Journal of Global Optimization (2006) 36: 1–19
DOI 10.1007/s10898-005-5371-6

Development and Evaluation of Decision-Making Model for Stock Markets

JOVITA NENORTAITE and RIMVYDAS SIMUTIS
Faculty of Humanities, Vilnius University Kaunas, Muitines 8, 44280 Kaunas, Lithuania
(e-mails: {jovita.nenortaite,rimvydas.simutis}@vukhf.lt)

(Received 17 November 2005; accepted 21 November 2005)

Abstract. The paper introduces an 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 for stock markets. The ANN are used to make the analysis of daily stock returns and to calculate one day forward decision for purchase of the stocks. Subsequently the Particle Swarm Optimization (PSO) algorithm is applied in order to select the "the best" ANN 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 forms of decision-making model: different number of ANN, ANN inputs, sliding windows, and commission fees. The paper introduces the decision-making model, its evaluation results and discusses its application possibilities.

Key words: Decision-making model, particle swarm optimization algorithm, stock markets

1. Introduction

Considerable efforts have been put into the investigation of stock markets. The main task of the researchers is to create a tool, which could be used for the prediction of stock markets fluctuations. The main motivation for that is the financial gain. The stock markets are influenced by various factors: new information, traders' behavior, technologies, etc. In financial marketplace, in order to be able to work efficiently and to get profit, traders have to have fast and powerful tools for decision making.

There are more and more applications appearing in the area of economic prediction, such as k-nearest–neighbors algorithm, Genetic algorithms, Neural Networks, Fuzzy Logic, Particle Swarm Optimization (PSO) algorithms, etc., which are used for the formation of optimal portfolio, prediction of stock market fluctuations, selection of profitable stocks, and bonds, etc. The use of Artificial Intelligence (AI) has made a big influence on the forecasting and investment decision-making technologies [11, 8]. As it is claimed by [4] in the comparison with conventional statistic tools the main *advantages* of AI tools are that they are able to learn to recognize patterns in the data set, they are flexible in a changing environments and they can build models when more conventional approaches fail. The advantages of AI tools applications are as well presented by Mirmirani and Li [14]. They are claiming that in comparison with statistical techniques, Artificial Neural Networks (ANN) makes less restrictive assumptions on the underlying distribution. Another AI tool, which already have shown promising results of its applications, is Swarm Intelligence (SI). The examples of SI applications were presented by Pavlidis et al. [16], Carlisle and Dozier [3], Po-Chang and Ping-Chen [17]. It was proven that having complex systems a collection of individuals often solve a problem better than an individual – even an expert [6, 1]. SI includes two algorithms: Ant Colony Optimization (ACO) algorithm and PSO algorithm. For the decision-making in stock markets it is more suitable PSO algorithm as it allows to make the search of "best" ANN on a current time and make decisions, based on its performance. Besides PSO algorithm and ANN there are created many tools for stock markets predictions. As one of such tools could be mentioned Wiener Gauss model. The Wiener Gauss model assumes an efficient premise in the markets [18]. In our case, we assume that markets are inefficient. As well almost all models are focused on the prediction of stock prices. The difference of our proposed model is that we are focusing on decision-making in stock markets, but not in its forecasting.

In this paper we present a decision-making model which combines two AI tools: ANN and PSO algorithm. The objective of this model is to analyze the daily stock returns and to make one day forward decisions related to the purchase of the stocks.

The application of ANN is common in financial markets. However, despite the optimistic view concerning the possibilities of ANN in financial forecasting [11, 4, 8], our investigations have shown, that the average prediction quality was not efficient while using feed-forward ANN and also ANN with pseudo-input variables [2]. Differently from our previous works [2] in this work, we are not making a direct prediction of stock markets, but we are working on one day forward decision making for buying/selling the stocks. For that we are developing a decision-making model, where besides the application of ANN we have decided to use PSO algorithm. From all other evolutionary computation paradigms the PSO algorithm was chosen, as PSO is the only evolutionary algorithm that does not incorporate survival of the fittest, which features the removal of some candidate population member [5]. In genetic algorithms (GA), differently from PSO algorithm, the learning is made through the genetic recombination and mutations. In that case it is very possible that the GA mutation process will likely result in a low-fitness chromosome that does not survive the selection process (the probability of survival decreases geometrically with generations). In the proposed decision-making model this feature of PSO learning process is very important. In some cases working with quickly changing environments the particles with low fitness can show good performance and give the right decision for some time period.

The paper is organized as follows: Section 2 presents decision-making model; Sections 3 is devoted for experimental investigations and evaluation of decision-making model. This section gives the ground for selection of different variable witch are used in the model, as well to the model structure. The main conclusions of the work are presented in Section 4.

