Neural Networks to Forecast Tourist Arrivals to Japan from the USA

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ABSTRACT: This paper uses neural networks to forecast tourist arrivals to Japan from the USA. Univariate forecasts are made for total tourism to Japan and for the two disaggregated categories of tourist and business travel. Multivariate forecasts are made using the same data, combined with national indicators of the tourist's country of origin. The national indicators used are income, imports and exports. The forecasting models are evaluated for accuracy by comparing actual data with the forecast during a test period.

Keywords: Neural Networks, Leading Indicators, Tourism Forecasting.

Introduction

Recent publications on tourism demand forecasting have been mainly based on traditional time series techniques such as the autoregressive and moving average methods and causal techniques such as the regression methods. More recently however, artificial neural networks (ANNs) have been used in quantitative forecasting but not much work has yet been published on the use of this technique in forecasting tourism demand. In areas where ANNs have been used as a forecasting tool, they have been shown to be only marginally superior to traditional methods. This paper is a study on the use of neural networks on Japanese data to forecast tourism demand.

The reason for selecting Japan as the subject country of this study is three-fold. First, Japan has well documented and reliable tourist data. Second, Japan is a significant travel destination both for business and pleasure. Third, no recent work has been published in the literature on tourism demand forecasts to Japan that use ANNs.

To improve the forecasting power of the method, this study will incorporate multivariate leading national indicator series together with tourism demand data in the ANN models. The indicators used would be personal income, imports and exports. The leading nature of these variables, as indicated in previous work (Turner, Kulendran and Fernando, 1997) would then improve the forecasting power of the ANN technique.

Time series data of total tourist arrivals to Japan and arrivals disaggregated by travel type will be used to develop forecasting models. This study will develop forecasting models for tourist arrivals to Japan from the USA. Separate models will be developed for the two travel types: tourist and business travel.

Monthly arrivals time series data for the period January 1978 to September 1998 were extracted from the Japan National Tourist Organisation publications. Model development is based on the data from January 1980 to September 1995. The data from October 1995 to September 1998 are used to test model performance. The national indicators, personal income, imports and exports were obtained from OECD data in the EconData database.

This study will test the forecasting power of the techniques used by applying the models developed, over a test period where the forecast is compared with actual demand. This comparison is made by measuring the error between the actual and the predicted during the test period, using root mean squared error (RMSE) and the mean absolute percentage error (MAPE).

Artificial Neural Networks

Artificial Neural Networks (Zhang, et al., 1998) have been used in the past, as a forecasting technique in many fields of research, and has its own merits and shortcomings. However, the performance of ANNs on time series forecasting has only been marginally better (Balkin, 1997) than that of traditional statistical methods. In this paper the performance of ANNs as a forecasting tool is further tested by developing models for time series tourism forecasting. Further, to improve the forecasting performance of the models, relevant leading economic indicator series are incorporated in the model. ANNs will be used to define a model for time series tourism and leading indicator data, and this model will then be used to make predictions on tourist arrivals and departures in future periods. The study uses national indicators as multivariate time series to define ANN forecasting models.

One type of ANN is the Multi-layer Perceptrons (MLP). It has several levels of nodes, each node being called a neuron and each level being referred to as a layer. A typical MLP would have an input layer, an output layer and a hidden layer in between the input and the output layers.

Neurons receive a weighted sum of inputs from connected units. The output could be a 1 or a 0 depending on whether the weighted sum reached a threshold or it could be a hyperbolic or other non-linear function of the weighted sum. Warner 1996, expresses the output y_i for neuron i as follows for a threshold of μ_i, where a_{ij} is the weight from neuron j to neuron i and x_i is the output for neuron j.

$$\textbf{netinput} = (\Sigma\, a_{ij}\, x_i - \mu_i) \quad \text{where } y_i = 1 \text{ if } \textbf{netnintput} >= 0 \quad \text{and } y_i = 0 \text{ otherwise}$$

Klimasauskas 1994, presents a hyperbolic function for neurons as follows:

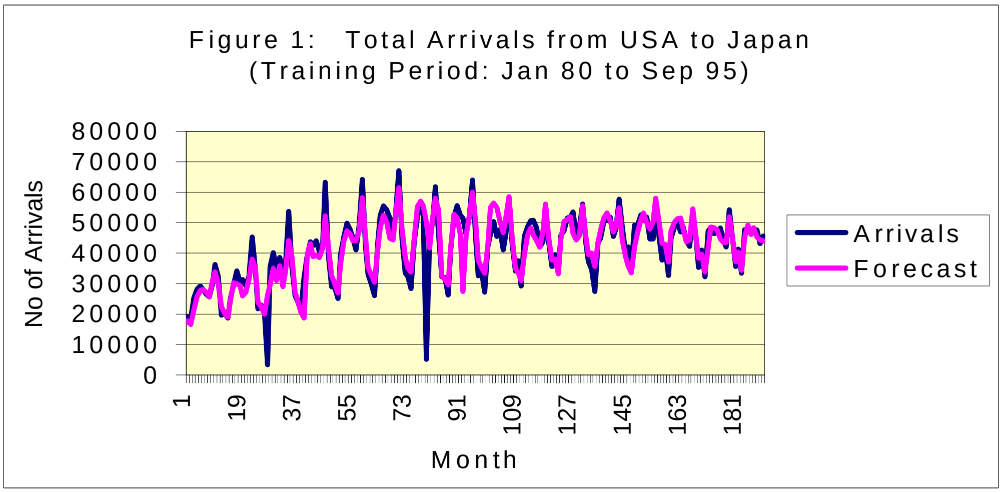
$$\begin{aligned}
Y &= \tanh\ (b_0 + b_1 p_1 + b_2 p_2 + b_3 p_3) \\
p_1 &= \tanh\ (a_{10} + a_{11} x_1 + a_{12} x_2) \\
p_2 &= \tanh\ (a_{20} + a_{21} x_1 + a_{22} x_2) \\
p_3 &= \tanh\ (a_{30} + a_{31} x_1 + a_{32} x_2)
\end{aligned}$$

