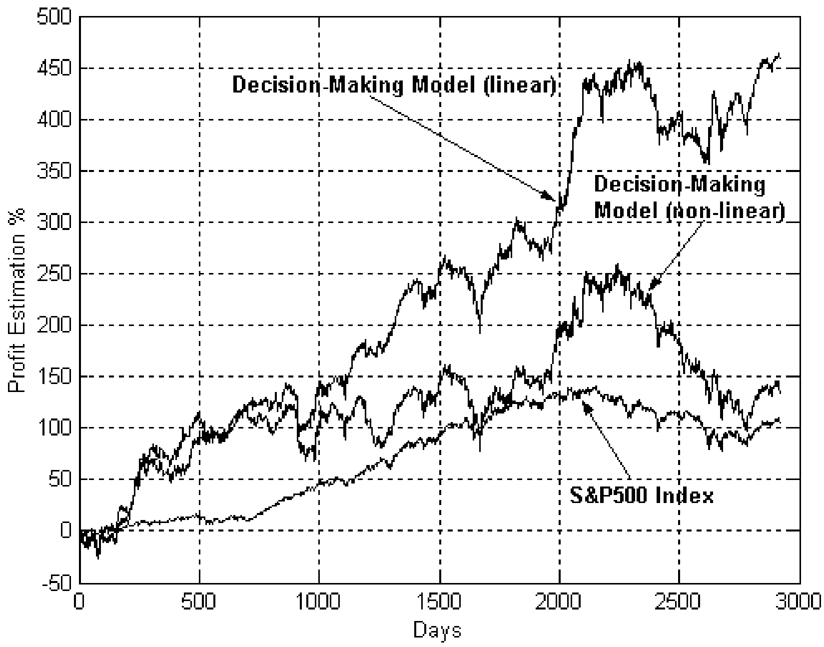

Fig. 5. **Comparison of the results**

In Fig. 5 there is presented the comparison of the results while having three cases: conservative investment approach (investments are done into S&P500 index by buying and holding it for all time period), and decision making model (linear case) application and decision making model (non-linear case) application. The presented results in the Fig. 5 show, that the application of PSO algorithm and training of ANNs towards the performance of the ``global best'' ANN give quite good results. Compare to the conservative approach the proposed decision making model lets to achieve almost 5 times better results (having the linear case of the model). The reason of that is that every day the investment decisions are made using the ``global best'' particle and at the same time all other particles are slightly moved towards it. Such training of ANNs ensures

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the movement towards the best decision. In the case of non-linear decision making model the results are not so good. That lets us to make an assumption, that in complex systems the more advanced decision making model not necessarily give better results. Non-linear case of decision making model is too complex and its different realizations can have big variations (see Fig. 6).

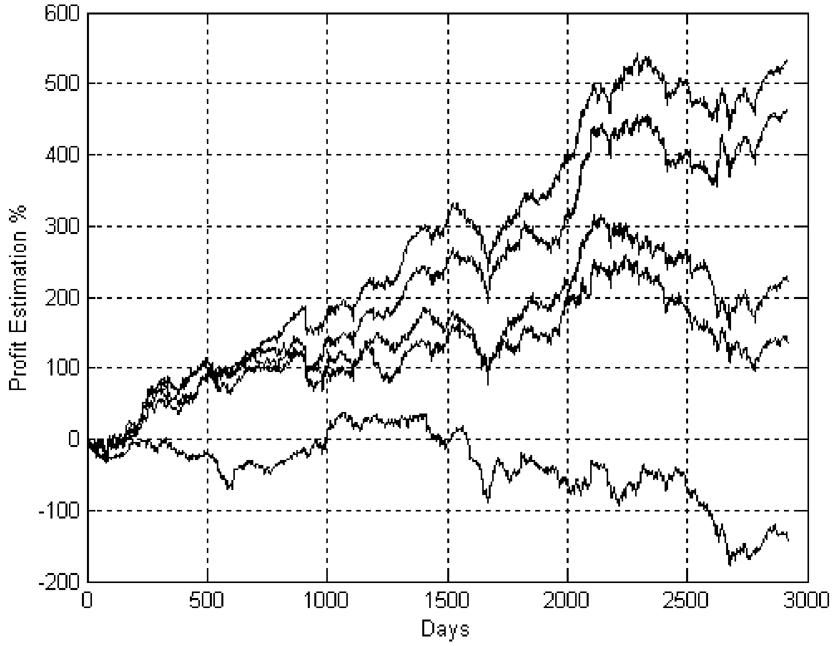

Fig. 6. **Non-linear decision making model (5 realizations)**

As it can be seen from Fig. 6, different realizations of non-linear decision making model give quite contradictory results. That let us to come to the conclusion, that non-linear decision making model is too complex for decision making in very noisy systems. The big variations of its different realizations show, that the non-linear decision making model is not stable and it can not ensure good results in decision making in stock markets.

Conclusions

In this paper we proposed the decision making model based on the application of ANN and PSO algorithm. The model was applied in order to make one-step forward profit estimation considering historical data of stocks returns fluctuations. The evaluation of the model showed that:

1. The linear decision making model can give quite good results (4-5 times better than in the case of conservative investment into S&P500 index).
2. The non-linear decision making model is not stable and it is too complex for decision making in noisy systems.

In the future we intend to make more detailed analysis of the proposed decision making model.

References

1. K. Bartholdson, J. M. Mauboussin, Thoughts on Organizing for Investing Success. Credit Suisse First Boston Equity Research, 2002
2. A. Carlisle, G. Dozier, Adapting Particle Swarm Optimization to Dynamic Environments. 2000 ICAI Proceedings, Las Vegas, 2000, 429-434
3. A. D. Engelbrecht, Computational Intelligence (An Introduction). John Wiley & Sons, London, 2002
4. N. R. Franks, Army of Ants: A Collective Intelligence. American Scientist, 1989
5. J. Kennedy, W. M. Spears, Matching Algorithms to Problems: An Experimental Test of the Particle Swarm and Some Genetic Algorithms on the Multimodal Problem Generator.

2\. http://www.aic.nrl.navy.mil/%7Espears/papers/wcci98.pdf, Current as of December 15th, 2003

3\. A. S. Khalil, An Investigation into Optimization Strategies of Genetic Algorithms and Swarm Intelligence. Artificial Life, 2001

ISBN 9984 – 779 – 06 – 8

4. N. G. Pavlidis, D. Tasoulis, M. N. Vrahatis, Financial Forecasting Through Unsupervised Clustering and Evolutionary Trained Neural Networks. Financial Forecasting Through Unsupervised Clustering and Evolutionary Trained Neural Networks, 2003
5. P. T. Pham, Neural Networks for Identification, Prediction and Control. Springer-Verlag, New York, 1995
6. Interactive Brokers. http://www.interactivebrokers.com , February 2004
7. R. C. Eberhart, Yuhui Shi, Comparison between genetic Algorithms and Particle Swarm Optimization, Evolutionary programming, 1998, 611-616
8. J. Nenortaite, R. Simutis, Workshop on Computational Methods in Finance and Insurance, Stocks' Trading System Based on the Particle Swarm Optimization Algorithm, Springer-Verlag LNCS 3039, 2004, 843-850

ISBN 9984 – 779 – 06 – 8