2. Decision-Making Model for Stock Markets

The proposed decision making model combines the application of ANN and PSO algorithm and is used for the calculation of one day forward decision (like buy, sell, or hold). The scenario of decision-making model is presented in Figure 1. The model scenario represents one day calculations which are made in order to get decision concerning the purchase of stocks. For the model realization there are used historical data of daily stock returns. In the first step of the model realization the daily stock returns variations are passed to the model (see the first block of model scenario). In the first model scenario block variable *m* presents the number of stocks and *S* – stocks. The group of the stocks, which are used for the calculations, can be selected by the user. The second block of decision-making model presents the group of ANN (swarm). In the pre-

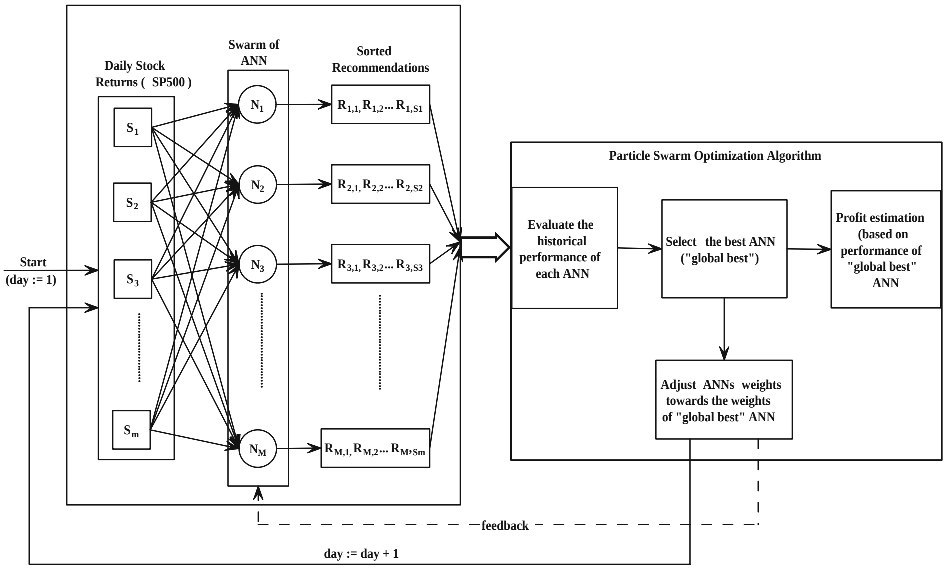

Figure 1. Decision-making model.

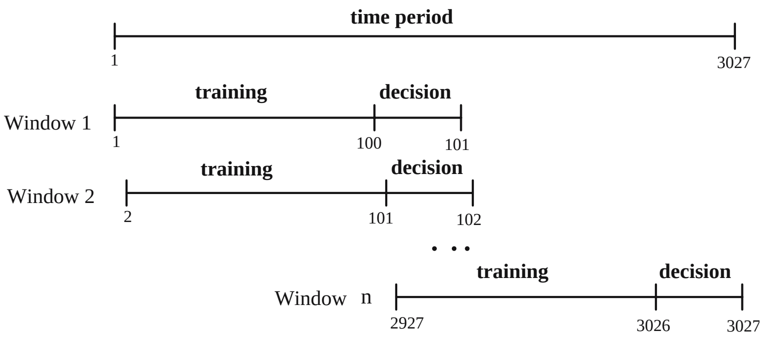

Figure 2. Sliding window.

sented decision-making model scenario (see Figure 1) variable N presents ANN and M is the number of ANN. All the data from the first block of the model are passed to the group of ANN. ANN are used for the calculation of the investment recommendations: sell, hold or buy. Each input of ANN has some predefined weight. The weights of ANN inputs are initialized randomly at the beginning of the procedure:

$$w = \mathrm{rand}(w, n) - 0.5, \tag{1}$$

where w is randomly initializes weights of ANN and n corresponds the number of ANN. The start weights are kept relatively small, and their mean is close to zero. In the decision-making model there are considered stocks returns for $k = 1{:}5$ interval of days (see Section 3.5). The ANN output are the buy/sell recommendations. For the calculation of the recommendations we are using hyperbolic tangent function. That is because we need to get recommendations in the range $[-1, 1]$. The recommendations are calculated according to the following equation:

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

where x is weighted sum of inputs (daily stock returns variations for 1:5 days). 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. When the recommendations are known all the stocks are sorted according to the calculated recommendations. Having sorted stocks we are taking into account first three stocks that have the highest recommendations. As the next step, the observation of these stocks on the next day follows.

It is important to mention, that decision-making model is based on the idea of sliding window. The size of sliding window shows how many times the cycle of the model has to be run in order to get the decision. For each days' decision a new sliding window is needed. An example of sliding window is presented in Figure 2. As it can be seen from the presented picture, sliding window represents the training part of each time interval. For the training of ANN there is used the PSO algorithm. At first the best ANN of the day is selected. The best ANN is called that ANN which have shown the best performance (the highest total profit for the selected sliding window). When the best ANN is know all other ANN are trained towards the performance of the best ANN. The ANN are trained by adapting the ANN weights towards the weights of the best ANN. The recalculation of ANN weights is made according to the following equation:

$$w_{\text{new}} = w_{\text{old}} + c * (w_{\text{best}} - w_{\text{old}}), \tag{3}$$

where w_{old} presents the weight of the explored ANN, w_{best} is the weight of the best ANN, and c – learning rate. The choice of learning rate is crucial as the exploring ability of PSO may cease to exist. It can happen that for each day the different "the best" ANN may be selected. Such training of ANN lets to move towards the best solution. The final investment decision *sell*, *hold*, or *buy* is calculated according to the recommendations of the best ANN at the end of the period.

3. Experimental Investigations

This part is devoted for the description of data and experimental investigations, which were run in order to evaluate the performance of the proposed decision-making model. In the first part of this section, we give a short introduction into data description. Further, we are focusing on the description of experimental investigations and evaluation of proposed model performance having different input variables and using different input data.

3.1. DATA DESCRIPTION

While choosing the stocks for experimental investigations a big importance was given to the liquidity ratio as it is correlated with the transaction fees while buying or selling the stocks. The model realization could be run having different groups of stocks (like SP500, Down Jones, DAX, etc.), indexes or other groups of securities.

