PREDICTION OF STOCK INDICES USING ARTIFICIAL NEURAL NETWORKS AND TECHNICAL INDICATORS

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Abstract: Predicting the behaviour of stocks, stock indices, and currency exchange rates as accurately as possible is crucial for successful decisions makings in financial markets. Artificial neural networks have proven to be a suitable tool for predicting non-stationary financial time series. The paper aims to analyse the contribution of technical indicators to the accuracy of stock index price prediction using artificial neural networks. We develop a robust prediction model using a nonlinear autoregressive neural network with eight technical indicators as external inputs. The prediction model is applied to the price index of the Prague Stock Exchange (PX index). The use of technical indicators increases the prediction accuracy compared to the prediction model based on a nonlinear autoregressive neural network without any external inputs.

Keywords: nonlinear autoregressive neural network with external input, prediction, stock index, technical indicators.

1 Introduction

Predicting stock prices as accurately as possible is a fundamental aspect of successful trading in financial markets. Economic and political events often cause movements in financial markets. The COVID-19 coronavirus pandemic currently has an extensive impact on the global economy and financial markets. Several tools can be used to predict the direction of stock price movements, including fundamental analysis, technical analysis, behavioural analysis, statistical prediction methods, and artificial intelligence tools. Artificial intelligence tools have become powerful methods of stock price prediction. One of these tools is an artificial neural network (ANN). ANNs are massive parallel computing systems that tend to store information and make it available for further processing. They can describe the dynamics of non-stationary time series, making them a suitable tool for predicting financial time series. Already in the 1990s, research papers about prediction systems advising when to buy and sell stocks based on ANNs (Kimoto, Asakawa, Yoda, and Takeoka, 1990); trend prediction and reversal recognition system for the stock market using a dual-module neural network (Jang, Lai, Jiang, Pan, and Chien, 1991); and about ANNs for stock return volatility prediction (Catfolis, 1996) were published.

In recent years, researchers have focused on the possibility of improving the predictive capabilities of neural networks by creating hybrid models of neural networks and classical statistical methods, hybrid models of neural networks and other tools of artificial intelligence, and neural networks using external inputs. Examples of hybrid models of neural networks and classical statistical methods are deep feedforward neural network hybrid based models and long short-term memory based hybrid models for prediction of the volatility of stock price index, which include various generalized autoregressive conditional heteroscedasticity models, developed by Kim and Won (2018); an adaptive hybrid ensemble learning paradigm integrating complementary ensemble empirical mode decomposition, autoregressive integrated moving average and sparse Bayesian learning for crude oil price prediction, developed by Wu, Chen, Zhou, and Li (2019); and hybrid deep-learning framework, which includes the feature pre-processing module (based on isolation forest and least absolute shrinkage and selection operator), the deep learning-based point prediction module (combines the deep belief network, long-short-term memory neural network, and convolutional neural network), the error compensation module, and the probabilistic prediction module (based on quantile regression) for day-ahead electricity price prediction, developed by Zhang, Li, and Ma (2020). Examples of hybrid models of neural networks and other tools of artificial intelligence are High-order-fuzzy-fluctuation-Trends-based Back Propagation Neural Network model for stock price prediction, developed by Guan, Dai, Zhao, and He (2018); hybrid model of the genetic algorithm and nonlinear autoregressive neural network with exogenous inputs for daily bitcoin price prediction, developed by Han, Kim, Jang, and Ri (2020); and multilayer perceptron–genetic algorithms model and multilayer perceptron–particle swarm optimization model for stock market trends prediction, developed by Ecer, Ardabili, Band, and Mosavi (2020).

