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Comparing ANN Based Models with ARIMA for Prediction of Forex Rates

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Abstract

In the dynamic global economy, the accuracy in forecasting the foreign currency exchange (Forex) rates or at least predicting the trend correctly is of crucial importance for any future investment. The use of computational intelligence based techniques for forecasting has been proved extremely successful in recent times. In this paper, we developed and investigated three Artificial Neural Network (ANN) based forecasting models using Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG) and Backpropagation with Baysian Regularization (BPR) for Australian Foreign Exchange to predict six different currencies against Australian dollar. Five moving average technical indicators are used to build the models. These models were evaluated using three performance metrics, and a comparison was made with the best known conventional forecasting model ARIMA. All the ANN based models outperform ARIMA model. It is found that SCG based model performs best when measured on the two most commonly used metrics and shows competitive results when compared with BPR based model on the third indicator. Experimental results demonstrate that ANN based model can closely forecast the forex market.

Introduction

The foreign exchange market has experienced unprecedented growth over the last few decades. The exchange rates play an important role in controlling dynamics of the exchange market. As a result, the appropriate prediction of exchange rate is a crucial factor for the success of many businesses and fund managers. Although the market is well-known for its unpredictability and volatility, there exist a number of groups (like Banks, Agency and other) for predicting exchange rates using numerous techniques.

Exchange rates prediction is one of the demanding applications of modern time series forecasting. The rates are inherently noisy, non-stationary and deterministically chaotic [3, 22]. These characteristics suggest that there is no complete information that could be obtained from the past behaviour of such markets to fully capture the dependency between the future rates and that of the past. One general assumption is made in such cases is that the historical data incorporate all those behaviour. As a result, the historical data is the major player (/input) in the prediction process. However, it is not clear how good is these predictions. The purpose of this paper is to investigate and compare two well-known prediction techniques, under different parameter settings, for several different exchange rates.

For more than two decades, Box and Jenkins' Auto-Regressive Integrated Moving Average (ARIMA) technique [1] has been widely used for time series forecasting. Because of its popularity, the ARIMA model has been used as a benchmark to evaluate many new modelling approaches [8]. However, ARIMA is a general univariate model and it is developed based on the assumption that the time series being forecasted are linear and stationary [2].

The Artificial Neural Networks, the well-known function approximators in prediction and system modelling, has recently shown its great applicability in time-series analysis and forecasting [20-23]. ANN assists multivariate analysis. Multivariate models can rely on greater information, where not only the lagged time series being forecast, but also other indicators (such as technical, fundamental, inter-marker etc. for financial market), are combined to act as predictors.

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In addition, ANN is more effective in describing the dynamics of non-stationary time series due to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties. ANNs are universal function approximators that can map any nonlinear function without a *priori* assumptions about the data [2].

In several applications, Tang and Fishwich [17], Jhee and Lee [10], Wang and Leu [18], Hill *et al.* [7], and many other researchers have shown that ANNs perform better than ARIMA models, specifically, for more irregular series and for multiple-period-ahead forecasting. Kaastra and Boyd [11] provided a general introduction of how a neural network model should be developed to model financial and economic time series. Many useful, practical considerations were presented in their article. Zhang and Hu [23] analysed backpropagation neural networks' ability to forecast an exchange rate. Wang [19] cautioned against the dangers of one-shot analysis since the inherent nature of data could vary. Klein and Rossin [12] proved that the quality of the data also affects the predictive accuracy of a model. More recently, Yao *et al.* [20] evaluated the capability of a backpropagation neural-network model as an option price forecasting tool. They also recognised the fact that neural-network models are context sensitive and when studies of this type are conducted, it should be as comprehensive as possible for different markets and different neural-network models.

In this paper, we apply ARIMA and ANNs for predicting currency exchange rates of Australian Dollar with six other currencies such as US Dollar (USD), Great British Pound (GBP), Japanese Yen (JPY), Singapore Dollar (SGD), New Zealand Dollar (NZD) and Swiss Franc (CHF). A total 500 weeks (closing rate of the week) data are used to build the model and 65 weeks data to evaluate the models. Under ANNs, three models using standard backpropagation, scaled conjugate gradient and Baysian regression were developed. The outcomes of all these models were compared with ARIMA based on three different error indicators. The results show that ANN models perform much better than ARIMA models. Scaled conjugate gradient and Baysian regression models show competitive results and these models forecasts more accurately than standard Backpropagation which has been studied considerably in other studies.