While preparing the data for experimental investigations we were focusing on the elimination of data incompleteness. After downloading the data it as noticed that is some cases the data of daily stock returns was missing (the data splits were detected). A data split is defined as any time period for which the price information was missing. We had to find a way, how to overcome such misalignment of price information, as price information is essential in evaluating the historical performance of the stocks. In order to solve this problem we have decided in a case of missing daily stock returns information to substitute the missing information with the day before available information for that stock. More precisely, if at time t we have stock price information but do not have stock price information for the next day $t+1$, we look for that stock price information on previous day. So, we made an assumption that stock price on the next day is the same as it was today.

All the experimental investigation which were run in order to select the right input variables of the decision-making model, were run using daily stock returns of 350 stocks. These stocks were selected from SP500 index group. The data set represents daily stock returns for 12 years (Oct/01/1991–Oct/01/2003). For all experimental investigations we consider the variations of market close prices. For that we are using market orders as it allows to simulate the buy action of stocks are the market closing time. All the experimental investigations were run according to the above presented scenario (see Figure 1) and were focused on the estimation of possible returns. At the beginning of each realization the start investment is assumed to be 10,000$. The expected returns are calculated considering transaction fees that are unavoidable in the stock markets. The transaction fee is paid for buying and selling stocks. The traders profit is calculated as a sum of stock returns (%):

$$P_{\text{end}} = \sum_{t=2}^{t} P_t, \tag{4}$$

where:

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

Here P_t represents the profit at time point t. If at the moment $t-1$ there were bought selected stocks for the total price K_{t-1}, then after one day the price of these stocks will be K_t and the profit (%) will be equal to the value of P_t. The value obtained on the last investigation day is considered as the profit. The average accumulated profit per day is calculated:

$$P_{\text{avg}} = \frac{P_{\text{end}}}{t_{\text{end}-1}}. \tag{6}$$

The model evaluation using the average profit can mislead the evaluation of the model. The misleading of the model will not appear if the fluctuations of model performance are not comparatively big from day to

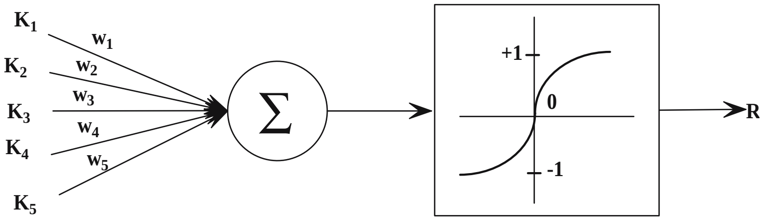

Figure 3. Artificial neural network.

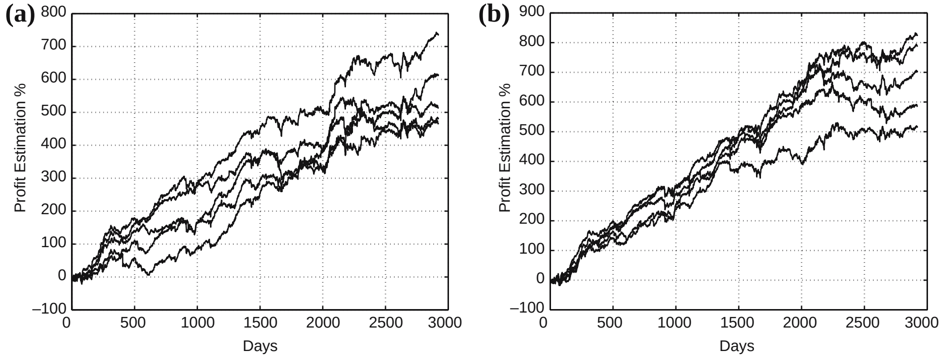

Figure 4. Profit estimation. (a) five ANN, sliding window of 100 days. (b) 30 ANN, sliding window of 100 days.

day. However, if we have big fluctuations in the model performance the model evaluation using average profit can give misleading results. In order to avoid that in the future we intend to use Sharpe Ratio for the model evaluation in order to avoid such errors. In all experimental investigations the training of ANN was made through the adjustment of ANN weights towards the weights of the best ANN. At the first stage of experimental investigations for the model evaluation there were used single-layer ANN (see Figure 3). The "single layer" ANN were chosen in order to check the suitableness of proposed model while having the most primitive case of it.

3.2. SELECTION OF MOVING TIME INTERVAL AND NUMBER OF NEURAL NETWORKS

The first part of experimental investigations was focused on the choice of optimal number of ANN and on the choice of the size of sliding window. The experiments were run taking into account different sliding windows and different number of ANN. The number of explored stocks and days was the same in all the cases. The results of experimental investigations are presented in Figure 4a and b.

From Figure 4a and b it can be seen that the swing of the results is much smaller when there were taken 30 ANN. As well the experimental investigations showed that the results are influenced by the choice of sliding window size. The obtained results let us to make several conclusions:

– The bigger number of ANN, with different initial weights, let us to achieve more stable results (see Figure 4a and b).
– The bigger sliding window lets to avoid unnecessary variations and to achieve better results.
– The experimental investigations showed that the best results are achieved while taking 30 ANN and the sliding window of 100 days.

In order to show the correlation between profit (% per day) and sliding window while having 30 ANN we are presenting Figure 5a. In the presented figure numbers $1, 2, \ldots, 10$ represent time intervals $10, 20, \ldots, 100$, respectively. As it can be seen from Figure 5a, the profit is growing while increasing moving time intervals.

