Macroeconomic Issues

Using New Information Technologies for Modelling Data on Global Markets: An Efficient Interaction between "Artificial" Human Brain and Economics

Dr. Alper Özün
Is Bank

Recent development of information technologies and telecommunications have given rise to an extraordinary increase in the data transactions in the financial markets. In large and transparent markets, with lower transactions and information costs, financial participants react more rapidly to changes in the profitability of their assets, and in their perception of the risks of the different financial instruments. In this respect, if the rapidity of reaction of financial players is the main feature of globalized markets, then only advanced information technologies, which uses data resources efficiently are capable of reflecting these complex nature of financial markets.

The aim of this paper is to show how the new information technologies affect modelling of financial markets and decisions by using limited data resources within an intelligent system. By using intelligent information systems, mainly neural networks, this paper tries to show how the the limited economic data can be used for efficient economic decisions in the global financial markets.

Advances in microprocessors and software technologies make it possible to enable the development of increasingly powerful systems at reasonable costs. The new technologies have created artificial systems, which imitate people's brain for efficient analysis of economic data. According to Hertz, Krogh and Palmer (1991), artificial neural networks which have a similar structure of the brain consist of nodes passing activation signals to each other. Within the nodes, if incoming activation signals from the others are combined some of the nodes will produce an activation signal modified by a connection weight between it and the node to which it is linked.

By using financial data from international foreign exchange markets, namely daily time series of EUR/USD parity, and by employing certain neural network algorithms, it has showed that new information technologies have advantages on efficient usage of limited economic data in modeling.

By investigating the "artificial" works on modeling of international financial markets, this paper is tried to show how limited information in the markets can be used for efficient economic decisions. By investigating certain neural networks algorithms, the paper displays how artificial neural networks have been used for efficient economic modeling and decisions in global F/X markets.

New information technologies have many advantages over statistics methods in terms of efficient data modeling. They are capable of analyzing complex patterns quickly and with a high degree of accuracy. Since, "artificial" information systems do not make any assumptions about the nature of the distribution of the data, they are not biased in their analysis.

By using different neural network algorithms, the economic data can be modeled in an efficient way. Especially if the markets are non-linear and complex, the intelligent systems are more powerful on explaining the market behavior in the chaotic environments.

With more advanced information technologies, in the future, it will be possible to model all the complexity of the economic life. New researches in the future need a more strong interaction between economics and computer science.

Introduction

Recent development of information technologies and telecommunications have given rise to an extraordinary increase in the data transactions in the financial markets. In large and transparent markets, with lower transactions and information costs, financial participants react more rapidly to changes in the profitability of their assets, and in their perception of the risks of the different financial instruments. In this respect, if the rapidity of reaction of financial players is the main feature of globalized markets, then only advanced information technologies, which uses data resources efficiently are capable of reflecting these complex nature of financial markets.

The aim of this paper is to show how the new information technologies affect modelling of financial markets and decisions by using limited data resources within an intelligent system. By using intelligent information systems, mainly neural networks, this paper tries to show how the the limited economic data can be used for efficient economic decisions in the global financial markets. For that aim, the daily EUR/USD parity end-day values from 01.01.2003 to 10.02.2006 will be predicted with its lags by using feedforward neural network architecture.

The paper is constructed as follows. In the first part, a literature review is presented to display the recent research results on predicting finacial time series by using new information technologies, mainly neural networks. The researces based on modeling EUR/USD parity are especially discussed. In the next part, data and methodology used in this paper are introduced. Feedforward neural network architecture and constructive algorithms are explained. In the empirical findings, certain test results such as MSE and R^2 are discussed in terms of efficient usage of limited data resources. In the concluding remarks, the findings are discussed for the efficiency of international financial markets, as well. The paper is concluded with suggestions for future research by highlighting alternative recent developments in new information technologies to model the financial markets.

Literature Review

Advances in microprocessors and software technologies make it possible to enable the development of increasingly powerful systems at reasonable costs. The new technologies have created artificial systems, which imitate people’s brain for efficient analysis of economic data. According to Hertz, Krogh and Palmer (1991), artificial neural networks which have a similar structure of the brain consist of nodes passing activation signals to each other. Within the nodes, if incoming activation signals from the others are combined some of the nodes will produce an activation signal modified by a connection weight between it and the node to which it is linked.

