



Biogeographic-Based Temporal Prediction of Link Stability in Mobile Ad Hoc Networks

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Abstract

A set of moving nodes communicating with each other without any infrastructure is considered a mobile ad hoc network (MANET). Stability is a big problem with this type of network due to its variable location and variable speed with respect to time. As a result, link failure is a big problem in MANET. When the link fails, the network faces high packet drop and higher delay in delivery of the packets due to a new routing setup in most cases. In this paper, we have proposed a method to frame up a stable link network using a temporal data analysis model. In this model, we first analyzed the mobility and position of neighbor nodes with respect to each node from the temporal snapshot of the network. The statistical model ARMA (Auto Regressive Moving Average) is used for predicting the stable neighbors of each node in a future time frame. These stable neighbors can be used for creating a link between different nodes. The combination between different nodes builds a path between the source and destination. We applied a BBO (Biogeographic-based optimization) technique to estimate parameters relevant to the optimal path from source to destination nodes. This optimal link offers a stable and reliable connection for the remaining lifetime of the data transfer for the said network.

Keywords Stable link · time series · ARMA · MANET · optimization · BBO

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1 Introduction

The main challenge of an infrastructure-less decentralized mobile network is to maintain the link between the nodes. The nodes may be changing locations regularly as they are sought to be mobile. Two nodes falling in their communication range can transfer a packet directly by forming a link between them. If they are out of their transmission range, they make a path by attaching several intermediate nodes to communicate with source-to-destination nodes. The creation and maintenance of this path is handled by routing algorithms. There have been lots of routing protocols established over the past few years for MANET and they can usually be classified into two categories: (1) proactive routing and (2) reactive routing protocols [1]. *Destination-Sequenced Distance Vector Routing (DSDV)* [15] is one of the representative examples of proactive routing protocols of MANET. In this protocol, each node holds the route information of all other nodes in a table and periodically updates that table, making it a table-driven routing scheme. The advantage of this protocol is that it always finds the single source's shortest path between source and destination, but involves a huge overhead by maintaining the routing table at each node. On the other hand, the reactive routing protocols establish routes on request. So, the routing overhead is comparatively less, but every time the link breaks, it searches for a new route. *Dynamic Source Routing (DSR)* protocol [8] is a representative reference of reactive routing protocol. In DSR, the route cache of the source node acquires multiple route information from previous routing information. So, before the new route discovery process starts, DSR protocol verifies the route cache information. For a confirmed route, there is no need to start the route discovery process, and it continues with the previous route. So, it can start the rapid communication. However, DSR protocol adds to the delivery packet the full address of each hop from source to destination. Thus, the packet overhead is very high, resulting in consumption of more bandwidth. *Ad hoc On-Demand Distance Vector (AODV)* is another example of on-demand routing protocol [14]. Here, AODV manages a technique of *destination sequence number (DSN)*. It is generated by receivers and regulates a contemporary path to the destination in this protocol. The node receives the DSN of the current packet. If it is greater than the DSN occupied presently by the node itself, then it upgrades the DSN. It modifies the information of that route accepted by the source. AODV uses a broadcast identifier number that inhibits multiple broadcast of the aforesaid packets. The intermediate nodes relay packets to the destination node and remove the duplicate copies of the packets. The source node broadcasts a *route request (RREQ)* to determine a route to the destination at the time of generating a new path. After receiving the RREQ, the hops decide whether they are one among the destination nodes or whether they have to be joined to a fresh route to the destination. The major problem with reactive routing protocols such as DSR and AODV is that they broadcast RREQ packets to their neighbors. The neighbors further forward it creating a huge army of RREQ packets. A number of proposals have been made to restrict this broadcast to a limited number of neighbors. Singh and Dutta [19, 20] have found that neighbors of a node and links between two nodes can be modeled using auto-regressive processes. That motivated us to investigate this topic and find a set of stable neighbor nodes to whom the RREQ packets can be broadcast.

In this article, we propose methodologies and algorithms find stable neighbors of a node and restrict the forwarding of RREQ packets to neighbors with whom the source has a stable link. The stable neighbors are found using time series analysis. Further,

those neighbors will forward RREQ to only neighbors with whom they maintain a stable link. The predicted subset of neighbors are further optimized by using *Biogeographic based optimization* (BBO) [17].

The rest of this paper is organized as follows. The related works are presented in Sect. 2. Our proposed model and algorithms are presented in Sect. 3. Section 4 contains the simulation settings and methodologies. The results and discussions are presented in Sect. 5, followed by discussion of the results in Sect. 6. In Sect. 7 we conclude the article.