The variations of the profit become more stable if the sliding window size is from 70 to 100 days (see Figure 5b). Figure 5b shows that having sliding window of 100 days (solid line) the swing between ANN is much smaller than having the sliding window of 10 days (dashed line) or 50 days (bold line). Here the swing of ANN is meant to be the choice of different best ANN for different time period. For example: having sliding window of 100 days (solid line) we can see that starting from the first day to until the 38th day the best ANN is the 20th. During the same time period, having sliding window of 10 and 50 days the best ANN is changing almost every third or fifth day. Might be it would be possible to increase these results taking into account bigger number of ANN and bigger sliding window. In this work there were not made such experimental investigations because of the limited computer capacity.

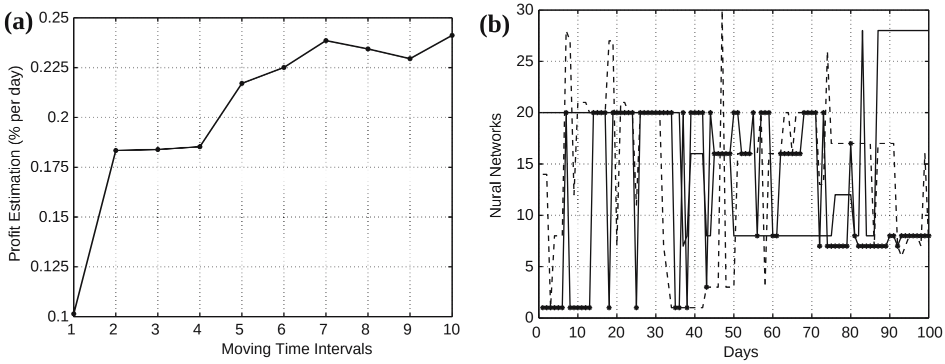

Figure 5. Influence of sliding window size. (a) Profit size. (b) The swing of ANN.

3.3. PROFIT DEPENDENCE FROM TRANSACTION FEE SIZE

Further experimental investigations were focused on the estimation of the profit considering different transaction fees. As the previous experimental investigations have shown that the best results are achieved having 30 ANN and sliding window of 100 days, these variable were used in all other experimental investigations. The analysis of the transaction fees of different e-brokers showed that transaction fee in real trading process is usually between 0.15 and 0.3%. For example, such transition fees are provided by the company of Interactive Brokers [10]. Having bigger selling and buying volumes this fee could be even smaller – 0.1%. In the first stage of transaction fee size determination we were considering the transaction fee of 0.15%. We were making an assumption that on the first trading day we are investing 1000$ into the market. Each day we are paying 0.15% of transaction fee for buying new stocks. The value got on the last investigated trading day is considered as the profit. For the trading of SP500 index the transaction fee is not considered. The experimental investigations showed that having the transaction fee of 0.15% we are able to earn more than the average of the market (see Figure 6a).

In order to determine the reasonable size of transaction fee there were made experimental investigations taking into account different size transaction fees. It was noticed that the situation is changing while the transaction fee is increasing (see Figure 6b). While having the transaction fee of 0.2% we are already slightly loosing compare to the profit that has been got from the investment into SP500 index (dashed line). In Table 1 there are presented detailed results on transaction fees size investigations. From above presented results we can conclude that our proposed decision-making model is suitable for financial funds that have a possibility to pay small (0.15%) transaction fees for buying and selling transactions. The experimental investigations have shown that the results, achieved with

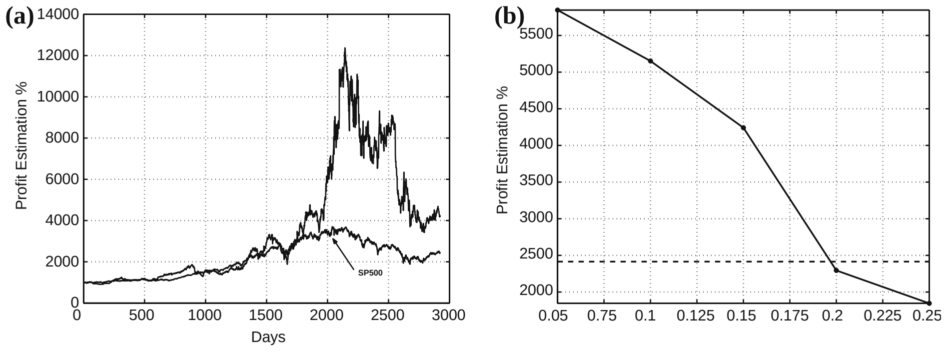

Figure 6. Influence of transaction fee size. (a) Profit estimation (fee 0.15%). (b) Profit size.

Table 1. Estimation of transaction fee influence on the performance of the model.

Fee (%)	Case 1 (Prof.%)	Case 2 (Prof.%)	Case 3 (Prof.%)	Case 4 (Prof.%)	Case 5 (Prof.%)	Avg. Prof. (%)
0.1	0.1625	0.2103	0.2406	0.2125	0.2031	0.2058
0.15	0.1906	0.1625	0.1615	0.1518	0.1307	0.1594
0.2	0.1615	0.1406	0.1125	0.1115	0.1235	0.1299
0.25	0.1318	0.1091	0.1514	0.1297	0.1186	0.1281
0.3	0.1307	0.1118	0.1396	0.0945	0.1048	0.1163

our proposed decision-making model, are better compare to the results achieve using ANN for the investigation of similar time series and its future changes forecasting [13, 20]. However, the proposed model still has to be improved in order to achieve better results while considering bigger transaction fees.

