Australian Forex Market Analysis Using Connectionist Models

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Abstract

The need for intelligent monitoring systems has become a necessity to keep track of the complex forex market. The forex market is difficult to understand by an average individual. However, once the market is broken down into simple terms, the average individual can begin to understand the foreign exchange market and use it as a financial instrument for future investing. This paper is an attempt to compare the performance of a Takagi-Sugeno type neuro-fuzzy system and a feed forward neural network trained using the scaled conjugate gradient algorithm to predict the average monthly forex rates. The exchange values of Australian dollar are considered with respect to US dollar, Singapore dollar, New Zealand dollar, Japanese yen and United Kingdom pound. The connectionist models were trained using 70% of the data and remaining was used for testing and validation purposes. It is observed that the proposed connectionist models were able to predict the average forex rates one month ahead accurately. Experiment results also reveal that neuro-fuzzy technique performed better than the neural network.

Keywords: Forex prediction, neurocomputing, neuro-fuzzy computing, scaled conjugate gradient

1 Introduction

Creating many international businesses, the globalization has made the international trade, international financial transactions and investment to rapidly grow. Globalisation is followed by foreign exchange market also known as forex. The forex is defined as a change in a market value relationship between national currencies (at a particular point in time) that produces profits, or losses, for all foreign currency traders (Long and Walter, 2001). As such, it plays an important role of providing payments in between countries, transferring funds from one currency to another and determining the exchange rate (Forexcapital, 2001).

The forex is the largest and the most liquid market in the world with a daily turnover of around 1 trillion U.S. dollars (Usfxm, 2001). It was founded in 1973 with the deregulation of the foreign exchange rate in the USA and other developed countries. Namely, before 1973 the fixed exchange rates regime was used for global currency relationships. It was based on the Bretton Woods' agreement from 1944 with American dollar as an anchor for all free world currencies. The American dollar has been a reserve currency for the world that was based on gold standard. No other country guaranteed to exchange its currency for a gold. However, in 1960s and early 1970s the global economic crisis brought on by the worldwide inflation has shown that The United States were not able any more to meet the gold standard. With a rise of inflation more dollars became worth less, and dollars holders around the globe sought the safety of gold. As a consequence, many nations were unable to maintain the value of their currencies under the Bretton Woods regime, and the U.S. gold reserves significantly fell. Then, in 1973 the floating exchange rate system was created establishing markets' prices rule. The system is dynamic, generating greater trade and capital flows. It is expanding with rapid technological innovations. In particular, the foreign exchange market has become an over-the-counter market with traders located in the offices of major commercial banks around the world. Today, communication among traders goes on using computers, telephones, telexes, and faxes. Traders buy and sell currencies, but also they create prices. The exchange of currencies, however, is in the form of an exchange of electronic messages.

Most of the trading in the forex market takes places in several currencies: U.S dollar, German mark, Japanese yen, British pound sterling, Australian dollar, Canadian dollar. More than 80 percent of global foreign exchange transactions are still based on American dollar. There are two reasons for quoting most exchange rates against the U.S. dollar. The first has to do with simplicity to avoid enormous number of dealing markets if each currency were traded directly against each other currency. A second is to avoid the possibility of triangular arbitrage. That is, since all currencies are traded with respect to the dollar, there is only one available cross rate and no possibility of arbitrage (Grabbe, 1996).

The forex market is 24-hour market with three major centers in different part of the world: New York, London, and Tokyo. It is the busiest in the early morning New York time since banks in London and New York are simultaneously open and trading. Its centers open and close one after the other. If it is open in Tokyo and Hong Kong, it is also open in Singapore. Then if it opens in Los Angeles in the after noon, it will be also open in Sydney the next day in the morning.

At present the forex market includes the participation of commercial banks around the globe, with a tendency to spread to corporate, funding and retail institutions.

At the forex market, traders create prices by buying and selling currencies to exporters, importers, portfolio managers, and tourists. Each currency has two prices: a bid price at which a trader is willing to buy and an offer price at which a trader is willing to sell. If being in the major money centers banks traders deal in two way prices, for both buying and selling. In market-making banks worldwide much of the trading take place by direct dealing, while the rest takes place through brokers. Today computerized services electronically match buy and sell orders using an automated brokerage terminal. As Grabbe quotes, about 85 percent of all forex trading is between market makers (Grabbe, 1996). With the rest the forex purchases and sales are by companies engaged in trade, or tourism. Since the most trading takes place between market makers it creates a space for speculative gains and losses. However, speculation in the forex market is potentially a zero-sum game: the cumulative profits equal the cumulative losses. The operations are inter-bank transactions were a single rumor can create eruptive reactions followed by huge and often-unpredictable capital flows. Now traders play against each other instead of playing against central banks as they did when currencies were not floating (Dormael, 1997).

