

A Modified Wavenet-Based Link Status Predictor for Computer Networks

Jassim M. Abdul-Jabbar* and Omar A. Hazim**
Computer Engineering Department, College of Engineering, University of Mosul, Mosul, Iraq.

* drjssm@gmail.com

** abdulkareemhazim@yahoo.com

Abstract

In this paper, a modified wavelet neural network (WNN) (or wavenet)-based predictor is introduced to predict link status (congestion with load indication) of each link in the computer network. On the contrary of previous wavenet-based predictors, the proposed modified wavenet-based link state predictor (MWBLSP) generates two indicating outputs for congestion and load status of each link based on the premeasured power burden (square values) of utilization on each link in the previous time intervals. Fortunately, WNNs possess all learning and generalization capabilities of traditional neural networks. In addition, the ability of such WNNs are efficiently enhanced by the local characteristics of wavelet functions to deal with sudden changes and burst network load. The use of power burden utilization at the predictor input supports some non-linear distributions of the predicted values in a more efficient manner. The proposed MWBLSP predictor can be used in the context of active congestion control and link load balancing techniques to improve the performance of all links in the network with best utilization of network resources.

Keywords— Computer Networks; Wavelet-Neural Networks; Prediction; MWBLSP; Congestion control, Link utilization, Link Load.

متنبىء مُعدَّل لحالة الوصلات في شبكات الحاسوب بإعتماد الشبكات العصبية المويجية

أ. د. جاسم محمد عبد الجبار* عمر عبد الكريم حازم**

قسم هندسة الحاسوب- كلية الهندسة- جامعة الموصل- الموصل- العراق.

** abdulkareemhazim@yahoo.com

* drjssm@gmail.com

المخلص

في هذه الورقة، تم اقتراح متنبىء مُعدَّل بإعتماد الشبكة العصبية المويجية (WNN) (أو wavenet) للتنبؤ بحالات الإكتظاظ مع بيان الحمل في كل وصلة في الشبكة الحاسوبية. وعلى العكس من المتنبىءات السابقة بإعتماد wavenet، فإن المتنبىء المُعدَّل المقترح لحالة الوصلة (MWBLSP) يولد إخراجين يشيران الى كل من الإكتظاظ وحالة الحمل لكل وصلة. وقد تم بناءهما على أساس إدخال قيم تربيعية من الاستغلال في كل وصلة في فترات زمنية سابقة. ولحسن الحظ، فإن الشبكات العصبية المويجية تمتلك كل قدرات التعلم والتعميم التي تمتلكها الشبكات العصبية التقليدية. وبالإضافة إلى ذلك، فإن أمكانيات هذا النوع من الشبكات العصبية يتم تحسينها بكفاءة من خلال الخصائص المحلية للدوال المويجة للتعامل مع التغيرات المفاجئة والكبيرة للحمل على الشبكة. إن استخدام القيم التربيعية لإستغلال الشبكة كمدخلات للمتنبىء يدعم بعض التوزيعات غير الخطية من القيم المتوقعة بطريقة أكثر كفاءة. ويمكن إستخدام المتنبىء MWBLSP المقترح في مضمار التحكم النشط بالإكتظاظ وتقنيات تحقيق توازن الحمل لتحسين أداء جميع الوصلات في الشبكة مع الاستغلال الأمثل لموارد تلك الشبكة.

1. Introduction

Network traffic prediction takes significant interest in many domains such as adaptive applications, congestion control, and network management [1]. Such prediction provides proactive network management while improving the global performance of the network through congestion control and prevention [2].

Data traffic in computer network can be considered as non-linear and non-stationary time signal that exhibits both characteristics of short range and high degree long range dependence such that classical prediction systems cannot model network traffic perfectly. Because of their characteristics and approximation capabilities, heuristic systems such as artificial neural networks can approximate non-linear systems more accurately [3].

