Forecasting International Bandwidth Capacity using Linear and ANN Methods

Abstract

An artificial neural network (ANN) can improve forecasts through pattern recognition of historical data. This paper evaluates the reliability of ANN methods, as opposed to simple extrapolation techniques, to forecast Internet bandwidth index data that is bursty in nature. A simple feedforward ANN model is selected as a nonlinear alternative as it is flexible enough to model complex linear or nonlinear relationships without any prior assumptions about the data generating process. These data are virtually white noise and provides a challenge to forecasters. Using standard forecast error statistics, the ANN and the simple exponential smoothing model provide modestly better forecasts than other extrapolation methods.

Keywords: artificial neural networks, packet data traffic, telecommunications forecasting

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I. Introduction

For electronic markets to successfully deliver IP-based telephony, video and TV requires a quality of service that matches their analogue counterparts. Clearly, traffic management is a key component of any business critical network. That is, as traffic patterns continue to rapidly evolve, service providers need to monitor, analyse and optimize traffic to forecast and accommodate future trends. Interestingly, the International Telecommunication Union (ITU) makes recommendations on best practices for network operation (Villén-Altamirano 2001). [1] ITU traffic engineering recommendations are identified by traffic demand characterization, grade of service objectives, traffic controls and dimensioning, and performance monitoring. In particular, forecasting is an important input into network traffic control and performance monitoring.[2] *Recommendation E.507* deals with methods deemed appropriate for forecasting traditional services based on historical data. The *Recommendation* provides an overview of existing mathematical techniques for forecasting that includes curve-fitting models, autoregressive models, autoregressive integrated moving average (ARIMA) models, state space models with Kalman filtering, regression models and econometric models. [3] However, *Recommendation E.507* does not explicitly consider appropriate mathematical and statistical techniques for forecasting packet-switched data traffic, which is bursty in nature.[4] While forecasting how broadband traffic flows arise is difficult because the composition of services provided over these networks is not well understood, more fundamentally, the focus of forecasting interest for packet-switched networks is different to that for circuit-switched networks. That is, the forecasting concern should be congestion spikes which slow the system, rather than predicting average network load.

Accordingly, this paper applies an artificial neural network (ANN) model to forecast Internet bandwidth traffic via pattern recognition of historical data. ANNs are potentially useful for this application as they require few *a priori* assumptions about the models for problems under study. In particular, ANNs are argued to learn from examples and capture subtle functional relationships among data even when the underlying relationships are unknown or hard to describe (Zhang *et al* 1998). In doing so the paper evaluates the relative reliability of ANN methods when compared with several linear extrapolation techniques. The paper is structured as follows. The nature and characteristics of plain old telephone service (POTS) and packet data traffic are considered in Section II. Section III reviews forecast methods employed in this study, and discusses error statistics used to evaluate forecast performance. Section IV provides a description of Internet router index data modelled in the study. These data allow the examination of traffic characteristics—most significantly, the burstiness of data traffic. Section V presents nonlinear test results. Section VI presents forecast results and, Section VII concludes.

II. POTS and Packet Data Traffic Behavior

The POTS network is a connection-oriented network where calls are assigned constant bandwidth. Commonly accepted fundamental assumptions about such traffic are: (a) within hour traffic fluctuations are reasonably well predicted with traffic models based on a Poisson arrival process; (b) beyond hourly variations are significant but follow patterns that tend to repeat, e.g., there is an hour of the day 'busy hour' that tends to bear the highest load; (c) there are predictable seasonal variations, e.g., there is a 'busy season' that is repeated annually; (d) annual traffic variation is generally gradual, and the use of linear forecasting techniques is well established; and (e) when excessive traffic is offered to the POTS network, new calls are denied access (Noll 1991). In this network, the ‘low-frequency’ traffic variations are either repetitive daily variations or of low magnitude annual variations. Higher-frequency variability caused by individual call attempts is well understood. Therefore, in a POTS network a major way to manage congestion is to engineer the network so congestion rarely occurs. However, when discussing data traffic, another paradigm is required as the dominant traffic variability is in the range of milliseconds, and packets and ‘packet trains’ enter the network at random times.[5] The variability at this time scale is enormous, with relatively low mean utilization and high burstiness.

III. Forecast Model Specification

Traditional approaches to times series prediction, such as Box-Jenkins, assume that series are generated by linear processes (Pankratz 1983). As many real world systems are nonlinear, the application of these methods to forecasting is problematic (Granger and Terasvirta 1993). An obvious alternative is the formulation and application of a pre-specified nonlinear model. However, nonlinear models face the difficulty of being general enough to capture all important features of these data. ANNs, which are nonlinear data driven approaches, are more flexible in that they can perform nonlinear modelling without any detailed *a priori* knowledge of relationships among input and output variables (Zhang *et al* 1998). Accordingly, this study examines the performance of an ANN against several linear extrapolation models in forecasting Internet bandwidth index data. This focus is interesting, as the received M-competition literature indicates that ANN methods are not superior to the relatively simpler extrapolation methods commonly employed by professional forecasters. However, Madden and Coble-Neal (2005) find that standard univariate linear time-series models perform poorly when forecasting Internet bandwidth index series. They argue that poor forecast performance is in part due to bandwidth index data not exhibiting underlying patterns for required extrapolation techniques to generate reliable forecasts. Further, data generated by complex processes, such as by Internet routers, can appear random. Accordingly, under these circumstances, the analysis of these data by a nonlinear ANN model is worthy of consideration.[6]

A commonly employed model is the single hidden layered feedforward network without any direct connections between inputs and outputs. This ANN is chosen because Hornik *et al* (1989) shows an ANN model with a single layer and a sufficient number of hidden nodes can approximate any continuous function to an arbitrary degree of accuracy. The ANN used here is assumed sufficient to capture any underlying nonlinear processes in these data. In particular, the ANN(p,q) model employed for forecasting is

$$y_t = \sum_{j=1}^{q} \beta_j G(y_t' \gamma_j) + \varepsilon_t \tag{1}$$

where y_t' is a vector series of p lagged dependent variables y_{t-j} $(j = 1, 2, \ldots, p)$ as inputs, q is the number of hidden layer cells, $G(\cdot)$ is the transfer function that connects the $p+1$ input components with the hidden layer and ε_t is white-noise error. A logistic (or sigmoid) transfer function:

$$G = (1 + \exp(-(\gamma_{0j} + \gamma_{0j} y_{t-1} + \gamma_{2j} y_{t-2} + \ldots + \gamma_{pj} y_{t-p})))^{-1} \tag{2}$$

is employed. While cosine, hyperbolic tangent, linear and sine functions are sometimes used, it is not clear whether different transfer functions have any substantial effect on the performance of networks (Zhang 2004).

