Neural Approach Self-Similar Traffic Prediction in ATM Networks

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Abstract
Recent studies have shown that conventional traffic models are unable to capture the real nature of traffic pattern in high-speed networks, such as ATM Networks. Instead, they found that self-similar model is a better model in representing this type of traffic pattern. The differences between conventional and self-similar models have significant implications in network design, management and analysis. Due to these significant differences, researches that suggest the implementation of neural network in traffic prediction could perform an effective and accurate forecast, should be reviewed by using this new traffic model. With this in mind, the use of neural network in predicting self-similar traffic in ATM Networks is observed in this research. Neural Network is used because it has been proven to have very good mapping abilities in some difficult tasks. In this paper, a (3-8-1) backpropagation neural network is trained with a suitable sample and then used to predict self-similar traffic in ATM networks. The results show that the trained neural network could effectively and accurately predict the self-similar traffics in ATM Networks.

Keywords: *traffic management, neural network, simulation.*

1. INTRODUCTION

ATM Networks have made a variety of new multimedia services, such as teleconferencing, live broadcasting etc., possible, but it also generates new problem in traffic management. Past investigations on ATM Networks focused on the use of Poison or Markovian Models to capture the nature of traffic pattern [1, 2]. Unfortunately, recent studies such as in [3] have shown that these models cannot exhibit the long-range dependence (LRD) characteristic that presented by high-speed network. Consequently, self-similar traffic model has been proposed to be a more suitable model in representing high-speed traffic because this stochastic process has autocorrelation function that decays hyperbolically, which matches the LRD characteristic [4, 5]. Self-similarity is a characteristic of a time-sequence that exhibits the same pattern regardless of its degree of resolution and magnification [6].

These distinct differences between conventional model and self-similar traffic have significant implications on network design, control and analysis. It has been proven with strong empirical results that researches based on conventional models provide very optimistic predictions, and solutions based on these predictions will degrade the network performance [7]. Therefore, these researches must be reviewed by using this new traffic model. Traffic prediction is one of the most important tasks in traffic management because an accurate prediction is able to help in improving network performance [1, 8, 9]. Therefore, this paper will focus on self-similar traffic prediction in ATM Networks.

Several methods can be used to perform the traffic prediction. In this research, artificial neural network is used because researchers have proved that very accurate prediction can be easily obtained using neural network and the results can provide useful information for other traffic management jobs [10]. Neural network is a distributed information processing structure that is able to perform both linear and non-linear mappings for several difficult tasks, such as pattern recognition and adaptive control [11-13]. Neural prediction of traffic pattern basically involves four stages. The first stage involves designing neural network architecture. Next is the generation of training data. The third stage is neural network training where it will adapt itself to the desired characteristic. The final stage is using the neural network to predict different data series and evaluate its performance.

This paper is organised as follows. In Section 2, the self-similar traffic is introduced together with the self-similar traffic generator used in this research. The use of neural networks in traffic prediction is discussed in Section 3. Section 4 presents the simulation results and analysis. This is followed by discussion and conclusion in Section 5.

2. SELF-SIMILAR TRAFFIC

Self-similar traffic is a widely used stochastic process with autocorrelation function that decays faster than exponential or it decays hyperbolically. This exhibits the LRD characteristic of the high-speed traffic. Therefore, it is more suitable than the conventional models in capturing the nature of traffic in high-speed networks such as ATM Networks. In addition, this model can be easily characterised by a single parameter called Hurst Parameter (H-parameter), where $0.5<H<1$. A series with H-parameter closer to 1 means it is more self-similar while a value of 0.5 means the self-similarity does not exist. Self-similar process has been long implemented in other fields of study such as mathematics, astronomy and economics, but only recently it has been used in network engineering. Self-similarity is defined as a time-sequence that shows the same pattern under different degree of resolution. This means it behaves the same when it is viewed under different scales of dimension [6]. Fig. 1 is a simple illustration that displays the pattern of self-similarity.

