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INVESTIGATION OF EXCHANGE MARKET PREDICTION MODEL BASED ON HIGH-LOW DAILY DATA

Jelena Stankevičienė[1], Nijolė Maknickienė[2], Algirdas Maknickas[3]

[1,2]Vilnius Gediminas Technical University, Faculty of Business Management,
Saulėtekio al. 11, LT-10223 Vilnius, Lithuania
Email: jelena.stankeviciene@vgtu.lt; nijole.maknickiene@vgtu.lt

[3]Vilnius Gediminas Technical University, Faculty of Informatics Technologies,
Saulėtekio al. 11, LT-10223 Vilnius, Lithuania
Email: algirdas.maknickas@vgtu.lt

Abstract. The model of Evolino recurrent neural networks (RNN) based on ensemble for prediction of daily extremes of financial market is investigated. The prediction distributions of each high and lows of daily values of exchange rates were obtained. Obtained distributions show an accuracy of predictions, reflects true features of direct time interval unpredictability of chaotic process. Changing of time series data from close to extremes allows to create new strategy of investment built on distributions basic parameters: standard deviation, skewness, kurtosis. Extension of close distribution to the pair of high-low distribution is opening extra capabilities of optimal portfolio creation and risk management for investors.

Keywords: artificial intelligence, ensemble, Evolino RNN, exchange market, forecasting, prediction, distribution.

JEL classification: G15, G17.

1. Introduction

Rapidly changing exchange market with high risk and high liquidity allows speculators to look for effective forecasting techniques and to develop reliable strategies. A way for accurately predicting the finance markets is a use of tools that are based on artificial intelligence.

Artificial intelligence developers seek to improve internal neural networks, genetic algorithms, fuzzy system parameters with the purpose to obtain the most accurate forecast of the financial market. In the experiments (Jin *et al.* 2013) was changed the number of data as input of the ANFIS model, the type of membership functions and the desired goal error, thereby increasing the complexity of the training. Oyewale (2013) improved training and learning process of model and used loss functions which are good indicators of measuring the forecast performance of these series, the series with the lowest function gave a best forecast performance. Ticknor (2013) proposed technique reduces the potential for overfitting and overtraining, improving the prediction quality and generalization of the network. Chen and Zhan (2013) revisited the determination of high-frequency exchange rates and have examined the differences between the method of genetic algorithms and that of the traditional estimation methods. In paper (Dong *et al.* 2013) there was explored one-step ahead and multi-step ahead predictions.

Other way to improve the forecasting tools based on artificial intelligence is to create a new architecture. An ensemble consists of a set of individually trained classifiers (such as neural networks or decision trees) whose predictions are combined when classifying novel instances (Maclin, Opitz 2011). Some researchers (Ao, Palade 2011; Melin *et al.* 2012, Adeodato *et al.* 2011; De Felice, Yao 2011) have shown that an ensemble is often more accurate than any of the single classifiers in the ensemble..

Well-coordinated internal parameters, with properly chosen model architecture enable for accurate and reliable predictions. However, the financial market has its own patterns and for successfully trade needs - good trading strategy. Created models based on artificial intelligence allow researchers to adapt known and develop new trading strategies. Evans *et al* (2013) implementing the optimal trading strategy, this model produced 23.3% annualized net return. Choudhury (2013) investigated a real time clustering and SVM based price-volatility prediction for optimal trading strategy. Research of Dunis *et al.* (2011) applied more sophisticated trading strategies using confirmation filters and leverage, the GM network produces remarkable results and outperforms all the other network architectures.

Decisions in finance market always are making in uncertainty and distributions of predictions are more informative then point predictions. Wurgler *et al.* (2010) investigated the exchange market using probability theory. Probabilistic neural network, made by Hua *et al.* (2011) is applied to the frontiers of forecast, and aimed at the characteristics of probabilistic neural network to pretreatment the exchange of data and forecast the tendency. Liu *et al.* (2012) introduced an uncertain currency model in uncertain financial markets based on the uncertain calculus theory

Probability theory is successfully used in asset allocation (Rutkauskas, Stasytytė 2011; He, Zhou 2011; Masteika, Rutkauskas 2012). The paper (Stankevičienė, Gembickaja 2012) presents an original examination of the behaviour of financial market practical aspects of momentum and contrarian anomalies.

