Stock Market Prediction using Artificial Neural Networks. Case Study of TAL1T, Nasdaq OMX Baltic Stock

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Predicting financial market changes is an important issue in time series analysis, receiving an increasing attention in last two decades. The combined prediction model, based on artificial neural networks (ANNs) with principal component analysis (PCA) for financial time series forecasting is presented in this work. In the modeling step, technical analysis has been conducted to select technical indicators. Then PCA approach was applied to extract the principal components from the variables for the training step. Finally, the ANN-based model called NARX was used to train the data and perform the time series forecast. TAL1T stock of Nasdaq OMX Baltic stock exchange was used as a case study. The mean square error (MSE) measure was used to evaluate the performances of proposed model. The experimental results lead to the conclusion that the proposed model can be successfully used as an alternative method to standard statistical techniques for financial time series forecasting.

Keywords: *artificial neural networks, NARX, principal component analysis, financial time series, stock prediction*

1 Introduction

Nowadays, financial time series prediction is an important subject for many financial analysts and researchers as accurate forecasting of different financial applications play a key role in investment decision making. Stock market prediction is one of the most difficult tasks of time series analysis since the financial markets are influenced by many external social-psychological and economic factors [1]. Efficient market hypothesis states that stock price movements do not follow any patterns or trends, and it is practically impossible to predict the future price movements based on the historical data [2].

However, financial time series are generally non-stationary, complicated and noisy, it is possible to design mechanisms for prediction of financial markets [3]. Technical analysis with statistical and machine learning techniques have been applied to this area in order to develop some strategies and methods to be helpful for financial time series forecasting. The statistical methods include autoregressive conditional heteroskedasticity (ARCH) [4], autoregressive integrated moving average (ARIMA) or Box-Jenkins model [5], and Smooth Transition Autoregressive (STAR) model [6]. In the area of stock prediction, feature selection plays a significant role in forecasting accuracy and efficiency. The main techniques for feature extraction include Principal Component Analysis (PCA) [7], Independent Component Analysis (ICA) [8]. Technical analysis assumes that past values of the stock have an influence on the future evolution of the market. In technical analysis, technical indicators created by special formulas are used to predict stock trends. In the past decades, complex machine learning techniques have been presented for time series prediction. Among them, artificial neural networks (ANNs) [9], Support vector machines (SVMs) [10], Genetic Algorithms [11] and Self Organizing Maps (SOM) [12] are the most common used machine learning techniques in financial time series prediction.

Since the early 1990's, ANNs have become the most popular machine learning techniques used as alternative to standard statistical models in financial time series analysis and prediction. Schoeneburg et al, [13] investigated the possibility of stock price prediction on a short term basis by different neural networks algorithms. Their results showed that neural networks can be successfully applied to design prediction models in financial time series analysis. Kimoto et al, [14] developed a prediction system based on modular neural networks for stocks on the Tokyo Stock Exchange and showed good experimental results. Kuan et al, [15] analyzed the potential of feed-forward and recurrent neural networks in forecasting the foreign exchange rate data. Chen et al,[16] examined several neural networks to evaluate their capability in stock price and trend prediction, and concluded that class-sensitive neural network (CSNN) is the best performing neural network in both cases. D. Olson et al, [17] compared NN forecasts of one-year-ahead Canadian stock returns with the prediction results obtained using logistic regression (logit) and ordinary least squares (OLS) techniques. Their results showed that back-propagation neural networks outperform other models in classification purposes and can be used in various trading rules. M. Ghiassi et al, [18] proposed a dynamic neural network model for forecasting time series events and showed that ANN-based dynamic neural network model is more accurate and performs significantly better than the traditional ANNs and autoregressive integrated moving average (ARIMA) models.

Other authors used hybrid techniques combining ANNs with different feature extraction techniques in financial market prediction. Among them, Abraham et al, [19] used PCA as a pre-processing step for hybrid system based on neural networks and neuro-fuzzy approaches for stock market prediction and trend analysis. Aussem al, [20] proposed a combined forecast model based on wavelet transform and neural networks. They used wavelet transform to decomopose the original data into varying scales of temporal resolution and then used dynamic recurrent neural network (DRNN) to forecast S&P500 stock closing prices. Chen and Shih, [21] applied SVMs and Back Propagation (BP) neural networks to predict Asian stock market indices and showed that both models perform better than the statistical autoregressive AR models. Zhao et al, [22] proposed a wavelet neural network to forecast Shanghai stock market returns and compared their results with back propagation neural network (BP) results. They showed that the simulation result of wavelet neural network is more accurate than that of BP neural network.