Predicting link status (congested, uncongested, loaded or unloaded) always helps the designers in developing some modified routing protocols that are capable to detect congestion in a network before it starts affecting the network performance. If congestion state is predicted in early stages, the effect of congestion may be avoided using some efficient congestion control techniques. Such techniques may use the predicted information to control the amount of traffic and manages network resources to prevent congestion problems or at least reduce their effects. Such congestion control techniques are called active congestion control [2].

In the present Internet, congestion control mechanisms rely on queue management algorithms (dropping packets randomly or based on their priority) or TCP

(Transmission Control Protocol) congestion avoidance (by reducing the sending rate). From the end-user perspective, these solutions are not optimal because they either result in some loss of packets or reduced bitrate operations, thereby affecting the quality of transmission. Therefore, some of new researches propose techniques for solving congestion by changing the paths of traffic to avoid congested links or by adding new paths [4].

Employing a prediction-based approach helps in a quick matching for different network resources to the traffic demand. Its speed is clarified in terms of congestion detection and elimination, unlike reactive approaches which detect congestion only after it significantly influenced the operation of the network [5].

This paper develops a simple topology independent predictor for congestion and loading states in next time interval based on wavenet neural networks and the power-law utilization values of the previous time intervals.

The rest of this paper is organized as follows: Section 2 briefly presents previous related works regarding prediction using artificial intelligence techniques. In section 3, wavenet fundamentals are given. Section 4 introduces the structure of the proposed MWBLSP predictor. In Section 5, the proposed predictor is tested and its performances are compared with one of the recent predictors on the same bases. Finally, Section 6 concludes this paper.

2. Related Works

Using some artificial intelligence techniques for traffic prediction and congestion control is a continuing research

field. There were many recent researchers that used neural network for predicting traffic patterns. J. Bivens and B. Szymanski [6] proposed a simple feed forward neural network to predict severe congestion in a network. They also used neural networks to predict the source or sources responsible for the congestion, and designed a simple control method for limiting the rate of the offending sources so that congestion can be avoided. Two different artificial neural network (ANN) architectures, multilayer perceptron (MLP) and fuzzy neural network (FNN) were used in [7] to predict one-step ahead value of the MPEG and JPEG video, Ethernet and Internet traffic data. The outputs of the individual ANN predictors were combined using different combination schemes for best performance. Z. N. Abdulkader [4] presented the uncongested shortest path first (USPF) algorithm to solve congestion problem in an open shortest path first (OSPF) based best effort network. An artificial neural network was trained to detect congested links based on a given traffic pattern. Then a simple feed-forward neural network was used to predict the congestion problem in the computer network links which were over utilized. A control method was applied to select the shortest paths, that excluding those links.

Recently, the applications of wavelet neural network were proposed in [3] for congestion prediction and then in [8] for congestion-load state predictions using previous link utilization values. More recently, a network traffic prediction hybrid model was proposed by S. Guang [9]. Such model was based on α Trous wavelet analysis and Hopfield neural network, which

can be used to predict the network traffic flow.

It is known that link utilization values reflect link congestion in a better manner than link loads [3], [8]. Thus, in this paper such idea is also applied for congestion prediction in a wavenet network but with some modification that is the use of the squared link utilization values. Results have proved that using these squared functions can improve the distribution of inputs and increase the sensitivity of congestion state prediction, resulting in very small missing rates of congestion prediction in the next time interval and in a less-complex predictive network.

3. Wavenet Theoretical Background

Wavenet can be considered as a particular case of the feed forward basis function neural network model. In ordinary network, several types of bases functions, such as radial basis functions, splines and polynomial functions of synapse neurons are used instead of sigmoidal function. The connection weights are taken to represent the corresponding coefficients. The output layer performs the sum of the output of all synapse neurons. Since wavelets have shown their excellent performance in non-stationary signal analysis and non-linear function modeling, then it can be easily proved that neural networks with wavelet basis function, or wavenets, can provide higher availability of rate of convergence for the approximation problem than any ordinary feed forward neural network [10].