LRD is a property that describes the behaviour of autocovariance function, $C(\tau)$, as time (τ) increases. It is a significant property of self-similar processes and this is the main factor why it is chosen to represent ATM traffic. In general, a short-range dependence (SRD) process has autocorrelation that decays exponentially. In contrast, an LRD process has autocovariance that decays hyperbolically. For example a stationary stochastic process $X = \{X_k, k = 1,2, \ldots, n\}$ is said to present self-similarity if the autocorrelation function can be represented by equation 1 and as shown in Fig. 2.

$$C(k) \sim |k|^{-(2-2H)}, \text{ as } |k| \to \infty \quad (1)$$

Several researches have been done in order to establish an accurate and effective algorithm for self-similar traffic generation [14, 15] and throughout this research, the algorithm used was the one proposed by Paxson [16]. This algorithm can generate an approximate sample path of Fractional Gaussian Noise (FGN) fast and accurately. The mathematics behind this algorithm is using Discrete Fourier Transform (DFT) to synthesise FGN from its power spectrum. After the sample paths $X = \{X_k, k = 1,2, \ldots, n\}$ are obtained, a linear transformation is needed to convert it to the actual cell arrival path, A(k). This method has been used in building the NIST ATM/HFC Network Simulator by the National Institute of Standards and Technology (NIST) [17]. The transformation is as follow:

$$A(k) = m + m*X_k / (c*\sigma) \quad (2)$$

where m is the mean bit rate for the sample generated; σ is the variance for sample path X and c is a scaling factor that ensures the value of A(k) belongs to interval (0, 2*m). The negative values and values greater than (2*m) are set to 0 and (2*m) respectively.

3. TRAFFIC PREDICTION USING NEURAL NETWORKS

Artificial neural network models are oversimplified version of biological networks which are implemented with engineering techniques to achieve the desired behaviour. They are powerful tools in performing linear and non-linear mappings. Below is the definition for neural network [18]:

Definition 1

A neural network is a parallel, distributed information processing structure consists of processing elements (which can possess a local memory and can carry out localised information processing operations) interconnected together with unidirectional signal channels called connections. Each processing element has a single output connection which branches ("fans out") into as many collateral connections as desired (each carrying the same signal – the processing element output *signal). The processing element output signal can be of any mathematical type desired. All of the processing that goes on within each processing element must be completely local: i.e. it must depend only upon the current values of the input signals arriving at the processing element via impinging connections and values stored in the processing element's local memory.*

Some of the important issues in designing neural network include network topology, activation function and the learning mechanism. As mentioned before, the neural prediction involves four stages.

3.1 Network Topology Design

In selecting the network architecture, there are several aspects that need to be considered. These include the numbers of layer in the network, numbers of neuron in each layer and also the connectivity between layers. In this research, a (3-8-1) fully connected neural network is used and shown in Fig. 3. The triple means a 3-layers neural network with 3 nodes in input layer, 8 hidden nodes and a single output. Besides, each node is fully interconnected with nodes in the neighbouring layers. Each nodes in hidden and output layers is also associated with a bias term that acts as zero adjustment for overall stimulus inputs.

3.2 Training Data Generation and Manipulation

The training data are obtained from the algorithm proposed by Paxson which is explained in section 2. In this research, the sample is generated at the mean rate of 50Mbps; this means the data rates will distribute between 0Mbps and 100Mbps. Since this research focuses on the ability of neural network in predicting traffic with high self-similarity, therefore the H-parameter is set to value that closes to 1 in order to obtain sample data that perform high self-similarity. Anyway, the H-parameter cannot be set to 1 because a prefect self-similarity model is not realistic.

For the training set, a total of 500 continuous data rates are obtained. These data are first normalised to values between 0 and 1 by dividing them with the peak data rate (100Mbps). There are three inputs and a single output for the neural network, so the training set should be divided into groups of 4 members each. The first three data are the inputs while the last member is the desired output that will be used for error calculation. Therefore, each cycle of training involves 497 groups of training vector. The data manipulation is shown in Fig 4.

