International Journal of Engineering &Technology, 8 (3) (2019) 302-307

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



Long Short-Term Memory Recurrent Neural Network based Mobility Prediction in MANET

J.Manimaran[1]*, Dr.T.Suresh[2]

[1]Assistant Professor, Department of Information Technology, Annamalai University, TamilNadu, India
[2]Assistant Professor, Department of Computer Science and Engineering, Annamalai University, TamilNadu, India
**Corresponding author E-mail:maranj006@gmail.com*

Abstract

A Mobile Ad hoc NETwork (MANET) is formed by a gathering of wireless nodes without any infrastructure and the wireless nodes are not static but dynamic in nature. The mobile nodes can be connected together dynamically to route data packets from other mobile node present in the network. The mobility of the nodes is a significant feature in the MANET. The nodes follow one of the different mobility patterns which affect the connectivity among the other nodes. The dynamic changes in the connectivity decides the performance of the routing protocol and hence the performance of the overall network. When considering these characteristics of the MANET it becomes essential to predict the mobility of the nodes in both service-oriented and as well as application-oriented aspects of the dynamic networking. At the network level the mobility prediction is useful in pre-configuring services, provisioning of QoS and reservation of net-work resources and whereas in application level the end user can be provisioned with route guidance, information on network traffic and broadcasting important information to users. The mobility prediction will lead to the estimation of the stability of the routing paths and the distances between the neighboring nodes. This helps to improve the overall performance of the network by reducing the frequent link failures and increasing packet delivery ratio. In this paper, a novel mobility prediction method is developed using the historical time and positioning data. Auto Regressive Integrated Moving Average (ARIMA) and Long Short Term Memory (LSTM) with Recurrent Neural Network (RNN) are utilized for mobility prediction based on the sequence of time series data.

Keywords:*ARIMA; LSTM; MANET; Mobility Prediction.*

1. Introduction

MANET is a gathering of wireless mobile nodes forming a temporary network without the guide of any centralized administration or standard support services. The topology of the MANET is dynamic in nature where the nodes dynamically change their position and enter or leave the network frequently. The MANET is characterized by decentralized control and no infrastructure to support network. A fully connected network is formed as the nodes not only send and receive the data packets but also receive and forward the data packets of other nodes present in the network. Consequently, finding an optimal route is critical for guaranteeing the timely delivery data packets from source node to destination. An intermediate node moves out of communication range with other node, the communication links breaks up and a new link must be formed based on its new position. The process of estimating the position of mobile nodes is termed as Mobility Prediction and the term position refers to access point to which the mobile node is associated, if the wireless network is an in-frastructure based one [1].

But in case of infrastructure-less network i.e. MANET it refers to geo-coordinates of the mobile nodes. This helps in further estimation of link expiration time. A mobility prediction method in Ad Hoc Networks by considering the positions of the mobile node as a time series is developed and tested. It is assumed that each node in the network is aware of its geo-position and it is recorded periodically. The time series values define the node trajectory and it can be denoted as $[(X^{t+1}, Y^{t+1}, Z^{t+1}), (X^{t+2}, Y^{t+2}, Z^{t+2}),\ldots\ldots, (X^{t+k}, Y^{t+k}, Z^{t+k})]$ where 't' is the initial time and 't+k' is the current time. By knowing these previous positions the upcoming position of the mobile node $(X^{t+k+1}, Y^{t+k+1}, Z^{t+k+1})$ can be estimated [2].

As the mobility prediction in MANETs has more benefits and considerable measure of present work has been established on this topic. There are certain issues and challenges in predicting the mobility of the nodes in the MANET and they are as follows

1) Adhoc Networks are highly dynamic in nature where the topology of the network changes frequently
2) Adhoc networks are used mostly in emergency situations like natural calamities and military operations where the movement of the nodes does not depend on previous movements.
3) Mobility prediction method must be lightweight as they are to be implemented on mobile nodes operating with less battery and computational power.