The structure of WNN is shown in Fig. 1, which comprised of an input layer, a wavelet layer, and an output layer. The N

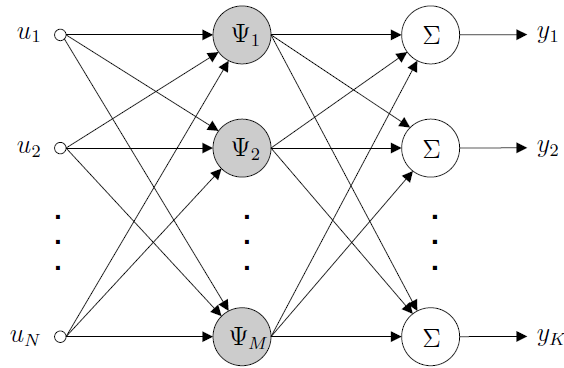


Figure 1 WNN structure.

dimensional input data in the input layer of the network is $U = [u_1 u_2 \dots u_N]$. The input data are directly transmitted into the wavelet nodes (wavelons) in the wavelet layer. In a wavelet transform, the mother wavelet function $\psi(u)$ can be presented with a dilation a and a translation b as follows:

$$\psi_{a,b}(u) = \frac{1}{\sqrt{a}} \psi\left(\frac{u-b}{a}\right) \quad \dots(1)$$

In this paper, the Mexican-hat function; the second derivate of the Gaussian function (shown in Fig. 2) is used as an activation function. It is expressed as follows:

$$\psi(u) = (1 - u^2)e^{-\frac{u^2}{2}} \quad \dots(2)$$

In the case of multi-dimensional input the wavelons will consist of multidimensional wavelet activation functions. They will produce a non-zero output when the input vector lies within a small area of the multidimensional input space [11]. The output is defined by:

$$y_k(x) = \sum_{j=1}^M W_{kj} \psi_j(u) \quad \dots(3)$$

with

$$\psi_j = \prod_{i=1}^N \psi_{a_j, b_j}(u_i) \quad \dots(4)$$

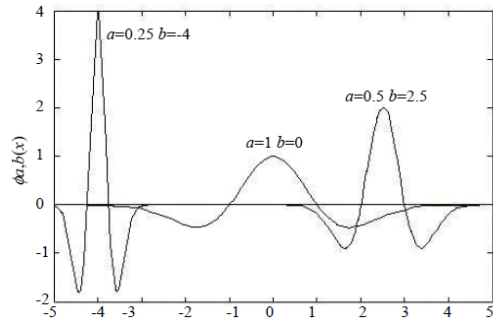


Figure 2 The Mexican-hat function with different dilation and translation values.

where φ_j , $j = 1, 2, \dots, M$ is used as a nonlinear transformation function of hidden nodes, and W_j , $j=1, 2, \dots, M$ is used as the adjustable weighting parameters to provide the function approximation [12]. It should be noted that the wavelon of (4) is equivalent to a multidimensional wavelet [11].

The applied training algorithm is the gradient that is commonly used to minimize the error and obtain the suitable network parameters. The process can be summarized as that the variations of error energy function with respect to each network parameter *i.e.*, the gradient factors are calculated. Then these factors are used as incremental factors to update the current network parameters in the direction leads to minimize the error [3].

4. The Proposed MWBLSP Structure

There is an independent WNN network for each unidirectional link in the computer network; all operate in parallel to compute the output prediction vectors. If there are k unidirectional links (bidirectional link is considered as a twice unidirectional links) in the computer network, then there are k independent WNN networks. Each WNN (as shown in Fig. 3) consists of 3 nodes in the

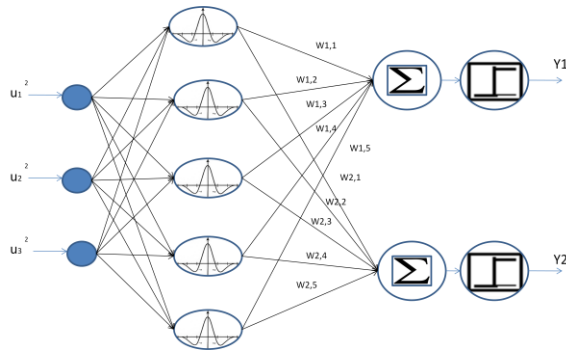


Figure 3 The structure of WNN for MWBLSP.