The total number of parameters for an ANN model estimated by (1) is equal to the number of lags and hidden layers. Lags of the series vary from 1 to 5, and hidden layers vary from 1 to 2 to determine the best ANN (p, q) model. Hence, the ANN model contains $(q+1)(p+1)-1$ parameters.

Due to the short length of sample series, an in-sample model selection criterion is employed. ANN model parameters are estimated by minimising the in-sample mean squared prediction error. The best fitting ANN model is chosen by comparing values of the generalised Akaike's Information Criteria (AIC), Bayesian Information Criterion (BIC) and a modified AIC (AICC) proposed by De Gooijer and Kumar (1992) and Granger (1993).[7] Comparison of test criterions under different parameter configurations leads to the estimation of 10 ANN models under each test criterion. The generalised AIC, the AICC and the generalised BIC test statistics are

$$AIC = \log(\hat{\sigma}^2_{(p,q)}) + \frac{2m^d}{T},$$

$$AICC = \log(\hat{\sigma}^2_{(p,q)}) + \frac{2m}{T-m-1},$$

and

$$BIC = \log(\hat{\sigma}^2_{(p,q)}) + \frac{m^d \log(T)}{T}.$$

$\hat{\sigma}^2_{(p,q)}$ is the variance of the residuals for an estimated ANN model in (1) with p and q.[8] T

is the number of observations, the exponential d is a constant, usually set greater than 1 for nonlinear models, adjusts the magnitude of the penalty term in the BIC test (De Gooijer and Kumar, 1992 and Granger, 1993) and m is the number of parameters of each particular ANN(p,q) model tested.[9]

The univariate linear extrapolation techniques used to allow forecast accuracy comparison with ANN forecasts are: Parzen's (1982) ARARMA, ARMA, Holt, Holt-D, Holt-Winters, Simple Exponential Smoothing (SES) and Grambsch and Stahel's (1990) Robust Trend (RT).[10] These latter forecast methods are shown reliable by Fildes (1992), Makridakis *et al* (1993), Fildes *et al* (1998) and Makridakis and Hibon (2000) by consistently performing well in the M-competition.[11]

Estimation by method begins at observation 8 to allow a subset of data of observation 1 to observation 7 to estimate each model.[12] This allows a possible maximum 7 period lag length for the estimation of parameters of the ARARMA and ARMA models.[13] Hence, the parameters by method are estimated from observation 8 to 202. Grid search for the optimal lag length for the ARMA, ARARMA are based on the lowest value of the AIC, while the ANN models are based on the lowest value of AIC, Modified AIC and BIC statistics.[14] Holt-D, Holt-Winters and RT models have fixed lag lengths and do not require grid search to select the best model.[15] The best model by series and method are used to generate 30 one-step forecasts. To evaluate forecasts, the last 30 series observations are set aside.

Forecast accuracy measures employed are guided by Armstrong and Collopy (1992), viz., mean absolute percentage error (MAPE), median absolute percentage error (MdAPE) and percent better (PB) (Shown in Appendix).[16]

IV. Data

Data used is acquired from the *Internet Traffic Report* and consists of 59 bandwidth traffic index series. Series are comprised of 232 observations.[17] These data are sampled from a continuous data generating process, and drawn daily at 7am Australian Eastern Standard Time weekdays from 18 February 2000 through 3 March 2001. A representative specimen of these data is shown in Figure I. Each series is an index measure of Internet traffic that oscillates between zero and 100, and appear to exhibit typical characteristics of stationary series.[18] A common feature of many series is the presence of occasional downward spikes. Spikes are outlier index values that indicate network congestion. In forecasting with linear models, where the goal is often mean prediction with minimum error, it is common practice to eliminate outliers from sample data. However, for packet data networks the accurate prediction of congestion spikes is a forecasting goal due to the nature of congestion, i.e., degraded network quality of service rather than access denial.

<Insert Figure I here>

Summary statistics indicate the frequency of the downward spikes with 27 of the 59 routers reporting at least one minimum value below the 25th percentile. Sampled regions include Australia, East Asia, Israel, North America, Russia, South America and Western Europe. Regions not included are Africa, Antarctica and most of the Middle East. The Denver denver-br2.bbnplanet.net router is recorded as providing the fastest response, while AOL1 pop1-dtc.atdn.net has the lowest response time. On average, the Perth1 opera.iinet.net.au router consistently provides the fastest response. Yahoo fe3-0.cr3.SNV.globalcenter.net typically records the slowest response.[19] The sample average coefficient of variation is 6.3 and the corresponding standard deviation is 1.8.

Following Fildes (1992), the frequency of outliers, strength of trend, degree of randomness and seasonality are analyzed. The results are shown in Figure II through Figure V. An observation X_t is treated as an outlier when either $X_t < L_x - 1.5(U_x - L)$ or $X_t > L_x + 1.5(U_x - L_x)$, where L_x denotes the lower quartile and U_x the upper quartile. The strength of trend is measured by the correlation between series (with outliers removed) and a time trend, with the absolute value of the trend indicating its strength. Randomness is measured by estimating the regression:

$$\mathrm{X}'_t = \alpha + \beta t + \delta_1 \mathrm{X}'_{t-1} + \delta_2 \mathrm{X}'_{t-2} + \delta_3 \mathrm{X}'_{t-3}\,, \tag{3}$$

where X'_t denotes the series X_t with outliers removed. $\overline{R}^2$ measures the variation explained by the model. High $\overline{R}^2$ indicates low randomness, while low $\overline{R}^2$ reveal high randomness. Deterministic seasonality is estimated by regressing the series on an intercept and dummy variables which equal one when $t = s$, where t denotes observation X_t's position in time and s corresponds to the frequency of the seasonality. For example, to test the hypothesis that Mondays are statistically different to bandwidth capacity for the rest of the week, t = {1, 2, 3, 4, 5, … , T}, s = {1, 5, 10, 15, … , T} and dummy variable $D_{Monday} = 0$ for t = s, zero otherwise.

