Forecasting of Financial Markets via Neural Network

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Abstract: - Artificial neural network is one of the intelligent methods in Artificial Intelligence. There are many decisions of different tasks using neural network approach. The forecasting problems are high challenge and researchers use different methods to solve them. The financial tasks related to forecasting, classification and management using artificial neural network are considered. The technology and methods for prediction of financial data as well as the developed system for forecasting of financial markets via neural network are described in the paper. The designed architecture of a neural network using four different technical indicators is presented. The developed neural network is used for forecasting movement of stock prices one day ahead and consists of an input layer, one hidden layer and an output layer. The training method is a training algorithm with back propagation of the error. The main advantage of the developed system is self-determination of the optimal topology of neural network, due to which it becomes flexible and more precise. The proposed system with neural network is universal and can be applied to various financial instruments using only basic technical indicators as input data.

Key-Words: neural networks, forecasting, training algorithm, financial indicators, backpropagation

1 Introduction

Artificial neural networks (ANNs) are used to solve different tasks in many problem domains. Nowadays accounting and financial classification and prediction problems are high challenge and researchers use different methods to solve them. Neural networks analyze traditional classification and prediction problems in accounting and finance due to their capabilities to solve many nonlinear, dynamic and hard formalized tasks in presence of huge statistical data. Prediction of financial data is very important issue and gives opportunity to demonstrate the features of different techniques of the artificial intelligence. The methods used for prediction could be divided into two main categories: fundamental analysis and technical analysis. The main economic indicators, which affect the supply and demand, are monitored in fundamental analysis.

Successful prediction can lead to substantial material benefits. At the same time financial markets are affected by a number of economic, political and other factors that often interact in a very complex way. Therefore the precise prediction the financial markets is extremely difficult [1].

The Artificial Neural Networks have the ability to discover the nonlinear relationship in the input data set. With the correct topology and appropriate weights of connections between neurons, neural networks can be trained to approximate each function expressing the dependence of the outputs from the inputs using certain training algorithm. Assuming the statement of the technical analysis that there are certain trends in the price data, the neural network can be used for detection of these trends automatically and then an estimate of future price movement should be made [2].

Neural networks are particularly popular because they do not require a deep understanding of the interconnection_between the source data and results. Significant advantages of neural networks are that they are not programmed in the usual sense of the word, they are trained, as well as their ability to generalize, i.e. ability to obtain an informed result based on new data.

Methods and instruments for short time prediction of financial operations using neural network are considered in this report. Particular attention is paid on input data selection of should be made carefully depending on the type of the prediction. In order to increase the accuracy of the output results and to facilitate the learning process, the raw data should be preliminary processed to eligible values for the neural network.

The proposed system with neural network is universal and can be applied to various financial instruments using only basic technical indicators as input data.

2 Financial tasks solved using neural networks

The main financial tasks related to forecasting, classification and management than could be solved using neural networks, are:

- **Financial time series prediction.** The nature of markets does not allow defining a single accurate indicator as the market conditions change over time and tasks are solved by considering a set of indicators. To this class tasks belong forecasting currency cross-rates, forecasting quotes and demand for shares on the stock market (for short-term investments) and forecasting balances on correspondent accounts in the bank. Forecasting of financial time series is in the basis of all investment activities in industry - all stock and non-stock trading systems with financial instruments [3];
- **Insurance activities.** Forecasting tasks relate to risk assessment of insurance investments based on analysis of the reliability of the project and risk assessment of insurance on the invested funds [4].
- **Predicting bankruptcy.** Analyzing the possibility of bankruptcy is particularly important because the company's management can influence the potential problems that need to be addressed. In addition, investors, as well as financial auditors use the financial ratios when evaluate the companies. Likelihood Ratio of bankruptcy of the company is defined on the basis of multi-criteria assessment [5];
- **Forecasting the results of taking credits.** Neural networks are used to determine the opportunities for lending to enterprises and rarely when granting loans without pledge. When granting loans without pledge is important to analyze additional information about the borrower [6].
- **Predicting the economic efficiency of the financing of economic and innovation projects and Investor's Behavior.** The neural networks based on time series are used for forecasting by analysis of previously realized projects. Nonlinear model of the neural network is used to predict to what extent the proposed project corresponds to the economic situation.
- **Bonds and shares of undertakings to investment funds.** The forecasting system could consist of several neural networks that are trained by the connections between the various technical and economic indicators as well as periods of buying and selling shares. The purpose of forecasting is to choose the best time to buy and to sell shares. They also solve tasks for the formation of a portfolio of securities and recognition of situations where the share prices sharply alter as a result of the play on the exchange, as well as tasks to determine the ratio between quotations and demand [6]