Starting from 1983 there were considerable changes in the Australian forex market. Like Australia most of developed and developing countries in the world welcome foreign investors. When foreign investors get access to invest in any country's bond equities, manufacturing industries, property market and other assets then the forex market becomes affected. This affect influences everyday personal and corporate financial lives, and the economic and political fate of every country on the earth. The nature of the forex market is generally complex and volatile. The volatility or rate fluctuation depends on many factors. Some of factors include financing government deficits, changing hands of equity in companies, ownership of real estate, employment opportunities, merging and ownership of large financial corporation or companies. The major attractions to the business of forex trading are threefold, namely, high liquidity, good leverage and low cost associated with actual trading. There are, of course, many other advantages attached with the dealing of forex market once one gets involved and understands it in more details.

Forex market traders can use many ways to analyze the directions of forex market. Whatever the method chosen, it is always related to activities of a price for some periods of time in the past. The pattern in which prices move up and down tends to repeat itself. Thus, the prediction of future price movements can be plotted out by studying the history of past price movements. It is well known that the forex market has its own momentum and using traditional statistical techniques based on previous market trends and parameters, it is very difficult to predict future exchange rates. In particular, it is difficult to predict exchange rates in a long-term, what would be very helpful for policy makers and traders while making crucial decisions. The aim of this paper is to propose an intelligent monitoring system for predicting the monthly average forex market rates for major currencies with respect to Australian dollar. The paper is organized as follows: Section two explores some theoretical background on neural networks and neuro-fuzzy computing. Section three points to the experiment through two stages: first, modeling the prediction systems by neuro-fuzzy computing and neurocomputing, and, second, performance evaluation. Paper ends with concluding remarks and future research directions.

2 Computational Intelligence (CI)

CI substitutes intensive computation for insight into how complicated systems work. Artificial neural networks, fuzzy inference systems, probabilistic computing, evolutionary computation etc were all shunned by classical system and control theorists. CI provides an excellent framework unifying them and even by incorporating other revolutionary methods. Artificial Neural Networks (ANNs) were designed to mimic the characteristics of the biological neurons in the human brain and nervous system. An artificial neural network creates a model of neurons and the connections between them, and trains it to associate output neurons with input neurons. The network "learns" by adjusting the interconnections (called weights) between layers. When the network is adequately trained, it is able to generate relevant output for a set of input data. A valuable property of neural networks is that of generalization, whereby a trained neural network is able to provide a correct matching in the form of output data for a set of previously unseen input data.

Backpropagation (BP) is one of the most famous training algorithms for multilayer perceptrons. Basically, BP is a gradient descent technique to minimize the error E for a particular training pattern. For adjusting the weight (w_k),in the batched mode variant the descent is based on the gradient ∇E ($\frac{\delta E}{\delta w_k}$) for the total training set:

$$\Delta w_k(n) = -\varepsilon \cdot \frac{\delta E}{\delta w_k} + \alpha \cdot \Delta w_k(n-1) \qquad (1)$$

The gradient gives the direction of error E. The parameters ε and α are the learning rate and momentum respectively. A good choice of both the parameters is required for training success and speed of the ANN.

In the Conjugate Gradient Algorithm (CGA) a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. A search is made along the conjugate gradient direction to determine the step size, which will minimize the performance function along that line. A line search is performed to determine the optimal distance to move along the current search direction. Then the next search direction is determined so that it is conjugate to previous search direction. The general procedure for determining the new search direction is to combine the new steepest descent direction with the previous search direction. An important feature of the CGA is that the minimization performed in one step is not partially undone by the next, as it is the case with gradient descent methods. An important drawback of CGA is the requirement of a line search, which is computationally expensive. Moller introduced the Scaled Conjugate Gradient Algorithm (SCGA) as a way of avoiding the complicated line search procedure of conventional CGA. According to the SCGA, the Hessian matrix is approximated by

$$E''(w_k)p_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k} + \lambda_k p_k \qquad (2)$$

where E' and E'' are the first and second derivative information of global error function $E(w_k)$. The other terms p_k, σ_k and λ_k represent the weights, search direction, parameter controlling the change in weight for second derivative approximation and parameter for regulating the indefiniteness of the Hessian. In order to get a good quadratic approximation of E, a mechanism to raise and lower λ_k is needed when the Hessian is positive definite. Detailed step-by-step description can be found in the literature (Moller, 1993).

