Link State Prediction in Mobile Ad hoc Network Using Markov Renewal Process

Hamzat A. Babatunde Computer Science Department,
University of Ibadan, Nigeria
abdulazeezhamzat@gmail.com

Akinola S. Olalekan Computer Science Department,
University of Ibadan, Nigeria
solom202@yahoo.co.uk

ABSTRACT: ***Unlike infrastructural networks, an ad hoc wireless network does not have any fixed communication infrastructure. For a Mobile Adhoc NETwork (MANET) the nodes' positions are continuously changing. Therefore routes are subject to frequent disconnections. In such an environment, it is imperative to minimize disruptions caused by dynamic topology for a better Quality of Service (QoS). This presents a difficult challenge for routing protocols, since constant change in topology cause link failure due to unstable route. In order to improve MANET QoS, a model was formulated for predicting link availability by applying Markov Renewal Process (MRP) to a dataset of real trace. MRP is based on probabilistic model which makes use of transition probability and sojourn time distribution to model link behaviour. By using homogeneous time interval, the model is able to predict link availability from time T to T+t_0. However, unlike Markov chains which make use of transition probabilities alone to predict link state, MRP also make use of state sojourn time in predicting link availability. The performance of MRP shows that link state can be predicted with high accuracy, which in turn can lead to a better QoS***

1. Introduction

Wireless Ad-hoc Network is the collection of nodes which can move freely and arbitrarily at any time to form a temporary network. Mobile Adhoc NETworks (MANETs) are the self-configuring, infrastructure less wireless ad hoc networks having the dynamic topology without any centralized administration [1, 2, 3]. Therefore, MANET are not constrained in their deployment by any need for underlying infrastructure and they can be deployed rapidly in situations where wireless access to a backbone is impossible and an infrastructure is difficult to install (e.g., disaster recovery).

In addition to the traditional problems of wireless networks (bandwidth optimization and transmission quality enhancement) MANET introduce new issues such as ad-hoc addressing, increased energy constraints, self-configuration and adaptive reconfiguration, as network topology is affected by node mobility. Furthermore, because of the real time nature of ad hoc network applications, data traffic is routed under timing constraints requiring proactive route construction and maintenance procedures [4]. Each device in a MANET is free to move independently in any direction, and will therefore change its links to other devices frequently. Each must forward traffic unrelated to its own use, and therefore acts as a router.

The primary challenge in building MANET equipment is making each device mobility-aware. The mobile nodes may follow different mobility patterns that may affect connectivity, and in turn protocol mechanisms and performance. Mobility prediction may positively affect the service oriented aspects as well as the application-oriented aspects of ad hoc networking. Improving Routing performance of MANET has been a major challenging area of research for a number of years. Researchers have shown over the years that accurate node mobility or link state predictions can improve the routing performance of MANETs [1, 4, 5, 6, 7, 8, 9].

The stability and reliability of links in wireless networks is dependent on a number of factors such as the topology of the area, proximity of nodes, weather conditions and so on. As such, there is no single way of modeling wireless link behaviour that will work in all cases, making it difficult to predict wireless link availability using mathematical models [10]. Specifically, several studies have shown that humans do not move in a completely random manner; instead, their movement patterns are predictable to some extent. Thus, there has been a growing interest in developing models that are based on real datasets [11]. However, very little work has been done on area of application of machine learning techniques to mobility prediction using real datasets, given its success and a number of sophisticated prediction tools it encompasses over the years and also comparing the robustness of proposed prediction methods and subsequent effects on routing performance. In this study, we propose a model for link availability prediction in Mobile Ad Hoc networks using a dataset of real trace mobility.

2. Related Works

Because of the importance of mobility prediction in ad hoc networks, there is a significant amount of research work on the topic; while in some cases the proposed techniques follow ideas or approaches used in fixed infrastructure type networks. However, prediction approaches for fixed infrastructure type networks are usually inappropriate in the case of ad hoc networks since according to Gavalas *et. al.*, [4]:

1. Prediction relied on static infrastructure, while in MANET the environment is highly dynamic.
2. There is dissimilarity in future node mobility.
3. Light weight algorithm is imperative due to memory and computational constraint.