Comparing with econometric models, modeling financial time series by neural networks have certain advantages. After training the network, the structure of the network provides a good prediction performance on unseen time series data. The network does not neither need to know how the data are interrelated with each other nor to make assumptions on the nature of the time series. For those reasons, the research made by neural networks does not know the certain assumptions about the statistical performance of data like normality, autocorrelation and heterosketasticity. As it was mentioned, the neural networks do not provide theoretical explanations for the models that they construct. However, the models are able to display non-linear relations among the data. By modeling exchange rates, displaying the nonlinear data within the time series is a remarkable task since the global exchange rate markets have deep participation among different countries and perceptions. In this respect, the task of the neural networks is to train reliable data and experiment which combinations of data are resulting optimal results.

During the last decade, different nonlinear models have been tested in the literature to model exchange rates. Some studies, such as Chang and Osler (1999) have argued that exchange rates are unpredictable, in other words, a random walk model is better than nonlinear models in modeling the exhange rates. Gencay (1999) also examines the predictability of daily spot exchange rates using four models applied to five currencies, mainly, FRF, DEM, JPY, CHF and GBP against a common currency from 1973 to 1992. The models include random walk, GARCH(1,1), neural networks and nearest neighbours. He copmares the model in terms of their forecasting accuracy and concludes that non-parametric models outperform parametric ones, and mainly nearest neighbours dominate neural network models.

However, the researches using neural networks models display that the F/X markets are predictable as well though it has huge volume and investors have non-linear behaviours. For example, Zhang and Hu (1998) predicts the exchange rate by using nonlinear models depending on its past values, and the model outperformes simple linear models.

Yao, Poh and Jasic (1996) examine the predictability of the GBP, DEM, CHF, JPY and AUD against the USD, from 1984 to 1995 on weekly data and conclude that neural network models produce a higher returns than ARMA models. What is more important is for our paper is that they argue that without the use of extensive market data or knowledge, accurate forecasting can be made and significant profit can be achieved.

Carney and Cunningham (1996) predicts four exchange rates over the period 1979 to 1995 to by using the single-step and multi-step prediction of the weekly GBP/USD, daily GBP/USD, weekly DEM/SEK and daily GBP/DEM exchange rates. They show that neural network models are useful techniques that can make sense of complex data defining traditional analysis. By using daily and weekly data, Hu et al. (1999) also diplay that neural network models have more accurate results in modeling exchange rates than a random walk model.

Another important comon result of the researches on modeling exchnage rates with artificial neurl networks is that the models are able to predict short-term currency behaviour in general. Evans (1997) and Jamal and Sundar (1997) argue that neural network models have advantages if the short-term forecasts are required.

On the other hand, exchange rates are modeled with neural networks by employing fundamental data as well. For example, Plasmans, Verkooijen, and Daniels (1998) display that artificial neural networks are accurate models to detect non-linear patterns when using certin macroeconomic indicators as independent values in the exchange rate models. In fact, it may be more useful and efficient to model exchange rate markrets not only by using technical dat but also fundamental macroeconomic variables. However, since the aim of this paper is to show that “limited” data resources can be used to model globla markets with intelligent systems, employing macroeconomic variables in the model is out of concern.

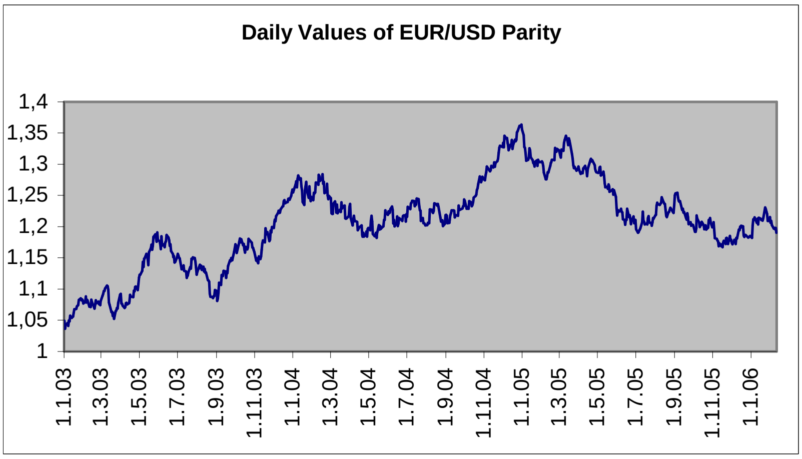
After a short literature review and explaining motivation behind this paper, data and methodology used in this paper are introduced in the next part.