2 Related Work

The status of a link can be predicted by using a probabilistic model as per Guo et al. [6]. A path availability model based on conditional probability in wireless network was defined in [12]. The technique to build a long time stable connected link was proposed by Torkestani and Meybodi [23]. Song et al. [21] proposed a model to estimate the link stability in the network layer based on link connectivity without using any extra device or low layer data. They used a sampling window of variable size to estimate the link transition rates. Jiang et al. [7] considered the link reliability with a dynamic nature of link status of MANET and developed a path selection model for routing metrics to improve the routing performances. Biradar et al. [2] suggested a link stability model on a random waypoint mobility pattern with a prior knowledge of some parameters of the mobility pattern. Authors of [16] proposed a *QoS Routing* (RSQR) protocol in MANET based on route stability. That model ensures the link stability of a data path is based on received signal strengths. A method of link availability prediction of AODV routing based on signal strength is reported in [26]. In this method, the nodes can inform the estimated node breakage time to the other nodes which reduces the average end-to-end delay and average packet drop ratio. This technique also improves the packet delivery ratio of the network with link prediction. The authors of [24] proposed a congestion control and reliable routing protocol of MANET to overcome the route errors by ignoring the current route. They created multiple paths between source and destination and selected the shortest path for efficient data transmission. Sridhar and Jacob [22] evaluated different performance metrics and compared between *Ad hoc On-demand Distance Vector* (AODV) routing with *Associativity Based Routing* (ABR). They also changed the protocol mechanism to reduce the packet size and evaluate the performance of the proposed model. Using the overhead information in ABR routing packets, they also developed a scheduling mechanism to increase the performance of the network. Authors of [9] developed a low transmission power routing strategy with some modification of AODV routing protocol. They suggested it as the AODV-RR and through it the communication overhead and overall energy consumption of the network can be minimized. Authors of [3] designed a biobjective optimization concept. They also proposed the *Link-stability and Energy aware Routing protocol* (LAER) for ensuring minimum drain rate of energy consumption. *Optimal Link State Routing* (OLSR) was proposed by Guo et al. [6] using a delay prediction mechanism. They integrated that prediction mechanism with a proactive ad hoc network routing protocol. They used a queuing delay technique for modeling a network in non-stationary time series. The authors of [19] performed the temporal analysis of node mobility in MANET. In [18], authors compared the path lengths of different routing protocols under different mobility models where DSDV routing takes the shortest path length to deliver the packets between various types of mobility patterns. It was also established that the path length distribution can be developed between mobile

nodes by an autoregressive ($AR(p)$) model for a suitable value of p . Wallace [25] proposed the evolutionary approach that was also applied to the travelling salesman problem by Mo et al. [13] to demonstrate its efficiency at optimizing a problem. Later Ergezer et al. [5] proposed *oppositional BBO* (OBBO) which is a variant of BBO and that operates *oppositional-based learning* (OBL) with BBO migration rates. Du et al. [4] embedded some distinctive features from other heuristic algorithms into BBO in order to improve the efficiency of BBO. This improvement was illustrated by F-tests and T-tests for different implementations of BBO. Ma et al. [10] have explored six different migration models and analyzed their behaviors, finding that among all the different models the sinusoidal migration curve would provide the best performance.

3 Proposed Work

The proposed system aims to find a stable shortest route from a source node to destination node. Figure 1 shows the flow chart of our proposed work.