Most authors use only one hidden layer, (Hornik et al., 1989) and a large number of hidden nodes. Some use two hidden layers (Sirinivasan et al., 1994) to achieve a higher efficiency in the training process but this requires additional processing power.
The concept of ANNs dates back to 1964. However, due to the non-availability of a training algorithm at that time for multi-layer networks, ANNs did not develop as a forecasting tool (Rumelhart, 1986). By 1986 the back-propagation method had been developed giving ANNs a boost as a useful forecasting technique. By 1988 ANNs with back-propagation out performed regression and Box-Jenkins methods, (Werbos, 1988). A further advantage of ANNs is that they do not limit the model to linearity. Lapedes and Farber (1987) concluded that ANNs can be used in forecasting non-linear time series. The traditional Box-Jenkins method assumes that the time series modeled by it are generated from linear processes,

(Box-Jenkins, 1976; Pankratz, 1983; Zhang 1998). The importance of non-linearity is recognised in the ARCH model, (Engle 1982) but here too a specific non-linear mathematical function has to be assumed at the outset without knowing whether it fits the data. ANNs on the other hand select a non-linear form by allowing the data to pass through its neurons, back-propagating until through a learning process a non-linear function is selected, that fits the data. The superiority of ANNs is therefore noteworthy as they “have more general and flexible functional forms than traditional statistical methods” (Zhang et al., 1998)
For time series forecasting the inputs are the past observations of the data series and the output is the future value. In this study the connectionist method presented by Kasabov (1996) is used.

Comparison of actual arrivals and forecasts

ANNs with two hidden layers using hyperbolic tangents and sigmoids as transfer functions are used to forecast arrivals from the USA. The actual data used is made trend free by subtracting a 12 month moving average. Figure 1 shows the actual and one step ahead forecast values of total tourist arrivals during the period January 1980 to September 1995 when the network is being trained. . Figure 2 shows the actual and one step ahead forecast values of total tourist arrivals during the period October 1995 to September 1998 which is the test period.



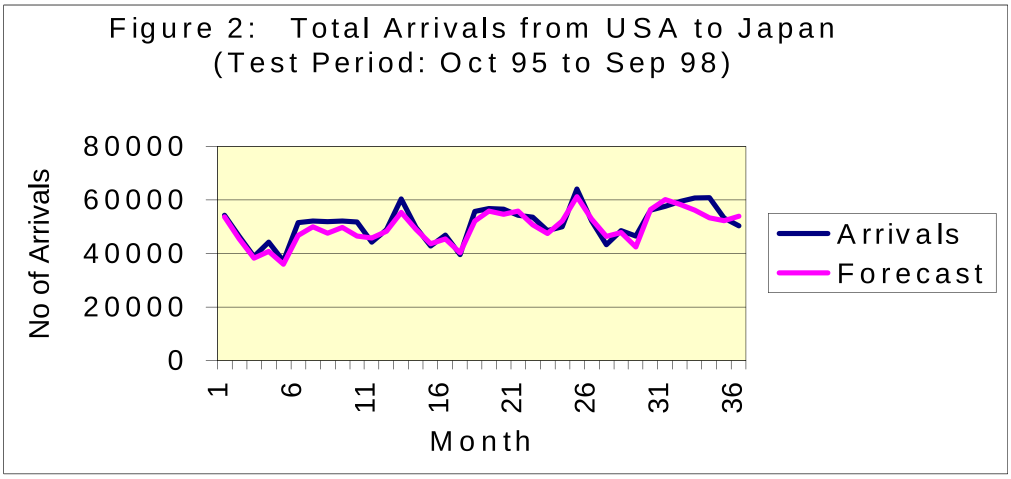
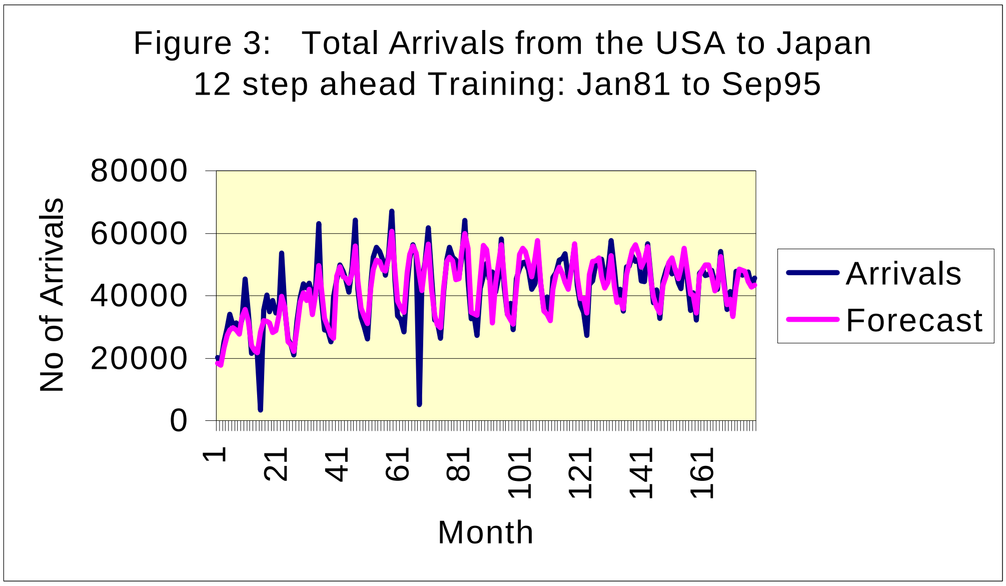