Speculative trading in exchange market has a specification of high risk and liquidity. Features of speculations are investigated in papers of Örnberg and Stenström (2004); Jylhä and Suominen (2011), Zenker (2014). Efficiency of speculations was analyzed by Beckmann and Czudaj (2013), Fattouh *at al.* (2013). How to measure efficiency of speculations in financial market solved Drożdż (2010), Klaassen and Jager (2011). One of ways to make speculations safely is to use risk premium (Mun, Morgan 2003). Effective strategies were proposed by Kim and Ryu (2012) and Menkveld (2013).

Trading using high and low daily prices was investigated in Corwin and Schultz (2012) work. Authors derive a spread estimator as a function of high-low ratios over one-day and two-day intervals.

The aim of this paper is to investigate Evolino RNN ensemble based model on high-low daily data, to get new strategy for investment using probability theory and calculate computability of this strategy. Daily high prices are most always buy orders and daily low prices are most always sell orders.

2. Distribution based prediction model

Schmidhuber *et al.* (2005) introduce a general framework for sequence learning, EVOlution of recurrent systems with LINear outputs (Evolino). Using the Long Short-Term Memory RNN Architecture, the method is tested in three very different problem domains: 1) context-sensitive languages, 2) multiple superimposed sine waves, and 3) the Mackey-Glass system. Authors of this paper have applied Evolino RNN for forecasting financial markets, accommodated parameters, and selected training data. By combining several Evolino RNN developed and have tested the some ensembles. In this investigation there was used Evolino RNN-based prediction model (Fig. 1), which uses 176 predictors. Investigation was with the phython program by the following steps.

– *Data step*. Getting historical financial markets data from Meta Trader-Alpari. For prediction was chosen NZDCAD (New Zealand Dollar and Canadian Dollar), USDCHF (US Dollar and Swiss Frank), exchange rates and their historical data for the first input, and for the second input, two years historical data for XAUUSD (gold price in US Dollars), XAGUSD (Silver price in US Dollars), QM (Oil price in US Dollars), and QG (Gass price in US Dollars). At the end of this step basis of historical data is set;
– *Input step*. The python script calculates the ranges of orthogonality of the last 80–140 points of the exchange rate historical data chosen for prediction, and an adequate interval from the two years historical data of XAUUSD, XAGUSD, QM, and QG. A value closer to zero indicates higher othogonality of the input base pairs. Eight pairs of data intervals with the best orthogonality were used for the inputs to the Evolino recurrent neural network. Influence of data orthogonality to accuracy and stability of financial market predictions was described in paper (Maknickas, Maknickienė 2012);
– *Prediction step*. One can choose n neural network forecasting. Neural networks can lead to the number of hours required for a decision. Selection the optimum number of ensemble was investigated in earlier work (Maknickienė, Maknickas 2013). Cycle of each predicting neural network was divided into equal intervals and every interval was calculated on separate processor node. Hardware acceleration was achieved using six nodes of Intel(R) Xeon(R) CPU E5645 @ 2.40 GHz on the clou www.time4vps.eu. Therefore calculations of ensemble of 176 predicting neural networks are 6.25 hours' time long. The forecast assumes the shape of the distribution. At the end of this step, one has a distribution with all parameters of it - mean, median, mode, skewness, kurtosis and etc.;

– *Investment decision*. Decisions of trading are making by composed portfolio of exchange rates by analyzing the distribution parameters.