Data and Methodology

New information technologies have many advantages over econometric methods in terms of efficient data modeling. They are capable of analyzing complex patterns quickly and with a high degree of accuracy. Since, “artificial” information systems do not make any assumptions about the nature of the distribution of the data, they are not biased in their analysis. In this paper, neural network architecture is used to model EUR/USD parity with technical data.

The selection of data is one of the most important starting point of neural network models. Since the motivation behind this paper is to show that limited data resources may be enogh to make efficient decisions in financial markets, daily end-day Bloomberg values of EUR/USD rates (as of at $24.^{00}$ every day) are used for European time from 01.01.2003 to 10.02.2006. In other words, the time series employed in the paper have 812 observations. The period is starting from 01.01.2003 since the paper aims to use limited data, in other words as much as less observations as possible. What is more, the beginning time of the data coincides the beginning of the new trend in the market since the FED has started to increase the short term interest rates of US treasury bill. The graph of the EUR/USD parity between selected period is presented below.

Graph 1: Daily Values of EUR/USD Parity Between 01.01.2003 and 10.02.2006



Since the aim is to use historical values of the parity to predict the future value, the paper uses different lag values of the EUR/USD exchange rates. Mainly, 1 day lag, 2 day lag, 3 day lag, 4 day lag and 5 day lag of the daily closing values.

Since the EUR/USD exchange market is the biggest financial markets in the world, it is not controlled by certain interest groups, in other words, it has a big volume and diversified participant groups. However, that does not mean that it is out of volatility concerns. Due to certian fundamental financial data, such as GDP, employment rates, inflation, international political instability, expectations and psychological reasons, the market has volatility. What is more, since the market participants have different perspectives in explaining the information come to the market, there is a collective power to follow the trend in the market. Although it is expected to be informationally efficient market due to deep volume and advanced structure, the EUR/USD market has been found predictable and therefore, non-efficient in many studies. The main reason for inefficiency in the EUR/USD market is that the participants follows and imitage each other by using technical indicators. The market as a whole moves according to the technical indicators and the fundamental data is only shape the direction in the long-run.

When predicting financial time series with neural networks, another important stage is to train a network which presents proper input patterns in order to minimize the error of the model and provide a high estimation performance. The weights should be adjusted to reach the computed output closer to the known output. Kecman (2001) states that this process should continue until the network provides the correct output for a given input. In the literature, the backpropagation training algorithm is suggested in creating neural networks for financial time series forecasting. The backpropagation algorithm compares the output of the processing elements of the output layer to desired outputs for the particular input patterns given. A measure of error is calculated as the squared difference between the actual and desired output. Since hidden layers do not have training target value, they should be trained according to the errors coming from previous layers. When the error terms are backpropagated through the nodes, the connection weights varies and the training occurs until the errors in the weights are enough small to reach an acceptable level.

There are three layers in design stage, mainly, an input layer, hidden layers and an output layer. The layer, into which data is transferred is called input layer; those where the nodes process the information passed to them by the input layer are labeled as hidden layers; and the layer where an output pattern, from a given input pattern processing through the preceding layers is called as output layer. At the input layer, the nodes receive the values of input variables and multiply them through the network, layer by layer. The number of hidden layers and nodes in each hidden layer can be selected arbitrarily, but too many nodes in the middle layer produce a neural network that merely memorizes the input data.

