Stability Oriented Routing in Mobile Ad Hoc Networks Based on Simple Automatons

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1. Introduction

With recent performance advancements in wireless communications technologies, advanced mobile wireless networking realizations are expected to be seen shortly. Meshed wireless network infrastructures and ad hoc wireless networks are growing to facilitate services for mobility-free networks users everywhere and anytime. Mobile ad hoc networks (MANETs) consist of a collection of independent mobile nodes that can communicate to each other via radio and that are free to move and even to switch off arbitrarily. These networks can be installed in isolation, or can be connected to other networks.

The ad hoc networks are often multihop networks. Some neighboring mobile nodes that are in communication range of each other can directly communicate, while others needs to use one or more intermediate router nodes to communicate with far nodes. So, a reliable routing functionality is fundamental in these networks.

Nodes and links can appear and disappear spontaneously due to the behavior of users (who may turn off/on a node), the depletion of battery power, etc. As nodes are free to move arbitrarily and may disappear, such networks can be characterized by a dynamic, often rapidly-changing, random and multihop topology. This ad hoc topology may also change when the nodes adjust their transmission and reception parameters (Corson & Macker, 1999). The continuous presence of these phenomenon implies a very dynamic and randomly evolving topology in both time and space.

Since wireless ad-hoc networks with mobile nodes have not stable topology, the classical network functions such as the routing are difficult to realize. The router nodes and the links between them are not stable and can appear and disappear randomly. So, classic routing algorithms cannot be used successfully. Many special reactive, proactive and hybrid routing algorithms have been proposed to solve the data transmission in multihop ad hoc networks. The principal propositions are cost, delay or energy oriented. However, new approaches should be used which deals with these dynamic changes. In the case of reactive routing, the proposed route to satisfy a new request can be volatile and so, the communication concerned by it may be frequently interrupted and new routes may be computed. As an example, we can cited AODV, which is a well known reactive on-demand routing protocol proposed in (Perkins & Royer, 1999). The dynamic source routing (DSR) also proposes the dynamic allocation of routes (Johnson & Maltz, 1996). Trivially, the establishment of the new routes involves additional latency and intensive communication for control purposes. When a proactive routing algorithm is applied, the topology changes must be broadcasted in the

whole network. The topology information is first monitored then periodically distributed and stored in routers. A typical example is the protocol DSDV (Perkins & Bhagwat, 1994) and an optimized control flooding based solution can be found in OLSR (Jacquet et al., 2001). The update of the topology information in proactive case is not immediate and cannot be executed permanently. The broadcasted control messages pass through the randomly congestioned network and achieve the different nodes with different random delays. In the case of both the reactive and proactive routing, the route information may be outworn and may not correspond to the routing objectives. So, the routing is based on uncertain and not necessary adequate information. In both cases, this information can be obsolete at the moment of its utilization. A wrong routing implies packet losses or additional delay. A route breaking issue from an expired information initiates expensive mechanisms to find a new route. Moreover, topology and/or route maintenance involves important control message overhead.
An alternative model for routing can be a solution that try to minimize the route changes and to estimate and to control the validity of the selected routes. A pertinent model should allow to handle uncertainties on routing information caused by unpredictable changes and information propagation delay. We will see that these kinds of uncertainties can be taken into account in some probabilistic routing models. To avoid frequent route requests and volatile routes due to uncertain information, the objective of the routing should correspond to the route stability. For instance, the goal of the route selection may be the selection of routes assuring a good and controlled longevity. Since the description and the handling of network elements which change randomly needs random variables as models, the route computation can also be based on random variables and becomes probabilistic routing. This chapter focuses on modeling the resilience of these information for ad hoc networks where topology information is uncertain. Our basic model is based on a dynamic graph where the existence of the nodes and of the communication capability between them are modeled by simple two state automaton where the transitions are initiated by random events. We present several methods to model the evaluation of the state of the network elements and of the relation between them and we exhibit closed form expressions for the existence probabilities of these network elements assuming different distributions for the random delay concerning the propagation of the routing information. Moreover we analyse, how additional information on the location and on the mobility of the nodes can improve the prediction of the network state.

2. Stability based routing in ad hoc networks

Generally classic proactive and reactive routing protocols apply a simple additive cost metric (often the hopcount) to compute shortest paths towards destinations. Often, shortest paths are not reliable when the network topology changes dynamically. To illustrate, let us imagine a shortest path with minimum number of hops. Such a path corresponds to links (hops) that rely far nodes in the space. This kind of links may be very unstable due to the mobility of the extremities. Finding more stable routes is an important goal in dynamic multi-hop ad hoc networks. Identifying stable paths permits to decrease control traffic and the number of route interruptions. A new routing paradigm can be obtained by considering the route stability or resiliency as routing metric. *Stability based routing* aims at choosing routes which are more stable in time. So, these latter can be more resilient to dynamic changes in the network topology.
If the events (such that the exact trajectory of the nodes, the power battery level, the associated user behavior, the network failures, etc.) are predictable and known in a MANET, then the best route can be computed to satisfy a communication request. Generally, these factors are

not predictable and so it is not possible to create a good deterministic routing model. Practical observation based and more sophisticated, statistical and probability based routing models exist to deal with longlife routing. In this section, we discuss the representative protocols in this domain.

2.1 Observations on link stability

Several simple propositions aiming with the improvement of the routing decision can be found in the literature. Some works established that choosing routes based on additional information as the position of the nodes, their battery level and the mobility pattern permits to design routing algorithms promising paths with better resilience to topological changes.
Most of stability oriented works on routing consider the link stability in the MANETs fundamental. Effectively, the stability of a path depends on the stability of its composing links. Several propositions for stability based routing use a classification of the network links. In (Dube et al., 1997) authors use the strength of the received signal of neighboring nodes to determine whether the associated link is either *weakly connected* or *strongly connected*. Routing is then performed through paths maximizing the received signal strength. The signal strength is used as central metric to establish a route with long lifetime in (Agarwal et al., 2000). In their routing method, the authors suggest a routing protocol called Route-Lifetime Assessment Based Routing protocol (RABR) wherein the route selection is done using an intelligent residual-route-lifetime prediction on the basis of affinity appraisal of the candidate routes. Affinity is an estimate of the time after which a neighbor will move out of the threshold signal boundary of a mobile host, and hence is a measure of link availability. A similar, cross-layer information based solution is proposed in (Trivino-Cabrera et al., 2006) to find long-live paths in ad-hoc networks. Since a path is broken if one of the used links is broken, the authors propose the minimal received signal strength along the candidate path as indirect measurement of the path livetime. Targn and al. approach also the link stability by considering the radio propagation effect on signal strength in (Targn et al., 2007). A stochastic radio propagation model is proposed to compute received signal strength between adjacent nodes and to predict path loss. The authors consider that the link stability is equal to the probability of the receiving signal strength exceeding a predefined threshold. So, the estimation of link stability is derived from the prediction of signal strength. Considering the stability of a route, they state that the least stable link within a route would be the bottleneck for the route. The life spans of multi-hop routes decrease by increasing the route length. To model the effect of route length on estimating route stability, the authors consider the route stability as the product of link stabilities (this assumption will also be discussed in Section 3). With awareness of link and route stabilities, then an Ad-hoc On-demand Stability Vector (AOSV) routing protocol is proposed to reactively discover and maintain stable routes adapted to radio channels.
Similarly, the authors in (Chen & Nahrstedt, 1999) also propose the classification of network links from the point of view of their stability. Their objective is to find a path with sufficient resources to satisfy a given delay or bandwidth requirement in a dynamic multihop mobile environment with the help of a distributed QoS routing algorithm. In their classification, links between stationary or slowly moving nodes are considered as *stationary links*. In contrast to this, links which exist only for a short period of time are handled as *transient links*. Newly formed links are also considered to be transient as they are more likely to break down. Routing should use then stationary links whenever this is possible. To discover stable routes, a multi-path scheme and a ticket-based probing procedure is proposed. Multiple paths are

searched in parallel to find the most qualified one. The ticket-based probing scheme achieves a balance between the less efficient single-path routing algorithms and the very expensive flooding algorithms. So, a near-optimal performance can be achieved with modest overhead by using a limited number of tickets and making intelligent hop-by-hop path selection. The algorithms can tolerate the imprecision of the available state information even if the degree of imprecision is high.

A simple and bandwidth-efficient distributed routing protocol based on the concept of associativity of nodes is proposed in (Toh, 1997). The Associativity Based Routing (ABR) apply a new metric called associativity which defines the stability of the link between two nodes: its corresponds to a counter which indicates the presence of a node in the neighbors. ABR considers that the longer two nodes have been neighbors, the longer they would stay connected. The optimal route towards a destination is the one maximizing its cumulative associativity metric. As the author state, the association property allows the routing protocol to exploit the spatial and temporal relationships of network nodes to construct long-lived routes, resulting in fewer route re-constructions and hence higher attainable throughput.

