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Darko Vukovic
Serbian Academy of Sciences and Arts

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FOREX PREDICTON WITH NEURAL NETWORK: USD/EUR CURRENCY PAIR

Prof. Yaroslav Vyklyuk, PhD.
Bukovinian University, Faculty of Computer Systems and Technologies,
Darvina 2A, Chernivtsi, Ukraine, 58000
Mobile: +380974065842
E-mail: vyklyuk@ukr.net
SoftComputing, Fractals, Econophysics, Mathematical modeling in Social System, GIS

Darko Vuković, PhD. Candidate, Teaching assistant
University of Union-Nikola Tesla, Faculty of Entrepreneurial Business
Cara Dusana 62-64, 11000 Belgrade, Serbia
E-mail: vdarko@hotmail.rs
Home: Valjevo 14000, Naselje Oslobodioci Valjeva 50a/11
Mobile: +38163 8381969
Macroeconomics, Microeconomics, Institutional Economy, Finance

Ana Jovanović, PhD, Associate Professor*
University of Union - Nikola Tesla, Faculty of Entrepreneurial Business
Cara Dušana 62-64, 11000 Belgrade, Serbia
E-mail: ajovanovic@fpb.edu.rs
Home: Beograd 11000, Miće Popovića 5/7
Mobile: +381642086747
Public Finances, Macroeconomics, Finance, Institutional Economics

ABSTRACT: In this paper we investigate and design the neural networks model for FOREX prediction based on the historical data movement of USD/EUR exchange rates. Given that the model analyzes historical data of exchange rates, neural networks can be used as an important technique of technical analysis. Unlike many other techniques of technical analysis which are based on price trends analysis, neural networks offer autocorrelation analysis and the estimation of possible errors in forecasting. This theory is consistent with the semi-strong form of the efficient markets hypothesis. The empirical data used in the model of neural networks are related to the exchange rate USD / EUR in the period 23.04.2012 - 04.05.2012. The results shows that the model can be used for FOREX prediction.

KEY WORDS: neural networks, historical data movement, forecasting, technical analysis.

Correspondence to: a.jovanovic@open.telekom.rs

Introduction

The foreign exchange market (FOREX) is a form of exchange for the global trading of international currencies. Many aspects of the FX markets remain constant despite the electronic revolution. As has been true for decades, the markets remain decentralized with high liquidity and continuous trading (Lyons, 2001; Rime, 2003; Osler, 2009). The importance of foreign exchange markets for the world economy is enormous. Foreign exchange markets affect: output and employment (through real exchange rates), inflation (through the cost of imports and commodity prices), international capital flows (through the risks and returns of different assets).

As FOREX is made up of commercial and financial transactions, the daily turnover of the world's currencies comes from two sources: foreign trade and speculation for profit with the share of 5% and 95%, respectively.

Global foreign exchange market activity consists of spot transactions, outright forwards, foreign exchange swaps, currency swaps, currency options and other foreign exchange products. The determination of the relative values of different currencies is mainly achieved through spot transactions (the exchange rate and the quantity to exchange are agreed initially and the funds are actually settled two business days later) and outright forward transactions (similar in structure to spot transactions, but settlement generally happens more than two business days later).

Given the pervasive influence of exchange rates, it is not a surprise that the dollar value of trading activity in spot and forward foreign exchange (FX) markets dwarfs most other economic measures (BIS, 2010). With daily average turnover most recently estimated at $2.0 trillion, the market is 36 times larger than the combined exports and imports for the world's 35 largest economies, 16 times their combined GDP, and roughly 10 times exchange-traded equity turnover. FX trading volume has exploded reflecting an electronic revolution that has lowered trading costs, attracted new groups of market participants, and enabled aggressive new trading strategies. Between 1998 and 2010 turnover in the FX market grew by over 250 percent (BIS, 2010). The associated 8.4 percent average annual growth rate far exceeds the contemporary 5.5 percent annual expansion of global real GDP (Norges Bank, 2011).

FOREX trading is used to speculate on the relative strength of one currency against another. Currencies trade in pairs and most traders focus on the biggest, most liquid currency pairs i.e. USD/EUR, USD/JPY and USDD/GBP. According to BIS (2010) turnover by currency pair (Table 1) shows a steady relationship with no major changes in ranking of currency pairs for more than a decade. USD/EUR remained by far the dominant pair (with a 28% share), followed at some distance by USD/JPY (with a 14% share) and USD/GBP (with a 9%).