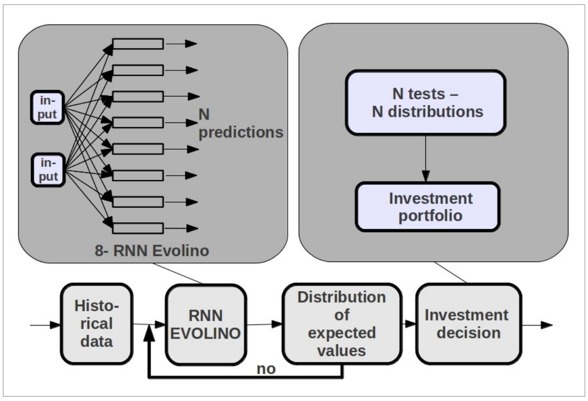

Fig. 1. Scheme of prediction model based on Evolino ENN ensemble (source: compiled by authors).

This model has been tested by the Forex market using the close-close trading rule. Good prediction results of this model allow concluding efficient portfolios, diversifying risk (Maknickienė 2014). A new strategy of trading was created and tested in present paper.

3. Strategies of speculations

Speculation in Foreign exchange (Forex) market is the practice of engaging in risky financial transactions in an attempt to profit from short or medium term fluctuations in the price of foreign currency. Speculation assumes a high degree of risk, with the distinct possibility of financial loss. Many speculators pay little attention to the fundamental value of a security and instead focus purely on price movements. Selected NZD/CAD and USD/CHF exchange rates have such averages of fluctuations of the daily prices (Table 1).

Table 1. Averages of fluctuations of daily prices (source: compiled by authors)

Currency rate	Close to close	High to low	High today low tomorrow
NZD/CAD (2005 – 2014)	0.004	0.009	0.009
USD/CHF (2003 – 2014)	0.006	0.011	0.011

The role of speculators is to absorb excess risk and to provide liquidity in the marketplace by buying or selling when no participants from the other categories are available. Successful speculation entails collecting an adequate level of monetary compensation in return for providing immediate liquidity and assuming additional risk so that, over time, the inevitable losses are offset by larger profits.

Proposed model is adapted and applied to predict the exchange rates and the result is a multimodal distribution of the expected values. For a long time the forecasts were analyzed using closing data. First trading rule *close-close* was unambitious:

If $f_{close} > a_{close}$ **then** *buy* **else** *sell,*

where:

f_{close} – is main mode of forecasting distribution for tomorrow,

a_{close} – is last known close value,

"*buy*", "*sell*" – operations in Forex market.

The aspiration of every speculator is to buy on minimal value and to sell on maximal, or vise versa and 1 table explain why – the average fluctuations of prices are twice more. Therefore some changes were made in the model, and forecasting is getting from high and low daily historical data. The result of prediction – two distributions of expected returns – high and low (Fig. 2).

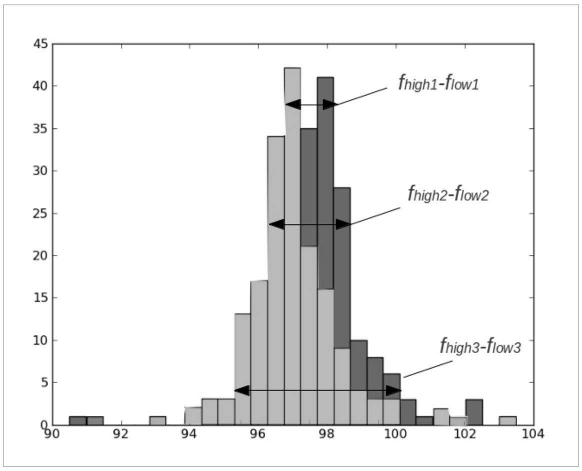

Fig. 2. Distributions of expected returns using high and low data (source: compiled by authors).

These distributions are very informative for speculators – they can choose different forecasted exchange rate changes (f_{high}-f_{low}), assessing the probabilities ($p_1<p_2<p_3$) of the decision. Shapes and parameters – standard deviation, skewness and kurtosis) allow evaluating and choosing the probability of which can be executed one or other transaction.