The predictive capability of ANNs can be improved by using external inputs such as the technical indicators, which have proven to be suitable external inputs. Lahmiri (2017) analysed the predictive capability of ANNs using technical indicators (Middle band, Upper band, Lower band, Momentum, Acceleration, Exponential Moving Average –EMA, Relative Strength Index – RSI, and Moving Average Convergence/Divergence – MACD) for historical volatility of currency exchange rate prediction. The ANNs were compared with generalized autoregressive conditional heteroscedastic (GARCH) models and exponential generalized autoregressive conditional heteroscedastic (EGARCH) models. ANNs using technical indicators outperform these models in terms of the mean absolute error, the mean square error, and Theil's inequality coefficient. The results indicate Their simple and effective approach is promising for currency volatility prediction tasks. Lee and Soo (2017) compared the results of the recurrent convolutional neural networks with technical indicators and the technical analysis alone for stock price prediction. They used the same technical indicators (Moving Average – MA, Stochastic Oscillator %K – %K, Stochastic Oscillator %D – %D) for neural networks and technical analysis prediction. The recurrent convolutional neural networks with technical indicators outperform the technical analysis. Nelson, Pereira, and de Oliveira (2017) developed a long-short-term memory neural network prediction model using technical indicators. They compared the results with three machine learning techniques - multilayer perceptron, random forest, and a pseudo-random model that outputs a class based on probabilities following the class distribution; and three investment strategies – buy and hold, optimistic, and pseudo-random. The proposed long-short-term memory neural network with technical indicators displayed considerable gains in terms of prediction accuracy. Vargas, dos Anjos, Bichara, and Evsukoff (2018) compared stock price predictions of deep learning models using financial news titles and two different sets of technical indicators as input. The first set of technical indicators included %K, %D, Momentum, RSI, Rate of change, Larry William's %R (%R), Accumulation/Distribution Oscillator (AD), and Disparity. The second set of technical indicators included EMA, MACD, RSI, On Balance Volume (OBV), and Bollinger Bands. They compared two machine learning models – a hybrid model composed of a convolutional neural network for the financial news and a long-short-term memory neural network for technical indicators; and a long-short-term memory neural network only for technical indicators. The results indicated that the financial news played a crucial role in stabilizing the results and that there was almost no improvement when comparing different sets of technical indicators.

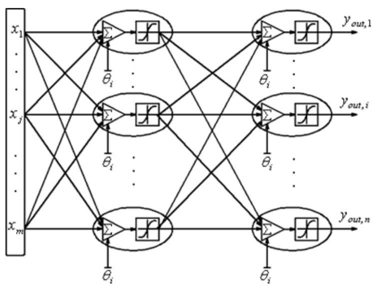
Chou and Lin (2019) developed a fuzzy neural network combined with technical indicators for the prediction of freight rate trend in the dry bulk shipping market. The prediction results were compared with the technical indicator approach and the fuzzy neural network approach. The best prediction of the Baltic Dry Index was obtained using the combination of a fuzzy neural network and technical indicators (%R, RSI, MACD, Commodity Channel Index – CCI, and MA). Lai, Chen, and Caraka (2019) introduced long-short-term memory neural network using average previous five days' stock market information (open, high, low, volume, close) and technical indicators (%K, %D, MACD, RSI, and OBV). They predicted the stock price index using data from Taiwan Stock Exchange. Lan, Kung, Ou, Lin, Hu, and Wang (2019) improved Taiwan Semiconductor Manufacturing Company stock price predictions of ANNs by including technical indicators and exchange rates among the input data of the backpropagation neural network. Naik and Mohan (2019) selected relevant technical indicators for the ANN-based prediction model using the Boruta feature selection unit. They considered 33 different combinations of technical indicators (Simple Moving Average – SMA, EMA, Momentum, %K, %D, MACD, RSI, %R, AD, and CCI) for various periods. Selected technical indicators were used as inputs for the ANN regression prediction model. The obtained results were compared with results of ANN without technical indicators. The proposed ANN model with technical indicators outperforms ANN in terms of the mean absolute error and the root mean square error. Picasso, Merello, Ma, Oneto, and Cambria (2019) proposed the exploitation of a feedforward neural network architecture into a trend classification problem. The model used technical indicators (SMA, EMA, MACD, RSI, Bollinger Bands, %K, %D, True Range – TR, Average True Range – ATR, %R, and CR indicator) and sentiment of news articles as inputs. The proposed robust predictive model was able to predict the trend of a portfolio composed of the twenty most capitalized companies listed in the NASDAQ100 index.