Table 1: Global Foreign exchange market by currency pair*
Daily averages in April, in billions of US dollars and percentages

Currency pair	2001		2004		2007		2010	
	Amount	%	Amount	%	Amount	%	Amount	%
US dollar/euro	372	30	541	28	892	27	1,101	28
US dollar/yen	250	20	328	17	438	13	568	14
US dollar/sterling	129	10	259	13	384	12	360	9
US dollar/Australian dollar	51	4	107	6	185	6	249	6
US dollar/Swiss franc	59	5	83	4	151	5	168	4
US dollar/Canadian dollar	54	4	77	4	126	4	182	5
US dollar/Swedish krona	6	0	7	0	57	2	45	1
US dollar/other	193	16	300	16	612	18	705	18
Euro/yen	36	3	61	3	86	3	111	3
Euro/sterling	27	2	47	2	69	2	109	3
Euro/Swiss franc	13	1	30	2	62	2	72	2
Euro/other	22	2	44	2	123	4	162	4
Other currency pairs	28	2	50	3	139	4	149	4
All currency pairs	1,239	100	1,934	100	3,324	100	3,981	100
*Adjusted for local and cross-border inter-dealer double-counting (ie "net-net" basis).								

BIS, 2010.

Figure 1: US dollar currency pairs

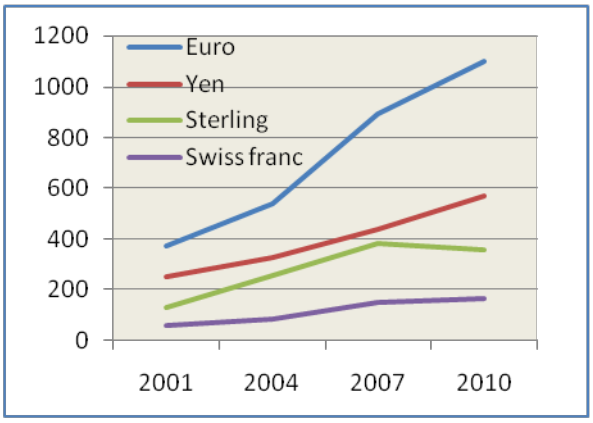
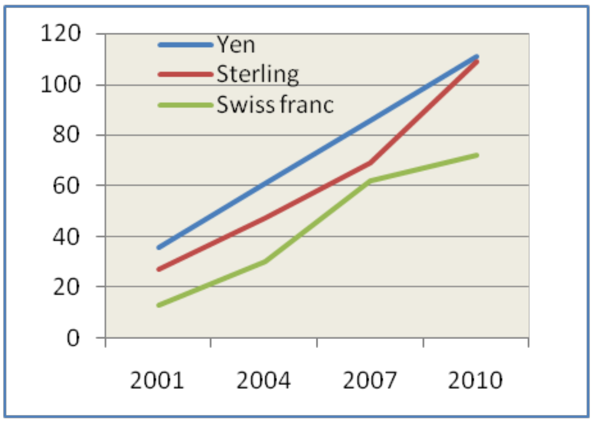


Figure 2: Euro currency pairs



BIS(2010), Authors.

Starting from the fact that US dollar and the Euro share the role of the world's key international money (Figure 1 and 2), the relationship between them is particularly important, not only for these large economic areas but also for the world economy as a whole. The EUR/USD exchange rate relationship in the period 1999-2012 is shown in the Figure 3.

Figure 3. USD/EUR historical rates

ECB, 2012.

FOREX prediction is one of the most challenging applications of modern time series forecasting. The rates are inherently noisy, non-stationary and deterministically chaotic (Deboeck, 1994; Kamruzzaman & Sarker, 2003). Many authors (Box & Jenkins, 1970; Jhee & Lee, 1993; Cao & Tay, 2001; Hwarng & Ang, 2002; Kamruzzaman & Sarker, 2003) have used historical data to predict exchange rates movement. The use of historical data in the FOREX prediction makes this kind of analysis as well as technical analysis, although there are some differences. Most of these authors use neural networks to predict future movements in exchange rates.