The study in (Lim et al., 2002) addresses to analyze the link stability and the lifetime of the routes computed by shortest path algorithms and also in SSA and ABR. The authors state that in a highly dense mobile ad-hoc network, shortest path routing finds unstable routes. Let us notice that they compare the analyzed algorithm with an ideal one which has a perfect link stability knowledge. In real world, this knowledge is impossible to have, but the ideal case illustrates the limits of the stability of the routes.

So, an interesting question can be formulated: if shortest paths are not good candidates for long-life routing, can longer routes be considered for this reason? Trivially, long paths using several short hops increase the congestion in the MANET. The distributions of the link lifetime and the corresponding route lifetime are also analyzed in (Cheng & Heinzelman, 2004). The analysis shows that increasing the route length by choosing short initial link distances may not be effective in extending the route lifetime. Moreover, the authors derive a closed form for link lifetime distribution and route lifetime distribution and try to characterize the relationship between node mobility and link stability. A polynomial time algorithm to determine the longest lifetime routes at different route lengths from all the possible routes between a source and a destination is developed. Using this algorithm, statistical results on the achievable maximum route lifetime improvement in random networks are gathered.

In (Sridhar & Chan, 2005) Sridhar and Chan investigated on the analysis of route stability MANET. In their empirical study, they demonstrate how residual link lifetime is affected by parameters such as speed and mobility pattern. The result shows that residual link lifetime is naturally a function of current link age and mobility of extremities but does not vary monotonically with age. The authors state that the conjecture saying that older links are more stable (which is used in existing stability-based routing algorithms like Associativity Based Routing), does not hold across a large spectrum of mobility speeds and models. In some cases, the reverse can be true. To find a good trade-off between cost, efficiency and route stability, this paper proposes an interesting, empirical based routing algorithm. The algorithm called SHARC is based on stability and hop-count information using DSR (cf. (Johnson et al., 2000)) as the basic routing protocol. The stability of a path is calculated using a simple histogram based estimator.

The availability of nodes is considered in the paper (Punde et al., 2003) which deals with the improvement of the reactive routing procedure. To find good paths, the authors propose a new parameter: the stability of the nodes which depends on the speed and on the observed packet processing ratio of the given node. Unstable nodes should not be used for routing.

2.2 Probability based route computations

Intensive research activities bring into focus the need for finding new and efficient models for ad hoc dynamic networks. The random behavior of ad hoc networks has been analyzed with the help of random graphs where the existence of an edge is characterized by a probability (for example in (Jacquet & Laouiti, 1999)). Let us notice that traditional random graph cannot model the dynamic behavior of the ad hoc networks.

The first analysis of the uncertainties were related to wired networks. In (Guérin & Orda, 1999) the network state is modeled with the help of random variables. In (Kuipers et al., 2005) the authors analyze the stability of paths in Internet like networks. They establish that monitoring any change along the Internet is not possible and they distinguish two kinds of changes: frequent changes and changes which occur infrequently. The infrequent changes can be broadcasted efficiently in the network; the convergence is fast compared to the change frequency. In the case of slight changes, it is not necessary to update the network with useless information. Since a constant update procedure of the network state information is very expensive (even not possible), the available network state information for routing is inherently inaccurate and the established paths can be broken at any time.

Two mobility models (respectively for a single node and for joint mobility of two nodes) are used to determine link and path availability in (Mcdonald & Znati, 1999b). Availability $A_{i,j}(t)$ of a link (i,j) is defined as the (conditional) probability that the link is active between two nodes i and j at time $(t_0 + t)$ given that it was active at time t_0. Similarly, the directed path availability $\Pi^k_{m,n}(t)$ is defined as the probability of the existence of a given path k between the source m and the destination n at time $(t_0 + t)$, supposing the existence of this same path at time t_0. If the independence of link failures is assumed, the path availability is given by the link availabilities that composed it: $\Pi^k_{m,n}(t) = \prod_{(i,j)\in k} A_{i,j}(t)$. In the opinion of the authors, this metric can be used for routing. The link and path availabilities are developed using the known random walk mobility model (cf. also in Section 6).

The authors in (Turgut et al., 2001) are interested by longevity computation of routes. Their goal is finding the right time to re-configure a route before its disruption and for this they study the predictability of the lifetime of the routes in different deterministic and Brownian mobility cases. Their analysis covers only the relation between two neighboring nodes. Trivially, the expected lifetime highly depends on the mobility pattern of the nodes. If the mobility is deterministic, the lifetime of links can be computed exactly. If there is no information about the mobility of nodes the prediction of the lifetime becomes difficult. Probabilistic methods may be used to determine the expected value of the lifetime of the different links. The expected value of a path lifetime corresponds to the minimum value of expected values of link lifetimes on the path.

In (Gerharz et al., 2003) statistical methods are proposed to estimate the stability of paths in a mobile wireless ad hoc environment. Several simulations illustrate the stability (and so the instability) of paths chosen according to a variety of strategies, including those used by the protocols AODV and DSR, under a variety of different mobility patterns. The authors state that selecting a path based on its estimated probability to persist for a minimum amount of time proved to reduce the number of route discoveries significantly. The number of route discoveries can also be reduced significantly by using a simple categorization of links into stable and unstable links, where the stability criterion is the age of the links. At the same time, the authors notices that this simple classification can lead to a severe increase in route failures.

They also confirmed the instability of shortest paths and state that for connections over longer distances, it is advantageous not to use a shortest path.
A fundamental question is: how to characterize the path stability? Different objectives and potential stability metrics are enumerated in (Gerharz et al., 2003) to find stable routes (the authors search additive link metrics for simple routing algorithms but the following propositions do not always permit the additive computation of path metrics). The proposed objectives are:

– *Minimize the number of unstable link.* If links can be classified as stable and unstable, the number of unstable links along the path can be used as a simple stability metric; the objective being to minimize this number.
– *Maximize the expected residual lifetime.* The residual lifetime of a path is equal to the lifetime of its more critical link. The expected residual lifetime of a link may be calculated from collected statistical data.
– *Maximize the persistence probability.* Similarly to the expected residual lifetime, the computation of the persistence probability of a link is proposed based on statistical data. Supposing the independence of the different links, the persistence probability of a path is a simple multiplicative metric. This metric directly aims at minimizing the number of interruptions during a certain time span.
– *Maximize a residual lifetime quantile.* The minimum residual lifetime that a path will reach with a given probability can be calculated from the path persistence probabilities. Using this objective, the path which maximizes this residual lifetime (depending on the desired probability) can be computed.
– *Avoid Instable Links.* Here the weakest link rule is applied: the stability of a path is the stability of the most instable link along the path. Obviously, the path avoiding the instable links is wanted.

A formal model to predict the lifetime of a route based on the random walk model is proposed in (Tseng et al., 2003). Links states are described with the help of a hexagonal cellular based system and node movements are modeled with the help of a state transition automaton, then route lifetime is derived. Lifetime of a route is computed as a function of the existence probability of each link component. The model permits to estimate the residual lifetime of routes which can be used for routing decision. Routing can be then made through the ones with maximum residual lifetime.
In (Chung, 2004) Chung proposes a probabilistic analysis of routes in MANETs when nodes move corresponding to a Random WayPoint model (cf. (Camp et al., 2002a)). An estimated probability density function is computed and analyzed. The analysis illustrates that the exponential distribution is a well candidate function to predict route behavior for stability and the time distribution of the routes is similar to a discrete Gamma distribution depending on the route length in hops (which is evident supposing independent links).
(Beraldi et al., 2006) suggests a "probabilistic" routing protocol in a MANET. Unlike the usual routing protocols, the packet forwarding in MANET's node is not driven by a previously computed path. Rather, the concerned nodes of the network exploit a set of routing meta-information which are called hints to discover the path to the destination on-the-fly. A node gathers hints from the nodes located within a small range of neighbors limited by a maximal number of hops (called the protocol look-ahead). A hint h_{id} from the node i with respect to the node d is defined as $h_{id} = \frac{\Delta_{id}}{\tau_{id}}$, where Δ_{id} is the time elapsed since d has most recently moved out of the transmission range of i, and τ_{id} is the duration of the last