After introduction, ARIMA, ANN based forecasting models and the performance metrics are briefly introduced. In the following two sections, data collection and experimental results are presented. Finally conclusions are drawn.

ARIMA: An Introduction

The *Box-Jenkins method* [1 & 2] of forecasting is different from most conventional optimization based methods. This technique does not assume any particular pattern in the historical data of the series to be forecast. It uses an iterative approach of identifying a possible useful model from a general class of models. The chosen model is then checked against the historical data to see whether it accurately describes the series. If the specified model is not satisfactory, the process is repeated by using another model designed to improve on the original one. This process is repeated until a satisfactory model is found.

A general class of Box-Jenkins models for a stationary time series is the ARIMA or autoregression moving-average, models. This group of models includes the AR model with only autoregressive terms, the MA models with only moving average terms, and the ARIMA models with both autoregressive and moving-average terms. The Bob-Jenkins methodology allows the analyst to select the model that best fits the data. The details of AR, MA and ARIMA models can be found in Jarrett [6 & 9]

Artificial Neural Network: An Introduction

In this section we first briefly present artificial neural networks and then the learning algorithms used in this study to train the neural networks.

Artificial Neuron

In the quest to build an intelligent machine in the hope of achieving human like performance in the field of speech and pattern recognition, natural language processing, decision making in fuzzy situation etc. we have but one naturally occurring model: the human brain itself, a highly powerful computing device. It follows that one natural idea is to simulate the functioning of brain directly on a computer. The general conjecture is that thinking about computation in terms of brain metaphor rather than conventional computer will lead to insights into the nature of intelligent behavior. This conjecture is strongly supported by the very unique structure of human brain.

Digital computers can perform complex calculations extremely fast without errors and are capable of storing vast amount of information. Human being cannot approach these capabilities. On the other hand humans routinely perform tasks like common sense reasoning, talking, walking, and interpreting a visual scene etc. in real time effortlessly. Human brain consists of hundred billions of neurons, each neuron being an independent biological information processing unit. On average each neuron is connected to ten thousands surrounding neurons, all act in parallel to build a massively parallel architecture. What we do in about hundred computational steps, computers cannot do in million steps. The underlying reason is that, even though each neuron is an extremely slow device compared to the state-of-art digital component, the massive parallelism gives human brain the vast computational power necessary to carry out complex tasks. Human brain is also highly fault tolerant as we continue to function perfectly though neurons are constantly dying. We are also better capable of dealing with fuzzy situations by finding closest matches of new problem to the old ones. Inexact matching is something brain-style model seem to be good at, because of the diffuse and fluid way in which knowledge is represented. All these serve a strong motivation for the idea of building an intelligent machine modeled after biological neuron, now known as artificial neural networks.

Artificial neural network models are very simplified versions of our understanding of biological neuron, which is yet far from complete. Each neuron's input fibre called *dendrite* receives excitatory signals through thousands of surrounding neurons' output fibre called *axon*. When the total summation of excitatory signals becomes sufficient it causes the neuron to fire sending excitatory signal to other neurons connected to it. Figure 1 shows a basic artificial neural network model. Each neuron receives an input x_j from other neuron j which is multiplied by the connection strength called weight ω_j (synaptic strength in biological neuron) to produce total net input as the weighted sum of all inputs as shown below.

$$net = \sum_j \omega_j x_j$$

The output of the neuron is produced by passing the net input through an activation function. The commonly used activation functions are hard limiter, sigmoidal or gaussian activation function.

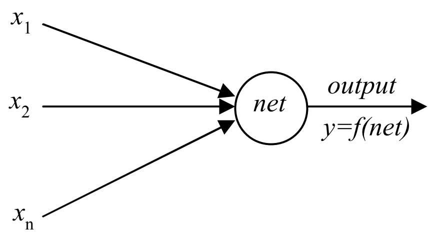


Fig.1. An artificial neuron.

Neural Network Architecture

Neural networks can be very useful to realize an input-output mapping when the exact relationship between input-output is unknown or very complex to be determined mathematically. Because of its ability to learn complex mapping, recently it has been used for modelling nonlinear economic relationship. By presenting a data set of input-output pair iteratively, a neural network can be trained to determine a set of weights that can approximate the mapping.

Multilayer feedforward network, as shown in Fig. 2, is one of most commonly used neural network architecture. It consists of an input layer, an output layer and one or more intermediate layer called hidden layer. All the nodes at each layer are connected to each node at the upper layer by interconnection strength called weights. x_i's are the inputs, ω's are the weights, y_k's are output produced by the network. All the interconnecting weights between layers are initialized to small random values at the beginning. During training inputs are presented at the input layer and associated target output is presented at the output layer. A training algorithm is used to attain a set of weights that minimizes the difference the target output and actual output produced by the network.