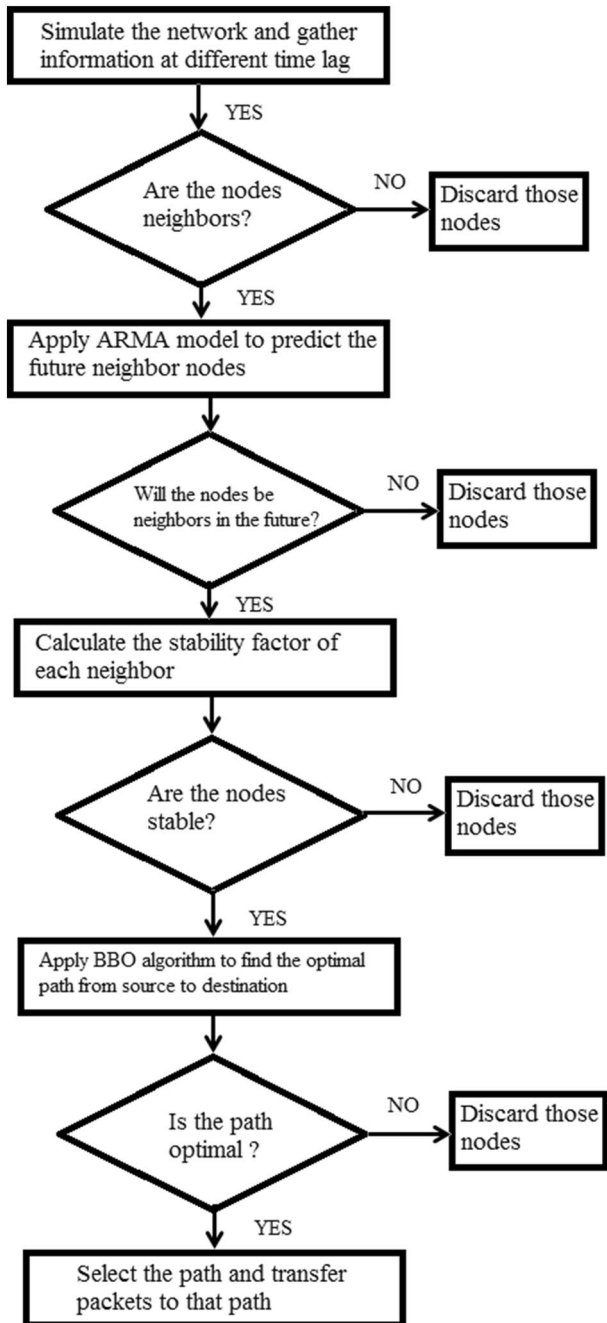
In order to achieve this objective, the overall system is distributed into several subsystems, as shown in Fig. 2. This figure shows that the nodes s and d are the source and destination nodes of this network respectively at time t . The dotted circle represents the transmission range of the center nodes s or d , and the nodes within the transmission range are the neighbor nodes of the center node. In this figure, the WHITE, BLUE and RED nodes are the neighbor nodes of s . The same scenario applies to node d . There is no overlapping between the transmission range of source and destination nodes. So, some intermediate nodes are used to create the path between them. The GREEN nodes are outside of the transmission range of s and d , and these nodes are used to create the path from s to d . The first step of our work deals with finding the stable neighbors. The stable neighbors are chosen based on the time series concepts as proposed by Singh and Dutta [19, 20]. Applying the time series model, we find that the BLUE and RED nodes would stay in the transmission range of source or destination node for a longer time in the future. In the next step, we calculate the stability factor of these nodes and select the RED nodes whose stability factor is greater than the stability index. The stability of these RED neighbor nodes are maximum. In this way, we find the stable neighbors of each node of the network. Thereafter, we calculate the various paths through the earlier identified stable links. The single line arrows show the multiple paths from source s to destination d . There would be a number of paths between a source and destination pair depending on the number of stable neighbors. The stable shortest path is calculated using BBO algorithm [17] as shown by the double line arrow in this figure. In order to explain the working of each subsection clearly, some notations as follows are given in Sect. 3.1.

3.1 Notation

The following notations are used throughout this article to define the various parameters:

- S : Set of nodes used for simulation
- m : Number of mobile nodes
- n : Total time of observations
- δt : Time lag

Fig. 1 Flow chart of the proposed work



- z_t^{ij} : Neighbor value between nodes i and j is the neighbor of it at time t . $z_t^{ij} = 1$ means the nodes i and j are neighbors. If $z_t^{ij} = 0$ then nodes i and j are not within their trans-

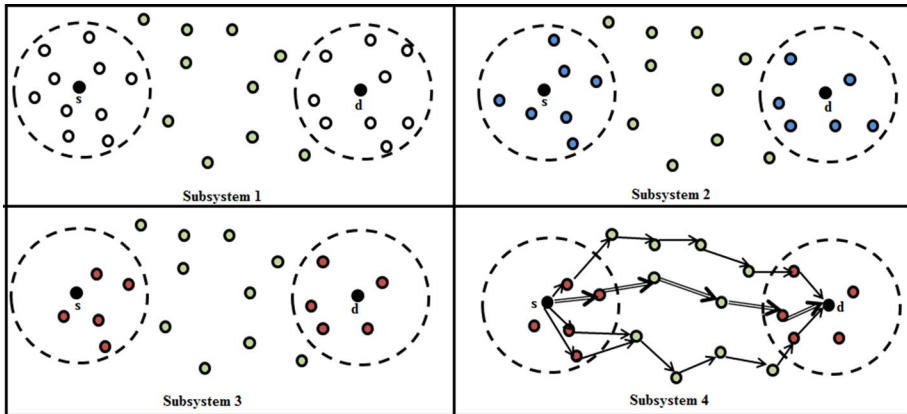


Fig. 2 Prediction of neighbor nodes and the routing scenario

mission range, i.e. they are not neighbors.

- u_t^{ij} : Stability value between node i and node j at time t . If $u_t^{ij} \rightarrow 1$, then node j is the stable neighbor of node i . If, $u_t^{ij} \rightarrow 0$ then node j is not the stable neighbor of node i .
- β : Stability index. $0 \leq \beta \leq 1$. If $u_t^{ij} \geq \beta$ that means node j is the stable neighbor of node i . As has already been indicated earlier, the choice of β happens to be crucial in respect of the performance.

