World Applied Sciences Journal 7 (Special Issue of Computer & IT): 08-16, 2009
ISSN 1818-4952

Exchange Rate Prediction Using an Evolutionary Connectionist Model

[1]Mansour Sheikhan and [2]Behzad Movaghar

[1]Department of Electrical Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran
[2]Department of Computer Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran

Abstract: Artificial neural networks (ANNs) have been applied to time series forecasting. Genetic algorithm (GA) can be used as an optimization search scheme to determine the near optimal architecture and parameters of a neural network, as well. In this study a rich evolutionary connectionist model is proposed, in which GA is used to determine the optimum number of input and hidden nodes of a feedforward neural network, the optimum slope of nodes' activation function and the optimum values of learning rates and momentum coefficients. Empirical results on foreign exchange rate prediction indicate that the proposed hybrid model exhibits effectively improved accuracy, when is compared with some other time series forecasting models.

Key words: Artificial neural networks . genetic algorithm . time series forecasting

INTRODUCTION

In time series forecasting, past observations of a variable are collected and analyzed to develop a model for extrapolating the time series into the future [1]. Over the past decades, many researchers focus on the development of time series forecasting models.

One of the popular time series models with widely usage in engineering, economic and social applications is auto-regressive integrated moving average (ARIMA). Although ARIMA models perform well over a short period of time and their implementations are easy, they have two kinds of limitations: "linear limitation" and "data limitation".

Several nonlinear models have been proposed to overcome the linear limitation. Autoregressive conditional heteroscedastic (ARCH) [2], general ARCH (GARCH) [3], bilinear [4], threshold autoregressive (TAR) [5] and Cobb-Douglas [6-11] are typical nonlinear models.

In the recent years, artificial neural networks (ANNs) have been applied to many areas of statistics. One of these areas is time series forecasting [12-20]. The major advantage of neural networks is their flexible capability in nonlinear modeling [21].

Using hybrid models has become a common practice to improve the forecasting accuracy since 1960s [22, 23]. Recently, more hybrid forecasting models have been proposed:

- Combining ARIMA and support vector machine (SVM) [24, 25],
- Hybrid of Grey and Box-Jenkins autoregressive moving average (ARMA) models [26],
- Integration of ANN and genetic algorithms (GAs) [27-29],
- Combination of generalized linear autoregression (GLAR) with ANN [30],
- Hybrid of artificial intelligence (AI) and ANN [31],
- Integration of ARMA and ANN [32, 33],
- Combining seasonal ARIMA with back-propagation (BP) ANN [34],
- Combination of several ANNs [35],
- Hybrid model by integrating self organizing map (SOM) neural network, GAs and fuzzy rule base (FRB) [36],
- Combining fuzzy techniques with ANN [37, 38],
- Hybrid of ARIMA and fuzzy logic [39],
- Hybrid based on particle swarm optimization (PSO), evolutionary algorithm (EA) and differential evolution (DE) for training a recurrent neural network (RNN) [40].

To improve the performance of ANNs in times series forecasting, in this paper the genetic algorithm is used to determine the optimum structure and parameters of network. In this way, the optimization process determines the number of hidden nodes of a multi-layer perceptron (MLP), the slope of nodes' activation function, the values of learning rates and momentum coefficients in hidden and output layers and the number of features (inputs of

Corresponding Author: Dr. Mansour Sheikhan, P.O. Box 11365/4435,
Post-Graduate Center, South Tehran Branch, Islamic Azad University, Iran

MLP). To evaluate the effectiveness of the proposed approach, foreign exchange rate (FOREX) prediction, as a benchmark application [41-46], is performed in this paper.

The rest of the paper is organized as follows. In the next section, we review the application of GA in optimization of ANN's architecture and learning parameters. The details of proposed hybrid methodology are presented in Section 3. Empirical results are reported in Section 4. Section 5 contains the concluding remarks.

EVOLUTIONARY NEURAL NETWORK MODELING APPROACH

Most of the neural-based time series data prediction use recent data points as input, with fixed number of neurons in the hidden layer to forecast the next data point [47, 48]. Genetic algorithm can be used as an optimization search scheme to determine the optimal or near optimal architecture and parameters of a neural network [49].