The subject of this paper is based on neural networks which can be used to create a model of forecasting. The aim is to use historical data of the movement of exchange rates and on the basis of these data, to create a neural network model which can be used for FOREX prediction.

Review of literature on the problem

For decades many authors criticized the technical analysis and its methodology in the study of price movements on the market (Fama, Blume 1966, Jensen, Benington 1970). This statement applies not only to the securities markets, but also for FOREX. Researches and evidences indicate that it is possible to rely on the ability of simple rules to predict price movements on the market and these are contrary to previous theories. However, those evidences are not too convincing but they certainly show that technical analysis is not in the least neglected in the analysis of price trends (LeBaron, 1999). Moreover today, investor, broker or other participant on financial market would not have approached the serious analysis of financial assets or exchange rates, ignoring the technical analysis methodology. Brown and Jennings (1989) point out that technical analysis is of great significance because the value of assets is not fully expressed in the prices and traders have rational predictions about the relationship between price and its signals.

Considering these attitudes there are still a number of theories dealing with the problem of forecasting the price trends. One of the most important theory is generally accepted efficient markets hypothesis, explained and surveyed by Fama (1991). According to the efficient markets hypothesis, the market prices follow a random walk and cannot be predicted based on their past behavior. This theory claims that there are three degrees of market efficiency (Leigh et al, 2002). The strong form states that all knowable information are immediately factored into the market's price for a security. If the strong form is confirmed, this would mean that all of those stock analysts are definitely wasting their time, even if they have access to private information. In the semi-strong form of the theory, all public information is considered to have been reflected in price immediately as it became known, but possessors of private information can use that information for profit. Finally, the weak form holds only that any information gained from examining the security's past trading history is immediately reflected in price. These authors argue that discoveries of "anomalies" create great conditions for investors to earn abnormal returns, violating strong and semi-strong form of efficient markets hypothesis (Leigh et al, 2002). According to these hypotheses, there are two dominant approaches in the analysis of financial assets: fundamental (the weak form of the efficient markets hypothesis) and technical analysis (semi-strong form of the efficient markets hypothesis). This analysis is sometimes referred to as market or internal analysis, because it is based on the monitoring of the market and trying to assess the supply and demand of securities on the entire market (Vukovic et al, 2012). According to the lead technical analyst Martin Pring (1985), technical analysis assumes that the stock market moves according to the trends that are determined by the changing views of investors in respect of a number of economic, monetary, political and psychological forces.

Robert Edward and John Magee (2001) have defined technical analysis as "the science of recording the actual history of trading (price changes, volume of transaction, etc.) in a certain stock or in „the averages" and then deducing from that pictured history the probable future trend". According to Kirkpatrick and Dahlquist (2011), in the basic form, technical analysis is a study of prices in freely traded markets with the intent of making profitable trading or investment decisions. Pring considered technical analysis as approach to investment is essentially a reflection of the idea that the stock market moves in trends which are determined by changing attitudes of investors to a variety of economic, monetary, political and psychological forces. "*The art of technical analysis, for it is an art, is to identify changes in such trends at an early stage and to maintain an investment posture until a reversal of that trend is indicated*" *(1985, p.2).* According to Achelis, "*The future can be found in the Past*" (2001, p.3). This author considers that if price are based on investor expectations, then knowing what security should seal for (fundamental analysis) becomes less important than knowing what other investors expect it to sell for.

Technical analysis relates to observation of price movements in the market, using charts and quantitative techniques to predict price trends. It represents the method of analysis of the history of trading of a particular financial instrument (stocks, futures, currencies) and on that basis, assesses a possible trend in the future (Bodie et al, 2009). Trends, moving averages, momentum and Elliott waves are the most frequently used methods and instruments of technical analysis. However, in recent years neural networks are increasingly applied in the field of technical analysis. If we can say that the moving averages or Elliot waves are adequate for the analysis of securities, it can also be said that the neural networks have become a good instrument for forecasting. Support of this claim was pointed out by the research of Chen and Teong (1995), who used a simple neural network to improve regular technical analyses. Carney and Cunningham (1996) have gone even further, arguing that neural network models are better than the conventional model methods in predicting foreign exchange rates. In addition to these authors, the other authors who deal with this issue can also be distinguished: Refenes et al., 1992; Chen & Lu, 1999; Giles et al., 1997. Green and Pearson (1995) used neural network to build a model system for financial market decision support. Ghoshray (1996) used a fuzzy inference method on the fuzzy time series data to predict movement of foreign exchange rates. Abraham and Chowdhury (2001) used NN model to predict the average FOREX rates accurately one month in advance.