Figure 3 shows the actual and 12 steps ahead forecast values of total tourist arrivals during the period January 1981 to September 1995 when the network is being trained. . Figure 4 shows the actual and 12 steps ahead forecast values of total tourist arrivals during the period October 1995 to September 1998 which is the test period.



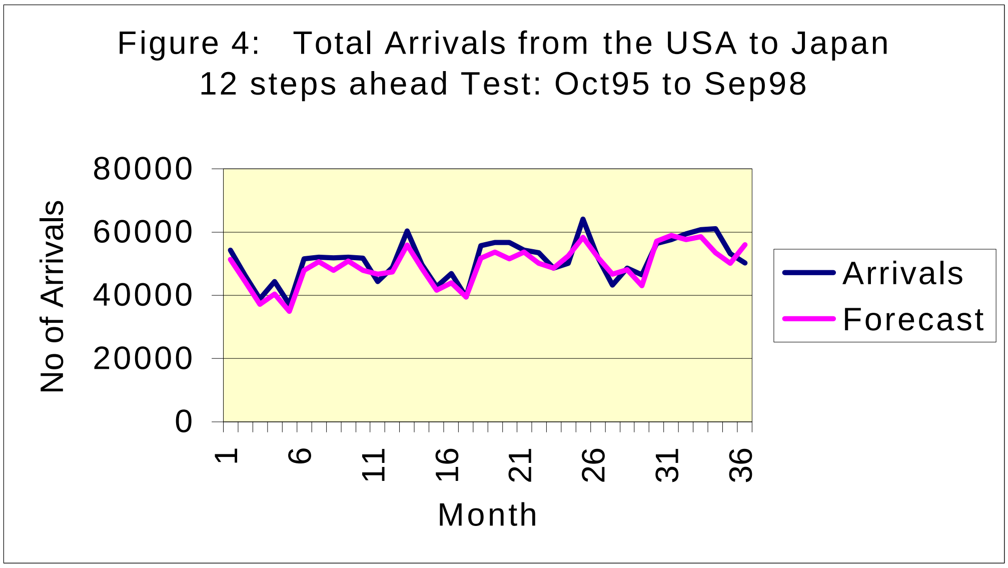
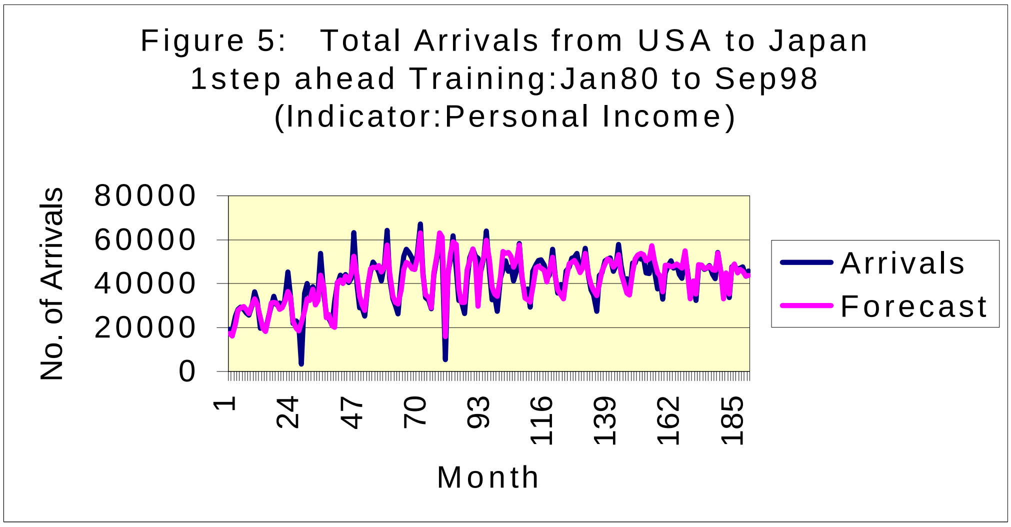


Figure 5 shows the actual and one step ahead forecast values of total tourist arrivals during the period January 1980 to September 1995 for a multivariate forecast where personal income is used as an indicator when the network is being trained. Figure 6 shows the actual and one step ahead forecast values of total tourist arrivals during the period October 1995 to September 1998 which is the test period.