The details of each subsystem are explained in following subsections.

3.2 Stable Neighbor Finding

Two mobile nodes i and j are called neighbors if they belong to their respective transmission range. Stable neighbors of a node i are those nodes which are going to be neighbors of node i in a future time period. We are trying to build a model which will calculate the probability of node j staying within the neighborhood of node i for a longer duration. The *autoregressive moving average* (ARMA(p,q)) model is employed to predict the stable neighbor nodes for suitable values of p and q .

Let $S = \{s_i, \forall i = 1, 2, \dots, m\}$ be the set of m number of distinct mobile nodes at the initial point. In our experiment, the node numbers are fixed throughout the whole experiment. We observe the neighbor nodes of all the simulating nodes at time $t = 0$ by the initial neighbor matrix Z_0 . Now, we consider the time lag is Δt . So, we define the neighbor matrix of a different time lag as Z_t with time at $t + \Delta t$. The elements in the matrix are denoted by z_t^{ij} where i and j are two mobile nodes at time $t + \Delta t$. If i and j are two neighbor nodes at time t , then we define:

$$z_t^{ij} = 1$$

i.e. node j is the neighbor of node i at time t . Otherwise,

$$z_t^{ij} = 0 \quad \forall i, j = 1, 2, \dots, n$$

Initially, at time $t = 0$, we considered that the matrix Z_0 is

$$Z_0 = \begin{bmatrix} z_0^{11} & z_0^{12} & \dots & z_0^{1n} \\ z_0^{21} & z_0^{22} & \dots & z_0^{2n} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ z_0^{n1} & z_0^{n2} & \dots & z_0^{nn} \end{bmatrix}$$

The higher order $ARMA(p, q)$ can be defined as

$$y_t = y_{t-1}\phi_1 + y_{t-2}\phi_2 + \dots + y_{t-p}\phi_p - \psi_1\varepsilon_{t-1} - \psi_2\varepsilon_{t-2} - \dots - \psi_q\varepsilon_{t-q} + \varepsilon_t \tag{1}$$

where ε_t are normally distributed with zero mean and constant finite variance σ^2 for $t = 1, 2, \dots, n$.

Now, we consider the $ARMA(p, q)$ process from Eq. 1 is

$$z_t^{ij} = v + \theta_1 z_{t-1}^{ij} + \dots + \theta_p z_{t-p}^{ij} + e_t + \alpha_1 e_{t-1} + \dots + \alpha_q e_{t-q} \tag{2}$$

where v is a constant.

To estimate the AR process, we need to determine its order p and the values of the parameters $\theta_1, \theta_2, \dots, \theta_p$ by a linear statistical model. e_t is the Gaussian white noise, which is an uncorrelated innovation process with mean zero and is independent of random variables at previous time points. We may estimate $\Theta_p = (\theta_1, \dots, \theta_p)'$ by the *least squares* (LS) method.

Replacing the random variables by their observed values, we generate the matrix X_p from Eq. 2:

$$z_p^{ij} = X_p \Theta_p + E \tag{3}$$

where,

$$z_p^{ij} = (z_{p+1}^{ij}, \dots, z_T^{ij})'$$

and

$$E = (e_{p+1}, \dots, e_T)'$$

and $T = p + t$

Let,

$$X_p = \begin{bmatrix} z_p^{ij} & z_{p-1}^{ij} & \dots & z_1^{ij} \\ z_{p+1}^{ij} & z_p^{ij} & \dots & z_2^{ij} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ z_{T-1}^{ij} & z_{T-1}^{ij} & \dots & z_{T-p}^{ij} \end{bmatrix}$$

This process is stationary and it has an *MA* representation:

$$z_t^{ij} = e_t + \alpha_1 e_{t-1} + \dots + \alpha_q e_{t-q} \tag{4}$$

To determine the order of *MA*(*q*), we consider a sample $z_1^{ij}, z_2^{ij}, \dots, z_T^{ij}$. The mean is

$$E[z_t^{ij}] = E[e_t] - \alpha E[e_{t-1}] = 0$$

and the variance is

$$\text{var}(z_t^{ij}) = (1 + \alpha^2)\sigma_e^2$$

where σ_e^2 is the variance of e_t .