3.3 Neural Network Training

Training is a process of adapting the neural network with the desired characteristic. This is done by changing the weight and bias term associated with each connection. In this research, backpropagation algorithm, which is the most widely used model nowadays, is used. There are three stages in this training: feedforward of inputs, backpropagation of errors and updating of weights and biases. In the feedforward stage, a sigmoid function with output range between 0 and 1, is used to obtain activation for the weighted sum inputs. This sigmoid function can be represented by equation 3 and as shown in Fig. 5.

$$f(x) = [1+\exp(-x)]^{-1} \tag{3}$$

The backpropagation algorithm used in this research is obtained from Fausett [19]. In neural network training, suitable stopping criteria are needed to determine when the training should be stopped. In this research, the training is stopped when the mean square error (MSE) of the output starts to increase. This is because further training will not increase the network performance.

3.4 Performance Evaluation

After the neural network training, the accuracy of this trained neural network in predicting other series of self-similar traffic in ATM Networks is observed. The test series are obtained with the same generator. There are 6 samples of testing set each with 3000 continuous data. The test sets are manipulated into groups of 3 members each and they are fed into the trained neural network to calculate the corresponding output. The predicted series are then compared with the corresponding series.

One of the most suitable performance measurements is the coefficient of determination (CoD) given by equation 4 [20].

$$\mathrm{CoD} = \frac{\sum_{i=1}^{n} (\hat{X}_i - \bar{x})^2}{\sum_{i=1}^{n} (X_i - \bar{x})^2} \tag{4}$$

where set X={X_i; i =1,2, …, n } is the input series with mean $\bar{x}$ and $\hat{X} = \{\hat{X}_i; i = 1,2,...,n\}$ is the predicted series. For a perfect prediction, the value should be one. Therefore, the closer the value to 1, the better the performance of the prediction.

4. RESULTS AND ANALYSIS

In the performance evaluation experiment, there are 3000 continuous data in each testing sample. Fig. 6 is a plot for the actual output and the predicted output for one of the samples. Also, for a better view of their patterns, only the first 500 data are displayed in the plot. For the rest of the test sets, only the measurement of CoD for each sample is displayed in Table 1. It can be observed that the same result is obtained.

5. DISCUSSION AND CONCLUSIONS

From the plot in Fig. 6 that compares the predicted series and the actual series, it is clear that the predicted series has the same pattern with the actual series. This is further supported by the measurement of the Coefficient of Determination (CoD) displayed in Table 1. From this measurement, we found that the trained neural network is able to forecast the self-similar traffic in an ATM network with great accuracy. This observation is useful for contemporary traffic engineering tasks because previous researches have shown that conventional models have significant implication in traffic engineering, but in this research, we found that the effects of LRD characteristic can be easily overcome by using the existing methods with minimum modification. This observation can greatly reduce the traffic engineers workload in redesigning methodology for various traffic management tasks to handle the LRD characteristic presented by ATM Networks. In conclusion, this research has shown that neural network is the most suitable tool for traffic prediction in ATM networks that present LRD characteristic.

REFERENCES

[1] Yu, E. S. and Chen, C.Y.R.: ‘Traffic Prediction Using Neural Networks’, GLOBECOM '93, Vol. 2 pp. 991 -995

[2] Liu, Y. C. and Douligeris, C. ‘Feedback Congestion Controller for ATM Networks Using a Neural Network Traffic Predictor’, Southcon’95, Conference Record pp. 398–402.

[3] Paxson, V. and Floyd, S.: ‘Wide Area Traffic: The Failure of Poisson Modeling’, IEEE/ACM Transactions on Networking, June 1995, 3(3) pp. 226–244.

[4] Leland, W. E., Taqqu, M. S., Willinger, W and Wilson, D. V.: ‘On the Self-Similar Nature of Ethernet Traffic (Extended Version)’, IEEE/ACM Transactions on Networking, February 1994, 2(1) pp. 1–15.

