Chapter VI

Summary, Implications and Scope for Further Research

A religious sect is predicting that the world will end at 10 P.M tonight. For more details, watch the news at eleven.

Forecasting exchange rate and stock returns is rather a hazardous operation as these variables are notorious for their unpredictability. These variables are often characterized by high volatility, complexity, and noise. It is widely agreed that both exchange rate and stock returns are conditionally heteroskedastic, unconditionally leptokurtic, and nonlinear without having a specific nonlinear pattern. Finally, it is believed by some researchers that both foreign exchange rate and stock markets are weakly efficient i.e. they follow a random walk. As a result, linear and parametric nonlinear forecasting methods find it difficult to trace the movements of exchange rate and stock returns.

In this thesis, our concern has been to use a nonparametric and nonlinear model called artificial neural network to model and forecast the exchange rate and stock returns. We also have compared the performance of neural network with two benchmark forecasting models, linear autoregressive and random walk in the prediction of exchange rate and stock returns. After noting, in chapter I, the peculiarities of exchange rate and stock returns, we go on to discuss the artificial neural network in detail in chapter II. We also spell out the linear autoregressive and random walk model in brief in this chapter. This is followed up by a select review of the literature on the application of neural network to forecast exchange rate and stock returns. The general picture obtained from the review suggests that the neural network technique is superior to other conventional forecasting techniques in exchange rate and stock returns prediction. With the motivation provided by these findings, we take up the task of applying neural network to the one-step-ahead prediction of exchange rate and stock returns, starting from chapter III. We have used eight performance
measures, root mean square error, mean absolute error, mean absolute percentage error, median absolute deviation, Pearson correlation coefficient, goodness of fit, direction accuracy and sign predictions for the comparison.

We first look at both daily and weekly exchange rate returns prediction in chapter III. In case of daily exchange rate returns, we find that neural network gives better in-sample prediction than both linear autoregressive and random walk model. However, in out-of-sample prediction, while neural network is better than random walk, the results are mixed with respect to linear autoregressive model. There is no clear winner between the two. These findings appear consistent with those of Kuan and Liu (1995). Linear autoregressive model is found to outperform random walk model in both in-sample and out-of-sample forecasting of daily exchange rate returns.

We also look at forecast horizon effects on the performances of neural network, linear autoregressive and random walk models under 1 month, 3 months, 6 months and 12 months forecast horizon using root mean square error and sign prediction as the performance measures. It is found that neural network performs better than random walk models under all four forecast horizons in terms of both measures in both in-sample and out-of-sample forecasting of daily exchange rate returns. As far as linear autoregressive model is concerned, neural network outshines it in in-sample prediction in all forecast horizons with respect to both measures. But linear autoregressive model outperforms neural network in out-of-sample prediction in all horizons with respect to root mean square error. However, neural network outperforms linear autoregressive model with respect to sign prediction. It is also found that as length of forecast horizon increases neural network's performance in out-of-sample forecasting in terms of RMSE increases and in terms sign prediction it decreases.

As far as forecasting of weekly exchange rate returns is concerned, our findings suggest that neural network has superior in-sample forecast than linear autoregressive and random walk models. As far as the out-of-sample forecasting is concerned, neural network outperforms random walk by all evaluation criteria, except
for Pearson correlation coefficient. Neural network is also found to beat linear autoregressive model by four out of six evaluation criteria in out-of-sample forecasting. We find that neural network gives superior in-sample forecasting in terms of RMSE as compared to linear autoregressive and random walk models under short as well as long forecast horizons. As far as the in-sample sign prediction is concerned neural network outperforms random walk in all forecast horizons and outshines linear autoregressive model in long forecast horizon. Here, contrary to results with daily exchange rate return, the findings suggest that neural network's out-of-sample performance, in terms of RMSE, decreases as the length of horizon increases but increases as the length of forecast horizon increases in terms of sign prediction. It is also found that neural network and linear autoregressive models are outperformed by random walk model in short forecast horizon in out-of-sample forecasting of weekly exchange rate returns. But as the length of forecast horizon increases, they start outperforming random walk model. However, the sign predictions of neural network and linear autoregressive models are equal in short forecast horizon and mixed in long forecast horizon.

We take up the task of predicting daily and weekly stock returns using the three studied alternative models in chapter IV. The findings suggest that neural network gives better in-sample forecasting of daily stock returns than linear autoregressive and random walk models by all performance measures. Linear autoregressive model also outperforms random walk model by all performance measures in in-sample forecasting. Neural network is found to have better generalizing capability, doing better in out-of-sample forecasting of daily stock returns than both linear autoregressive and random walk models. Linear autoregressive model outperform random walk by most of the performance measures.

As far as the effects of horizon are concerned the results convey that irrespective of forecast horizons, neural network performs better than linear autoregressive and random walk models in terms of RMSE and sign predictions in in-sample forecasting of daily stock returns. The neural network's performance improves in terms of RMSE and sign predictions as forecast horizon extends. We find that the
out-of-sample performance of neural network in terms of RMSE gets better as the length of forecast horizon increases. However, network's out-of-sample performance becomes worse in terms of sign prediction as the forecast horizon increases. In addition, it is also found that neural network gives better in-sample and out-of-sample predictions in terms of RMSE and sign prediction than linear autoregressive and random walk models under all forecast horizons.