Genetic algorithm improves the performance of ANNs by selecting the best input features, optimization of network parameters (e.g. learning rate, momentum coefficient, number of hidden layers, number of nodes in hidden layer and initial weights), modification of nodes' activation function and determination of weights.

The genetic algorithm optimization process is described in the following procedure:

- Randomize population.
- Evaluate the fitness function (1/(1+MSE)) for each individual in the population.
- Select the first two individuals with the highest fitness values and copy directly to the next generation without any genetic operation.
- Select the remaining individuals in the current generation and apply crossover and mutation genetic operations accordingly to reproduce the individuals in the next generation.
- Repeat from the second step until all individuals in population meet the convergence criteria.
- Decode the converged individuals in the final generation and obtain the optimized parameters.

In our experiments, we use different operators for select and crossover operations (Table 1).

EVOLUTIONARY CONNECTIONIST MODEL IMPLEMENTATION

A multilayer perceptron with one hidden layer and sigmoid activation function (Eq. 1) is chosen as the base neural structure in this paper:

$$f(x_i) = \frac{1}{1+\exp(-\beta x_i)} \tag{1}$$

β in Eq. (1) is the slope of sigmoid function.

The Newton algorithm with momentum term is used as learning function (Eq. 2):

$$\Delta w_i(n+1) = -\eta \nabla w_i + \rho \Delta w_i(n) \tag{2}$$

in which η is the learning rate and ρ is the momentum coefficient.

Mean squared error (MSE) during the training of network and its normalized version (NMSE) are calculated using equations (3) and (4):

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{N \times P} \tag{3}$$

$$NMSE = \frac{P \times N \times MSE}{\sum_{j=0}^{P} \frac{N\sum_{i=0}^{N} d_{ij}^2 - (\sum_{i=0}^{N} d_{ij})^2}{N}} \tag{4}$$

Table 1: Description of different operators for select and crossover operations in GA

Operation	Operator	Description
	Roulette	The chance of a chromosome getting selected is proportional to its fitness.
Select	Top percent (x)	Randomly selects a chromosome from the top x percent of the population.
	Best	Selects the best chromosome.
	Random	Randomly selects a chromosome from the population.
	One point	Randomly selects a crossover point within a chromosome, interchanges the two parent chromosomes at this point to produce two new offspring.
Crossover	Two point	Randomly selects two crossover points within a chromosome, interchanges the two parent chromosomes between these points to produce two new offspring.
	Uniform	Decides which parent will contribute each of the gene values in the offspring chromosomes.