Neuro-Fuzzy (NF) computing is a popular framework for solving complex problems (Abraham and Chowdhury, 2001), (Abraham, 2001), (Abraham and Nath, 2000). If we have knowledge expressed in the form of linguistic rules, we can build a Fuzzy Inference System (FIS), and if we have data, or can learn from a simulation (training) then we can use ANNs. For building a FIS, we have to specify the fuzzy sets, fuzzy operators and the knowledge base. Similarly for constructing an ANN for an application the user needs to specify the architecture and learning algorithm. An analysis reveals that the drawbacks pertaining to these approaches seem complementary and therefore it is natural to consider building an integrated system combining the concepts. While the learning capability is an advantage from the viewpoint of FIS, the formation of linguistic rule base will be advantage from the viewpoint of ANN. We used the Adaptive Neuro Fuzzy Inference System (ANFIS) implementing a Takagi-Sugeno type FIS. We modified the ANFIS model to accommodate the multiple outputs (Jang et al. 1997). Figure 1 depicts the 6- layered architecture of multiple output ANFIS and the functionality of each layer is as follows:

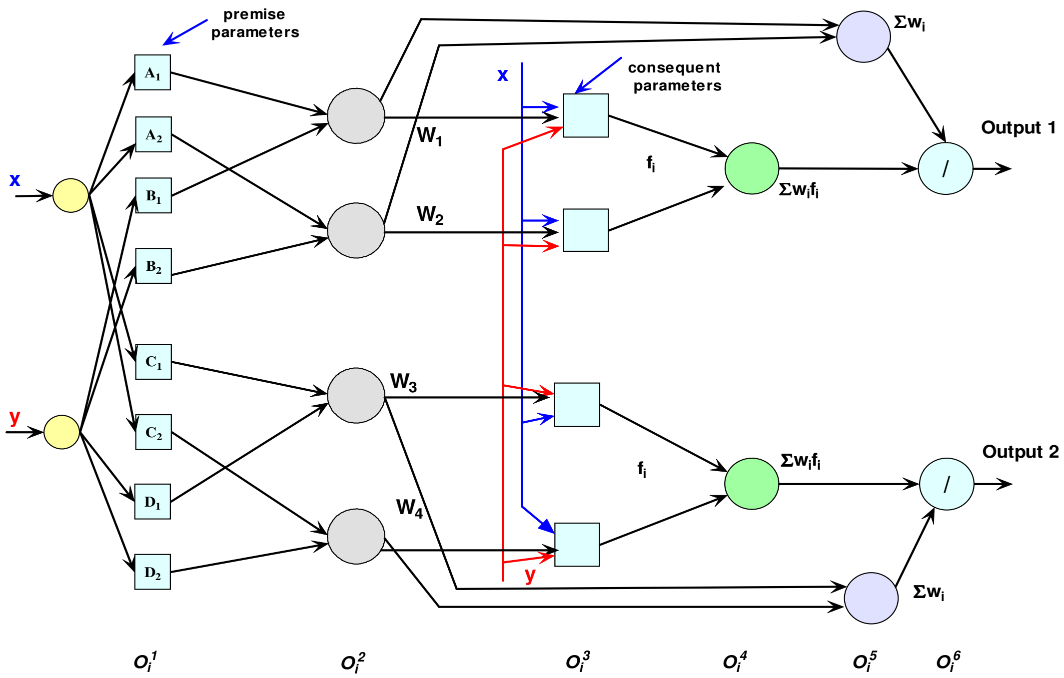

Figure 1. Architecture of ANFIS with multiple outputs

Layer-1. Every node in this layer has a node function. $O_i^1 = \mu_{A_i}(x)$, for i =1, 2 or $O_i^1 = \mu_{B_{i-2}}(y)$, for i=3,4,…. O_i^1 is the membership grade of a fuzzy set A (= A_1, A_2, B_1 or B_2) and it specifies the degree to which the given input *x* (or *y*) satisfies the quantifier A. Usually the node function can be any parameterized function. A gaussian membership function is specified by two parameters *c* (membership function center) and *σ* (membership function width). guassian (x, c, σ) = $e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}$. Parameters in this layer are referred to premise parameters.

Layer-2. Every node in this layer multiplies the incoming signals and sends the product out. Each node output represents the firing strength of a rule.

$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1,2......$, In general any T-norm operator that perform fuzzy "AND" can be used as the node function in this layer.

Layer-3. The rule consequent parameters are determined in this layer.

$O_i^3 = f_i = xp_i + yq_i + r_i$, where $\{p_i, q_i, r_i\}$are the rule consequent parameters.