input layer, 5 nodes (wavelons) in the hidden layer and 2 nodes in the output layer. Each input is the square of the average link utilization for one minute in the near past and can be given by

$$U_i = [u_1^2 u_2^2 u_3^2] \dots (5)$$

Accordingly, the total inputs of the proposed WNN reflect the utilization behavior during the last three minutes. The squared values of the averages of link utilizations are applied as inputs. The square function has a very attractive nonlinear mapping property. It has been noticed that such power burden can contribute to redistributing the inputs in a more efficient manner, resulting in decreasing the complexity of the WNN network.

The Mexican-hat wavelet is used as an activation function in the hidden layer nodes since it is very appropriate for function approximation and prediction because it is continuous, differentiable, provide a softer output, and improve the interpolation capabilities. It also reduces the number of iterations resulting in a faster convergence and a good escaping from local minima [3].

Each WNN generates two bit-string outputs representing both congestion and load states of the corresponding link. In the

first output, the congestion bit is set when one of the average of utilization values of the last three minutes is greater than 70% or the average of utilization values of current minute may be greater than 70%, else the output is cleared [4], [13]. On the other hand, for more stable network operation, the loading bit is set when one of the average of utilization values of the last three minutes is greater than 40% or the average of utilization values of current minute may be greater than 40%. The total predicted state is described by two vectors the congestion vector and load vector. If a computer network consists of k links, there will be k bits in the each vector.

5. Simulation and Results

For training and testing purposes, OPNET 14.5 simulator is used to simulate the two network topologies used in [3]. Figures 4 and 5 show these two topologies (Topology 1 and Topology 2, respectively), highlighting how LANs and servers are connected to them.

For the purpose of accuracy, three network applications (HTTP, FTP and EMAIL) are used in the simulation in three different scenarios. They are

Scenario 1: some LANs apply heavy loads in some times and light loads in some others, while the other LANs apply only light loads.

Scenario 2: all LANs apply heavy and light loads so that the congestion appears on network links in non-simultaneous fashion.

Scenario 3: all LANs apply heavy loads on a network so that the congestion appears in a simultaneous fashion.

All these scenarios run for 6 hours using OSPF routing protocol in both topologies.

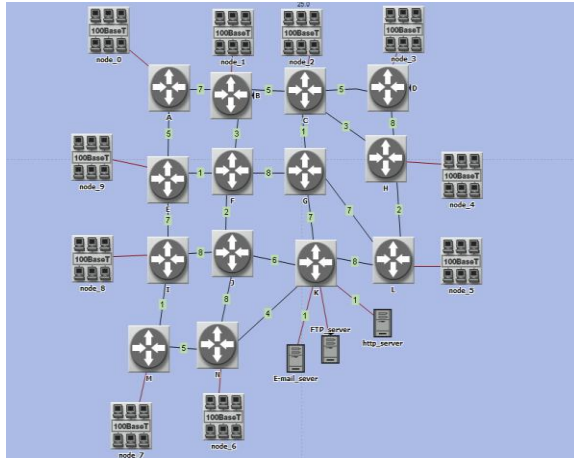


Figure 4 Network Topology 1.

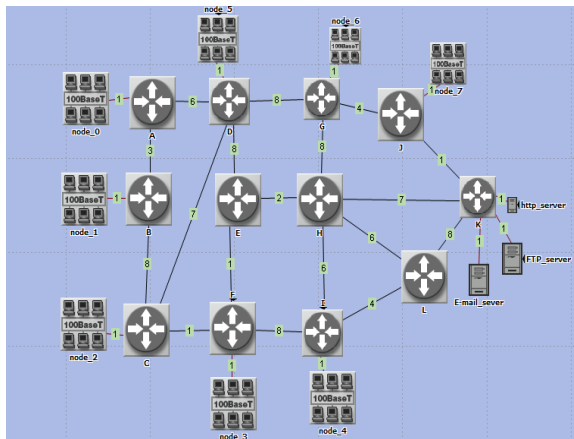


Figure 5 Network Topology 2.

