Predicting Node Proximity in Ad-Hoc Networks: A Least Overhead Adaptive Model for Selecting Stable Routes

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Abstract—**This paper presents a strategy for quantifying the future proximity of adjacent nodes in an ad-hoc network. The *proximity model* provides a quantitative metric that reflects the future stability of a given link. Because it is not feasible to maintain precise information in an ad-hoc network, our model is designed to require minimal information and uses an adaptive learning strategy to minimize the cost associated with making a wrong decision under uncertain conditions. After computing the initial baseline *link availability* assuming random-independent mobility, the model adapts future computations depending on the expected time-to-failure of the link based on the independence assumption, and a parameter that reflects the the environment. The purpose for defining this metric is to enhance the performance of routing algorithms and better facilitate mobility-adaptive dynamic clustering in ad-hoc networks.**

I. Introduction

This paper examines the problem of finding *stable* links for routing in ad-hoc networks. It considers the question of link availability—how long will two nodes remain in close enough proximity for a link between them to remain active? More precisely, with what probability will two nodes remain within a given distance threshold of one another over time? The paper builds on the probabilistic model for link availability presented in [1] by proposing an adaptive learning strategy to discover with high probability when two nodes are effectively moving together. The objective is to limit the cost of incorrectly predicting that a link is stable using minimal information. The purpose for defining this metric is to enhance the performance of routing algorithms and better facilitate mobility-adaptive dynamic clustering in ad-hoc networks.

Knowledge of node mobility and location information can be used to improve the control and management of ad-hoc networks. Mobility information can be used to choose more stable routes, organize more stable clusters, limit the search space of reactive probing, and limit the dissemination of control information. Hence, mobility models can be used to achieve a better balance in the tradeoff between response and efficiency—a necessary objective in achieving a broader vision of ad-hoc networking that extends beyond niche applications.

The first strategies factoring node mobility into the route selection process were based on *fixed thresholds*: Associativity based routing (ABR) proposed by Toh [2] favors routes with *longer lived* links according to the *associativity* of the incident nodes. A pair of nodes are considered *associated* if they have remained in direct radio contact beyond some predefined threshold time. The threshold reflects the observation that mobile users tend to alternate through periods of relatively rapid movement and *rest*. A rest period also reflects nodes that remain in motion, yet are moving more-or-less together. A similar approach was proposed in [3] for Signal Stability-Based Routing, however, it considers both location *and* signal stability in the computation of routes. The signal strength threshold differentiates between *weakly connected* and *strongly connected* nodes. The *associativity clicks* threshold is used to assess relative location stability.

More recent work addresses the problem of predicting future link status in a quantitative way [4, 5, 6]. However, these models alone are not sufficient. The model presented in [4] requires complete GPS information reflecting all nodes in the network; whereas, the models presented in [5, 6] assume random-independent movement at all times, hence, cannot adjust to reflect *associativity* as in ABR. To address these shortcomings a strategy is needed that can capture the positive attributes of the minimum information probabilistic models, and the threshold based *stability* models using adaptive techniques that reflect the mobility profiles of the nodes. This paper presents such a strategy. It is referred to as the node *proximity model*—The remainder of this paper is organized as follows: In Section-II. the rationale underlying the proximity model is explained. The detailed development of the model is presented in Section-III.. Conclusions and future work are discussed in Section-IV..

II. Model Rationale

Future ad-hoc networks may be described as either being *application oriented* or *service oriented.* In a service oriented arrangement the nodes cooperate in order to facilitate general communications. The only necessary conditions are that the users share physical proximity and that they agree to cooperate in the delivery of basic network services—e.g.. routing. In an application oriented ad-hoc system the nodes share a common objective beyond communications services. For example, they may involve people working together on a project, or sharing computing resources. It is also possible for ad-hoc networks to exhibit *both* types of arrangements concurrently.

Group relationships and dynamics differentiate alternative ad-hoc scenarios. Hence, from a network control perspective it is important to consider the impact of these differences on performance. Specifically, group related activities that are characteristic of application oriented ad-hoc networks, and environmental factors, e.g. vehicles moving along a highway, etc., may lead to some degree of stability of the network links. Knowledge of these relationships can be used to help select the most stable paths, thus reducing the overhead associated with topological changes. Consequently, the ability to capture these effects can be used to improve the efficiency of ad-hoc network routing.