The covariances of the process z_t^{ij} are

$$\text{cov}(z_t^{ij}, z_{t+k}^{ij}) = E[z_t^{ij} z_{t+k}^{ij}] = \begin{cases} \sigma_e^2 + \alpha^2 \sigma_e^2 & \text{if } k = 0 ; \\ -\alpha \sigma_e^2 & \text{if } k = \pm 1; \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The autocorrelations of the *MA*(*q*) are

$$\rho_k = \begin{cases} \frac{\sum_{i=0}^{q-k} \alpha_i \alpha_{i+k}}{\sum_{i=0}^q \alpha_i^2} & \text{for } k = 0, 1, \dots, q; \\ 0 & \text{for } k > q. \end{cases} \tag{6}$$

Thus the order of an *MA* corresponds to the maximum *k* for which ρ_k is nonzero. After getting the order of *AR*(*p*) and *MA*(*q*), we can calculate the matrices Z_t for $t = 0, 1, \dots, n$ using Eq. 2 and then generate the matrices Z_t , i.e.

$$Z_t = \{z_t^{ij} \mid \forall i, j = 1, 2, \dots, m \text{ and } t = 1, 2, \dots, n\} \tag{7}$$

These z_t^{ij} are the predicted neighbor values of different nodes at different time instants. We can also observe the actual neighbor values of different nodes at different times which is estimated as \hat{z}_t^{ij} .

So, after considering the following parameters:

- z_t^{ij} = The predicted neighbor value by using *ARMA* at time *t*
- \hat{z}_t^{ij} = The original neighbor value at time *t*
- ψ = The sampling probability weight factor, $0 \leq \psi \leq 1$.

The probability of a node *i* being the neighbor of node *j* at time *t* can be calculated by Eq. 8 as:

$$u_t^{ij} = \hat{z}_t^{ij} \times \psi + z_t^{ij} \times (1 - \psi) \tag{8}$$

u_t^{ij} is the probability of node *j* being the neighbor of node *i* at time *t*.

Now, β is the stability index. $u_t^{ij} \geq \beta$ indicates high probability of node *j* remaining the neighbor of node *i* at time *t*+1. So,

$$U_t = \{u_t^{ij} \mid \forall i, j = 1, 2, \dots, m \text{ and } t = 1, 2, \dots, n\} \tag{9}$$

where,

$$u_{t+1}^{ij} = \begin{cases} u_t^{ij} & \text{if } u_t^{ij} \geq \beta \\ 0 & \text{if } u_t^{ij} < \beta \\ 0 & \text{if } i = j \end{cases}$$

3.3 Stable Path Finding

Once the stable neighbors are identified, the links between two stable neighbors can be concatenated to get stable paths. In fact, we get a number of stable paths, as shown in Fig. 2 at subsystem 4. The next phase is to find the shortest stable path, which is done using the BBO algorithm.

3.4 BBO Optimization

In this algorithm, we take the input matrix U_t from Eq. 9. The U_t shows the stable neighbors of each node depending on the probability based on stability factors. The BBO algorithm is used to find the optimal and the stable path between the source mobile node N_s and destination mobile node N_d . It uses each of the possible solutions as a habitat and exploits migration to exchange information among different habitats to obtain a better solution. It starts by considering U_t matrix. This matrix represents the probability of sustaining of adjacent nodes corresponding to node. This matrix is primarily used to determine the optimal path between a pair of nodes. The overall procedure is described by Algorithm 1.

The BBO algorithm returns an optimal stable path, which is presented in the double line arrow of Fig. 2 at subsystem 4.

4 Simulation Model

We used the network simulator NS-2 [11] for simulation of the network. The simulation time was set at 4000 s. The simulation of the first 3000 s was ignored as this is the time required by the nodes to distribute uniformly in the simulation area. The next 1000 s was used to collect all the results. All the nodes are restricted within the simulation area. We have taken constant speed in a time lag and different speed in a different time lag. We placed all the nodes in the simulation area according to the uniform distribution and they may change their positions with time accordingly. Here, we have considered,

$$\sum_i^n PN_i = \text{Predicted number of neighbor nodes at time } \Delta t_i$$

Similarly, we can consider the actual number of neighbor nodes at time Δt_i is AN_i . So,

$$\sum_i^n AN_i = \text{Actual number of neighbor nodes at time } \Delta t_i$$

$$PNA = \frac{\sum_i^n PN_i}{\text{Max}\left(\sum_i^n PN_i, \sum_i^n AN_i\right)} \times 100 \text{ for } i = 1, 2, \dots, n$$

is the percentage of accuracy to find out the exact number of neighbor nodes.

We also considered that the transmission range of each node is the same and that its value is 10 m. We have used IEEE 802.11 MAC protocol for the simulation and the initial energy of all nodes was set to be equal for this simulation. For further processing of simulation results, MATLAB is used where ARMA modeling and BBO algorithm were implemented.

5 Results

The performances of our proposed model was compared with two reactive routing protocols: AODV and DSR. We have evaluated the parameters like *Packet delivery fraction* (PDF), number of hop counts, network throughput, number of link faults and neighbor prediction accuracy in this experiment. These observations are divided into two categories. In one group, we have kept all the parameters the same and observed the results at different time intervals. It actually shows that there is an effect of previous data values in future time series prediction. We compared our proposed model with two proactive routing models: AODV and DSR. In another category, we change the speed of the mobile nodes in different time intervals. So, our aim is to prove that this time series prediction model and BBO technique can generate a more stable and the shortest route between source and destination in comparison with the other two routing models.

