



Traffic prediction algorithm based on multi-path routing for MANETs

C. R. Mamatha^a, M. Ramakrishna^{a,*}

^aVemana Institute of Technology, India

(Communicated by Madjid Eshaghi Gordji)

Abstract

The efficiency of routing in ad-hoc networks depends on the node traffic. One of the methods of improving the network efficiency in MANETs is by predicting the network traffic. It is very important to predict the characteristics of the future network traffic from the previous parameters. In this paper, we propose TPAM-a a multipath routing based traffic prediction algorithm that uses RNN architecture. TPAM consists of two modules, which includes a multipath routing algorithm and a network congestion discovery using RNN. It is clear from the simulation results that RNN architecture provides promising results in predicting the network traffic under varying conditions. Further, the algorithm has improved efficiency in routing by using the multipath selection method. Finally, the proposed algorithm has a less end-to-end delay, lower overhead and a high success ratio.

Keywords: multi-path route, network traffic, traffic prediction

1. Introduction

The newer type of wireless access network that is being extensively studied currently is the mobile ad-hoc networks also called as MANETs. Wireless MANETs are more cost efficient in terms of deployment for broader network access. MANETs have several pros, for example wider network coverage, multi-hop routing, higher reliability, self-structuring and self-healing function, which are not present in other wireless networks. Furthermore, MANET routers support multiple types of network access technologies. As there are many advantages of wireless MANETs, they are increasingly gaining importance for communicating among various wireless networks systems. Since the main process

*Corresponding author

Email addresses: mamathapradeep1983@gmail.com (C. R. Mamatha), mramakrishna15975@gmail.com (M. Ramakrishna)

in MANETs deals with broadband multimedia services, better support for QoS is required. But MANETs have to undergo few challenges such as frequent topology changes, that may lead to the limitation of mobile terminals and network heterogeneity. Therefore, maintaining MANETs end-to-end QoS becomes very difficult and challenging and has to be solved for the further development of wireless mobile ad hoc networks. To guarantee that packets reach the destination and load is distributed uniformly throughout the networks, Multipath routing is introduced [2]. A distributed multipath routing algorithm is proposed to enhance the energy efficiency of ad-hoc network that suffers from constant mobility of the network nodes. The algorithm considers that, during every session the traffic load is mainly distributed in two paths [9]. Authors [6] proposed an energy efficient authentication scheme in grid based wireless sensor networks to improve life time of wireless sensor networks. The multipath routing based on the traffic prediction is more viable than the existing routing algorithms. Hence, the interest towards the multipath routing based on traffic prediction has been researched extensively.

Prediction of network traffic plays a remarkable role in assuring that network QoS is guaranteed. The proposed method mainly focuses on traffic prediction parameters, which plays a vital role in solving the specific prediction task involving traffic prediction. The analysis of MANETs node traffic is complicated due to the mobility and therefore effective mathematical model implementation is difficult. The prediction methods such as ARIMA that were used earlier are complicated. In this paper by analysing the characteristics of MANETs traffic, a nonlinear prediction model based on neural networks is modelled because these models are capable of learning complex patterns through powerful self-learning and self-adaptability. Neural Network can predict any function virtually for unknown data relationships.

Neural networks are a non-parametric adaptive modelling approach, based on the experimental data. The neural networks are entirely based on data set and not on any mathematical model. The parameters in RNN architecture are recalled based on the random interval. The RNN allows mechanism of handling the input observations by specifying user defined order. This promises RNN to learn the sequences in order to predict traffic more accurately. RNN allows to learn temporal dependence and can be used to compare different sequence learning methods [?].

The proposed algorithm uses one path as primary path and few backup paths are set up from the initial node to destination node. The setup is done by considering the XOR distance among nodes, the bandwidth and the residual energy. Initially, a node in the network uses the primary path to forward the incoming data. An advance notification message alerting about the network congestion is sent to the initial node, by any of the nodes that lie on the primary path. These nodes predict the congestion by using real-time traffic. These causes the backup path 1 and 2 to be successively triggered to transmit the network traffic by the initial node. Once the condition prevails to its normal the backup path 1 and 2 are disabled and the transmission of data is now done only by using the nodes in the primary path. By analysing the Simulation results the TPAM using Recurrent neural network has better prediction rate and the model can be used for real-time traffic prediction including MANETs. In comparison with existing QoS routing protocols, TPAM can lower the end-to-end delay and increase packet delivery ratio with efficient load balancing. Hence, QoS parameters of wireless MANETs can be guaranteed.