Layer-4. Every node i in this layer is with a node function

$$O_i^4 = \sum \overline{w_i} f_i = \sum \overline{w_i}(p_i x + q_i y + r_i)$$, where $\overline{w_i}$ is the output of layer 2

Layer-5. Every node in this layer aggregates all the firing strengths of rules

$$O_i^5 = \sum_i \overline{w_i} \cdot$$

Layer-6. Every i-th node in this layer calculates the individual outputs.

$$O_i^6 = \overline{Output} = \frac{\sum \overline{w_i} f_i}{\sum_i \overline{w_i}}, i = 1,2.....$$

ANFIS makes use of a mixture of backpropagation to learn the premise parameters and least mean square estimation to determine the consequent parameters. A step in the learning procedure has two parts: In the first part the input patterns are propagated, and the optimal conclusion parameters are estimated by an iterative least mean square procedure, while the antecedent parameters (membership functions) are assumed to be fixed for the current cycle through the training set. In the second part the patterns are propagated again, and in this epoch, backpropagation is used to modify the antecedent parameters, while the conclusion parameters remain fixed. This procedure is then iterated.

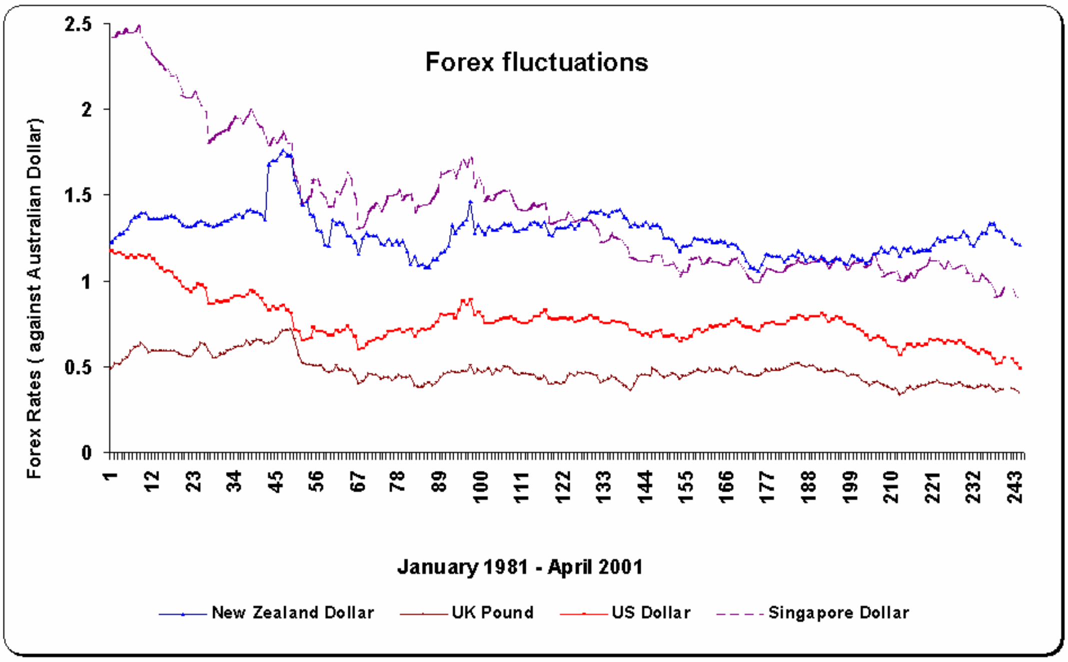

Figure 2. Forex fluctuations during the period January 1981 – April 2001 for four different currencies.

3 Experimentation Set-up – Training and Performance Evaluation

The data for our study were the monthly average forex rates from January 1981 to April 2001. We considered the exchange rates of the Australian dollar with respect to the Japanese yen, US Dollar, UK pound, Singapore dollar and New Zealand dollar. Figure 2 shows the forex fluctuations during the period January 1981 – April 2001 for the four different currencies. The experimental system consists of two stages: modelling the prediction systems (training in the case of soft computing models) and performance evaluation. For network training, the six selected input descriptor variables were: the month, exchange rates for the Japanese yen, US Dollar, UK pound, Singapore dollar and New Zealand. 70% of the data was used to train the neural network and 30% for testing purposes. Experiments were repeated three times and the worst errors were reported. The test data will be then passed through the trained network to evaluate the learning efficiency of the considered models. Our objective is to develop an efficient forex prediction system capable of producing a short-term forecast .The required time-resolution of the forecast is monthly, and the required time-span of the forecast is one month ahead. This means that the system should be able to predict the forex rates one month ahead based on the values of the previous month. We used a Pentium II, 450 MHz platform for simulating the prediction models using MATLAB.