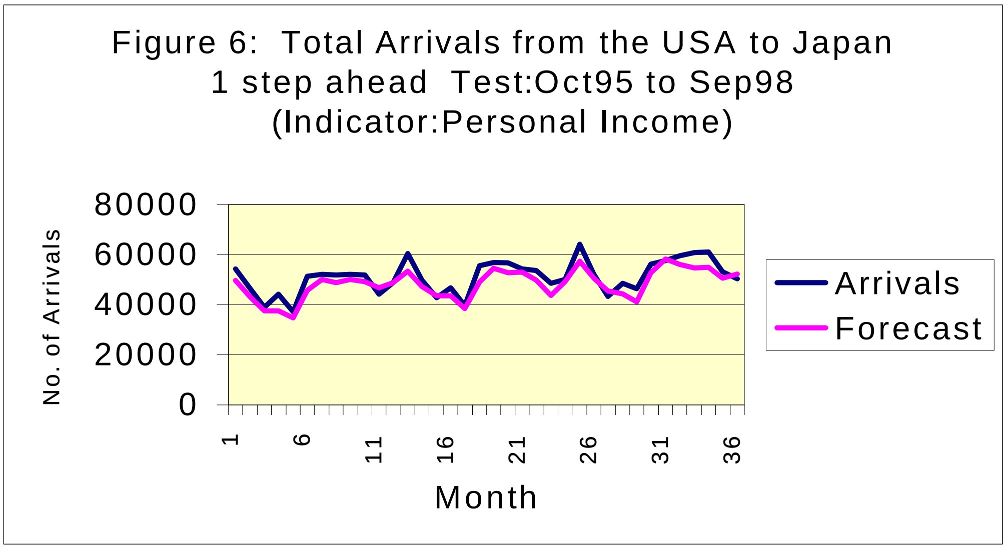
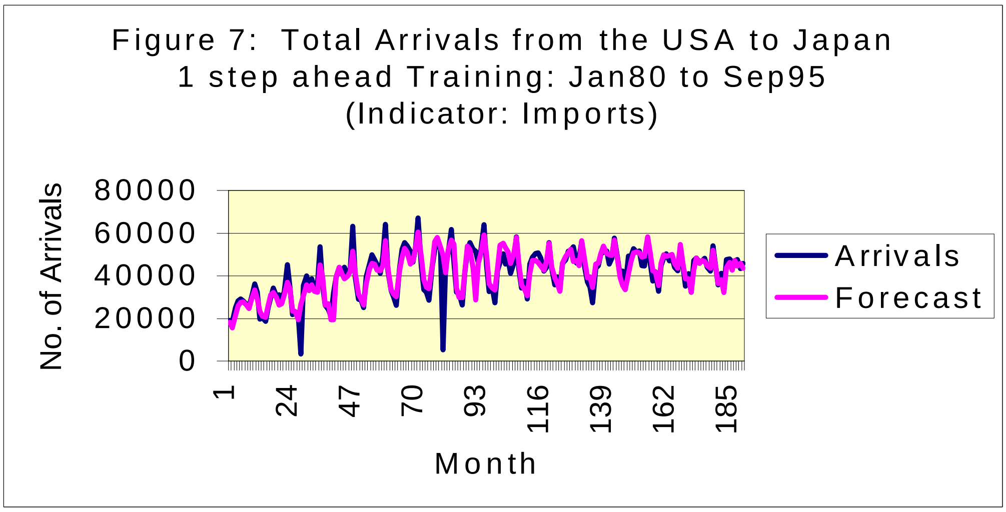


Figure 7 shows the actual and one step ahead forecast values of total tourist arrivals during the period January 1980 to September 1995 for a multivariate forecast where imports is used as an indicator when the network is being trained. Figure 8 shows the actual and one step ahead forecast values of total tourist arrivals during the period October 1995 to September 1998 which is the test period.



