7th International Scientific Conference
"Business and Management 2012"
May 10-11, 2012, Vilnius, LITHUANIA

ISSN 2029-4441 print / ISSN 2029-929X online
ISBN 978-609-457-116-9 CD
doi:10.3846/bm.2012.017
http://www.bm.vgtu.lt

APPLICATION OF NEURAL NETWORK FOR FORECASTING OF EXCHANGE RATES AND FOREX TRADING

Nijolė Maknickienė[1], Algirdas Maknickas[2]

[1]*Vilnius Gediminas Technical University, Saulėtekio ave. 11, LT-10223 Vilnius, Lithuania*
Email: nijole.maknickiene@vgtu.lt

[2]*Vilnius University, Universiteto str. 3, LT-01513 Vilnius, Lithaunia*
Email: algirdas.maknickas@vgtu.lt

Abstract. Expert methods, which widely applied for human decision making, were employed for neural networks. It was developed an exchange rates prediction and trading algorithm with using of experts information processing techniques - Delphi method and prediction compatibility. Proposed algorithm limited to eight experts. Each of experts represented recurrent neural network, Evolino-based Long Short-Term Memory (LSTM) by using of genetic learning algorithm, EVOlution of recurrent systems with LINear Outputs (EVOLINO). Statistical investigation of offered algorithm shows the significantly increase of the reliability of prediction. Developed algorithm was applied for trading of historical forex exchange rates. Obtained test trading results were presented

Keywords: financial market, prediction, Delfi method, compatibility, reliability.

Jel classification: C15, C32, C53

1. Introduction

The problem of stock index prediction is one of the most popular targets for various prediction methods in the area of finance and economics. According to Wong et al. (1997), the most frequent arias of neural network applications are production/operations (53.5 %) and finance (25.4 %).

A stock market prediction system using Modular neural networks is presented by Kimoto and Asakawa (1990). The system is based on expert modules. Each expert had its own input domain and pre-processing unit. For inputs were used vectors of interest rate, Down Johns New York average, turnover, foreign exchange rate. This algorithm applied for investigation of TOPEX (Tokyo Stock Exchange Index).

Prediction system, useful in forecasting mid-term price trend in Taiwan stock market, was proposed by Jung et al. (1996). Authors used an ARIMA (Autoregressive Integrated Moving Average) based recurrent neural network. This system is capable of predicting up to 6 weeks market trend with acceptable accuracy. Modification and acceleration of MNN (Modular Neural Network) operating principles was described in article of Schmidt and Bandar (1997).

Other authors investigate in the papers the GA (Genetic Algorithms) approach for the prediction of Stock prices indexes (Szoto, Fong 2000; Kim, Han 2000; Mandziuk, Jaroszewicz 2007; Choudhry 2008) and exchange market (Sher 2011). Also Hassan et al. (2007) proposed and implemented the fusion model by combining the HMM (Hidden Markov Model) and GA to forecast financial market behaviour.

Fuzzy Boolean Neaural (FBN) network models (Tomė, Carvalho 2005) have also been used for prediction of stock market indexes. This model has been proposed as nets capable to learn qualitative rules and reasonably to use these rules. The idea behind this approach is reasonably obtain the next value from passed values, assuming the variable behaviour can be described by a set of qualitative rules.

Qiang et al. (2005) presents an improved neural network model titled Amnestic neural network, which simulates human cognitive behaviour of forgetting, to solve the problem of cross-temporal data selection. The effective of this model was tested by the application to stock price prediction in the stock market of China.

Multi-branch neural networks (MBNN) could have higher representation and generalization ability than conventional NN's (Yamashita, Hirasawa 2005). It was investigated in this paper the accuracy of prediction of TOPIX (Tokyo stock exchange prices indexes) using MBNN. Using of inputs for MBNN TOPIX related values of time series and other information could learn the characteristics of time series and predict the TOPIX values of the next day.

The Multi-layer perceptron as well as Radial Basis Function neural network architectures were implemented as classifiers to forecast the closing index price performance (Patel, Marwala 2006). Following networks classifiers were based on a profitable trading strategy that outperforms the long-term "Buy and hold" trading strategy which was used for investigation of Dow Jones Industrial Average, Johannesburg Stock Exchange All Share, Nasdaq and the Nikkei Stock indices.

Authors Rai and Rai (2011) summarized the comparison of different Neural Network types for stock prediction. Despite enormous previous efforts and a wide range of methods applied to this problem, efficient stock market prediction remains a difficult task mainly due to complex and varying in time dependencies between factors affecting the price.