There will be a utilization sample each minute. The first 10 minutes are canceled because they may contain a transient data, so the total number of training samples is 350 samples per link. Six links are selected from Scenario 2 of Topology 1 to produce 2100 training samples that are used to train a single WNN in the proposed MWBLSP predictor. For comparison purposes, these samples are also used to train the wavenet-based congestion predictor with link indication (WBCP-LI) [8] which also uses WNN for congestion and loading state prediction. The six links are selected in a manner so that there are two congested links

and 2 loaded uncongested links and two unloaded links.

The data gathered from previously mentioned scenarios are used to test the proposed MWBLSP and the WBCP-LI. The prediction accuracy is computed for each scenario by dividing the total number of correct prediction to the total number of samples. For Topology 1, the total number of samples is equal to $44 \times (5 \times 60 + 50) = 15400$ samples and for Topology 2, it is $36 \times (5 \times 60 + 50) = 12600$ samples.

The false indication rate is the ratio of the number of incorrect prediction of congestion or loading while the link is not congested to the total number of samples. The miss error rate is the ratio of the number of incorrect missing of congestion or loading while the link is congested or loaded into the total number of samples. The two predictors (the proposed MWBLSP and the WBCP-LI) are tested and their performances are compared for the two pre-mentioned topologies. Such performances are shown in Figs. 6 to 17, including prediction accuracies, miss errors and false indications of both congestion state prediction and loading state prediction. It should be noted that, the differences of the results between MWBLSP and WBCP-LI occur only on congested links for congestion prediction and on loaded links for loading prediction. While the prediction accuracy is 100% in both predictors for uncongested links in congestion prediction and for unloaded links in loading prediction.

From Figs. 6 to 9, it can be noticed that both predictors possess high prediction accuracy. Despite that in Figs. 10 to 17, WBCP-LI shows a balancing properties

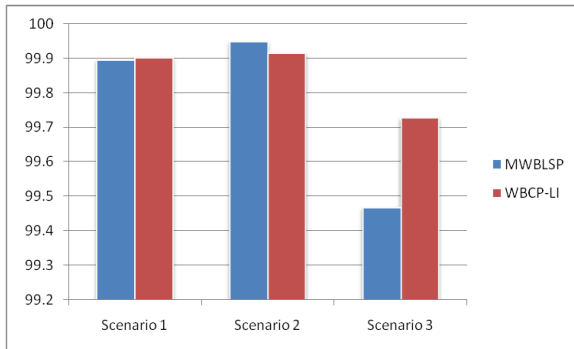


Figure 6 Prediction accuracy of congestion state prediction for Topology 1.

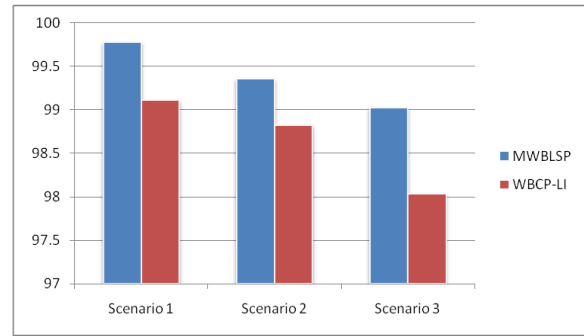


Figure 9 Prediction accuracy of loading state prediction for Topology 2.