In this paper, we propose Recurrent Neural Networks a methodology for predicting network traffic and to solve the efficient route path finding. A TPAM algorithm based on the network traffic prediction using RNN is proposed to guarantee the QoS in the network.

The rest of the paper is organized as follows. The literature survey on the existing work is given in Section 2. The proposed traffic prediction model for MANET's based on Recurrent Neural Network is presented in Section 3. Also The Traffic Prediction Model Selection algorithm was proposed to

select the multipath for routing packets from source to destination in this section. The simulation and evaluation results of our algorithm is in Section 4. Finally the conclusion about our algorithm is presented in Section 5.

2. Related Works

The IEEE 802.11 [3] created task group to address the issues related to interconnection of different networks with IEEE 802.11. The group also addresses security issues in wireless communication. The security was achieved with confidentiality in different types of frames.

The IEEE 802.15 [4] task group was created to provide the high precision data communication and throughput. The data rates in this are made scalable with less power consumption and covers larger ranges. The cost of implementation is made less.

The IEEE 802.16 [5] task group addressed the connection issue in wireless metropolitan area networks as First-Mile/Last-Mile. The bandwidth utilization is more efficient and proper utilization of available frequency. The multiple physical layers are used to utilize the frequency band.

Authors [5] proposed a secure mechanism to improve the efficiency of wireless network. Proposed approach uses digital signature algorithm to improve security and thereby enhances the life time of the sensor node.

The authors in [2] proposed to use generic algorithms to improve the efficiency of routing in the presence of overlays. The Algebraic Notion of Equivalence Relationships were developed to improve the number of disjoint paths. The independent secure network was created without any dependent networks infrastructure.

The authors in [9] have proposed a novel multipath switching approach based on prediction of traffic and features of open network. The network traffic was predicted using Wavelet Neural Network since the property of wavelet has very good approximation. The WNM has self-learning adaptive quality in networks. The technique uses primary path initially, if fails it uses secondary path for routing packets.

[8] For any wireless network, the primary goal would be the networking protocol design for improving transmission capacity. The wireless links of WMN (wireless mesh networks) strongly interfere with each other. Therefore the challenge here would be improving the network capacity. To achieve this goal WMN networking design adopts a cross-layer design approach. This approach also guarantees Quality of Service (QoS).

In wireless networks the interference plays an important role on the performance of network. The authors in [17] have proposed with all pair shortest path routing to increase the throughput of network. The best possible route is selected among the available routes with optimized wireless link capacities.

In wireless networks, another important criteria is to provide QoS. Few of the existing routing algorithms are highly complex, low flexibility and are not scalable [7].

In [1], proposes the Hybrid Salp Swarm Firefly (HSSFF) method, which combines two optimization algorithms: Salp Swarm and Fire Fly. The QoS specifications, such as delay and estimated transmission count, are minimised in this document. Two different instances are used to test the simulation performance. The HSSFF method is also tested against many other methods.

The authors in [15] have proposed Multiple Routing Algorithm based on Traffic Prediction (MRATP) to overcome the limitations of existing algorithms. The algorithm has multiple routing paths based on WNN prediction and load balancing. The algorithm has higher success ration and low delay.

To improve the WNN based prediction, the authors in [12] proposed Adaptive wavelet neural networks for Short Term Price Forecasting (STPF). The Feed Forward Neural Network method was used for the effectiveness of the proposed method.

The authors in [14] have proposed cooperative routing in Wireless networks to increase the lifetime of network. The applications are prioritised and scoring function is used to prioritize. The applications get the required resources based on the threshold values. The high priority applications will be assigned resources immediately.

The authors in [13] have used the properties of trust and intelligence of a node to select the routing path. The cooperative routing path is selected keeping in view of trustiness and how intelligent in choosing the best possible route and avoids count to infinity problem.

The Network Simulator (NS) [11] tool is used by researchers for simulations of both wired and wireless networks and its protocols like TCP, UDP, Routing Protocols.