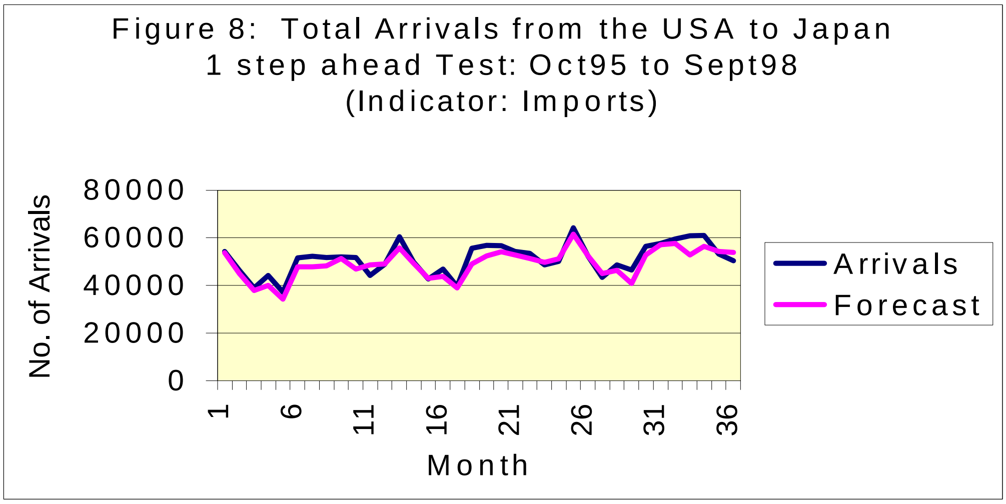
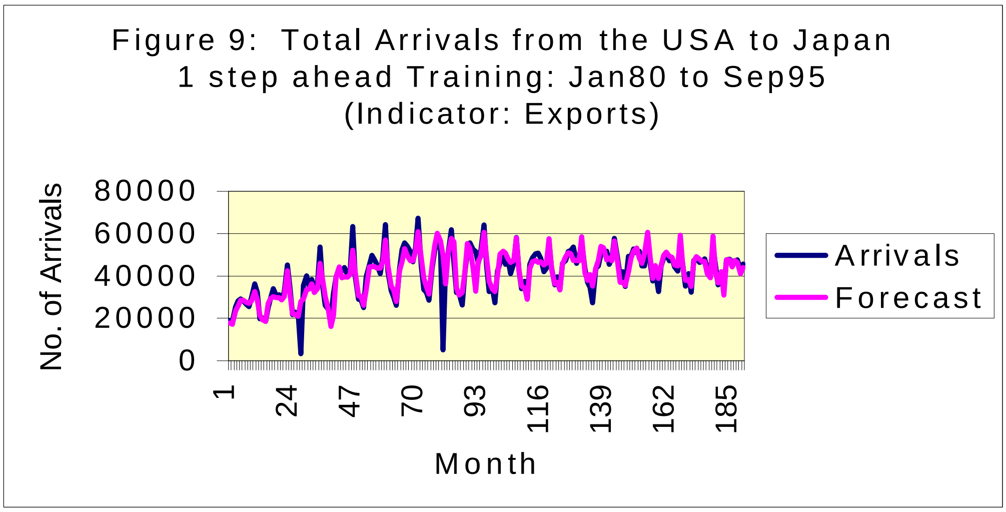


Figure 9 shows the actual and one step ahead forecast values of total tourist arrivals during the period January 1980 to September 1995 for a multivariate forecast where exports is used as an indicator when the network is being trained. Figure 10 shows the actual and one step ahead forecast values of total tourist arrivals during the period October 1995 to September 1998 which is the test period.



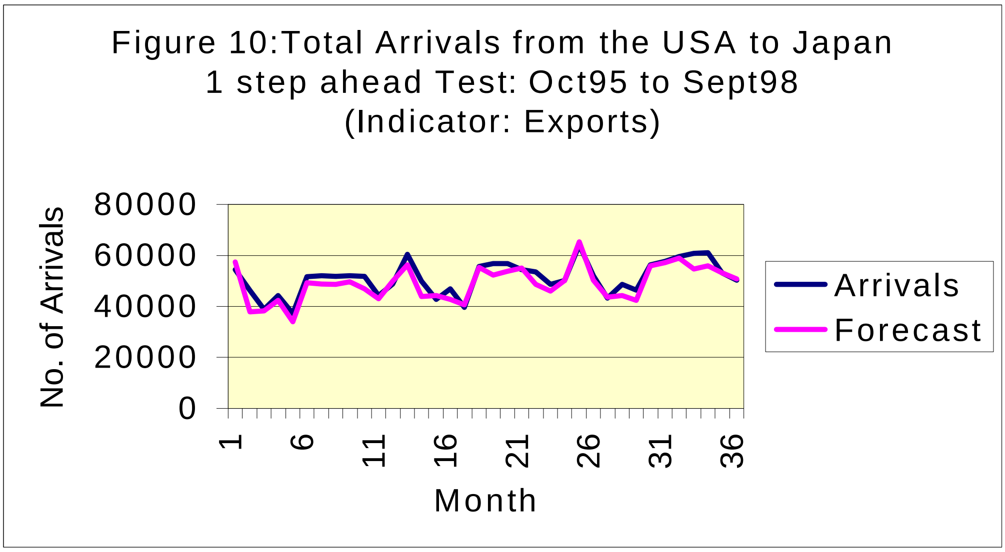
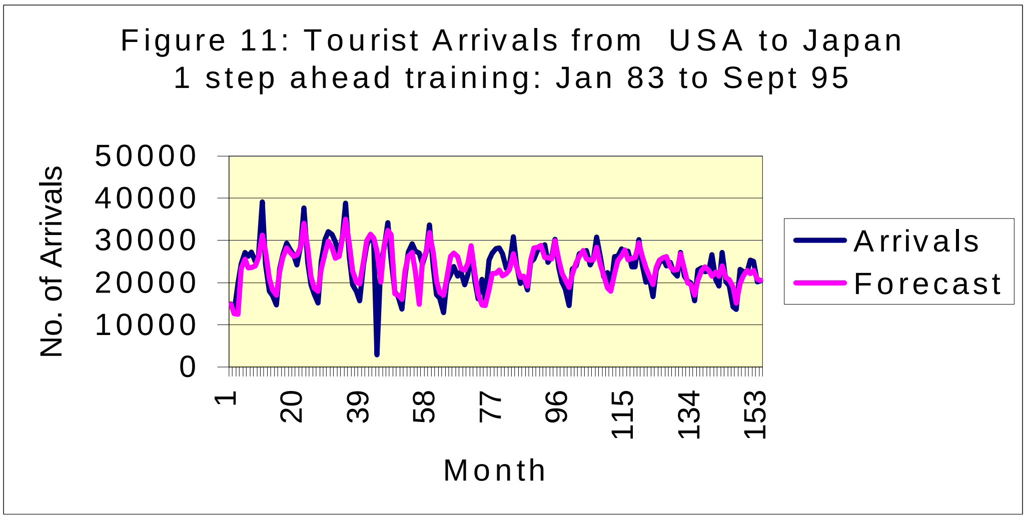


