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Efficient Routing Algorithm using MLP and RBX in a Four Model Neural Networks

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Abstract

Two important paradigms which are contradicting by nature namely: the efficient routing information diffusion and adaptability to dynamic network conditions using wireless routing protocols have been researched in recent years. One way of solving this issue is by using the past experiences of a node in network traffic condition through intelligent algorithm to predict the network traffic condition in the future. In this methodology we propose an algorithm which is used to to predict one hop delay per packet during routing process using neural networking. The one hop delay that is predicted is then further used by the participating nodes for information diffusion during routing. Experimental analysis indicate that using tapped delay line radial basis function and tapped delay line multilayer perceptron, it is possible to predict mean delays as a time series. The inputs used for prediction are mean delay time series with traffic loads and mean delay time series itself. The pros and cons of the proposed work are also present in this paper.

Keywords: Multiple Criteria Decision Making, Simple Additive Weighting, Quality of Service, virtual machine, Cyber physical systems

1. Introduction

Wireless networks hold a number of special features like broadcasting style signal dissemination, serious energy restriction, Ad-Hoc nature [1] of network organisation and dynamic network topology. These special features provide a number of opportunities to design

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wireless routing protocol and also hold a number of challenges simultaneously [2]. Attaining adaptability for the different network conditions along with traffic and dynamics of topology is one of the most crucial aspects of wireless routing protocol. However in order to attain this goal a crucial unavoidable issue needs to be addressed which is overhead of routing information diffusion [3]. This includes responses to route requests and periodical message exchange. In order to sustain adaptability, heavy routing control overhead [4] is essential according to the network's dynamic nature. Similarly efficient routing information diffusion also affects the performance of the system. Depending on the ability to attain this figure, the scalability of the wireless routing protocol is determined [5]. To attain these important goals, hybrid, reactive and proactive routing strategies are developed. Based on the frequency of discovered route valid time and periodic routing information exchange [6], the reliability of the system is determined. This is based on the assumption that there is not much change in the network conditions during execution. However to predict the future values of routing metrics, systematically generated prediction will also be able to provide better response. This will lead to better adaptability. In traditional routing strategies [7], the experience of network condition remains unutilized. In this paper we have incorporated prediction of future aspects based on previous experience by the node. It is also possible for the predicted values over a longer period of time when compared with valid time of discovered routes and routing information exchange period. Thus, routing control communication is achieved [8]. It is crucial to understand that predicting the routing metric of multi-hop based on the heavy control overhead is not advisable.

Hence, in this paper, prediction of the associated routing metrics is made by the individual nodes [9] and the values predicted are used for routing responses as well as exchanging information. To reduce routing control overhead [10] and to enhance packet delivery ratio [11] it will be fruitful to incorporate the prediction strategy in the nodes. One of the most important characteristics of neural networks is adaptive learning capability [12]. This methodology e operates on parallel structure and is capable of providing quick data processing in neural networks. In this paper, prediction of 'delay' is the primary objective approach that is dealt with, with the help of a number of neural network approaches. Similarly residue in energy

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[13] can also be predicted with the help of neural networks. Thus prediction of the routing metrics is typically a crucial decision making process, taking into consideration multiple criteria to arrive at a concrete solution based on a reliable neural network algorithm. This paper is further organised into related work in section 2 and to delay prediction using neural network models in section 3. Section 4 laser experimental results and discussion why section 5 drugs conclusion to the paper.

2. Related Work

In the field of telecommunication networks, a number of neural network techniques have been proposed over the years. In [14], the authors have introduced a feed forward neural network that can be used for controlling call admissions. The neural network studies the relationship between main per packet delays and the different classes of packets. It was observed that when a large window of previous readings was used, the neural network could be trained accordingly [15] and the output showed positive, accurate control values and a very minimal amount of calls were observed through stray away from the actual values. In [16], the authors have introduced a neural network controller which enables maximisation of performance-index function based on the training methodology [17]. Coding rate and number of cells in the buffer are combined in order to arrive at the solution. These values are measured in the continuous space and then felt as the inputs with delay, to back propagation neural networks [18]. Here the neural networks output adjusts the control signal for the subsequent time interval. The current number of cells [19] as well as outputs in the buffer to be used for computation of performance index value [20] and our intern used to command the update of the nodes weight. An important reinforcement learning technique is used for this purpose. Thus congestion level and Delay time dependencies and demonstrated using these two neural networks applications [21]. This methodology also indicates flexible mapping of the various parameters for node specific network conditions with networking metrics.