wireless link established between i and d. The hint value indicates the chance of i being in the neighborhood of d. Packets are forwarded as follows. On receiving a packet with destination d by a node i, this latter forwards the packet to the neighbor with the best (lowest) hint which not yet received the packet. If the selected node cannot be reached, another one can promptly be used. Since there is no guarantee that the next-hop node lies on a path towards the destination, the protocol is considered as a "probabilistic" one (cf. (Beraldi et al., 2006)). The main statistical properties of hints have been investigated through an analytical model in the paper. Since hint values are periodically updated, the protocol assure robustness against topological changes, while requiring a communication overhead. The hint-based probabilistic protocol was recently improved by omitting control messages. In the new proposition, the nodes reuse the feedback information carried in unicast packets for routing purpose without introducing any extra overhead. The efficiency of the proposed scheme is demonstrated through both mathematical analysis and an extensive simulations study in (Nejad et al., 2010).
A route discovery mechanism in mobile ad hoc networks called FResher Encounter SearcH (FRESH) using encounter ages is proposed in (Dubois-Ferriere et al., 2003). The proposition focus on the case of "blind routing protocols", *i.e.* , where nodes have no notion of coordinates (there is no GPS or localization). In their solution, nodes maintain a record of their recent encounter times with all other nodes. Two nodes encounter each other when they are directly connected. The authors consider that the history of last encounters between nodes contains valuable, but noisy information about the current network topology. To create a route, the source node searches for any intermediate node that encountered the destination more recently than did the source node itself (if it exists). The intermediate node then searches for a node that encountered the destination yet more recently, and the procedure continues until the destination is reached. So, FRESH performs a succession of small searches instead of a large route request, resulting in a cheaper route discovery. The performance of the solution depends on the node mobility. With standard mobility conditions the route discovery cost can be decreased by an order of magnitude.
The family of Parametric Probabilistic Routing (PPR) protocols which are called light-weight adaptive routing protocols is proposed in (Barrett et al., 2005). The protocols are considered probabilistic, because a re-transmission probability function is associated with each node, indicating with what probability a node will forward a received message. As it is explained, the re-transmission probability function can depend on various factors such as the hop-distance to the destination, the hop-distance of the source to the destination, the number of hops that the packet has already traveled, the number of times a node has already forwarded the same packet, the number of neighbors a node has, etc. PPR protocols thus perform a multipath-routing using directed, controlled flooding with multiple packet copies.
A general ad hoc network model and some derived statistical results on link and path availability properties using a particular random walk mobility model is presented in (Yu et al., 2003) (cf. also Section 6). In the proposed mobility model, each node moves with a randomly chosen velocity vector corresponding to a direction and a speed. The direction is a uniformly distributed random variable ϕ while the distribution of the speed v can be arbitrary. The availability study details link and path available time. At first, the computation model of the relative velocity and its probability density (PDF) between two nodes are expressed in order to give the distance and the move between two nodes a and b when the nodes are in continuously movement. The probability for a relative velocity vector V_r is trivially the summation over all the possible combination of V_a and V_b that forms a triangle with V_r. Using a mobility model, in some cases the distribution can be formulated or in other cases it can be

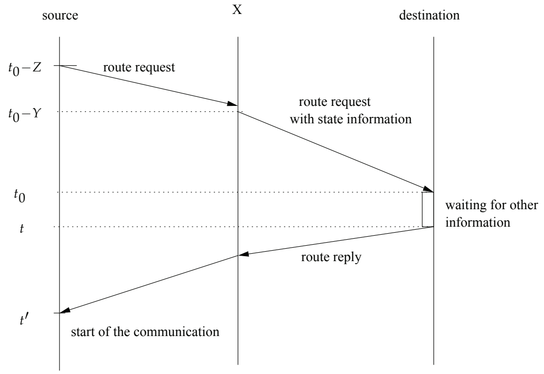
approached. The computation method of the cumulative density function (CDF) of relative velocity is expressed in general case and then the link available time distribution computation of a one-hop link is given, which serves as the basis for multi-hop cases. This paper gives a good mathematical formulation of the bases for probabilistic routing design.
Zhang and Dong found out in (Zhang & Dong, 2007) that traditional path stability computation methods which suppose link independence are idealized and so their results do not accord with the reality. As it was presented earlier, if the assumption of link independence is adopted, then the route stability can be computed by multiplying the stability of the links along this path. However, the traditional methods have not considered the dependencies among links, and Zhang and Dong state that the so computed routes may be far from the real case. In fact, in ad hoc networks, the existence of wireless links is more or less correlated. To take into account the correlation, the usual methods are too complicated to be practical. To solve this dilemma, the authors propose a novel path stability computation model, in which a correlation factor is introduced to describe the dependency degree between arbitrary adjacent links. Based on the correlation factors, a simple and universal expression for computing the stability probability of a path is derived. The construction of the dependency structure between adjacent links is proposed which permits the computation of the joint stability of adjacent links.
To complete the state of the art on stability based routing methods, some special propositions based on localization and mobility models will be presented in Sections 5 and 6.

3. Probabilistic routing framework

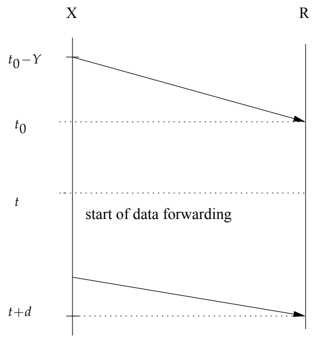
In highly dynamic networks, when a route request arrives in a router, the information used to select a path is more or less inaccurate. We now enumerate rapidly the major causes of uncertainties.

3.1 Uncertainties of routing information

In the case of *reactive* routing protocols, the route is build following an explicit route request and without any *a priori* knowledge on the network state. The request corresponds to a new communication or to the restoration of a broken route. Generally, the source broadcasts a request and the destination answers using a route selected on the base of the received state information on the components of the route. Then the route is configured in the routers and used until its break. The state information can be volatile. The temporal progression of the process is shown in Figure 1 (a). The figure illustrates the use of the state information on an intermediate element X of the selected route. The source sent the request at time $(t_0 - Z)$ which is treated at time $(t_0 - Y)$ by an intermediate element. The state information on X arrives to the destination at time t_0. The destination selects the route on the base of received overall information at time t. The route reply containing the decision arrives at the source at t' and the communication can begin. If the component X does not exist when the route reply reaches the configuration of X, then the route is considered as broken. Even if the configuration succeeds, the state of the element X can change rapidly after the configuration of the selected route.
When using a *proactive* routing protocol, state information on the network component are broadcasted regularly (often periodically) and each router maintains a database on the network state. If a route request is presented, the router decides which route should be used toward the given destination. The decision is based on the local network state database. This database can contain obsolete information. The typical use of the state information on an



(a) Events in a reactive routing



(b) Events in a proactive routing

Fig. 1. Typical scenarii in routing protocols

element X by a router R is illustrated in Figure 1 (b). The state information of X is sent to R at time $(t_0 - Y)$ and received at t_0. This information will be used at time t for routing until the end of the routing period if all right.
In both cases state information for routing can be non correct because of rapid and unpredictable changes in the network and because of (often) random propagation delay of information.

3.2 Our network model

The aim is to model the availability of the network elements in dynamic ad hoc networks. We distinguish two kind of elements:

- *nodes* (often mobile devices) which can manage their presence in the network autonomously (for example, they can arbitrarily disappear for power conservation reason using PSM option of the IEEE 802.11 standard).
- *potential communication capabilities* between node pairs. In our model, two nodes are capable to communicate if they are in the communication range one of the other, independently of their operational state. This concept is not equal to the traditional link concept. Naturally, a communication link exists between the nodes if the potential communication capability is true and if the two nodes are on.

Our model (which was basically proposed in (Marie et al., 2007)) contains also nodes representing the network nodes and edges corresponding to the potential communication capabilities (which are binary relations). At a given time, each element can be in the state UP (U) or in the state DOWN (D). The whole network model corresponds to a complete graph with n nodes and $n(n-1)/2$ edges representing the communication capability relations. The state of an element (which can be a node or an edge) can be modeled by a two state automaton. In the current analysis, we suppose that these automatons correspond to continuous time Markov chains.

3.3 The existence probability of a path

A path contains an ordered set of consecutive links $\{L_1, L_2, ..., L_m\}$ between the ordered, adjacent nodes $\{n_0, n_1, ..., n_m\}$ which are also in the path.

Let us consider the link L_i between two consecutive nodes n_{i-1} and n_i on the path. Let $R(n_{i-1}, n_i)$ be the binary random variable which indicates the potential communication capability between them. $R(n_{i-1}, n_i) = 1$ when they are one with the range of the other (corresponding to the state UP) and 0 otherwise. In the following, we use in the same way the name n of a node to indicate the fact that the node is present (it is in the state UP). So, n corresponds likewise to a discrete random variable having two possible values. Also to simplify, in the place of the probability $\mathbb{P}(x = 1)$ we will use the expression $\mathbb{P}(x)$ and this probability will indicate the probability that the element x is available. Moreover, we are interested by the availability of the elements on the time interval $[t, t + \Delta]$ without interruption.