Exploit of RNN (Recurrent Neural Network) based on genetic learning algorithm (EVOLINO) has a statistically significant number of successful predictions, when parameters of RNN are properly chosen for prediction, but not without risk by investing (Maknickienė *et al.* 2011). The most popular way of increasing confidence among investors is the investment portfolio. The concepts of effectiveness, riskiness and reliability are three cornerstones of possibilities investing in exchange and capital markets (Rutkauskas, Stasytytė 2009). Adequate investments portfolio seems to be theoretically sound and practically effective instrument for investment decision making in global capital and exchange markets (Rutkauskas et al 2009; Rutkauskas 2005; Stasytytė 2008). The adequate investment portfolio anatomy and decisions using the imitative technologies (Rutkauskas 2006), forecasting by artificial intelligence (Lawrence 1997; McNelis 2005; Zhang, Xiao 1999; Rutkauskas *et al.* 2010) - all forecasting models are confronted with the reliability and risk reduction decision.

Complex problems, which are solving by number of competent professionals, often carried out using the methods of experts. Traditional paper-based on Delfi procedures, Web- based Delfi process (Colton, Haatcher 2004; Hsu, Sandford 2007) can be used to answer difficult questions.

Aim of this paper is to use recurrent neural networks based on genetic learning algorithm (EVOLINO) as the experts for using their decisions in the trading and research profitability of this model.

2. Description of EVOLINO neural network

It is very important to achieve stability of the forecasting, when a certain amount of unknown data sets in time could be found with some precision. On the other hand, predicted data must be examined at first on historical data sets for evaluating correlation between them.

One of the best known neural networks tools for non- linear prediction is recurrent neural network (Zhang, Xiao 2000) LSTM (Schmidhuber *et al.* 2006). Schmidhuber et al introduced a general framework of sequence learning algorithm, EVOlution of recurrent systems with LINear Outputs (EVOLINO) (Schmidhuber *et al.* 2005; Schmidhuber *et al.* 2006). Evolino uses evolution to discover good RNN hidden node weights, while using methods such as linear regression or quadratic programming to compute optimal linear mappings from the hidden state to the output.

When quadratic programming is used to maximize the margin, it is impossible to obtain the first evolutionary recurrent support vector machines. Evolino-based Long Short-Term Memory (LSTM) can solve tasks that Echo State nets can't (Schmidhuber *et al.* 2005). There was introduced a new class of recurrent, truly sequential SVM-like devices with internal adaptive states, trained by a novel method called EVOlution of systems with KErnel-based outputs (EVOKE), an instance of the recent Evolino class of methods.

Evoke evolves recurrent neural networks to detect and represent temporal dependencies while using quadratic programming/support vector regression and pseudo-inverse regression. Evoke is the first SVM-based mechanism which knows how to classify a context-sensitive language. It also outperforms recent state-of-the-art gradient-based recurrent neural networks (RNNs) on various time series prediction tasks. RNN learning is used for context-sensitive languages recognition and is a difficult and often increasing problem for standard recurrent neural networks (RNNs), because it requires unlimited memory resources. Authors (Goodman, Brette 2008; Schmidhuber *et al.* 2005; Schmidhuber *et al.* 2006) found that Evolino based LSTM learns on average faster and it is able to generalize substantially better that gradient-based LSTM. It is possible using Evolino to learn functions composed of multiple superimposed oscillators such as double sine and triple sine. Investigated network reached good learning and still makes very accurate predictions (Schmidhuber *et al.* 2005; Schmidhuber *et al.* 2006; Wierstra *et al.* 2005).

The Mackey-Glass system is a standard benchmark for non linear time series prediction.

Authors (Schmidhuber *et al.* 2005) show deviation between the curves of Evolino generated and Mackey-glass system. Evolino is capable of making precise (0.0019) prediction in tasks like the Mackey-Glass benchmark.

The block diagram of Evolino recurrent neural network is shown in Figure 1. Evolino RNN forms LSTM network with $N = 4n$ memory cells, where N is total amount of neurons and n is amount of memory cells. The genetic evolution algorithm is applied to each quartet of memory cells separately. The cell has an internal state S together with a forget gate G_F , which determines how much the state is attenuated at each time step. The input gate G_I controls access to the cell by the external inputs that are summed into the $\sum$ unit, and the output gate G_O controls when and how much the cell fires.