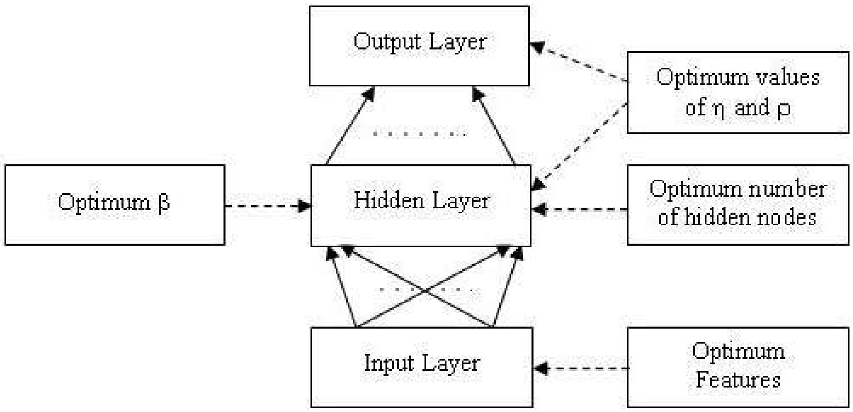

Fig. 1: Conceptual architecture of the proposed evolutionary connectionist model

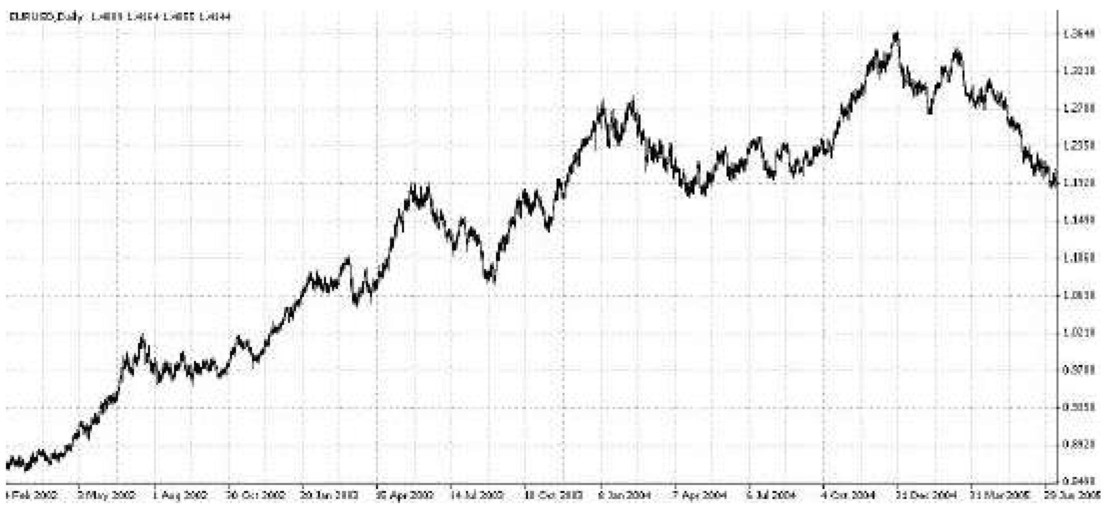

Fig. 2: EUR/USD exchange rate, 2002-2005

Table 2: Target parameters of ANN to be optimized by GA

Parameter	Range of values
Number of inputs	[1, 30]
Number of hidden nodes	[3, 25]
Slope of hidden nodes' activation function	[0, 2]
Learning rate	[0, 1]
Momentum coefficient	[0, 1]

in which N is the number of training patterns and P is the number of output nodes. y_{ij} and d_{ij} are actual output and desired value, respectively.

The conceptual architecture of the proposed model is shown in Fig. 1.

In this paper, GA is used to globally optimize the parameters listed in Table 2. The ranges of values for these parameters are reported, too. NeuroSolutions Toolbox is used for simulations in this paper [50].

To predict foreign exchange rate, as a benchmark application, the indices which are calculated based on close prices of daily exchange rates of Euro/US Dollars (EUR/USD) and Euro/GB Pound (EUR/GBP) are used for training MLP. The information used in this investigation consists of 2000 working day observations of the mentioned exchange rates from February 2002 to October 2008. Parts of this data for EUR/USD in the interval of 2002-2005 and for EUR/GBP in the interval of 2005-2008 are shown in Fig. 2 and 3, respectively [51].

This information is divided into three parts in our experiments: 65% for training, 25% for validation and 10% for test. The input and target values are normalized and training data is applied in a random order to remove the effects of current trends on the output.

Using the raw prices as the inputs of the network is misleading and this approach does not lead to accurate

Fig. 3: EUR/USD exchange rate, 2005-2008

Table 3: Selected input indices for training ANN

Index type	Index
Price and volume related inputs	(High-Low), (Close-Open)/Open, (High-Low)*Volume, (Close-Open)*Volume
Trend following indicators	SMA[a] with the periods of 5, 10, 20, 30, 50, 70, 90, 120, 150 and 200 days, difference between two SMAs with the periods of 4-8, 5-10, 5-20, 10-20, 10-40, 20-40, 20-80, 40-80 and 40-160 days, awesome oscillator
Market strength and direction indicators (in 14 days)	ADX[b](14), DI+[c](14), DI-[d](14)
Momentum indicators	CCI[e](14), RSI[f](14), accelerator oscillator

a. Simple Moving Average; b. Average Directional Movement Index; c. Plus Directional Movement Index; d. Minus Directional Movement Index; e. Commodity Channel Index; f. Relative Strength Index

predictions at the output [52-55]. A set of indices are generated by using MetaTrader software [51] and are used as the inputs of MLP, instead of raw prices (Table 3).

The experiments are performed in two steps. In the first step, the best operators are chosen for select and crossover operations. In this step, constant values are assumed for mutation probability, initial population and number of generations. These values are set 3%, 250 and 50, respectively. In the next step, the effect of choosing different values for mutation probability, initial population and number of generations on the prediction error is investigated. The crossover probability is assumed to be 0.9 in all of the experiments.