Alonso-Monsalve, Suarez-Cetrulo, Cervantes, and Quintana (2020) performed an analysis of the predictive capabilities of neural networks in predicting the trend of cryptocurrency exchange rates. ANNs used 18 trend-following technical indicators - AD, CCI, %R, MACD, Momentum, RSI, SMA (5, 10, 20, 30, and 60 minutes), %D, %K, and Weighted Moving Average (WMA) (5, 10, 20, 30, and 60 minutes). The authors compared results of a convolutional neural network, a hybrid convolutional neural network and long-short-term memory neural network, a multilayer perceptron, and a radial basis function neural network. The results of the analyses showed that the most suitable neural network was a hybrid convolutional neural network and long-short-term memory neural network, which significantly outperformed all the rest analysed networks. A combination of the daily trading data, technical indicators, and macroeconomic variables as inputs was used by Gao, Zhang, and Yang (2020). They presented multilayer perceptron, long-short-term memory neural network, convolutional neural network, and attention-based neural network for the day ahead prediction of stock index price. They achieved the best results with the attention-based neural network using open/close price and trading volume (daily trading data), MACD and Average True Range (technical indicators), and exchange rate and interest rate (macroeconomic variables). Nabipour, Nayyeri, Jabani, Mosavi, Salwana, and Shahab (2020) analysed the predictive capabilities of a decision tree, a bagging, a random forest, an adaptive boosting, a gradient boosting, and an eXtremegradient boosting, and ANNs, a recurrent neural network, and a long-short-term memory network. They used ten technical indicators (SMA, WMA, Momentum, %K, %D, RSI, MACD, %R, AD, and CCI) as the inputs for each of the prediction models. They achieved the best prediction results using long-short-term memory neural network.

2 Artificial Neural Network

Artificial neural networks, one of the soft computing methods, can process data with imprecisions, uncertainties, and approximations. Complex problems, that are difficult to accurately describe by mathematical models, can be solved using ANNs and their complex algorithms (Ibrahim, 2016). ANNs are inspired by the human brain and its ability to learn. Learning enables ANNs to improve their performance and the accuracy of their results. A neuron, the basic building unit of the ANN, is a simplified model of a biological neuron with similar functions and structure. The neurons of the ANN process the information from their input with an activation function and transmit it via oriented weighted connections. These connections are organized into layers - input layer, hidden layers, and output layer. The layers of the ANN differ in the sources of their inputs and the use of their outputs. The input layer processes the data of the independent variables (inputs of the ANN) and transmits it to the next network layer. Hidden layers process outputs from previous layers and transmit them to the next layer. The output layer processes the outputs of the previous hidden layer and gives the value of the dependent variable as an output (Parot, Michell, and Kristjanpoller, 2019, Yildirim, 2019). Figure 1 shows an architecture of a multilayer feedforward neural network. The signal proceeds through the network through directed connections in one direction – forward. Unlike static feedforward networks, the dynamic recurrent neural networks use not only the feedforward connections but also feedback connections that allow the network to store information for further use (Mahmud and Meesad, 2016).

Figure 1: Architecture of the multilayer neural network.



Source: Elaborated by the authors.

ANN learns and stores acquired knowledge by adjusting the connection's weight values and neuron threshold values (θ). The acquired knowledge is stored in the adjusted weights of the neural network connections. Several learning laws can be applied to the neural network training process. In the paper, we use Levenberg-Marquart (LM) learning algorithm, which is the fastest converging learning algorithm for ANNs that contain less than a few hundred weights (Shahbazi, Memarzadeh, and Gryz, 2016). Chandar, Sumathi, and Sivanandam (2015) achieved the best prediction accuracy of the foreign currency exchange rate using ANN trained with LM learning algorithm. The LM learning algorithm is a variation on the Backpropagation algorithm. Li, Cheng, Shi, and Huang (2012) described the Backpropagation algorithm in two steps. In the first step, the operating signal is propagated forward through the network layers, and the error signal is computed as the difference between the real and the expected network output. In the second step, the error signal is backpropagated through the network. To minimize the error signal and therefore optimize the network performance, the weight values and threshold values are adjusted using the gradient descent method. The slow speed of convergence is a disadvantage of the Backpropagation algorithm. LM algorithm is one of the variations of the Backpropagation algorithm, which speeds up the convergence.