Inside an arbitrary time interval, the link L_i exists between n_{i-1} and n_i, if and only if both nodes are in state UP and are also one with the range of the other during the period. Naturally the link does not exist if one of the extremities shuts down or if $R(n_{i-1}, n_i)$ becomes equal to zero.

$$\mathbb{P}(L_i) = \mathbb{P}(n_i \, , \, n_{i-1} \, , \, R(n_{i-1}, n_i)) \tag{1}$$

Generally, the existence of a node is independent from the existence of an other and from the location of the nodes. The potential communication capability $R(n_{i-1}, n_i)$ between the nodes depends only on the distance between them, on the radio communication circumstances and on their ranges. This potential communication capability is completely independent from the activity state of the nodes. Due to the independence, the probability of the existence of a link in the MANET can be determined by

$$\mathbb{P}(L_i) = \mathbb{P}(n_i) \cdot \mathbb{P}(n_{i-1}) \cdot \mathbb{P}(R(n_{i-1}, n_i)) \tag{2}$$

The computation can be generalized easily to express the probability of the existence of a whole path. Let us consider that a potential path $(s, d) = \{s, n_1, ..., d\}$ relies the source s to the destination d (so, $n_0 = s$ and $n_m = d$ in the previous definition of the path). This path exists if and only if all the nodes on the path are in UP states and if each successive pair of nodes on the path can communicate (the potential communication capability is true between them).

$$\mathbb{P}(s, d) = \mathbb{P}(n_0 \, , \, ... \, , \, n_m \, , \, R(n_0, n_1) \, , \, ... \, , \, R(n_{m-1}, n_m)) \tag{3}$$

We suppose that the existences of the nodes are always and completely independent from the other facts. So, the nodes do not appear and disappear in a correlated manner. As it is indicated in (Zhang & Dong, 2007), generally, the neighbor links are not independent in MANETs because of the uncertain presence of the common extremity nodes and their mobility. The presence of a node n_i is separately represented in our model and its probability corresponds to $\mathbb{P}(n_i)$.

Concerning the communication capabilities, the discussion on path stability given in (Zhang & Dong, 2007) is worth considering. In our model, an end-to-end communication capability of a path is expressed by $R(n_0, n_1)$, ... , $R(n_{m-1}, n_m)$. Since the communication capabilities which do not share any common endpoint are independent, the probability of the end-to-end communication capability is equal to:

$$
\begin{aligned}
\mathbb{P}(R_{s,d}) &= \mathbb{P}\left(\bigcap_{i=1}^{m} R(n_{i-1},n_i)\right) \\
&= \mathbb{P}(\bigcap_{i=1}^{m-1} R(n_{i-1},n_i)) \cdot \mathbb{P}(R(n_{m-1},n_m)| \bigcap_{k=1}^{m-1} R(n_{k-1},n_k)) \\
&\vdots \\
&= \mathbb{P}\left(R(n_0,n_1)\right) \prod_{j=2}^{m} \mathbb{P}(R(n_{j-1},n_j)| \bigcap_{k=1}^{j-1} R(n_{k-1},n_k))
\end{aligned}
\tag{4}
$$

But, since the communication capabilities which do not share any common endpoint are independent,

$$\mathbb{P}(R_{s,d}) = \mathbb{P}\left(R(n_0,n_1)\right) \prod_{j=2}^{m} \mathbb{P}(R(n_{j-1},n_j)|R(n_{j-2},n_{j-1})) \tag{5}$$

or

$$\mathbb{P}(R_{s,d}) = \mathbb{P}\left(R(n_0,n_1)\right) \prod_{j=2}^{m} \frac{\mathbb{P}\left(R(n_{j-1},n_j),R(n_{j-2},n_{j-1})\right)}{\mathbb{P}\left(R(n_{j-2},n_{j-1})\right)} \tag{6}$$

If we suppose that the different potential communication capabilities are independent, that is to say, we suppose that the nodes approach one to the others in an uncorrelated way as it has been made in (Yu et al., 2003), then the probability of the common event can be computed as the product of the probabilities of elementary events:

$$\mathbb{P}(s,d) = \prod_{i=0}^{m} \mathbb{P}(n_i) \cdot \prod_{i=1}^{m} \mathbb{P}(R(n_{i-1},n_i)) \tag{7}$$

A nice observation permits to simplify the path probability computation. Namely, let us notice that the source $n_0 = s$ and the destination $n_m = d$ belong trivially to each path from s to d. So, the existence probability of both nodes does not influence the path selection for any routing algorithm. Moreover, in real cases, the path is wanted to ensure the connection between two existing nodes s and d (the routing has not importance when the source or the destination is failed). The simplified conditional probability of the path existence is the following:

$$\mathbb{P}(s,d|sd) = \prod_{i=1}^{m-1} \mathbb{P}(n_i) \cdot \prod_{i=1}^{m} \mathbb{P}(R(n_{i-1},n_i)) \tag{8}$$

3.4 Routing with maximal probability of existence

Since the path will be used between the source and the destination from the route request at t until the end of the routing period, it should be stable in the time interval $[t, t+\Delta]$. The optimal path corresponds to the path with the higher existence probability in this interval. Remember that the probabilities in our study indicate the probability that the elements are available on the time interval $[t, t+\Delta]$. Let $T_{s,d}$ be the set of paths between the nodes s and d. The most stable path T_{opt} can be found as :

$$T_{opt} = \arg\max_{T \in T_{s,d}} \mathbb{P}(T) \tag{9}$$

Since the logarithm function is a monotone increasing function:

$$T_{opt} = \arg \max_{T \in T_{s,d}} \ln \mathbb{P}(T) \tag{10}$$

or:

$$T_{opt} = \arg \min_{T \in T_{s,d}} (-\ln \mathbb{P}(T)) \tag{11}$$

Taking into account the development of the existence probability of the paths:

$$T_{opt} = \arg \min_{T \in T_{s,d}} \left(\sum_{i=1}^{m-1} - \ln \mathbb{P}(n_i) + \sum_{i=1}^{m} - \ln \mathbb{P}(R(n_i, n_{i-1})) \right) \tag{12}$$

The optimal path corresponds to a shortest path in a valuated graph which contains special values associated to the nodes and to the edges. Let $G' = (V, E)$ be a complete graph with the same nodes as the complete topology graph of the network. Let us associate to each node n the value $-\ln \mathbb{P}(n)$ and the value $-ln\mathbb{P}(R(n,m))$ to each edge (n,m). Such a valuated graph is illustrated in Figure 2. To find the shortest path between s and d, the graph G' can be easily transformed to a graph G'' valuated only on the edges. To obtain G'', it is sufficient to replace each node (except the source and the destination) with a small complete sub graph having as many nodes as the degree of the node is in G'. In each of these complete sub graphs the edges are valuated uniformly with the value of the corresponding original node in G'. This transformation is illustrated on the second part of Figure 2 supposing that the more stable path is asked between the nodes b and d. Since G'' is valuated with positive values, to find the shortest path between the source and the destination, one of the well known algorithms (as the algorithm of Dijkstra or the one of Bellman-Ford, ...) can be applied.

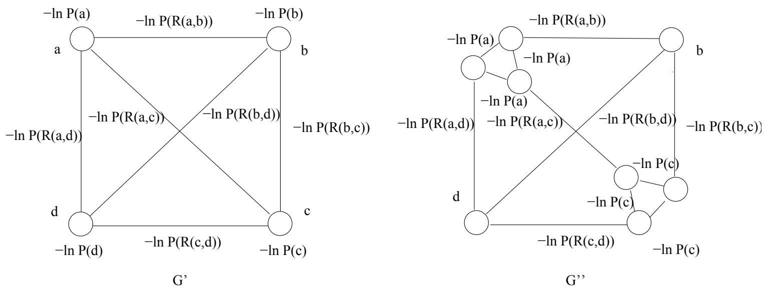


Fig. 2. The valuation of the topology graph

4. On-off automaton based model for the network elements

Our goal is to determine the route which guarantees the maximal existence probability for a time interval beginning with the route selection event. For this, the computation of the existence probability of the different elements based on the beforehand received information is needed.

4.1 Existence probability of an element at a given time

In this section we look for the probability for a given element to be UP at time t given the latest information received. In the following section we will look for the probability for the given element to be UP on all the interval $[t, t + \Delta]$.