In MANET several node mobility models have been used and three of the commonly used models are following [3]

i) Random Walk model – identifies the movement of nodes from one position to next position in random speed and direction.

Copyright © 2019 J. Manimaran, Dr. T. Suresh. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

ii) Random Waypoint Model – identifies the movement with a series of live and dead periods, and Reference Point Group Mobility Model.
iii) Reference Point Group Mobility Model (RPGM) –identifies the nodes in the network formed as a mobility groups with a logical group centre termed as the Reference Point.

The Random Waypoint model is the most usually utilized and adopted for the experiments and simulations in this study. By this model the node remains at a position for a fixed period of time called pause time before travelling to the next position in random way with an uniform speed ranging between 0 to MAXSPEED.

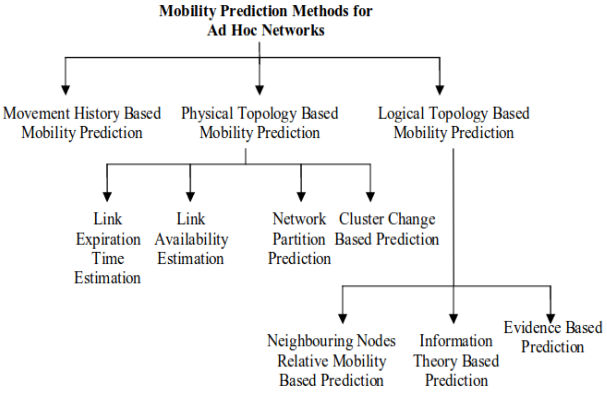


Fig. 1: Classification of Mobility Prediction methods.

Similar to the Mobility Models the mobility prediction methods have been classified in to three categories [4] namely

i) Predicting mobility based on movement history – the upcoming position of a mobile node is detected based on the previous historical node movement pattern.
ii) Predicting mobility based on the physical topology –using the Global Positioning System (GPS) the exact position of the node and their mobility information can be detected.
iii) Predicting mobility based on the Logical topology –using a clustering structure predicting the mobility information without using GPS.

The paper is organized as follows. In Section 2 we summarize the related works. The Section 3 describes the need and importance of mobility prediction in Ad Hoc networks and the method for the estimation of link availability time. The Section 3.1 describes the methodology adopted in this paper for mobility prediction. The Section 4 explains the experimental procedure and provides an analysis of the mobility predictions as a long time series forecast and concluding remarks in section 5.

2. Related works

The stability of the links can be determined by predicting themobility of the nodes. This prediction helps us to locate themobile nodes and understand the topology of the network at a time [9]. In [10] using GPS mechanism the mobility prediction isimplemented for constructing a reliable routing protocol. The prediction task is carried out by estimating the velocity and the position of the mobile nodes. The position is determined with the help of the GPS devices. The prediction does not consider the change in the direction or the velocity of the mobile nodes.

In [11] a method to calculate the link availability time between a source and destination node is introduced and the whole information is presented in the form of time-prediction table. In [11], [12] a Markov model is developed to predict the position of the mobile nodes as single user and collaborative. The Markov model is built by using the GPS data recorded over a period of time. Similar to the previous prediction methods this method does not considers velocity and direction detail.The prediction can be done for only the geographic areas where the GPS data are recorded.

In [13] a novel method for prediction of vehicle mobility using artificial neural network was introduced and the neural models are trained using certain road conditions.

In [14], [15] for a better routing decision process the results of the prediction along with the geographical routing protocol is used. The prediction method is using the pedestrian data to forecast the node position in MANET.

In [16] the variation in the strength of the signal has been utilized to identify the node position. The node position is estimated either towards or away from the estimating node. The signal strength is considered as the QoS parameter to estimate the stability of the link while deciding the routes. Extensive research has been conducted to identify the links that are more stable i.e, the set of intermediate nodes which has high lifetime.