Decision of trading depends of last known value. Trading can be accomplished using the second rule *low-high*:

Wait for $a=f_{low}$ **then** *buy* ,
wait for $a= f_{high}$ **then** *sell*

or the third rule *high-low*:

wait for $a=f_{high}$ **then** sell ,
wait for $a=f_{low}$, **then** *buy,*

where:

a – value of exchange rate;
f_{low} – mode of low forecasting distribution;
f_{high} – mode of high forecasting distribution.

Second operation can be done with second days forecasting value. Speculator can use different probabilities for trading decision. 68% probability bounds can be used for finding of take profit value, 95% probability bounds can be used for finding stop loss value.

4. Testing model with *high-low* rules

Speculation strategies were tested in Forex market in period from 14–01–2014 to 14–02–2014 with two exchange rates – NZD/CAD and USD/CHF. Data for prediction and models learning was got from Metatrader in period from 2005 to 2014 years. Decision making following the second and the third rules is shown in Fig. 3.11–02 2014. Evolino RNN ensemble gives forecasting for tomorrow (12–02–2014) – two distributions of expected returns. One (grey in Fig. 3 and Fig. 4) is getting using historical data of daily low values and other (black in Fig. 3 and Fig. 4) – using historical data of daily high values.

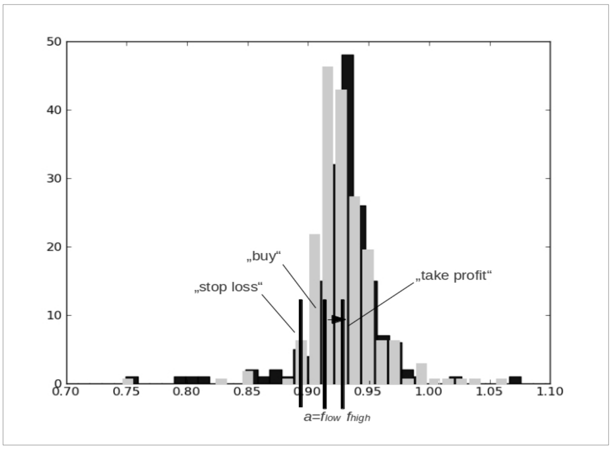

Fig. 3. Making decision using two distributions of NZD/CAD predictions: grey – expected returns of low values; black – expected returns of high values (Source: compiled by authors).

Exchange rates value at present observation a determine what rule one should choose – the second or the third. If closest from a is $f_{lof,}$ then the second, and if closest from a is f_{high} – the third. In this experiment closest to a = 0,9063 is f_{low}=0.910, so one uses the second rule and buys. One's take profit is f_{high}=0.919, stop loss one sets according to the probability of distributions. Probability of falling of exchange rates to 0,89 is significant enough, so it is one's stop loss.

In Fig. 4 is shown probabilities of decision making: square of distribution of high values represents the probability of expected return. Grey side of picture present profit and white side – loss. In this case probability of profit is more than probability of loss. Result of this particular speculation in demo version of "Oanda", in case that one investment 30 000 units (EUR), equal 77,3862 (EUR).

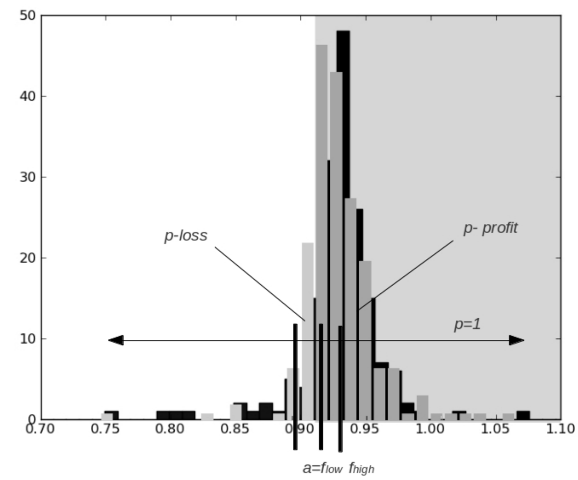

Fig. 4. Probability of decision using two distributions of NZD/CAD predictions: grey side – profit, white side – loss. (Source: compiled by authors).