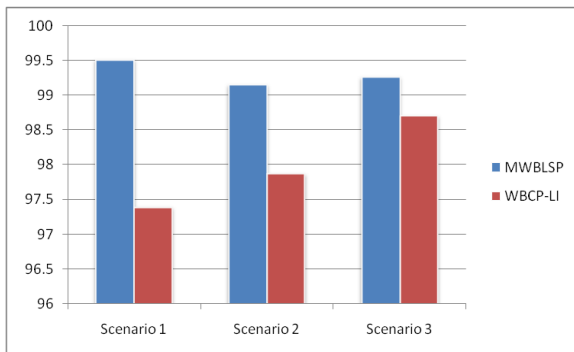


Figure 7 Prediction accuracy of loading state prediction for Topology 1.

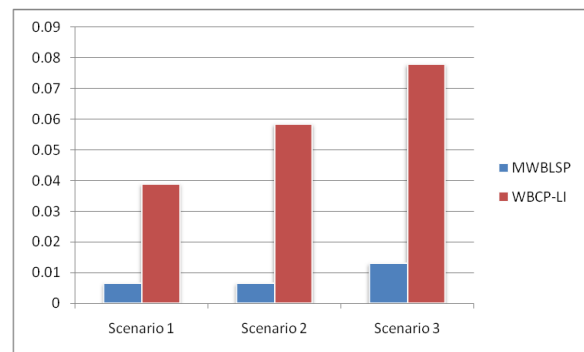


Figure 10 Miss error rates for congestion prediction for Topology 1.

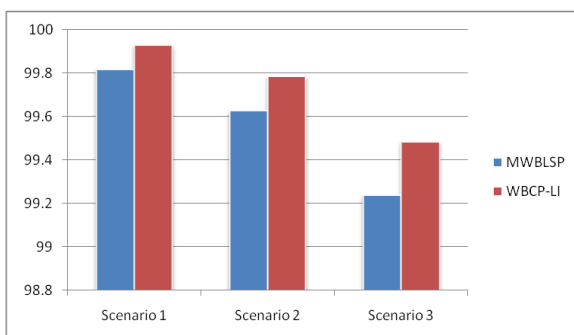


Figure 8 Prediction accuracy of congestion state prediction for Topology 2.

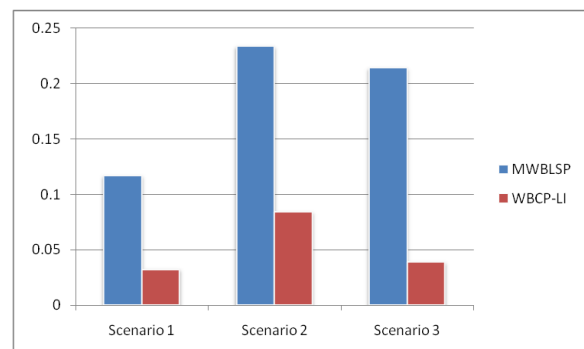


Figure 11 Miss error rates for loading prediction for Topology 1.

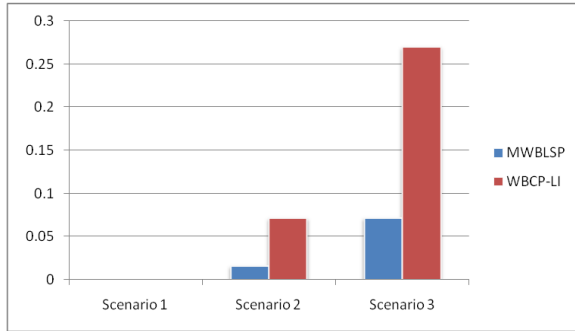


Figure 12 Miss error rates for congestion prediction for Topology 2.

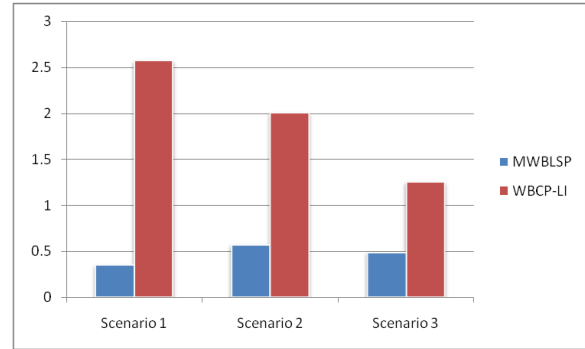


Figure 15 False indication rates for loading prediction for Topology 1.

