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An Investment Strategy for the Stock Exchange Using Neural Networks

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***Abstract*—This paper describes a neural system which helps to make the current investment decisions. Some well known financial indicators usually considered by investors are inputs of the system. The basic problem is to select appropriately the indicators which would give the best predictor. Two methods are used and compared: the combination method and the correlation method. To analyze the problem daily quotations of companies included in the Warsaw Stock Exchange Index (WIG20) are used.**

Keywords: Stock exchange, prediction, nonlinear modeling, neural networks, soft computing.

I. Introduction

NEURAL networks [5] are universal approximators [6]. It means that a network with at least one hidden layer is capable of approximating any nonlinear smooth function to an arbitrary accuracy (provided that the number of hidden units is sufficient enough). Multilayer perceptron neural networks are most common. As the practical experience indicates, they can be successfully used in numerous application, including e.g.: pattern recognition [1], [12], numerical methods [2], biomedical engineering [7], optimization [9], fault diagnosis [8], robotics [11], load forecasting in a power system [13] and control algorithms [14], [15]. Neural network can be also used in financial forecasting [4], [16]. Usually, a stock exchange time-series model is trained the role of which is to predict the future price of shares. Although such a "black-box" approach is commonly used in system identification but it is completely different from the classical technical analysis methods [3], [10] popular in banks and in the financial community. In this work neural networks are used for developing an investment strategy. Unlike "black-box" approaches some technical analysis indicators are used as inputs of the system. Investors often consider those indicators before making decisions because they have intuitive interpretation. Because there are various indicators used in the technical analysis, the basic problem to solve is to select the indicators which would give the best predictor.

II. Description of the problem

One of the very interesting investment strategies is based on stock quotes. In some periods the stock quotes stabilize for some time and share price fluctuations are very small. Such a time period is named stagnation. It is not difficult to find such periods on the price chart because the value of the shares should be analyzed from the last 4 weeks (20 market days). From observations of the stock quotes it can be observed that they appear immediately after a period of stagnation followed by a sharp change in the value of shares (either upward or downward). The investment strategies frequently used by investors use the popular technical analysis indicators. The "buy", "sell" and "hold" decisions are made taking into account the values and behavior of selected indicators in periods of stagnation points of interest.

In this paper the investment strategy shortly described above leads to developing a neural network which would be able to serve as the decision support systems. The neural network uses the information represented by the classical technical indicators well understand by the investors. The objective of the neural network is to answer the question whether or not the investor should invest. To analyze the problem daily quotations of the last 10 years of the biggest 20 companies included in the Warsaw Stock Exchange Index (WIG20) are used. This choice was made due to the fact that the stock market of WIG20 is the most liquid, it allows for greater investment in less time.

For determination of important points associated with finding periods of stagnation of stock prices a time window of variable width of 20 days is used, which measures changes in the average value of the shares. It is assumed that the interesting point is when the change in value of the shares is greater than the average change in the time window, while the previous two trading points are characterized by below-average volatility of the window.

Fig. 1 shows the interesting points on the background of the graph of a company's share price. It can be observed that in the periods prior to the occurrence of these points there are periods of stagnation of stock prices, and in the near future from the important points share price rises or falls rapidly.

III. The neural predictor

The set of all points of interest is divided in half: the first part is the training data set for the neural network, the second part is the test data set.

From an analysis of all the points of interest it can be concluded that 93% of those points actually lie before significant changes of stock prices. The interesting points that lie before increases in the shares of companies described as positive points, but those points, followed by the decline in stock prices described as negative points. The analysis of points of interest is shown in Table I.