3. Traffic Prediction Model for Wireless MANETs

The non-linear prediction model, RNN has various applications since they are capable of handling various input and output types. The individual learning and adaption of the Neural network model makes its efficient and furthermore has non-linear estimation work [15]. But model convergence factor is less and only gets a confined sub-optimal solution. One approach to build the exactness of foreseeing traffic in the system should be possible by using the RNN model. The RNN performance is superior in preparing and in variation productivity when contrasted with other neural networks. The recurrent neural network architecture is similar to any traditional neural network. The RNN uses the concept of memory that differentiates it from other traditional neural networks, and it exists in the form of a different type of link. In RNN the output of one layer is given as input to another layer unlike FFNN. Further it helps to analyse the sequential data where the traditional neural networks are incapable. Also, the RNN does not restrict on the length of the input. The paper demonstrates that the recurrent neural network model has great prediction properties contrasted with other techniques.

3.1. Traffic Prediction Model Using Recurrent Neural Network

The survey shows that the Feed Forward Neural Network has better network traffic prediction than standard linear forecasting models. For FFNN the input is feature vector and output is hidden layer vector. Let $x = (x)$ is input vector and $h = (h1, \dots, hn)$ is output vector. The output vector is next fed into the activation function to produce the next hidden layers vector $y = (y1, \dots, yn)$. The process of computing next hidden layer is from the previous hidden layer using the following relation.

$$H = f(Wx + bh)$$

$$Y = g(Wh + by)$$

Where w : specifies neural network weight matrices of the consecutive layers,

b : represents each layer's bias vector,

f : specifies hidden Layers activation function and

g : specifies output layer activation function

These functions are used for classification of different vectors. The network is trained based on numerical optimization methods to reduce loss function. The method used for optimization is a back propagation algorithm named stochastic gradient descent techniques [16, 10].

The traditional FFNN model is modified to develop an RNN model which is more efficient. The RNN model allows the output on one layer to be fed back to next layer in the network in the cyclic manner. This technique of RNN creates a dependency among different layers which is not present

in FFNN model. The input vector in the RNN model has a sequence of vectors $x = (x_1, \dots, x_T)$ and produces output as a sequence of hidden vectors $h = (h_1, \dots, h_T)$ and a sequence of output vector $y = (y_1, \dots, y_n)$. The hidden vector and output vector is computed using the formula for t ranging from 1 to T :

$$ht = f(Wxhxt + Whhht - 1 + bh)$$

$$yt = Whyht + by$$

where, W_{ij} specifies layer i to layer j weight matrix. RNN model uses same optimization techniques as FFNN however a back propagation time algorithm might be used for computation of the gradient values [12].

In our model to predict the network traffic we have collected the network data set from the network for every 10 seconds. From the collected data set we have counted the number of packets sent via each path within the network and across the network. This technique helps us to predict the future traffic across each path in the next 10 seconds. Based on the future traffic prediction the window size has been formulated. We formally define the network traffic prediction problem for the given sampled time series $((l_1, p_1, b_1), \dots, (l_T, p_T, b_T))$ for every 10 seconds and to predict future n steps $((l_T + 1, p_T + 1, b_T + 1), \dots, (l_T + n, p_T + n, b_T + n))$ is used for the next 10 seconds. Here l represents path, p represent packet count and b represents total number of bytes.

Our model is trained using sliding window method. The sliding window technique uses the data size for each path at time t as xt and predicts the future data size for $xt + 1$. In this set up we are able to create a data set for n data points and our training data matrix has $(N - t)$ -by- t matrix. Each data point represents sampled data size within a 10 second window and also a data size for each path within the network is predicted.

Finally a data matrix is been created for training and test cases are generated for evaluation. In the data matrix each column specifies particular flow of path and our model is trained using sliding window technique. The test cases on these columns are used for future time steps traffic prediction. The extensive simulation is carried out at regular intervals for each data set.

3.2. Traffic Prediction Algorithm Model for MANET's

To manage the wireless MANET adequately and to make the TPAM highly scalable, the nodes have been developed using a topology having three layers, as show in the figure 1. While IPv4 or IPv6 protocols are used to address the nodes that are present in the network topology. The nodes present in the wireless MANETs are categorized as Super nodes, Terminal nodes and Root nodes according to their abilities. The Root nodes stores the information of their contiguous Root nodes, and also about the Super nodes under their management. The Super nodes stores the information of their contiguous Super nodes and the information of Terminal nodes in AS. While the Terminal nodes store the information of the Terminal nodes that are contiguous only.