In [17] framework has been proposed to predict the changes in the upcoming topology of the network. The framework is constructed using a hybrid neural model built by combining MultiLayer perceptron and Extreme Learning Machine. In [1] a novel approach was proposed to predict the mobility of nodes by using the historical data and the evolutionary algorithm. This approach drastically improved the performance of the MANET routing protocol. The genetic algorithm is used in the work and it removes the outlier using the heuristics. The frequent link failures in the network due to node mobility affect the packet delivery [18]. If it is possible to predict the mobility of the node in advance the link failures can be handled without affecting the packet delivery either by choosing a stable link for routing or rerouting the data packets before the link gets failed. In [19] based on a single feed-forward layer architecture also called as the extreme-learning machine the mobility prediction is carried. Extreme Learning Machines does not need the initialization of the weights and tuning of model hyper parameters as like in Multi-Layer perceptron models. An easy way to comply with the paper formatting requirementsis to use this document as a template and simply type your text into it.

3. Estimation of routing path/link availability time

In Ad Hoc Network it is always better to select the most stable path during the route selection. The stable paths can be determined based on the predicted position of the mobile nodes. If an intermediate node in a path is slowly drifting away from the currently connected node's communication range then the link will get broken and the packets will be dropped. To avoid this type of packet drops due to abrupt link failures caused by intermediate node movement, the routing protocol must select stable paths by predicting the mobility of the nodes. The routing path must be selected only if all the intermediate nodes present in the chosen path are available within the communication range for the entire transmission period. The time duration for which a chosen routing path or link will be stable is termed as routing path availability time.

Consider two nodes A and B in an Ad Hoc Network and let (x^A,y^A) and (x^B,y^B) be the positions of nodes respectively. Also let v^A and v^B be the speeds, θ^A and θ^B the moving positions of the nodes A and B respectively. Then the time T for which the link will be available is given by [5]

$$T = \frac{-(ab+cd)+\sqrt{(a^2+c^2)TX^2-(ad-cb)^2}}{(a^2+c^2)} \quad (1)$$

Where $a=v^A\cos\theta^A-v^B\cos\theta^B$, $b=x^A-x^B$, $c = v^A\sin\theta^A-v^B\sin\theta^B$, $d = y^A-y^B$. Thus based on the predicted mobile node position it is possible to estimate link expiration time which in turn useful for re-route construction or for selecting a more stable path [6].

4. Methodology - mobility prediction

The problem of predicting the upcoming positions of the mobile node is formulated as Multivariate Time Series Forecasting and solved using two methods namely ARIMA [7] and LSTM with Recurrent Neural Network [8]. The problem is multivariate since we need to estimate the X and Y coordinates of the mobile nodes. For a time series data X^t where t is an index and $X^t$are real numbers the ARIMA model can be given by

$$ARIMA(p',q) \rightarrow X^t - \alpha^1 X^{t-1} - \cdots - \alpha^{p'} X^{t-p'} = \varepsilon^t + \theta^1\varepsilon^{t-1} + \cdots + \theta^q\varepsilon^{t-q} \quad (2)$$

Where p denotes the number of lagged observation used in the model and q denotes the size of the moving average window. α^i are the parameters of the model and $\theta^i$are the parameters of moving average part of the model and ε^t are the error terms.

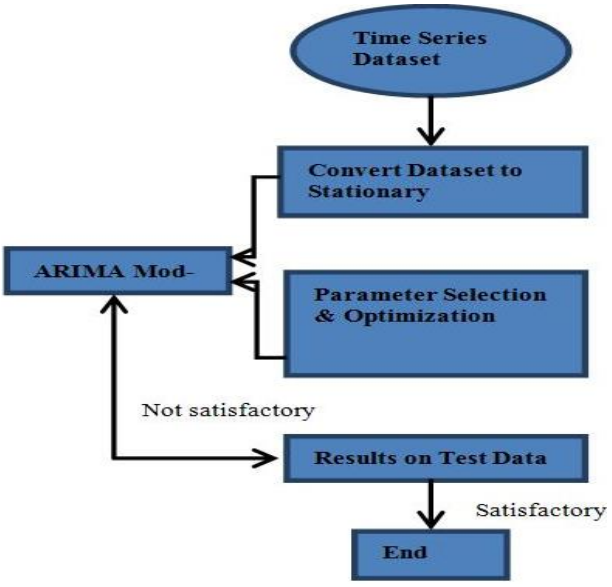


Fig. 2: ARIMA Modeling Process.