EMPIRICAL RESULTS

Based on the optimum values of MLP parameters, which are determined by using GA, the empirical results are reported in this section. To evaluate the performance of ANN in EUR/USD and EUR/GBP exchange rate prediction, the values of MSE and NMSE after online training and for various optimum conditions are presented in Table 4 and 5, respectively.

As shown in these tables, different operators are used for select and crossover operations in GA. In each combination of these operators, the optimum values for the number of input and hidden nodes and the slope of activation function are reported in tables.

When the combination of "Top percent (20)" and "One point" operators is used, the NMSE in EUR/USD exchange rate prediction is minimized (Table 4). The best combinations for EUR/GBP exchange rate prediction, in terms of MSE, are "Top percent (30)-One point" and "Top percent (10)-Two point", as well (Table 5).

To find the most relevant indices in exchange rate prediction, the number of selection of inputs is depicted in Fig. 4. As shown in Fig. 4, the rate of change (ROC=(Close-Open)/Open) and relative strength index in 14 days (RSI(14)) are the most relevant features. The moving average in 150 days (MA(150)) is the least relevant feature in these predictions.

Table 4: Performance of the proposed model in EUR/USD exchange rate prediction

Selection operator	Crossover operator	Number of inputs	Number of hidden nodes	ß	MSE	NMSE
	One point	20	6	0.14	0.0032	0.052
Best	Two point	12	4	1.16	0.0033	0.053
	Uniform	17	7	0.15	0.0043	0.069
	One point	12	11	0.28	0.0038	0.060
Top percent (30)	Two point	17	19	0.17	0.0035	0.055
	Uniform	13	17	0.21	0.0032	0.052
	One point	12	3	0.55	0.0029	0.047
Top percent (20)	Two point	20	15	0.06	0.0032	0.052
	Uniform	15	5	0.61	0.0031	0.050
	One point	15	14	0.05	0.0033	0.052
Top percent (10)	Two point	15	21	0.19	0.0034	0.054
	Uniform	11	18	0.16	0.0033	0.053
	One point	15	12	0.07	0.0037	0.059
Roulette	Two point	19	23	0.11	0.0031	0.050
	Uniform	18	23	0.10	0.0042	0.068
	One point	11	7	0.22	0.0049	0.075
Random	Two point	17	24	0.04	0.0034	0.055
	Uniform	14	23	0.01	0.0036	0.058

Table 5: Performance of the proposed model in EUR/GBP exchange rate prediction

Selection operator	Crossover operator	Number of inputs	Number of hidden nodes	ß	MSE	NMSE
	One point	14	14	0.33	0.0014	0.070
Best	Two point	14	8	1.24	0.0011	0.057
	Uniform	15	8	0.84	0.0013	0.063
	One point	11	24	0.43	0.0010	0.049
Top percent (30)	Two point	15	9	0.26	0.0015	0.076
	Uniform	16	19	0.33	0.0013	0.067
	One point	15	19	0.39	0.0013	0.064
Top percent (20)	Two point	9	23	0.49	0.0011	0.055
	Uniform	10	10	0.29	0.0012	0.061
	One point	9	15	1.05	0.0011	0.057
Top percent (10)	Two point	12	13	0.22	0.0010	0.051
	Uniform	16	11	0.25	0.0013	0.058
	One point	16	14	0.78	0.0014	0.071
Roulette	Two point	13	8	0.18	0.0011	0.054
	Uniform	12	12	0.59	0.0021	0.082
	One point	14	5	0.12	0.0023	0.097
Random	Two point	21	17	0.52	0.0075	0.290
	Uniform	12	8	0.38	0.0016	0.067

Table 6: Performance comparison of the proposed mode1 with some other forecasting models

Model	Application	MSE	Research group
Hybrid of ARIMA and ANN [33]	Canadian lynx forecasting	0.0170	Zhang (2003)
ANN [12]	Canadian lynx forecasting	0.0140	Katijani *et al.* (2005)
Hybrid of ARIMA and ANN [56]	Canadian lynx forecasting	0.0130	Khashei *et al.* (2009)
Hybrid of Elman recurrent ANN and ARIMA [57]	Canadian lynx forecasting	0.0090	Aladag *et al.* (2009)
Hybrid of ARIMA, fuzzy logic and ANN [38]	Exchange rate prediction	0.0043	Khashei *et al.* (2009)
Hybrid of GA and ANN (proposed)	Exchange rate prediction	0.0010	