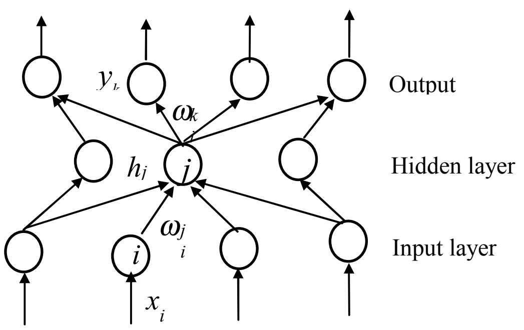


Fig. 2. A multiplayer feerforward ANN structure.

There are many different neural net learning algorithms found in the literature. No study has been reported to analytically determine the generalization performance of each algorithm. In this study we experimented with three different neural network learning algorithms, namely standard Backpropagation (BP), Scaled Conjugate Gradient Algorithm (SCG) and Backpropagation with regularization (BPR) in order to evaluate which algorithm predicts the exchange rate of Australian dollar most accurately. In the following we describe the three algorithms briefly.

Training Algorithms

Standard BP: BP [16] uses steepest gradient descent technique to minimize the sum-of-squared error E over all training data. During training, each desired output d_j is compared with actual output y_j and E is calculated as sum of squared error at the output layer.

The weight ω_j is updated in the n-th training cycle according to the following equation.

$$\Delta \omega_j (n) = -\eta \frac{\partial E}{\partial \omega_j} + \alpha \Delta \omega_j (n-1)$$

The parameters η and α are the learning rate and the momentum factor, respectively. The learning rate parameter controls the step size in each iteration. For a large-scale problem Backpropagtion learns very slowly and its convergence largely depends on choosing suitable values of η and α by the user.

SCGA: In conjugate gradient methods, a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions [5]. In steepest descent search, a new direction is perpendicular to the old direction. This approach to the minimum is a zigzag path and one step can be mostly undone by the next. In CG method, a new search direction spoils as little as possible the minimization achieved by the previous one and the step size is adjusted in each iteration. The general procedure to determine the new search direction is to combine the new steepest descent direction with the previous search direction so that the current and previous search directions are conjugate as governed by the following equations.

$$\boldsymbol{\omega}_{k+1} = \boldsymbol{\omega}_k + \alpha_k \boldsymbol{p}_k ,$$
$$\boldsymbol{p}_k = -E'(\boldsymbol{\omega}) + \alpha_k \boldsymbol{p}_{k+1}$$

where $\boldsymbol{p}_k$ is the weight vector in k-th iteration, $\boldsymbol{p}_k$ and $\boldsymbol{p}_{k+1}$ are the conjugate directions in successive iterations. α_k and β_k are calculated in each iteration. An important drawback of CG algorithm is the requirement of a line search in each iteration which is computationally expensive. Moller introduced the SCG to avoid the time-consuming line search procedure of conventional CG. SCG needs to calculate Hessian matrix which is approximated by

$$E''(\boldsymbol{\omega}_k)\, \boldsymbol{p}_k = \frac{E'(\boldsymbol{\omega}_k + \sigma_k \boldsymbol{p}_k) - E'(\boldsymbol{\omega}_k)}{\sigma_k} + \lambda_k \boldsymbol{p}_k$$

where E' and E'' are the first and second derivative of E. $\boldsymbol{p}_k$, σ_k and λ_k are the search direction, parameter controlling the second derivation approximation and parameter regulating indefiniteness of the Hessian matrix. Considering the machine precision, the value of σ should be as small as possible ($\leq 10^{-4}$). A detailed description of the algorithm can be found in [15].

BPR: A desired neural network model should produce small error on out of sample data, not only on sample data alone. To produce a network with better generalization ability, MacKay [14] proposed a method to constrain the size of network parameters by regularization. Regularization technique forces the network to settle to a set of weights and biases having smaller values. This causes the network response to be smoother and less likely to overfit [5] and capture noise. In regularization technique, the cost function F is defined as

$$F = \gamma E + \frac{1-\gamma}{n}\sum_{j=1}^{n}\omega_j^{2}$$

where E is the sum-squared error and γ (<1.0) is the performance ratio parameter, the magnitude of which dictates the emphasis of the training. A large γ will drive the error E small whereas a small γ will emphasize parameter size reduction at the expense of error and yield smoother network response. Optimum value of γ can be determined using Bayesian regularization in combination with Levenberg-Marquardt algorithm [4]