3 Technology for prediction of financial markets

The tasks of forecasting in the financial area can be separated two major sub-tasks: building a model of the neural network, which is convenient for the task and training of the network. The model is selected according to subject area and important role have a set of input variables, the method of formation of output variables, the method of a learning rule, the architecture of the neural network and the method of its training [8].

The methods used for prediction could be divided into two main categories: fundamental analysis and technical analysis. The main economic indicators (political, economical and social), which affect the supply and demand, are monitored in fundamental analysis. For example, there are certain economic news, which significantly influence the movements of the market. The fundamental analysis is appropriate for prediction in the long term. Technical analysis on the other hand is a method of forecasting through observation and study of historical data, primarily price movement and volume and is used to predict stock trends [3].

A typical sequence of actions in solving tasks of predicting financial indicators via neural networks is shown in fig. 1.

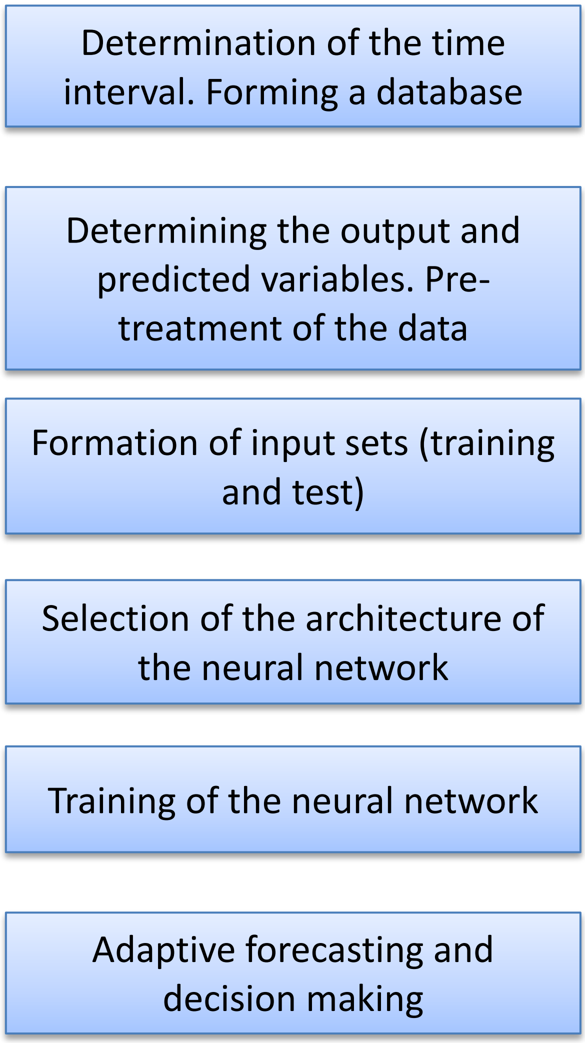

Fig. 1. Block diagram of the technological cycle of forecasting of financial markets via neural network

4 Design of the system

4.1 Selection of input data

When designing the system, the input data should be carefully selected depending on the type of forecast. When the aim is to make long term predictions, it must be taken into account a greater number of fundamental variables. In case the aim is to make long term predictions, it must be taken into account a greater number of fundamental variables. If the aim is to make short-term forecasts, it will be better the system to read more technical input data, as it is with the projected system.