Figure 11 shows the actual and one step ahead forecast values of disaggregated arrivals of the tourist category during the period January 1983 to September 1995 when the network is being trained. Figure 12 shows the actual and one step ahead forecast values of the disaggrgated tourist arrivals during the period October 1995 to September 1998 which is the test period.



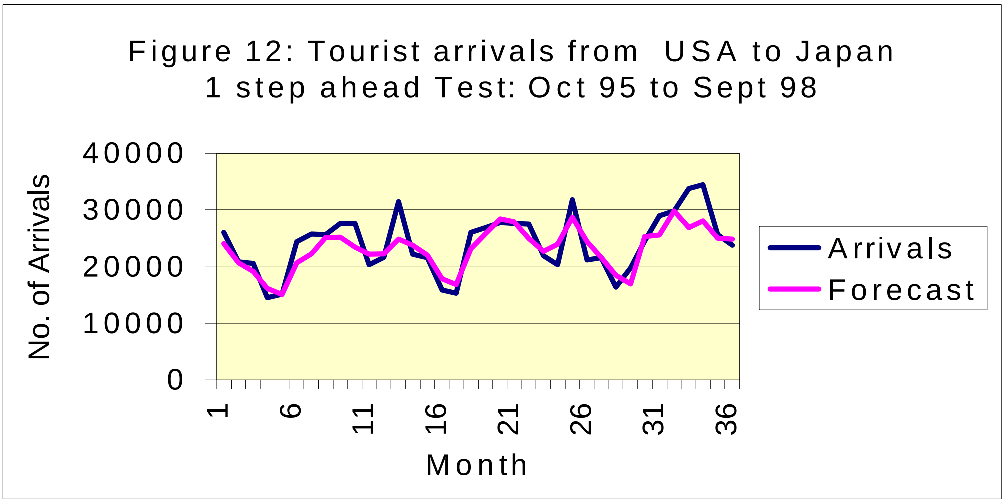
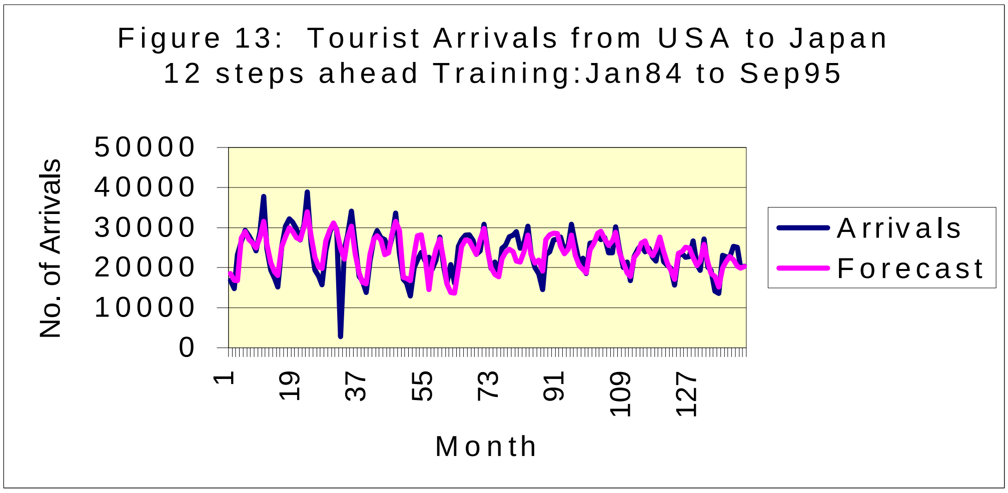


Figure 13 shows the actual and 12 steps ahead forecast values of disaggregated arrivals of the tourist category during the period January 1984 to September 1995 when the network is being trained. Figure 14 shows the actual and 12 steps ahead forecast values of the disaggrgated tourist arrivals during the period October 1995 to September 1998 which is the test period.