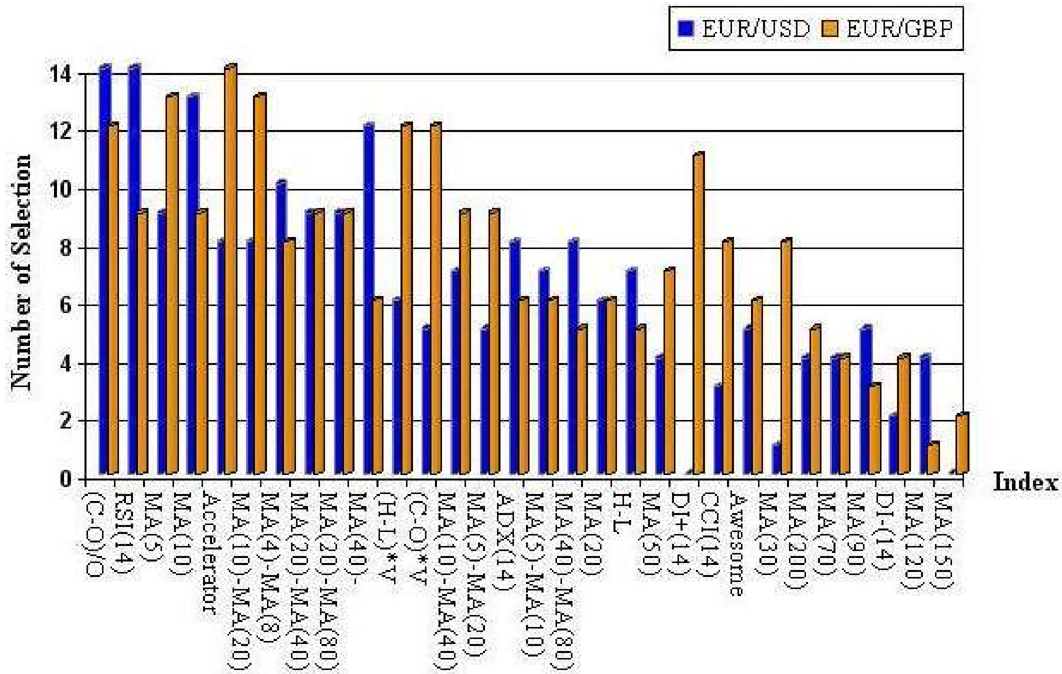

Fig. 4: Number of input index selection in EUR/USD and EUR/GBP exchange rate predictions