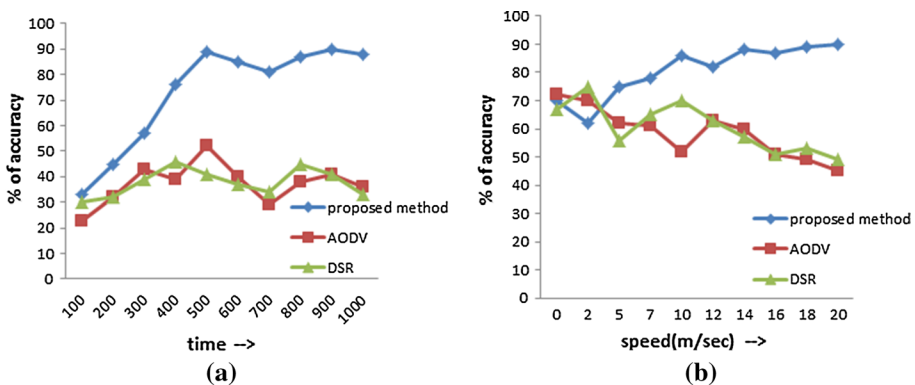


Fig. 3 Neighbor prediction accuracy at **a** different time lag with same node speed and **b** different node speed at a different time lag

Neighbor prediction scheme can predict the neighbors of a node at a different time lag. It actually finds the neighbors on the basis of the time series prediction model using previous observations. The stability of the network actually depends on the stable neighbors. The neighbor prediction accuracy of our proposed model is very high compared to the other two protocols as shown in Fig. 3a where we keep all the parameters unchanged at a different time lag. At increasing speeds of the mobile nodes, our proposed model can perform better, as shown in Fig. 3b. The other two routing models cannot perform better neighbor prediction because they do not use the time series prediction model.

Algorithm 1 Optimal Path Finding Algorithm Using BBO

Require: U_i matrix, k as number of habitat, N_s as the source node, N_d as the destination node, n as maximum number of species, E as maximum emigration rate and I as immigration rate.

Ensure: Vector containing the optimal path

procedure BBO

for each Habitat H_i in $H_1 \dots H_k$ **do** ▷ Habitat Initialization

$H_i.SIV =$ Random Path from N_s to N_d

$H_i.HSI = \sum_{(i,j) \in SIV} Var(i, j)$ ▷ $Var(i, j)$ is calculated from U_i matrix

for each Species count S in $0 \dots n$ **do**

$\lambda_S = I \left(\frac{S}{n} \right)$ ▷ Calculation of Immigration rate

$\mu_S = E \left(\frac{S}{n} \right)$ ▷ Calculation of Emigration rate

for each Species count S in $0 \dots n$ **do** ▷ Calculation of Initial Probability

if $S = 0$ **then**

$$P(S) = \frac{1}{1 + \sum_{i=1}^n \frac{\lambda_0 \lambda_1 \dots \lambda_{S-1}}{\mu_1 \mu_2 \dots \mu_i}}, S = 0$$

else

$$P(S) = \frac{\lambda_0 \lambda_1 \dots \lambda_{S-1}}{\mu_1 \mu_2 \dots \mu_S + \sum_{i=1}^{S-1} \frac{\lambda_0 \lambda_1 \dots \lambda_{S-1}}{\mu_1 \mu_2 \dots \mu_i}}, 1 \leq S \leq n$$

do ▷ Main Loop for Migration and recalculation of parameters

for each Habitat H_i in $H_1 \dots H_k$ **do** ▷ Assign Species Count

$H_i.S \propto H_i.HSI$

for each Habitat H_i in $H_1 \dots H_k$ **do** ▷ Migration

$A = H_i.S$ ▷ Assign species count of H_i to A

if $P(A) \propto \lambda_A$ **then**

for each Habitat H_j in $H_1 \dots H_k$ **do** ▷ Assign Species Count

$B = H_j.S$ ▷ Assign species count of H_j to B

if $P(B) \propto \mu_A$ **then**

Select a portion of SIV and exchange between them.

After Exchange recalculate all the Habitat parameters.

for each Species count S in $0 \dots n$ **do** ▷ Calculation of Probability

if $S = 0$ **then**

$$P(S) = P(S+1)\mu_{S+1} - P(S)(\lambda_S + \mu_S)$$

if $1 \leq S < n$ **then**

$$P(S) = P(S+1)\mu_{S+1} + P(S-1)\lambda_{S-1} - P(S)(\lambda_S + \mu_S)$$

if $S = n$ **then**

$$P(S) = \lambda_{S-1}.P(S-1) - (\lambda_S + \mu_S).P(S)$$

while until optimal HSI count is not found

Return the SIV of the optimal Habitat.