We know that at time t_0 we received the information on the latest status of the element but this information was issued and sent at a time $(t_0 - Y)$which is unknown. In our case, we consider Y as a given non negative random variable. It is assumed that the dynamic of the changes of the element states is modeled by a two state continuous time Markov chain. U denotes the UP state ; respectively, D denotes the DOWN state.
When ordering the two states as (U, D), the infinitesimal generator is given by

$$A = \begin{bmatrix} -\lambda & \lambda \\ \mu & -\mu \end{bmatrix} \tag{13}$$

Let us first consider the transition probability function $h_{ij}(x)$ that gives the conditional probability that the element is in state j at time x given that it was in state i at time zero.
Let $H(x)$ denotes the 2×2 matrix such that

$$H(x) = \left(h_{ij}(x)\right) = \begin{pmatrix} h_{UU}(x) & h_{UD}(x) \\ h_{DU}(x) & h_{DD}(x) \end{pmatrix} \tag{14}$$

It is well known (cf. (Trivedi, 1982)), that this function $H(x)$ satisfies

$$H(x) = e^{Ax} \tag{15}$$

where by definition

$$e^{Ax} = \sum_{n=0}^{\infty} \frac{(Ax)^n}{n!} \tag{16}$$

For this two state CTMC, it is not too difficult to find the formal expression of this exponential matrix

$$e^{Ax} = \begin{bmatrix} \eta + (1-\eta)e^{-(\lambda+\mu)x} & (1-\eta) - (1-\eta)e^{-(\lambda+\mu)x} \\ \eta - \eta e^{-(\lambda+\mu)x} & (1-\eta) + \eta e^{-(\lambda+\mu)x} \end{bmatrix} \tag{17}$$

where $\eta = \frac{\mu}{(\lambda+\mu)}$.
In our case $e^{A(t-t_0)}$ will gives the conditional probabilities that the element is in state U or in state D at time t given that it was in state U or in state D at time t_0. But the knowledge we have for sure on the state of the element was issued at time $(t_0 - Y)$ where Y is a random variable. So the problem consists also in finding a probability matrix $M = \left(m_{ij}\right)$ where m_{ij} gives the conditional probability that the element is in state j at time t_0 given that it was in state i at time $(t_0 - Y)$.
It seams reasonable to model the random time Y as the sum of a constant time T_0 and of a random variable Z, where this random variable models the delay due to traffic congestion and the constant part corresponds to the physical propagation delay on the route.
In this study, we consider three possibilities for the distribution of the random variable Z : *i)* Z is exponentially distributed with mean $1/\gamma$, *ii)* Z follows an Erlang-n distribution (representing a random delay with weak dispersion) and *iii)* Z follows an hyperexponetial distribution (representing a random delay with high dispersion).

4.1.1 Case 1 : Z is exponentially distributed

Let us here look for the expression of M when the random variable Z is exponentially distributed with mean $1/\gamma$. First let us consider the probability matrix $B = \left(b_{ij}\right)$ such that b_{ij} is the conditional probability that the element is in state j at time t_0 given that it was in state i

at time $(t_0 - Z)$. Following Ross (see (Ross, 1987)), these conditional probabilities satisfies the following linear system

$$b_{ij}(Z) = \frac{\tilde{a}_i}{\tilde{a}_i + \gamma} \sum_{k \neq i} \frac{a_{ik}}{\tilde{a}_i} b_{kj}(Z) + \frac{\gamma}{\tilde{a}_i + \gamma} \xi_{ij} \tag{18}$$

with $i, j = U, D$; ξ_{ij} corresponding to the Kronecker symbol and $\tilde{a}_i$ denoting the departure rate of state i.
The formal resolution of this linear system gives the following expressions

$$B = \begin{bmatrix} 1 - \frac{\lambda}{\sigma} & \frac{\lambda}{\sigma} \\ \frac{\mu}{\sigma} & 1 - \frac{\mu}{\sigma} \end{bmatrix} \tag{19}$$

where $\sigma = (\mu + \lambda + \gamma)$.
In this case where the random time Y is the sum of a constant time T_0 plus the random variable exponentially distributed with mean $1/\gamma$, then the conditional probabilities are given by the matrix M such that

$$M = e^{AT_0}\, B \tag{20}$$

If M_1 denotes the matrix of the transition probability functions that give the conditional probabilities that the element is in state j at time t given that it was in state i at time $(t_0 - Y)$ (where Y is the sum of the constant time T_0 plus the exponentially distributed random variable with mean $1/\gamma$), then we have :

$$M_1 = Me^{A(t-t_0)} = e^{AT_0}\, Be^{A(t-t_0)} \tag{21}$$

It is possible to prove that matrices e^{AT_0} and B do commute and therefore that M_2 can still be written as

$$M_1 = Be^{A(T_0+t-t_0)} \tag{22}$$

For example, $(M_1)_{UU}$ gives the conditional probability that the element is in state U at time t given that it was declared in state U by the last issued message (at time $(t_0 - Y)$). From the knowledge of matrices B and $e^{A(T_0+t-t_0)}$, we get

$$(M_1)_{UU} = (1 - \frac{\lambda}{\sigma})(\eta + (1-\eta)e^{-(\lambda+\mu)(T_0+t-t_0)}) + \frac{\lambda}{\sigma}(\eta - \eta e^{-(\lambda+\mu)(T_0+t-t_0)}) \tag{23}$$

After some simplifications and in order to help in understanding the influence of the different parameters, we can write the matrix M_1 as :

$$M_1 = \begin{bmatrix} \frac{\mu}{(\lambda+\mu)} + (\frac{\lambda}{(\lambda+\mu)} \frac{\gamma}{(\lambda+\mu+\gamma)})e^{-(\lambda+\mu)(T_0+t-t_0)} & \frac{\lambda}{(\lambda+\mu)} - (\frac{\lambda}{(\lambda+\mu)} \frac{\gamma}{(\lambda+\mu+\gamma)})e^{-(\lambda+\mu)(T_0+t-t_0)} \\ \frac{\mu}{(\lambda+\mu)} - (\frac{\mu}{(\lambda+\mu)} \frac{\gamma}{(\lambda+\mu+\gamma)})e^{-(\lambda+\mu)(T_0+t-t_0)} & \frac{\lambda}{(\lambda+\mu)} + (\frac{\mu}{(\lambda+\mu)} \frac{\gamma}{(\lambda+\mu+\gamma)})e^{-(\lambda+\mu)(T_0+t-t_0)} \end{bmatrix} \tag{24}$$

In such a form, we can see the influence of parameters λ, μ, γ, T_0 and $(t - t_0)$ on these expressions.
If we let $\rho = \lambda/\mu$ and $\beta = \gamma/\mu$, the matrix M_1 can also be written as a function of μ, ρ, β, T_0 and $(t - t_0)$:

$$M_1 = \frac{1}{(1+\rho)} \begin{bmatrix} 1 + \rho \left(\frac{\beta}{1+\rho+\beta}\right) e^{-\mu(1+\rho)(T_0+t-t_0)} & \rho - \rho \left(\frac{\beta}{1+\rho+\beta}\right) e^{-\mu(1+\rho)(T_0+t-t_0)} \\ 1 - \left(\frac{\beta}{1+\rho+\beta}\right) e^{-\mu(1+\rho)(T_0+t-t_0)} & \rho - \left(\frac{\beta}{1+\rho+\beta}\right) e^{-\mu(1+\rho)(T_0+t-t_0)} \end{bmatrix} \tag{25}$$

4.1.2 Case 2 : Z follows an erlang-n distribution

Let us know look for the expression of M when the random variable Z follows an Erlang-n distribution with mean $1/\gamma$. First let us consider the probability matrix $C = \left(c_{ij}\right)$ such that c_{ij} is the conditional probability that the element is in state j at time t_0 given that it was in state i at time $(t_0 - Z)$.

Remembering that an Erlang-n distribution with mean $1/\gamma$ is equivalent to the sum of n independent and identically distributed random variables following the exponential distribution with rate $n\gamma$, the matrix C is such that (cf. (Ross, 1987))

$$C = C_1^n \tag{26}$$

where the probability matrix C_1 is obtained from B by replacing γ by $n\gamma$ (in notation σ):

$$C_1 = \begin{bmatrix} 1 - \frac{\lambda}{\sigma'} & \frac{\lambda}{\sigma'} \\ \frac{\mu}{\sigma'} & 1 - \frac{\mu}{\sigma'} \end{bmatrix} \tag{27}$$

with $\sigma' = (\mu + \lambda + n\gamma)$.

C_1 being a 2×2 probability matrix, it is possible to show after classical technical manipulation that matrix C (also a stochastic matrix) can be written as :

$$C = \frac{1}{1+\rho} \begin{bmatrix} 1 + \rho\left(\frac{n\gamma}{\sigma'}\right)^n & \rho - \rho\left(\frac{n\gamma}{\sigma'}\right)^n \\ 1 - \left(\frac{n\gamma}{\sigma'}\right)^n & \rho + \left(\frac{n\gamma}{\sigma'}\right)^n \end{bmatrix} \tag{28}$$

Then, the conditional probability matrix M will be such that

$$M = e^{AT_0}\, C \tag{29}$$

and the elements of the conditional probability matrix M_1 can be obtained similarly to the previous case. For example we get after some simplifications

$$(M_1)_{UU} = \frac{1}{(1+\rho)} \left[1 + \rho\left(\frac{n\gamma}{\sigma'}\right)^n e^{-(\lambda+\mu)(T_0+t-t_0)}\right] \tag{30}$$

4.1.3 Case 3 : Z follows an hyperexponetial distribution

We now consider the case where, for each outcome, with probability α (resp. $(1-\alpha)$), Z takes the value of an exponentially distributed random variable with rate γ_1 (resp. γ_2). With this hyperexponential distribution, it is always possible to find a triplet $(\alpha, \gamma_1, \gamma_2)$ satisfying a given mean and a given coefficient of variation greater than one, in order to model a random delay with high dispersion. Let us introduce the random variable J such that $J = 1$ (resp. $J = 2$) if the outcome corresponds to the first (resp. the second) exponentially distributed random variable.