Effective delivery of data packets while minimizing connection disruption is crucial in ad hoc networks. Su *et al*, [10] examined the use of mobility prediction to anticipate topology changes and perform re-routing prior to route breaks. Prediction was applied to commonly used MANET protocols. Simulation results indicate that with mobility prediction enhancements, more data packets were delivered to destinations while the control packets were utilized more efficiently. Routes that are the most stable and stay connected longest are chosen by utilizing the mobility prediction.

Model for MANET using Recurrent Neural Network (RNN) and Extended Kalman Filter (EKF) was also proposed in Sharma *et al*, [3]. The Kalman Filtering addresses the estimation of a state vector in a linear model of a dynamic system. In order to apply EKF for estimating optimal weights of RNN, weights of network were interpreted as transition matrix for the system state. In order to evaluate the result, they simulated reference point group mobility MANET trained with RNN using Levenberg-Marquardt algorithm and the performance was found satisfactory.

The routing algorithm based on the mobility prediction was proposed by Wu and Li, [11] to provide the information about the mobile nodes. The interpolation prediction algorithm is to solve the problem of identifying the speed of the mobile nodes. The prediction based routing algorithm has two phases: spray phase, multiple copies of the RREQs broadcast in the binary tree way, forwarding phase, the node carry out the location prediction and send message to the node which is very closer to the destination node.

Muthuramalingam *et al*, [5] investigated mobility prediction in cluster MANET using linear auto regression and cluster formation. The Linear Auto Regression is among the many techniques available for prediction. The past positions or the history is used in predicting the future positions. Clustering is then performed based on the predicted value. They are able to show that the Weighted Clustering Algorithm when modified with liner auto regression prediction is more efficient form of Clustering. It is evident that this technique is not suitable for network with high mobility as Cluster Head (CH) tends to change frequently thereby increase routing overhead.

In Manisha and Yashpal, [7] directional mobility model is considered for communication over the mobile network. Here the inter cluster and intra cluster communication is performed over the network. The work includes the cluster based communication within the network for both inter and intra cluster communication. The intelligent cluster selection technique is defined based on throughput, capacity and idle rate based evaluation.

The selection of reliable paths is also a difficult task. Link Availability-Based Routing Protocol (LBRP) is proposed for predicting the link in short span of time. The link available time is focused from t_0 to $t + t_0$ and the statistical and probabilistic expression is derived for the link available time based on the Random Way point mobility model. In this approach, Poisson distribution is used to predict the link availability [12]. This LBRP algorithm predicts the links only when the nodes are within the range. The authors failed to test the performance of LBRP algorithm with a more realistic mobility model.

In an attempt to improve route stability, one strategy is to select a route that satisfies different conditions that would affect the stability of the route. Koul *et al*, [13] have used the current parameters such as distance between two nodes, frequency and Receiver Signal Strength Indicator (RSSI) to decide whether a link should be used. However, this method only uses the current parameters, no historical records nor future predictions have been used in the route selection decision making.

Route stability is the major issue in mobile Ad hoc networks. For the stability of the nodes new approach was proposed and considered. The path stability was predicted by the link connectivity changes in the network layer. Initially, Link Connectivity Model was designed between two nodes under the assumption of the Markov chain model. In this approach the non-stationary movements, for example, the speed of nodes with respect to time was considered. This prediction method does not need prior knowledge about the mobility pattern of the network [14].

For the stability of the paths in MANETs, Link breakage prediction was implemented. In this approach, RSSI is transmitted to each node. If the RSSI is less than the threshold value, the node immediately is Sent To Link Breakage Warning (SLBW) and after receiving the SLBW the intermediate node sends the Modified Route Request (MREQ) to the source and creates the new route to destination [15].