Neural Network Forecasting Model

Technical and fundamental analyses are the two major financial forecasting methodologies. In recent times, technical analysis has drawn particular academic interest due to the increasing evidence that markets are less efficient than was originally thought [13]. Like many other economic time series model, exchange rate exhibits its own trend, cycle, season and irregularity. In this study, we used time delay moving average as technical data. The advantage of moving average is its tendency to smooth out some of the irregularity that exits between market days [21]. In our model, we used moving average values of past weeks to feed to the neural network to predict the following week's rate. The indicators are MA5, MA10, MA20, MA60, MA120 and X_i, namely, moving average of one week, two weeks, one month, one quarter, half year and last week's closing rate, respectively. The predicted value is X_{i+1}. So the neural network model has 6 inputs for six indicators, one hidden layer and one output unit to predict exchange rate. Historical data are used to train the model. Once trained the model is used for forecasting.

Experimental Results

In this section, we present the data collection procedure and the results of experiments.

<u>Data Collection</u>

The data used in this study is the foreign exchange rate of six different currencies against Australian dollar from January 1991 to July 2002 made available by the Reserve Bank of Australia. We considered exchange rate of US dollar, British Pound, Japanese Yen, Singapore dollar, New Zealand dollar and Swiss Franc. As outlined in an earlier section, 565 weekly data was considered of which first 500 weekly data was used in training and the remaining 65 weekly data for evaluating the model. The plots of historical rates for US Dollar (USD), Great British Pound (GBP), Singapore Dollar (SGD), New Zealand Dollar (NZD) and Swiss Franc (CHF) are shown in Figure 3, and for Japanese Yen (JPY) in Figure 4.

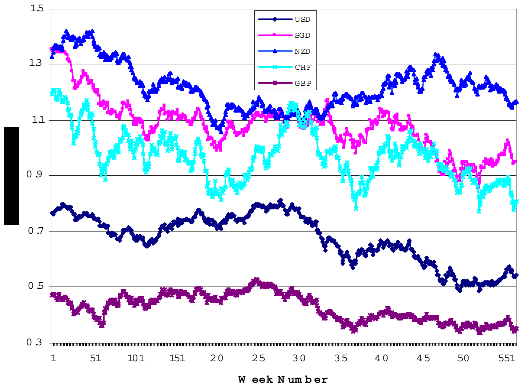


Figure 3. Historical rates for USD, GBP, SGD, NZD and CHF

<u>Performance Metrics</u>

The forecasting performance of the above mentioned models is evaluated against three widely used statistical metric, namely, Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE) and Directional Symmetry (DS). These criteria are defined in Table 1. NMSE and MAE measure the deviation between actual and forecasted value. Smaller values of these metrics indicate higher accuracy in forecasting. DS measures correctness in predicted directions and higher value indicates correctness in trend prediction.

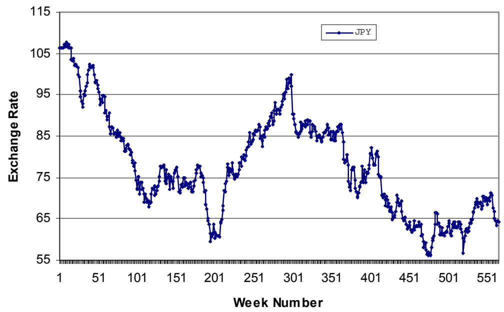


Figure 4. Historical rates Japanese Yen

Table 1: Performance metrics used in the experiment.

$$NMSE = \frac{\sum_k (x_k - \hat{x}_k)^2}{\sum_k (x_k - \bar{x}_k)^2} = \frac{1}{\sigma^2 N} \sum_k (x_k - \hat{x}_k)^2$$

$$MAE = \frac{1}{N} \left| x_k - \hat{x}_k \right|$$

$$DS = \frac{100}{N} \sum_k d_k ,$$

$$d_k = \begin{cases} 1 & \text{if } (x_k - x_{k-1})(\hat{x}_k - \hat{x}_{k-1}) \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Simulation Results

Simulation was performed with different neural networks and ARIMA model. The performance of a neural network depends on a number of factors, e.g., initial weights chosen, different learning parameters used during training (described in section 2.3) and the number of hidden units. For each algorithm, we trained 30 different networks with different initial weights and learning parameters. The number of hidden units was varied between 3~7 and the training was terminated at iteration number between 5000 to 10000. The simulation was done in MATLAB using modules for SBP, SCG and BPR from neural network toolbox. The best results obtained by each algorithm are presented below. The ARIMA model (with parameters setting 1,0,1) was run from Minitab on a IBM PC.