ARIMA model uses the dependent relationship between sampled observation and few of lagged observations. The dependency between an observation and a residual error [estimated by applying the moving average model to the lagged observations] is also used. The parameters of the model are estimated using a fitting procedure to find the coefficients of the regression model. The Fig 2 describes the overall process of modeling a ARIMA model for time series forecasting. Initially the time series must be converted in to stationary and then the model parameters are to be estimated. This process is repeated until the test results are found to be satisfactory.

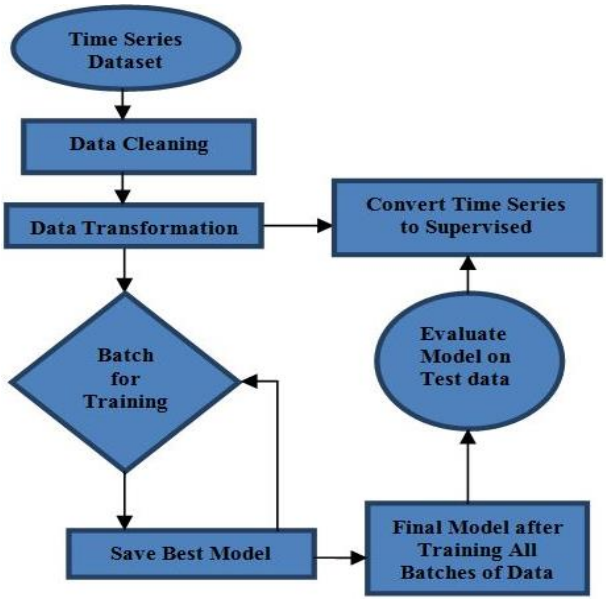


Fig. 3: LSTM Recurrent Neural Network Modeling Process.

The second method used in our experimental study is LSTM Recurrent Neural Network which extends the RNN architecture. In LSTM RNN the conventional neurons are replaced by a memory cell and a gating mechanism. The gating mechanism regulates the flow of information within the network. The gating mechanism is composed on three units namely input unit, forget unit and output gate. The memory cell has a linear unit termed as Constant Error Carousel (CEC) which is recurrently self-connected. The CEC provides the short term memory storage for an extended period of time.

LSTM considers the dependency of the time series sequence in which the data is being given to model during training. Another advantage of using LSTM when compared to ARIMA model is that LSTM can handle huge data. For multivariate time series analysis using LSTM model the time series data must be converted in to a supervised learning data.

The modeling of LSTM RNN involves a preprocessing step of transforming the time series in to a logarithmic scale before sending the time series in to the decomposition algorithm. The whole process of modeling the LSTM RNN for time series forecasting is presented in Fig 3. For accurate forecasts the de-seasonalizing of data prior to modeling becomes essential. Seasonal and Trend decomposition using Loess (STL) is used to divide a time series into three components namely trend, seasonal, and remainder. STL is considered to be one of the robust methods for time series decomposition. As in the initial stage of modeling the time series data is log transformed, finally the forecasts results are back-transformed into their actual scale by finding the exponential value. The transformation stabilizes the variance of the time series input and also it is essential for decomposition of time series data. The transformation makes the time series into additive as suitable for STL decomposition which is an additive decomposition method.