In this research, five models are created with technical/historical data. The models are presented below:

Model 1: $(EUR/USD)_t =$ a + b$(EUR/USD)_{t-1}$
Model 2: $(EUR/USD)_t =$ a + b$(EUR/USD)_{t-2}$
Model 3: $(EUR/USD)_t =$ a + b$(EUR/USD)_{t-3}$
Model 4: $(EUR/USD)_t =$ a + b$(EUR/USD)_{t-4}$
Model 5: $(EUR/USD)_t =$ a + b$(EUR/USD)_{t-5}$

Each model has one input, one hidden and one output layer. Feedforward neural network architecture based on backpropagation algorithm is employed for the analysis. The important point in terms of modeling in this research is that, in the models, the lags are feed with the prior lags. In other words, for example in the Model 3, the independent variable, namely, $(EUR/USD)_{t-3}$ includes information coming from first and second lags, as well. The feedforward algorithm can be described as follows:

Figure 1 displays a one hidden layer feedforward network with inputs $x_1,...,x_n$ and output $\hat{y}$ as it is used in this paper. Each neuron performs a weighted summation of the inputs, and the inputs passes a nonlinear activation function σ. When the network is trained, its parameters are adjusted until the training data reaches the desired mapping, in other words, until $\hat{y}(\theta)$ matches the desired output *y* as closely as possible up to a maximum number of iterations[1].

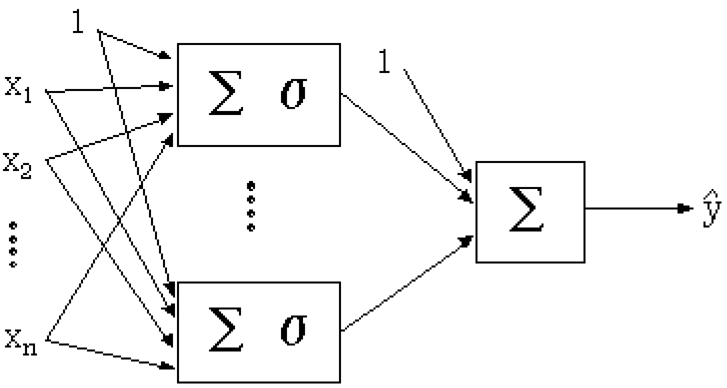


Figure 1. A feedforward network with one hidden layer and one output (www.wolfram.com)

"Forecaster" as an "artificial" intelligent technology is used in the analysis. "Forecaster" uses constructive algorithm to train network and select the topology. As a result, the program trains the data with feedforward network topology based on backpropagation. The program automatically ends the training and fixes the model when the MSE reaches a minimum acceptable level. The empirical results of the analysis are presented and discussed in terms of efficiency of the global finnacial markets.

Empirical Findings

The data is trained by using random selection of daily closing values, and a 20 days short-term period is used for testing. Since the algorithm is designed as feedforward topologhy, when the model uses, for example, 2 lags as the output layer, it feed the first lag within the second lag as well. In other words, when the model test the 2 lags as the independend variable, the second lag is feed by the fitted values of forecasts in the first lag.

The model transacts the fitted values from first lag to the next. Therefore, the fifth lag includes information transforming from the first, second, third and fourth lags into the fifth lags. From that point of view, the model feed back the input layer and have advantages over econometric models.

As it can be seen on the Table 1, the importance level increases into 89,206 % as the lag of the variable reaches to fifth.

Table 1: Input Importance in ANNs(t-5) Model

	Importance(%)
t-1	**0,704%**
t-2	**0,253%**
t-3	**8,414%**
t-4	**1,423%**
t-5	**89,206%**

When the test results of the artificial neural network models are compared, it can be clearly differentiated that the ANN model using fifth lag of the variable, which includes the feedback values of the first four lags as well, has high importance in the model.

The test results displayed on the Table 2 support the fact that the ANN models have statistical capacity to predict the future values of EUR/USD parity. High R^2 values and accurate MSE values for training set encourage test the model for out of sample forecasting.