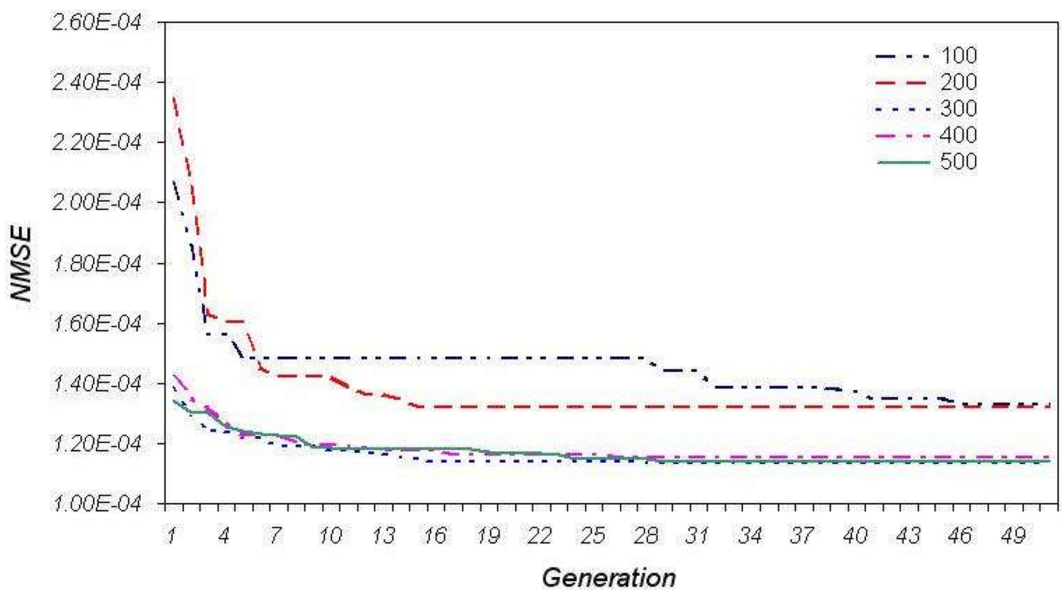

Fig. 5: Error performance in various initial populations and new generations

The performance of the proposed model in EUR/GBP exchange rate prediction for various initial populations (100 to 500), is depicted in Fig. 5. As shown in this figure, increasing the number of initial population above 300 does not improve the performance and there is no need to search in parameter space after 30 generations.

CONCLUSIONS

Genetic algorithm was used in this paper to optimize the parameters of a multilayer perceptron's structure (e.g. number of input and hidden nodes and the slope of nodes' activation function) and its learning coefficients (learning rate and momentum). To evaluate the effectiveness of the proposed approach, EUR/USD and EUR/GBP exchange rates were predicted.

Empirical results showed that the proposed evolutionary-connectionist hybrid model has better performance, when is compared with some other time-series forecasting models (Table 6).

REFERENCES

1. Box, P. and G.M. Jenkins, 1976. Time Series Analysis: Forecasting and Control, Holden-day.
2. Engle, R.F., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation. Econometrica, 50: 987-1008.
3. Bollerslev, T., 1986. Generalized Autoregressive Conditional Heteroscedasticity. Journal of Econometrics, 31: 307-327.
4. Granger, C.W.J. and A.P. Anderson, 1978. An Introduction to Bilinear Time Series Models, Vandenhoeck & Ruprecht.
5. Tong, H. and K.S. Lim, 1980. Threshold Autoregressive, Limit Cycles and Cyclic Data. Journal of Royal Statatistical Society, Series B, 42: 245-292.
6. Eurescom P901 Project Report, 2000. Investment Analysis Modelling, Deliverable 2, Annex B (Market Modelling).
7. Sheikhan, M. and M.E. Kalantari, 2008. Forecasting the Number of Telecommunication Services' Subscribers for the Next Years in the Country. Iranian Journal of Electrical and Computer Engineering, (In Farsi), 6: 111-118.
8. Sheikhan, M. and M.E. Kalantari, 2008. Prediction of Capital Investment in Fixed-Telephony Network's Switching Equipments in Tandem with NGN Migration based on Cobb-Douglas Model for Demand Forecasting. Esteghlal Engineering Journal-Isfahan University of Technology, (In Farsi), 27: 1-16.
9. Sheikhan, M. and M.E. Kalantari, 2009. Estimation of the Required Capital Investment in Mobile Telephony Network's Equipments Based on Cobb-Douglas Demand Forecasting Model. Iranian Journal of Electrical and Computer Engineering (Article in Press, In Farsi).
10. Sheikhan, M., F. Razaghian and M.E. Kalantari, 2008. Using Cobb-Douglas Demand Forecasting Model to Assess Capital Investment in National Access Network and DAI. In the Proceedings of the 16th Iranian Conference on Electrical Engineering, (In Farsi), pp: 957-963.