[5] Tsybakov, B. and Georganas, N. D.: ‘Self-Similar Processes in Communications Networks’, IEEE Transactions on Information Theory, September 1998, 44(5) pp. 1713–1725.

[6] Stallings, W.: ‘High Speed Networks: TCP/IP and ATM Design Principles’, Prentice Hall International Inc., 1998 International Edition.

[7] Huang, C., Devetsikiotis, M., Lambadaris, I. and Kaye, A. R.: ‘Self-Similar Traffic and Its Implications for ATM Network Design’, 1996 International Conference on Communication Technology, ICCT’96, vol. 2 pp. 1053–1056.

[8] Tarraf, A., Habib, I. and Saadawi, T.: ‘Congestion Control Mechanism for ATM Networks Using Neural Networks’, IEEE International Conference on Communications 1995, ICC '95 Seattle, vol. 1 pp. 206–210.
[9] Kotze, N. J. H. and Pauw, C. K.: ‘The use of Neural Networks in ATM’, Proceedings of the 1997 South African Symposium on Communications and Signal Processing, COMSIG '97, South African, pp. 115–119.
[10] Hiramatsu, A.: ‘ATM Communications Network Control by Neural Network’, 1989 International Joint Conference on Neural Networks, ICJNN’89, vol. 1 pp.259-266.
[11] Lee, C. K. and Yeung, K.F.: ‘Waveform Recognition and Classification Using Unsupervised Neural Network’, Proceeding of 1993 International Joint Conference on Neural Networks, IJCNN’93-Nagoya, vol. 3 pp. 2710-2713.
[12] Hara, Y., Atkins, R. G. and Yueh, S. H.: ‘Application of Neural Networks to Radar Image Classification’, IEEE Transactions on Geoscience and Remote Sensing, January 1994, 32(1) pp. 100–109.
[13] Zalama, E., Gaudiano, P. and Lopez-Coronado, J.: ‘A Real-time Unsupervised Neural Network for the Control of a Mobile Robot’, IEEE World Congress on Computational Intelligence, 1994 IEEE International Conference on Neural Networks, vol. 5 pp. 2848–2853.
[14] Fan, Z. and Mars, P.: ‘Self-similar Traffic Generation and Parameter Estimation Using Wavelet Transform’, GLOBECOM '97, Vol. 3, pp. 1419 –1423
[15] Lau, W.C., Erramilli, A., Wang, J. and Willinger, W.: ‘Self-similar Traffic Generation: The Random Midpoint Displacement Algorithm and Its Properties’, IEEE International Conference on Communications 1995, ICC '95 Seattle, vol. 1 pp. 466 -472
[16] Paxson, V.: ‘Fast Approximation of Self-Similar Network Traffic’, Laurence Berkeley Laboratory, University of California, Berkeley, LBL-36750, April 1995.
[17] Golmie, N., Mouveaux, F., Corner, M., Saintillan, Y., Koenig, A. and Su, D.: ‘The NIST ATM/HFC Network Simulator: Operation and Programming Guide Ver. 4’ (NIST, 1998).
[18] Hecht-Nielsen, R.: ‘Theory of the backpropagation Neural Network’, International Joint Conference on Neural Networks, IJCNN’89, vol. 1 pp. 593-605.
[19] Fausett, L.: ‘Fundamentals of Neural Networks: Architectures, Algorithms and Applications” (Prentice Hall International, Inc., 1994)
[20] Owen, F., Jones, R: ‘Statistics’, Pitman Publishing, London, 1994 4th ed..