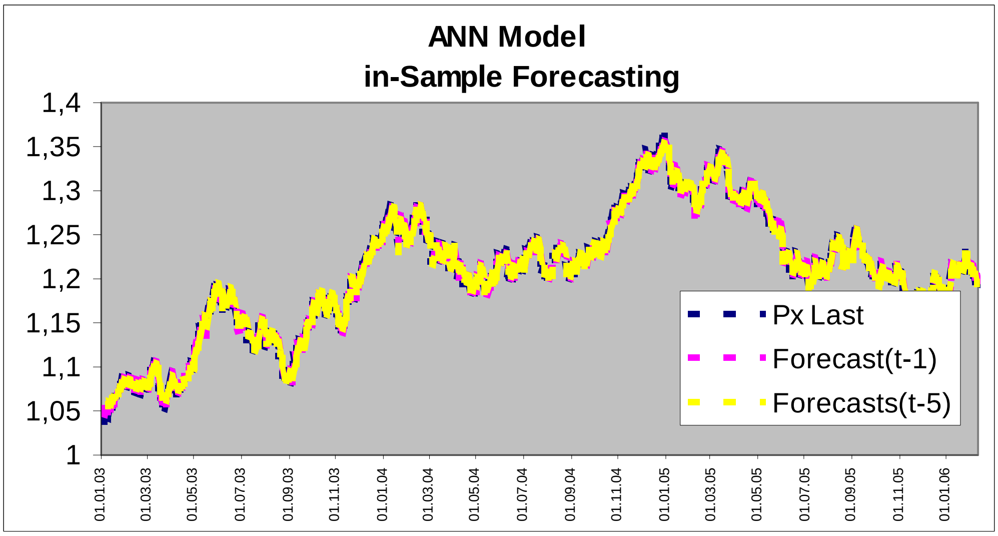
Table 2: Summary of ANNs Test Results

	ANNs(t-1)	ANNs(t-5)
Average MSE(Training Set)	0.00005919	0,0060377
Average MSE(Test Set)	0.00004981	0,0067923
Number of Good Forecast	673	670
(Training Set)	(100%)	(100%)
Number of Good Forecast	138	137
(Test Set)	(100%)	(100%)
R^{2*}	0,9882	0,9870
Correlation*	0,9941	0,9935

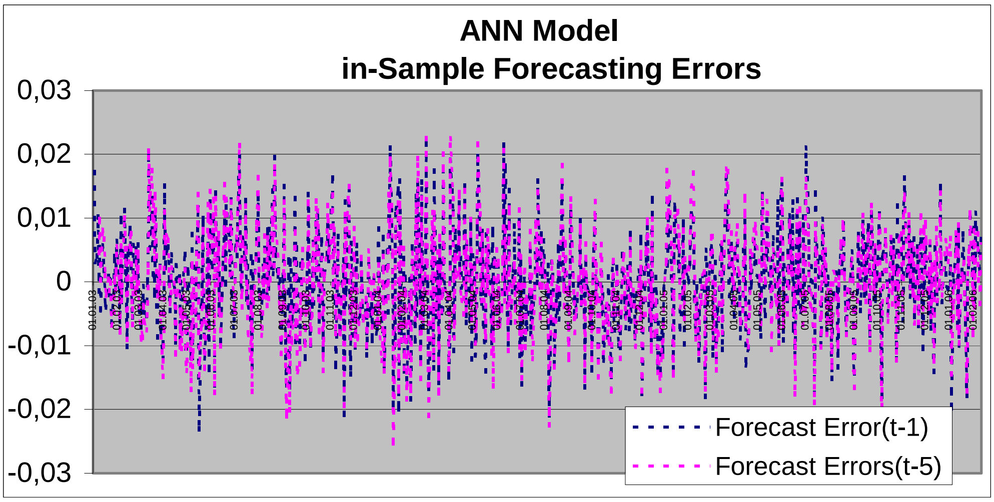
* Correlation and R^2 between actual and forecasted values

In-sample forecasting performance and errors of the Model 1 and Model 5 are showed on the Graph 2 and Graph 3, respectively.