In the last two decades, neural networks have become popular technique of financial market prediction. Neural network is an information processing system that consists of a graph representing the processing system as well as various algorithms, which are able to adapt, to recognize patterns, to generalize, and to cluster or to organize data. Carney & Cunningham (1996) consider that neural network "learn" the structure of the data set and that learning is accomplished by providing sets of connected input/output units where each connection has a weight associated with it. According to these authors (1996), learning by adjusting the weights so that the application of a set of inputs produces the desired set of outputs.

However, neural networks have one major characteristic that set them apart from other methods and instruments of technical analysis. Neural networks analysis does not presume any limitations on type of input information as technical analysis does. In contrast to technical analysis, which is based on common recommendations, neural networks are capable to find optimal, for given financial instrument, indicators and build optimal, for given time series, forecasting strategy. According to Kamruzzaman & Sarker (2003), neural networks have been used for modeling nonlinear economic relationship because of their ability to extract complex nonlinear and interactive effects. Neural networks are a class of nonlinear model that can approximate any nonlinear function to an arbitrary degree of accuracy and have the potential to be used as forecasting tools in many different areas.

Finally, it is necessary to explain specific price categories which we will use in our analysis. Achelis (2001, p.6), the fields that define security's price and volume are explained below.

Table 2.Definitions

Open	The price of the first trade for the period. When analyzing daily data, the open is especially important as it is the consensus price after all interested parties were able to "sleep on it".

Close	The price of the last trade during the period. This price is used most often for the analysis. The relationship between the open and the close price is considered significant by most technicians.
High	This is the highest price that the asset traded during the period. It is the point at which there were more sellers than buyers.
Low	This is the lowest price that the asset traded during the period. It is the point at which there were more buyers than sellers.
Volume	This is the number of assets that were traded during the period. The relationship between prices and volume is very important (e.g., increasing prices accompanied by increasing volume).

Source: Achelis, 2001

Designing a NN forecasting model: USD/EUR

Variable selection and data collection

As parameters of forecasting the indicators HIGH and LOW were selected. The statistics data from 02.09.2010 to 20.04.2012 were taken as training sample. The changes of indicators for every day except holidays were fixed. In the whole 425 records were included into the training sample.

Data preprocessing

Knowledge Discovered in Databases (KDD) was used for the construction of the model and for further forecasting (Fayyad et al, 1996). According to this methodology "raw" data were subjected to preprocessing. First of all, for correct neural network training the unknown indexes of currencies in the holidays were removed by linear smoothing. The spectral processing was performed to eliminate the "white" noise from the training sample. To do it in such a way the series were decomposed into Fourier series by solving of linear multiple regression problem. The output variable was real time series (HIGH and LOW), and independent variables: sinus function of all possible discrete frequencies:

$$X_{HIGH(LOW)}^{t} = a_0 + \sum_{k=1}^{q}\left(a_k \cdot cos(\lambda_k \cdot t) + b_k \cdot sin(\lambda_k \cdot t)\right) \tag{1}$$

$$\lambda_k = 2 \cdot \pi \cdot \frac{k}{q} \tag{2}$$

where q - bandwidth

The best results were obtained when q = 25.

Thus, as in the paper the impact of various factors on the rate of USD / EUR was not explored, the only assumption is that the course is affected by the data of prior periods. The autocorrelation analysis was performed to determine the degree of influence (Dunn, 2005). Results are given in Table. 3.