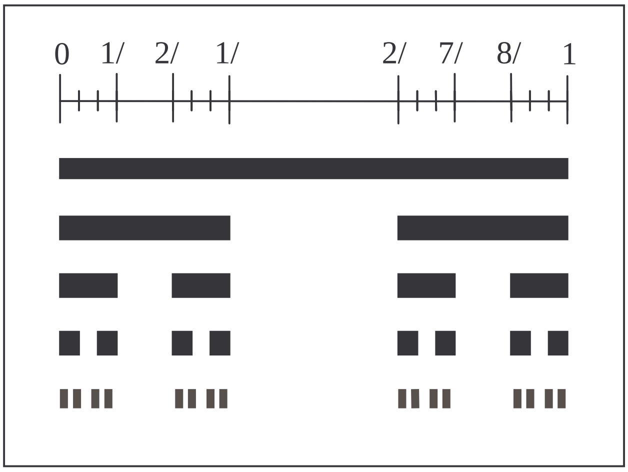

Fig. 1 Simple Illustration of Self-similarity

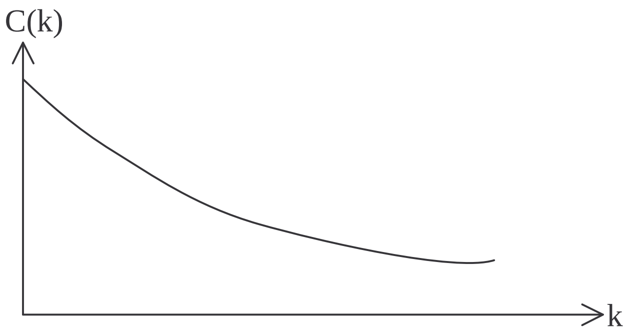

Fig. 2 Autocorrelation Function for LRD

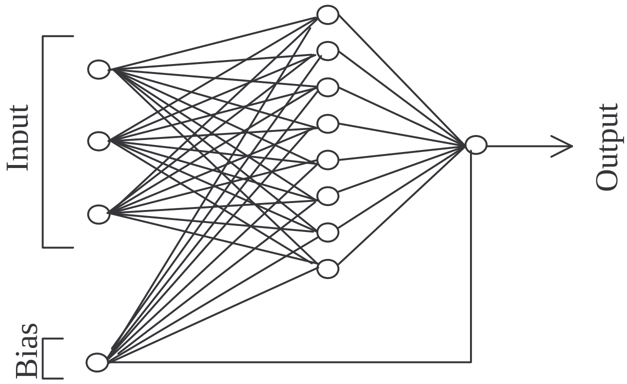

Fig. 3 Neural Network Architecture Used

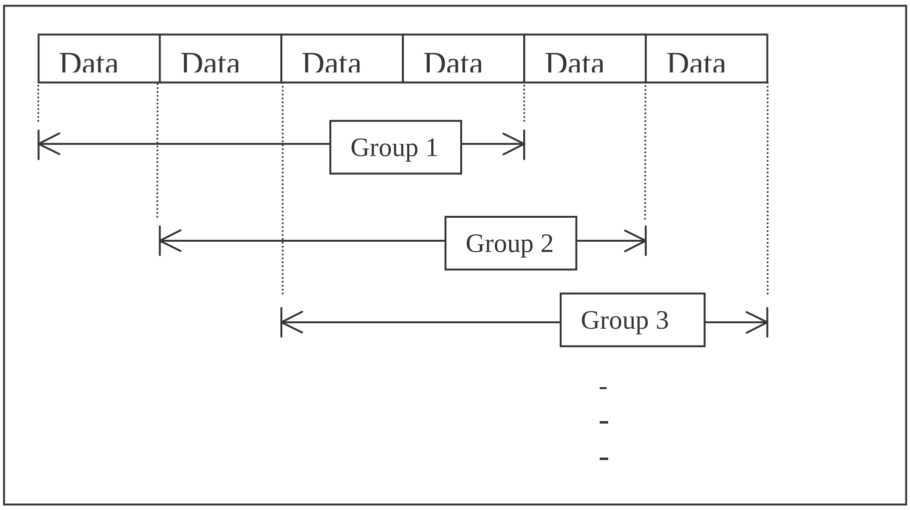

Fig. 4 Training Vector Manipulation