Dark black nodes represent the multiplication function and the linear regression. Moore-Penrose pseudo-inverse method used to compute the output (light big circle). The detail description of Evolino RNN algorithm could be found in (Schmidhuber *et al.* 2005; Schmidhuber *et al.* 2006).

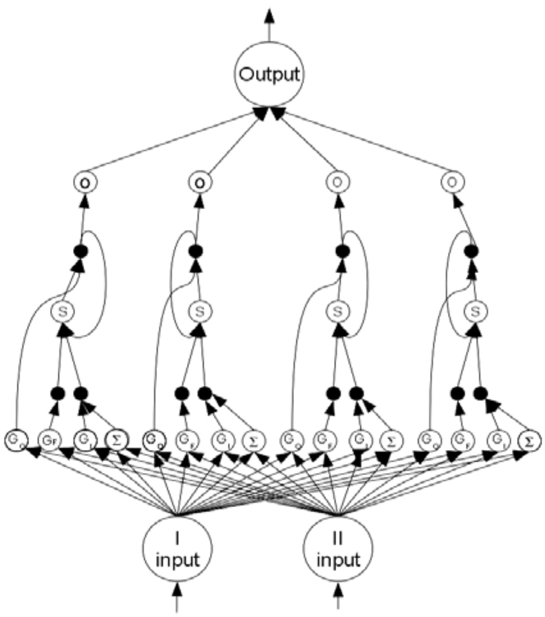

Fig.1. LSTM network with four memory cells (Source: Schmidhuber *et al.* 2005)

Authors (Maknickienė *et al.* 2011) found high dependence of correct chosen imputs and successful time series predictions of learned RNN.

3. Expert prediction model

Expert prediction model incorporate three main stages: Delphi method, compatibility of neural networks predictions and reliability of forecasting.

The Delphi method is based on the assumption that group made decision are more valid than individual made decision. Our observations of neural network prediction shows, that some of the predictions are very accurate, but the others are in a contradictory, unstable and must be rejected. Delphi method makes it possible to achieve a certain consensus or clustering of forecasts. Three steps were needed for applying of Delphi method accordingly: finding of historical orthogonal data; forming of eight data sets; calculating of medians and quartiles.

At first the upper and lower quartiles must be determined, where value of a lower range quartile Q_1 evaluates cuts off lowest 25 % of data and value of upper range quartile Q_3 is cuts off highest 25 % of data. Thus, the median and two quartiles Q_1, Q_{avg}, Q_3 forms four considered the most desirable intervals. Now must be calculated compatibility of neural networks predictions, as a consensus of experts.

Consequently, the Dlephy method could be continuously iterated until consensus is determined and achieved. In practice, the amount of iterations is limited in decision making process.

The next stage was compatibility of neural nets predictions. The evaluation of the performance could be considered enough reliable only if all evaluations of experts give the good compatibility of responses. Therefore it is necessary to achieve the compatibility of expert assessments. There are two ways to obtain the compatibility. First is variational response. In this case, the distance measured between the two events, usually measured in min and max of interval. Second, there are interquartile coefficients. Variational response is the difference between the first and third quartiles $Q_3 - Q_1$. Interquartile coefficient is the ratio of variational response and median:

$$q = \frac{Q_3 - Q_1}{Q_{avg}}, \quad (1)$$

Interquartile coefficient ranges from -1 to +1 and is near zero, when the distribution is symmetrical with very small variation. It could be noted, that as in human-expert evaluations so in neural network assessment, one estimate of each experts may be more fair than as a whole groups.

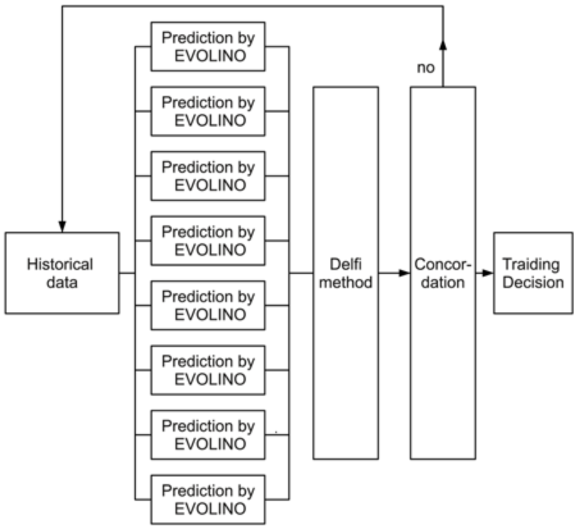

Fig. 2. Block diagram of trading model (Souce:made by authors)

The last stage was reliability of forecasting. Historical data of time series were used to confirm the reliability of forecasting. It was investigated actual values *y(t)* at each time step *t*, where *t=1,...,N* and y_f *(t)* - forecast values at the sometime step *t*. The Pearson's correlation coefficient was chosen for verification of the accuracy and reliability of the model.