Table 3. Results of autocorrelation analysis

HIGH				LOW			
Lag	R	Lag	R	Lag	R	Lag	R
0	1,00	21	0,66	0	1,00	21	0,66
1	0,98	22	0,65	1	0,99	22	0,65
2	0,96	23	0,63	2	0,97	23	0,64
3	0,95	24	0,62	3	0,95	24	0,62
4	0,93	25	0,61	4	0,94	25	0,61
5	0,92	26	0,60	5	0,92	26	0,60
6	0,90	27	0,59	6	0,91	27	0,59
7	0,88	28	0,58	7	0,89	28	0,57
8	0,86	29	0,56	8	0,87	29	0,56
9	0,85	30	0,55	9	0,86	30	0,55
10	0,83	31	0,54	10	0,84	31	0,54
11	0,82	32	0,53	11	0,82	32	0,53
12	0,80	33	0,52	12	0,81	33	0,51
13	0,78	34	0,51	13	0,79	34	0,51
14	0,77	35	0,50	14	0,77	35	0,50
15	0,75	36	0,50	15	0,76	36	0,50
16	0,74	37	0,49	16	0,74	37	0,49
17	0,72	38	0,49	17	0,72	38	0,49
18	0,70	39	0,48	18	0,71	39	0,48
19	0,69	40	0,48	19	0,69	40	0,47
20	0,68	41	0,47	20	0,68	41	0,47

Source: Authors

As the table shows, the exchange rate of USD / EUR depends linearly on the date of the last 2 weeks, according to the high correlation coefficients (R> 0.8). The exchange rate for the last 3-4 weeks also influences significantly not linearly the next day's rate (0.6 <R <0.8). As can be seen from Kamruzzaman & Sarker (2003) forecasting with a lag only 7 or 14 is too low to get high precision calculations. That's why it's advisable to neglect the nonlinear effect of 3 and 4 weeks. So to build a neural network the input data sample was transformed to the training set, tuples of which are as follows:

$$L_{HIGH} = \langle HIGH_t; HIGH_{t-1}; \dots; HIGH_{t-25} \rangle \quad (3)$$

$$L_{LOW} = \langle LOW_t; LOW_{t-1}; \dots; LOW_{t-25} \rangle \quad (4)$$

According to such a transformation the power of training set comprised $card\left(L_{HIGH(LOW)}\right) = 400$. The first attribute of tuples serves as the initial value, the next 25 are the input parameters.

Neural-network structure

As shown in Yao & Chew (2000), large databases should use multilayer neural networks of back propagation to pay attention to the nonlinear relationships. The empirical correlation was used to determine the structure NN (Круглов et al, 2001):

$$\frac{mN}{1+log_2 N} \le L_w \le m\left(\frac{N}{m}+1\right)(n+m+1)+m; \tag{5}$$

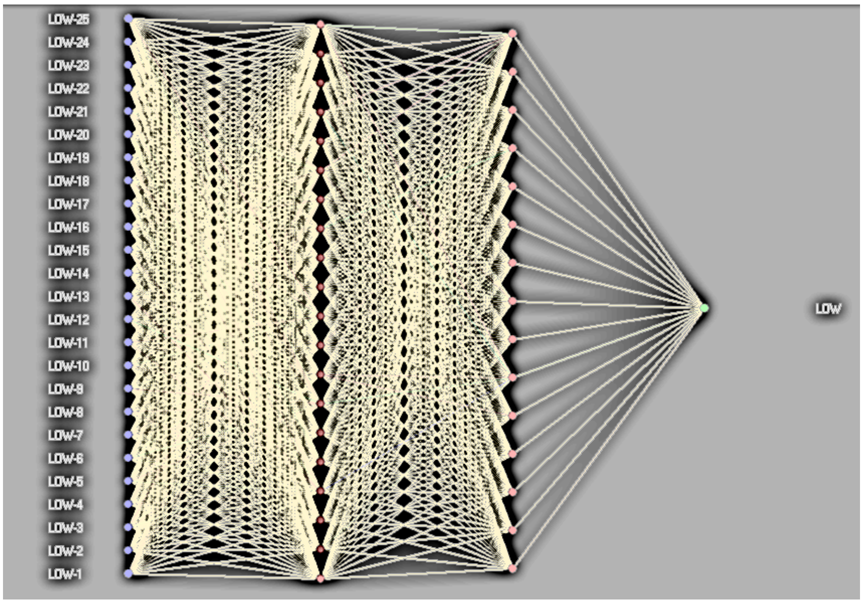
where n - the dimension of the input signal, m - dimension of the output signal, N - power of the training set, L_w - the number of synaptic connections of the neuron network

Defining the scopes of synaptic weights changes enables us to determine the number of neurons in a two-layer neural network:

$$L = \frac{L_w}{n+m}. \tag{6}$$

Exchange rate is the aggregate indicator of complex socio-economic system. The multi-model approaches must be used for modeling such systems. That's why in the calculations for forecasting of each indicator every 3 neural networks were constructed and trained. According to formulas (5) and (6) in the two-layer neural network with sigmoid activation function were used. The structures of neural networks are as follows: [25 × 20 × 20 (15,10) × 1] (Figure 4.).