Graph 2: In-Sample Forecasting Comparison of ANN Models



Graph 3: In-Sample Forecasting Errors Comparison of ANN Models

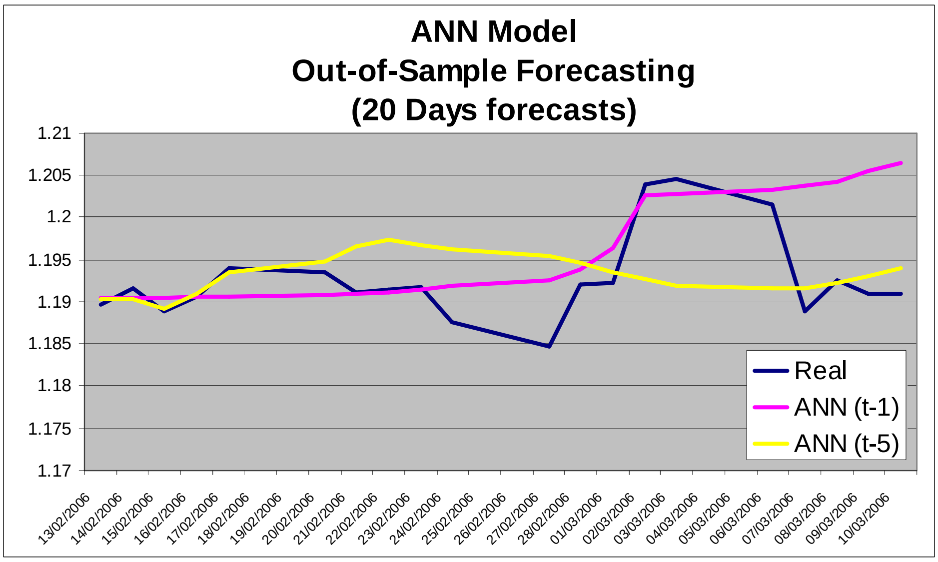


However, in order to compare the performance of the strategies, it is necessary to evaluate them on previously unseen data. By creating a out of sample with last 20 observations, the forecasting accuracy and trading performance of the models are compraed. A short period is selected since as explained in the literature review, the ANN models in predicting exchange rates are valid in short terms according to the past researches.

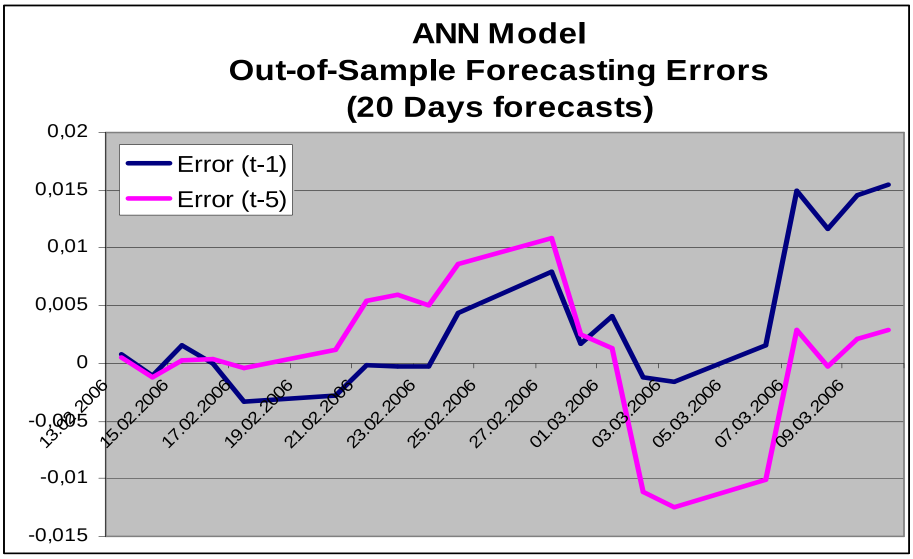
As it is known statistical performance measures are often inappropriate for financial markets. Modelling techniques are optimised using a mathematical criterion, but ultimately the results are analysed on a financial criterion upon which it is not optimised. By creating an out of sample, the trading sucsess of the model is performed.

The results of the estimation and the errors are showed on the Graph 4 and Graph 5, respectively.