Let us consider the probability matrix $D = \left(d_{ij}\right)$ such that d_{ij} is the conditional probability that the element is in state j at time t_0 given that it was in state i at time $(t_0 - Z)$. We have, for all i, j :

$$d_{ij}(Z) = \alpha d_{ij}(Z|J=1) + (1-\alpha)d_{ij}(Z|J=2) \tag{31}$$

This gives us

$$D = \alpha D_1 + (1-\alpha)D_2 \tag{32}$$

where the probability matrix D_1 (resp. D_2) is obtained from B by replacing γ by γ_1 (resp. γ_2) (using the notation $\sigma_i = (\mu + \lambda + \gamma_i)$ for D_i, $i = 1,2$).

If we let σ^* such that $\frac{1}{\sigma^*} = \frac{\alpha}{\sigma_1} + \frac{(1-\alpha)}{\sigma_2}$, it is possible to show that

$$D = \begin{bmatrix} 1 - \frac{\lambda}{\sigma^*} & \frac{\lambda}{\sigma^*} \\ \frac{\mu}{\sigma^*} & 1 - \frac{\mu}{\sigma^*} \end{bmatrix} \tag{33}$$

From that point, the elements of the conditional probability matrix M_1 can be obtained similarly to the previous cases.

4.2 State probability of an element on a given time interval

In this section, we now consider that at time t we want to know the probability for the given element to be UP on all the interval $[t, t+\Delta]$. Let us denote this probability by $\mathbb{P}(x(t,\Delta))$. From classical results on the exponential distribution, we know that the probability that the element stays up on all the interval $[t, t+\Delta]$ given that it is up at time t is equal to $e^{-\lambda\Delta}$.
Then the conditional probability that the considered element stays up on all the interval $[t, t+\Delta]$ given that it was declared in state U by the last issued message is equal to $(M_1)_{UU}.e^{-\lambda\Delta}$. Respectively, the conditional probability that the considered element stays up on all the interval $[t, t+\Delta]$ given that it was declared in state D by the last issued message is equal to $(M_1)_{DU}.e^{-\lambda\Delta}$.
Let us express these conditional probabilities in the special case when Z is exponentially distributed. Using the indicator function I_x such that $I_x = 1$ when the element x is in state U at time $(t_0 - Y)$ (else 0), the probability that this element x stays up on all the interval $[t, t+\Delta]$ is formally equal to:
a) if the element was declared in state U by the last issued message :

$$P(x|I_x = 1) = \frac{e^{-\mu\rho\Delta}}{(1+\rho)}\left[1 + \rho\left(\frac{\beta}{1+\rho+\beta}\right)e^{-\mu(1+\rho)(T_0+t-t_0)}\right] \tag{34}$$

b) if the element was declared in state D by the last issued message :

$$P(x|I_x = 0) = \frac{e^{-\mu\rho\Delta}}{(1+\rho)}\left[1 - \left(\frac{\beta}{1+\rho+\beta}\right)e^{-\mu(1+\rho)(T_0+t-t_0)}\right] \tag{35}$$

The two figures illustrate the existence probability of an element depending on the value of the normalized product $\mu(T_0 + t - t_0)$. In both cases the parameters of the corresponding automaton are $\lambda = 0.20$ and $\mu = 0.1$. Figure 3 presents the obtained probabilities from the three cases of probability distributions considered for the random variable Z with with $\gamma = 1.0$ and $\Delta = 2.0$. When the product $\mu(T_0 + t - t_0)$ is equal to zero, the elapsed time since the element was declared up corresponds to the random delay Z. This is why the probabilities on the figure do not equal one when the product is null. Moreover, since the expectation of the random variable Z is relatively important ($E[Z] = 1$ for the three cases), the influence of the probability distribution of Z is not negligible. Figure 4 presents also the obtained probabilities from the three cases of probability distributions considered for the random variable Z but with $\gamma = 10.0$ and $\Delta = 1.0$. In that situation, the expectation of Z is relatively small ($E[Z] = 0.1$) and the influence of the probability distribution is not important. The curve corresponding to the Erlang-5 distribution is not distinguishable from the curve corresponding to the exponential distribution.

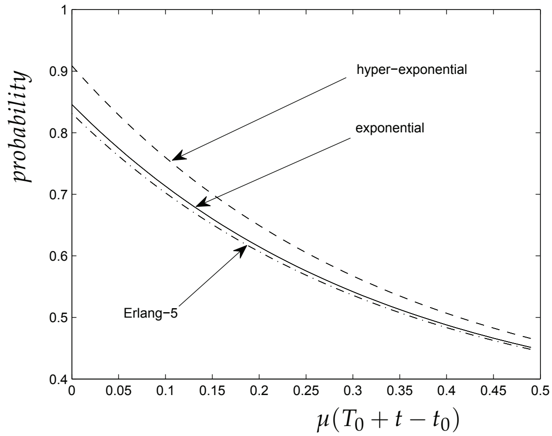


Fig. 3. Existence probability with $\gamma = 1.0$ and $\Delta = 2.0$

5. Localization based computations

Several routing protocols have been proposed using location information of the nodes (obtained for example using the GPS system). In (Ko & Vaidya, 2000), the authors propose two schemes of Location-Aided Routing (LAR) protocol for route discovery. The LAR protocols use this location information (which may be out of date) to reduce the search space for the desired routes. For the nodes concerned in route requests, an "expected zone" is computed based on the knowledge that the node was at a given location at a given time. So, route discovery may be limited to certain zones. Limiting the search space results in fewer route discovery messages.

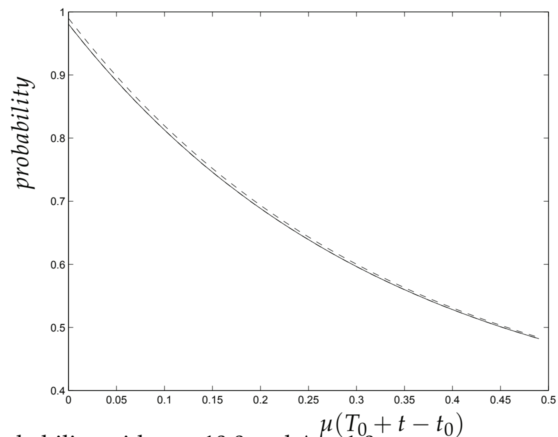


Fig. 4. Existence probability with $\gamma = 10.0$ and $\Delta = 1.0$

The location based protocol called DREAM (as Distance Routing Effect Algorithm for Mobility) was proposed in (Basagni et al., 1998). The DREAM protocol corresponds to a proactive routing procedure. When the sender node s want to send a message to the destination node d, it uses the location information for d to compute the direction of d, The source transmits the message to all its one hop neighbors in the direction of d. The subsequent nodes repeat the same procedure until the destination node is reached.

An other location based protocol, the Greedy Perimeter Stateless Routing (GPSR) has been described in (Karp, 2000). GPSR makes greedy forwarding decisions using only information about the neighbors of nodes in the network topology. By keeping state only about the local topology, GPSR scales better in per-router state than shortest path based ad hoc routing protocols as the number of network destinations increases. Under topology changes, GPSR can use local topology information to find correct new routes quickly. In certain cases of location inaccuracy GPSR disconnects some routes in the graph and hence the packets will not be routed. In (Tomar & Tomar, 2008) an algorithm is proposed, which removes some of the drawbacks of the GPSR algorithm.

A quorum based location service has been proposed in (Stojmenovic et al., 2008), in which source nodes try to find the destinations using their location information. In a previous version of this service, nodes report their new positions to their neighbors whenever a link is broken or created. So, nodes regularly forward their new position to all nodes located in its area of routing to help the stable route creation.

New perspectives are given with the discovery of 3D routing problems in MANETs (cf. a recent routing proposition in (Liu et al., 2008)) but a good survey on 3D routing problems is actually wanted. An earlier survey on position based routing protocols can be found in (Mauve et al., 2001).