<Insert Figure II here>

Figure II reveals half the series contain between 1% and 5% outliers. In percentage terms these data appear slightly more heterogeneous than Fildes (1992) telecommunications data. Figure III shows that these data are generally not correlated with time. This contrasts with Fildes, where the data there exhibit strong negative trends. Moreover, histograms contained in Figure III and Figure IV reveals that variation in these data presents a high degree of randomness with little serial correlation.

<Insert Figures III & IV here>

Finally, Figure V presents some evidence of regularity in weekly capacity variation aggregated by region. There appear regular dips occurring on different days across regions. Typically, Asia experiences lower traffic volumes from Wednesday through Friday, while most Australian routers have excess capacity from Monday through Tuesday. Conversely, Europe and North America experience a smoother traffic flow—perhaps due to more sophisticated capacity pricing and network management systems. Finally, South American Internet traffic variation is tied to particular routers.

<Insert Figure V here>

Regressions are also conducted to test for regularity of both weekly and monthly traffic patterns. Weekly variation is not apparent with only 6 routers reporting regular spikes across weeks. Surprisingly, given the short time-series, substantial monthly variation was found for 95% of sampled routers.[20] Although the sustained increase in traffic is too haphazard across routers to reveal a cyclical pattern. Most routers experience significant increase for an average of 2 months, with some routers showing surges of up to 3 months. This pattern may reflect the average lagged response time required before routers are expanded to cope with the increased traffic. Once expanded, the Internet traffic index for the router is likely to increase, reflecting a permanent increase in capacity. To sum, these data exhibit a high degree of randomness with not infrequent spikes in index scores apparent. Compared to telecommunications data analyzed in Fildes (1992) and Fildes *et al* (1998), these data appear considerably more heterogeneous and so less predictable.

V. Tests for Nonlinearity

To further uncover the structure of the data, several parametric nonlinearity tests are performed.[21] Tests employed are the Ljung-Box (1978) *Q* test (LBQ), McLeod and Li (1983) test (Mc&Li), Engle's (1982) autoregressive conditional heteroscedasticity test (ARCH), Ramsey's (1969) regression error specification test (RESET), Tsay's (1989) threshold autoregressive test (TAR) and White's (1989,1990) ANN test.[22]

Each of the tests is sensitive to linear and nonlinear correlation. Hence, it is important to control for the presence of linear autocorrelation prior to performing tests on the data by filtering the linear autocorrelation of traffic index series before the nonlinear tests are employed. This pre-whitened process applies the best fitting $\text{ARMA}(p,q)$ model by series based on the lowest value AIC statistic.[23] The nonlinear tests are then applied to the residuals of the best fitting ARMA model by series.

<Insert Table I here>

From the normality test performed on the residuals of pre-whitened series indicate residuals are highly non-normal. This suggests the ARMA model is unable to capture data characteristics. This result is similar to Madden and Coble-Neal (2005) suggesting univariate methods such as ARMA may not be suitable for modelling the bursty Internet traffic data. The JB test suggests possible misspecification of the ARMA model. However, Ramsey's RESET test, shows no nonlinearity in these data.[24] The RESET test show only 8.47% (5 of 59 index data series) and 3.39% of series tested at the 5% and 1% significance levels, respectively, are misspecified.

To further investigate the data structure, Tsay's TAR test, LBQ(5) test and Engle's ARCH(5) test are employed. The results of the TAR test shows 13.56% and 6.36% of series have threshold breaks in the traffic data series at the 5% and 1% significance, respectively, indicating most series do not exhibit breaks in mean value.[25]

Next, to examine these data for ARCH effects, the LBQ(5), Mc&Li(5) and ARCH(5) tests are conducted. No ARCH effects are present in these data. The LBQ(5) show 10.17% and 1.7% of series do not have any cross correlations in the residuals at the 5% and 1% significance levels, respectively. ARCH(5) tests indicate a similar finding, as 10.17% and 5.08% of tested series do no exhibit ARCH effects at 5% and 1% significance, respectively. Despite mixed evidence of nonlinearity, White's ANN test strongly rejects linearity. *P*-values of White's ANN test are estimated using the Bonferroni technique and Hochberg's (1988) modified Bonferroni technique at 5% and 1% significance.[26] The nonlinearity captured using the ANN test may be the result of interactions between the lags of the traffic series. This means employing a more flexible modelling technique using the ANN model may improve the forecasting of traffic index data.

<Insert Table II here>

To ascertain if the characteristics of the sample series are homogeneous, a randomly chosen sub-sample of geographical regions is examined.[27] The results are reported in Table II. The Internet traffic index across regions are stationary but are not normally distributed. Table II shows routers in Asia typically face congestion on the Internet networks with highest variance. This is followed by the North American and South American regions. Although the Australian router has the lowest variance, the results also suggest nonlinear behaviour is present.

VI. Forecasts

To identify the most accurate forecast model, aggregate results (either mean or median of 59 forecasts) by method are compared through an output sample forecast horizon. A maximum 30 steps (days) ahead forecasts using MAPE, MdAPE and PB error statistics are considered.[28] Table IV and Table V present the MAPE and MdAPE results.[29] The MAPE error statistic confirm the ANN model as best forecast method for all horizons (short, intermediate and long horizon), as it consistently yields lowest percentage error when compared to sample data. The only exception is for the 12-day horizon, where the Holt-D has the lowest percentage error. The best fit ANN model selected by AIC, AICC or BIC yields similar results, indicating there is no advantage in using either statistic when selecting the best fit ANN model.[30] For short-horizon forecasts, the RT model performs well when forecasting the 1 day ahead (not shown).

The MdAPE results show slightly different results. The MdAPE shows the SES model is best for forecasting short horizons of 6 days and 12 days, and the long horizon of 30 days ahead. For the intermediate horizon forecasts of 18 days and 24 days ahead, the ANN model and the Holt-W model yield the lower errors.

The results on the PB statistic reported in Table VI, confirming those of Table IV and Table V, and show the ANN and SES models are consistently the best methods for forecasting bursty broadband data. Figure VI, Figure VII and Figure VIII illustrate forecasts for 1 day to 30 days ahead for the best forecast methods. Figure VI and Figure VIII show the SES and ANN models forecast better for most forecast horizons. The only exception is the RT model for 1 day ahead forecasts (not shown).

<Insert Table IV here>

<Insert Table V here>

<Insert Table VI here>

To sum, Figure II, Figure III and Figure IV suggest the SES and ANN methods provide an improvement over other linear extrapolation techniques and indicate the SES and ANN models considered here are useful for establishing relatively accurate judgement-free projections of bandwidth loads up to 30 days ahead. The results of the SES and ANN models are superior for most forecast horizons. For short-horizon forecasts (1 day ahead), a naïve extrapolation based on the last observation is sometimes best.