The link stability estimation scheme was proposed by Song *et al*, [16]. Their approach was based on link connectivity changes. The scheme focuses on a probabilistic model and the estimation results have explicit meanings both in theory and practice. To estimate the transition rates, they used Continuous Time Link Connectivity Model (CTLCM) for estimation scheme, they estimated the transition probabilities in the Discrete Time Link Connectivity Model (DTLCM). The proposed scheme was simpler than the methods using GPS or low layer measurements, and it is not restricted to a specific network topology.

Mobility prediction in cellular network using Markov Renewal Theory was proposed by Abu-Ghazaleh and Alfa [22], which helps to predict that mobility of nodes, can be available at anywhere and anytime. The Markov Renewal theory helps both the process of predicting the mobility model and transition of the next time.

The predicting technique also is used to estimate the traffic load activity and the network's coverage area. In this model, the entire network area is divided into zones. Each zone has the zone IDs. These zone IDs coordinates and predicts the nodes. The Semi Markov Process (SMP) access the transition probabilities. Cumulative distribution function is utilized for computing the network model.

From the above literature it is evident that the mobility model commonly employed by researchers are random way point (RWP) or random walk models such as Brownian motion (BM) and Markovian mobility. Some of these models are simple enough to be theoretically tractable and, at the same time, to be emulated in network simulators in a scalable manner. However, no empirical evidence exists to prove the accuracy of such models [17]. Others opined that unrealistic model could degrade performance of MANET [19]. However most agrees there is no single way to model or represent network state or mobility scenarios of MANET. Morote [20] proposed a model for simulation of MANET in more realistic environment combining different mobility scenario such as disaster area, pathway, shopping mall etc. However the author did not utilize mobility prediction with these scenarios, also predicting occurrence of events most especially in disaster area or war zone for mobility scenario modelling remains impossible.

The employment of mobility prediction techniques is very crucial in the design of efficient routing schemes. Not only that, Munjal *et al*, [19] suggest that performance of routing protocols should be evaluated using real traces. They also opined that more datasets are required to explore other real mobility scenarios such as office, disaster, and military scenarios contrary to campus scenario trace that were mostly employed. However, very few researchers have captured mobility prediction using real trace or test their prediction algorithms using real trace. In this study, we intend to address these lapses, by proposing a method for link state prediction in Ad Hoc networks using a dataset of real trace mobility.

3. The Prediction Model

Markov chain is based on well-established theory and it is widely used in prediction modelling. Mobility model such as Random Way Point (RWP), Random Walk Mobility (RWM), Reference Point Group Mobility (RPGM) [21] has been used with Markov chain for link state prediction, though these models are based on mathematical models rather than real life scenario. Even though the performance of Markov chain had been found satisfactory in modeling these stochastic events, the performance is yet to be tested with trace based mobility - mobility based on real life events. Thus in our prediction model, we intend to train Markov chain for predicting link state in MANET with real trace.

Figure 1 represents the predictive model. We processed our trace to conform to random but equally distributed events with equal time step interval. The probability of link state is then calculated based on the number of occurrences before we compute our transition matrix for training. We trained our Markov chain to learn the occurrence of link state overtime and be able to predict future link availability for efficient routing. We then evaluate our prediction for accuracy.

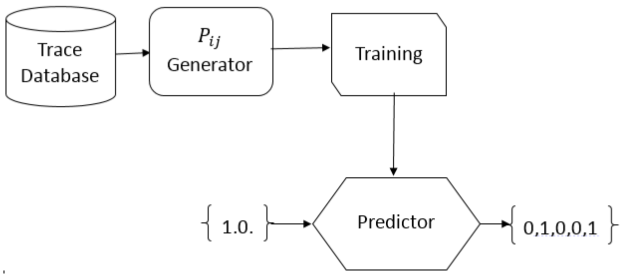

Figure 1: Markov chain prediction model

In this study, our focus is mainly in showing how to better model the link behaviour of MANET nodes in a wireless network. Thus we further proposed an enhanced model for our link state prediction, in which we model link as a Semi-Markov Process (SMP). The model can primarily be applied for predicting next link state, along with anticipating the duration between the transitions of link state. We train our Markov model the same way as our Discrete Time Markov Chain (DTMC). To the best of our knowledge, the use of semi-Markov for mobility or link state is alien to MANET. However similar idea was proposed by Abu-Ghazaleh and Alfa, [22] to predict user next-location in a cellular network.