To use efficiently our simple dynamic network model based on two-state automatons and presented in Section 3, the transitions of the automatons should be computed as realistic as possible. Since the network elements in a MANET alternate their state between UP and DOWN states, the behavior of the automatons modeling the nodes and the communication capabilities may correspond to the dynamic of the network. Nevertheless, the entire specification of the automaton is difficult. The problem resides in the fact that the transition dates are not known and are random dates. The more the details are known on the (random) behavior of the elements, the more the automatons may be designed precisely.

5.1 Availability of nodes

In our previously proposed model, the automatons associated with the network nodes model the random behavior of both the machines and the human operators. Without any knowledge on the reliability of these actors, a good choice can be the exponential distribution modeling the availability of an existing element. The rate of this distribution can correspond to estimated availability of the machine and its operator. If the machines are unreliable and/or the operators can quit the network, this kind of transition functions are faithful. If the actors are considered stable, then their existence probability is near to 1 and the lifetime of the corresponding node is infinite compared to the (generally) short routing period. To simplify, in this section we suppose than the nodes present at the beginning of a routing period are available in the entire period (the automatons corresponding to the present nodes are in UP state).

5.2 Communication capability between nodes

In the following, we investigate on the determination of simple transition functions associated with communication capability automatons. At first, we describe how the simple information on the node localization can be used to approach the parameters of the two state automatons. The next section illustrates that by learning the parameters of node movements, the communication capabilities and so the link stability can be computed more precisely.

The simple location based computation model for the two state automaton associated with the communication capability was firstly proposed in (Belghith et al., 2008). We assume that the residence time of the element e in state UP is governed by an exponential distribution with rate λ_e. Similarly, the residence time in state DOWN is governed by an exponential distribution with rate μ_e. The choice of the parameters λ_e and μ_e should reflect the dynamic behavior of the network. Indeed, if these parameters increase for a communication capability type element, this indicates unstable communication capacity in time and frequent oscillations between the UP and DOWN states. High values reflect strong mobility of nodes which involves frequent changes in communication capability states. If one of the parameters is very small, this indicates rather stable elements in UP or DOWN state over time. For instance, if λ_e is very small, nodes tend to stay together. Using the two state automatons with exponential transitions, the main question is to choose the values of λ_e and μ_e for the automaton of e. This element e is in state UP if its extremities are within transmission range and independently from the state of these extremities. Nevertheless, it is clear that the communication capability depends on the actual distance separating these nodes. Let R denote the identical transmission range of nodes and let d_e denote the distance separating the nodes corresponding to e. Hence these two nodes are capable of communication only if d_e is less than or equal to R. However, the shorter is d_e the more stable is the corresponding communication capability. So, the automaton of a communication capability is some how related to the distance separating the extremities.

It is known that the transient state of an exponential function based two state automaton falls off rapidly to reach its steady state. Consequently, one can discuss the transition functions by considering and relying on the steady state probabilities. Consider two nodes, which are capable to communicate at the beginning of the routing period. That is d_e for these nodes is no larger than R. The transient probability of being UP $P_{UU}(e,t)$ starts equal to one and then will falls off rapidly to its steady state probability β. This steady state probability should tend to one when the distance d_e is small; yet it should tend to one half as d_e approaches R. Now let us consider an element e in state DOWN at the beginning of the routing period. The transient probability of being in state DOWN $P_{DD}(e,t)$ starts equal to one and then will converge rapidly to its steady state probability $1-\beta$. This latter probability should be near to one when d_e gets farther and should equal to one half as d_e approaches R. So, λ is an increasing function (respectively μ as a decreasing function) of d_e/R. For each automaton, the following parameters were proposed in (Belghith et al., 2008) :

$$\lambda_e = C\left(\frac{d_e}{R}\right)^k \qquad \mu_e = C\left(\frac{R}{d_e}\right)^k \tag{36}$$

with k and C two given positive constants. The value of k permits to define the speed at which λ and μ increases and decreases respectively.

This first computation for transition functions is very simple because it relies only on distances separating nodes, but it can be far from the reality as it is illustrated in the following.

6. Random walk mobility based computations

The more information are known on the behavior of nodes in an ad hoc network, the better can be the probabilistic routing to ensure route stability. Mobility models permit to describe the movement pattern of mobile nodes, *i.e.* their probable location, direction and speed evolution over time. Using mobility models, one can estimate the neighboring relation of nodes without exact knowledge on their future movements. Due to their impact on the network control and management function, the mobility models of nodes are analyzed intensively in the literature (cf. large surveys in (Camp et al., 2002b) and (Lin et al., 2004)).

Frequently used mobility models in MANET are random models and the most known model is the Random Way-point model proposed in (Broch et al., 1998). In this model, nodes move independently to a randomly chosen destination with a randomly selected velocity. This model is the commonly used one when no additional information is available on the mobility, even if stochastic properties of this model are particular (Bettstetter et al., 2002).

The Random Walk model has similarities with the Random Way-point model, but in this model, the nodes change their speeds and directions *at each time interval*. At the beginning of a period, each node chooses randomly and uniformly its new direction and its new speed following a uniform distribution or a Gaussian distribution. It is also referred to as the Brownian Motion (cf. (Kac, 1947)). These random models are Markovian.

Mobility of a node may be constrained by physical laws. The inertia limits the acceleration, the velocity and the changes of direction. Hence, the current velocity of a mobile node may depend on its previous state. So, the mobility is not always Markovian. Several mobility models considering temporal dependency are proposed. Such a model is the Gauss-Markov Mobility Model (Liang & Haas, 1999) in which the velocity of node is correlated with the previous values and modeled as a Gauss-Markov stochastic process. In the Smooth Random Mobility Model (Bettstetter, 2001) proposed by Bettstetter, the nodes change their speeds and directions incrementally and smoothly. The speeds do not follow a purely uniform distribution but nodes chose some preferred speeds with high probability, which corresponds better to the frequently observed behavior of the nodes. The speed change is assumed to be a Poisson process.

In (Su et al., 2001) the authors propose some improvement of location based routing protocols. Their starting-point corresponds to the fact that in typical mobile networks, nodes exhibit some degrees of regularity in the mobility pattern. By exploiting the knowledge on this non-random mobility pattern, the future state of the network topology can be predicted more precisely. The prediction is based on the knowledge of location and on speed parameters of nodes to estimate the lifetime of links. However prediction based on the learning of the inertia of mobiles or the prediction of the speed changes are not developed.

In the previously described random models, nodes move independently one from others. However, in real applications team collaboration may exist between the users. Therefore, the mobility of a mobile node could be influenced by other neighboring nodes. Since the velocities of different nodes are "correlated" in space, spatial dependency models can improve the mobility model as it is the case in the Reference Point Group Mobility (RPGM) Model and other group mobility based route computations (Hong et al., 1999; Jayakumar & Ganapathi, 2008; Ochirsuren et al., 2008).

In (Cho & Hayes, 2005) a simple but mathematically tractable model of node motion is presented: the constant velocity model, which is used to derive a precise relation between mobility and connection stability. It is demonstrated that *link duration* has a strong invariant

relationship with the stability of multi-hop connections for a wide range of mobility models, and thus is an excellent mobility metric.
Random Direction Mobility Model based computation of stable routes is analyzed in (Carofiglio et al., 2009). The authors study the availability and the duration probability of a route that is subject to disruption caused by node mobility. They derive both exact and approximate expressions of these probabilities (using the Random Direction model) and propose an approach to improve the efficiency of reactive routing protocols.
The impact of mobility on the link and route lifetimes in ad hoc networks is analyzed in (Lenders et al., 2006) using real data gathered from a real network of 20 test users. Link and route lifetime distributions are then analyzed. The authors state that besides link breakage due to node mobility, links might also break due to diverse sources of interference or to packet collisions. They develop a statistical framework to distinguish between the mobility and interference or collision errors and determine the lifetime distributions for both error types separately. The paper validates two commonly used stochastic mobility models namely the random way-point and the random reference group mobility model. The results show that the distributions of the two stochastic mobility models match very closely the empirical link lifetime distribution.
Additional knowledge on human operators and on their relations can improve the performance of the routing. For example, in (Musolesi & Mascolo, 2006) the authors model mathematically the possible association between humans. In their paper they propose a new mobility model founded on social network theory. The model allows collections of hosts to be grouped together in a way that is based on social relationships among the individuals.
To limit the perimeter of our study in this chapter, we propose a simple Random Walk (RW) model based computation of the transition functions of our automatons corresponding to the communication capabilities. The computation can easily be extended to other mobility models using the adequate node distribution functions. Our hypothesis are the following.

- At the beginning of a routing period (which is supposed here to start at $t = 0$), the localization of the nodes is known (each node has knowledge on the position of its neighbors).
- We have also information on the node mobility, but only the maximal velocity v_{max} of the nodes is known. We suppose that the nodes move randomly without stopping. So, the RW model can be used to describe the movement (cf. a detailed description here after).
- To simplify, we suppose that there is no obstacle in the space and the communication range of nodes is R.
- As the routing protocol is periodic, we are interesting to determine the relative node position distributions between the nodes for $0 < t < T$. Then this relative node position distribution permits to compute the probability that an existing communication capability at $t = 0$ may exist in the interval $[t, t + \Delta]$ without interruption.