The LM learning algorithm combines the gradient descent method and the Gauss-Newton method. It minimizes a non-linear function with a numerical solution (Gavin, 2020). According to Yu and Wilamowski (2011), the learning rule of LM algorithm is given by:

$$w_{k+1} = w_k - (\boldsymbol{J}_k^T \boldsymbol{J}_k + \mu \boldsymbol{I})^{-1} \boldsymbol{J}_k \boldsymbol{e}_k,$$

where w_{k+1} and w_k are components of wight vector $\boldsymbol{w}$; μ is a combination coefficient with positive value; $\boldsymbol{I}$ is the identity matrix; $\boldsymbol{e}_k$ is a vector of training errors defined as $\boldsymbol{e}_k = y_k - \widehat{y_k}$, where y_k are target values and $\widehat{y_k}$ are output values; $\boldsymbol{J}$ is the Jacobian matrix defined as:

$$J = \begin{bmatrix} \frac{\partial e_{1,1}}{\partial w_1} & \frac{\partial e_{1,1}}{\partial w_2} & \cdots & \frac{\partial e_{1,1}}{\partial w_N} \\ \frac{\partial e_{1,2}}{\partial w_1} & \frac{\partial e_{1,2}}{\partial w_2} & \cdots & \frac{\partial e_{1,2}}{\partial w_N} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial e_{1,M}}{\partial w_1} & \frac{\partial e_{1,M}}{\partial w_2} & \cdots & \frac{\partial e_{1,M}}{\partial w_N} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial e_{P,1}}{\partial w_1} & \frac{\partial e_{P,1}}{\partial w_2} & \cdots & \frac{\partial e_{P,1}}{\partial w_N} \\ \frac{\partial e_{P,2}}{\partial w_1} & \frac{\partial e_{P,2}}{\partial w_2} & \cdots & \frac{\partial e_{P,2}}{\partial w_N} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial e_{P,M}}{\partial w_1} & \frac{\partial e_{P,M}}{\partial w_2} & \cdots & \frac{\partial e_{P,M}}{\partial w_N} \end{bmatrix}, \tag{2}$$

where N is a number of weights, M is a number of outputs and P is a number of patterns.

The dynamic neural networks are appropriate for the financial time series prediction due to the dependence of the financial time series values on its previous values. We use a nonlinear autoregressive neural network with external input (NARX) and a nonlinear autoregressive network (NAR) in the paper. NARX a recurrent dynamic network based on a linear autoregressive model with exogenous variables (ARX). NAR is a recurrent dynamic network based on a linear autoregressive model (AR). The architecture of both NARX network and NAR network consists of feedback connections and tapped delay lines (TDL). The TDL unit returns a vector consisting of input data from the current time-step to the required number of time delays (Stokes and Abou-Zaid, 2012). In supervised learning, the actual previous values of the time series are known and can be used to replace the feedback connections. After modification of the network to feedforward architecture, static Backpropagation in the network training process can be used, which reduces the time required for calculations. After training of the ANN, it is possible to iterate the prediction of several time steps ahead using the original network architecture containing the feedback connections. Leaving a purely feedforward architecture, the network would be able to predict only one-step-ahead. Equation (3) is the defining equation for the NARX model, and equation (4) is the defining equation for the NAR model (Shahbazi, Memarzadeh, and Gryz, 2016).

$$y(t) = F(y(t-1), y(t-2), \dots, y(t-d_y), u(t-1) \\ u(t-2), \dots, u(t-d_u)\,), \tag{3}$$

$$y(k) = F\big(y(t-1), y(t-2), \dots, y(t-d_y)\,\big), \tag{4}$$

where $y(t)$ is the value of the financial time series at time t, d_y is a number of time delays for the financial time series, $u(t)$ is the value of the independent (external/exogenous) input signal at time t, and d_y is a number of time delays for the independent input signal.

3 Technical Indicators

Technical indicators are one group of tools of technical analysis. Technical analysis uses historical stock quotes (prices and trading volumes) for the prediction of possible behaviours of the stock prices. We classify technical indicators into four categories: trend indicators, momentum indicators, volatility indicators, and cycle indicators (Bley and Saad, 2020). Oriani and Coelho (2016) found that the use of technical indicators as inputs to Multilayer Perceptron leads to high-quality predictions of stock closing prices. A combination of Technical and Fundamental analysis-based indicators for stock pricing prediction using machine learning-based models was found most efficient by Beyaz, Tekiner, Zeng, and Keane (2018). In the following section, we present the technical indicators used in the paper with their mathematical formulas as given by Kara, Boyacioglu, and Baykan (2011) and Achelis (2003).