3.1 Markov Chain Link State Prediction Method

In this study, the Markov Chain link state prediction method was implemented by using a discrete time Markov model proposed by Hwang and Kim, [21] that predicts the next link state between any two nodes in the network. This Markov model consists of two states (connected, *c*, and disconnected, *d*).

- $p_{dc} = p\{X_t = c | X_{t-1} = d\}$ is the probability of any two nodes disconnected at time $t-1$ becomes connected at time t;
- $p_{cd} = p\{X_t = d | X_{t-1} = c\}$ is the probability of a connected link at time $t-1$ being disconnected at time t;
- $p_{cc} = p\{X_t = c | X_{t-1} = c\} = 1 - p_{cd}$ is the probability of two nodes staying connected from time $t-1$ to time t; and
- $p_{dd} = p\{X_t = d | X_{t-1} = d\} = 1 - p_{dc}$ is the probability of two nodes remaining disconnected from time $t-1$ to time t.

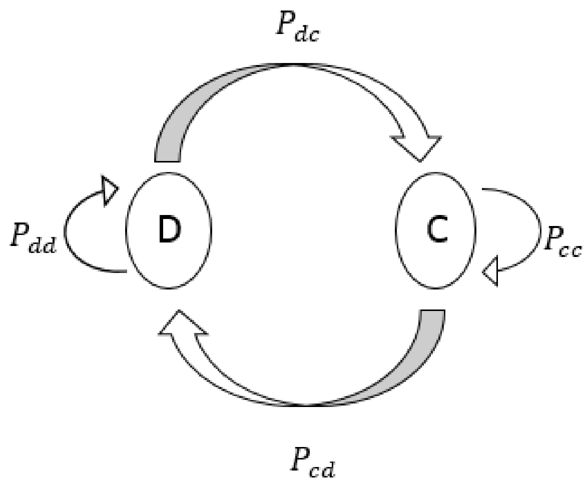

Figure 2: Transition Diagram

Figure 2 depicts the transition probabilities to and from different states. Thus we derive our transition P as

$$P = \begin{bmatrix} 1 - p_{dc} & p_{cd} \\ p_{dc} & 1 - p_{cd} \end{bmatrix} \ldots\ldots (1)$$

To describe the long-term behaviour of the connection, the behavior of P^t for a large t value needs to be calculated. The matrix P has Eigen values 1 and $1 - p_{dc} - p_{cd}$ if $0 < p_{dc}, p_{cd} < 1$. Because of $|1 - p_{dc} - p_{cd}|$ <1, the stationary probability of the transition matrix is given as

$$\lim_{t\to\infty} P^t$$

$$= \begin{bmatrix} p_{cd}/(p_{dc} + p_{cd}) & p_{cd}/(p_{dc} + p_{cd}) \\ p_{dc}/(p_{dc} + p_{cd}) & p_{dc}/(p_{dc} + p_{cd}) \end{bmatrix} \ldots (2)$$

From the equation, we know that the link remains in the connection state with $p_{dc}/(p_{dc} + p_{cd})$ ratio and in the disconnection state with $p_{cd}/(p_{dc} + p_{cd})$ ratio.

Thus, we can now deduce the probability that a link is connected at time t, $p_c(t)$, and the probability that a link is disconnected at time t, $p_d(t)$as:

$$\lim_{t\to\infty} p_c(t) = {p_{dc}}/{(p_{dc} + p_{cd})} \dots\dots (3)$$

$$\lim_{t\to\infty} p_d(t) = {p_{cd}}/{(p_{dc} + p_{cd})} \dots\dots (4)$$

3.2 Training

A Markov Chain model is required to be trained before it can be used for making predictions. Figure 2 shows simple prediction engine for Markov chain which contains a trace database of link availability history, this history is used to compute the state transition probability matrix, which we used for prediction. For this Markov Chain model, we obtained the state transition probability matrix by counting the number of times the link state remains at either state c or state d over n time steps (during the training phase). Through simulation, the probability that a link is connected and disconnected can be computed using N_c/n and N_d/n respectively, where N_c the number of times the link is connected, N_d is the number of times the link is disconnected, and n is the number of time steps. We calculated the state transition probabilities by substituting these values into Equations 3 and 4. Hence, the link state can be predicted using the state transition matrix. After the training, the transition matrix was then used to make predictions for the remaining time, given the current state as input, and during this time, we continue to update state transition at each time step during the prediction stage.

3.3 Markov Renewal Processes (MRP)

Combining renewal processes and Markov chains yields Semi-Markov Processes (SMP), and the former are special cases of the latter [23]. A more detailed description of how we formulated our MRP model can be found in [22, 24, 25]. Consider a stochastic process which moves from one state to another of a finite number of states $\{X_0, X_1, X_2, \dots\dots\dots, X_n\}$ with successive states forming a Markov chain, whose transition matrix is given by $P = P_{ij}$. Furthermore, the process stays in a given state a random length of time, "the wait", the distribution function $Q_{i,j}(t)$of which depends on the initial stateX_i as well as the one to be visited next, X_j . Let us write $K_t$for the state occupied at time t, then $\{K_t\, ; t \geq 0\}$ is called a semi-Markov process. Associated with this process is a Markov renewal process which records at each time t the number of times the $K_t$process has visited each of the possible states up to time t. Thus MRP is a SMP, where the successive state occupancies are governed by the transition probabilities $P_{ij}$of a Markov process and the sojourn time in any state depends on both the current-state and the next-state transition.

$$Q_{ij}(t) = Pr\{X_{n+1} = j\, , T_{n+1} - T_n = t |\, X_n = i\} \dots (5)$$

Where T_n and T_{n+1} represent the time at which nth and $(n+1)th$ transitions occur. Also $Q_{ij}(t)$ denotes the probability that transition from i to j occurs at unit time t. Then$Q_{ij}(t)$ is called a mass function or a one-step transition probability for the Markov renewal process. The matrix $Q(t)$ is composed of $Q_{ij}(t)$, i.e.,

$$Q(t) = [Q_{ij}(t)] \dots\dots (6)$$

is called a semi-Markov kernel. The one-step transition probability $Q_{ij}(t)$ is the probability that, after making a transition into state i, the process next makes a transition into state j (possibly $i = j$) in an amount of time less than or equal to t. The one-step transition probabilities satisfy the following:

$$Q_{ij}(t) \geq 0, \sum_{j=0}^{m} Q_{ij}(\infty) = 1$$
$$(i, j = 0,1,2, \dots \dots, m) \dots \dots \dots \dots (7)$$

Then

$$P_{ij} = \lim_{t \to \infty} Q_{ij}(t) = Pr\{X_{n+1} = j \mid X_n = i\} \dots \dots \dots \dots (8)$$

P_{ij} is the eventual transition Probability that the process can move from state i to state j, neglecting the sojourn time in state i. The eventual transition probability is also known as embedded Markov chain. If we assume only well-behaved distributions, the behaviour of the Markov renewal process is governed by the embedded Markov chain by ignoring all the sojourn times among the state transitions; that is, our prediction approach will be the same as Markov chain proposed earlier. If $P_{ij} > 0$ for some i and j, then we can define

$$F_{ij}(t) = {Q_{ij}(t)}/{P_{ij}} \dots \dots (9)$$

and if $P_{ij} = 0$ for some i and j , then we can define $Q_{ij}(t) = 0$ for all $t \geq 0$ and $F_{ij}(t) = 1(t)$ (a step function). The distribution $F_{ij}(t)$is a distribution of the sojourn time that the process spends in state i given that the next visiting state is j. The sojourn time in this case follows an arbitrary distribution, thus allows a more representation of temporal behaviour.