Graph 4: Out-of-Sample Forecasting Comparison of ANN Models



Graph 5: Out-of-Sample Forecasting Errors Comparison of ANN Models



As it can be followed from the graphs, the models have good performance in two week periods. The Model 1 is able to predict with tolerable error until the 16th day value of the EUR/USD parity. On the other hand, although the Model 5 does not see the volatility in the very short-term, it can be used to predict the exchange rate market behaviour for two weeks period. Another important result of the analysis is that unless there is a shock in the market, the models perform well with the long-term memory. However, in case of shock, it is not clearly known how the model react since "the memory" of the model does not include a shock.

For the theory of finance, on the other hand, the analysis displays that it is possible to earn money with historical data in the global exchange rate markets, which means that the market is not efficient.

Suggestions for Future Research

By using financial data from international foreign exchange markets, namely daily time series of EUR/USD parity, and by employing feedfprward neural network topology, it has showed that using new information technologies and models have advantages on efficient usage of limited financial data in modeling.

By investigating the "artificial" works on modeling of international financial markets, this paper is tried to show how limited information in the markets can be used for efficient economic decisions. By using different neural network models, the limited economic data can be modeled in an efficient way. Especially if the markets are non-linear and complex, the intelligent systems are more powerful on explaining the market behavior in the chaotic environments. The neural networks have the ability to detect non-linearity in the financial time series where it is not easy to provide reasons since taking everything into account is just not possible.

By predicting EUR/USD parity in two weeks period, it has showed that the artificial neural network models have forecasting ability in the global F/X market in which taking everything into account is not possible due to complexity and widespread market participants in the market. For practice, the analysis has showed that technical analysis in the global F/X market is valuable in making profit. In terms of finance theory, on the other hand, it has displayed that the global F/X market is not efficient.

When focusing on the issue of importance of new information technologies in modeling complex financial markets, it is excepted that with more advanced information technologies, in the future, it will be possible to model all the complexity of the economic life. The artificial neural networks are still black boxes for the financial modeling and only their little capacities have been used by the researchers and traders. New researches in the future need a more strong interaction between finance, economics and computer science.

References

Chang, P., and C. Osler (1999), “Methodical Madness: Technical Analysis and The Irrationality of Exchange-Rate Forecasts”, *The Economic Journal*, Vol. 109, p. 636–661.

Carney J., and P. Cunningham (1996), “Neural Networks and Currency Exchange Rate Prediction”, Trinity College Working Paper.

Evans, O.V., (1997), “Short-Term Currency Forecasting using Neural Networks”, *ICL Systems Journal*, Vol. 11/2, p.1–17.

Gencay, Ramazan (1997), “Linear, Non-Linear and Essential Foreign Exchange Rate: Prediction With Simple Technical Trading Rules”, *Journal of International Economics*, Vol. 47, p. 91–107.

Hertz J., A. Krogh and R. Palmer (1999), *Introduction to the Theory of Neural Computation*, Reading, MA: Addison-Wesley .

Hu, M. Y., G. Q. Zhang, C. Z. Jiang, and B. E. Patuwo (1999), “A Cross-Validation Analysis of Neural Network Out-of-Sample Performance In Exchange Rate Forecasting”, *Decision Sciences*, Vol. 30/1 p. 197-216.

Jamal, A.M.M. and C. Sundar (1997), “Modeling Exchange Rate Changes with Neural Networks”**,** *Journal of Applied Business Research*, Vol. 14/1, p. 1–5.

Kecman, V., (2001), *Learning and Soft Computing: Support VectorMachines, Neural Networks, and Fuzzy Logic Models*, Cambridge, MA: The MIT Press.

Plasmans, J.,W. Verkooijen, and H. Daniels (1998), “Estimating Structural Exchange Rate Models by Artificial Neural Networks”, *Applied Financial Economics*, Vol. 8, p. 541–551.

Yao, J.T., H.-L. Poh, T. Jasic (1996), “Foreign Exchange Rates Forecasting With Neural Networks**”,** Proceedings of the International Conference on Neural Information Processing, Hong Kong, September, p. 754-759.