3.1 Technical indicators formulas

Simple Moving Average (SMA):

$$SMA(k)_t = \frac{\sum_{i=0}^{k} C_{t-i}}{k},$$

where C_t is the closing price at time t, and k is the number of time periods in the moving average.

Exponential Moving Average (EMA):

$$EMA(k)_t = EMA(k)_{t-1} + \alpha \cdot (C_t - EMA(k)_{t-1}),$$

where $\alpha = \frac{2}{k+1}$ is a smoothing factor.

Moving Average Convergence/Divergence (MACD):

$$MACD_t = EMA(12)_t - EMA(26)_t.$$

Relative Strength Index (RSI):

$$RSI_t = 100 - \frac{100}{1 + (\sum_{i=0}^{n-1} Up_{t-i}/n)/(\sum_{i=0}^{n-1} Dw_{t-i}/n)},$$

where Up_t is the upward price change at time t, and Dw_t is the downward price change at time t.

Momentum:

$$Momentum_t = C_t - C_{t-n}.$$

Accumulation/Distribution Oscillator (AD):

$$AD_t = \frac{H_t - C_{t-1}}{H_t - L_t},$$

where H_t is the high price at time t, and L_t is the low price at time t.

Stochastic Oscillator %K (%K):

$$\%K_t = \frac{C_t - LL_n}{HH_n - LL_n} \cdot 100,$$

where HH_n is the highest high in the last n days, and LL_n is the lowest low in the last n days.

Stochastic Oscillator %D (%D):

$$\%D_t = \frac{\sum_{i=0}^{n-1} \%K_{t-i}}{n}.$$

Larry William's %R (%R):

$$\%R_t = \frac{HH_n - C_t}{HH_n - LL_n} \cdot 100.$$

4 Data and methodology

We analyse the accuracy of the prediction of the PX index, the official price index of the Prague Stock Exchange, using ANNs and ANNs with technical indicators as external inputs. The PX index is a free-float weighted price index made up of the most liquid stocks, and it is calculated in real-time. The robust prediction models are developed using historical prices from January 5, 2000, to October 15, 2020, which represents 5214 values.