More recent studies include: Lu, [23] proposed a hybrid technique with ICA and neural network model for stock price prediction. The model used ICA for denoising the time series data and the rest of ICs used to build the neural network model. Kara et al, [24] compared two models based on ANNs and SVMs in prediction of directional movements in the daily Istanbul Stock Exchange (ISE) National 100 Index and concluded that ANN model performs better than SVM model. A. Fagner et al., [25] applied a neural network based model for the short term prediction of change in direction (POCID) of closing prices of the financial market, combining technical and fundamental analysis. Wang et al, [26] used a stochastic time effective function neural network (STNN) with PCA to forecast different stock indices. Their results displayed better performance of proposed two-stage model compared with standard neural network models.

This paper presents an integrated method based on PCA and ANNs for financial time series prediction. Considering the fact that the optimal variable search plays an important role for better accuracy of forecasting results, technical analysis has been conducted to calculate technical indicators helping to predict the stock prices. The proposed approach first uses PCA technique to extract principal components from the various technical indicators then uses the filtered variables as the input of

ANN-based technique to build the forecasting model. In order to evaluate the prediction accuracy of the proposed model, the mean squared error (MSE) measure was used as an evaluation metric. The historical data set was selected from Nasdaq OMX Baltic stock exchange.

The rest of the paper is organized into five chapters: Chapter 2 introduces a dynamic neural network called nonlinear autoregressive network with exogenous input (NARX). Chapter 3 describes the research methodology, including data collection, data normalization, technical analysis, principal component analysis (PCA) and evaluation metric. Chapter 4 presents the summarized and discussed experimental results. Finally, Chapter 5 concludes the research results and presents the future work.

2. Nonlinear autoregressive network with exogenous input (NARX)

The nonlinear autoregressive network with exogenous input (NARX) is a recurrent dynamic network, with feedback connections encompassing multiple layers of the network (figure 1).

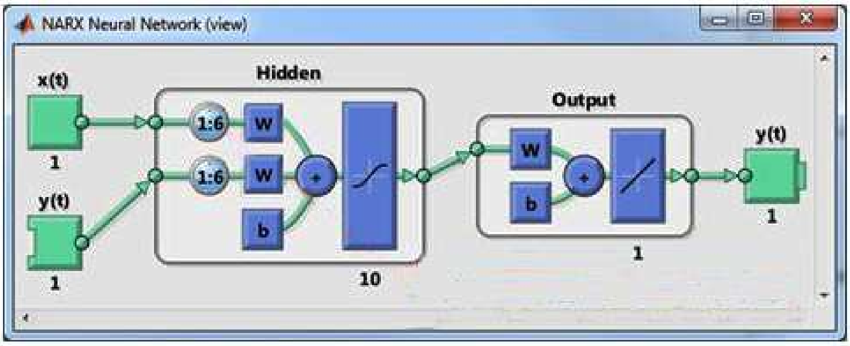

Fig. 1. The architecture of nonlinear autoregressive network with exogenous inputs (NARX)

The NARX model can be mathematically described as,

$$y(t) = f\left(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)\right) \quad (1)$$

where, *y* is the variable of interest and *u* is externally determined variable that influences the *y*. The previous values of *y* and *u* help to predict future values of *y*.

The prediction model can be defined as,

$$\hat{Y}_{(t+p)} = f_{ANN}\left(Y_t^{(d)}, X_t^{(d)}\right) \quad (2)$$

$$Y_t^{(d)} = \{Y_t, Y_{t-1}, Y_{t-2}, \dots, Y_{t-d}\} \quad (3)$$

$$X_t^{(d)} = \{X_t, X_{t-1}, X_{t-2}, \dots, X_{t-d}\} \quad (4)$$

where Y_t is the stock closing value at the moment of time t. $\hat{Y}_{(t+p)}$ is the forecasted value of the stock price for the prediction period p, and d is the delay expressing the number of pairs $(X_k, Y_k), k = t, t-1, \dots, t-d$ used as input of the neural model. For each *t*, we denote by $X_t = (X_t(1), X_t(2), \dots, X_t(n))^T$ the vector whose entries are the values of the indicators significantly correlated to Y_t,

In this study, the network training function is carried out by an improved backpropagation method proposed by Plagianakos et al. in [27].