In weekly forecasting of stock returns, neural network has better in-sample and out-of-sample predictions than linear autoregressive and random walk models. The results show that the neural network's in-sample performance gets worse as the forecast horizons increase in terms of both RMSE and sign predictions. Similarly, neural network gives better out-of-sample sign prediction in the short run than in the long run. On the other hand, it is found that its out-of-sample performance improves in terms of RMSE as the length of forecast horizon increases. The findings also suggest that neural network gives better out-of-sample forecasting of weekly stock returns, in terms of RMSE, than random walk in longer horizons than shorter horizons. However, random walk is found to outperform neural network in all forecast horizons when sign prediction is considered as performance measure. Linear autoregressive performs better than neural network in out-of-sample forecasting in all forecasting horizons in terms of RMSE. On the other hand, neural network outperforms linear autoregressive model in short forecast horizon than long forecast horizon in terms of sign prediction.

There are two other points worth noting. The forecasting encompassing test, which tests for statistical significance of in-sample and out-of-sample results of neural network, linear autoregressive and random walk models was carried out for daily and weekly exchange rate and stock returns. The test shows that no model encompasses the other in both daily and weekly out-of-sample forecasting of exchange rate and stock returns. In addition to these findings, it is also found that neural network's performance is more sensitive to the number of input nodes than the number of hidden nodes both in case of daily and weekly exchange rate and stock returns prediction.
This is consistent with the findings of Tang and Fishwick (1993), Zhang and Hu (1998) and Hu et al (1999).

One problem in neural network training is overfitting which in fact leads to poor out-of-sample forecasting. We address this problem in chapter V. In this chapter, we have tried to improve the out-of-sample performance of neural network in the forecasting of weekly exchange rate and stock returns by using Bayesian regularization and early stopping technique. Results show that both techniques improve out-of-sample performance of neural network, but the improvement is more in the case of weekly stock returns than in weekly exchange rate returns. Also, early stopping technique results in greater improvement in out-of-sample forecasting than Bayesian regularization. In addition to these findings, we also find that network with Bayesian regularization and early stopping technique outperform linear autoregressive and random walk models in the out-of-sample forecasting of weekly exchange rate and stock returns.

**Implications of the Study**

In a nutshell, this study has the following key implications. First, neural network is found superior to linear autoregressive and random walk models in forecasting exchange rate and stock returns. Further, linear autoregressive model is found to do better than random walk in most cases. From this, we can draw the inference that financial markets i.e. foreign exchange and stock markets do not follow the random walk. Thus, the weak form of efficient market hypothesis stands refuted. This opens up the possibility of extracting information from prices to explain the future behaviour of an asset. Second, superiority of neural network model in forecasting over linear autoregressive and random walk models is because of its flexibility to account for potentially complex nonlinear relationships not easily captured by traditional forecasting methods. Third, the findings suggest that in most cases neural network gives better out-of-sample short-term forecasts than both linear autoregressive and random walk models. This should clearly make neural network the preferred forecasting tool for investors and traders in the foreign exchange and stock markets.
because their buy-and-sell decisions are primarily based on short-term forecasts. Finally, we find neural network gives a better performance in the stock market than in the foreign exchange market. Thus, neural network can be more profitably used in the stock market than the foreign exchange market.

**Limitations of the Study and Scope for Further Research**

This work must be treated only as a starting point. The results are encouraging, but they provide only limited evidence supporting the usefulness of neural network models. First, we have limited our study to only the Indian rupee/US dollar exchange rate returns on the one hand, and BSE 30 stock returns on the other. Needless to say, we must exercise caution in generalizing to other exchange rate and stock returns. Second, the same can be said regarding the performance measures used. We have restricted our attention to only eight performance measures. The findings may change if other performance measures are used. Third, we have also considered only one-step-ahead forecasting. Multi-step-ahead forecasting could yield different results. Fourth, we have not used any other exogenous variable and have used only past returns as inputs or explanatory variables for neural network and linear autoregressive model. Finally, we have been limited by the software we have used. We have had to use fairly primitive software i.e. Matlab, since we did not have access to more specialized software on neural network. We hope to bring all this into our further research.

The other fruitful areas for further research are the following. First, is to combine methodology of linear models and neural networks. It is suspected that most time series contain a linear trend and a nonlinear component. Hence, a combination approach in which linear model captures linear patterns and neural network captures nonlinear patterns is expected to produce even better results than either linear or neural network model used singly. Second, in this thesis we have optimized the network architecture through systematic and rigorous experimentation. However, recently a new optimizing technique called genetic algorithm has come into increasing use to find the optimum network architecture. This we hope to do in our
further research. Third, the robustness of neural networks to the changing structures, or turning points typically associated with exchange rates and stock prices can be investigated in further research by using multiple training and test samples systematically chosen from the original series. Fourth and finally, we have only used past returns as inputs to the network. However, technical trading rules can be profitably used in the set of inputs to the network to make more accurate forecast of exchange rate and stock returns.