A Model for Traffic Prediction in Wireless Ad-Hoc Networks

Mahsa Torkamanian Afshar[1], M.T. Manzuri[2]
[1]International Campus of Sharif University of Technology
Department of Science and Technology
Kish Island, Iran
[2]Sharif University of Technology
Department of Computer Engineering
Tehran, Iran
Mahsa_torkamanianafshar@yahoo.com, Manzuri@sharif.edu

ABSTRACT: *In recent years, Wireless Ad-hoc networks have been considered as one of the most important technologies. The application domains of Wireless Ad-hoc Networks gain more and more importance in many areas. One of them is the control and management of the traffic of packets. In this paper our goal is to control the performance of different sections of the pipeline of a factory by checking the network, periodically. Along the factory the traffic is modeled with a Poisson process. With this model we can produce packets. The numbers of packets which are sending from a typical node to the other nodes are controlled by a fuzzy system. We show that having the traffic packets at time (t) for each node in Wireless Ad-hoc Network, we can completely train a Neural Network and successfully predict the traffic at time (t+1) for each node. By this means we can recognize the inefficient sections of the factory and try to fix them. The results of different experiments have shown that the proposed model has acceptable performance.*

Keywords: Wireless Ad-Hoc Networks, Traffic Prediction, Neural Networks, Fuzzy system

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1. Introduction

Wireless Ad-hoc Networks includes a set of wireless nodes that communicate with each other by direct communication links without the need for a central controller node [1]. Wireless system is not a desired option to the wired counterpart, because the wireless network will not ensure guaranteed Quality of Service (Qos) due to the unpredictable reaction of network traffic [2]. The different parameters such as user mobility, arrival pattern and diversified network requirement of user application are unpredictability.

In [3] the authors present various methods for traffic prediction. Some methods gather a large of historical traffic flow information data and analysis them to achieve useful traffic pattern. One of these methods is network traffic prediction based on Neural Network that several researches have executed such kind of network traffic modeling and prediction.

In [4] it is shown that the traffic of ad-hoc networks can be estimated over the different links by using an exponential filter. In [5] the authors have proposed a new algorithm which is called degree algorithm which uses node degree to allocate time slots based on the relative traffic estimation of a node. In this algorithm each node can specify its own degree by monitoring transmissions from neighbor nodes. The limitation of this method is that they supposed equal traffic load distribution on each route.

In [6] an adaptive routing algorithm is presented and the link cost is appointed using a fuzzy system. The traffic is re-routed to nodes which are smaller part or amount over-crowded.

In [7] authors present the improvement of accuracy in network traffic prediction with Seasonal Neural Network (SNN), a dynamic seasonal Time Serious Neural Network prediction model is proposed based on Artificial Neural Network (ANN) theory.

In [8] the prediction of video stream with Neural Network for an efficient bandwidth allocation of the video signal is shown. Since Neural Networks are the efficient methods to model, evaluate and predict the behavior of non-linear and non-stationary systems [9], and the network traffic is self-similar and non-linear, so we used Neural Networks for prediction. In this work the wireless ad-hoc network traffic is modeled according to a Poisson process.

2. Structure of neural network

One of the most functional Neural Networks is multilayer perceptron that is called MLP networks that is trained by the help of back-propagation educational algorithm or BP.

This training method is known as back-propagation of error algorithm or in short form back-propagation or generalized delta rule. In a simple way we can consider BP algorithm as a reduced gradient for minimizing total square error from computed outputs by network. In fact BP training network belongs to gradient based training algorithm. In general the MLP network has an input layer, an output layer and also one or more hidden layers.

Here we prefer the situation in which this network has just one hidden layer with 30 neurons and we use the Levenberg–Marquardt algorithm (LMA) for analyzing the Neural Networks.

3. Proposed model

Application of this project is for controlling the performance of every sections of pipeline of the factory. In this project we consider each part of the pipeline as a node and make a wireless ad-hoc network. We know that in each pipeline the ingredients should be added to each other sequentially to achieve our object finally.

When each pipeline does its task trustily, create one packet and send it to next pipeline which is as our next node. This packet contains number of the node, name of the material, time of passing and the IP address which has been created in physical layer.