<Insert Figure VI here>

<Insert Figure VII here>

<Insert Figure VIII here>

VII. Conclusion

The paper compares linear extrapolation and an ANN model forecasts for bursty packet-switched broadband data that exhibits little structure. Bursty broadband packet data is generated by not well understood underlying patterns and so can appear random, resulting in standard extrapolation techniques being unable to provide to reliable forecasts—especially of congestion spikes. Therefore, a feedforward ANN model is considered as an alternative forecasting method. ANNs are a non-linear data driven techniques that learn from underlying data patterns. Importantly, these techniques do not require any *a priori* assumptions as to the underlying data generating process. The sample forecast MAPE and MdAPE error statistics, and PB measure show that the SES and ANN models provides more reliable forecasts than the linear extrapolation methods suggested by the ITU. This outcome suggests ITU *Recommendation E.507* for forecasting network data should be amended. First, ANN models should be included. Second, the ITU should also provide separate traffic forecasting recommendations for traditional POTS and packet-switched data as they are different in nature. The encouraging findings from this study suggest that further gains in forecast accuracy may be obtained from experimenting with an ANN model that includes a feedback loop that is a feature of congested packet data network networks.

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Appendix

Following the recommendations of Armstrong and Collopy (1992) and Fildes (1992), the error measures used are the mean absolute percentage error (MAPE), median absolute percentage error (MdAPE) and percentage better (PB). To estimate the MAPE of a particular method *i* for horizon *h* using series *j*, the absolute percentage error $APE_{i,h,j}$ is first estimated;

$$APE_{i,h,j} = \left| \frac{F_{i,h,j} - A_{h,j}}{A_{h,j}} \right| ,$$

where $F_{i,h,j}$ is the forecast for method *i* for horizon *h* using series *j*. and $A_{h,j}$ is the actual value at horizon *h* for series *j*. Hence, the $MAPE_{i,h,j}$ is summarised across series;

$$MAPE_{i,h,j} = mean\ (APE_{i,h,j}),$$

The symmetric MAPE is not used here as it generates a higher penalty for high forecasts then low forecasts (Goodwin and Lawton, 1999 and Koehler, 2001). The advantage of using MAPE is the MAPE is scale-invariant. As none of the observations in the data are negative, the MAPE is most appropriate. The root mean squared error (RMSE) is not considered as included because of it is affected by the scale of the data. The $MdRAE_{i,h,j}$ error statistic is also derived from the $APE_{i,h,j}$, the median of the $APE_{i,h,j}$ is:

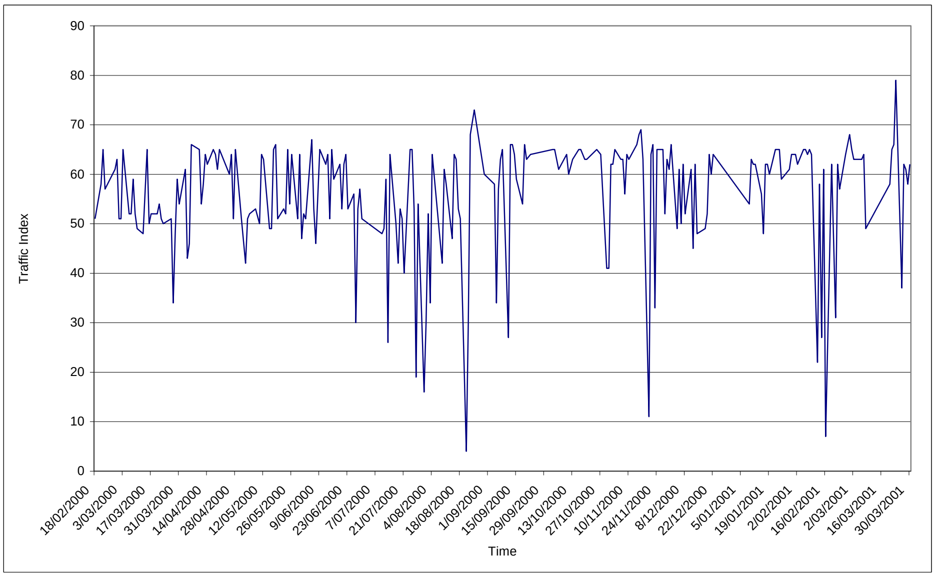
$$MdRAE_{i,h,j} = Median(APE_{i,h,j}),$$

where the MdAPE is observation $\frac{j+1}{2}$ if j is odd, or the mean of observations $\frac{j}{2}$ when j is even, when the $APE_{i,h,j}$ observations are ordered by rank. The percentage better (PB) statistic counts and reports the proportion that a given method has a forecasting error larger than a relative method. The relative method for forecasting compared in this study is the random walk model.

$$PB_{i,h,j} = \left[\frac{1}{s} \sum_{j=1}^{n} \delta_{ijt} \right] * 100$$

where $\delta_{ijt} = \begin{cases} 1 & if \left|F_{i,h,j} - A_{h,j}\right| \prec \left|F_{rw,h,j} - A_{h,j}\right| \\ 0 & otherwise \end{cases}$ $PB_{i,h,j}$ is the proportion of times a particular model i forecasting horizon h for series j has a lower forecast error than the random walk model and s is the total number of series forecasted. A value of greater than 50 for $PB_{i,h,j}$ indicates the forecasts obtained for a particular forecasting method i is more accurate than the random walk.

Figure I: Malaysia fe1-0.bkj15.jaring.my



Source. Opinix (2001).