3.4 Markov Renewal Processes (MRP) Prediction model

We can model MANET link state behaviour using MRP, the transition between each state and the amount of time spent in the states. The model can be constructed using transition probabilities and conditional distributions of the sojourn time spent in each state, using aggregated link availability history. The probability$Q_{ij}(t)$ defined above can be computed to evaluate the predictions of arbitrary node link connectivity and the transition between connected and disconnected depends on the length of time spent in the current state. Also for our prediction model we compute our probabilities as follows.

- $p_{dc} = p\{X_t = c | X_{t-1} = d\}$ is the probability of transition from $D \to C$
- $p_{cd} = p\{X_t = d | X_{t-1} = c\}$ is the probability of transition from $C \to D$
- $p_{cc} = p\{X_t = c | X_{t-1} = c\}$ is the probability of transition from $C \to C$
- $p_{dd} = p\{X_t = d | X_{t-1} = d\}$ is the probability of transition from $D \to D$

We assume that $p_{cd} = 0$ and $p_{dd} = 0$ since this model describes a Renewal process for predicting future transitions.

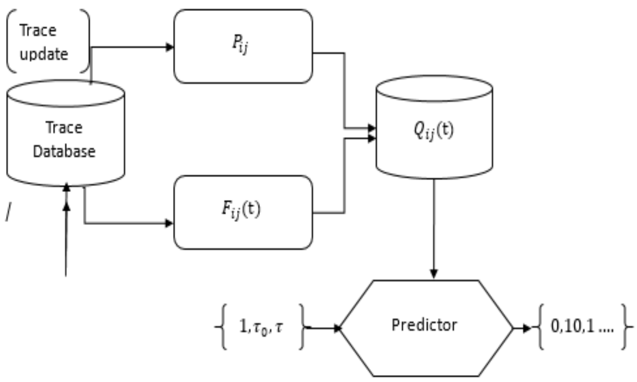

Figure 3: MRP Prediction Model

3.5 Training

For each of the probabilities previously given, we compute the semi-Markov kernel $Q_{dc}(\mathrm{t})$. The sojourn times collected from the MANET traces are also computed using a distribution function that can be formulated in the form given by equation 9. The block diagram in **Figure 3** shows the basic sequence of procedures that are needed to implement the proposed MRP based predictor. The trace database holds a record of the aggregate node link availability history. The information contained in these logs are needed to compute our state transition probabilities p_{ij} and the state sojourn time distributions $F_{ij}(\mathrm{t})$ for all valid (i, j) pairs of transitions. These components can periodically be updated, based on new trace that are received by the network and updated in the database. The $Q_{ij}(\mathrm{t})$ database keeps a record of computed elements, which is directly queried by the predictor to evaluate the probabilities. The predictor takes in as its inputs the current state i, the current sojourn time τ_0 in state i, and the time length τ from the current time τ_0, during which, a transition is expected to be made. Given those inputs, the predictor queries the $Q_{ij}(\mathrm{t})$ database to compute the values $Q_{ij}(\tau_0 + \tau)$ for all d, $c \in \mathrm{S}$ and outputs $(0, 1, 0, 1, 0, ..)$ as the next most likely outcome to occur τ time units from the current time. The step by step pseudo code of our prediction model is as follows

Figure 4: Markov Chain prediction accuracy
Step 1: load link availability log
Step 2: count the number of state transition
Step 3: compute the transition probability

P_{ij}

Step 4: compute the state sojourn time
Step 5: compute the sojourn time distribution

$F_{ij}(\mathrm{t}) = \int_0^{\infty}(1 - H(\mathrm{t}))\mathrm{dt}$

Step 6: compute the semi-Markov kernel $Q_{dc}(\mathrm{t})$
Step 7: compute the transition vector
Step 8: Predict the next state at time t
Step 9: End

1.1 3.6 Evaluation of the Accuracy of Prediction Methods

The term “link state” is used to describe the state of a link such that if the link state between two nodes is connected, the two nodes are in range, and if the link state between two nodes is disconnected, the two nodes are out of range. To assess the accuracy of the predictions, we simply chose to measure the number of times that a correct prediction was made from the total number of prediction attempts per node.