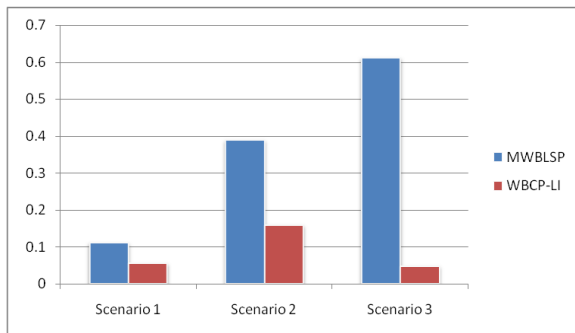


Figure 13 Miss error rates for loading prediction for Topology 2.

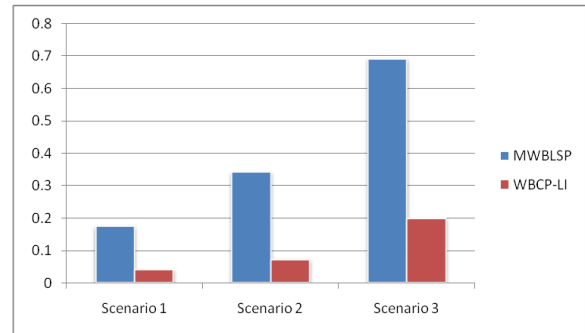


Figure 16 False indication rates for congestion prediction for Topology 2.

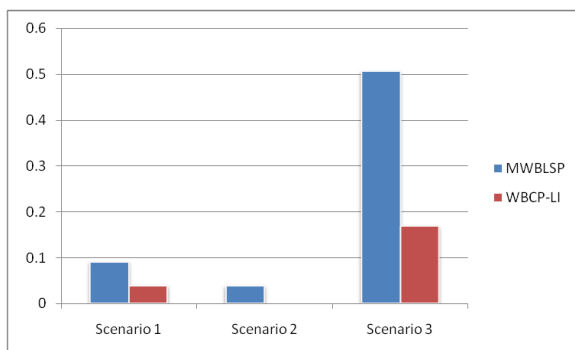


Figure 14 False indication for congestion prediction for Topology 1.

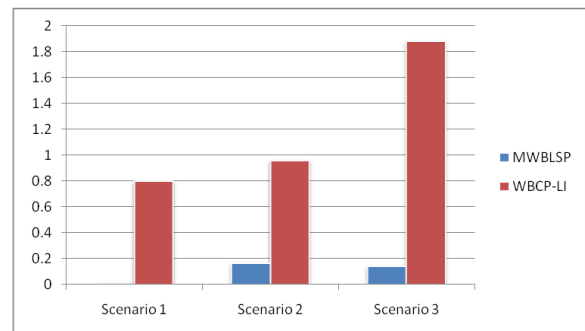


Figure 17 False indication rates for loading prediction for Topology 2.

between the two types of errors in congestion prediction (it shows less false indication rate than MWBLSP with higher miss error rate in congestion prediction), the proposed MWBLSP is more sensitive in congestion prediction than WBCP-LI because it has low miss error rates. Although, there is a simple bias in congestion state prediction accuracy for WBCP-LI but the cost of miss error is more than that of false indication in congestion because unlike false indicating an uncongested link, the missing of a congested one may affect the overall performance of the computers network.

Figures 7, 9, 11, 13, 15 and 17 indicate that the loading state predictions in different cases of WBSLP are more accurate than WBCP-LI and show less sensitivity. That because of their less false indications compared to WBCP-LI which is more sensitive, indicating the fact that the squared input utilization values in MWBLSP can enhance large values and reduce the small ones. As a result of that, MWBLSP predictor shows more sensitivity for congestion than WBCP-LI and less sensitivity for loading.