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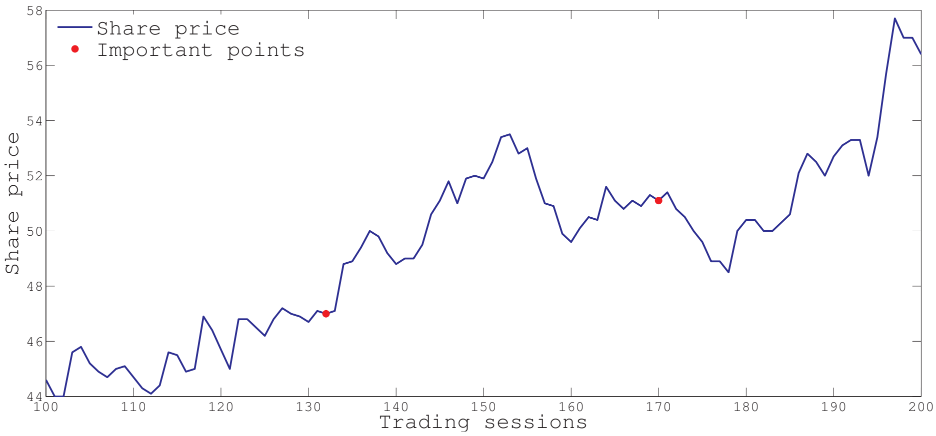

Fig. 1. Interesting points on the background of the graph of a company's share price

TABLE I
ANALYSIS OF A SET OF POINTS OF INTEREST

Data set	Positive points	Sum of all points	Good investments (%)
All data	1187	2251	52.73%
Training data set	582	1126	51.69%
Testing data set	605	1125	53.78%

While analyzing data from a set of points of interest one can identify a strategy that conventionally is called "the trivial strategy". It is based on the fact that if the investor finds an interesting point, he or she invests. The percentage of all positive points in the set of all points of interest is 52.73%. It means that if the investor uses any signal of an interesting situations to invest in the stock market, in 52.73% of such situations he or she would be successful.

It can be argued that "the trivial strategy" is "buy" and "hold". However, the art of investing in the stock market, which is characterized by quickly transfer money between investments so that the whole time money is working in an optimal way.

The task of the intelligent investor and the proposed neural decision support system is to analyze the points of interest, reject the situations that lead to losses, and recognize those that generate profit. In order to analyze the problem considered in the article it is necessary to answer the following questions:

1) Do the indicators proposed by the investors carry the necessary information that allows the choice of the positive points?
2) Are all the indicators proposed by the investors required to make the correct decision?
3) Is it possible to construct a computerized system of investment, which would give the results much better than the trivial strategy?

IV. CREATING A NEURAL NETWORK

A multi-layer perceptron neural network with nonlinear (tanh) hidden neurons and one linear output neuron is used for modeling. Due to the fact that the study is based on finding the correct classification of investment situation, in the output layer of neural network one linear neuron is used. When the network output gives a positive value, the investment situation is recognized as opportunity and the system suggests to invest. Whet the network output gives a negative value, the system suggests to omit the investment. The linear output neuron is chosen, because it can show general suggestion of investing or omitting the investment, but also magnitude of this signal can tell the investor if this investment situation is clear or it is difficult to take a decision. When the system gives a positive value, but this value is close to 0, the investor should be aware of the increased risk of this particular investment. On the other hand, when there is a big output value, it may suggest that the investment situation is clear and the risk is small. The risks is understood as the number of conflicting signals from the analyzed indicators. If a large majority of indicators generates the same signal, the risk of making a wrong decision is small.

The following assumptions are made:

1) All the indicators suggested by the investors are chosen as network inputs.
2) Neural network with different number of hidden nodes are trained and compared.
3) During training the network classification error is calculated for the training data set, the test data sets are used to finally choose the structure of the neural system.

The neural network are trained by means of the Levenberg-Marquardt algorithm. Initial experiments indicate that after 200 iterations of the training procedure the classification error stabilizes and further training does not bring better results. Thus, in all further experiments, the number of training iterations is 200.

Classification accuracy (percentage of hits in a good investment) for different number of hidden nodes is shown in Fig. 2. The network with 15 hidden neurons is finally chosen because it gives classification results better than the results obtained by means of all other networks (the test data set is taken into account). Smaller networks have low approximation abilities whereas bigger networks are overparameterized, they have too many parameters (weights).