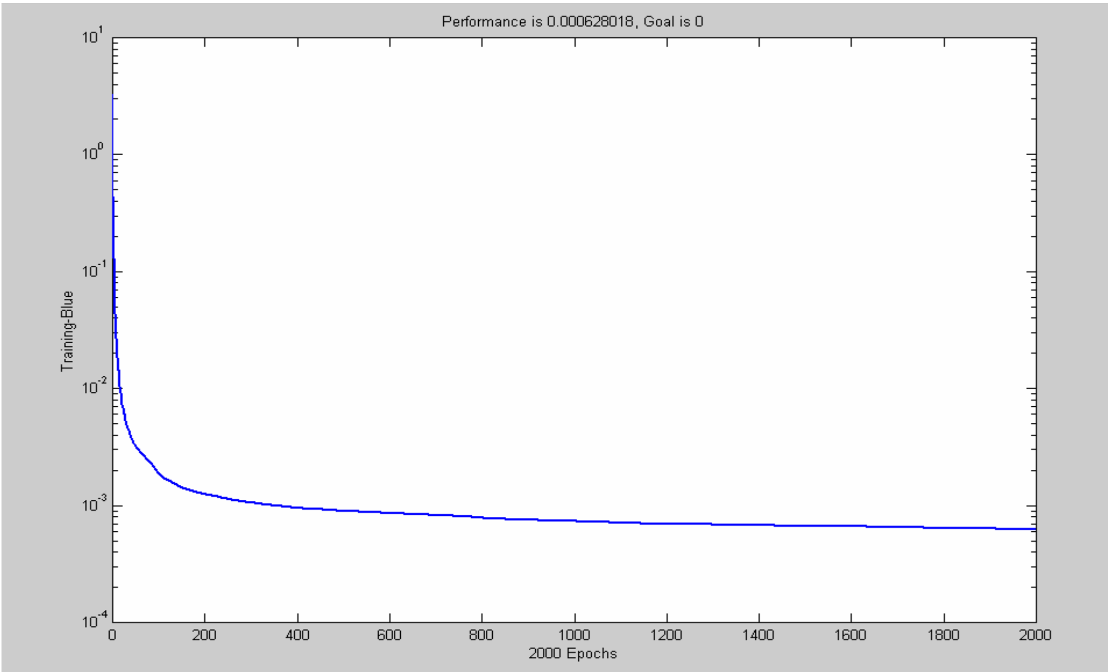

Figure 3. Convergence of SCGA training.

Training of Connectionist Models

Our preliminary experiments helped us to formulate a feedforward neural network with 1 input layer, 2 hidden layers and an output layer [6-14-14-1]. Input layer consists of 6 neurons corresponding to the input variables. The first and second hidden layers consist of 14 neurons respectively using tanh-sigmoidal activation functions. Training was terminated after 2000 epochs and we achieved a training error of 0.0251. Figure 3 shows the convergence of SCGA during the 2000 epochs training. For training the neuro-fuzzy (NF) model, we used 4 gaussian membership functions for each input variables and 16 rules were learned using the hybrid training method. Training was terminated after 30 epochs. For the NF model, we achieved training RMSE of 0.0248.

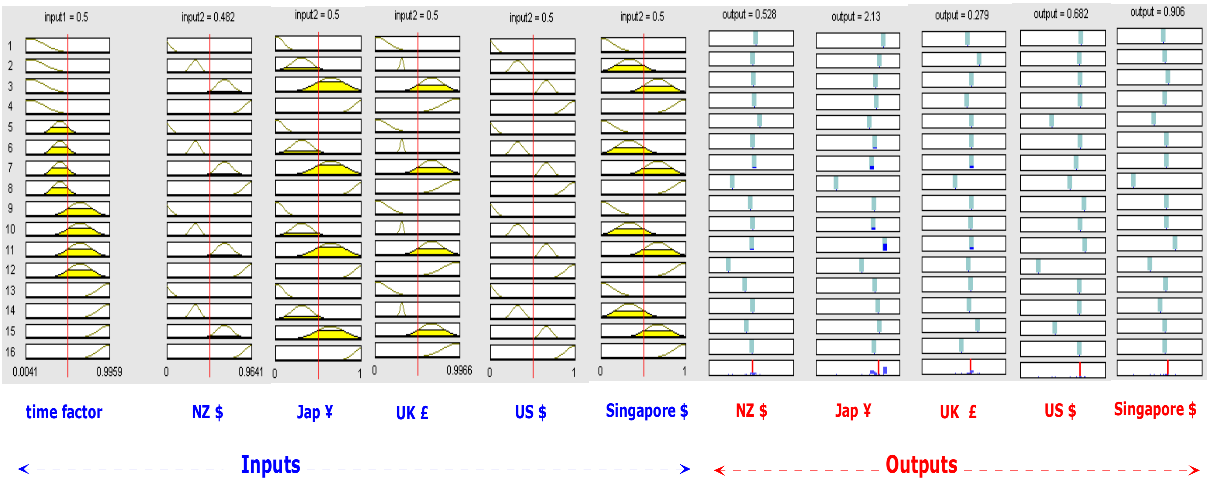

Figure 4. Developed Takagi-Sugeno type fuzzy inference model for forex prediction