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The objective of the proximity model is to provide the capability for nodes to *learn* and *report* on the future stability of their incident links. A metric is desired that quantitatively reflects the future proximity of a given pair of nodes. This measure should be simple to compute based on readily available information requiring minimum communications and computation overhead. The idea is that if you know nothing about the movement of a pair of nodes or the environment, other than their *mobility profiles* as defined below, it should be be possible to derive an initial *baseline* measure that predicts the future availability of the link assuming random-independent movement. Over time, however, it may become increasingly apparent that the relative movement of a given pair of nodes is neither random, nor independent. For example, if a link survives significantly longer than expected in the random-independent case it becomes increasingly less risky to assert that the nodes are moving together, and hence that the link can be expected to remain available.

III. Analytical Framework

In this section an analytical framework is presented for extending the random-independent link availability model from [1, 5] to capture the effects of correlated movement. Link availability is a probabilistic model which predicts the future status of a wireless link. It is assumed that link status (up/down) is determined by a distance threshold.

Definition 1 Link availability *is defined as the probability that there is an active link between two mobile nodes at time* $t_0 + t$*, given that there is an active link between them at time* t_0 [1]. *Let* $\mathcal{L}_{m,n}(\tau)$ *be the status of the link between nodes n and m at time* τ: $\mathcal{L}_{m,n}(\tau) = 1$ *if the link is up, and* $\mathcal{L}_{m,n}(\tau) = 0$ *if the link is down. Then* link availability *is defined as:*

$$\mathcal{A}_{m,n}(t) \equiv Pr(\mathcal{L}_{m,n}(t_0 + t) = 1 | \mathcal{L}_{m,n}(t_0) = 1)$$

In [5] a discrete approximate model for Brownian motion was presented that provides the basis for the analytical derivation of *random-independent link availability*. According to this model each node's movement consists of a sequence of random length intervals called *mobility epochs* during which a node moves in a constant direction at a constant speed. The *mobility profile* of a given node n moving according to a random ad-hoc mobility model is specified based on three parameters as follows: $< \lambda_n, \mu_n, \sigma_n^2 >$. The following list adapted from [5] defines these parameters for node n:

- The lengths of mobility epochs are IID exponentially distributed with mean $1/\lambda_n$.
- The speed, V_n^i, during each mobility epoch i is an IID distributed random variable with mean μ_n and variance σ_n^2, and remains constant only for the duration of the epoch.
- The direction, θ_n^i, of the node during each mobility epoch i is IID uniformly distributed over $(0, 2\pi)$, and remains constant only for the duration of the epoch.

[1] A link is considered available at time $t_0 + t$ even if it experienced failures during one or more intervals (t_i, t_j); $t_0 < t_i < t_j < t_0 + t$.

The salient feature of the model is that it uses knowledge of the mobility profiles of adjacent nodes, which can be learned by periodically acquiring Global Positioning Systems (GPS) [7] information, and computes the probability the nodes remain within a threshold distance, or *proximity* of each other at any time t in the future assuming a random-independent mobility pattern.

If the actual movement of adjacent nodes exhibit high positive correlation, the pair will remain *associated* for a substantial interval of time. In this case the model will *underestimate* the probability of future proximity. If the movement of a pair of adjacent nodes exhibit substantial negative correlation, as indicated by the pair moving rapidly and persistently in opposite directions the model will tend to be overly optimistic.

The effect of underestimating the availability of a path on a routing decision, is that a highly stable path may be bypassed in favor of a less stable path. This leads to increased reaction by the routing algorithm to topological changes, which in turn may lead to increased routing overhead. Most currently proposed ad-hoc routing algorithms treat every link equivalently. Consequently, if the availability metric is used to favor higher availability routes, the selected paths will be *at least* as stable as paths selected by these proposed algorithms.

It is shown in [5] that randomly moving nodes drift away from one another over time. Therefore, it becomes unlikely that two nodes are moving in a truly random-independent pattern when the link between them survives significantly longer than predicted. We propose a strategy that tracks the amount of time each link survives and uses the mobility profiles to compare that time to its expected random-independent survival. Beyond this time the metric value is gradually *increased* to reflect increasing confidence of link stability.