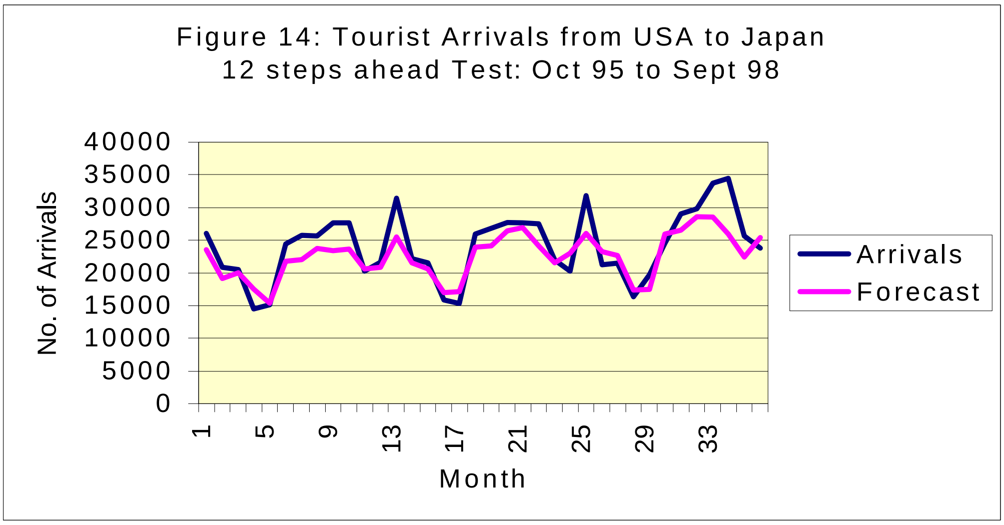
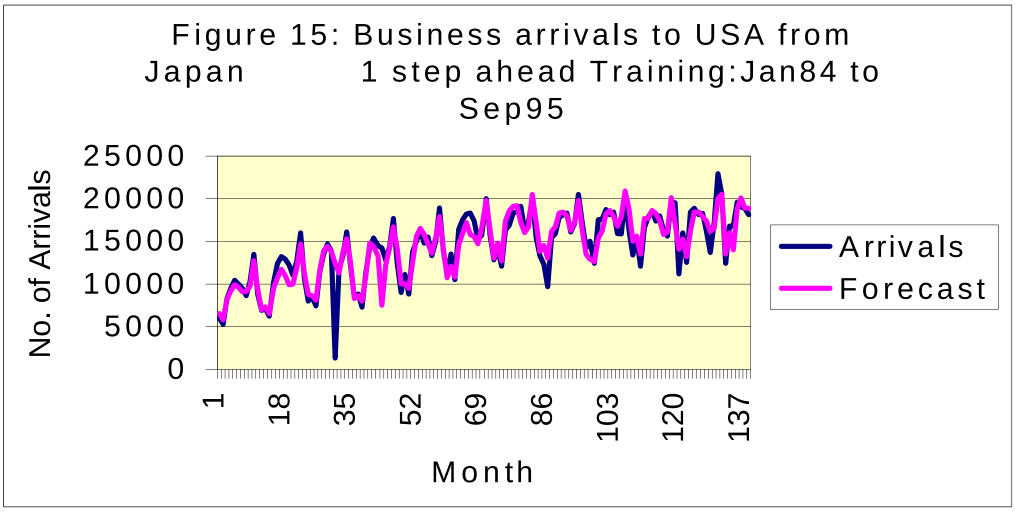


Figure 15 shows the actual and one step ahead forecast values of disaggregated arrivals of the business category during the period January 1984 to September 1995 when the network is being trained. Figure 16 shows the actual and one step ahead forecast values of the disaggrgated business arrivals during the period October 1995 to September 1998 which is the test period.