After a model is built, exchange rate is forecasted for each currency over the test data. Prediction performance is measured in terms of MNSE, MAE and DS over 35 weeks and 65 weeks by comparing the forecasted and actual exchange rate. Figures 5(a)~(c) and 6(a)~(c) present the performance metrics graphically over 35 and 65 weeks respectively.

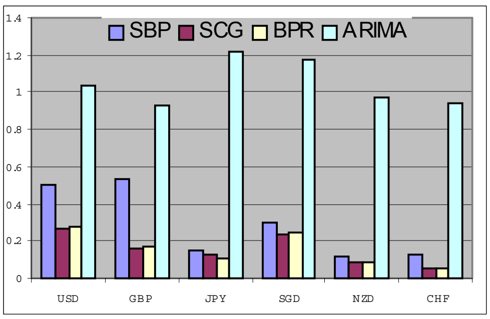


Fig. 5(a) NMSE over 35 weeks

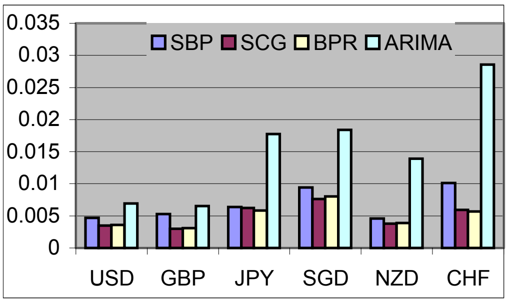


Fig. 5(b) MAE over 35 weeks

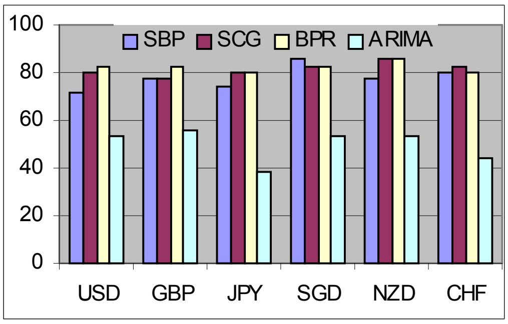


Fig. 5(c) DS over 35 weeks

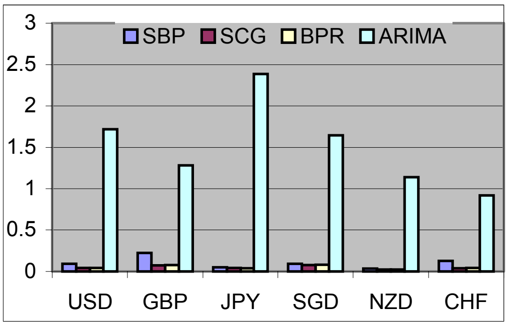


Fig. 6(a) NMSE over 65 weeks

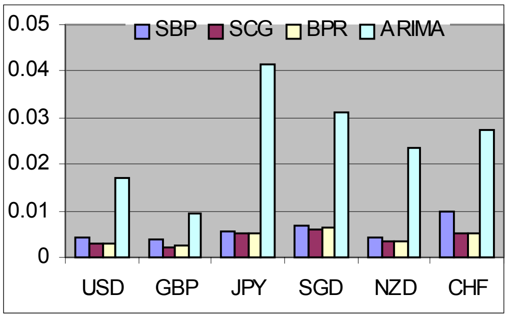


Fig. 6(b) MAE over 65 weeks

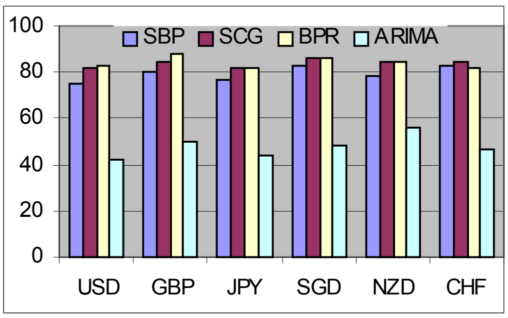


Fig. 6(c) DS over 65 weeks

From Figures 5, 6 and 8, it is clear that the quality of forecast with ARIMA model deteriorates with the increase of the number of periods for the forecasting (/testing) phase. In other words, ARIMA could be suitable for shorter term forecasting than longer term. However, the results show that neural network models produce better performance than the conventional ARIMA model for both shorter and longer term forecasting which means ANN is more suitable for financial modelling.