The answers to the questions put above (in the previous section) require the study of the influence of the neural network inputs on the classification accuracy. Thus, the above questions are equivalent to the following:

1) Do the neural network input signals allow the classification and selection of positive points?
2) What is the number of inputs that allows the best classification and selection of positive points?
3) Does the best possible network achieves better results than the trivial strategy?

A. Technical analysis indicators used in the investment strategy

When one has a set of interesting points, the next step is to calculate the value of technical analysis indicators for the points. As recommended by investors from the Warsaw Stock Exchange, seven indicators are taken into account: the slow stochastic oscillator %K %D, the Moving Average Convergence-Divergence (MACD), the Commodity Channel Index (CCI), the Relative Strength Index (RSI), the three backward linear regression values for the 5, 10 and 15 days.

1) The slow stochastic oscillator %K %D (the 1^{st} *input):* Stochastic oscillator [3] is commonly used by traders. It tracks the relationship of each closing price to the recent high-low range. The stochastic oscillator consists of two lines: a fast line called %K and a slow line called %D. The first step is to calculate the %K from this equation:

$$\%\text{K} = \frac{C_{tod} - L_n}{H_n - L_n}$$

where C_{tod} – today's close, L_n – the lowest point for the selected number of days, H_n – the highest point for the selected number of days, n – the number of days. The second step is to obtain %D. It is done by smoothing %K over a three-day period:

$$\%\text{D} = \frac{\text{3-day sum of } (C_{tod} - L_n)}{\text{3-day sum of } (H_n - L_n)} \cdot 100$$

Fast stochastic oscillator is very sensitive to the returns on the market, but it leads to many erroneous signals. Many investors use the slow stochastic oscillator, which is less sensitive. The value of %D of fast stochastic oscillator becomes the %K of slow stochastic oscillator and is smoothed by repeating step 2 to obtain the value of %D of slow stochastic oscillator. An example slow stochastic oscillator is demonstrated in Fig. 3. The stochastic lines help identify top and bottom areas when they move above or below their reference lines. The stochastic oscillator gives its best signals when it diverges from prices.

2) Moving Average Convergence-Divergence (the 2^{nd} *input):* The MACD index [3] consists of three Exponential Moving Averages (EMAs). It appears on the charts as two lines whose crossovers give trading signals. The original MACD indicator consists of two lines: a solid line (called the MACD line) and a dashed line (called the signal line). The MACD line is made up of two Exponential Moving Averages. It responds to changes in prices quickly. The signal line is made up of the MACD line smoothed with another Exponential Moving Average. It responds to changes in prices more slowly. Fig. 4 demonstrates an example MACD index. To create MACD one has to:

1) calculate a 12-day EMA of closing prices,
2) calculate a 26-day EMA of closing prices,
3) subtract the 26-day EMA from the 12-day EMA, and plot their difference as a solid line (it is the fast MACD line),
4) calculate a 9-day EMA of the fast line and plot the result as a dashed line (it is the slow Signal line).

When the fast MACD line crosses above the slow signal line, it gives the "buy signal". When the fast line crosses below the slow line, it gives the "sell signal".

3) Commodity Channel Index (the 3^{rd} *input):* The CCI [10] is an oscillator originally developed by Donald Lambert. Since its introduction the indicator has grown in popularity and it is now a very common tool for traders to identify cyclical trends. The CCI was developed to determine overbought and oversold levels. It is done by measuring the relation between price and a moving average (MA), or, more specifically, normal deviations from that average. The value of the CCI is calculated from

$$\text{CCI} = \frac{1}{0.015} \cdot \frac{p_t - \text{SMA}(p_t)}{\sigma(p_t)}$$

where p_t – typical price (average of the maximum price, minimum price and closing price), SMA – the arithmetic moving average, σ – the absolute deviation. Fig. 5 demonstrates an example CCI index.

Possible "sell" signals are:

- the CCI crosses above 100 and has started to curve downwards,
- there is bearish divergence between the CCI and the actual price movement, characterized by downward movement in the CCI while the price of the asset continues to move higher or moves sideways.