3.4. SELECTION OF LEARNING RATE

Another important part of experimental investigations was the selection of ANN learning rate. The training procedure of ANN includes several stages: first – the best ANN is selected, second – all other ANN performance is compared to the performance of the best ANN and the adjustment of its weights towards the weights of the best one is made. In order to make the training of ANN we had to select the learning rate. The experimental investigations on learning rate selections are presented in Figure 7. In the presented Figure 7 x-axis presents the learning rate and y-axis presents the average expected profit (%) per day. The presented results were achieved using sliding window of 100 days and 30 ANN. As it can be seen from Figure 7 the best results are achieved while taking into account the learning rate of 0.05. After this rate is increased the decision-making model performance is slightly decreasing. After the learning rate of ANN is increased to 0.6, the results start change significantly and the average profit start to decrease. That means, that the bigger learning rate cause bigger fluctuations in selection of the best ANN (different best ANN are selected for the different day). At the same time these fluctuations cause instability of the model and the reduction of its performance results. From the presented Figure 7 it can be seen, that the optimal ANN learning rate is 0.05. In that case the percentage of average profit per day reaches 0.2846%. Such learning rate is used in all experimental investigations on decision-making model evaluation.

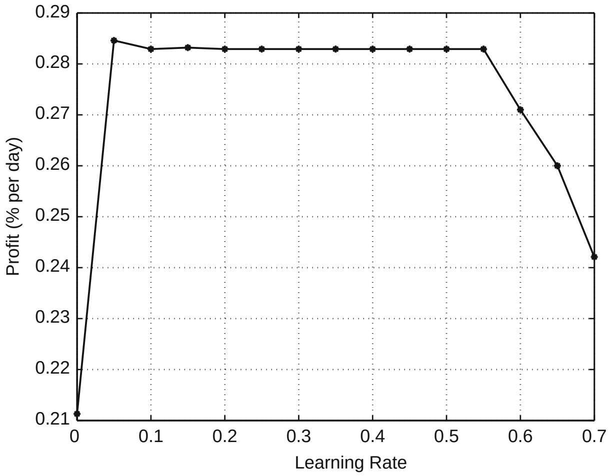

Figure 7. Profit dependency from learning rate.

3.5. SELECTION OF DECISION-MAKING MODEL STRUCTURE

In the previous investigation of decision-making model we were taking the sliding window of 100 days, 0.05 learning rate, single layer ANN, and ANN input values (daily stock returns) for $k = 1{:}5$ days. The next experimental investigation were focused on the evaluation of the following decision-making model features:

1. Number of inputs. The selection of inputs number is crucial for the model performance. The aim of these experimental investigations was to find an optimal number of ANN inputs. In the proposed model the ANN inputs are daily stock returns for different time periods k. By setting different k values we get measures telling how much the stock price has changed per day since its start value k days ago. The goal of experimental investigation is to analyze what k value gives the best results.
2. ANN structure (the number of layers). These experiments were focused on the evaluation of model performance while taking different structure ANN. The goal is to check if the model performance results could be improved by the application of ANN with more complicate structure.

The more detailed descriptions of these experimental investigations are presented in the sections below.

3.5.1. *Selection of Inputs Number*

In the initial version of decision-making model (single layer ANN) there were considered stock returns of $k = 1{:}5$ step interval. In order to validate

Table 2. Model performance evaluation (different number of inputs)

k	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	Profit estimation %
ANN Inputs	+	+	+	+	+	+	0.19 ($\sigma=0.06$)
	+	+	+	+	+		0.25 ($\sigma=0.05$)
	+	+	+	+			0.17 ($\sigma=0.06$)
	+	+	+				0.16 ($\sigma=0.07$)
	+	+					0.12 ($\sigma=0.07$)
						+	0.14 ($\sigma=0.07$)
					+		0.15 ($\sigma=0.05$)
				+			0.14 ($\sigma=0.06$)
			+				0.14 ($\sigma=0.06$)
		+					0.11 ($\sigma=0.06$)
			+		+		0.17 ($\sigma=0.06$)

such choice there were run experiments considering different k intervals. In order to achieve reasonable results we have made 10 realizations of each different case. Each realization is run with different initial weights. The average performance (profit estimation (%)) and standard deviation (σ) of each case are presented in Table 2.

In Table 2 presented results show, that the best performance of decision-making model is reached while taking stock returns for $k = 1{:}5$. It means that such k inputs have the biggest influence on the next day stock returns and using these inputs quite good results could be achieved. More clear evaluation of ANN inputs number is shown in Figure 8. The figure presents the experimental results which were achieved having step values of $k=5$, $k=1{:}5$, and $k=3$ & $k=5$. Form Figure 8 can be seen, that having $k=5$ ANN inputs, the results of decision-making model are decreasing compare to the case of $k=1{:}5$ ANN inputs. While having ANN inputs of $k=3$ & $k=5$ the results are slightly better than in the case of $k=5$. The best results are achieved while having $k=1{:}5$ ANN inputs.