As we can see in Figure 5 and 6, both SCG and BPR forecasts are better than SBP in terms of all metrics. In our experiment this is consistently observed in all other currencies also. In terms of the most commonly used criteria, i.e., NMSE and MAE, SCG perform better than BPR in all currencies except Japanese Yen. In terms indicator DS, SCG yields slightly better performance in case of Swiss France, BPR slightly better in US Dollar and British Pound, both perform equally in case of Japanese Yen, Singapore and New Zealand Dollar. Although we reported only the best predictions in this paper, a sample outputs based on error indicator NMSE for the best and worst predictions produced by SBP for British-Pound are shown in Figure 7. The actual and forecasted time series of six currency rates using ARIMA, and SCG model are shown in Figures 8 and 9 respectively. From Figures 5 and 6, one can easily imagine the superiority of ANN based models over ARIMA.

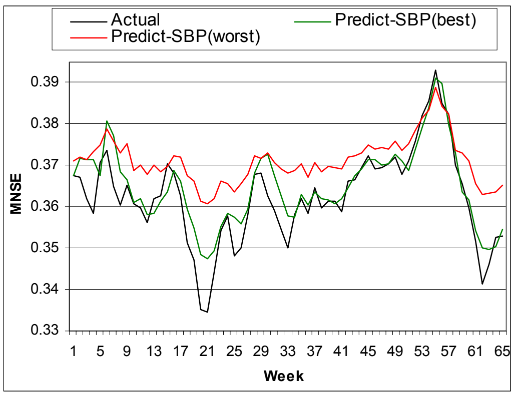


Figure 7. Sample worst and best predictions

Conclusion

In this study, we investigated three ANN based forecasting models to predict six foreign currencies against Australian dollar using historical data and moving average technical indicators, and a comparison was made with traditional ARIMA model. All the ANN based models outperformed ARIMA model measured on three different performance metrics. Results demonstrate that ANN based model can forecast the Forex rates closely. Among the three ANN based models, SCG based model yields best results measured on two popular metrics and shows results comparable to BPR based models when measured on the indicator DS.

References

[1] G. E. P. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*, Holden-Day, San Francosco, CA.

[2] L. Cao and F. Tay, “Financial Forecasting Using Support Vector Machines,” *Neural Comput & Applic*, vol. 10, pp.184-192, 2001.

[3] G. Deboeck, *Trading on the Edge: Neural, Genetic and Fuzzy Systems for Chaotic Financial Markets*, New York Wiley, 1994.

[4] F. D. Foresee and M.T. Hagan, “Gauss-Newton approximation to Bayesian regularization,” *Proc. IJCNN 1997*, pp. 1930-1935.

[5] M.T. Hagan, H.B. Demuth and M.H. Beale, *Neural Network Design*, PWS Publishing, Boston, MA, 1996.

[6] J. Hanke and A. Reitsch, Business Forecasting, Allyn and Bacon, Inc., Boston, 1986.

[7] T. Hill, M. O’Connor and W. Remus, “Neural Network Models for Time Series Forecasts,” *Management Science*, vol. 42, pp 1082-1092, 1996.

[8] H. B. Hwarng and H. T. Ang, “A Simple Neural Network for ARMA(*p,q*) Time Series,” *OMEGA: Int. Journal of Management Science*, vol. 29, pp 319-333, 2002.

[9] J. Jarrett, Business Forecasting Methods, Basil Blackwell, Oxford, 1991.

[10] W. C. Jhee and J. K. Lee, “Performance of Neural Networks in Managerial Forecasting,” *Intelligent Systems in Accounting, Finance and Management*, vol. 2, pp 55-71, 1993.

[11] I. Kaastra and M. Boyd, “Designing a Neural Network for Forecasting Financial and Economic Time-Series,” *Neurocomputing*, vol. 10, pp215-236, 1996.

[12] B. D. Klein and D. F. Rossin, “Data Quality in Neural Network Models: Effect of Error Rate and Magnitude of Error on Predictive Accuracy,” *OMEGA: Int. Journal of Management Science*, vol. 27, pp 569-582, 1999.

[13] B. LeBaron, “Technical trading rule profitability and foreign exchange intervention,” *Journal of Int. Economics*, vol. 49, pp. 124-143, 1999.

[14] D.J.C. Mackay, “Bayesian interpolation,” *Neural Computation*, vol. 4, pp. 415-447, 1992.