3. Proposed methodology

3.1 Data collection

The research data used in this study is historical data taken from the Nasdaq OMX Baltic stock exchange and accurately chosen technical indicators. The whole data set covers the period from March 12, 2012 to December 30, 2014, a total of 700 daily observations. The historical data consists of daily closing price, opening price, lowest, highest prices, traded volume, turnover data of Tallink Grupp AS shares (symbol TAL1T) and 30 indicators chosen from technical analysis of the stock market. Tallink stock closing price was used as a forecasting variable for this research. Historical data was collected from the Nasdaq OMX Baltic official website.

3.2 Technical analysis

Technical analysis is a security analysis method for directional prediction of prices by analyzing the historical data [28]. In other words, technical analysis relies on the assumption that past trading variables, such as price and volume can help to forecast future market trends. A technical indicator is a fundamental part of technical analysis. It presents a mathematical calculation based on the historical data.

There are in total 30 technical indicators used in this research. The complete list of all calculated technical indicators and stock based variables are given in Table 1. Some of these indicators are chosen as input variables of forecast model. The feature selection process is described in the section 3.4.

3.3 Data normalization

As the collected data has different values with different scales, it is necessary to adjust and normalize the time series at the beginning of the modelling for improving the network training step. The data normalization range is chosen to be [0,1] and the equation for data normalization is given by,

$$V = \frac{v - v_{min}}{v_{max} - v_{min}} \quad (5)$$

where V is the normalized data, v is the original data value, v_{max} and v_{min} are maximum and minimum values of the series.

Table 1. List of all 36 variables used in PCA

Technical indicator	TALL1T stock
Bollinger Bands	Opening price
Exponential Moving Average (EMA)	Closing price
Kaufman Adaptive Moving Average (KAMA)	Highest price
Simple Moving Average (MA)	Lowest price
Weighted Moving Average (WMA)	Turnover
Triangular Moving Average (TRIMA)	Traded volume
On Balance Volume (OBV)	
Average True Range (ATR)	
Average Directional Movement Index (ADX)	
Absolute Price Oscillator (APO)	
AROON	
Balance Of Power (BOP)	
Commodity Channel Index (CCI)	
Chande Momentum Oscillator (CMO)	
Directional Movement Index (DX)	
Moving Average Convergence Divergence (MACD)	
Money Flow Index (MFI)	
Momentum	
Percentage Price Oscillator (PPO)	
Rate Of Change (ROC)	
Relative Strength Index (RSI)	
%K stochastic oscillator	

%D	
Ultimate Oscillator	
Williams %R	
Minus Di	
Plus Di	
Minus Dx	
Plus Dx	
Chaykin oscillator	

3.4 Principal component analysis

The feature selection process is one of the important parts of the prediction model. It is used to filter irrelevant features from the given data set in order to to improve the prediction accuracy. Principal component analysis (PCA) is a statistical technique for feature extraction and data representation.

The main idea in PCA is to find the component vectors that explain the maximum possible amount of variance by linearly transformed components.

In signal processing, PCA can be defined as a transformation of a given set of n input vectors with the same length K formed in the n-dimensional vector $x = (X_1, X_2, \dots, X_n)^T$ into a vector y by:

$$y = A(x - \mu_x), \qquad (6)$$

where the vector μ_x is the vector of the means of the input variables x.

The matrix A is determined by the covariance matrix C_x as the orthonormal rows of matrix A are formed from the eigenvectors of the matrix C_x.