4. Trading model

The trading model could be described in four basic steps as follows (Fig. 2):

– Most orthogonal historical data, found for eight data sets, are bringing into two inputs of each RNN.

– The resulting eight predictions are arranging in ascending order.

– The median and quartiles are calculating. Extreme predictions are rejecting.

– The compatibility of the remaining forecasts is calculating. Decision maker assume, if new trade could be made, else the calculations repeats.

4.1. Validation of prediction

Validation of this prediction was made by calculating Pearson's correlation coefficients between historical and predicted values of EUR/USD exchange rates.

Sixty-five percents of Pearson's correlation coefficients for the three trading days between predicting and historical values was obtained in range [0.6–1.0] and 83 % of the predicted market direction for all forecasts was true.

Table 1. Pearson's correlation coefficient at each trading day (Source: made by authors)

No	3 days	5 days	No	3 days	5 days
1	0,5439	0,2174	13	0,9963	0,538
2	0,8929	0,7754	14	0,9874	0,3413
3	0,9822	0,9151	15	-0,988	-0,8537
4	0,1198	0,7569	16	0,8142	0,7823
5	0,9816	0,8601	17	0,5422	0,52241
6	0,9134	0,0379	18	0,9954	0,6245
7	0,7709	0,5938	19	0,9700	-0,441
8	0,9832	0,9832	20	0,2167	0,1467
9	0,9322	0,4032	21	-0,742	0,4894
10	-0,9969	-0,3612	22	0,7652	0,8703
11	0,9552	-0,3370	23	0,9738	0,5271
12	-0,0453	-0,5983			

Five trading day's prediction's accuracy was 35 % and the correctly predicted market directions were 78 % of all trading days. Such model accuracy is enough to ensure a stable income growth in EUR/USD day trading. All correlations of historical and predicted data are given in Table 1.

4.2. Trading of EUR/USD exchange rate

For proving of efficiency of proposed traging model were used EUR/USD (European euro and United States dollars) daily historical exchange rates. Three and five day forecasts were investigated in our proposed trading model. All tradings were made on interval 11/2011–12/2011 when difficult global economic conditions were observed. The world felt in the threat of global economic crisis, and the euro zone will face considerable problems by the case of large Eurozone countries' debt. We are always faced uncertainty in our forecasts. Three and five days trading period was chosen. For finding of acceptable orthoganality of 100 point inputs two years time series data were used.

Evolino RNN, using the selected inputs, calculed eight outputs as 3, 5, 7 and 10-points forecasts. Each eight predictions were arranged in ascending order and medians and quartiles were calculated.

It was assumed, prediction must be in range [Q_1;Q_3], and therefore our program calculated interquartile coefficient and a graph drawn. It was very important to determinate whether the prediction was enough reliable for making decision to do regard transaction on the market. The interval, where interquartile coefficient for enough reliable prediction must be, was in range [0.00‒0.02]. All predictions out of that range treated as not reliable, so they were rejected and prediction procedure repeated again. During observation time was rejected 7 out of 30 predictions, which did not satisfy the selected conditions of compatibility.

Three trading days steps were chosen to invest, because the model prediction accuracy for three days was the most. 10.000 units of conditional cash were invested every time with the gains or losses. Three tests were performed at one time one by one, day after day.

The percentage of profit growth during the investigation period, using three days predicting steps, shown in Figure 3.

The same test repeated with period of 5 trading days, 5 tests was performed in one time, one by one, day after day. The predictions of five trading days were more risky, but the profitability wasn't higher. The percentage growth of profit during the investigation period, using five days predicting steps, shown in Figure 4.