The first variable is the very price of the financial instrument to be predicted (currency, stock, commodity, index). When the technical variables are selected, the input data for the neural network should not be the absolute prices, but different proportions and technical indicators based on price. The raw data used for developed system are: opening price, highest price, lowest price and closing price of the selected financial instrument every single day. In this form data are not submitted as input variables to the neural network. On the base of raw data are generated the most popular technical indicators which are used as input data of the neural network for prediction [4].

Mathematical methods for trading offer an objective view of price activity. The technical tools used in mathematical methods for trading are moving averages and oscillators.

Moving average – the most commonly used technical indicator showing the average value of a financial instrument for a certain period of time. It is calculated by the following formula:

$$SMA(N) = \frac{P_t + P_{t-1} + \ldots + P_{t-N}}{N} \tag{1}$$

where $\mathrm{P_t}$, $\mathrm{P_{t-1}} \ldots \mathrm{P_{t-N-1}}$ are the prices of the financial instrument at a time t, t-1… t-N, and N is the period for which the moving average is calculated (averaging period). There are different versions of moving averages, but the most commonly used moving averages are simple moving averages and exponential moving averages. The length of time for the moving average can be selected (20, 50, 200 days).

Averaging is usually applied to the closing prices but highest, lowest and opening prices also can be averaged. When calculating the consecutive values, the new value is added to the amount, and the oldest one is removed. This way the recalculation of the total amount could be avoided and high performance could be achieved:

$$\mathrm{SMA_t} = \mathrm{SMA_{t-1}} - \frac{\mathrm{P_{t-N}}}{\mathrm{N}} + \frac{\mathrm{P_t}}{\mathrm{N}} \tag{2}$$

Standard deviation – measured variance or deviation of the data from their average estimated [5]. Low standard deviation means that data are closely distributed around their mean value, while high value of the standard deviation indicates that the data are arranged in a wider range.

$$\sigma_N = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \quad (3)$$

where $x_1, x_2, ..., x_N$ are monitored values and $\bar{x}$ - their average value.

Stochastic oscillator – shows the whereabouts of current value in relation to its variation for a given period of time. This indicator tries to predict where the price changes its direction of motion. It is calculated as follows:

$$\%K = 100\frac{P - Low_N}{High_N - Low_N} \quad (4)$$

where P is the current price, $High_N$ is the highest price for the last N periods and Low_N is the lowest price for the last N periods.

Relative strength index – is another popular oscillator, which is used to measure speed and change of price movements. Its value changes from 0 to 100. It is calculated as the ratio between positive and negative differences of the closing price for a certain period of time - usually 7 to 14 days:

$$RSI = 100 - \frac{100}{1 + U_N/D_N} \quad (5)$$

where U_N is the average of all positive differences between the closing prices for the period N, and D_N is the average of all negative differences between the closing prices for the same period. If D_N is 0, the value of RSI is considered to be 100.

Day of the week - There is no consensus on which day of the week is most volatile, since volatility can occur based on investor fears, major world events and other financial uncertainties, and even holidays. Ffinancial markets are closed on weekends, so the daily return for working days could be calculated using the following expression:

$$R_n = \frac{C_n - C_{n-1}}{C_{n-1}} \quad (6)$$

where, R_n is return of the n^{th} day, C_n is closing price for n day andC_{n-1} is closing price for n-1 day of the week.

A larger number of input variables are selected at the first stage of system design. In the next phase, on which an analysis how a variable affects the output results are conducted, some of the variables may drop out. It is also possible input data to include raw price data and ratios of other financial instruments, which are different from predicted one.