5. Experiments and results

For conducting the experiments Mobility Scenarios for MANET simulation are generated using an extension tool of NS2 network simulator. The mobility scenario generator of NS2 accepts inputs like the pause time, number of node, Maximum node speed, maximum value of X and Y co-ordinates, and simulation time period. Finally it generates the mobility scenarios for the whole simulation time. The generated mobility series are restructured to make it suitable for time series forecasting. In each time series, the mobility information of each node is clustered and the mobility data of a particular node alone is saved in a separate file for training the model. In the mobility scenarios the value of pause time is chosen a minimum value of 0.5 seconds so that the nodes are highly dynamic. The plot in Fig. 4 presents a portion of trajectory movement of a mobile node during the simulation period. The total number of nodes considered in simulation is 50 and the total simulation period is 5000seconds.

The error measure for assessing the performance of the time series forecasting is the root mean squared error (RMSE)

$$\text{RMSE}=\sqrt{\frac{\sum_{k=1}^{n}(y^k-t^k)^2}{n}} \quad (3)$$

For LSTM model the number of hidden layers is selected by a heuristic approach. A small variation in the number of hidden layer affects the prediction accuracy. The value of number of hidden layers fixed such that the generalization error of the LSTM model is low. The predicted trajectory of the test data is deduced from predicted value of X and Y co-ordinates. When compared to the ARIMA model the LSTM predictions seems to be more nearer to actual trajectory of the test data. The plots in Fig 5 and 6 presents the predicted trajectory of LSTM and ARIMA respectively. The root mean square error of test data for ARIMA model is high and is presented in Table 1.

Table 1: RMSE of Time Series Forecasting

Model	X Co-ordinate	Y Co-ordinate
ARIMA	2.636285	3.065942
LSTM	1.884144	1.962142

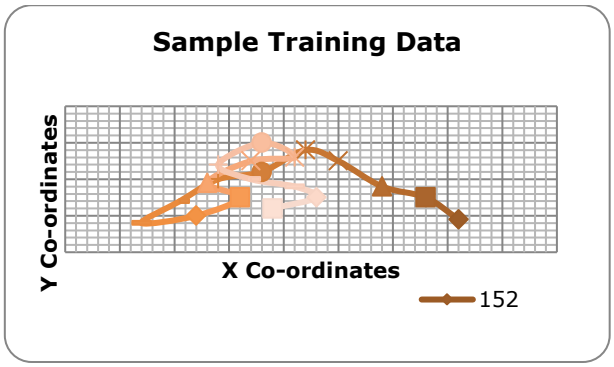


Fig. 4: Trajectory of A Node's Mobility.

Once the mobility prediction model is constructed the impact of the mobility on the mobile nodes are tested based on the following parameters like the velocity of the mobile node, the data arrival rate and the size of the mobile node. The initial position of the mobile nodes has a greater influence on the prediction of the mobility of the nodes. Fig 7 presents the comparison of various arrival rates using a poison distribution model.

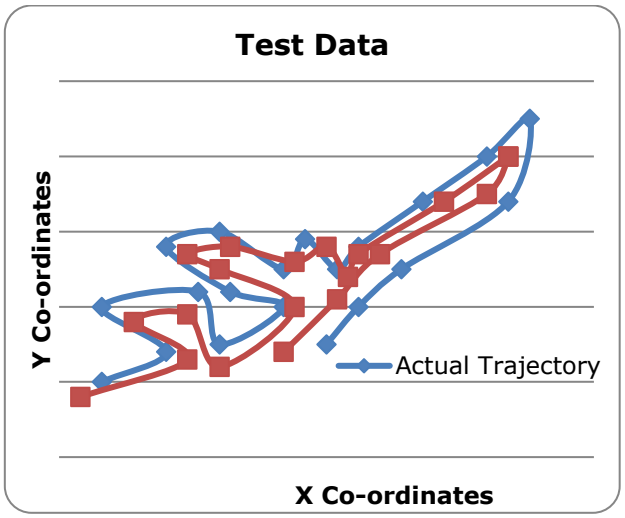


Fig. 5: Plot of Predicted Trajectory – LSTM.