Possible "buy" signals are:

- the CCI crosses below -100 and has started to curve upwards,
- there is a bullish divergence between the CCI and the actual price movement, characterized by upward movement in the CCI while the price of the asset continues to move downward or sideways.

4) Relative Strength Index (the 4^{th} *input):* The RSI index [3] measures the strength of any trading vehicle by monitoring

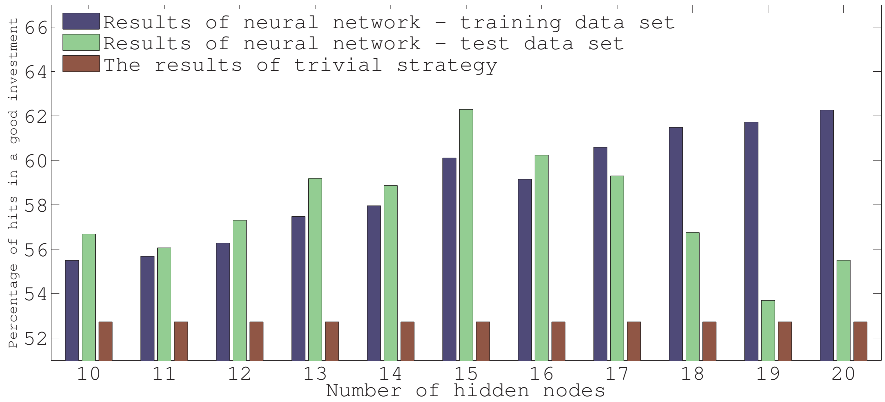

Fig. 2. Testing different structure of neural network

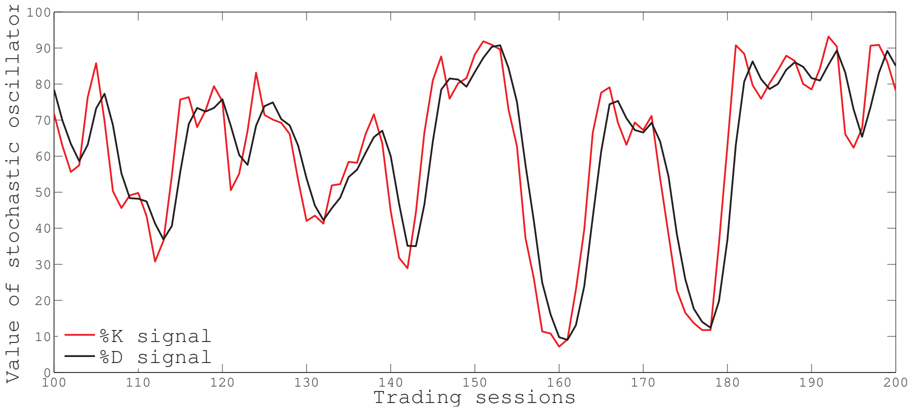

Fig. 3. The example slow stochastic oscillator

changes in its closing prices. It is a leading indicator, it is never a laggard. Its value is

$$\mathrm{RSI} = 100 - \frac{100}{1 - \mathrm{RS}}$$

where

$$\mathrm{RS} = \frac{\text{average of net UP closing changes for n days}}{\text{average of net DOWN closing changes for n days}}$$

The RSI fluctuates between 0 and 100. When RSI reaches a peak and turns down, it identifies a top. When RSI falls and then turns up, it identifies a bottom. Fig. 6 demonstrates an example RSI index.

Divergences between RSI and prices give the strongest “buy” and “sell” signals. They show when the trend is weak and ready to reverse. Horizontal reference lines must cut across the highest peaks and the lowest valleys of RSI. They are often drawn at 30 and 70.

Bullish divergences give “buy” signals. They occur if prices fall to a new low but RSI makes a more shallow bottom than during its previous decline. One buys as soon as RSI turns up from its second bottom. “Buy” signals are strong if the first RSI bottom is below its lower reference line and the second bottom is above the line.