Observe that the mobility of two nodes may be either independent or correlated; however, in most cases it will be uncertain which condition holds. Hence, an expression for the total link availability, $\mathcal{A}_{m,n}^T(t)$, can be given by Equation-1, where $\mathcal{A}_{m,n}^i(t)$ is the link availability when nodes n and m move independently, $\mathcal{A}_{m,n}^c(t)$ is the link availability when nodes n and m move in a correlated manner, and P_i is the probability that the two nodes are moving independently.

$$\mathcal{A}_{m,n}^T(t) = \mathcal{A}_{m,n}^i(t) P_i + \mathcal{A}_{m,n}^c(t)(1 - P_i) \quad (1)$$

$\mathcal{A}_{m,n}^i(t)$ is equivalent to the link availability as derived in [1]. This metric assumes independent movement, consequently, with respect to the total availability it reflects the case when $P_i = 1.0$ The error in the metric depends on the actual value of P_i and the characteristics of $\mathcal{A}_{m,n}^c(t)$. P_i depends upon the nature of the network application, the group properties of the nodes, the size of the population and the characteristics of the environment. In a very large ad-hoc network of nomadic users with few movement constraints—reflecting the service oriented scenario—it is reasonable to expect large values for P_i; however, if nodes travel frequently in groups, or are constrained to move in certain directions and speeds, smaller values for P_i would be expected—this reflects the application oriented scenario. The value of $\mathcal{A}_{m,n}^c(t)$ depends on the degree of correlation in movement. If two nodes move in lock-step with one another, we assume that $\mathcal{A}_{m,n}^c(t) = 1.0$ for all t.

Without specific knowledge of the environment, or knowledge of how two nodes are related it is very difficult to quantify correlation and even more difficult to reflect this correlation quantitatively in the analytical framework for node mobility. The objective is to define criteria for deciding that a pair of nodes are moving in a pattern that establishes a stable link between them, and to adaptively *bias* the random independent metric to reflect this assumed association. A reasonable criteria should have limited risk without being overly conservative. ABR adopts a similar approach; however, cannot reflect actual mobility characteristics or minimize the cost associated with incorrectly assuming nodes are associated. It applies a two-state model which tracks the time that a pair of nodes remain adjacent. If $t < t_{thr}$, where t_{thr} is a predefined threshold value, then effectively $\mathcal{A}^{T}_{m,n}(t) = 0$. However, if $t \geq t_{thr}$, then the nodes are assumed to be *associated*, effectively making $\mathcal{A}^{T}_{m,n}(t) = 1$.

Based on the approach used in ABR two question arise. First, how should the value of t_{thr}, which is the criteria for assessing link stability, be determined? To reflect the dynamic mobility characteristics of different nodes we observe this value should be adaptive. Second, how can we limit the risk of incorrectly asserting that a pair of nodes are associated? We propose a model for enhancing the link availability metric that adopts a similar approach, yet addresses both of these questions. Each node must specify its own value for the application dependent system parameter, P_i. A node operating in a tightly coupled group, or a vehicle moving on a highway should specify a relatively *small* value for P_i; whereas, a nomadic user in an un-obstructed environment should specify a *higher* value for P_i. Evaluation of this metric consists of modulating the independent link availability, $\mathcal{A}^{i}_{m,n}(t)$, according to a continuous approximation of a two-state model; specifically, the model is based upon characterization of the following two operational *modes* with respect to the links:

1. **Associated Mode:** The link has survived significantly longer than expected; consequently, the node movement is assumed to be correlated.
2. **Independent Mode:** The default case when nothing else is known about the nodes. Link availability is evaluated according to the independent model.

The idea is to initially assume that the endpoints of a link are moving independently, and to evaluate the link availability based on the independent model, $\mathcal{A}^{i}_{m,n}(t)$. Any link which survives longer than its expected *time-to-failure* begins to gradually transition into *Associated Mode* based upon an exponential smoothing function. If the transition is excessively abrupt, there is a greater chance of making an error. However, if the availability is sufficiently small, such that *very few* independent pairs survive this long, the overall risk of making an error is lower. Consequently, the rate of this function depends on the elapsed time since the expected *time-to-failure* and the magnitude of the *Independent Mode* availability.

Let $\mathcal{A}'_{m,n}(t)$ be an approximate model for $\mathcal{A}^{c}_{m,n}(t)$, ($\mathcal{A}'_{m,n}(t) \approx \mathcal{A}^{c}_{m,n}(t)$), and $MTTF$ be the expected (mean) *time-to-failure* for a given link. Equation-1 shows how to evaluate the enhanced link availability metric given that each node specifies P_i, and $\mathcal{A}'_{m,n}(t)$ is evaluated as follows:

$$\mathcal{A}'_{m,n}(t) = (1 - \exp(-\lambda\Delta) + \mathcal{A}^{i}_{m,n}(t)\exp(-\lambda\Delta) \quad (2)$$