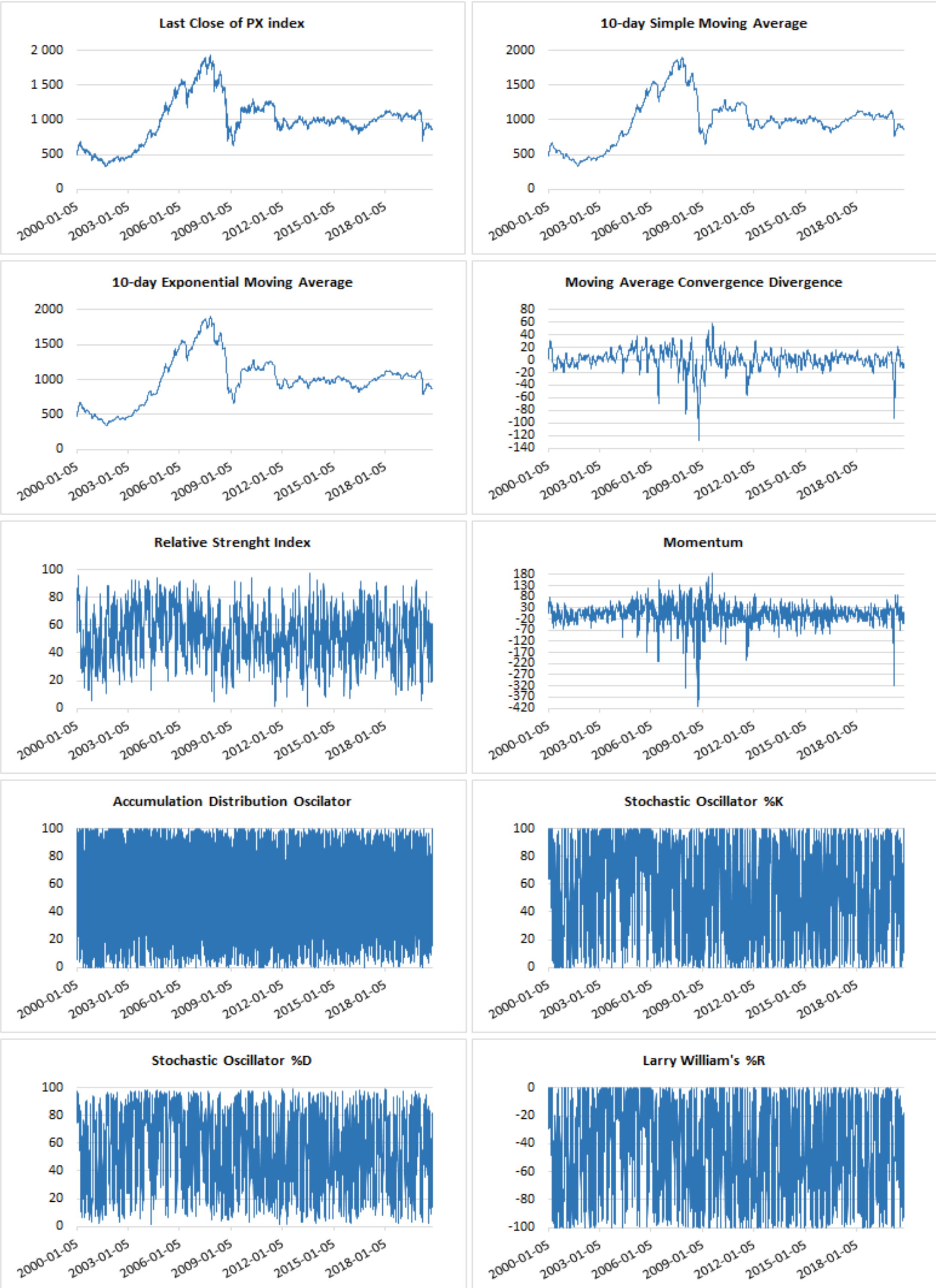
We calculate the values of the eight technical indicators of the PX index. We use 10-day SMA, 10-day EMA. MACD, RSI, Momentum based on 12-day difference, AD, %K based on 10-day difference, %D based on 3-day EMA, and %R based on 14-day difference. Figure 2 shows the tracking period of the PX index and the technical indicators.

The calculations are performed, and prediction models are constructed in the MATLAB R2019b software. We normalize the input data of the neural network to simplify the problem of the outliers in the neural network (Shahbazi, Memarzadeh, and Gryz, 2016). We use equation (14) for data normalization, which was proposed by Markechová, Stehlíková, and Tirpáková (2011).

$$U = \frac{X-\mu}{\sigma}, \tag{14}$$

where U is the normalized variable, X is the original variable, μ is the mean value of the variable and σ is the standard deviation of the variable. We divide the pre-processed data into training set, validation set, and testing set in a ratio of 70:20:10. To predict the stock index, we develop and validate NARX networks with technical indicators as external (endogenous) inputs. To compare the NARX network performance, we develop and validate the NAR network. The networks use tansig transfer function and LM learning algorithm.

Figure 2: The PX index and technical indicators.



Source: Elaborated by the authors based on data from Prague Stock Exchange (2020).

We optimize the network architecture of both NARX and NAR networks, using different numbers of the hidden layer's neurons and the different number of time delays. We construct networks with 5, 10, 15, 20, 25, 30 days' time delay and 5, 10, 15, 20, 25, 30 neurons in the hidden layer for each value of time delay. We construct, train, validate and test 36 NARX networks and 36 NAR networks. We use the mean square error (MSE) and the determination coefficient (R^2)to evaluate the network performance. We calculate MSE and R^2 values for training, validation, and test data set.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \quad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \quad (16)$$

where n is the number of data points, y_i are target values,$\hat{y}_i$ are output values and $\bar{y}$ is the mean of target values.