5) Backward linear regressions (the 5^{th}, 6^{th} and 7^{th} inputs): The last information that investors take into account are backward linear regressions. Based on trading behavior in the recent past, investors are trying to guess the future behavior of the market. Three backward linear regressions are taken into account: 5, 10 and 15 days. Investors are interested whether these regressions indicate an increasing or a decreasing trend. The relationships between these trends suggest further course of trading stocks. Fig. 7 shows the example trends of the linear regressions of the corresponding points of interest.

One of the basic rules used by investors is to invest in accordance with the medium-term trend when the linear regressions of 15 and 10 days reference the same trend. Fig. 7 shows two interesting points, one of which meets the above condition. Linear regressions 15 and 10 days for the second point shows the different trends, so there is a signal to omit the investment.

6) Network output – 21 days forward linear regression: All the indicators describing the selected points of interest are enough for investors to make a decision to proceed with the investment or its omission. In the case of neural network modeling the given signal is used which indicates whether the situation related to the point, in fact, is an important investment

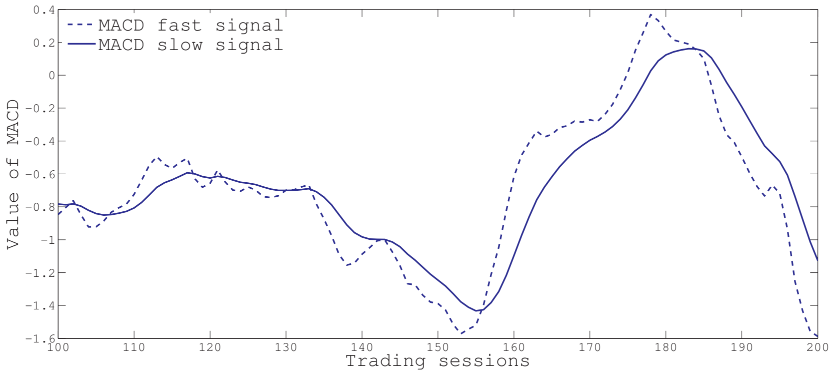

Fig. 4. The example Moving Average Convergence-Divergence (MACD) index

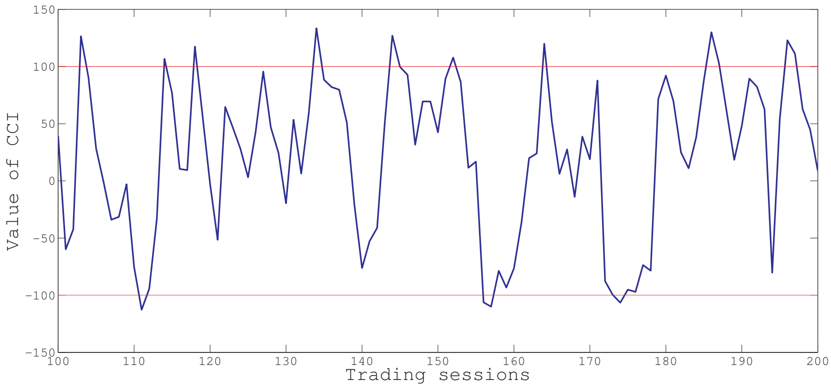

Fig. 5. The example Commodity Channel Index (CCI)

situation (it is possible to make money on it) or not. The investment horizon is also determined by investors and its value is 21 days. The linear regression is used to check if at the relevant time horizon value of the shares is in an uptrend or not. An example of the 21 days forward linear regression is shown in Fig. 8.

V. The choice of inputs of the neural predictor

The basic problem is therefore the choice of inputs of the neural network and determination how many inputs and how their combination allows to achieve the best results. Two approaches which make it possible to choose the inputs of neural networks are discussed. Those methods were chosen to represent the exemplary approach to solve the problem, but there is a whole class of different approaches that can give different results. In the first method all possible combinations of inputs are considered, neural models are trained, compared, and finally the best model is selected which produces the best results. The second method is based on the elimination of inputs approach, which are most correlated with the rest of the inputs. The numerical results are given only for the test data set, the training data set is used only for training.