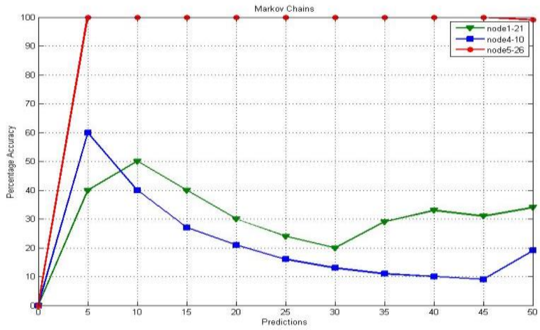

Figure 4: Markov Chain Prediction Accuracy

$$P_a = {\sum P_{ij}}/{N} \; ... ... (10)$$

Where P_a is the prediction accuracy and P_{ij} is the total number of link correctly predicted and N represents the actual link state.

1.2 4.Prediction and Accuracy

In this section, the accuracy of the proposed link availability prediction was examined and compared with conventional prediction scheme. To evaluate the accuracy of our prediction model, the models was trained as discussed in chapter three. The model was then used to predict link availability between any two nodes. The model evaluation has been done between the intervals of every 5th prediction made.

Figure 4 and figure 5 shows the evaluations of both MRP and Markov chains. To better demonstrate the performance of MRP model we have deduced the accuracy of prediction made by Markov chain model for a selected link state prediction between any two

MANET nodes. Figure 4 shows accuracy recorded by Markov chains in predicting link availability between node 1-21, 4-10, and 5– 26. A varying accuracy has been recorded, when the state that are mostly populated during the training phase will be the most to be predicted, as we can see in the case of links between nodes 5-26 and performance dropped drastically when it is otherwise. It is important to note that the prediction accuracy. The time spent in a particular state during the training phase of MRP model will influence further link state prediction. Figure 5 depicts various accuracies deduced from the MRP model.

The model recorded high accuracy for a number of predictions before a steady decline i.e., the link behaviour between node 4 - 10. We recorded a very low accuracy between node 1 and 21, this may be due to the fact that nodes that are connected for a long duration during the training phase of our MRP model may remain disconnected for a number of predictions made. The positive outcome of the results collected from applying the MRP mobility model also indicates the possible existence of a correlation between the node's mobility and the location sojourn

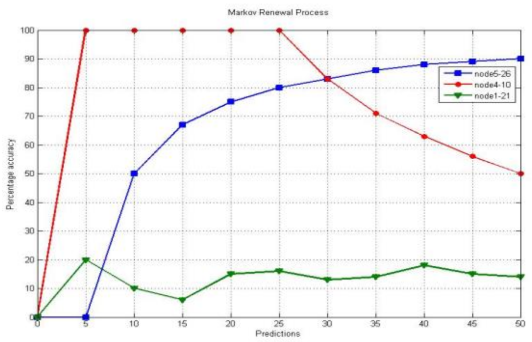

Figure 5: Markov Renewal Process (MRP) prediction accuracy

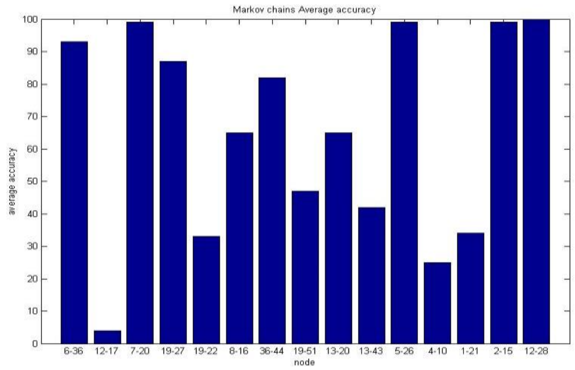

Figure 6: Markov Chains average prediction accuracy

times (or the connection association time with the access points).

Moreover, the accuracies of the results are expected to change with varying sojourn time, i.e., higher dependencies will likely increase the average prediction accuracies between nodes.