Finally all of these packets are evaluated. So we can predict what will happen on our pipeline in the next time by using of Neural Networks. Sometimes in some of our pipeline we may face the increasing or decreasing of packets, therefore, we know that these data have a difference with data which Neural Network is learned and predicted. Then we notice the deficiency of pipeline.

4. Finding traffic packets of each node

When we are discussing network traffic packet prediction, we need to determine the traffic model. Considerable factors in our traffic model are the packet size and the arrival time of ingredients material.

We suppose that the sizes of packets are constant. On the other hand, the arrival time of ingredients and the packet sizes along the length of factory are modeled with a Poisson processes. The method for predicting traffic is depended to Back Propagation algorithm.

First of all, the distance between the nodes discussed as a primary test. It should be pointed out that these nodes are in a specific range and standard distance from each other, and they are in a direct line along the factory. Size of the sent packets recognize as follow: number of the node, name of the material, time of passing and the IP address which creates in physical layer. These primary values use in simulation and begin collecting dataset as follow. We consider two dimensional arrays of the nodes number (first node, second node, etc.) and the materials number (first material, second material, etc.). When each material reaches to the related node, the time determines (arrival time).

For creating the related packets, it is necessary to add the time of packet creating to the time of material arriving. By this way, we determine the packet in which nodes has been created and the time programming has completed. With this model we can produce packets; the sending packets to the other nodes are controlled with fuzzy systems.

For modeling a problem with fuzzy methods, first of all we need to recognize input parameters and explaining the proper fuzzy membership function with the effect of different quantity of the parameters on each of them in the output. Then after mixing different conditions of this membership function, all the possible rules will be achieved. For this reason making fuzzy process should be done for the input as well as the output.

In this work we use two parameters; number of seen materials and the capacity of node queuing in network for making decision. These are present in Table 1 and Table 2.

Membership functions of materials	
Low Risk	<7
Moderate Risk	7-35
Borderline high	35-90
High risk	90-280
Very high risk	>280

Table 1. Membership functions of materials

Membership functions of queuing capacity	
Optimal	<15
Borderline	15-90
High	>90
Very high	>280

Table 2. Membership functions of queuing capacity

$$\mu_{(x)\,\text{Low Risk}} = \begin{cases} 1 & x < 5 \\ -0.2\,(x - 5) & 5 < x < 10 \\ 0 & x > 10 \end{cases} \tag{1}$$

$$\mu_{(x)\,\text{Moderate Risk}} = \begin{cases} 0 & x < 0 \\ 0.1\,(x) & 0 < x < 10 \\ 1 & 10 < x < 20 \\ -0.05\,(x - 20) & 20 < x < 40 \\ 0 & x > 40 \end{cases} \tag{2}$$

$$\mu_{(x)\,\text{Borderline Risk}} = \begin{cases} 0 & x < 20 \\ 0.05(x - 20) & 20 < x < 40 \\ 1 & 40 < x < 60 \\ -0.025(x - 60) & 60 < x < 100 \\ 0 & x > 100 \end{cases} \tag{3}$$

$$\mu_{(x)\,\text{High Risk}} = \begin{cases} 0 & x < 50 \\ 0.02(x - 50) & 50 < x < 100 \\ 1 & 100 < x < 200 \\ -0.01(x - 200) & 200 < x < 300 \\ 0 & x > 300 \end{cases} \tag{4}$$

$$\mu_{(x)\,\text{Low Risk}} = \begin{cases} 0 & x < 200 \\ 0.01\,(x - 100) & 200 < x < 300 \\ 0 & x > 30 \end{cases} \tag{5}$$

Where μ is the membership function and x is the variable of the membership function. The diagram of these fuzzy membership functions are presented in Figure. 1