A. The combination method

Table II shows the results of the conducted experiments. It is interesting that the best results are achieved with 5 inputs of neural network, which included the stochastic oscillator %K %D, oscillator MACD, RSI index and backward regressions 5 and 10 days. The best result of the neural network for the 5 inputs is 67.42% accurate decisions on positive points. When the neural network suggests that analyzed point of interest is the negative point, the investment decision is the omission of buying the shares. Otherwise, the neural network over 67% of the time classified as a positive point of interest properly. The result is much better than the result of the trivial strategy.

In the case of neural networks operating with all the inputs indicated by the investor, the result is clearly worse but still higher than the result of a trivial strategy. Therefore one can conclude that the two indices that analyze the investors, in fact, do not bring valuable information and even obscure the decision-making situation. It is likely that the CCI indicators and backward linear regression for 15 days carry conflicting information from other indicators, which makes the classifier more was wrong, when all indicators are taken as inputs.

Comparison of the results of the neural network and trivial strategy is shown in Fig. 9. It is worth noting that the neural networks of the worst matched inputs achieve results far worse than trivial strategy and is approximately 40%. It is an experimental proof that a key consideration is the choice of set of inputs, and that from the proposed inputs by investors there are combination which gives very bad results.

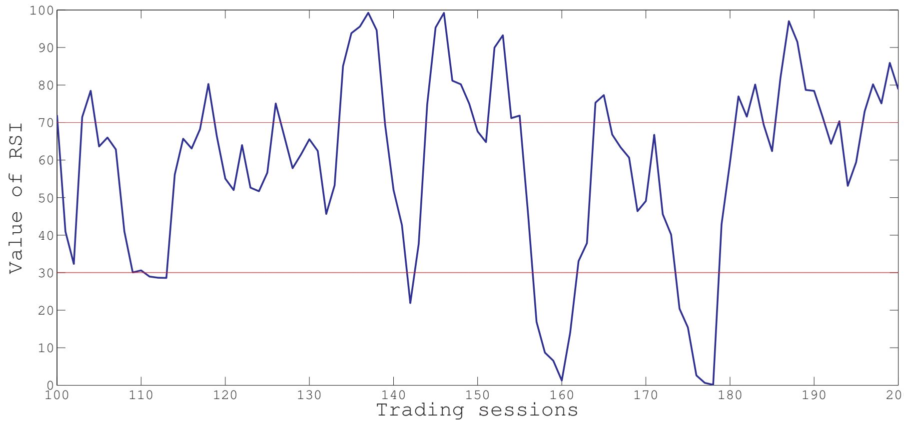

Fig. 6. The example Relative Strength Index (RSI)

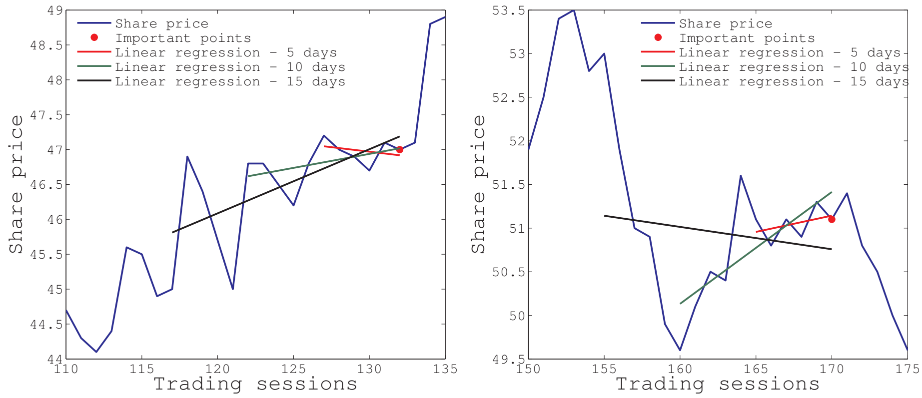

Fig. 7. The backward linear regression for 5, 10 and 15 days

TABLE II
THE RESULTS OF THE NEURAL NETWORK FOR THE BEST COMBINATION OF INPUTS

Number of inputs	**Best inputs**	**Positive points found**	**Good investments (%)**
1	4	312	60.00%
2	2 7	388	60.95%
3	2 4 6	377	63.33%
4	2 5 6 7	368	63.57%
5	1 2 4 5 6	300	67.42%
6	1 2 3 4 5 6	329	65.93%
7	1 2 3 4 5 6 7	377	62.29%

B. The correlation method

Although in the combination method the best result can be found, as many as 1270 neural networks are learned, which takes a lot of time.