The covariance matrix can be calculated by the equation:

$$C_x = E\left\{(x - \mu_x)(x - \mu_x)^T\right\} \qquad (7)$$

Let $x = (X_1, X_2, \dots, X_n)^T$ be the n-dimensional random vector, and $a_1, a_2, \dots, a_n$ be the corresponding eigenvectors of correlation matrix R where the covariance between X_i and X_j is given by,

$$Cov(X_i, X_j) = \Sigma_{i,j} = \sigma^2 R_{i,j} = \lambda_j a_i^T a_j$$

, for i,j=1,2,...,n. (8)

Define W_1 to be the first principal component of the sample x by the linear transformation,

$$W_1 = a_1^T x = \sum_{i=1}^{n} a_{i1} x_i, \qquad (9)$$

where the vector $a_1 = (a_{11}, a_{21}, \dots, a_{n1})$ and $a_1^T x = 1$.

It follows that, the first principal component W_1 has the highest possible variance $var[W_1] = a_1^T R a_1$ and the largest eigenvalue among all linear combinations of the x, such that $var[W_1] \geq var[W_2] \geq \dots \geq var[W_n]$, $\lambda_1 > \lambda_2 > \dots > \lambda_n > 0$.

The problem of computing the principal components of a certain dataset can be solved many ways. Clearly, we can directly apply the above mentioned result and compute the principal components based on the correlation matrix resulted from the available data. This way, the quality of the resulted principal components depends on the distance between the theoretical correlation matrix and the one computed from data.

Some alternative strategies, for example specialized neural networks, have been proposed to perform principal component analysis (PCA) tasks. The study of the convergence properties of different stochastic learning PCA algorithms is usually performed by reducing the problem to the analysis of asymptotic stability of a dynamic system trajectories. The evolution of such systems is described in terms of an ODE. The Generalized Hebbian Algorithm (GHA) extends the Oja's learning rule for learning the first principal components using the Hotteling deflation technique. A series of experimentally established conclusions regarding the performance and efficiency of some of the most frequently used PCA learning algorithms implemented on neural architectures are reported in [29].

3.5 Performance criteria

The prediction performance is evaluated using the mean square error (MSE) evaluation method:
MSE error measure is defined by,

$$MSE(T,P) = \frac{1}{n}\sum_{i=1}^{n}\left(T(i) - P(i)\right)^2 \quad (10)$$

where $T = (T(1), T(2), \dots, T(n))$ is the vector of target values, $P = (P(1), P(2), \dots, P(n))$ is the vector of predicted values and n is the number of data samples.

3.6 Prediction model based on NARX and PCA techniques

In this study, a two-stage prediction model combining PCA and NARX techniques is presented for stock market prediction. Fig 2 is the outline of the proposed prediction model. First, pre-processing step is applied to data which include: technical analysis to select proper technical indicators, data normalization to adjust and normalize the data set, and principal component analysis for features selection and data reduction. Second, the NARX model is constructed based on the feature subset from PCA. Then, data sample is trained by series-parallel architecture. After the training step, the series-parallel architecture is converted into a parallelized network, in order to execute the forecast task. The experimental results based on this model are given in the next chapter.