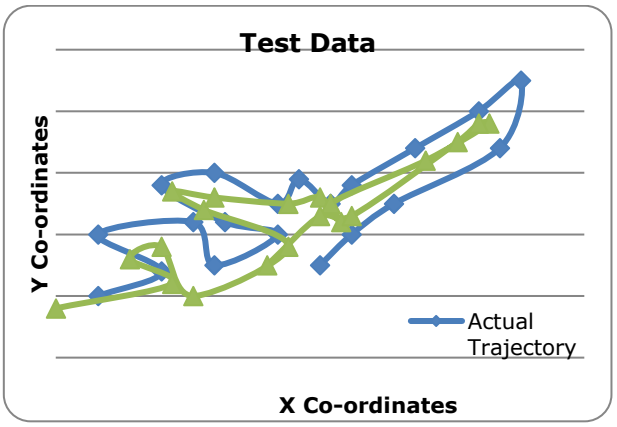


Fig.6: Plot of Predicted Trajectory – ARIMA.

From the experimental results obtained it can be observed that when the arrival rate is increased the shape of the distribution changes to normal form. It is also observed that when the arrival rate is increased the properties of the Poison distribution changes in to normal distribution form.

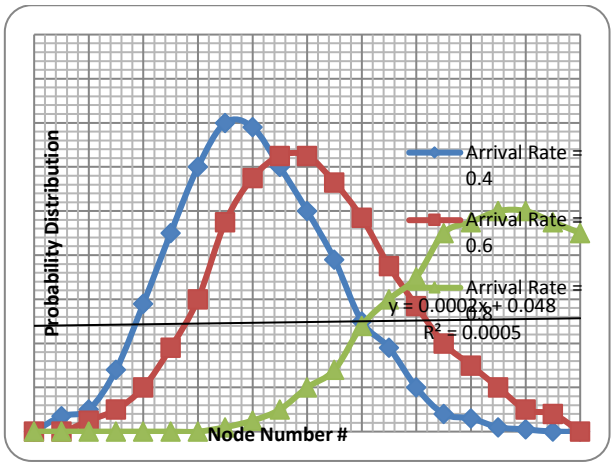


Fig. 7: Comparison of Node Arriving at Time T with Different Arrival Rate.

6. Conclusion

In this paper the mobility prediction is framed as along time series forecasting problem and solved using ARIMA and LSTM RNN models. The test results proved that LSTM is better in handling large time series data when compared to ARIMA model. To implement the LSTM for multivariate, the time series problem has been converted into supervised learning problem. The mobility prediction in MANET helps in improving the overall packet delivery ratio by reducing the packet drops due to frequent link failures. During the route maintenance or initial route selection period stability of the link i.e. the link availability time is estimated and the data packets can be rerouted if a link failure due to node mobility is predicted in advance.The future work will be focused towards developing a mobility prediction based routing protocol which limits the packet losses due to node mobility.

References

[1] R. Suraj, S. Tapaswi, S. Yousef, K. Pattanaik, and M. Cole.: Mobility prediction in mobile ad hoc networks using a lightweight genetic algorithm. Wireless Networks, 22(6), 1797–1806, 2016.https://doi.org/10.1007/s11276-015-1059-0.

[2] A. Pamanik, B. Choudhury, T.S Arif and W Mehedi.: Simulative study of random waypoint mobility model for mobile ad hoc networks. Proceedings of 2015 Global Conference on Communication Technologies (GCCT), p 112-16, 2015.https://doi.org/10.1109/GCCT.2015.7342634.

[3] V. K. Jain, and B. Sharma.: A Survey on mobility Models and Its Applications. International Journal of Recent Trends in Engineering and Research. 2(3), 35-41, 2016.

[4] GBox, G.M Jenkins, and G.C Reinsel.: Time Series Analysis: Forecasting and Control. 4th edn. Wiley, Chichester, 2008.https://doi.org/10.1002/9781118619193.