$$\Delta = max(0, t - (t_0 + MTTF)) \quad (3)$$

$$\lambda = 1 - \mathcal{A}^{i}_{m,n}(t) \quad (4)$$

For all time $t \leq (t_0 + MTTF)$, availability is evaluated directly according to the independent model. This value monotonically decreases as time progresses. However, starting at time $t = (t_0 + MTTF)$, this decrease begins to be offset by an amount which varies from $(1 - \mathcal{A}^{i}_{m,n}(t))$ to 1. The amount of this offset increases with time and the magnitude of $(1 - \mathcal{A}^{i}_{m,n}(t))$. As $t \to \infty$, $\lambda \to 1$ and $\Delta \to \infty$, $\mathcal{A}'_{m,n}(t) \to 1$, the desired value for associated nodes. It is assumed that a pair of adjacent nodes with highly correlated movement have a *correlated* link availability, $\mathcal{A}^{c}_{m,n}(t) = 1$, for all t. Consequently, $\mathcal{A}'_{m,n}(t)$ is designed to approach this value as $t \to \infty$.

To complete the development of this model we must evaluate the $MTTF$ for each initial condition described in [5] and summarized below: Depending on the initial status and location of nodes n and m, two cases of link availability are identified. Assuming node n is active at time t_0, the theorems in [5] characterize the link availability between two mobile nodes, n and m, as reflected by the following initial conditions:

1. Node Activation: Node m activates at time t_0 at a random location within range of node n.
2. Link Activation: Node m moves within range of node n at time t_0 by reaching the boundary defined by R_{eq}, and is located at a random point around the boundary.

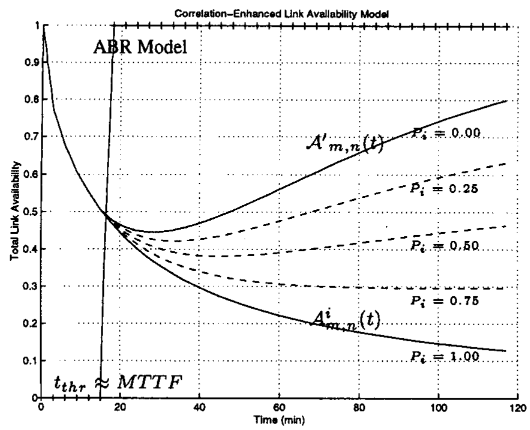
The analysis in [8] presents the derivation of the the distance, Z, a mobile node must travel before reaching the boundary of a cell with an effective radius of R_{eq}, when the mobile moves in a random uniform direction. Distributions of Z are derived for cases which are equivalent to the two cases described above. It is shown in [5] that link availability is equivalent to the probability that the equivalent random mobility vector [2], $\vec{\mathcal{R}_{m,n}}(t)$, is less than or equal to Z.

Expressions for $MTTF$ are derived by equating the expected value of $\vec{\mathcal{R}_{m,n}}(t)$ to the expected value of Z and solving for t. Let $< \lambda_n, \mu_n, \sigma_n^2 >$ and $< \lambda_m, \mu_m, \sigma_m^2 >$, be the random ad-hoc mobility profiles of node n and node m, respectively. Note, the profiles reflect the mean and standard deviation of the speed and rate of direction change under the random mobility model [5]. The distribution of $\vec{\mathcal{R}_{m,n}}(t)$ is given in [5]. The expected value for this distribution can then be expressed as follows:

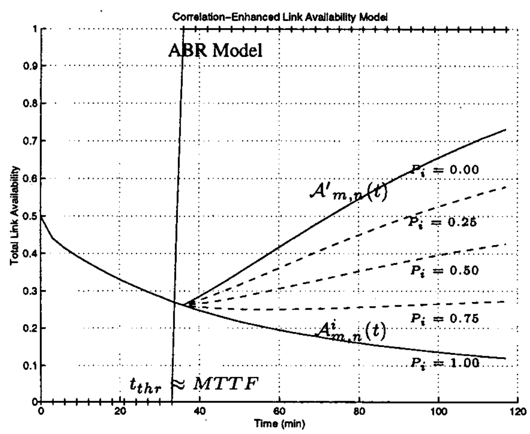
$$E[\vec{\mathcal{R}_{m,n}}(t)] = \sqrt{\frac{\pi t}{2}\left(\frac{1}{\lambda_m}(\sigma_m^2 + \mu_m^2) + \frac{1}{\lambda_n}(\sigma_n^2 + \mu_n^2)\right)} \quad (5)$$

Let the distribution of Z according to the node activation case be given by $Z_{Node\_Activation}$ and the distribution according to the link activation case be given by $Z_{Link\_Activation}$. Both distributions can be found in [1]. The expected values for each of these distributions can be expressed as follows:

[2] *The equivalent random mobility vector* characterizes the relative movement of one node with respect to the other over an arbitrary interval of time.