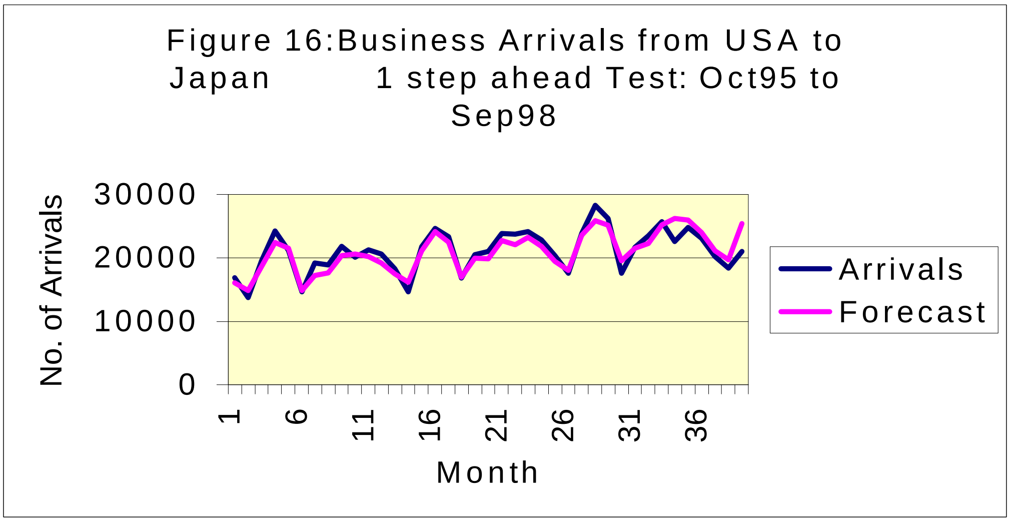
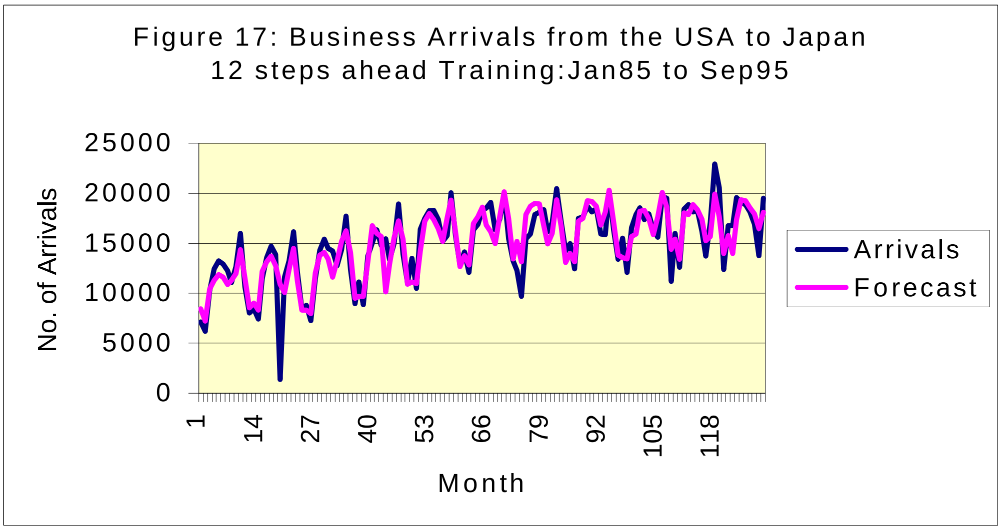


Figure 17 shows the actual and 12 steps ahead forecast values of disaggregated arrivals of the business category during the period January 1985 to September 1995 when the network is being trained. Figure 18 shows the actual and 12 steps ahead forecast values of the disaggrgated business arrivals during the period October 1995 to September 1998 which is the test period.



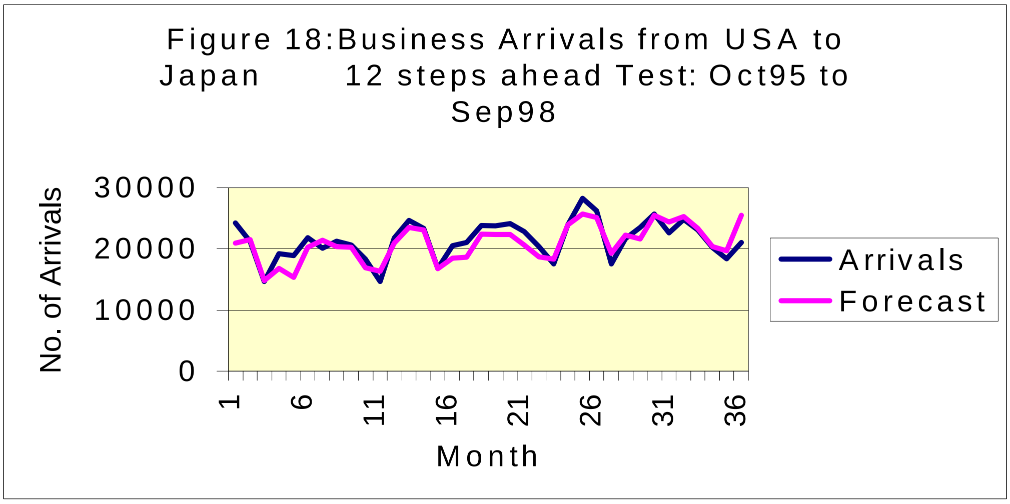


Figure 19 Comparison of RMSE and MAPE for Neural Network Models

Country	Type	Forecast	Indicator	RMSE	MAPE
USA	Total	1 step ahead		2836	0.04
USA	Total	12 steps ahead		3166	0.05
USA	Total	1 step ahead	Personal Income	3841	0.06
USA	Total	1 step ahead	Imports	3262	0.05
USA	Total	1 step ahead	Exports	3307	0.05
USA	Tourist	1 step ahead		2784	0.08
USA	Tourist	12 steps ahead		2978	0.09
USA	Business	1 step ahead		1267	0.05
USA	Business	12 steps ahead		1716	0.06

Conclusions

Forecasts for total tourist arrivals from the USA to Japan, using neural network models are very close to the actual arrivals during the test period. The forecasts errors for up to 36 month periods were of the order of 5% (MAPE = 0.05).

Economic indicators used in multivariate forecasts did not provide improved forecasting accuracy to the univariate forecast of total arrivals. (MAPE = 0.06). This may be due to the very steady pattern in the data for tourist arrivals.

The disaggregated models showed error levels between 5 and 8% indicating that disaggregating data does not improve forecasting accuracy. This may be due to inherant errors in the data resulting from incorrect classification of the type of travel.

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