In our model, the instantaneous communication capability of nodes depends only on the distance between them. So, we focus on the evaluation of this distance in order to estimate the probability of the communication capability between the nodes in the routing period. The evaluation can be characterized with a spatial distribution of the nodes. Let A and B be two nodes and d_0 the initial distance between them at $t = 0$. If $d_0 > R$, the nodes can not communicate at this moment. Only node pairs with $d_0 \leq R$, are interesting for an eventual path computation. We determine the distance of the nodes (more precisely the relative position of the nodes) at the moment t as follows.

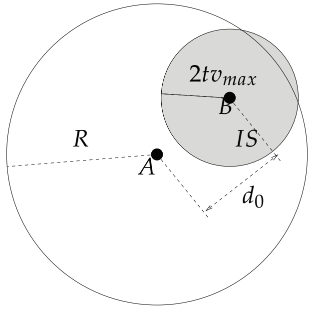


Fig. 5. The relative position af nodes at t.

As the nodes move following the RW model, their distance develops randomly. The moments of changes concerning the relative velocity corresponds to the moments when one of the nodes changes its velocity. Trivially, the relative velocity is the vectorial sum of the node velocities. To simplify the computation of the distance, we can suppose that one of the nodes (for example A) does not move and the other node (node B) moves using a random mobility model with maximal velocity $2v_{max}$. Figure 5 illustrates the position of B relative to A at t. Since the movement of B is limited by $2v_{max}$, B is in the circle of radius $2t \cdot v_{max}$ at the moment t (disk in grey). The nodes can communicate if B is in the communication range of A (with radius R). The probability of this communication capability can be expressed using the geometrical node distribution function of the mobility model at t.

Concerning the dispersion of B in side the disk, we use the random walk model proposed by in (McDonald & Znati, 1999a). This model is a continuous time stochastic process describing the movement of a node in the following way. First consider a Poisson process with rate λ producing events to change the velocity at times $t_i, i = 0, 1, 2, \ldots$. Let $T_i = t_i - t_{i-1}$ be the i^{th} interval. During an interval, the node is supposed to have a constant speed corresponding to a constant vector $\overrightarrow{v_i}$ (with a constant direction Θ_i and a constant module $|\overrightarrow{v_i}|$). At each occurrence of the Poisson process the vector of speed changes from $\overrightarrow{v_{i-1}}$ to $\overrightarrow{v_i}$. The random variables are independent. The module of the speed follows a given distribution function with a mean μ and a finite variance σ^2. The direction follows a uniform distribution over$[0, 2\Pi]$. The speed vectors are independent of the interval duration.

After a time t, if $N(t)$ denotes the number of occurrences of the Poisson process, the position of the node which is initially at $(0,0)$ will be given by the vector

$$\overrightarrow{z(t)} = \sum_{i=1}^{N(t)} \overrightarrow{v_i} T_i \tag{37}$$

The coordinate on the plane are $(x(t), y(t))$. Trivially:

$$x(t) = \sum_{i=1}^{N(t)} |\overrightarrow{v_i}| T_i \cos\theta_i \tag{38}$$

$$y(t) = \sum_{i=1}^{N(t)} |\overrightarrow{v_i}| T_i \sin\theta_i \tag{39}$$

It is known from the theory that the asymptotic distribution of this random position is a two-dimensional Gaussian distribution. $x(t)$ and $y(t)$ are independent, identically and

normally distributed with
$N(0, \frac{t}{\lambda}(\mu^2 + \sigma^2))$.
The probability that B and A can communicate may be computed as the geometrical probability that B is in the intersection IS of the two circles representing the communication range of A and the probable positions of B respectively:

$$P_t(dist(A,B) < R) = \int_{IS} p(x,y) \tag{40}$$

Figure 6 shows the existence probability of an element corresponding to the communication capability between two nodes computed with the following values: $\lambda = 20.0$, $\mu = 0.35$, $\sigma = 0.1$, $R = 10.0$, $d_0 = 6.0$, $v_{max} = 0.5$. The limited speed of nodes permits to adjust the existence probability. If the maximal speed of nodes v_{max} is known, one can compute the first moment t_d when the communication capacity may disappear:

$$t_d = \frac{R - d_0}{2v_{max}} \tag{41}$$

With the data used in Figure 6, t_d equals 4 and we can see that the existence probability stays to 1 from $t = 0$ to $t = 4$. The obtained instantaneous existence probability function can be used to compute the availability of the communication capability between the nodes during the interval $[t, t + \Delta]$.

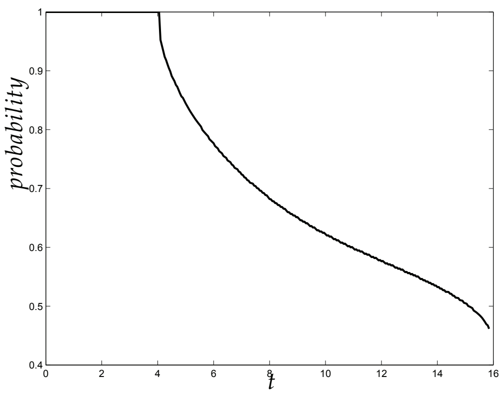


Fig. 6. The existence probability of the communication capability between two nodes when using the random mobility model

Let us notice that the limited speed of nodes permits also to adjust the transition function of the automatons in our dynamic network model. The exponential function based transitions of the automatons corresponding to communication capabilities are not realistic having the information on the position and on the velocity of nodes. Using an exponential transition function as it was proposed in the previous section, the probability of the interruption of an existing communication capability between two nodes becomes positive just after the start-point (cf. the curve with dotted line in Figure 7). In more realistic cases, when the maximal speed of nodes v_{max} is known, the first moment t_d when the communication capacity may disappear can be computed as it is indicated above. Before this date, an existing communication capability cannot disappear. Consequently, the transition function P_{UU} of our automaton modeling this communication capability is more realistic by chosen for example:

$$P_{UU}(t) = \begin{cases} 1 & \text{if } t \leq t_d, \\ \delta + (1-\delta)\exp -(\lambda+\mu)(t-t_d) & \text{if } t > t_d \end{cases} \tag{42}$$

Trivially, if $t_d \leq T$, then the communication capability exists in the whole period. The values λ and μ can be calculated supposing the probabilities $P_{UU}(t_d) = 1$ and $P_{UU}(T) = P_T(dist(A,B) < R)$. Based on this idea, the transition functions $P_{UD}(t)$, $P_{DU}(t)$ and $P_{DD}(t)$ of the automaton corresponding to the communication capability between A and B can also be obtained in the same way.

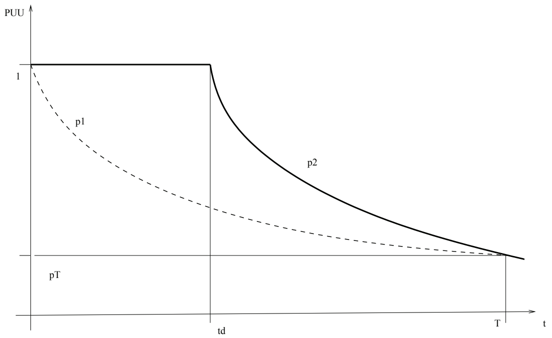


Fig. 7. A more realistic transition function P_{UU} in the time.

7. Conclusion

Because of dynamic topology changes, routes may frequently break in ad hoc networks. Topology and route maintenance involve important control message overhead. Selection of stable routes can diminish the control traffic and the packet losses. Moreover, the topology information in the routers can be inaccurate at the moment of its utilization. In the current chapter, we presented the most important heuristic and probability based ideas to obtain routes as stable as possible. We presented a simple mathematical model in order to predict the uncertainties due to unexpected changes and to random propagation delay of network state information. The proposed network model corresponds to a trade-off between faithfulness (which is expensive) and tractability. Our model deals with mobility, break-down of elements and also disappearances and re-appearances of stations in a simple way: by using an automaton based dynamic graph. It permits to express the joint effect of the state changes of the network elements and of the random propagation delay of control messages. We obtained closed form expressions for the existence probabilities of the network elements. The expressions allow to effect more precisely the network functionality (*e.g.* the routing) which are based on the network state information. The routing algorithm finding the more stable path for a given time interval corresponds to finding a shortest path on an equivalent graph. The estimation of automaton parameters based on the collected topology information is a crucial element for the routing protocol. The chapter illustrates how to use additional information as the location and the mobility of nodes to compute the parameters of the two-state automatons. Future work is needed to adjust the simple automaton-based model for cases where the mobility pattern is different from the here presented random mobility.

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