[15] A.F. Moller, “A scaled conjugate gradient algorithm for fast supervised learning,” *Neural Networks*, vol. 6, pp.525-533, 1993.

[16] D.E Rumelhart, J.L. McClelland and the PDP research group, *Parallel Distributed Processing*, vol. 1, MIT Press, 1986.

[17] Z. Tang and P. A. Fishwich, “Back-Propagation Neural Nets as Models for Time Series Forecasting,” *ORSA Journal on Computing*, vol. 5(4), pp 374-385, 1993.

[18] J. H.Wang and J. Y. Leu, “Stock Market Trend Prediction Using ARIMA-based Neural Networks,” *Proc. of IEEE Int. Conf. on Neural Networks*, vol. 4, pp. 2160-2165, 1996.

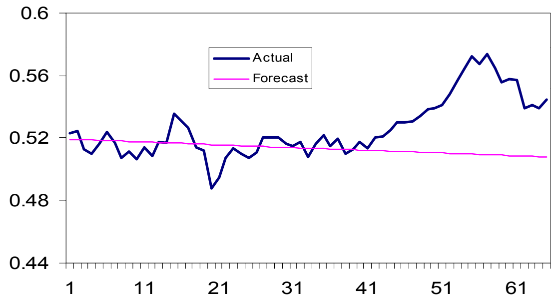
[19] S. Wang (1998) An Insight into the Standard Back-Propagation Neural Network Model for Regression Analysis, *OMEGA: Int. Journal of Management Science*, 26, pp133-140.

[20]J. Yao, Y. Li and C. L. Tan, “Option Price Forecasting Using Neural Networks,” *OMEGA: Int. Journal of Management Science*, vol. 28, pp 455-466, 2000.

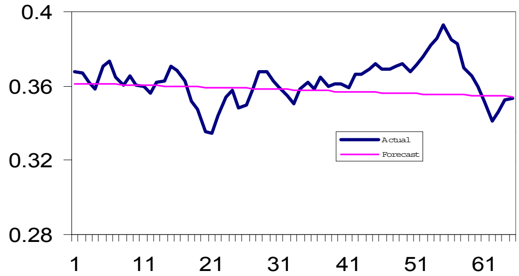
[21] J. Yao and C.L. Tan, “A case study on using neural networks to perform technical forecasting of forex,” *Neurocomputing*, vol. 34, pp. 79-98, 2000.

[22] S. Yaser and A. Atiya, “Introduction to Financial Forecasting,“ *Applied Intelligence*, vol. 6, pp 205-213, 1996.

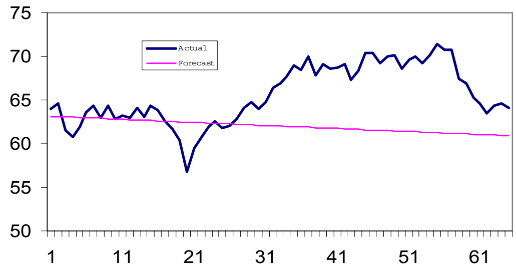
[23] G. Zhang and M. Y. Hu, “Neural Network Forecasting of the British Pound/US Dollar Exchange Rate,” *OMEGA: Int. Journal of Management Science*, 26, pp 495-506, 1998.



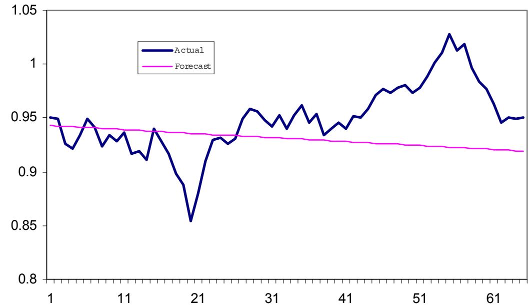
(a) USD/AUD



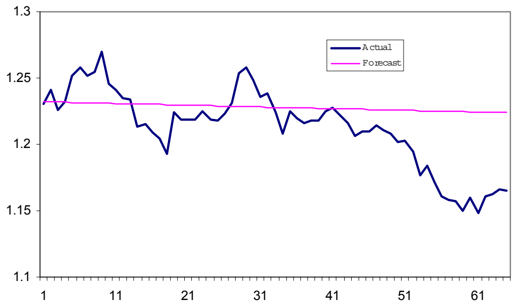
(b) GBP/AUD



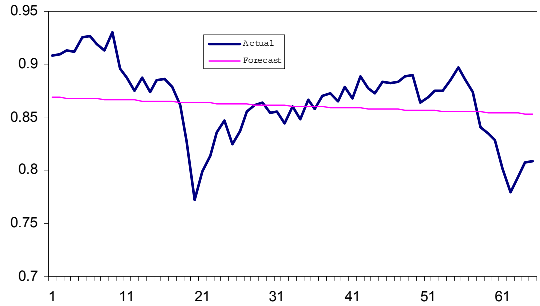
(c) JPY/AUD



(d) SGD/AUD



(e) NZD/AUD



(f) CHF/AUD

Figure 8. Forecasting of different currencies by ARIMA model over 65 weeks.