11. Sheikhan, M. and G.R. Amin, 2008. Telecom and Utility Networks' Estimated Capital Investment in NMS and CCBS Using Cobb-Douglas Model. In the Proceedings of New Mathematical Ideas in Engineering Applications Symposium, Paper Code: 1105.
12. Katijani, Y., W.K. Hipel and A.I. McLeod, 2005. Forecasting Nonlinear Time Series with Feedforward Neural Networks: A Case Study of Canadian Lynx Data. Journal of Forecasting, 24: 105-117.
13. Yao, J., Y. Li and C.L. Tan, 2000. Option Price Forecasting Using Neural Networks. Omega, 28: 455-466.
14. Chakraborty, K., K. Merotra, C.K. Mohan and S. Ranka, 1992. Forecasting the Behavior of Multivariate Time-Series Using Neural Networks. Neural Networks, 5: 461-470.
15. Zemouri, R., D. Racoceanu and N. Zerhouni, 2003. Recurrent Radial Basis Function Network for Time Series Prediction. Engineering Applications of Artificial Intelligence, 16: 453-463.
16. Chen, Y., B. Yang, J. Dong and A. Abraham, 2005. Time-Series Forecasting Using Flexible Neural Tree Model. Information Sciences, 174: 219-235.
17. Zahang, J. and E. Marsic, 2006. Link Quality and Signal to Noise Ratio in 802.11 WLAN with Fading: A Time-Series Analysis. In the Proceedings of the 64th Vehicular Technology Conference, 5: 1-5.
18. Harpham, V. and C.W. Dawson, 2006. The Effect of Different Basis Function on Radial Basis Function Network for Time Series Prediction: A Comparative Study. Journal of Neurocomputing, 69: 2161-2170.
19. Giordano, F., M. La Rocca and C. Perna, 2007. Forecasting Nonlinear Time Series with Neural Network Sieve Bootstrap. Computational Statistics and Data Analysis, 51: 3871-3884.
20. Jain, A. and A.M. Kumar, 2007. Hybrid Neural Network Models for Hydrologic Time Series Forecasting. Applied Soft Computing, 7: 585-592.
21. Hornik, K., M. Stinchcombe and H. White, 1989. Multilayer Feedforward Networks Are Universal Approximators. Neural Networks, 2: 359-366.
22. Bates, J.M. and W.J. Granger, 1969. The Combination of Forecasts. Operation Research, 20: 451-468.
23. Clemen, R., 1989. Combining Forecasts: A Review and Annotated Bibliography with Discussion. International Journal of Forecasting, 5: 559-608.
24. Pai, P.F. and C.S. Lin, 2005. A Hybrid ARIMA and Support Vector Machines Model in Stock Price Forecasting. Omega, 33: 497-505.
25. Chen, K.Y. and C.H. Wang, 2007. A Hybrid ARIMA and Support Vector Machines in Forecasting the Production Values of the Machinery Industry in Taiwan. Expert Systems with Applications, 32: 254-264.
26. Zhou, Z.J. and C.H. Hu, 2008. An Effective Hybrid Approach Based on Grey and ARMA for Forecasting Gyro Drift. Chaos, Solitons Fractals, 35: 525-529.