FIGURE II. Outlier Frequency

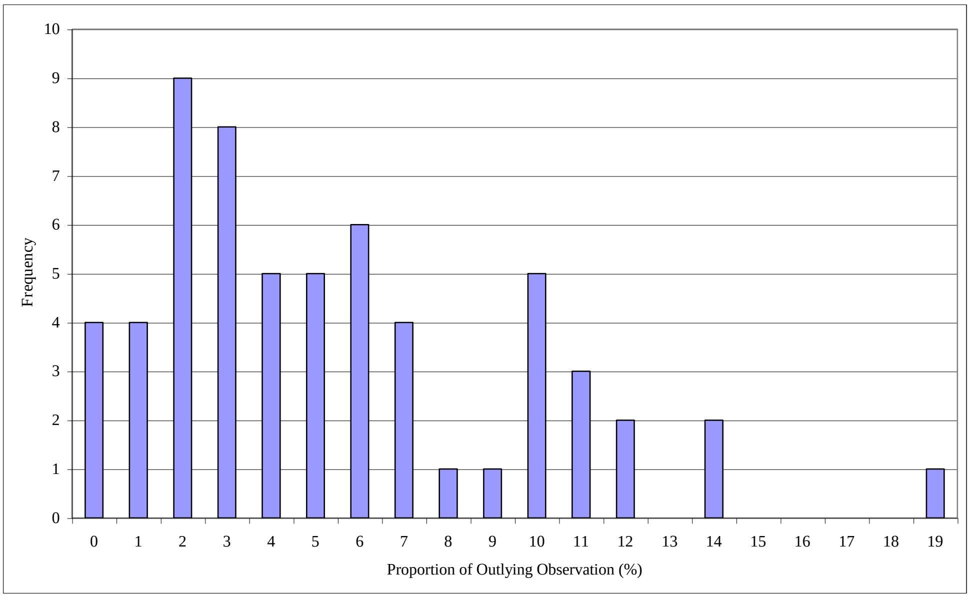


FIGURE III. Strength of Linear Trend

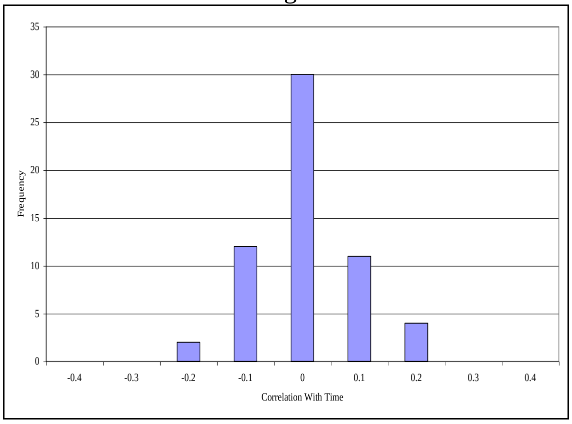


FIGURE IV. Variation Explained by Linear/AR

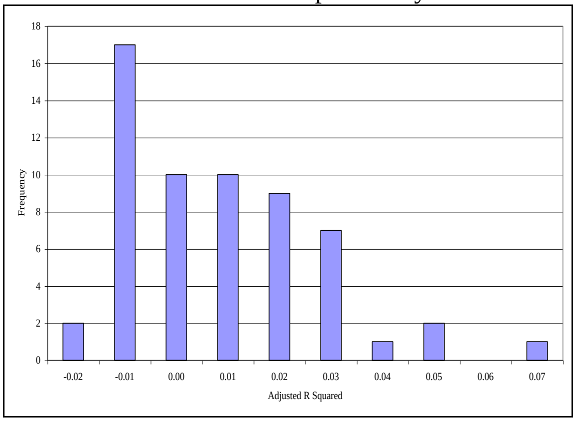


FIGURE V. Daily Variation in Capacity Utilization

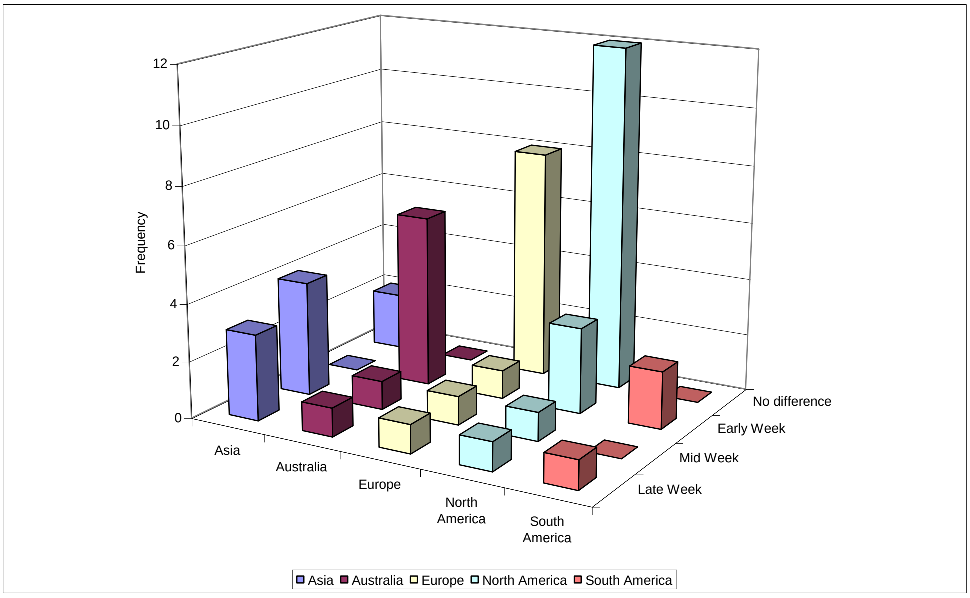


Table I. Percentage of Traffic Index Series with Significant Tests

Significance Level	5%	1%
Normality	5.08%	1.70%
LB-Q(5)	10.17%	1.70%
Mc&Li(5)	27.12%	20.34%
ADF(5)	100.00%	100.00%
ARCH(5)	10.17%	5.08%
TAR(5)	13.56%	6.36%
RESET(3)	8.47%	3.39%
White's ANN Test (Simple Bonferroni)	100.00%	100.00%
White's ANN Test (Hochberg 's (1988) Bonferroni)	100.00%	100.00%

Note: The number of series tested is 59. The results shown are the proportion of traffic found to be significant. All tests (except for the ADF(5) Test) are performed on the residuals of a best fitting ARMA model (lowest AIC statistic). Normality is the Jarque–Bera normality test; LB-Q(5) is the Ljung-Box (1978) portmanteau test of autocorrelation order 5; Mc&Li(5) is the McLeod and Li test order 5; ADF(5) is the augmented Dickey-Fuller unit root test with 5 lags; ARCH(5) is Engle's LM test for ARCH with 5 lags; TAR(5) is Tsay's TAR-test for determining the presence of thresholds in the data series using up to 5 lags; RESET(3) is Ramsey's RESET test with a power of 3; White's ANN Test is an ANN nonlinear test.