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Analysis and incorporation of novel algorithms on a number of routing based neural network applications were also experimented. Smart packets [22] are used to find the path to a particular destination by the nodes in the cognitive packet network. When the smart packet is received the receiving node will trigger reinforcement learning [23] on a random neural network which in turn will compute the optimal next hop using the information extracted from the smart packet. However, the drawback with this methodology is that there is no clarity on how information on the networking parameters is disseminated or collected [24]. Similarly reinforcement learning is possible only when a smart packet is received which will lead to difficulty in sustaining the continuous learning process of the individual nodes. This is crucial to sustain the accuracy of the control decisions [25] and influence the behaviour of the independent nodes. In this proposed work we aim to achieve effective and efficient independent continuous learning with the help of supervised learning methodologies in a dynamic network environment [26].

3. Delay Prediction Scheme

3.1 Analysis of Energy Consumption

In this methodology, we assume that the packet transmission takes place using a single network interface while routing takes place with a simple FIFO queuing discipline. Moreover, this methodology uses a fixed bandwidth [27] through which a channel is shared by the outbound packets. Hence all the outbound packets will undergo a similar local condition as that of a delay. A full duplex channel is assumed with the nodes, which shows that in reception and transmission of the packet [28], interference [29] does not occur.

3.2 One-hop Mean Delay Time Series- Prediction Target

In this part of the paper, a general delay prediction algorithm is outlined. A prediction process is carried out with an adaptive neural network training that takes place offline by every node continuously and independently.

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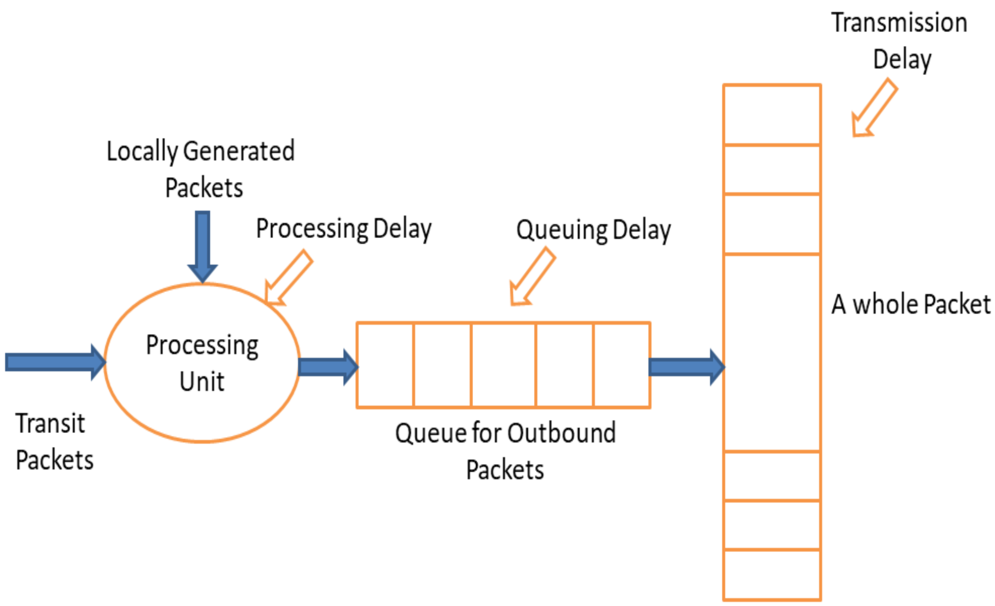

Figure 1. Outbound Packet and its Delay

For the purpose of calculation, only the queueing delay is taken into account and the total routing evaluation delay is formed along with the addition of fixed transmission delay. This algorithm can be carried out in four main steps which are as follows:

- The mean queueing delay is measured on every node in every time interval based on the average per-packet queuing delay during a particular time period. The can be calculated using the formula:

$$\overline{DQ_k} = \frac{T_b + \sum_{i \in P} Q_i/B}{N_k} \times \frac{TQ_k}{L}$$

Here Tb denotes the time taken for node backed off, T_k represents the channel contention, L is the length of every interval of time, TQ_k is the duration when the queue is occupied, P denotes the aggregation of the packets in queue and Qi

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is the queuing size for total bytes. Similarly, N_k is the packets which are in the queue and K is the index of the current time interval.

- The term Tb is not essential if channel contention does not cause any issue. Similarly, the node which is calculating will have access to all data and variables that are available locally. For determining utilization level of the routing queue, TQk/L is calculated. This will help to decrease the mean queuing delay as the ratio of idle period time interval with the total time interval.

- It should be noted that this will not be impacted by the size of the packet. Hence, irrespective of the packet size, it will not result in much change in queuing delay.

- Once the traffic load and mean delays of a specific set of data are recorded, a neural network is introduced in the system in order to train these values. For time series prediction, a certain type of neural networks is used. In this work, Radio Basis Function (RBF) and Multi-Layer Perceptron (MLP) are the two types of algorithms that are used for feedforward neural network.