Link faults occur when the connected node moves out of the range. The reactive routing protocols create the paths on demand. So, they take some extra time to build them. If the link fault occurs, the victim node further broadcasts the control packets to reconfigure the path. So, more link faults increase the data loss and end-to-end delay. But our proposed model, on the other hand, can predict the stable nodes before the creation of the path. In Fig. 4a, it can be observed that our proposed model can find the stable neighbors so that the link breakage rate is very low. It also increases the stability with time. This is because

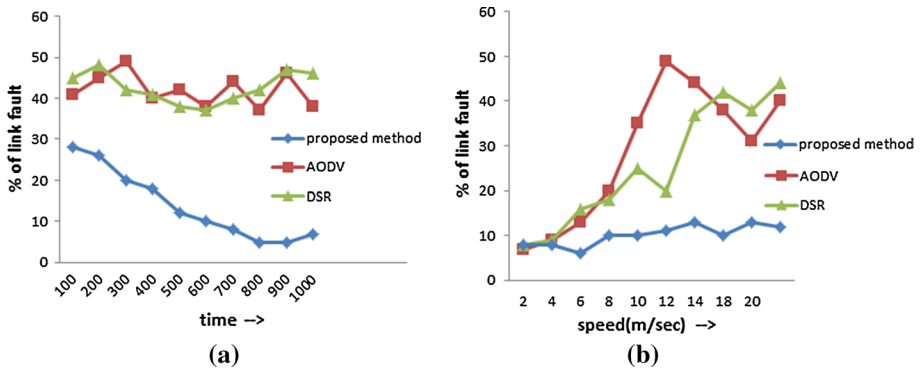


Fig. 4 Percentage of Link fault rate at different time lag with **a** constant node speed and **b** different node speed

it uses the time series prediction model which can predict the future value more accurately than the other two routing protocols. The increasing speed of the mobile nodes can break the link more frequently. So, we need to be concerned about the relative velocity of the neighbor nodes. By this experiment, we choose only those neighbors whose relative velocities are almost the same. So, in Fig. 4b, our proposed model shows a best result than the other two routing protocols.

The *packet delivery fraction* (PDF) is also an important parameter to measure the flow of the network. PDF shows the delivery rate, which may be defined as the ratio between the number of packets received and the number of packets sent by the nodes. In Fig. 5a, we consider the parameters of the network to be unchanged at different time intervals and it shows that the PDF is high and almost a straight line, i.e. the PDF is almost same at different time intervals because the stable network reduces the flow of control packets and increases the flow of data packets. In the case of the other two routing protocols, the PDF value is haphazard due to the instability of the network. In Fig. 5b, we changed the speed of the mobile nodes at each time interval. This shows that the PDF is decreasing with respect of the increasing speed of the mobile nodes in AODV and DSR routing protocols. But our

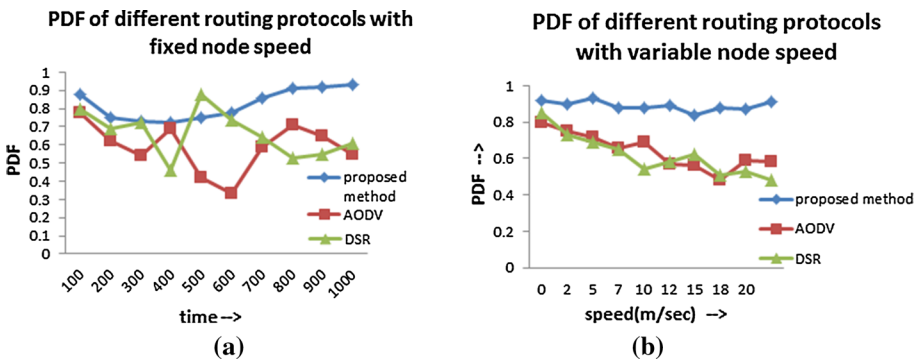


Fig. 5 PDF of different routing protocols with **a** fixed node speed with different time intervals and **b** different node speed with different time intervals