4.2 Preliminary processing of the data

This is a critical stage of system design because presenting of input data directly affects their behavior. Before analyzing of the input data by the neural network, they should be pretreated in order to increase the accuracy of the output results and to facilitate the learning process. The most commonly used techniques for the preprocessing of the data are transformation and normalization [5]. The transformation include the modeling of the raw data, while the normalization is used for is used for even distribution and scaling of data to eligible values for the neural network. These methods for selecting the input data represent the transformations of the raw values.

The data normalization is the last step of pretreatment. The purpose of normalization is the data to be scaled within a specified interval (usually [-1, 1] or [0, 1]).

Various methods can be used for normalization depending on what is known about the data.

If the maximum and minimum values of the modification are available, the following formula can be used for scaling the data in the interval [0, 1]:

$$\delta = \frac{x - Min}{Max - Min} \quad (7)$$

where *x* is the scaled value, *Min* and *Max* are respectively the smallest and largest value in the data set.

From selected input data, the relative strength index and stochastic oscillator could be normalized easier, since they vary in the range [0, 100]. It is enough from their values to be removed 50 and the result to divide by 50 to obtain the normalized data in the interval [-1, 1].

An interesting problem is the presentation of the day of the week in the range [-1, 1]. As the days of the week are known in advance (Monday to Friday) they may accept contingent equidistant values in the range [-1, 1], i.e. Monday -1 Tuesday -0.5 Wednesday 0 Thursday 0.5 and Friday + 1.

4.3 Sensitivity Analysis of developed neural network

The sensitivity analysis is the process which determines whether an input variable affects the output of neural network or not. For this purpose the neural network is put in operation with or without specific input and to examine variations in the output. If no significant changes, it certainly means that this input variable could be excluded completely. This usually happens when an input variable is highly correlated with other one. The removal of interrelated input variables can significantly improve the performance of the neural network.

5 Architecture of the neural network

The architecture of a neural network used four different technical indicators, which are based on the raw data and the current day of the week is presented. The number of input and output neurons is fixed and the number of neurons in a single hidden layer is not fixed and methods for determination of these numbers are shown. In this way the system becomes adaptable and its ability could be significantly improved.

The training algorithm of developed system is training algorithm with back propagation of the error, which includes two phases.

The modeling of the neural network needs significant number of experiments with network parameters.

The main advantage of the developed system is self-determination of the optimal topology of neural network, due to which it becomes flexible and more precise, as well as significantly reduces the time that users should devote for multiple experiments in finding the optimal neural network architecture.

Due to the nature of financial data and their high degree of non-linearity a fixed architecture of the neural network is not used for the designed system.

An algorithm for determination of the optimal number of hidden layers and neurons in them is presented. In this way the system becomes adaptable and its ability could be significantly improved. Only the number of input and output neurons is fixed.

5.1 Input layer

The Neural network will use four different technical indicators, which are based on the raw data and the current day of the week [6, 7]. In order to bring in appropriate structure for the purposes of predicting, the data is converted using a special scheme by the method of "time windowing” with the size of the window 5, i.e. the forecast for the direction of price movement will be formed on the base of the data for the previous five days. Thus the total number of input variables and the input neurons becomes 21. All input variables, needed to predict the direction of price movement for the time moment t + 1, are given in Table 1.

Table 1. Input variables of the neural network

Moving Average (SMA)					Standard Deviation (σ)					Relative Strength Index (RSI)					Stochastic Oscillator (%K)					Day
SMA_t	SMA_{t-1}	SMA_{t-2}	SMA_{t-3}	SMA_{t-4}	σ_t	σ_{t-1}	σ_{t-2}	σ_{t-3}	σ_{t-4}	RSI_t	RSI_{t-1}	RSI_{t-2}	RSI_{t-3}	RSI_{t-4}	$\%K_t$	$\%K_{t-1}$	$\%K_{t-2}$	$\%K_{t-3}$	$\%K_{t-4}$	D_{t+1}

The neural network has a single output (one output neuron), resulting in one case the predicted direction of movement for the next day is up and 0 in predicted movement of the price is down compared to today's closing price.