3.5.2. *Selection of ANN Structure*

For the initial analysis of the decision-making model “single layer” ANN were used. When having the working model we were looking for any possible solutions, how to increase its performance. One of the possibilities to do that was decided to be the application of two-layer ANN. An example of two layer ANN is presented in Figure 9. While applying single layer ANN we were checking what results could be achieved while having the simplest case of the decision making model. The application of two-layer ANN with two nodes lets to check if a bit more advanced case of decision-making model lets to improve the model performance results. Figure 10 presents the comparison of the decision-making model perfor-

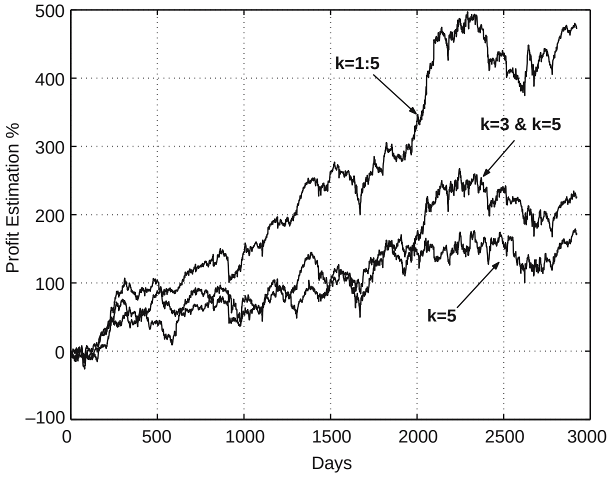

Figure 8. Estimated profit ($k = 5$, $k = 1{:}5$, and $k = 3$ & $k = 5$).

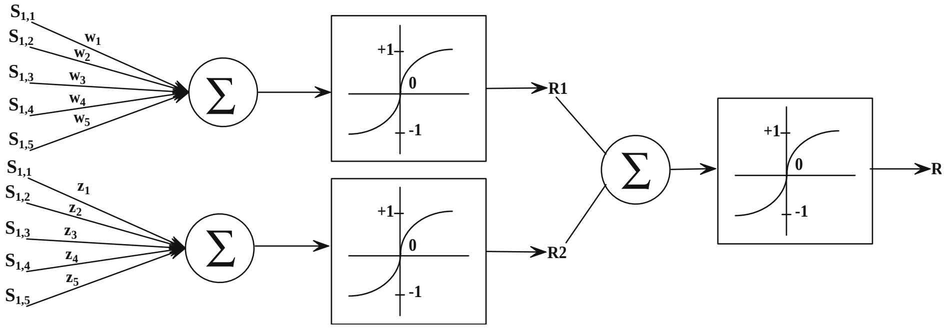

Figure 9. Two layer ANN.

mance results. Three different cases were analyzed: conservative investment approach (investments are done into SP500 index by buying and holding it for all time period), application of decision-making model with single layer ANN, and application of decision-making model with two-layer ANN. In Figure 10, there are presented average results of each case. The presented results show, that the application of PSO algorithm and training of ANN towards the performance of the best ANN give quite good results. Compare to the conservative approach the proposed single layer ANN decision-making model lets to achieve almost five times better results (applying single layer ANN). The reason of that is that every day the investment decisions are made using the best ANN and at the same time all other ANN are moved towards it. In the case of two-layer ANN application in decision-making model the results are not so good. That can be explained by the complexity of the model. Working with complex environments the more advanced decision-making model does not necessarily give

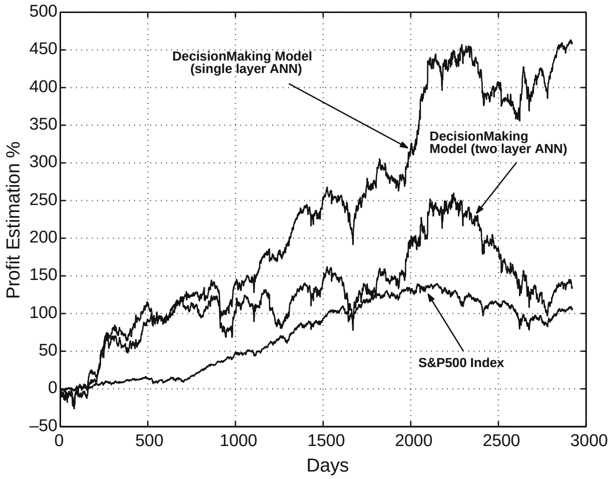

Figure 10. Single layer ANN and two layer ANN application (average results).

better results. While applying single layer ANN we have got that the average profit estimation (%) is 0.245, while in the case of two-layer ANN it is only 0.114. As well the evaluation of different model realizations showed that model performance with two-layer ANN is not stable and is dependent on the initial weights of ANN (see Figure 11). Compare to single layer ANN application the variation of different realizations is 2.3 times bigger. As it can be seen from Figure 11, different realizations of decision-making model with two layers ANN give quite contradicting results. That let us to come to the conclusion, that application of two layers ANN in decision-making model is a bit too complex for decision making in very noisy environments. Depending from the situation in the market it could give good results, but the average performance shows that such cases are quite rare. The big variations of its different realizations show, that such decision-making model can not ensure stable results in decision-making in stock markets.