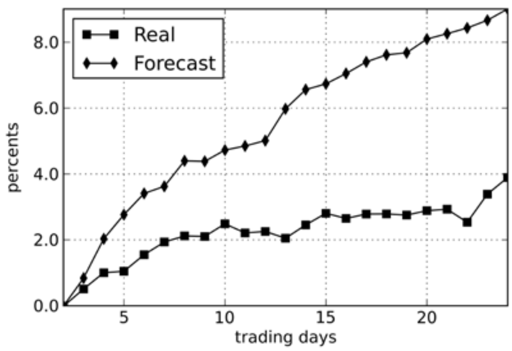

Fig. 3. The percentage growth of profit for 3 trading days steps. 1 – forecasted profit, 2 – obtained profit (Source: made by authors)

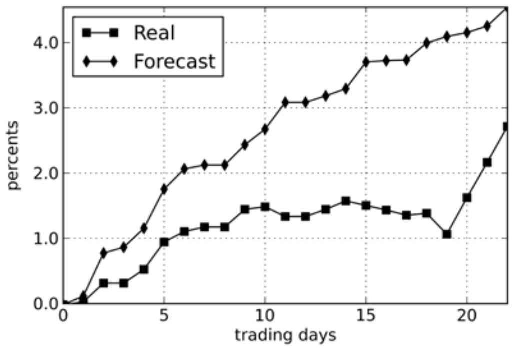

Fig. 4. The percentage growth of profit for 5 traiding days steps. 1 – forecasted profit, 2 – obtained profit (Source: made by authors)

5. Conclusions

Neural network predictions could be treated as human like experts predictions. The same characteristics reliability and compatibility of opinion could be successfully used and for ANN-experts. Experts methods adapted to the neural networks can improve the quality of forecasting and profit accordingly. The usage of proposed trading model allowed to achieve up to 4 % profit in testing period for EUR/USD cross ratios.

Investigation of trading model for historical data shows a consistent profit growth by using the Delphi method and the calculation of the compatibility of forecasting of LSTM based recurrent neural networks. The Delphi method improved boundaries of predictions.

Furthermore, the compatibility of opinion of ANN-experts enabled elimination of absolutely wrong predictions. The short term investing adoption of proposed model needs future investigations in a longer trading period with a different input data of exchange rates.

References

Choudhry, R.; Garg, K. 2008. A Hybrid Machine Learning System for Stock Market Forecasting, *World Academy of Science, Engineering and Technology* 39: 315–318.

Colton, S.; Haatcher, T. 2004. The Web-based Delphy Research technique as a Method for Content validation on HRD and Adult Education Research, *Academy of Human Resources Development International Conference (AHPD)*, 183–189.

Goodman, D.; Brette, R. 2008. Brian: a simulator for spiking neural networks in Python. Front, *Neuroinform* 2: 5. http://dx.doi.org/10.3389/neuro.11.005.2008

Hassan, M. R.; Nath, B.; Kieley, M. 2007. A fusion model of HMM, ANN and GA for stock market forecasting, *Expert Systems with Applications* 33(1): 171–180. http://dx.doi.org/10.1016/j.eswa.2006.04.007

Hsu, Ch.; Sandford, B. A. 2007. The Delphi Technique: Making Sense of Consensus, *Practical Assessment Research and Evolution* 12(10): 1–8.

Kim, K.; Han, I. 2000. Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index, *Expert Systems with Applications* 19(2): 125–132. http://dx.doi.org/10.1016/S0957-4174(00)00027-0

Kimoto, T.; Asakawa, K.; Yoda, M.; Takeoka, M. 1990. Stock market prediction system with modular neural networks, *International Joint Conference* on San Diego, CA, USA, 1: 1-6.

Lawrence, R. 1997. Using Neural Network to Forecasting Stock Market Prices, *Department of Computer Science, University of Manitoba working paper*.

Maknickienė, N.; Rutkauskas, A. V.; Maknickas, A. 2011. Investigation of financial market prediction by recurrent neural network, *Innovative Technologies for Science, Business and Education Vilnius*: *Vilnius Business College* 2(11): 3–8. ISSN 2029-1035.

McNelis, P. D. 2005. *Neural Networks in Finance: Gaining Predictive Edge in the Market*, Elsevier Academic press. London. 262 p. ISBN 0-12-485967-4.

Patel, P. B.; Marwala, T. 2006. Forecasting closing price indices using neural networks, in *Systems, Man and Cybernetics SMC '06, IEEE International Conference* 2351−2356. ISBN: 1-4244-0099-6.

Rai P.; Rai K., 2011. Comparison of Stock Prediction Using Different Neural Network Types, *International Journal of Advanced Engineering & Application* 1: 157−160.

Rutkauskas, A. V. 2005. Portfelio sprendimai valiutų kursų ir kapitalo rinkose, *Verslas: teorija ir praktika* [Business: theory and practice]. Vilnius: Technika 6(2): 107−116. ISSN 1648-0627.