Table II. Representative Sample of Selected Summary Statistics by Geographical Location and Tests

Router Series	A (Asian Router)	B (Australian Router)	C (European Router)	D (N. American Router)	E (S. American Router)
Mean	56.09**	60.34**	50.00**	50.59**	58.90**
Variance	135.42	55.69	77.00	85.45	80.82
Skewness	- 1.87**	-2.56**	-1.11**	-0.87**	-1.82**
Kurtosis	4.30**	9.46**	1.67**	-0.01	4.17**
Normality	307.29**	1094.57**	73.47**	28.48**	289.84**
LB-Q(5)	0.70	0.92	1.79	2.11	2.64
Mc&Li(5)	12.68**	14.56**	5.93	6.78	1.97
ADF(5)	-5.77**	-5.12**	-7.05**	-5.94**	-6.41**
ARCH(5)	12.82	14.08*	5.36	5.88	2.39
TAR(5)	1.22	3.74**	1.06	0.87	0.90
RESET(3)	0.47	0.81	0.27	0.08	1.27
White's ANN Test	219.21**	224.61**	219.92**	220.56**	221.22**

Note: The number of series tested is 59. Geographical regions are from the *Internet Traffic Report*. All results (except ADF(5) test) are performed on residuals of the best fitting ARMA model (lowest AIC statistic). Normality is the Jarque–Bera normality test; LB-Q(5) is the Ljung-Box portmanteau test of autocorrelation order 5; Mc&Li(5) is the McLeod and Li test order 5; ADF(5) is the augmented Dickey-Fuller unit root test with 5 lags; ARCH(5) is Engle's LM test for ARCH with 5 lags; TAR(5) is Tsay's TAR-test for determining the presence of thresholds in the data using up to 5 lags; RESET(3) is Ramsey's RESET test with power 3; White's ANN Test is an ANN nonlinear test. * and ** denote significance at the 5% and 1% levels, respectively.

Table III. Results of White's ANN Test of the Random Sub-sample Data Series

Series	A (Asian Router)	B (Australian Router)	C (European Router)	D (N. American Router)	E (S. American Router)
Simple Bonferroni (*p*-values)	0.00**	0.00**	0.00**	0.00**	0.00**
Hochbeg (1988) Bonferroni (*p*-values)	0.00**	0.00**	0.00**	0.00**	0.00**

Note: Number of lags in estimation of White's test are randomly chosen. White's test is significant for all series using either the simple or Hochberg (1988) Bonferroni *p*-value. * and ** denote significance at the 5% and 1% levels, respectively.

Table IV. Mean Absolute Percentage Error

Forecast Method	Forecast Horizon				
	6	12	18	24	30
RT	20.29	63.52	18.06	24.08	23.55
ARMA	11.78	58.49	12.44	16.76	16.62
HOLT	12.30	71.59	22.87	40.85	35.07
HOLT-D	12.58	**57.00**	12.12	16.83	16.55
HOLT-W	11.94	57.92	13.39	20.01	17.49
ARARMA	58.42	58.35	63.13	80.95	53.67
SES	11.14	60.75	12.37	20.11	15.76
ANN-AIC	11.41	59.20	11.05	**16.54**	15.75
ANN-AICC	11.26	59.14	10.72	16.73	**15.30**
ANN-BIC	**11.09**	59.40	**10.67**	16.60	15.38

Note: RT is the robust trend model; ARMA is the autoregressive moving average model; HOLT is Holt's linear no trend model; Holt-D is Holt's model with exponential smoothing; HOLT-W is the linear no trend Holt-Winters model; ARARMA is the long memory model; SES is the linear no trend simple exponential smoothing model; ANN-AIC is best fitting ANN model; ANN-AICC is the best fitting ANN; ANN-BIC is best fitting ANN model selected. Percentages in bold are models with the lowest mean absolute percentage of error.

Table V. Median Absolute Percentage Error

Forecast Method	Forecast Horizon				
	6	12	18	24	30
RT	16.39	21.48	14.74	16.90	17.96
ARMA	10.39	11.52	9.06	6.91	13.00
HOLT	9.58	14.27	12.53	21.19	17.40
HOLT-D	10.12	9.87	7.74	5.65	10.61
HOLT-W	9.75	9.99	8.20	**5.13**	11.40
ARARMA	61.38	84.78	76.09	87.71	48.62
SES	**8.20**	**9.58**	7.52	6.69	**7.96**
ANN-AIC	9.60	11.63	7.83	7.10	9.22
ANN-AICC	8.70	11.52	7.46	6.02	8.47
ANN-BIC	8.89	10.29	**6.54**	7.27	8.42

Note: RT is robust trend model; ARMA is the autoregressive moving average model; HOLT is Holt's linear no trend model; Holt-D is Holt's model with exponential smoothing; HOLT-W is the linear no trend Holt-Winters model; ARARMA is the long memory model; SES is the linear no trend simple exponential smoothing model; ANN-AIC is best fitting ANN model; ANN-AICC is the fitting ANN model; ANN-BIC is best fitting ANN model. Percentages in bold are models with the lowest median absolute percentage of error.

Table VI. Percent Better

Forecast Method	Forecast Horizon				
	6	12	18	24	30
RT	25.42	45.76	35.59	47.46	28.81
ARMA	32.20	72.88	42.37	81.36	42.37
HOLT	38.98	52.54	30.51	37.29	27.12
HOLT-D	40.68	71.19	47.46	79.66	44.07
HOLT-W	38.98	71.19	45.76	76.27	47.46
ARARMA	13.56	25.42	22.03	25.42	18.64
SES	**45.76**	**74.58**	**57.63**	76.27	**50.85**
ANN-AIC	42.37	72.88	52.54	84.75	45.76
ANN-AICC	42.37	**74.58**	50.85	**86.44**	47.46
ANN-BIC	44.07	71.19	50.85	84.75	**50.85**

Note: RT is robust trend model; ARMA is the autoregressive moving average model; HOLT is Holt's linear no trend model; Holt-D is Holt's model with exponential smoothing; HOLT-W is the linear no trend Holt-Winters model; ARARMA is the long memory model; SES is the linear no trend simple exponential smoothing model; ANN-AIC is best fitting ANN model; ANN-AICC is best fitting ANN model; and ANN-BIC is best fitting ANN model. Percentage better statistic is the proportion of series for a model that is better than the random walk forecast. Percentages in bold are models with the highest percentage accuracy.