3.6. MODIFICATION OF ALGORITHM INCLUDING SHORT SELLING ACTIVITIES

When an investor makes a decision to act upon a stock, he/she is choosing what position to take: long or short. Taking a long position means buying the stocks first. Such buying of stocks is based on the anticipation of its price going up, so that the stock can be sold at a profit. There is another possibility: to sell the stock first. In the case, when investor expects that the price of the stock will go lower, he/she can sell the stock and buy it back cheaper in the future. Such process is called shorting or short position. All before presented experimental investigation were made considering long position. The experimental investigations, presented in this section

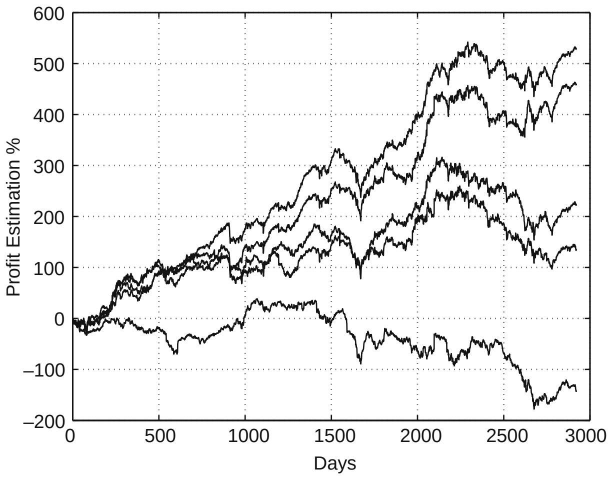

Figure 11. Two layer decision-making model (average results).

are focused on the evaluation of decision-making model while applying short selling of stocks (see Figure 12). In the case of short selling, the decision-making algorithm is the same as in the case of long position. The difference is, that having short selling of stocks, instead of buying three best stocks (long position), three stocks with the lowest recommendations are sold. As it can be see, in Figure 12 there are presented the results of the following experimental investigations: decision-making model application for buying the stocks (long position), decision-making model application for short selling of the stocks (short position), combination of these two strategies and the results of conservative investment case. The

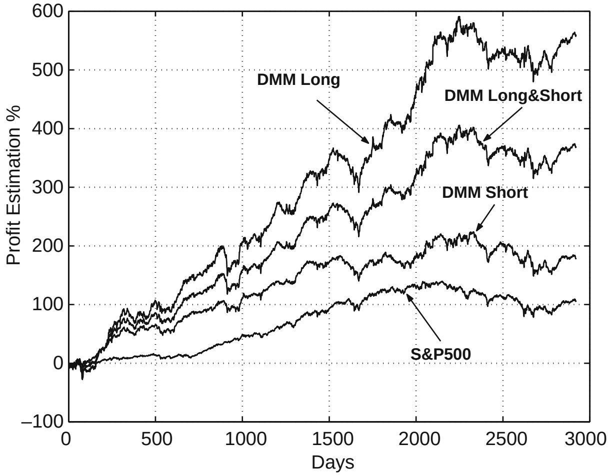

Figure 12. Comparison of the results (average results).

presented results show, that the performance of decision-making model is decreasing, while applying it for the short selling of the stocks. As well it can be seen that the combination of long and short-position astrategies shows lower performance compare to the decision-making model performance application only for the long position. The performance curve of long and short strategies combination is becoming a bit smoother compare to other cases of decision-making model application. That let us to come up to the conclusion that the combination of these to strategies lets to achieve more stable results. The big peaks in the model performance curve show the disadvantages of the model. If the investor decides to apply the suggested decision-making model and makes an investment at the top of the curve pick, the loss of the money is not avoidable. If the pick is big, the loss can be crucial for the investor. As well, the results presented in Figure 12 let us to ground the above presented conclusion: decision-making model performance results are quite promising and give better results than and application of conservative investment strategy.

3.7. APPLICATION OF THE MODEL FOR TRADING OF STOCK MARKET INDEXES

All above presented experimental investigations were focused on decision-making model evaluation while trading stocks. This part of experimental investigations is focused on the model evaluation while trading stock market indexes. Investment into indexes is quite popular among independent investors and investment funds. As indexes include only well selected companies an investment into stock market indexes can reduces the investment risk. Widely known stock markets indexes are Dow Jones, SP500, NASDAQ, Nikei 225, CAC 40, DAX, FTSE 100, etc. While making an investment into stock market indexes an investor purchases stocks or indexes option which belong to investment fonds. Popular brokerage companies are trying to give an investor a possibility to invest into the markets of different countries. For example: the company of Interactive Brokers is offering a possibility to trade securities and indexes of 14 different countries.

For experimental investigations we have decided to use historical data of stock market indexes which represents its monthly changes for time period from 07/01/1998 to 04/01/2001. We have selected indexes of 30 countries. For the investigations there was chosen the sliding window of 40 months. The results of experimental investigations are presented in Figure 13.

In presented Figure 13 there are shown two lines: the first line presents the performance of decision-making model while making investment into stock indexes and the second line presents the case of investment into SP500 index. The estimated average profit (%) is almost six times big-

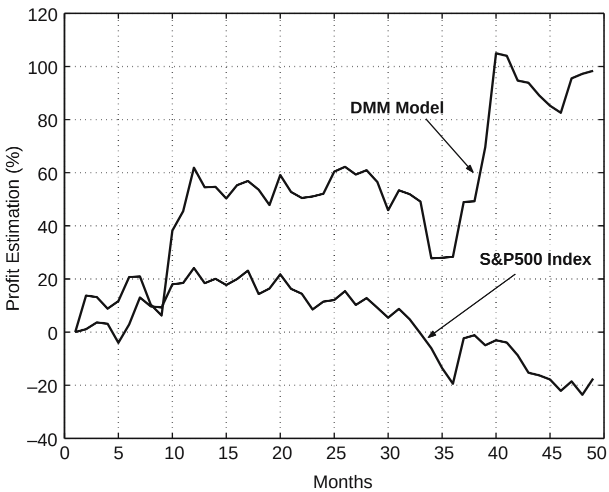

Figure 13. Trading indexes (average results).

ger compare to the case of conservative investment. The investigations have shown that the proposed decision-making model can be successfully applied not only for trading stocks but as well for trading stock market indexes. In the future it would be worth to check the proposed model using different data set of stock market indexes. In these investigations the data presents monthly changes of stock market indexes. In order to make model to work efficiently we hat to increase the size of sliding window. The more efficient performance of the model should be achieved having daily changes of stock market indexes, as in that case we could reach more efficient training of ANN.