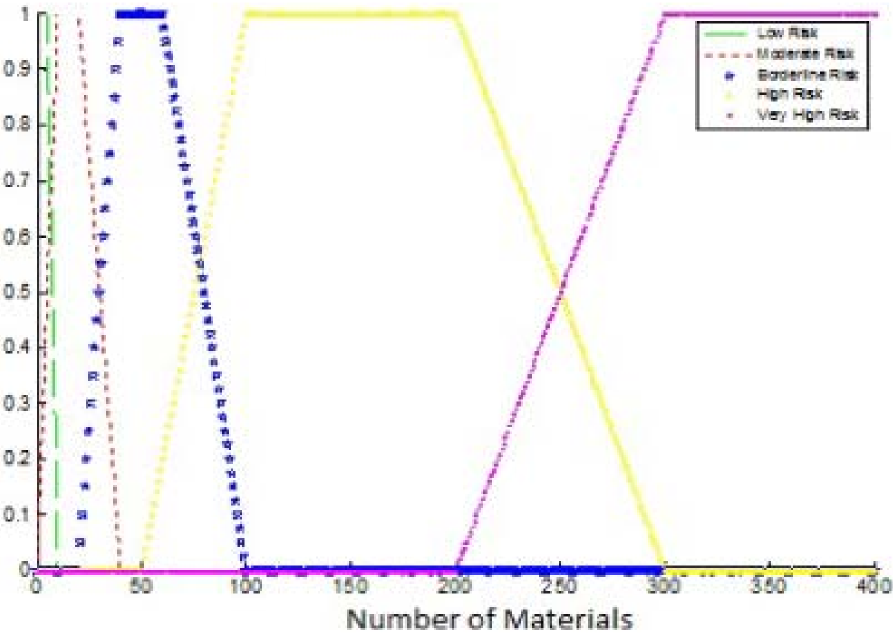

Figure 1. Membership function of materials

Also for the capacity of queuing the fuzzy membership functions are presented as in (6), (7), and (8):

$$\mu_{(x)\,\text{Optimal}} = \begin{cases} 1 & x < 10 \\ -0.1(x - 10) & 10 < x < 20 \\ 0 & x > 20 \end{cases} \tag{6}$$

$$\mu_{(x)\,\text{Borderline}} = \begin{cases} 0 & x < 10 \\ 0.033(x - 10) & 10 < x < 40 \\ 1 & 40 < x < 80 \\ -0.05(x - 80) & 80 < x < 100 \\ 0 & x > 100 \end{cases} \tag{7}$$

$$\mu_{(x)\,\text{High Risk}} = \begin{cases} 0 & x < 50 \\ 0.02\,(x - 50) & 50 < x < 100 \\ 1 & x > 100 \end{cases} \tag{8}$$

Where μ is the membership function and x is the variable of the membership function. The diagram of these fuzzy membership functions are presented in Figure. 1 According to network conditions four fuzzy membership functions has been chosen as low, moderate, high and very high. For changing output to real number the method of gravity center is used. Considering too much numbers of rules here, only two rules are pointed out.

Rule 1: if the numbers of materials are low and the queuing capacity is moderate then the node output is low.

Rule 2: if the numbers of materials are moderate and the queuing capacity is moderate then the node output is moderate.

Example 1: For using Neural Network in predicting wireless ad-hoc network traffic we should arrange the scenario in such a way that we can reach to the same range of traffic for different clocks in continual reputations. By using input data and the traffic which has been created out of it, we can train Neural Network. If we design the scenario in such a way that we can provide Neural Network's input, in contrast we should interfere in the factors that have effects on the process of the network. Some primary parameters of simulation, present in Table 3.

Typically, Figure. 2 show the real value of traffic packets in node 6 at time (t +1), and Figure. 3 show the predicted value of traffic packets at time (t + 1) in wireless ad-hoc network. By comparing these two diagrams we consider that the prediction by Neural Networks is reasonable and observe that in node 6 the traffic packets are the same as the dataset.

Parameters	Value
Distance between nodes	20m
Factory length	2000m
Number of nodes	Factory length/node distance
Packet size	10*8bit
Packet create time	1s
Bandwidth	8000 bit per second
Number of hidden neuron	30