Figure VI. Mean Absolute Percentage Error

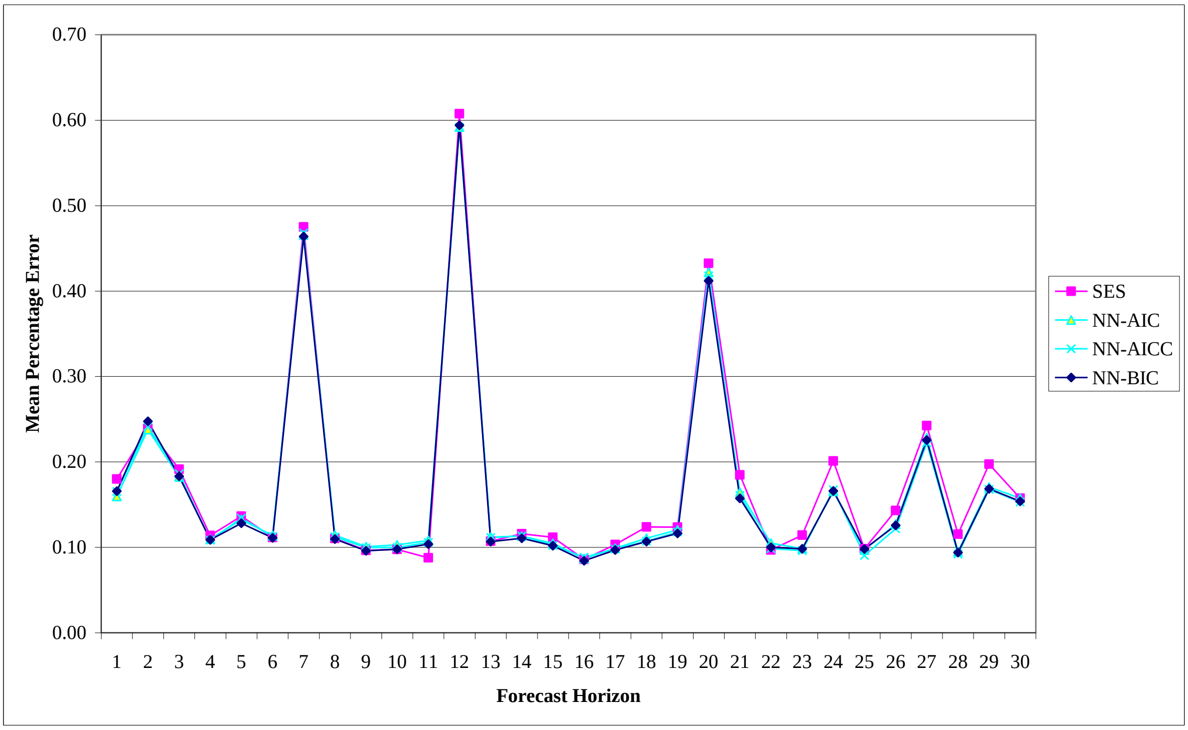


Figure VII. Median Absolute Percentage Error

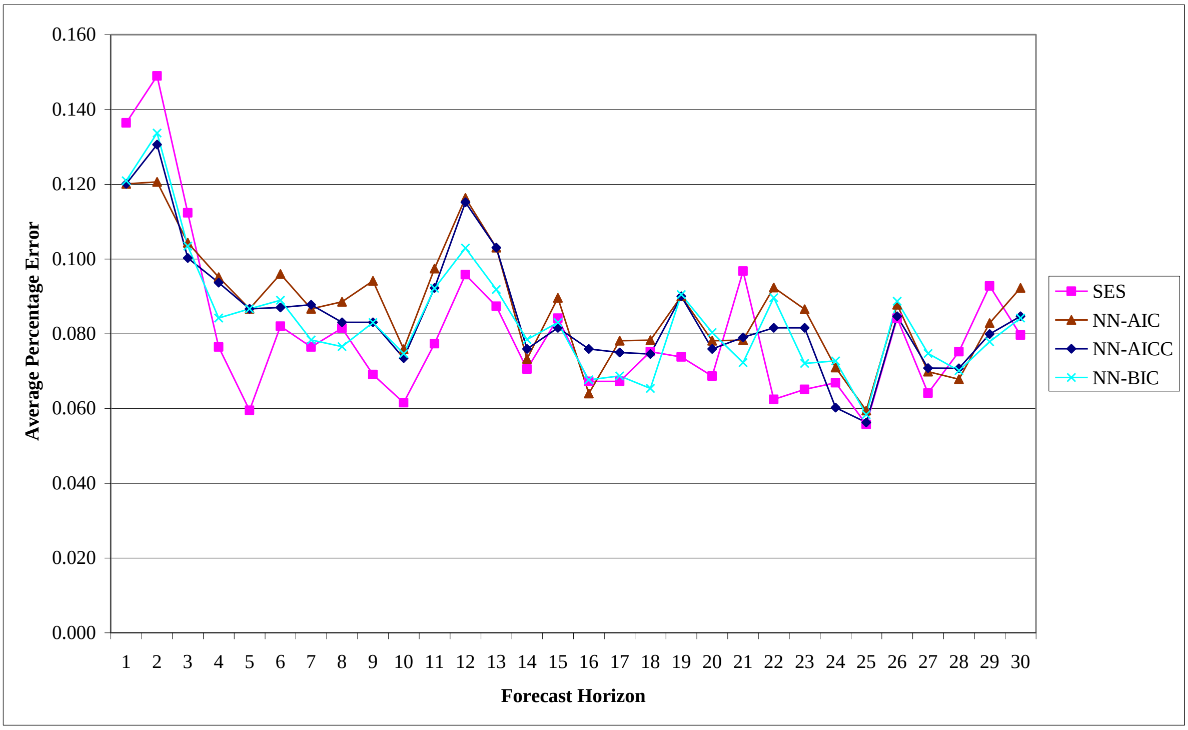
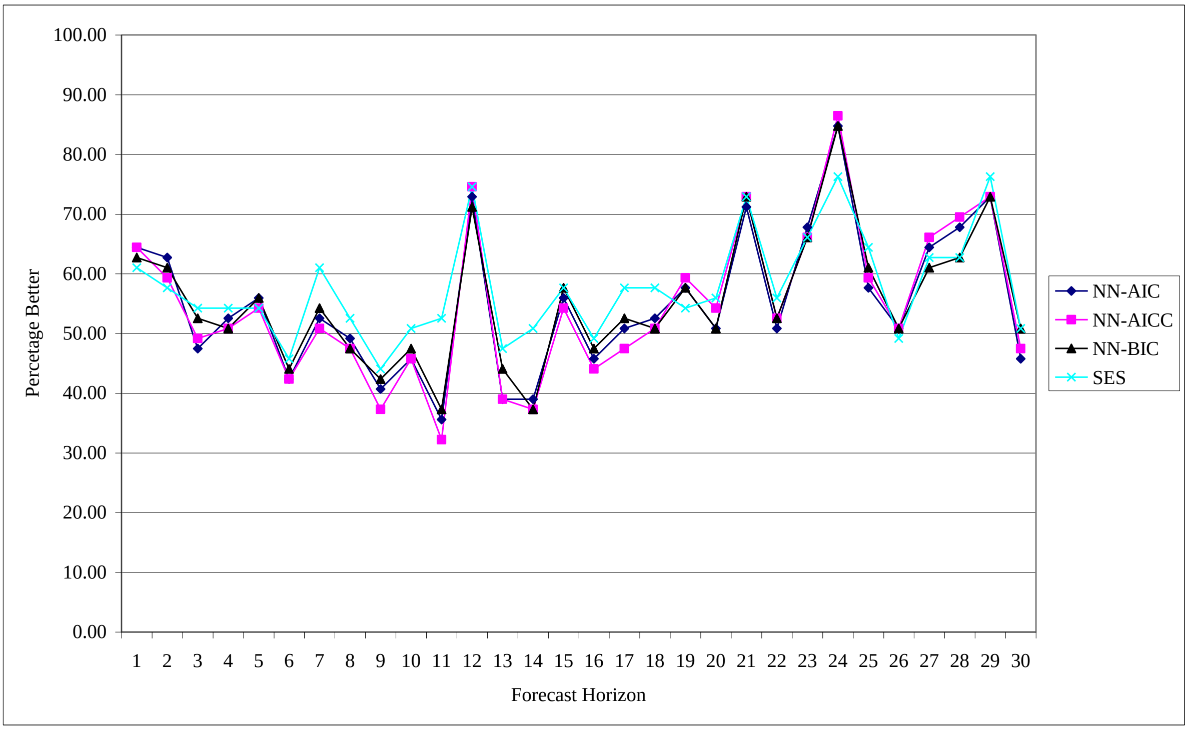