STEP 1: First the final node is to be located.

STEP 2: If the final node lies in AS, then a route will be set up between the initial node and the final node by using the TPAM algorithm.

STEP 3: Otherwise a recursive search for the nodes present at the higher level is employed, until destination node is found.

STEP 4: the process of route discovery is completed using TPAM algorithm.

The fundamental thought of TPAM is to set up an essential path and a few backup routes from the initial node to the final node by using the XOR distance method among the nodes, residual energy and the bandwidth. The figure 1 shows the primary path labelled as path 1, whereas, path 2 and path 3 are labelled as the backup paths respectively. First the path 1 i.e., the primary path is used to forward data. Once any node that lies on the primary path 1 predicts that a congestion can

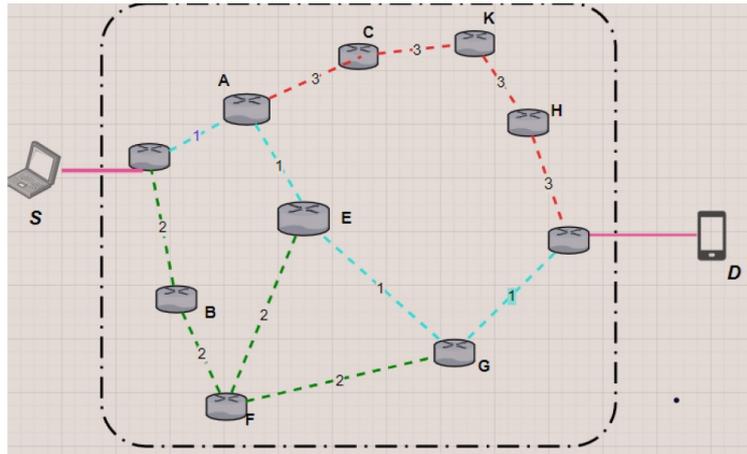


Figure 1: Schematic diagram of multi-path routing for MANETs

occur in the network by the real-time traffic at any moment, then the alert message is been sent in advance to the initial node by these nodes informing about the upcoming congestion. The backup path 2 is then triggered so that initial node network traffic is transmitted. After the congestion is resolved, backup path 2 and 3 are disabled respectively. During this time only primary path 1 actively transmits the data. The initial node activates the backup path 3 once it finds that backup path 2 has been congested.

Our TPAM algorithm consists of three steps.

Step 1: Building of Multiple Paths for Routing.

Step 2: RNN based Traffic Prediction.

Step 3: Traffic Load Balance using Multipath Routing.

Step 1: Building of Multiple Paths for Routing.

A undirected graph $G = (V, E)$ is created for MANETs for all the nodes. The adjacency square matrix is created with the distances among the neighbour nodes. The cost is calculated by XORing the distances among the neighbour nodes. The performance of the node is derived based on the bandwidth B and residual energy E of node V_i .

$$P = \alpha B + \beta E \text{ where } \alpha \text{ and } \beta \text{ ranges from } 0 \text{ to } 1 \text{ and } \alpha + \beta = 1.$$

The pseudo code for TPAM is as follows:

Let Src represent the source node, Dst represent destination node, V represent the input node, V_i represent future hop output node

Procedure Future_hop (V_i)

Begin

for each node V_j

find minimum cost using

$$\text{minimum } PxC[i][j] = \text{minimum } \{(\alpha B + \beta E)xC[i][j]\} \text{ where } j \text{ is } i\text{'s neighbour}$$

end for

End

Procedure Route_Path (Src, Dst)

Begin

Vtemp=Source, path=NULL, i=0;

```

while(Vtemp!=Dest)
  path [i]=Vtemp=Future_hop (Vtemp)
  i++
wend
End

```

Using the step 1 create a secondary path by changing minimum value to obtain sub optimal path. The sub optimal path is used as backup path.