Figure 4. The structure of the neural network [25 × 20 × 15 × 1]



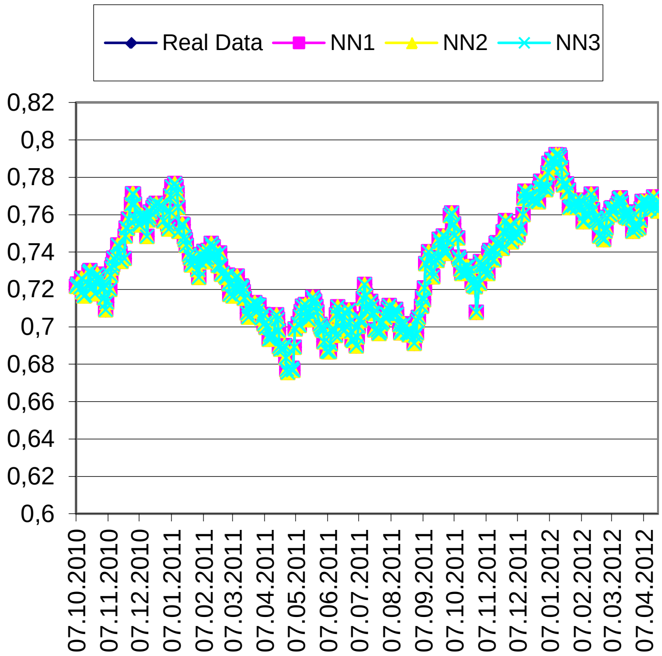
Source: Authors

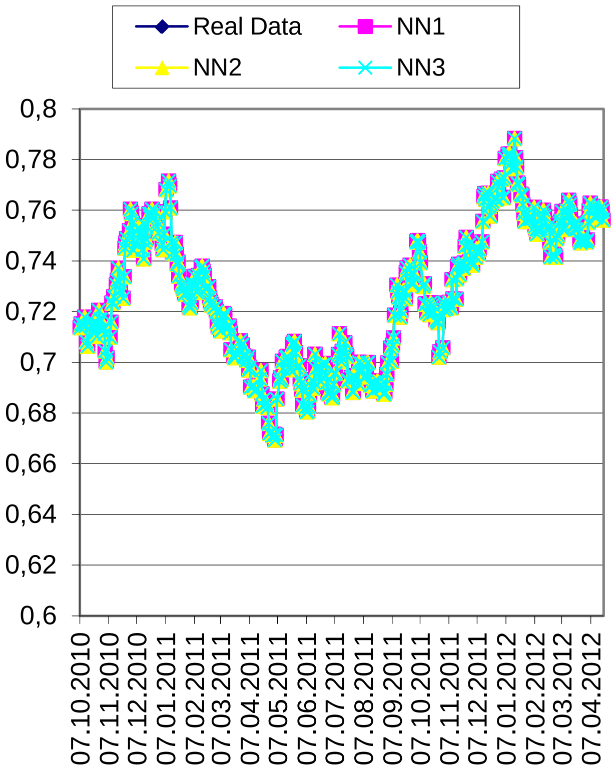
Training, testing and validation sets

As noted above, the method of back-propagation errors was selected as a teaching method. To test the accuracy of the neural network the Initial set was divided into training and test sets in the ratio (95% (380 entries) 5% (20 entries)). The maximum allowable a relative error for the test set was considered 5%. Training lasted for 10 000 epochs.

As a result of studies 6 Neural Networks of test and training sets were recognized as 100%. The average maximum error of training (test) sets was 0.1-0.2 (0.7-1.0)%, and the average 0.01-0.05 (0.5-0.9)%. The results of calculations for this training set are shown in Figure 5 and 6.

Figure 5 and 6. The results of calculations by neural networks according to the real training set





Source: Authors

Evaluation measure

To check the accuracy of the received models the calculation of predictive values of HIGH and LOW rates for 12 days was performed and its further comparison with the actual values which were not included into the training set. The calculations of average values of 3 neural networks were performed either. Test results are shown in Tables 4 and 5 and Figure 7 and 8.