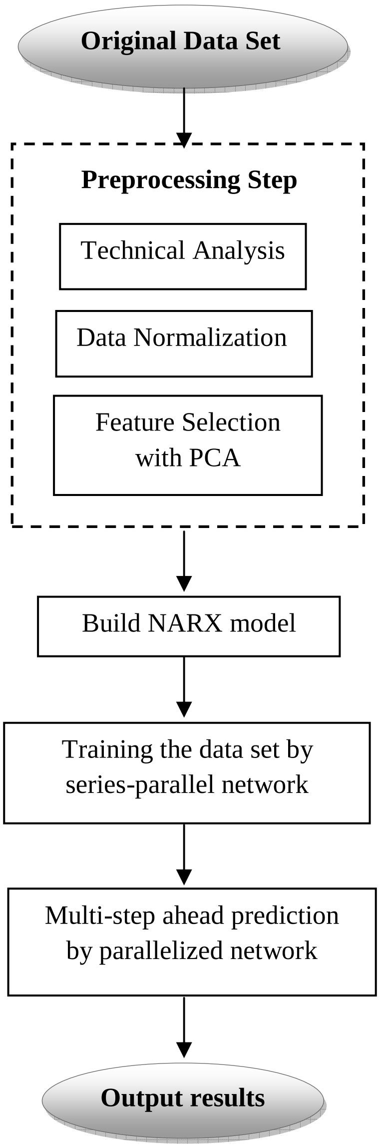

Fig. 2. The architecture of the prediction model based on NARX and PCA

4. Experimental results

Experiments have been conducted to evaluate the performance of the presented method. A data set from Nasdaq OMX Baltic stock exchange was used to conduct the experiments. The whole data set covers the period from March 12, 2012 to December 30, 2014, a total of 700 daily observations. Data set includes the traded volume, turnover, opening, closing, highest, lowest prices and 35 technical indicators. Experiments include two different forecasting periods of the same data set. The first experimental data set is divided into two parts. The first part (500 pairs of observations) is used for training, testing and validation phases. The second part (200 pairs of observations) is reserved for prediction step. The second experiment uses 550 data samples for training and validation tests and 150 data samples for prediction task. The goal of the experiment is to predict the closing price of the Tallink stock (symbol TALL1T).

The input variables are selected by feature selection method called PCA. In PCA, each component is uncorrelated with all of the preceding components. For this reason we will have maximally uncorrelated variables used as input for prediction models. The scientific data analysis software called PAST was used to implement PCA for time series. In PCA, the correlation coefficients provide the measure of the relation between considered 36 variables. Table 2 shows the total variance of the original variables. The cumulative contribution to the total explained variance of 10 largest eigenvalues out of 36 components is 96.6% which is much higher than the normal criterion 70%. Thus, the first 10 principal components provide the most information of original data and can be selected to form the output subset.

After pre-processing step, the NARX model was developed for data training and prediction. Experiments with NARX prediction model were performed by using the software MATLAB. In the experiments with NARX model with the architecture 2×10×1, where input variables are chosen to be 10 variables which correspond to the selected 10 PCs, and the output variable is the closing price of Tallink stock. Delay was set equal to 2 using auto-correlation function of all variables. The number of neurons in the hidden layer is set according to the following equation, $2\sqrt{(m+2)N}$ where *m* stands for the number of the neurons of the output layer and *N* is the dimension of input data.

Table 2. Principle components of 36 variables

PC	*Eigenvalue*	Variance %	Cum. variance %
1	1.04985	49.796	49.796
2	0.500825	23.755	73.551
3	0.133046	6.3105	79.8615
4	0.097486	4.6239	84.4854
5	0.070471	3.3425	87.8279
6	0.05544	2.6296	90.4575
7	0.0477	2.2625	92.72
8	0.034688	1.6453	94.3653
9	0.023855	1.1315	95.4968
10	0.022894	1.0859	96.5827
11	0.016476	0.78147	97.36417
12	0.010009	0.47471	97.83888
13	0.009175	0.43518	98.27406
14	0.007363	0.34925	98.62331
15	0.006329	0.30021	98.92352
16	0.004273	0.20266	99.12618
17	0.003963	0.18796	99.31414
18	0.003799	0.18019	99.49433
19	0.003026	0.14353	99.63786
20	0.002596	0.12311	99.76097
21	0.001872	0.088811	99.84978
22	0.00115	0.054523	99.9043
23	0.000815	0.038637	99.94294
24	0.000445	0.021128	99.96407
25	0.000225	0.010659	99.97473
26	0.000143	0.0067673	99.9815
27	0.000122	0.0057873	99.98728
28	8.44E-05	0.0040046	99.99129
29	6.81E-05	0.0032319	99.99452
30	5.58E-05	0.0026458	99.99716
31	3.10E-05	0.0014708	99.99864
32	2.45E-05	0.0011619	99.9998
33	1.14E-05	0.00053899	99.99982
34	4.91E-06	0.00023269	99.99985
35	1.61E-07	7.66E-06	99.99992
36	6.23E-34	2.96E-32	100

Figure 3 and 5 show the values of the TALL1T stock and the predicted values and horizon. Figure 4 and 6 show the predicted and actual values of TALL1T stock with PCA-NARX model in two different forecast time periods. The blue line is the predictions of the proposed model and the green line is the actual values.

From the figures, it can be observed that this method forecasts values closely to the actual values in most of the time period.

The prediction performances are evaluated using the standard evaluation measure called mean squared error (MSE).

$MSE_{150} = 0.0011703$

$MSE_{200}=0.0034567$

The experimental results show that this method is effective and efficient in forecasting stock prices compared with other research studies in the field of stock market prediction.