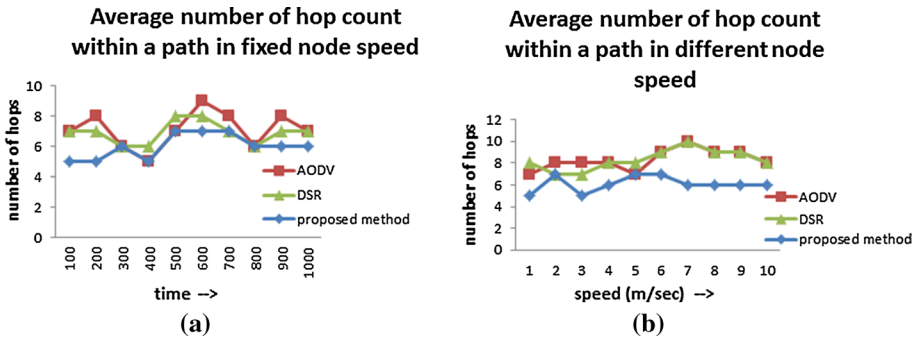


Fig. 6 Average number of hop count within a path of different routing protocols with **a** same node speed and **b** different node speed

proposed model maintains almost a constant PDF value for the link stability model. So, in a high-speed network, it works better than other routing protocols.

In Fig. 6a, we calculated the average number of intermediate hops or nodes between source and destination nodes. For this purpose, we have used the BBO technique to optimize this path. The optimized path can reduce the end-to-end delay and routing overhead. The BBO algorithm can find the shortest route. The proposed algorithm shows that it has the minimum number of intermediate hops in a path unlike the other two routing techniques. In Fig. 6b, we considered the same scenario but increased the speed of the mobile nodes at different time intervals. Here also our proposed method performs better than the other routing protocols because of the stable neighbor prediction model. The relative velocity of the stable nodes are almost the same, which actually prevents the link fault.

The evaluation of throughput of a network is also an important part of the experiment. The number of data packets sent per second is considered as the throughput of the network. In our proposed method, the link failure rate is very low. So, this network sends more data packets than the control packets and the throughput is comparatively higher than the two other routing protocols, as shown in Fig. 7a. If all the parameters remain the same, our proposed method can give more throughput due to the stability of the network. In Fig. 7b, we changed the speed of the mobile nodes at a different time lag. But the stable neighbors

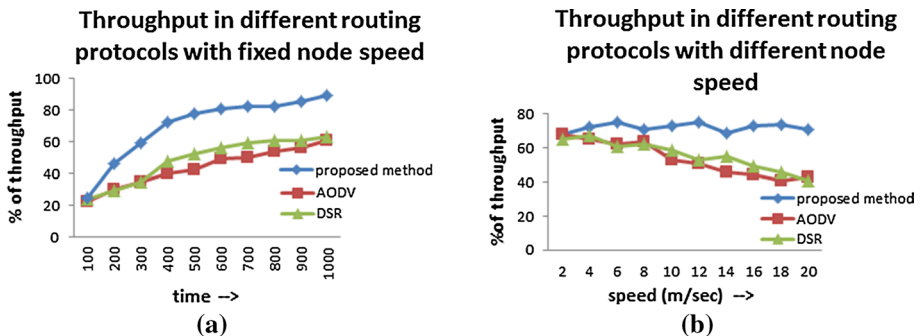


Fig. 7 Throughput of different routing protocols with **a** fixed node speed and **b** different node speed

keep the link between the nodes. So, it shows the high throughput value unlike the other routing techniques.

6 Discussion

The infrastructure-less and multi-hop characteristics of mobile ad hoc networks can work perfectly if the collaborative behaviors of the nodes can be studied properly. The ability of the network depends on the stability of the neighbor nodes. If the links between nodes are stable, the network broadcasts more data packets than the control packets. More data packets transmission increases the throughput of the network. Our proposed model can give better performance in different parameters when compared with two other proactive routing protocols. It also establishes that the time series prediction model can predict the future data on the basis of the past data set. In our experiment, this prediction rate is very satisfactory and can be applied to a real network configuration. The BBO optimization technique can optimize the shortest path between source and destination nodes. This technique can reduce the end-to-end delay, routing overhead and energy of the network, as shown in our experiment. This optimization technique does not create more overhead of the network. So, our proposed method, which is the combination of a time series prediction model and a BBO scheme, shows a measurable performance difference in comparison with the other two routing protocols.

7 Conclusion

In this article, we have proposed a novel technique to find out the stable neighbors of mobile nodes in a time series framework and then modeled it to find the shortest optimum path between source and destination using the BBO technique. In comparison with other routing paradigm-oriented link stability schemes, the proposed technique offered a statistical model which supports an efficient communication in MANET. The simulation results observe that this link stability model can predict the stable neighbors and make an optimum path between source and destination for different data sets. The increasing speed of the mobile nodes and variation of mobile hops in the network area can also be evaluated perfectly by our proposed model. The proposed technique increases the throughput and packet delivery rate while decreasing the end-to-end delay between the two nodes. The only limitation of this proposed method is that initially it requires past data sets which may not be available at the starting time of the simulation. Future work can be focused on developing an artificial intelligent scheme to predict more accurately and design a reliable stable route.

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