There were also a small number of cases where the proposed MRP prediction scheme performed the worst, one of such cases is the accuracy of predictions between node 1 and 21. However, this could also be due to a number of factors apart from the distribution of sojourn time mentioned earlier, such as loss of connection, attenuation and other incidence that could cause link failure i.e., change in strategy during group mobility.

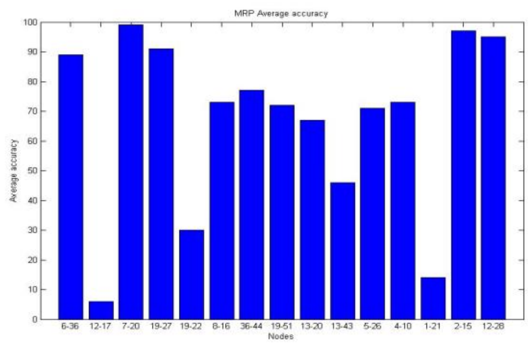

Figure 7: MRP average prediction accuracy

Taking a closer look at our prediction evaluation, we also noticed that in most cases MRP prediction scheme tends to have higher accuracy between first 4 to 5th intervals. This may be due to temporal dependencies of nodes. In the case of the results given in Figures 6 and 7, these show average accuracy of link availability between MANET nodes.

The average of these correct predictions for each of these links was then recorded and plotted on the histograms. For example, Figure 7 shows that Markov chains predictions were anywhere, on average, between 99% and 51% accuracy for about 9 of these links, i.e., 99 – 51% of the link availability in about 9 out of every 15 in the data set could have accurately been predicted with Markov chain model. Figure 7 also shows that on average, between 99 and 51% accuracy was obtained for about 11 of these links, i.e., 99 – 51% of the link availability in about 9 out of every 15 in the data set could have accurately been predicted with our MRP model. Nevertheless, the proposed MRP based mobility prediction displayed a significant improvement in the overall prediction with a higher prediction accuracy than what was achieved using the transition probabilities alone.

1.3 4.1 Discussion of Results

Mobility prediction in ad hoc networks is important because it can improve routing significantly in wireless ad hoc networks, by improving the stability and the number of connection interruptions. In this study, the technique of probabilistic algorithm is utilized to make a history based mobility prediction. It has been shown that link state prediction with high accuracy is possible.

The use of transition probability in link availability has been found to achieve similar accuracy in literature using simulation and synthetic trace. Not only that this probabilistic model has been validated using real trace mobility, but also a new probabilistic model was also proposed which provides a more accurate prediction, by taking into account the sojourn time distribution. The technique is very different from the existing probabilistic mobility prediction schemes. This technique opens up new possibilities in the field of mobility prediction for mobile nodes in an ad hoc network and can lead to better QoS than other approach such as heuristic and deterministic.

The drawback of deterministic and heuristic approach is imminent, the former rely on the fact that all environmental parameter should be observable which is not possible in most cases. The latter requires high computational power and memory for storage in a mobile node which may degrade the performance of the overall network. Even though both have been found to equally attain high prediction accuracy, yet the stochastic approach still remains the algorithm of choice when it comes to link availability prediction in MANET.

1.4

1.5 5. Conclusion

Mobile Adhoc NETworks (MANETs) are strongly impacted by the mobility of the ad hoc nodes. One of the main challenges in MANETs is the requirement that the link must be continuously available for a period of time to enable uninterrupted data transmission and a smooth media performance. A Markov Renewal Process (MRP) based model was proposed for link availability estimation and its accuracy was also discussed. The results and discussion of this work can help other researchers in the design of experiments and protocols with a realistic approach.

The accuracy of our prediction models are mostly high during the first few transitions followed by a dwindling decrease or fluctuated accuracy. In order to improve on this, we suggest an interval of regenerating points between successions of Markov model predictions. This approach will likely deal with the issues that emanate from permanent link failure. To further this research, we recommend implementation of MRP prediction alongside MANET routing protocols and evaluating its accuracy using metrics such as packet delivery ratio, delay, throughput etc.

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