[5] K. Namuduri, S. Devaraj, M. Srinivasan, and R. Pendse.: Analytical estimation of path duration in mobile ad hoc networks. IEEE SensorsJ. 12(6), 1828–1835, 2011.https://doi.org/10.1109/JSEN.2011.2176927.

[6] Wenjing Yang, Xinyu Yang, Shusen Yang, Yage Gong.: Improving Route Stability in Mobile Ad Hoc Networks Based on Link Lifetime. Journal of Communications, 6(3), 205–214, 2011.https://doi.org/10.4304/jcm.6.3.205-214.

[7] M.Khashei,M.Bijari.: A novel hybridization of artificial neural networks and ARIMA models for time series forecasting. Appl.SoftComput.11 (2), 2664–2675, 2011.https://doi.org/10.1016/j.asoc.2010.10.015.

[8] X Ma, Z Tao, and Y Wang.: Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transport.Res. Part C: Emerg. Technol. 54, 187–197, 2015.https://doi.org/10.1016/j.trc.2015.03.014.

[9] Kulkarni, S.B., Yuvaraju, B.N.: Node connectivity, energy and bandwidth aware clustering routing algorithm for real-time traffic multicasting in MANET. In: Proceedings of the Advance Computing Conference (IACC), IEEE International, pp. 760–763, 2015.https://doi.org/10.1109/IADCC.2015.7154809.

[10] Ashbrook, D., Starner, T.: Learning significant locations and predicting user movement with gps, In: Wearable Computers, (ISWC 2002) Sixth International Symposium, pp. 101 – 108, 2002.

[11] Creixell, W., Sezaki, K.: Mobility prediction algorithm for mobile ad hoc network using pedestrian trajectory data. In: Proceedings of the TENCON 2004. 2004 IEEE Region 10 Conference, pp. 668–671, 2004.

[12] Zaidi, Z.R., Mark, B.L.: Mobility estimation for wireless networks based on an autoregressive model. In: Proceedings of IEEE GLOBECOM, Dallas, Texas, USA, Nov–Dec 2004.

[13] Basarkod, P.I., Manvi, S.S., Albur, D.S.: Mobility based estimation of node stability in MANETs. In: Proceedings of the International Conference on Emerging Trends in Computing, Communication and Nanotechnology (ICE-CCN), pp 126–130, 2013.https://doi.org/10.1109/ICE-CCN.2013.6528477.

[14] Park, R., Kim, W., Jang, S.: Improved AOMDV to increase path stability by utilizing the node mobility information in MANET. In: Proceedings of the International Conference on Information Networking (ICOIN), pp 417–422, 2013.

[15] Mohsin, R.J., Woods, J., Shawkat, M.Q.: Density and mobility impact on MANET routing protocols in a maritime environment. In: Proceedings of the Science and Information Conference (SAI), pp. 1046–1051, 2015.https://doi.org/10.1109/SAI.2015.7237271.

[16] Palani, U., Alamelumangai, V., Nachiappan, A.: Hybrid routing and load balancing protocol for wireless sensor network. Wirel. Netw. (8), 2659–2666, 2016.https://doi.org/10.1007/s11276-015-1110-1.

[17] Rajalakshmi, C.: Mobility prediction in MANET using neural learning methods. Artif. Intell. Syst. Mach. Learn. 9(2), 39–42, 2017.

[18] Nagwani, R., Singh Tomar, D. Mobility Prediction based Routing in Mobile Adhoc Network using Hidden Markov Model. International Journal of Computer Applications. 59(1), 39–44, 2012.https://doi.org/10.5120/9516-3919.

[19] Ghouti L, Sheltami TR, Alutaibi KS. Mobility prediction in mobile ad hoc networks using extreme learning machines. Procedia Computer Science. 19, 305–312, 2013.https://doi.org/10.1016/j.procs.2013.06.043.