Step 2: RNN based traffic prediction

A random variable R represents network traffic. R_i represents current network traffic at time i which is been analysed for a month at the same time and observed that R_i follows the normal distribution. The network traffic threshold is set as Max. At any instance of time if the probability of prediction $t + l$ steps exceeds the threshold $P(l)$ is computed as

$$P_t(l) = P(X_{t+1} > \max | X_t, X_{t-1}, X_{t-2}, \dots, X_{t-m}) \quad (3.1)$$

Here, m is the mean value of m observed value X_t

$$\therefore P(\hat{X}_{t+1} \leq \max) = P\left(\frac{\hat{X}_{t+1} \leq \max}{\sigma x} \leq \frac{\max - \mu x}{\sigma x}\right) = \Phi\left(\frac{\max - \mu x}{\sigma x}\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{\max - \mu x}{\sigma x}} e^{-\frac{t^2}{2}} dt \quad (3.2)$$

$$\therefore P_{t(l)} = 1 - P(\hat{X}_{t+1} \leq \max) = 1 - \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{\max - \mu x}{\sigma x}} e^{-\frac{t^2}{2}} dt \quad (3.3)$$

Step 3: Traffic Load balancing using multipath routing Initially the node V_i uses the primary path to route packets from source S to destination D at time t . At time $t + l$ if the primary path is predicted to be congested based on step 2 the node V_i sends the notification message to the source node informing about the path congestion. The source node now uses backup path as routing path. In order to balance the load on the network 25% of network traffic still is been routed on the primary path and remaining 75% of the network traffic is routed on the backup path. In case of increase in network delay in both primary and backup path, an additional back up path may be activated for the smooth data flow.

4. Simulation Results

4.1. Simulation Setup and Evaluation

We have simulated the working model of TPAM using python. We have tested simulation results with the existing traffic prediction models. As a pre-processing step, the initial data needs to be cleared and mounted to zero unit variance and mean. The existing methods uses cross-validation techniques to decide appropriate values for the hyper-parameters.

Figure 2 clearly shows TPAM routing algorithms performance and it shows steady at ideal state. Also, the algorithm's performance is unstable under the condition of the dynamic topology changes, which clearly shows the algorithm cannot guarantee QoS. The average loss of TPAM is slightly less

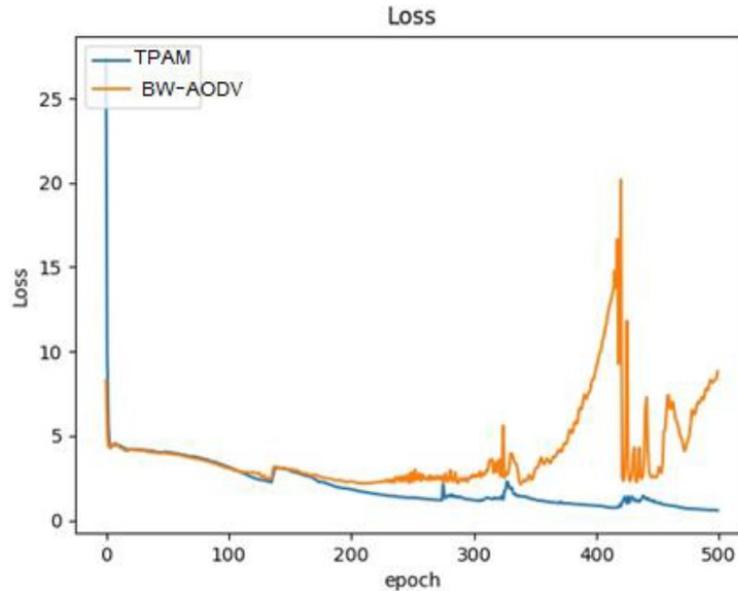


Figure 2: Average prediction rate and less end-to-end delay of routing data packets against elapsed time.

than that of the existing BW-AODV. However, the total time taken by TPAM is less compared to BW-AODV due to the adoption of Multipath based traffic prediction. The graph clearly shows better prediction rate and less end-to-end delay.

The performance of our proposed algorithm is evaluated using the Mean Absolute Percentage Error (MAPE) defined as:

$$MAPE = \frac{100}{n} \sum_{t=1}^n \frac{|yt - \hat{y}t|}{yt}$$

Where n represents number of data points, t specifies the number of steps with reference to time, yt is the actual value and $\hat{y}t$ is the predicted value.

Figure 3 shows the average MAPE values for each day and at all times to test (the 400 epoch model is used). The graph clearly shows that most of the values of RNN algorithm have their lowest MAPE during the day prediction under normal traffic condition and has high MAPE value during peak network traffic. Our proposed TPAM has consistent prediction of network traffic under all conditions and the same is presented in the graph.