Besides the fact that the proposed MWBLSP has less missing congestion errors than WBCP-LI and presents more accuracy in loading state prediction, MWBLSP costs only 3 nodes in the input layer and 5 wavelons in the hidden layer. Therefore, it is recommended to use MWBLSP in congestion and loading prediction instead of using WBCP-LI which contains 5 nodes in the input layer and 7 wavelons in the hidden layer.

6. Conclusions

A modified wavenet based link status predictor (MWBLSP) has been proposed, tested and compared with one of previous wavenet based predictor that is the WBCP-LI. It has been shown that a high prediction accuracy and more efficient prediction can result by adding the benefits of squaring the input utilization values applied to the predictor.

It has been shown also that MWBLSP is topology independent and load independent (congestion-load) predictor based on simple wavenet neural network to produce detailed congestion- load state indicator with few-bytes vectors and less implementation complexity.

References

- [1] S. Chabaa and A. Zeroual, "Predicting Packet Transmission Data over IP Networks Using Adaptive Neuro-Fuzzy Inference Systems", Journal of Computer Science, Vol. 5, No.2, 2009, pp. 123-130.
- [2] M. Barabas, G. Boanea and V. Dobrota "Multipath Routing Management using Neural Networks-Based Traffic Prediction", The Third International Conference on Emerging Network Intelligence, 20-25 Nov., 2011, pp. 118-124.
- [3] J. M. Abdul-Jabbar, M. Alwan and A. Jasim "A New Wavenet-Based Network Congestion Predictor – WBCP", International Conference on Future Communication Networks, 9-12 April, 2012, pp. 12 - 17.
- [4] Z. N. Abdulkader, "Path Finding with Reduced Congestion in Computer Networks

using Artificial Neural Network”, M. Sc. Thesis in Computers and Mathematic Sciences, University of Mosul, 2010.

[5] L. Cai, J. Wang, C. Wang, and L. Han, ”A Novel Forwarding Algorithm over Multipath Network”, International Conference on Computer Design and Applications, Qinhuangdao, China, 25-27 June, 2010, pp. V5-353–V5-357.

[6] J. Bivens, M. Embrechts and B. Szymanski, “Network Congestion Arbitration and Source Problem Prediction using Neural Networks”, Smart Engineering System Design Journal, Vol. 4, 2002, pp.243-252

[7] A. Khotanzad and N. Sadek, “Multi-Scale High-Speed Network Traffic Prediction using Combination of Neural Networks”, Proceedings of The International Joint IEEE Conference on Neural Networks, Vol. 2, 20-24 July, 2003, pp. 1071 - 1075.

[8] A. A. Jasim, “Wavenet-Based Computer Network Routing with Congestion Control”, Ph. D. Thesis in Electrical Engineering, Basrah University, 2012.

[9] S. Guang ,”Network Traffic Prediction Based on The Wavelet Analysis and Hopfield Neural Network”, International Journal of Future Computer and Communication, Vol. 2, No. 2, April 2013, pp. 101-105.

[10] J. M. Abdul-Jabbar, “Multi-Basis Wavenet-Based Stator Resistance Identification in DCT Induction Motor System”, Al-Rafidain Engineering Journal, Vol. 18, No. 2, 2010, pp. 1-14.

[11] D. Veitch , “Wavelet Neural Networks and Their Application in The Dynamical Systems”, M. Sc. Thesis in Data Analysis, Networks and Nonlinear Dynamics, Department of Mathematics, University of York, 2005.

[12] C. Lin, “Wavelet Neural Networks with a Hybrid Learning Approach”, Journal of Information Science and Engineering, Vol. 22, 2006, pp. 1367-1387.

[13] D. Medhi and K. Ramasamy, “Network Routing Algorithms, Protocols, and Architectures”, ISBN 13: 978-0-12-088588-6, Elsevier Inc., USA, 2007.