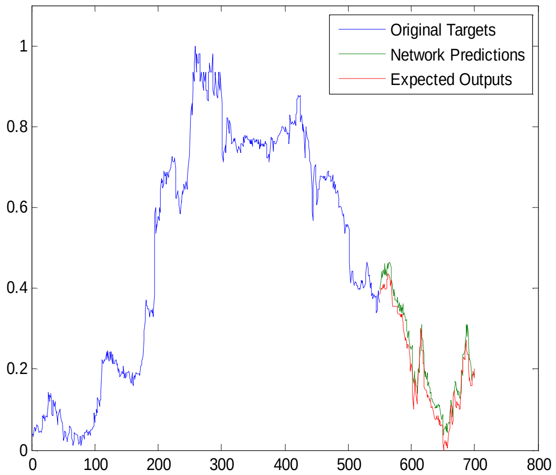

Fig. 3. Prediction results of TALL1T stock in case of 150 samples

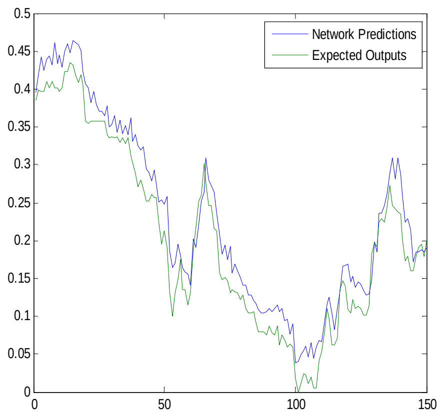

Fig. 4. Actual data and predicted data comparison of 150 samples

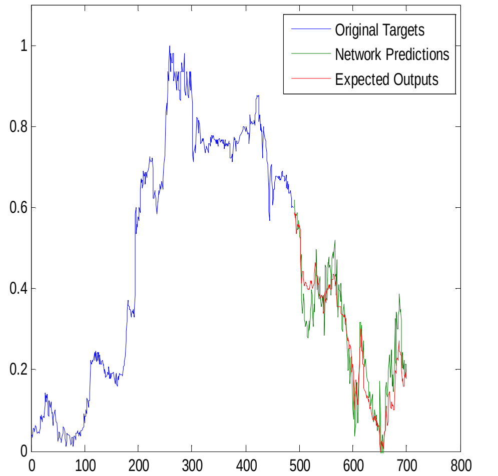

Fig. 5. Prediction results of TALL1T stock in case of 200 samples

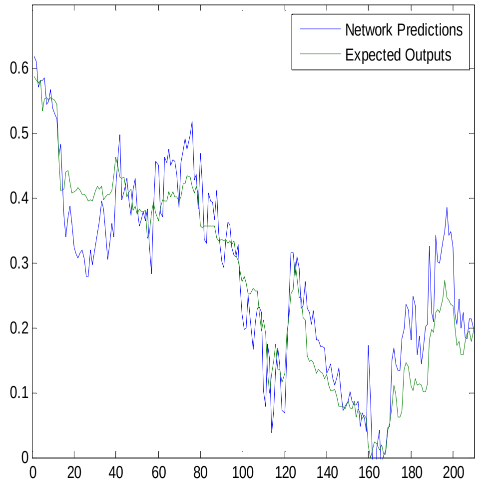

Fig. 6. Actual data and predicted data comparison of 200 samples

5. Conclusions and future work

Forecasting stock market changes is an important issue for many researchers and investors. Moreover, it is one of the challenging tasks of nowadays time series analysis. In this paper, we have presented the hybridized prediction model for financial time series forecasting. In special case study, 30 technical indicators were calculated based on technical analysis. The prediction model was constructed based on two-stage architecture, combining principal component analysis (PCA) and artificial neural networks (ANNs). This study used PCA to select proper input variables from technical indicators, and NARX model to forecast the future values in stock exchange. The experimental results obtained using the proposed neural network approach proved better results from the point of view of MSE measure. This study allows us to conclude that PCA-NARX prediction model provides a promising alternative tool to other ANN based methods in financial time series forecasting.

This research considers only technical indicators and stock based information as stock affecting indicators. In the future work it is designed to include more stock market influencing factors, based specifically on fundamental and technical analyses compared with other prediction models.

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