5.2 Hidden Layer

The system of neural network uses a single hidden layer and the number of neurons in it is not fixed and is determined so that the success of the neural network to be maximal.

The algorithm used for determination of optimal number of neurons in the hidden layer starts with construction of the neural network with at least N/2 hidden neurons, where N is the number of input variables. The neural network is trained a certain number of times and tested for a certain period of preselected input data. After completing of these procedures, the percentage of the wrong predictions is defined and saved. A new neural network, which has with one more hidden neurons than the previous is created and again is repeatedly trained and tested on the same already available input data. The learning process for the new created neural networks is repeated many times and every time starts with different random weights of connections between neurons.

Applying the algorithm for back propagation of the error, the weights are reset so that the error of the network to be minimized. The values of weights, that gave the best results in the training of the network, are saved of all the iterations of training. The number of training iterations for each of the established networks is a parameter of the algorithm and is determined experimentally.

Upon completion of the testing of the neural network on the base of the unknown data during training is determined whether the newly established neural network is better than the previous (the number of false predictions is smaller). The process of creation of new neuron networks with gradually increment of the number of hidden neurons finishes when the new created networks are better than the previous, i.e. when the first neural network show worse results (big mistake) or until a predetermined maximum number of hidden neurons is reached. It is recommended that the maximum number of hidden neurons does not exceed N.

5.3 Output layer

Prediction of exact amount of the price of a specific financial instrument is extremely difficult because of the nature of price movement. Therefore, it is much more useful to make a prediction of the direction of movement, compared to a selected reference point. This leads to significantly better success rate of the neural network.

The proposed method is to create an output variable that effectively measures the direction of the expected price movement compared to the closing price of the previous day (8).

$$\mathrm{V} = \frac{\mathrm{Close_t} - \mathrm{Close_{t-1}}}{\mathrm{Max(Close_{t-1}, Close_t)}} \tag{8}$$

The activation function is determined experimentally or depends on the problem presented to the neural network. The network is trained to predict deviations from a value and for this purpose the use of hyperbolic tangent gives the best results. Therefore, the activation function of all neurons of the neural network has the form:

$$\tanh(\mathrm{x}) = \frac{\mathrm{e^x - e^{-x}}}{\mathrm{e^x + e^{-x}}} \tag{9}$$

and the input data are normalized to the interval [-1; 1], so as to be suitable for the activation function.

5.4 Training algorithm

Once the number of all layers in the neural network and the number of neurons in them are determined, the weights of the connections between neurons should be set in such a way in order to minimize the error in the predictions made by the neural network. This is the role of the training algorithm [8].

The developed system uses a training algorithm with back propagation of the error, which includes two phases. In the first phase, the free parameters (the weights of synapses) of the neural network are fixed, and the input signal passes through the network layer-by-layer.

During the second phase, the error e_i is distributed across the network in reverse – from the output to the input, hence the name of the algorithm. In this phase, adjustment of the available parameters of each neuron is made in order to minimize the error e_i in statistical terms. The both phases are repeated until the performance of the neural network becomes sufficiently good.

6 Conclusion

Experimental results show, that the system has an average success rate of 70% in predicting the direction of movement, which is a good success rate in predicting the direction of the price movement one day ahead, considering the complexity of the high nonlinearity of financial data. The results show also that the number of hidden neurons is different for particular financial instruments. This means that the presented algorithm for the optimal topology determination of the network significantly improves the system performance in comparison with using a fixed neural network. This significantly reduces the time that users have separated from numerous attempts at finding the optimal neural network.

Weak link using neural networks in forecasting financial markets is the high number of possible outputs that make difficult the training of the system.

Several factors have a significant impact on the efficiency of neural network: choice of input variables, pre-processing of data and the architecture of the neural network. The combination of the different technical features increases the number of input variables and the amount of data for learning, but is the basis for obtaining more accurate forecast results.

Designed system with neural network is universal and can be applied to various financial instruments using only basic technical indicators as input data.

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