Table 3. Simulation Parameters

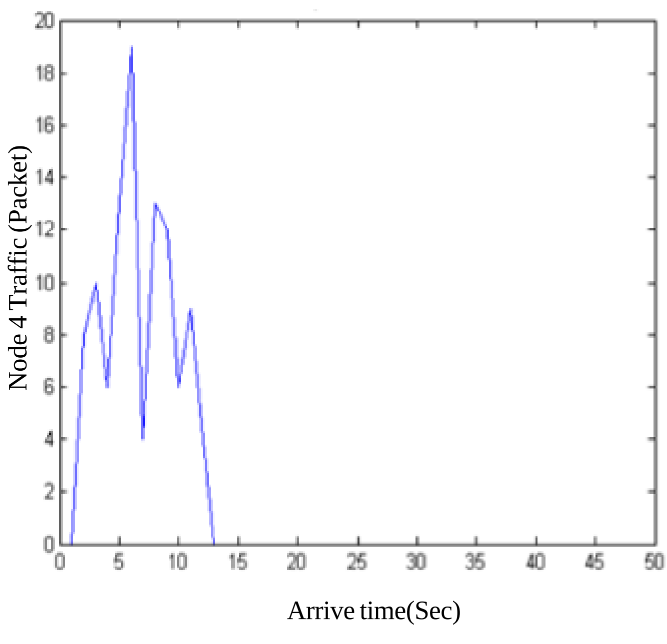

Figure 2.Traffic packets for node 6 at time (t + 1)

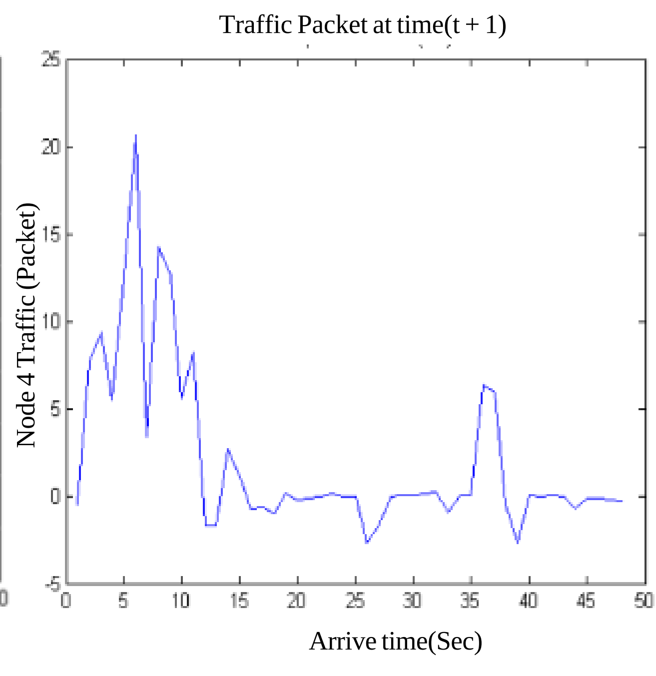

Figure 3. Predicted value of traffic packets for node 6

5. Results

5.1 Performance Plot

The plot of the training errors, validation errors, and test errors appears, is shown in the Figure. 4

The result is reasonable no significant over fitting has occurred by iteration 12 (where the best validation performance occurs). As we see the error rate at epoch 1, 2, 3… 10 has a descending rate. In epoch 12 it shows the best situation.

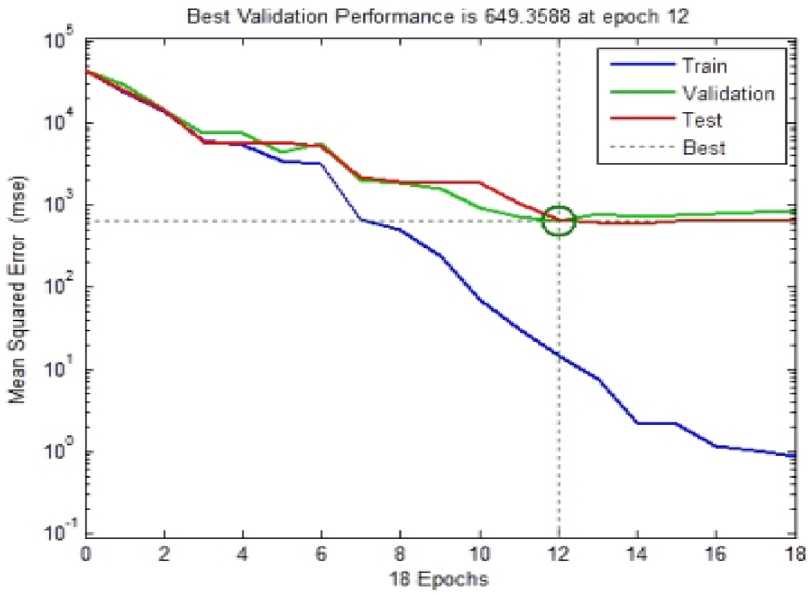

Figure 4. Performance Plot

5.2 Regression Plot

If we click Regression in the training window, we can perform a linear regression between the network outputs and the corresponding targets. The output tracks the targets very well for training, testing, and validation, and the R-value is over 0.97 for the total response. Figure. 5 show the results.