Table 1. Test results and performance comparison of forex forecasting

	Japanese Yen	US $	UK £	Singapore $	New Zealand $
Artificial neural network					
Training time =200 seconds, learning epochs: 2000, training data RMSE = 0.0251					
Testing data RMSE	0.028	0.0340	0.023	0.030	0.021
Neuro-Fuzzy system					
Training time =35 seconds, learning epochs: 30, training error (RMSE) = 0.0248					
Testing data RMSE	0.026	0.0340	0.037	0.029	0.020

Test results

Table 1 summarizes the training and test performances of the neuro-fuzzy system and neural network. Figure 4 shows the developed Takagi-Sugeno type fuzzy inference model for forex prediction. Figure 5,6, 7 and 9 illustrates the test results for forex prediction using NF system and Figure 8 using ANN.

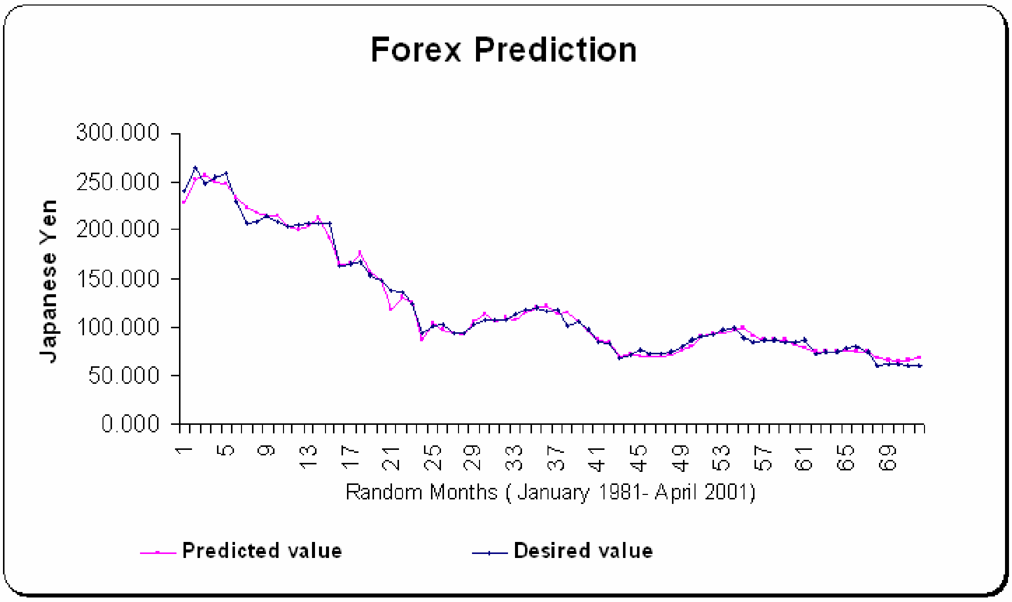

Figure 5. NF test results for Japanese Yen

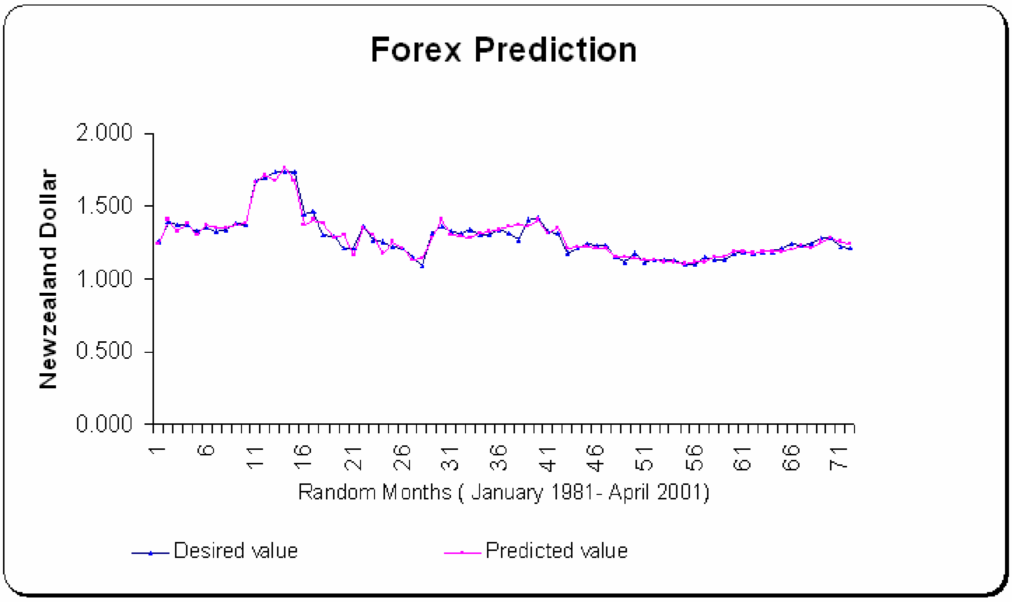

Figure 6. NF test results for New Zealand dollar

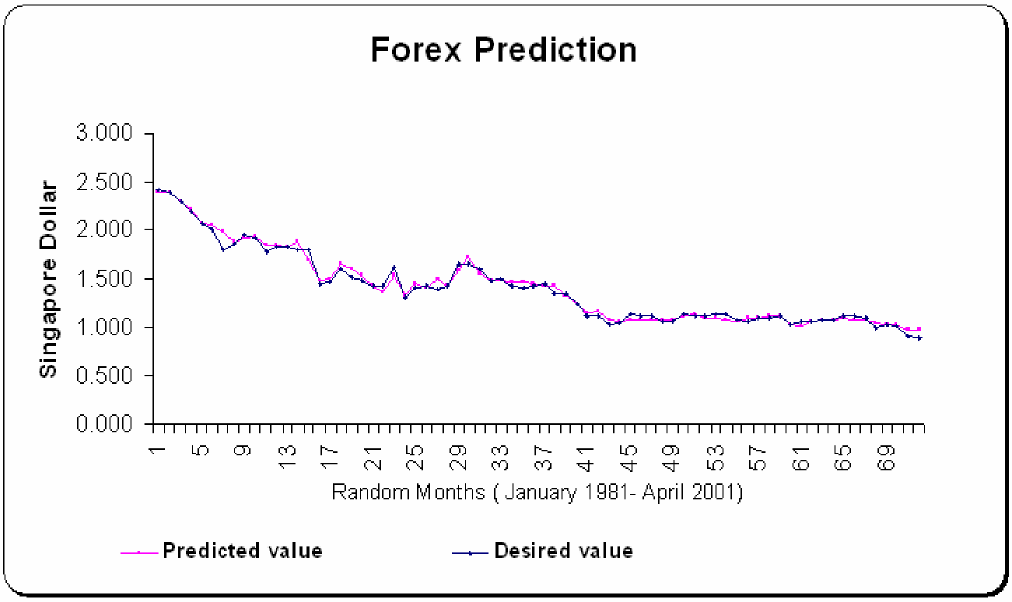

Figure7. NF test results for Singapore dollar

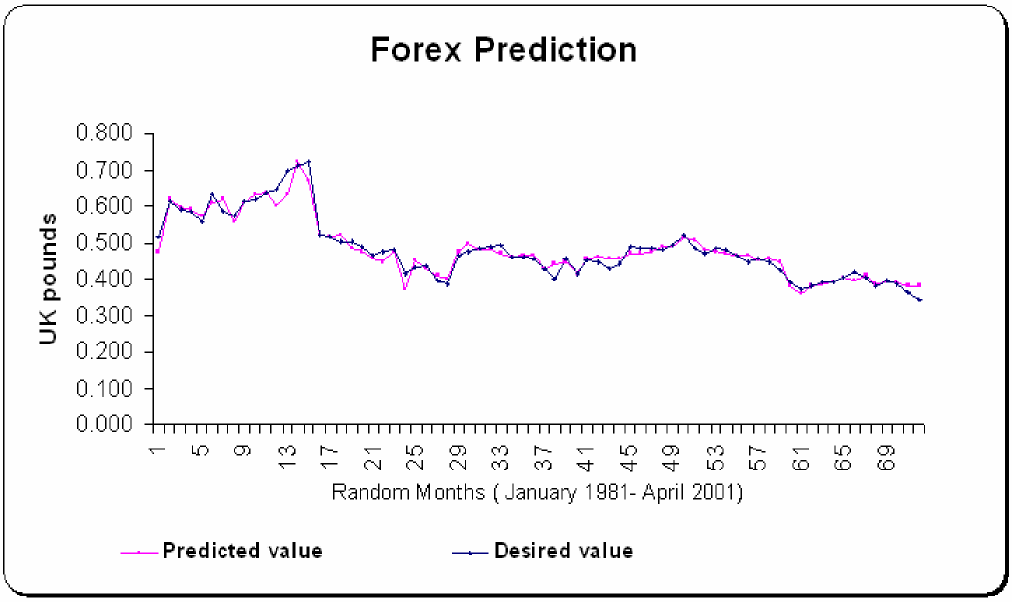

Figure 8. ANN test results for UK pounds

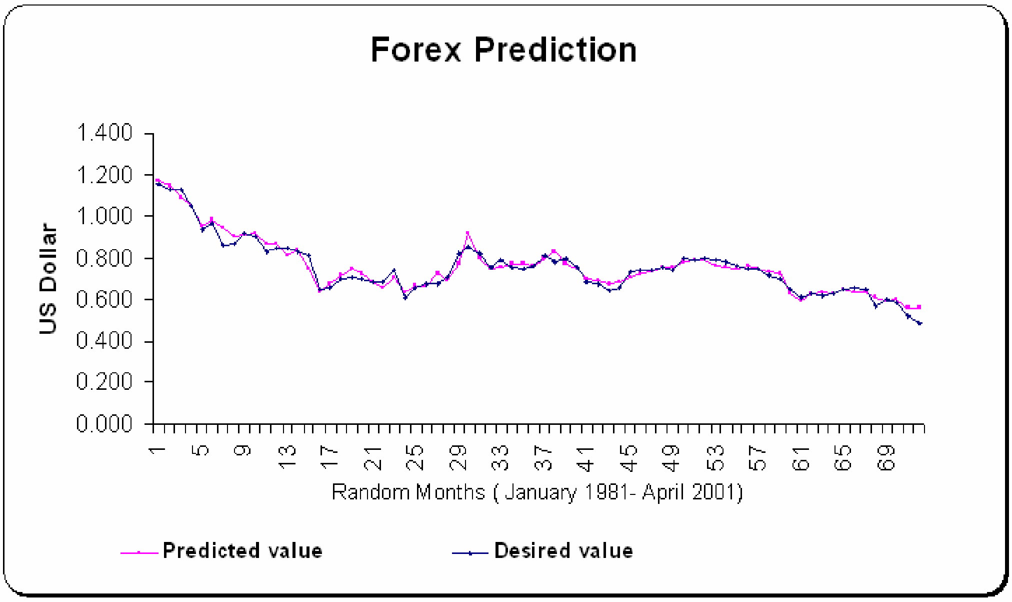

Figure 9. NF test results for US dollar

4. Conclusions