5 Results and discussion

We compare the performance of the NARX network with technical indicators as external inputs and the NAR network for the PX index prediction. We construct, train, validate and test 36 NARX networks and 36 NAR networks. To visualize the results of the developed networks, we select the network with the best prediction accuracy for each of the used time delays for both NARX and NAR networks. Table 1 shows these results. We use the MSE values for the validation data set to select the network with the highest prediction accuracy as proposed by Moghaddam, Moghaddam, and Esfandyari (2016).

Among the created NARX networks, the network with 20 time delays and 5 neurons in the hidden layer achieves the best results. The network has the lowest MSE of the validation set with the value 1.4787E-03. Among the created NAR networks, the network with 15 time delays and 10 neurons in the hidden layer achieves the best results. The network has the lowest MSE of the validation set with the value 2.3930E-03. It is apparent that NARX networks with external inputs performed better for all the time delays compared to NAR networks. Neural networks using technical indicators as external inputs performed superior over other neural networks in the studies by Nelson, Pereira, and de Oliveira (2017), Naik and Mohan (2019), and Lan, Kung, Ou, Lin, Hu, and Wang (2019). Our results confirm these findings and indicate the suitability of using NARX networks with technical indicators as external inputs for stock index price prediction. The network architecture, the number of time delays, and the number of hidden layer neurons must be adapted and validated individually for each financial time series.

Tab. 1: NARX and NAR networks results.

	Time delays	Hidden neurons	MSE			R^2		
			Train	Valid	Test	Train	Valid	Test
NARX	5	15	1.2428E-03	1.5230E-03	1.7743E-03	9.9938E-01	9.9927E-01	9.9907E-01
	10	5	1.5008E-03	1.5310E-03	1.8497E-03	9.9924E-01	9.9929E-01	9.9900E-01
	15	5	1.4824E-03	1.4957E-03	2.1985E-03	9.9926E-01	9.9926E-01	9.9890E-01
	20	**5**	**1.5508E-03**	**1.4787E-03**	**1.4044E-03**	**9.9922E-01**	**9.9930E-01**	**9.9925E-01**
	25	10	1.1195E-03	1.8965E-03	1.9390E-03	9.9945E-01	9.9903E-01	9.9903E-01
	30	10	1.2586E-03	1.7898E-03	2.3093E-03	9.9939E-01	9.9908E-01	9.9885E-01
NAR	5	20	2.7630E-03	2.9624E-03	4.1591E-03	9.9629E-01	9.9729E-01	9.9288E-01
	10	25	3.1420E-03	2.7027E-03	2.5531E-03	9.9320E-01	9.9533E-01	9.9730E-01
	15	**10**	**3.1498E-03**	**2.3930E-03**	**2.9726E-03**	**9.9220E-01**	**9.9341E-01**	**9.9820E-01**
	20	5	2.9431E-03	3.1497E-03	2.9305E-03	9.9825E-01	9.9615E-01	9.9631E-01
	25	15	3.0106E-03	2.6585E-03	3.7965E-03	9.9122E-01	9.9735E-01	9.9406E-01
	30	5	2.9418E-03	2.9611E-03	3.7436E-03	9.9425E-01	9.9423E-01	9.9308E-01

Source: Elaborated by the authors.

6 Conclusion

Predicting the behaviour of stocks, stock indices, and currency exchange rates as accurately as possible is crucial for successful decisions makings in financial markets. Predicting the behaviour of financial time series is complicated by their non-stationarity and nonlinearity. ANNs can describe the dynamics of non-stationary time series, making them a suitable tool for predicting financial time series. In the paper, we analyse the predictive capabilities of ANNs using technical indicators as external (exogenous) inputs. We develop and validate a robust prediction model using the NARX network with eight technical indicators as external inputs. The prediction model is applied to the price index of the Prague Stock Exchange (PX index). The obtained prediction results are compared to results of the NAR network without any external inputs. The use of technical indicators increases the prediction accuracy, and we can therefore conclude that technical indicators are suitable as external inputs of ANNs for stock index price predictions.

Our research has the following limitations: the analysis of the predictive capabilities of ANNs is conducted on only one stock index, and the selection of the included technical indicators is only based on previous researches. In our future research, we will focus on the selection of the most appropriate technical indicators for ANN prediction models of stock index prices.

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Primary Paper Section: A

Secondary Paper Section: AH