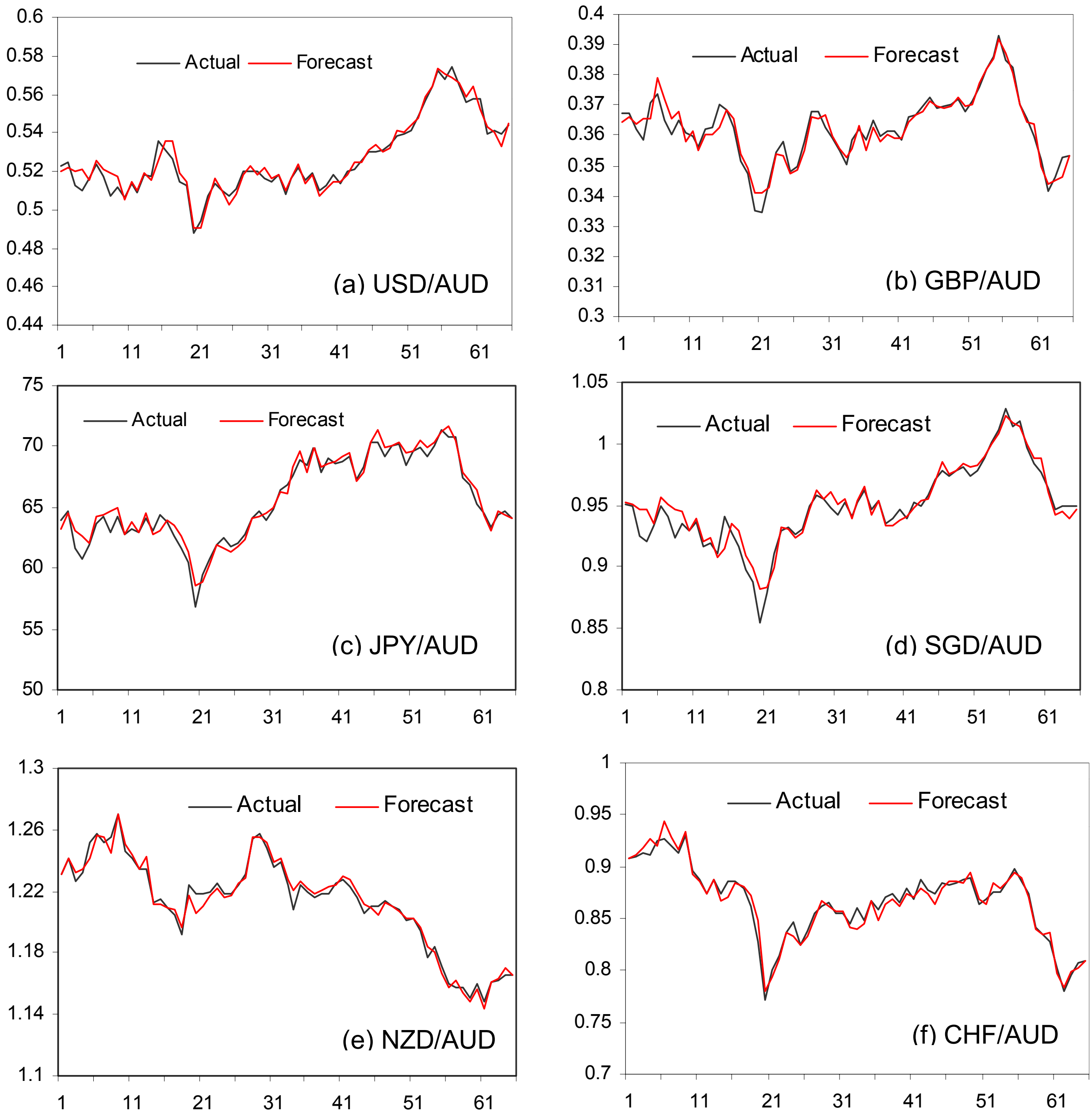


Figure 9. Forecasting of different currencies by SCG based neural network model over 65 weeks.