In this paper, we have proposed an intelligent monitoring system for predicting the monthly average forex rates of US dollar, UK pounds, Singapore dollar, New Zealand dollar and Japanese yen with respect to Australian dollar. Test results reveal that the proposed connectionist models are capable of predicting the results accurately. Compared to artificial neural network, neuro-fuzzy system performed better in terms of RMSE and training time. Another important advantage of neuro-fuzzy system is the interpretability of the results using *if-then* rules. It is also interesting to note that neural network performed better for the prediction of UK pounds. The proposed intelligent system might be useful for policy makers, investors, traders, companies engaged in international business etc. In our research we considered the monthly forex data from January 1981 to April 2001. Performance could have been improved by providing more training data. Our future research will be directed towards short-term forecast (daily, hourly etc.) of forex data using more intelligent systems.

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References

ABRAHAM, A. and CHOWDHURY, M. (2001): An Intelligent Forex Monitoring System, In Proceedings of IEEE International Conference on Info-tech and Info-net, Beijing, China, IEEE Press, pp.523-528.

ABRAHAM, A. (2001): Neuro-Fuzzy Systems: State-of-the-Art Modeling Techniques, Connectionist Models of Neurons, Learning Processes, and Artificial Intelligence, Lecture Notes in Computer Science, Jose Mira and Alberto Prieto (Eds.), Germany, Springer-Verlag, LNCS 2084: 269-276.

ABRAHAM, A. and NATH, B. (2000): Designing Optimal Neuro-Fuzzy Systems for Intelligent Control, Proceedings of the Sixth International Conference on Control Automation Robotics Computer Vision (ICARCV 2000), Singapore.

DORMALE, A. V. (1997): The Power of Money, Macmillan Press, London.

FOREXCAPITAL. (2001): Introduction to Forex Market. http://www.forexcapital.com, Accessed on 14-Sept.-2001.

GRABBE, J. O. (1996): International Financial Markets, Englewood Hills, Prentice Hall Inc.

JANG, S. R., SUN, C. T. and MIZUTANI, E. (1997): Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, US, Prentice Hall Inc.

LONGL, K. and WALTER, K. (2001): Electronic Currency Trading for Maximum Profit, Prima Money, Roseville, California.

MOLLER, A. F. (1993): A Scaled Conjugate Gradient Algorithm for Fast Supervised Learning, Neural Networks. 6:525-533.

USFXM. (2001): Foreign Exchange Market in the United States, http://www.ny.frb.org/pihome/addpub/usfxm. Accessed on 14-Sept.-2001.