(a) Node Activation



(b) Link Activation

Figure 1: Enhanced Link Availability Metric: $\mathcal{A}^T_{m,n}(t)$.

$$E[Z_{Node\_Activation}] = \frac{8R_{eq}}{3\pi} \quad (6)$$

$$E[Z_{Link\_Activation}] = \frac{4R_{eq}}{\pi} \quad (7)$$

Assuming a homogeneous scenario in which $\lambda_n = \lambda_m = \lambda$, $\mu_n = \mu_m = \mu$, and $\sigma_n^2 = \sigma_m^2 = \sigma^2$, the MTTF for each case is expressed in terms of the mobility parameters as follows:

$$MTTF_{Node\_Activation} = \frac{64R_{eq}^2}{9\pi^3}\frac{\lambda}{\sigma^2 + \mu^2} \quad (8)$$

$$MTTF_{Link\_Activation} = \frac{16R_{eq}^2}{\pi^3}\frac{\lambda}{\sigma^2 + \mu^2} \quad (9)$$

Figure-1 illustrates results from the enhanced link availability model, $\mathcal{A}^T_{m,n}(t)$, for values of P_i ranging from 0.0 to 1.0. In the example two identical nodes moved with the same mobility profiles at a mean speed of 10 kilometers-per-hour (kph) with distance threshold $R_{eq} = 1.0$ kilometers (km). Figure-1(a) compares the results when the initial condition was node activation, and Figure-1(b) when the initial condition was link activation. The results are compared to an example of the ABR model in which it is assumed that $t_{thr} \approx MTTF$. The figure shows that $\mathcal{A}^T_{m,n}(t)$ reduces to $\mathcal{A}^i_{m,n}(t)$ when $P_i = 1.0$, and to $\mathcal{A}'_{m,n}(t)$ when $P_i = 0.0$. It also shows how the ABR result shifts its view of link stability abruptly from one extreme to the other based on the value of t_{thr}. Depending on the value of t_{thr}, the strategy used in ABR will do better when the nodes are actually highly correlated; however, the cost may be high when the nodes are not actually correlated because there is no way to limit the probability of an incorrect decision.

The region in both figures which lies to the left of $MTTF$ defines *Independent Mode* operation; whereas, the region to the right of $MTTF$ defines *Associated Mode* operation. Prior to reaching $MTTF$, the curves for $\mathcal{A}^T_{m,n}(t)$ are identical regardless of the value of P_i. However, if the link survives beyond $MTTF$, it becomes less risky to assert that two nodes are moving together. Consequently, the figures demonstrate a gradual increase in confidence that a link is *more stable* than if its endpoints truly moved independently. The parameter P_i places an upper limit on how this effects the resulting availability metric, since it reflects an application and environmental based probability that a given node exhibits group mobility.

In contrast to the random-independent model in which link availability decreases with time, using the proximity model link availability increases beyond $MTTF$. $\mathcal{A}^T_{m,n}(t)$ effectively represents a conditional probability that reflects increasing confidence in the stability of a link. If $P_i = 0.0$, $\mathcal{A}^T_{m,n}(t) \to 1$, as $t \to \infty$, which approaches the ABR model over time; whereas, if $P_i = 1.0$, $\mathcal{A}^T_{m,n}(t) \to 0$, which *is* the independent result. These results agree with the design objectives of the model.

With proper specification of P_i, $\mathcal{A}^T_{m,n}(t)$ can achieve benefits through the detection of associated movement patterns; however, it is not possible to detect negative correlation without a-priori information. Consequently, a third *mode*, referred to as *Transit Mode*, is proposed to reduce the cost associated with routing over potentially *short-lived* links. A link with a $MTTF$ that is significantly *less* than the mean $MTTF$ of the remaining links incident to the same node, will effectively be removed from the routing process by setting $\mathcal{A}^T_{m,n}(t) = 0$ for all t. Thus, only the strongest links will be used for routing.

IV. Conclusions

In this paper a node proximity model was developed that is designed to efficiently compute a metric that reflects future link stability based on minimum information. The model combines the features of the probabilistic approach of the random independent model proposed earlier, with a stability threshold based approach similar to ABR; however, the strategy proposed here adaptively selects the threshold and utilizes an exponential fading approach to minimize the *cost* associated with incorrectly determining that a link is stable.

The strategy proposed in this paper is a component of work focusing on mobility-adaptive dynamic clustering in ad-hoc networks. The purpose of the metric is to define a low-overhead technique for improving the stability characteristics of our clustering algorithm that work well under a range of mobility scenarios. Our on-going work includes a simulation based performance analysis to assess the quality of this new metric relative to the original random-independent metric and to the step-function approach.

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