- Taking into consideration the mean delays measured previously, every node continuously and independently predicts the mean hop, for a specific window of prediction

- On determining the mean delay of the time interval based on the predicted values, a comparison is drawn between the measured values in real time with that of the predicted values from the algorithm.

- The discrepancy is recorded as the prediction error. A threshold for the same is set and the system is designed such that if the error crosses the threshold value, the prediction will be suspended. Then retraining of the neural network takes place with the help of the latest set of mean delays that are measured. However,

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if this modification also results in a cross over the threshold range, it might indicate the need for a new delay pattern along with mean delays gathered from various other delay patterns. Accordingly, the neural network is trained if the required sets of mean delays are measured after the occurrence of discrepancy.

- The primary goal of this paper is to identify the feasibility of the proposed neural network model with delay prediction.

4. Neural Network Models for Prediction

In this paper, four neural network modes are used and are categorized based on the type of inputs and neural network. Tapped delay line radial basis function (RBF) and Tapped Delay line Multi-Layer Perceptron are the two types of neural networks used. eXtra input signal in AutoRegressive algorithm and AutoRegressive (AR) are the algorithm used. An extra layer of memory is used in this methodology which is used to save the previous output and input values and the layer is referred to as “tapped-delay-line”. ARX and AR differs in terms of their use of lagged traffic loads and mean delays as inputs. Similarly, the difference between the RBF network and the MLP network is the target pattern surface- hyperspheres and hyperplanes respectively.

5. Results and Discussion

Experimental analysis of the proposed work is carried out and the best prediction performances are observed and recorded. Based on the observations, it is found that it is possible to predict the mean delay for the neural network models in multiple future time intervals with high accuracy predictions. Fig.2 shows the prediction accuracy of the AR RBF algorithm. Here more number of iterations is required for training.

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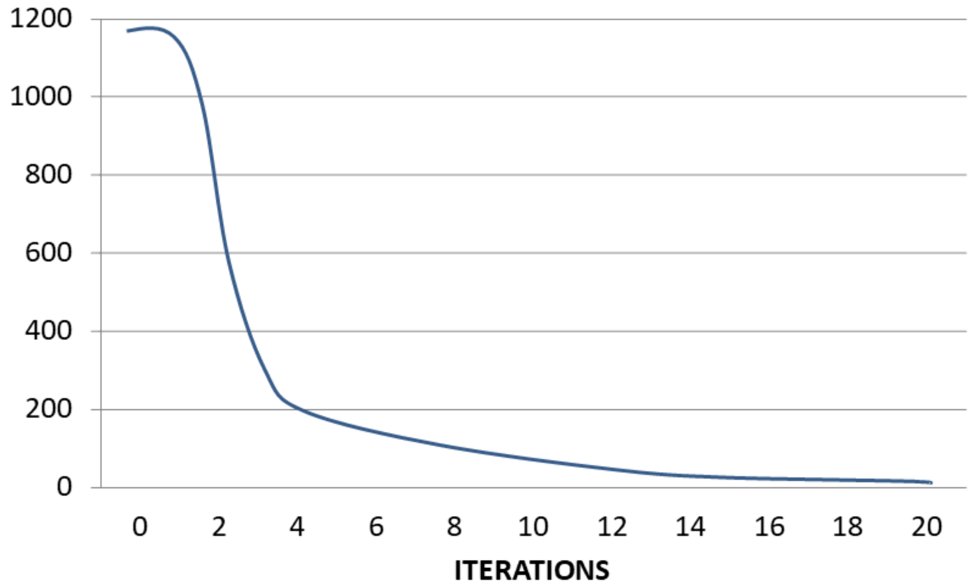