The correlation method of selecting the inputs of the neural network consists of eliminating inputs that are most correlated with other inputs. This method is based on the belief that inputs that are correlated with each other can be removed, and the other inputs take over the role of the removed inputs. Following this rule it is sufficient to examine the correlation between all inputs, and then eliminate the ones that carry the most common information with other inputs. The optimal set of inputs for each number of inputs is given in Table III. One may conclude that the achieved results are not optimal. It should be noted, however, that the best combination of inputs determined by this method differs a little from the optimum. The process of elimination gives the best result of the neural network with 5 inputs, which corresponds to the best global result. Selection of inputs is also very similar, because only one indicator is only different.

Computing effort of the second method is much smaller than searching all possible combinations of inputs of neural networks. Fig. 10 shows the results of this method against the results of a trivial strategy. Referring to the results of

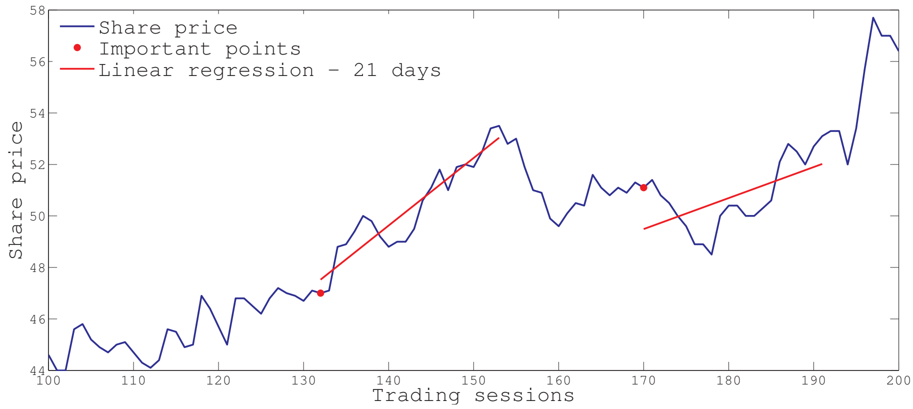

Fig. 8. The output of neural network – 21 days forward linear regression

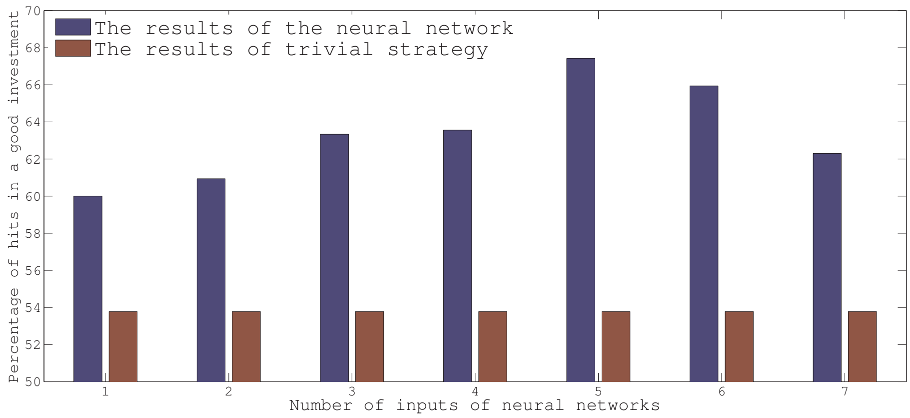

Fig. 9. The percentage of good results depending on the number of inputs of the neural network

TABLE III
THE RESULTS OF NEURAL NETWORK THE LEAST CORRELATED INPUTS COMBINATIONS

Number of inputs	Best inputs	Positive points found	Good investments (%)
2	1 4	338	60.14%
3	1 4 6	303	60.00%
4	1 3 4 6	357	60.61%
5	1 3 4 5 6	279	62.48%
6	1 3 4 5 6 7	373	59.39%
7	1 2 3 4 5 6 7	377	62.29%

the strategy proposed by the investors one must concede that the results obtained by the method of elimination of most correlated inputs are a little better from the results when all indicators are used, as suggested by the investors.