4. Conclusions and Future Work

In this paper there was presented the decision-making model based on the application of ANN and PSO algorithm. The model was applied in order to make one-step forward decision considering historical data of daily stock returns. The experimental investigation have shown:

– The best decision-making model performance is achieved having 30 ANN and sliding window of 100 days.
– Valuable transactions transaction fee was decided to be 0.15%. Such transaction fee makes the model attractive to financial funds, which are able to get the right to trade with lower transaction fees.
– The most efficient training of ANN is reached while having the learning rate of 0.05.
– The best results are achieved while having $k = 1{:}5$ ANN inputs.

- The application of two layers ANN in decision-making model is a bit too complex for decision making in very noisy environments. In some cases, depending from the situation in the market, it could give good results.
- The combination of long and short selling strategies lets to achieve more stable results.
- The investigations have shown that the proposed decision-making model can be successfully applied not only for trading stocks but as well for trading stock market indexes.

In the future it would be worth to check model performance using different data set of stock market indexes. As well we are planing to use Sharp Ratio for the model evaluation. Model evaluation using Sharp Ratio could give more valuable results as sometimes having big model performance fluctuations the model evaluation using average profit can give misleading results.

However, while making computations with the proposed model we have faced some problems. The big amount of data and complex computations do not allow us to ensure the fast decision making which is necessary while working in stock markets. In the future, as the solution for this problem we are planing to use grid computational technologies.

References

1. Bartholdson, K. and Mauboussin, J.M. (2002), Thoughts on organizing for investing success, *Credit Suisse First Boston Equity Research*.
2. Blandis, E. and Simutis, R. (2002), Using principal component analysis and neural network for forecasting of stock market index, *Bizinesa augstskola Turiba SIA*, Zinatne, Riga, pp. 31–35.
3. Carlisle, A. and Dozier, G. (2000), Adapting particle swarm optimization to dynamic environments, In: *Proceedings of ICAI Conference on Artificial Intelligence*, Las Vegas, USA. pp. 199–204.
4. Din, A. (2002), Optimization and Forecasting with Financial Time Series, *Note from Seminar at CERN*.
5. Eberhart, R.C. and Yuhui Shi, (1998), Comparison between genetic algorithms and particle swarm optimization, *Evolutionary Programming* 611–616.
6. Franks, N.R. (1989), Army of ants: a collective intelligence, *American Scientist* 77(2), 138–145.
7. Gudise, V.G. and Venayagamoorthy, G.K. (2003), Comparison of particle swarm optimization and backpropagation as training algorithms for neural networks. In: *Proceedings of the 2003 IEEE on Swarm Intelligence Symposium*, SIS '03, 24–26 April, 110–117.
8. Hellstrom, T. (2001), Optimizing the sharpe ration for a rank based trading system, *Lecture Notes in Artificial Intelligence*, LNA 2258 Springer-Verlag, New York, pp. 142–155.
9. Hellstrom, T. and Holmstrom, K. (2000), The relevance of trends for predictions of stock returns, *International Journal of Intelligent Systems in Accounting, Finance & Management* 9(1), 23–34.
10. Interactive Brokers (2004), http://www.interactivebrokers.com.

11. Kaastra, I. and Milton, B. (1996), Designing a neural network for forecasting financial and economic time series, *Neurocomputing* 10(3), 215–236.
12. Lu, W.Z., Fan, H.Y. and Lo, S.M. (2003), Application of evolutionary neural network method in predicting pollutant levels in downtown area of Hong Kong, *Neurocomputing* 51, 387–400.
13. Lowe, D. and Webb, A.R. (1991), *Time Series Prediction by Adaptive Networks: A Dynamical Systems Perspective*, IEEE computer society press.
14. Mirmirani, S. and Li, C.H. (2004), Gold price, neural networks and genetic algorithms, *Computational Economics* 23(2), 193–200.
15. Nenortaite, J. and Simutis, R. (2004), Workshop on computational methods in finance and insurance, *Stocks' Trading System Based on the Particle Swarm Optimization Algorithm*, Springer-Verlag, New York, vol. 10, pp. 843–850.
16. Pavlidis, N.G., Tasoulis, D. and Vrahatis, M.N. (2003), Financial forecasting through unsupervised clustering and evolutionary trained neural networks, In: *Proceedings of the 2003 Congress on Evolutionary Computation*, Canberra Australia.
17. Po-Chang, K. and Ping-Chen, L. (2004), A Hybrid swarm intelligence based mechanism for earning forecast. In: *Proceedings of the 2nd International Conference on Information Technology for Application (ICITA 2004)*, pp. 193–198.
18. Rejas, L.M.P., Ponce, E.R.R. and Silva, J.E.B. (2001), The wiener gauss stochastic process: an application to the food index at the madrid stock exchange, In: *Proceeeings of 2001 The Journal of Global Business Perspedtives*, International Business Association (IBA).
19. Simutis, R. (2003), Stock trading systems based on stock's price ranks (in Lithuanian), *Ekonomika* 62, 157–164.
20. White, H. (1998), Economic prediction using neural networks: The case of IBM daily stock returns, *IEEE International Conference on Neural Networks*, IEEE Press, New York, pp. 451–458.