Experimental results of forecasting NZD/CAD rate (Table 2) and USD/CHF (Table 3) during period from 14–01–2014 to 14–02–2014 describe the distributions and assess the reliability of prediction. Standard deviation of distribution represents the riskiness of prediction. Skewness of distribution quantifies how symmetrical the distribution is.

Kurtosis quantifies whether the shape of the data distribution matches the Gaussian distribution. In this research kurtosis is computed by adding 3 to the value reported by Prism. With this definition, a Gaussian distribution is expected to have a kurtosis of 3.0. Shape of distributions is more stochastically informative for investor or speculator than point prediction.

Table 2. Experimental NZD/CAD prediction results and accuracy APE (absolute prediction error)

NZD/CAD	Prediction					Real values		APE	
Data	Stdev.	skewn	kurt	high (a_{max})	low (a_{min})	high (f_{max})	Low (f_{min})	High *(a-f)/a*	Low *(a-f)/a*
14-01-2014	0.104	0.8218	-0.4	0.9					
15-01-2014	0.15	0.745	-1.345	0.915		0.91819		0.0035	
	0.02	0.699	-0.48		0.912		0.91111		0.0043
16-01-2016	0.646	1.744	1.42	0.92		0.91349		0.0038	
	0.01	0.26	-1.79		0.915		0.90604		0.0099
17-01-2014	0.499	1.369	0.3097	0.915		0.91317		0.0020	
	0.1062	1.196	-0.056		0.905		0.90359		0.0016
22-01-2014	0.249	1.304	0.101	0.915		0.92135		0.0069	
	0.0156	0.837	-1.2713		0.91		0.91064		0.0007
23-01-2014	0.3046	1.648	1.1787	0.92		0.92803		0.0087	
	0.0166	1.158	0.278		0.91		0.9193		0.0101
24-01-2014	0.0218	1.69	1.31	0.925		0.92212		0.0031	
	0.06	0.68	-1.323		0.92		0.90959		0.0114
28-01-2014	445.52			unrealt		0.92481			
	0.087	0.02	-1.052		0.9		0.91287		0.0141
30-01-2014	0.97	1.845	1.677	0.92		0.91817		0.0020	
	0.292	1.5	0.7		0.91		0.90682		0.0035
06-02-2014	0.2882	1.6044	1.0317	0.91		0.9175		0.0082	
	1.48	1.58	0.9249		0.9		0.90792		0.0087
07-02-2014	0.294	0.292	-1.7689	0.915		0.91549		0.0060	
	0.0598	0.8	-0.631		0.91		0.90756		
12-02-2014	0.317	0.915	-0.238	0.92		0.9194		0.001	
	0.023	0.376	-1.568		0.91		0.91312		0.003
13-02-2014	0.162	0.811	-1.119	0.915		0.91934		0.005	
	0.138	1.76	1.487		0.91		0.9127		0.003
							MAPE (%)	**0.4**	**0.6**

If the standard deviation exceeds 20%, the investment is too risky, and it is appropriate to repeat the predictions or not investing on this day

If the skewness is greater than 1.0 (or less than –1.0), the skewness is substantial and the distribution is far from symmetrical and this shape of distribution can affect our forecasting. If the skew direction coincides with the direction of change in the exchange rate, the prediction reliability is increased, otherwise – weakens.

Positive kurtosis describes more basic mode probability and negative – smaller, and therefore more risky trading operation. All this information helps investor to make a profitable decision in finance market.

In this research forecasting computability is calculating using MAPE (Mean Absolute Presentable Error):

$$M = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{a_t - f_t}{a_t}\right|, \qquad (1)$$

where:

n– number of fitted points,

a_t– actual value at time t,

f_t– forecasting value.