C. Comparison of methods

To compare the two methods used for the selection of neural network inputs it is necessary to look into the results from two perspectives. First, the combination method, of course, gives the best results. The method of eliminating most correlated inputs also brings good results, but it fails to find solutions much better than the approach suggested of investors. Secondly, considering the computational burden necessary to carry out all experiments, one can see the undoubted advantage of the second approach. Both methods brought similar results, so it can be concluded that the impact on the result of the trend predictor is associated with the selection of uncorrelated inputs that carry a consistent information. Fig. 11 shows a comparison of the results of both methods.

VI. SUMMARY

This paper describes the development of the neural investment strategy system. In order to determine the best set of the model inputs the two methods are compared: the neural networks for all possible combinations of inputs can be evaluated or the elimination method can be used. The first

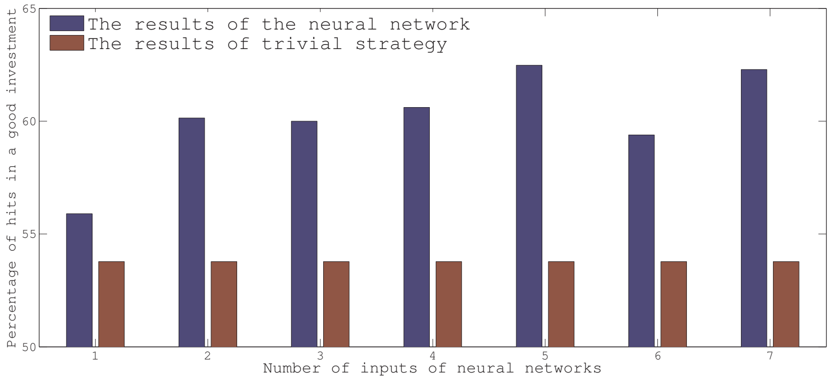

Fig. 10. The percentage of good results in correlation method

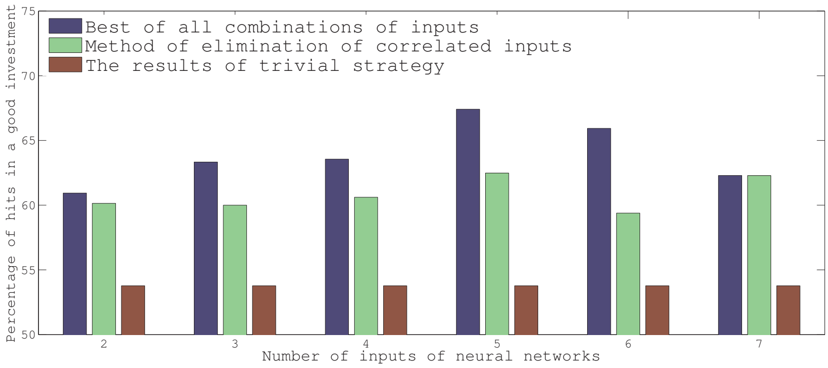

Fig. 11. Comparison of methods for the selection of inputs of neural network

method makes it possible to find the best model, but is very time consuming since as many as 1270 neural networks must be trained. The second method is much more effective and practically gives the neural model of the same accuracy.

It is necessary to emphasize that the discussed investment strategy is based on both the economic knowledge and intuition. The neural predictors are not entirely "black-box" time-series models, but technical analysis indicators are used as the input signals. The obtained experiments shows that the selected indicators make it possible to obtain 62% of investment efficiency. When the number of indicators is reduced, the neural system is able to realize investment decisions of 67% success rate, which indicates that the redundant indicators could give wrong signals to investors.

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