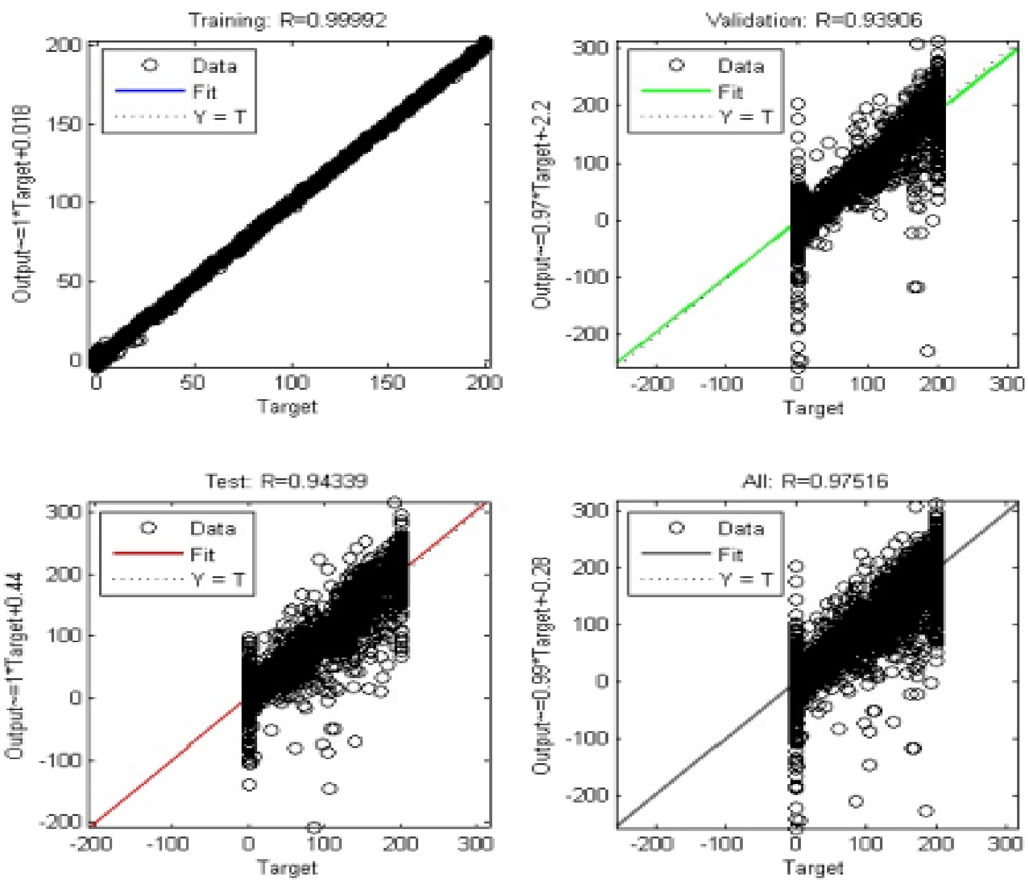

Figure 5. Regression Plot

5.3 Training state Plot

As we see in this diagram, the gradient value has a descending path, which means error rate is decreasing by training. Validation section shows us the best situation that has been trained and it is at 12th epoch. If we deduce all the epochs that have been trained, from validation that is 6, it shows the best epoch rate. Figure. 6 show the results.