Table 3. Experimental USD/CHF prediction results and accuracy

	Prediction					Real values		APE	
data	std	skew	kurt	high (a_{max})	low (a_{min})	high (f_{max})	Low (f_{min})	High *(a-f)/a*	Low *(a-f)/a*
14-01-2014	0.01	0.22	-1.9	0.895					
15-01-2014	0.036	1.749	1.439	0.895		0.91071		0.017	
	1.14	1.686	0.813		0.89		0.90223		0.014
16-01-2016	0.008	1.51	0.828	0.906		0.91029		0.005	
	0.154	0.637	-1.311		0.89		0.90308		0.014
17-01-2014	0.0306	1.3203	0.5252	0.9		0.9119		0.013	
	0.1402	0.9426	-0.3027		0.91		0.90434		0.006
22-01-2014	0.1554	1.2366	0.085	0.91		0.91219		0.002	
	0.837	1.8	1.5645		0.91		0.90886		0.001
23-01-2014	0.0999	1.315	0.135	0.904		0.91331		0.010	
	17.1	1.849	1.686		0.895		0.89631		0.001
24-01-2014	0.03	1.252	0.06	0.898		0.89906		0.001	
	0.376	1.237	-0.0016		0.9		0.89029		0.011
28-01-2014	0.047	0.5447	-1.059	0.895		0.90093		0.007	
	0.3	1.828	1.632		0.89		0.89536		0.006
30-01-2014	0.346	1.8456	1.677	0.895		0.9047		0.011	
	0.096	1.5449	0.8559		0.89		0.8942		0.005
6/2/2014	0.048	0.62	-1.6	0.895		0.90627		0.012	
	1.65	1.63	1.64		0.9		0.89677		0.004
07—2-2014	0.07	1.703	1.3	0.9		0.90214		0.002	
	0.0627	1.016	-0.5		0.9		0.89597		
12-02-2014	0.054	1.846	1.679	0.902		0.90375		0.02	
	0.019	1.56	0.98		0.90		0.89674		0.04
13-02-2014	0.0197	0.50	-1.655	0.902		0.90092		0.01	
	0.072	0.70	-0.7027		0.90		0.89177		0.09
							MAPE (%)	**0.7**	**0.7**

Prediction accuracy using high and low data for prediction is sufficient. The probability of quite direction of changing of exchange market is the same, but the investment using high and low distributions, according to Table 1, should be nearly twice as efficient. Two probabilities have twice informative factors for decision making then one. For example, two probabilities of profit and two probabilities of lost, two standard deviations, two skeweness and other.

One–month studies cannot prove that the trading with separate currencies in the real market will be successful. However, given the experience of using the first rule, one can see that second and the third rules do not impair the use of predictive process. Further studies must be carried out by risk diversification and creating portfolios. Using of two distribution reveal new features of the foreign exchange market dynamics.

In this study, authors only have tested the availability of the difference between the highest and lowest values of the daily exchange rate. Further studies should examine the riskiness, profitability and reliability, and to identify the most effective marketing strategy for speculators.

5. Conclusions

Evolino RNN ensemble provides forecasts a distribution that is more informative than the single point forecast. Present work describes two distributions, which reflect the expected exchange rate dynamics. Two distributions are more stochastically informative for decision making in Forex market then one.

If predictions are accurate enough *high-low* (second) and *low-high* (third) rules are profitable. High and low expected values distributions provide sufficient information about direction of exchange rates changes, risks and reliability of investment. Accordingly, area defined by distribution reflects the probability of a decision.

Prediction accuracy MAPE in present research was obtained in the range from 0,4 % to 0,7% and it is same like using one distribution (Maknickienė, Maknickas 2013). If conditions of forecasting are equal, trading using two distributions of expected returns of lowest and highest values are almost as twice effective nor trading using closing data and one distribution of expected returns.