Figure 2. Training Iteration for nh=10 and na=7 in AR RBF

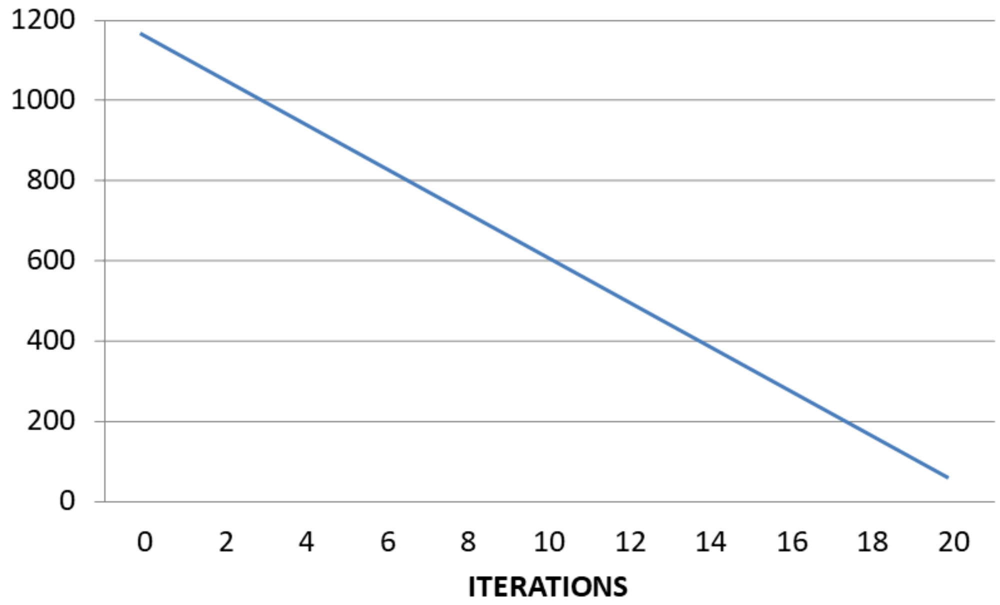

Figure 3. Training Iteration for nh=10 and na=7 in ARX RBF

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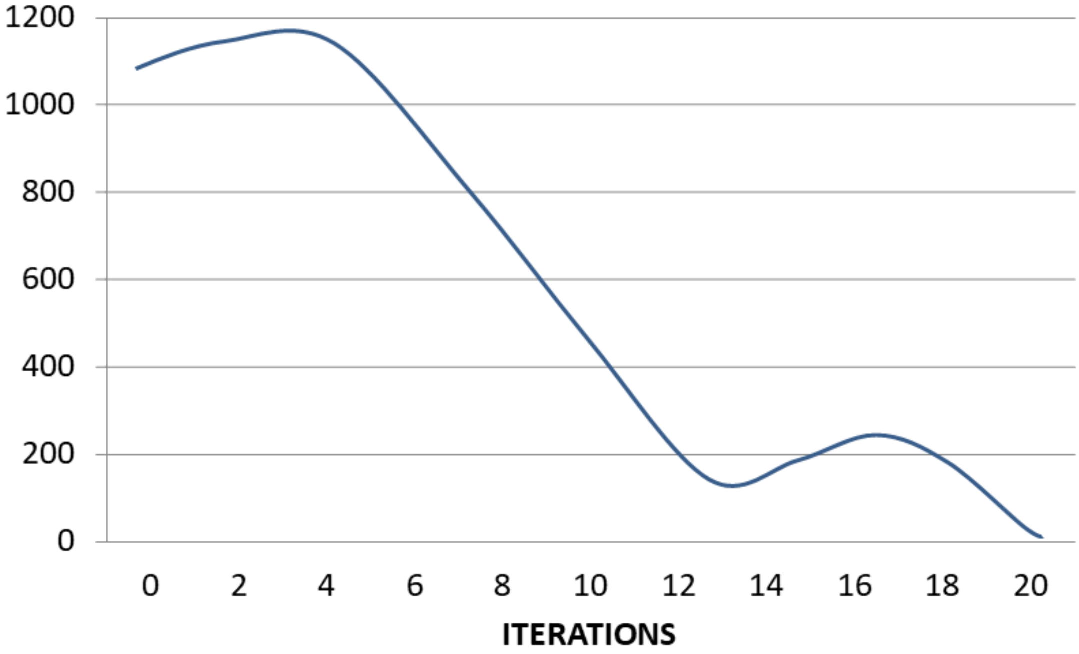

Figure 4. Training Iteration for nh=10 and na=7 in ARX MLP

On the other hand Fig.3 indicates the prediction accuracy of ARX model in RBF. In this methodology it is found that the hidden iterations as well as inputs related to the ARX model are less when compared with the MLP network mode. Fig.4 shows the MLP network model which is able to perform its functions at a quicker pace in comparison to the other methodologies. However, the drawback with the MLP network is that they require a larger amount of memory space to save state variables as well as to construct the network.

6. Conclusion

A delay prediction scheme is proposed in this paper which incorporates Radial Basis Function and Multi-layer Perceptron in the neural network for mobile wireless networking. It is found that by reducing the overhead of routing information exchange and enhancing adaptability of routing protocol the delay prediction will also improve accordingly. Similarly, this experiment also indicated that when using either of the neural networks proposed it is

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possible to attain high prediction accuracy. Identify that the RBF that networks perform better than the MLP networks. This is primarily because MLP requires lesser number of neurons and have higher iterations of training. It is found that the same amount of power is used MLP performs at a rate lower than that of RBF network, free training accuracy of prediction and achieving quicker learning. Using this methodology it is possible to predict future delays with the help of the record of previous delays resulting in an efficient routing network.

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