Table 4. Forecasting value of the indicator HIGH

Date	HIGH					Relative error			
	Real data	NN1	NN2	NN3	Average	NN1	NN2	NN3	Average
23.04.2012	0,76313	0,757855	0,760669	0,761061	0,759862	-0,69%	-0,32%	-0,27%	-0,43%
24.04.2012	0,76086	0,752883	0,762893	0,756474	0,757417	-1,05%	0,27%	-0,58%	-0,45%
25.04.2012	0,7593	0,748965	0,751956	0,748394	0,749771	-1,36%	-0,97%	-1,44%	-1,26%
26.04.2012	0,75855	0,749363	0,758164	0,739665	0,749064	-1,21%	-0,05%	-2,49%	-1,25%
27.04.2012	0,75982	0,750745	0,759958	0,739408	0,750037	-1,19%	0,02%	-2,69%	-1,29%
30.04.2012	0,75706	0,749877	0,759195	0,736237	0,748436	-0,95%	0,28%	-2,75%	-1,14%
01.05.2012	0,75717	0,75906	0,75951	0,732523	0,750364	0,25%	0,31%	-3,26%	-0,90%
02.05.2012	0,76191	0,766952	0,766691	0,728222	0,753955	0,66%	0,63%	-4,42%	-1,04%
03.05.2012	0,76371	0,769848	0,771016	0,717432	0,752766	0,80%	0,96%	-6,06%	-1,43%
04.05.2012	0,76464	0,767849	0,776344	0,71202	0,752071	0,42%	1,53%	-6,88%	-1,64%
07.05.2012	0,77065	0,762854	0,778916	0,717831	0,753201	-1,01%	1,07%	-6,85%	-2,26%
08.05.2012	0,7703	0,760652	0,782065	0,724175	0,755631	-1,25%	1,53%	-5,99%	-1,90%

Source: Authors

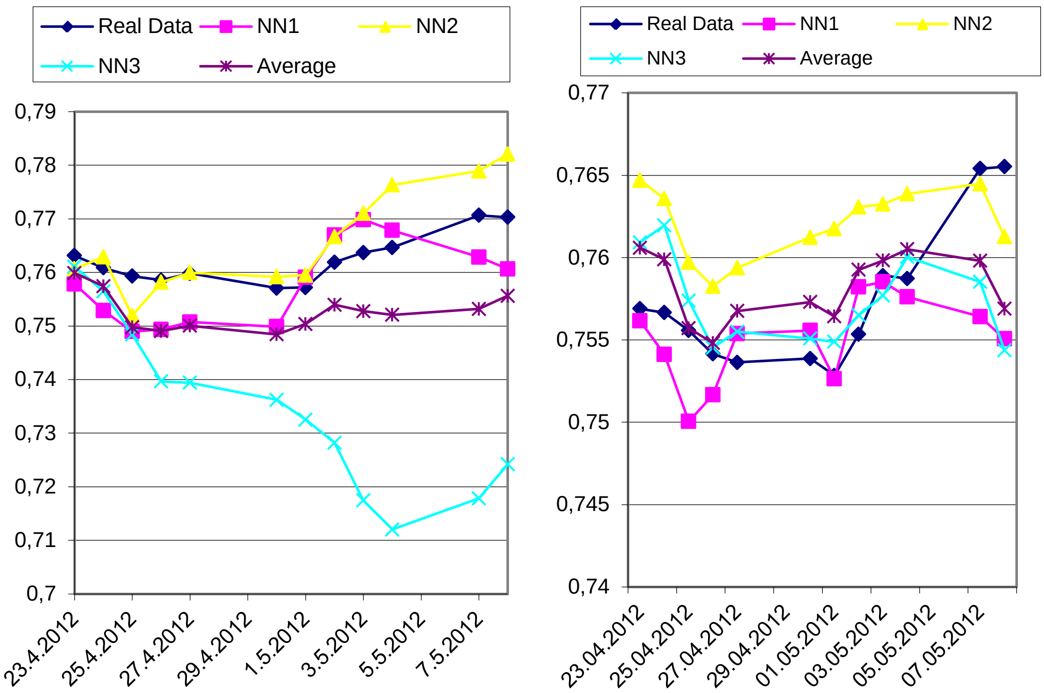
Table 5. Forecasting value of the indicator LOW