Figure VIII. Percentage Better



[1] The ITU is an organization sponsored by the United Nations that makes recommendations on network traffic management.

[2] Traffic forecasting is necessary for strategic analysis, e.g., on the introduction of a service and for network planning, such as equipment and circuit provision and plant investment.

[3] *Recommendation E.507* also describes methods to evaluate and select an appropriate technique, depending on available data and forecast period.

[4] Congestion occurs only when there is visible degradation of network performance to users. Thus, when the network traffic load is heavier than usual, but performance is acceptable, congestion has not occurred. Bursty traffic is characterized by extremely high peak-to-mean ratios in traffic volumes. The burstiness of traffic is an important test of the congestion management capability of high-speed integrated-service networks.

[5] A packet train is a closely-spaced sequence of packets between a source and destination.

[6] For an extensive discussion of ANN models and their properties, see Kuan and White (1994), Warner and Mistra (1996), Zhang *et al* (1998) and Zhang (2004)

[7] Both criteria are generalisations of Rissanen's (1987) complexity criterion.

[8] Other selection criteria are not considered as they are not widely used.

[9] Following Qi and Zhang (2001), the value of $d = 3$, gives the most parsimonious model. Hence, generalised AIC and BIC statistics are calculated with $d = 3$.

[10] Following suggestions by Rob Hyndman, the no trend, no seasonal version of the simple exponential model (SES) is included in the analysis. The SES model used is $y_t = y_{t-1} + \alpha e_t$, with $\alpha = 0.3$. The results for other α values are not reported.

[11] Quantile forecasting is performed in an attempt to forecast congestions. However, the forecasts did not perform as well as univariate linear methods and are not reported.

[12] Estimation method is by minimisation of sum of squared errors.

[13] Total possible lags for the ARARMA model is 7 as the ARARMA is estimated by applying an appropriate AR model (lags 1 and 2). Residuals are estimated with another ARMA model (ARMA lags are 1 to 5) to generate the ARARMA model.

[14] While use of the AIC, modified AIC and BIC for this purpose are open to criticism, there is no clearly superior test in all situations. See, for example, De Gooijer and Kumar (1992) or Qi and Zhang (2001).

[15] Only the linear, no trend and non-seasonal versions of the Holt and Holt-W methods are considered. The Holt-D model is the exponentially smoothed version of the Holt model. The parameters for the models are estimated from data rather than being fixed arbitrarily.

[16] Mean square error measures are avoided as they are scale dependent and sensitive to outliers.

[17] The Internet Traffic Report URL is http://www.internettrafficreport.com.

[18] The use of index data is effectively an external normalization with training data in [0,100].

[19] Time-of-day and scale of demand effects may impact on router performance. For example, the Perth router services a small market and likely to have relatively low early morning congestion, while the Yahoo router may experience peak demand in the mid-to-late afternoon.

[20] Comparisons between consecutive months are considered.

[21] Nonlinear parametric tests employed are parametric as data set is too small to employ non-parametric nonlinear tests.

[22] The McLeod and Li (1983) test is a squared residual analogue of the Ljung-Box (1978) *Q* test.

[23] The number of (p,q) lags used to pre-whiten each series is from 1 to 5.

[24] The RESET test is a general test to examine if a functional form is misspecified.

[25] This result is expected as ADF(5) tests show all series are stationary. In addition, traffic index data oscillates in [0,100].

[26] The Bonferroni *p*-value is $\alpha = kp_l$, where the k is the number of random draws of the hidden units used to estimate the ANN model and p_l is the lowest *p*-value for *k* draws. Hochberg's (1988) modified Bonferroni *p*-value method is estimated by the lowest α value calculated by multiplying the i^{th} *p*-value using *m* draws by $(m-i-1)$.

[27] Geographical regions are from the *Internet Traffic Report*. At http://www.internettrafficreport.com

[28] There is no consensus best fit ANN metric. The criteria used are least AIC, AICC and BIC statistics.

[29] The MAPE, MdAPE and PB statistics for the ANN model with direct connections (not shown) lie between ANN models without direct connections. Hence, the results of NN-AIC, NN-AICC and NN-BIC specifications are the best ANN model without direct connections.

[30] This is consistent with Qi and Zhang (2001) that show the AIC, AICC and BIC are equally useful with $d = 3$ in choosing the best ANN(p,q) model.