The time slot variation predicts the average MAPE value as shown in figure 4. The simulation results in graph as well theoretical analysis shows that TPAM has higher adaptability and strength than the others. As shown in the TPAM guarantees the prediction of network path for efficient routing when compared with BW_AODV. Hence, we conclude that the TPAM algorithm guarantees the QoS routing.

4.2. Performance Evaluation

In this section, the performance of the proposed TPAM algorithm is compared with BW-AODV for different network parameters. We have investigated average end to end delay and improved performance of the network prediction in our proposed algorithm.

It is very clear that the TPAM routing algorithm performance is steady at ideal state. But, due to dynamic changes in the topology the performance of the algorithm becomes unstable which will not guarantee QoS in MANETs. While the performance of TPAM and BW-AODV algorithm are relatively stable which do not appear to jitter. The TPAM performance is good with reference to

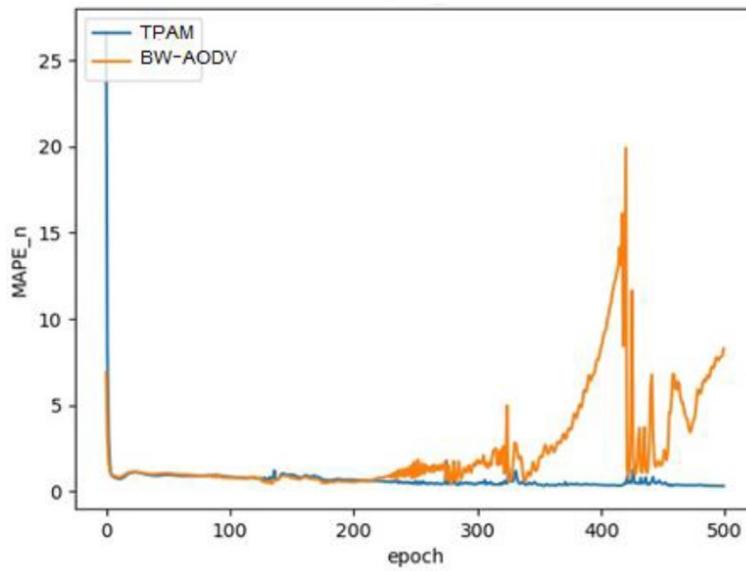


Figure 3: Average MAPE values for each day and at all times

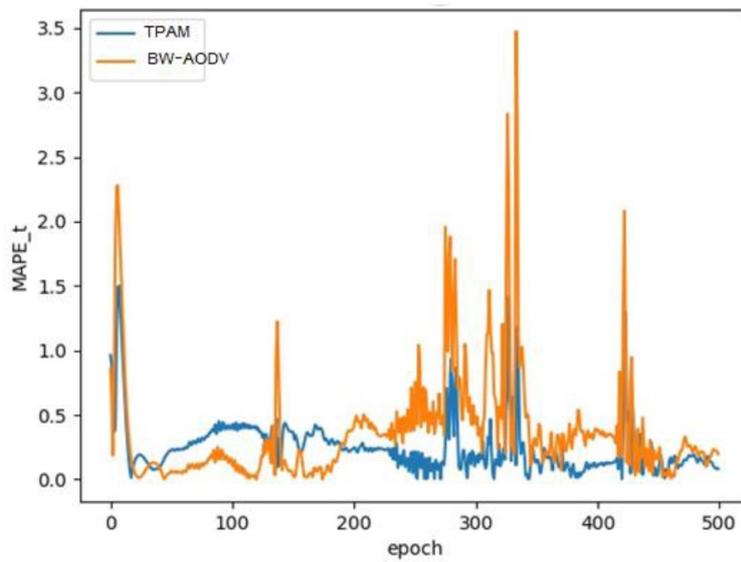


Figure 4: The time slot variation predicting the average MAPE value.

end-to-end delay when compared with BW-AODV. The TPAM also performs very well when the same amount of data is sent to destination, the total time taken by the TPAM is much less than that of the BW-AODV. The proposed TPAM adopts the multi-path streaming mechanism, which is based on RNN traffic prediction.