Date	LOW					Relative error			
	Real data	NN1	NN2	NN3	Average	NN1	NN2	NN3	Average
23.04.2012	0,75689	0,756153	0,764695	0,760926	0,760591	-0,10%	1,03%	0,53%	0,49%
24.04.2012	0,75666	0,754112	0,763582	0,761954	0,759883	-0,34%	0,91%	0,70%	0,43%
25.04.2012	0,75557	0,75005	0,759709	0,757391	0,755717	-0,73%	0,55%	0,24%	0,02%
26.04.2012	0,75415	0,751663	0,758248	0,754525	0,754812	-0,33%	0,54%	0,05%	0,09%
27.04.2012	0,75364	0,755382	0,759376	0,755499	0,756752	0,23%	0,76%	0,25%	0,41%
30.04.2012	0,75386	0,755568	0,761236	0,755079	0,757295	0,23%	0,98%	0,16%	0,46%
01.05.2012	0,75284	0,752641	0,761757	0,754886	0,756428	-0,03%	1,18%	0,27%	0,48%
02.05.2012	0,75534	0,758221	0,763074	0,756505	0,759267	0,38%	1,02%	0,15%	0,52%
03.05.2012	0,7589	0,758528	0,763244	0,757694	0,759822	-0,05%	0,57%	-0,16%	0,12%
04.05.2012	0,75873	0,757608	0,763868	0,760042	0,760506	-0,15%	0,68%	0,17%	0,23%
07.05.2012	0,7654	0,756412	0,764486	0,758525	0,759808	-1,17%	-0,12%	-0,90%	-0,73%

08.05.2012	0,76552	0,755062	0,761264	0,754371	0,756899	-1,37%	-0,56%	-1,46%	-1,13%

Source: Authors

Figure 7 and 8. Forecasting values of the indicators HIGH and LOW



Source: Authors

As can be seen from the figures, the best agreement with real data is shown by the average value of neural networks. In addition the table shows that the lowest error is observed in figures LOW. It is less than 1% for all data and only for the last 12 days' forecast it's bigger than 1%. For HIGH error is higher. The main contribution to the deviation makes neural network 3 ([25 × 20 × 10 × 1]). This network is the simpliest structure that during training showed the result which did not differ from other neural networks. However, averaging lets to reduce the error of calculations from 7% to 2%. This result is a good enough predictive indicator.

This confirms the fact that modeling of exchange rates using neural networks, for which there are no clear rules for determining the structure, method of teaching and learning outcomes of which depends on the stochastic variables should be carried out in accordance with multi-model approach.

Conclusion

In this paper, Knowledge Discovered in Databases was used for the construction of the model of forecasting. The model is based on the monthly data USD and EUR exchange rates movements. Information on the movement of exchange rates was used in order to create neural networks, which showed that the period of the last two weeks exchange rate movements is the most appropriate for measurement. The data showed that the exchange rate of USD/EUR depends linearly to this two-week period, whereas correlation coefficients is high (R> 0.8). In addition, the model shows that the correlation decreases when the measurement period increases. After the testing, the model showed that average value of neural networks have the lowest error, that can be taken as a enough predictive indicator.

Even though neural networks are not a "standard" model or even a tool of technical analysis (compared with moving averages or some other often used techniques), this model can be used for forecasting. Since the model uses public information from the past and these information have been reflected in price immediately as it became known, possessors of private information can use that information to generate profits. According to Leigh et al (2002), this hypothesis is semi-strong form of the efficient markets hypothesis - which is a technical analysis.

The exchange rate is the price of domestic currency per unit of foreign currency, which allows the creation of price trends. The ability to predict a turnaround in this trend, provides important information for investor's making decisions. More specifically it provides the ability to detect earnings. It can be said that technical analysis can predict the trends of any kind of price, but the model or techniques of this analysis adapts to the instrument which is the subject of this analysis (for example: securities or foreign exchange rates). Bearing this in mind, the neural network model would be a certainly adequate for forecasting.

Finally, it should be noted that the forecasting is very important not only for the macro-economy, but also for daily decision-making of investors, banks, insurance companies and even individuals whose well-being is affected by the movement of exchange rates.

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