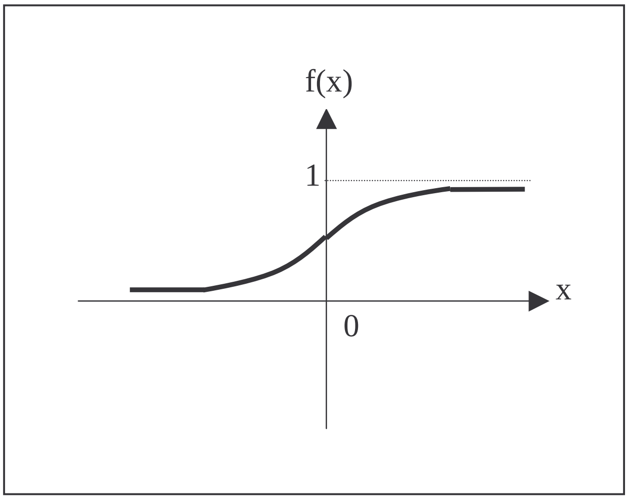

Fig. 5 Sigmoid Function

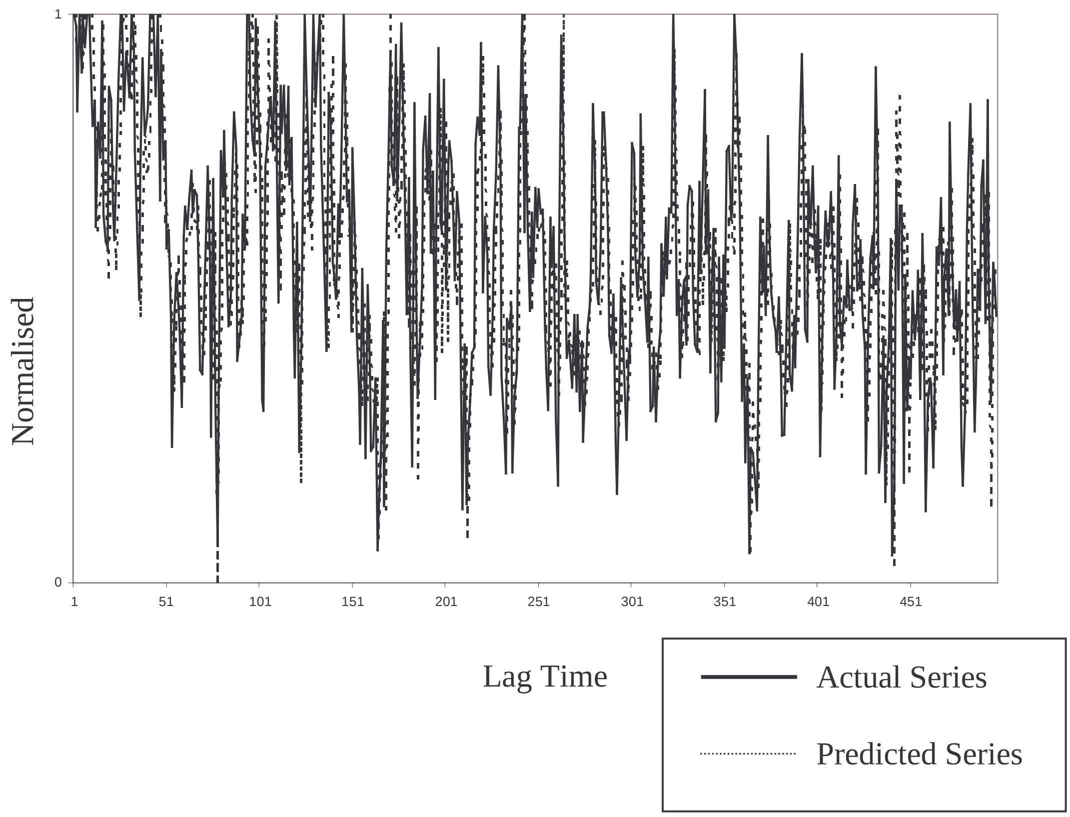

Fig. 6 Plot for actual and predicted series

Table 1: Coefficient of Determination for predicted series

Set	CoD
a	0.7754
b	0.8075
c	0.7921
d	0.7812
e	0.7875
f	0.7758

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