References

Adeodato, P. J.; Arnaud, A. L.; Vasconcelos, G. C.; Cunha, R. C.; Monteiro, D. S. 2011. MLP ensembles improve long term prediction accuracy over single networks, *International Journal of Forecasting* 27(3): 661–671. http://dx.doi.org/10.1016/j.ijforecast.2009.05.029

Ao, S. I.; Palade, V. 2011. Ensemble of Elman neural networks and support vector machines for reverse engineering of gene regulatory networks, *Applied Soft Computing* 11(2): 1718–1726. http://dx.doi.org/10.1016/j.asoc.2010.05.014

Beckmann, J.; Czudaj, R. 2013. Oil prices and effective dollar exchange rates, *International Review of Economics & Finance* 27: 621–636. http://dx.doi.org/10.1016/j.iref.2012.12.002

Chen, Y.; Zhang, G. 2013. Exchange rates determination based on genetic algorithms using Mendel's principles: Investigation and estimation under uncertainty, *Information Fusion* 14(3): 327–333. http://dx.doi.org/10.1016/j.inffus.2011.12.003

Choudhury, S.; Ghosh, S.; Bhattacharya, A;; Fernandes, K. J.; Tiwari, M. K. 2013. A real time clustering and SVM based price-volatility prediction for optimal trading strategy. Neurocomputing.Attaran, M. 2007. RFID: an enabler of supply chain operations, *Supply Chain Management: An International Journal* 12(4): 249–57. http://dx.doi.org/10.1108/13598540710759763

Corwin, S. A.; Schultz, P. 2012. A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices, *The Journal of Finance* 67(2): 719–760. http://dx.doi.org/10.1111/j.1540-6261.2012.01729.x

De Felice, M.; Yao, X. 2011, April. Neural networks ensembles for short-term load forecasting, in *Computational Intelligence Applications In Smart Grid (CIASG), 2011 IEEE Symposium* 1-8.

Dong, G.; Fataliyev, K.; Wang, L. 2013. One-Step and Multi-Step Ahead Stock Prediction Using Back-propagation Neural Networks, in *the 9th International Conference on Information, Communications and Signal Processing (ICICS 2013)*, 10–13.

Drożdż, S.; Kwapień, J.; Oświ□cimka, P.; Rak, R. 2010. The foreign exchange market: return distributions, multifractality, anomalous multifractality and the Epps effect,. *New Journal of Physics* 12(10): 105003. http://dx.doi.org/10.1088/1367-2630/12/10/105003

Dunis, C. L.; Laws, J.; Sermpinis, G. 2011. Higher order and recurrent neural architectures for trading the EUR/USD exchange rate, *Quantitative Finance* 11(4): 615–629. http://dx.doi.org/10.1080/14697680903386348

Evans, C.; Pappas, K.; Xhafa, F. 2013. Utilizing artificial neural networks and genetic algorithms to build an algo-trading model for intra-day foreign exchange speculation, *Mathematical and Computer Modelling* 58(5): 1249–1266. http://dx.doi.org/10.1016/j.mcm.2013.02.002

Fattouh, B.; Kilian, L.; Mahadeva, L. 2013. The role of speculation in oil markets: What have we learned so far?, *Energy Journal* 34(3). http://dx.doi.org/10.5547/01956574.34.3.2

He, X. D.; Zhou, X. Y. 2011. Portfolio choice via quantiles, *Mathematical Finance* 21(2): 203–231.

Hua, W.; Bing-xiang, L.; Xiang, C.; Xuan, X. 2011. An exchange rate forecasting method based on probabilistic neural network, *in Electronic and Mechanical Engineering and Information Technology (EMEIT), 2011 International Conference on* (6): 3124–3126.

Jin, X. B.; Wang, J. F.; Zhang, H. Y.; Cao, L. H. 2013. ANFIS Model for Time Series Prediction, *Applied Mechanics and Materials* 385: 1411–1414. http://dx.doi.org/10.4028/www.scientific.net/AMM.385-386.1411

Kim, H.; Ryu, D. 2012. Which trader's order-splitting strategy is effective? The case of an index options market, *Applied Economics Letters* 19(17): 1683–1692. http://dx.doi.org/10.1080/13504851.2012.665590

Klaassen, F.; Jager, H. 2011. Definition-consistent measurement of exchange market pressure, *Journal of International Money and Finance* 30(1): 74–95.

