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Connectivity Model for Mobile Ad-Hoc Networks

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***Abstract*—We propose a probabilistic connectivity model suitable for imitating link connectivity in large mobile ad hoc networks. The model is based on a two state Markov chain and captures the vital aspects that successive connectivity states exhibits dependence, and that link connectivity is a function of distance between transmitter and receiver. The maximum likelihood estimator is used to estimate parameters from measurement data. The model is found to outperform the common fixed range connectivity model.**

***Index Terms*—connectivity, model, markov chain, MANET**

I. Introduction

Mobile ad hoc networks (MANETs) offer advantages due to their flexibility, ease of deployment and self-management ability. MANETs can provide connectivity where infrastructure based networks are unavailable or infeasible. High specialization of the MANET is often required to meet the communication requirements, which may span from low power sparse communication in networks tracking nomadic animals, to high throughput low latency communication in tactical military operations. Thus, communication protocols and applications will need to adapt to the prevailing conditions which affect the wireless communication link between transceivers of the MANET. We consider link connectivity to be the description of whether a transmission from transmitter to receiver can be performed successfully. In analytical and simulation based research and development a model of the link connectivity is an essential component in the design of e.g. MAC and routing protocols [1], [2].

Modeling the link connectivity has been done at different levels of complexity following different approaches. Common for the approaches is a dependence on device positions from which distance between devices can be derived. Wymeersch et al. [3] used a fixed range disc connectivity model as a basis for cooperative localization in which devices are able to communicate when the Euclidean distance between them is below a threshold. Hwang et al. [4], Ferreira et al. [5] and Naushad et al. [6] utilize the same fixed range connectivity model, but extend the connectivity model to include the mobility model, providing a stochastic description of connectivity over time. Mesbahi and Dahmouni [7] also account for interference from simultaneous transmissions in their evaluation of link and path lifetime.

Savic and Zazo [8] specify the probability of connectivity as an exponentially decaying function of distance in which transmission range is a parameter and use it for localization. Gorce et al. [9] propose a similar probabilistic model and base the connection probability on deterministic signal loss due to propagation and probabilistic bit error rate which is affected by shadow and multi-path fading. However, neither of [8] and [9] consider a temporal dependence in the link connectivity. Song et al. [10] propose a two state Markov model to describe the connection state of a link over time and derive a link stability estimator. They assume that the state transitions are fixed in a confined amount of time due to a slow moving or stationary network, and are concerned with determining the state transition probabilities.

Numerous measurement campaigns have been performed to calibrate fading and propagation models, which can in term be used to model link connections as proposed by Gorce el at. However, as pointed out by [11], the data used in such calibration is often censored, i.e. missing data due to a disconnected link, where the signal strength had fallen below the measurement equipment sensitivity. While this might lead to adequate modeling of the non-censored links, the connectivity might be overestimated [12].

In this paper, we formulate a connectivity model based on connectivity data from a large scale MANET measurement campaign, rather than relying on a combinatorial model based on distinctly defined models for pathloss, fading, noise, interference, bit error rate, mobility pattern and/or connectivity range. Thereby, we achieve a lightweight model, suitable for most analytical and simulation based studies, which maintain an ability to mimic link connectivity in a MANET with a high degree of realism. Specifically, the contribitions of this paper are:

- We propose a connectivity model which captures the temporal aspects of link connectivity in a wireless mobile ad hoc network.
- We formulate the maximum likelihood estimator for the proposed model and estimate parameters based on a comprehensive measurement campaign.
- We show that the proposed model outperforms the fixed range connectivity model in terms of connection probability and uninterrupted connection duration.

II. Connectivity Model

We consider a broadcasting system where devices transmit and receive packets over a wireless medium. A receiving device is connected by a link to a transmitting device if it is able

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to receive (that is decode without error) the broadcast from that particular transmitter. Otherwise, the link is disconnected. As the packets are transmitted periodically, the state of the link is observed in discrete time steps, as illustrated in Figure 1. The state of a link is governed by the ratio between the power of the signal in which the packet is encoded and the power of any noise and interference along with the specific detection performance of the receiver. The major component affecting the power of the received signal, is the distance between transmitter and receiver. Note, that links between two transceivers are not reciprocal, since the noise and interference conditions depend on spatial placement of the transceiver.

A. *Proposed model*

We propose a two state discrete time Markov chain model. At fixed link distances, the Markov chain is time homogeneous, and the state transition matrix and stationary distribution vector expanded below have row sums equal to one,

$$\mathbf{P} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \qquad \boldsymbol{\pi} = \begin{bmatrix} \pi_0 & \pi_1 \end{bmatrix} \tag{1}$$

Since the stationary distribution fulfills $\boldsymbol{\pi} = \boldsymbol{\pi}\mathbf{P}$, specification of the two state Markov chain requires only specification of one of the transition probabilities and one of the stationary probabilities.