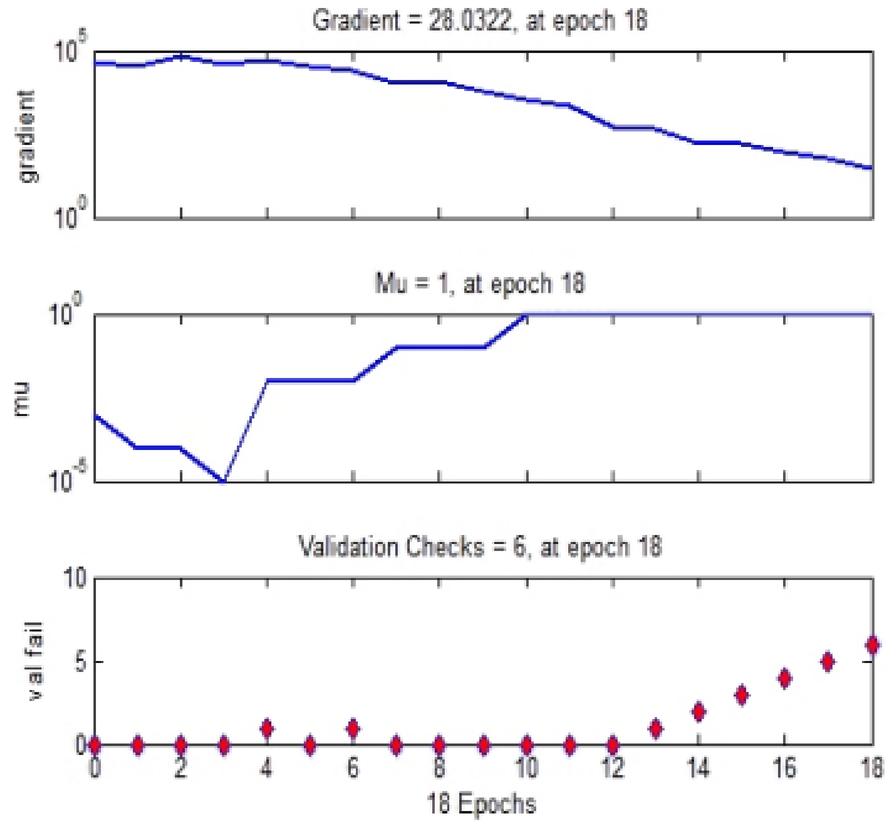

Figure 6. Training state Plot

The results of experiment have shown that proposed model have acceptable performance. Since the final mean-square error is small, the test set error and the validation set error has similar characteristics and no significant over fitting has occurred where the best validation performance occurs so the predictor reliability is reasonable.

6. Conclusion

The obtained results show that our proposed model based on the MLP Neural Network is the acceptable model to recognize the inefficient sections in the factory that cause problems. Also this project has the management aspect besides the control aspect, because performance of each section from production line recognize by learning machine of Neural Network after time. However, the managers can recognize bottleneck in each section of production line by evaluating dataset and optimize that section of production line by changing the equipment and human resources. In this paper we assumed that our simulation environment is collision free and no packet loss can occur. The real world applicability of the proposed solution needs to be proven through hardware implementation.

References

[1] Michail, Ephremides, A. (2001). Algorithms for routing session traffic in wireless ad-hoc networks with energy and bandwidth limitations, *In*: Proceedings of 12th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications.
[2] Gowrishankar, A., Satyanarayana, P. S. (2008). Neural Network Based Traffic Prediction for Wireless Data Networks, p. 373 - 389.

[3] Gowrishankar, Satyanarayana, P. S. (2007). Recurrent neural network based BER prediction for NLOS channels, *In*: 4th international conference on mobile technology, applications, and systems and the 1st international symposium on Computer human interaction in mobile technology, USA, p. 410 - 416.
[4] Mushabbar Sadiq, S. (2004). Traffic estimation in mobile ad-hoc networks, M. S. thesis, Royal Institute of Technology, Stockholm, Sweden.
[5] Robertazzi, T., Shor, T. (1993). Traffic sensitive algorithms and performance measures for the generation of self- organizing radio network schedules, *In*: Proceedings of IEEE Trans Commun., 41 (1) 16 - 21.
[6] Jantan, A. B., Natsheh, E., Khatun, S. (2006). Adaptive Fuzzy Route Lifetime for Wireless Ad-hoc Networks, *International Arab Journal of Information Technology*, 3, 283-290.
[7] Guang, Ch., Lianqing, X. (2004). Nonlinear-periodical Network Traffic behavioral Forecast Based on Seasonal Neural Network Model, *In:* Proc. International Conference on Communications Circuits and Systems, p. 683 - 687.
[8] Oravec, M., Petráš, M., Pilka, F. (2008). Video Traffic Prediction Using Neural Networks, 5 (4) 59 - 78.
[9] Gowrishankar, S. (2008). A time series modeling and prediction of wireless network traffic, Georgian Electronic Scientific Journal: Computer Science and Telecommunications, No. 2.