Liu, Y. H.; Chen, X.; Ralescu, D. A. 2012. Uncertain currency model and currency option pricing. International, *Journal of Intelligent Systems, to be published.*

Maclin, R.; Opitz, D. 2011. *Popular ensemble methods: An empirical study*. arXiv preprint arXiv:1106.0257.

Maknickas, A.; Maknickienė, N. 2012. Influence of data orthogonality on the accuracy and stability of financial market predictions, in *IJCCI 2012 : 4th International Joint Conference on Computational Intelligence*, Barcelona, Spain, 5-7 October, 2012. Setubal : INSTICC, 616–619.

Maknickienė , N.; Maknickas, A. 2013. Investigation of prediction capabilities using RNN ensembles, in *IJCCI 2013 : 5th International Joint Conference* *on Computational Intelligence, 20th to 22nd September, 2013*, Vilamoura, Portugal. INSTICC, 391-395.

Maknickienė, N. 2014.Selection of orthogonal investment portfolio using evolino RNN trading, in *The 2-dn International Scientific conference „Contemporary Issues in Business, Management and Education 2013*. Amsterdam : Elsevier Science Ltd. ISSN 1877-0428 (110): 1158–1165. http://www.sciencedirect.com/science/article/pii/S1877042813056024

Masteika, S.; Rutkauskas, A. V. 2012. Research on futures trend trading strategy based on short term chart pattern, *Journal of Business Economics and Management* 13(5): 915–930. http://dx.doi.org/10.3846/16111699.2012.705252

Melin, P.; Soto, J.; Castillo, O.; Soria, J. 2012. A new approach for time series prediction using ensembles of ANFIS models, *Expert Systems with Applications* 39(3): 3494–3506. http://dx.doi.org/10.1016/j.eswa.2011.09.040

Menkveld, A. J. 2013. High frequency trading and the< i> new market</i> makers, *Journal of Financial Markets* 16(4): 712–740. http://dx.doi.org/10.1016/j.finmar.2013.06.006

Mun, K. C.; Morgan, G. E. 2003. Risk premia on foreign exchange: a direct approach, *Journal of Multinational Financial Management* 13(3): 231–250. http://dx.doi.org/10.1016/S1042-444X(02)00053-1

Örnberg, J.; Stenström, P. 2004. *Foregin currency speculation. An interest parity approach to investigate the opportunities for making speculative profits in the foreign exchange market*. rapport nr.: Masters Thesis.

Oyewale, A. M. 2013. Evaluation of artificial neural networks in foreign exchange forecasting, *American Journal of Theoretical and Applied Statistics* 2(4): 94–101. http://dx.doi.org/10.11648/j.ajtas.20130204.11

Rutkauskas, A. V.; Stasytytė, V. 2011. Optimal portfolio search using efficient surface and three-dimensional utility function, *Technological and economic development of economy* 17(2): 291–312. http://dx.doi.org/10.3846/20294913.2011.580589

Schmidhuber, J.; Wierstra, D.; Gomez, F. 2005. Evolino: Hybrid neuroevolution/optimal linear search for sequence prediction, in *Proceedings of the 19th International Joint Conference on Artificial Intelligence (IJCAI).*

Stankevičienė, J.; Gembickaja, N. 2012. Market behavior case studies of NASDAQ OMX BALTIC. *Business, Management & Education/Verslas, Vadyba ir Studijos* 10(1).

Ticknor, J. L. 2013. A Bayesian regularized artificial neural network for stock market forecasting, *Expert Systems with Applications* 40(14): 5501–5506. http://dx.doi.org/10.1016/j.eswa.2013.04.013

Wurgler, J.; Bradley, B.; Baker, M. 2011. Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly, *Financial Analysts Journal* 67(1).

Zenker, A. 2014. Theories of Currency Speculation in Fixed Exchange Rate Regimes, in *Currency Speculation in Fixed Exchange Rate Regimes*. Springer Fachmedien Wiesbaden, 23–71. http://dx.doi.org/10.1007/978-3-658-04829-7_3