Rutkauskas, A. V. 2006. Adekvačiojo investavimo portfelio anatomija ir sprendimai panaudojant imitacines technologijas. *Ekonomika* [Economic]. Vilnius: Vilniaus universiteto leidykla, 75: 52-76. ISSN 1392-1258.

Rutkauskas, A. V.; Stasytytė. V.; Stankevičienė J. 2009. Profit, riskness and reliability - three-dimensional base for investment decisions management. Modeling and Analysis of Safety and Risk in Complex Systems: in *Proceedings of the Ninth International Scientific School MA SR* Russia, Saint Petersburg: SUAI, 105−110. ISBN 9785808804609.

Rutkauskas, A. V.; Stasytytė, V.; Borisova, J. 2009. Adequate portfolio as a conceptual model of investment profitability, risk and reliability adjustment to investor's interests, *Ekonomika ir vadyba* [Economics and management] Kauno technologijos universitetas, 14: 1170−1174. ISSN 1822-6515.

Rutkauskas, A. V.; Maknickienė, N.; Maknickas, A. 2010. Modelling of the history and predictions of financial market time series using Evolino, in *The 6th International Scientific Conference Business and Management*. *Selected papers*. Vilnius: Technika, 1: 170–175. ISSN 2029-4441.
http://dx.doi.org/10.3846/bm.2010.024

Schmidt, A.; Bandar, Z. 1997. A Modular Neural Network Architecture with Additional Generalization Abilities for Large Input Vectors, in *Third International Conference on Artificial Neural Networks and Genetic Algorithms (ICANNGA 97),* Norwich/England.

Schmidhuber, J.; Gagliolo, M.; Wierstra, D.; Gomez, F. 2006. Evolino for Recurrent Support Vector Machines, in *ESANN'2006 proceedings - European Symposium on Artificial Neural Networks Bruges (Belgium)*: 593−598. ISBN 2-930307-06-4.

Schmidhuber, J.; Wierstra D.; Gomez, F. 2005. Evolution: Hybrid Neuroevolution / Optimal Linear Search for Sequence Learning in *Proceedings of the 19th International Joint Conference on Artificial Intelligence*, 466−477.

Sher, G. I. 2011. Evolving chart pattern sensitive neural network based forex trading agents. *2011arXiv1111.5892S.*

Stasytytė, V. 2008. From two-dimensional profit-risk to three-dimensional profit-reliability-risk in capital markets, in *EURO mini conference "Continuous optimization and knowledge-based technologies" (EurOPT'2008): the 20th international conference*. Neringa, Vilnius: Technika: 149−153. ISBN 9789955282839.

Szeto, K. T.; Fong, L. Y. 2000. How Adaptive Agents in Stock Market Perform in the Presence of Random News: A Genetic Algorithm Approach, in *IDEAL '00 Proceedings of the Second International Conference on Intelligent Data Engineering and Automated Learning, Data Mining, Financial Engineering, and Intelligent Agents.* Springer-Verlag London, UK 2000: 505−510. ISBN:3-540-41450-9.

Tome, J. A. B.; Carvalho, J. P. 2005. Market index prediction using fuzzy Boolean nets Hybrid Intelligent Systems, in *HIS '05, Fifth International Conference*. ISBN: 0-7695-2457-5.

Wang J. H.; Leu, J. Y. 1996. Stock market trend prediction using ARIMA-based neural networks, in *Neural Networks, 1996, IEEE International Conference on Washington DC, USA*, 4: 2160−2165.

Wierstra, D.; Gomez, F. J.; Schmidhuber, J. 2005. Modeling Systems with Internal State using Evolino, in *Conference on genetic and evolutionary computation GECCO, Washington, D. C.*, ACM Press, New York, NY, USA, 1795−1802.

Wong B. K., Bodnovich T. A., Selvi Y. 1997 Neural network applications in business. A review and analysis of the literature (1988-95), *Decision Support Systems* 19: 301−320.
http://dx.doi.org/10.1016/S0167-9236(96)00070-X

Yamashita, T.; Hirasawa, K.; Jinglu Hu. 2005. Application of multi-branch neural networks to stock market prediction Neural Networks, in *IJCNN '05, Proceedings IEEE International Joint Conference* 4: 2544−2548. ISBN: 0-7803-9048-2.

Zhang, J.; Xiao, X. 2000. Predicting Chaotic Time Series Using Recurrent Neural Network. *Chin.Phys. Lett*., 17(2): 88. http://dx.doi.org/10.1088/0256-307X/17/2/004