27. Tian, L. and A. Noore, 2005. On-Line Prediction of Software Reliability Using an Evolutionary Connectionist Model. Journal of Systems and Softwares, 77: 173-180.
28. Armano, G., M. Marchesi and A. Murru, 2005. A Hybrid Genetic-Neural Architecture for Stock Indexes Forecasting. Information Sciences, 170: 3-33.
29. Kim, H. and K. Shin, 2007. A Hybrid Approach Based on Neural Networks and Genetic Algorithms for Detecting Temporal Patterns in Stock Markets. Applied Soft Computing, 7: 569-575.
30. Yu, L., S. Wang and K.K. Lai, 2005. A Novel Nonlinear Ensemble Forecasting Model Incorporating GLAR and ANN for Foreign Exchange Rates. Computers & Operations Research, 32: 2523-2541.
31. Tsaih, R., Y. Hsu and C.C. Lai, 1998. Forecasting S&P 500 Stock Index Futures with a Hybrid AI System. Decision Support Systems, 23: 161-174.
32. Wedding, D.K. and K.J. Cios, 1996. Time Series Forecasting by Combining RBF Networks, Certainty Factors and Box-Jenkins Model. Neurocomputing, 10: 149-168.
33. Zhang, G.P., 2003. Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model. Neurocomputing, 50: 159-175.
34. Tseng, F.M., H.C. Yu and G.H. Tzeng, 2002. Combining Neural Network Model with Seasonal Time Series ARIMA Model. Technological Forecasting & Social Change, 69: 71-78.
35. Ginzburg, I. and D. Horn, 1994. Combined Neural Networks for Time Series Analysis. Advanced Neural Information Processing Systems, 6: 224-231.
36. Chang, P., C. Liu and Y. Wang, 2006. A Hybrid Model by Clustering and Evolving Fuzzy Rules for Sales Decision Supports in Printed Circuit Board Industry. Decision Support Systems, 42: 1254-1269.
37. Huarng, K. and T.H.K. Yu, 2006. The Application of Neural Networks to Forecast Fuzzy Time Series. Physica A, 336: 481-491.
38. Khashei, M., M. Bijari and G.A. Raissi Ardali, 2009. Improvement of Auto-Regressive Integrated Moving Average Models Using Fuzzy Logic and Artificial Neural Networks (ANNs). Neurocomputing, 72: 956-967.
39. Tseng, F.M., G.H. Tzeng, H.C. Yu and B.J.C. Yuan, 2001. Fuzzy ARIMA Model for Forecasting the Foreign Exchange Market. Fuzzy Sets and Systems, 118: 9-19.
40. Potter, C., G.K. Venayagamoorthy and K. Kosbar, 2008. MIMO Beam-Forming with NN Channel Prediction Trained by a Novel PSO-EA-DEPSO Algorithm. In the Proceedings of the International Joint Conference on Neural Networks, pp: 3338-3344.
41. Yao, J. and C.L. Tan, 2000. A Case Study on Using Neural Networks to Perform Technical Forecasting of FOREX. Neurocomputing, 34: 79-98.
42. Ince, H. and T.B. Trafalis, 2006. A Hybrid Model for Exchange Rate Prediction. Decision Support Systems, 42: 1054-1062.
43. O' Connor, N. and M.G. Madden, 2006. A Neural Network Approach to Predicting Stock Exchange Movements Using External Factors. Knowledge-Based Systems, 19: 371-378.
44. Zhang, Y.Q. and X. Wan, 2007. Statistical Fuzzy Interval Neural Networks for Currency Exchange Rate Time Series Prediction. Applied Soft Computing, 7: 1149-1156.
45. Yu, L., K.K. Lai and S. Wang, 2008. Multistage RBF Neural Network Ensemble Learning for Exchange Rates Forecasting. Neurocomputing, 71: 3295-3302.
46. Yu, L., S. Wang and K.K. Lai, 2009. A Neural-Network-Based Nonlinear Metamodeling Approach to Financial Time Series Forecasting. Applied Soft Computing, 9: 563-574.
47. Aljahdali, S.H., A. Sheta and D. Rine, 2002. Predicting Accumulated Faults in Software Testing Process Using Radial Basis Function Network Models. In the Proceedings of the 17th International Conference on Computers and their Applications, pp: 26-29.
48. Leung, F.H.F., H.K. Lam, S.H. Ling and P.K.S. Tam, 2003. Tuning of the Structure and Parameters of a Neural Network Using an Improved Genetic Algorithm. IEEE Transactions on Neural Networks, 14: 79-88.
49. Hochman, R., T.M. Khoshgoftaar, E.B. Allen and J.P. Hudepohl, 1996. Using the Genetic Algorithm to Build Optimal Neural Networks for Fault-Prone Module Detection. In the Proceedings of the 7th International Symposium on Software Reliability Engineering, pp: 152-162.
50. Principe, J., C. Lefebvre, G. Lynn, C. Fancourt and D. Wooten, 2002. NeuroSolutions Documentation-Genetic Operators Inspector. NeuroDimension Incorporation, (http://www.neurosolutions.com).
51. Alpari (UK) Broker's MetaTrader Software (www.alpari-idc.com).
52. Yao, J., C.L. Tan and H.L. Poh, 1999. Neural Networks for Technical Analysis: A Study on KLCI. International Journal of Theoretical and Applied Finance, 2: 221-241.

53. Yao, J. and C.L. Tan, 2000. A Case Study on Using Neural Networks to Perform Technical Forecasting of FOREX. Neurocomputing, 34: 79-98.
54. Chuna, S.H. and S.H. Kim, 2003. Impact of Momentum Bias on Forecasting Through Knowledge Discovery Techniques in the Foreign Exchange Market. Expert Systems with Applications, 24: 115-122.
55. Kim, K.J. and I. Han, 2000. Genetic Algorithms Approach to Feature Discretization in Artificial Neural Networks for the Prediction of Stock Price Index. Expert Systems with Applications, 19: 125-132.
56. Khashei, M. and M. Bijari, 2009. An Artificial Neural Network (p, d, q) Model for Time Series Forecasting. Expert Systems with Applications, (Article in Press).
57. Aladag, C.H., E. Egrioglu and C. Kadilar, 2009. Forecasting Nonlinear Time Series with a Hybrid Methodology. Applied Mathematics Letters, 22: 1467-1470.