5. Conclusion

There are a few confinements concerning the current QoS directing calculations in wireless MANETs. To defeat the restrictions, a traffic prediction algorithm for MANETs (TPAM) is proposed in wireless MANETs. At first, the recurrent neural system with a traffic prediction model was built in this paper, and afterward relying upon the model TPAM is formulated. The three different parts of TPAM include an algorithm on multi-path routing, a traffic prediction congestion discovery mechanism based on recurrent neural network, and an algorithm for balancing the load on the network using multi-path. Whenever the network is congested or the link between the paths is broken, it is clear from the simulation results that the TPAM offers better adaptability and robustness. When TPAM is compared with the present available algorithms, it shows better scalability, decreased end to end delay, and good success ratio. The end to end QoS in wireless MANETs can be guaranteed using TPAM. We will further study the multi-path routing algorithm under the condition of multi-channel and dynamic topology to ensure QoS in MANETs.

References

- [1] S. Ambareesh and A. Neela Madheswari, *Hybrid Salp swarm firefly algorithm based routing protocol in wireless multimedia sensor networks*, Int. J. Commun. Syst. 34(3) (2021) 1–22.
- [2] M.S. Artigas, P.G. Lopez and A.F.G. Skarmeta, *A novel methodology for constructing secure multipath overlays*, Internet Comput. 9(6) (2005) 50–57.
- [3] IEEE 802.11 Standard Group, *IEEE 802.11 [EB/OL]*, 2007, <http://www.ieee802.org/11/>.
- [4] IEEE 802.15 Standard Group, *IEEE 802.15 [EB/OL]*, 2007, <http://www.ieee802.org/15/>.
- [5] H.C. Kantharaju and K.N. Narasimha Murthy, *Enhancing energy efficiency of cluster wireless sensor networks by secure data transmission*, J. Adv.Res. Dyn. Control Syst. 9(17) (2017) 582–598.
- [6] H.C. Kantharaju, K.N. Narasimha Murthy, *An energy efficient authentication scheme based on hierarchical IBDS and EIBDS in grid-based wireless sensor networks*, Int. J. Info. Comput. Secur. 13(1) (2020) 48–72.
- [7] H.C. Kantharaju, K.N. Narasimha Murthy, *Enhancing performance of WSN by utilising secure QoS based explicit routing*, Int. J. Comput. Aided Eng. Tech. 13(1/2) (2020) 101–123.
- [8] C.E. Koksal and H. Balakrishnan, *Quality-aware routing metrics for time-varying wireless mesh networks [J]*, IEEE J. Selected Areas Commun. 24(11) (2006) 1984–1994.
- [9] S.J. Lee and M. Gerla, *Split multipath routing with maximally disjoint paths in Ad-hoc networks*, Proc. IEEE Int. Conf. Commun. (2001) 3201–3205.
- [10] J.C. Lu, Z.H. Gu and H.Q. Wang, *Research on the application of the wavelet neural network model in peak load forecasting considering of the climate factors*, Proc. Fourth Int. Conf. Machine Learn. Cybernet. IEEE, Guangzhou, China, (2005) 538–543.
- [11] Information Sciences Inc., *Network simulator ns-2 [EB/OL]*, <http://www.isi.edu/n-nsam/ns>.
- [12] N.M. Pindoriya, S.N. Singh and S.K. Singh, *An adaptive wavelet neural network-based energy price forecasting in electricity markets*, IEEE Tran. Power Syst. 23 (2008) 1423–1432.
- [13] H.P. Srinivasa, V.N. Kamalesh, *An intelligent neighbour node cooperative routing protocol for Ad-Hoc networks*, Int. J. Adv. Sci. Tech. 28(13) (2019) 119–129.
- [14] H.P. Srinivasa, V.N. Kamalesh, *Energy efficient co-operative routing mechanism for mobile Ad-Hoc networks*, Int. J. Future Gener. Commun. Network. 13(1) (2020) 1528–1538.
- [15] L.P. Wang and X. J. Fu, *Data Mining with Computational Intelligence*, Springer, Berlin, 2005.
- [16] L.P. Wang, K.K. Teo and Z.H. Lin, *Predicting time series with wavelet packet neural networks*, Proc. IJCNN 2001 (2001) 1593–1597.
- [17] Z. Xu, C. Huang and Y. Cheng, *Interference-aware QoS routing in wireless mesh networks [C]*, 4th Int. Conf. Mobile Ad-hoc and Sensor Networks, (2008) 95–98.