We observe in the data that connection probability is low at long distances, e.g. due to path loss. At very short distances the connectivity is low when the received signal power is high enough to saturate the receiver. Therefore we propose the following two parameter exponential model for the stationary probability of being in a connected state,

$$\pi_1(d) = \exp(-d^2/\alpha - \beta/d) \tag{2}$$

We assume for simplicity that the transition probability between connected and unconnected states is independent of distance, thus we set p_{10} constant.

The remaining Markov chain parameters can be expressed in terms of π_1 and p_{10} as follows

$$\begin{array}{ll} \pi_0(d) = 1 - \pi_1(d), & p_{00}(d) = 1 - p_{01}(d) \\ p_{01}(d) = \frac{\pi_1(d)p_{10}}{1-\pi_1(d)}, & p_{11}(d) = 1 - p_{10} \end{array} \tag{3}$$

In summary, the proposed models leave three scalar real parameters for estimation: $\theta = (\alpha, \beta, p_{10})$

An important metric related to the connectivity model is the contiguous time a connection is maintained between two devices. For a given link between two devices, let the random variable X describe the contiguous time steps in which the link remains in a connected state (also denoted as the sojourn time in the connected state, the link lifetime or the connection duration). Given the Markov property it is straight forward to show that X follows a geometric distribution with cdf

$$F_X(x) = p_{10} \sum_{n=1}^{x} (1 - p_{10})^{n-1} \tag{4}$$

B. *Maximum likelihood estimation*

To estimate θ, we consider measurements of connectivity taken from a multi-link communication system at discrete time instances. Measurements of N links are acquired at $I + 1$ discrete instances. From link $l^{(n)}$ we record a set of connection states at given distances between transmitter and receiver.

$$l^{(n)} = \{(c_i^{(n)}, d_i^{(n)})\}, \quad n = 1, 2, \ldots, N, \quad i = 0, 1, 2, \ldots, I, \tag{5}$$

where $c_i^{(n)} = \{0, 1\}$ is the connection state, and $d_i^{(n)}$ is the distance between transmitter and receiver of link $l^{(n)}$ at time step i. The probability mass function of the link connection state is fully specified as:

$$\begin{array}{ll} \begin{array}{l} P(c = 1|d_i) = \pi_1(d_i) \\ P(c = 0|d_i) = 1 - \pi_1(d_i) \end{array} & i = 0 \\ \begin{array}{l} P(c = 1|d_i, c_{i-1}) = \begin{cases} p_{01}(d_i), & \text{if } c_{i-1} = 0 \\ 1 - p_{01}(d_i), & \text{if } c_{i-1} = 1 \end{cases} \\ P(c = 0|d_i, c_{i-1}) = \begin{cases} 1 - p_{01}(d_i), & \text{if } c_{i-1} = 0 \\ p_{10}(d_i), & \text{if } c_{i-1} = 1 \end{cases} \end{array} & i \geq 1 \end{array} \tag{6}$$

Assuming that link states are independent, and depend only on the previous state (Markov property), the likelihood for θ based on observations from all links reads

$$P(l_1, l_2, \ldots, l_N; \theta) = \prod_{n=1}^{N} P(c_{n0}|d_{n0}) \prod_{i=1}^{I} P(c_{ni}|d_{ni}, c_{ni-1}) \tag{7}$$

The maximum likelihood estimate $\hat{\theta}_{\text{MLE}} = \arg\max_{\theta} P(l_1, l_2, \ldots, l_N|i, \theta)$, is easily computed numerically.

III. Model Calibration and Discussion

We calibrate the model based on data collected from a measurement campaign performed in the Philippines. A set of transceivers were configured to broadcast a beacon at a fixed interval. Transceivers would log reception of beacons and GPS position, from which it is straight forward to deduce the link connection states and link distances, as illustrated in Figure 1, where crosses mark the position of a transceiver, red lines indicate the movement of the transceiver since the previous measurement and the grey lines indicate connections. For further details on the measurement campaign, refer to [12]. Applying the maximum likelihood estimator on the data yields the values in Table I. A low relative standard deviation of the estimate is achieved. Figure 2 illustrates traces of two links. The black line indicates the separation distance between transmitter and receiver. The colored underlay indicates the periods of connectivity based on data from the measurements and from simulation with the proposed model and the fixed range model. The upper link trace shows how the measured link is mostly disconnected when the link is only a few meters long. In the lower link trace the measured connectivity is highest when the link is between 50 m and 200 m. Connectivity on long links is less likely, but happens even at link distances around 400 m. The proposed model mimics the behavior from

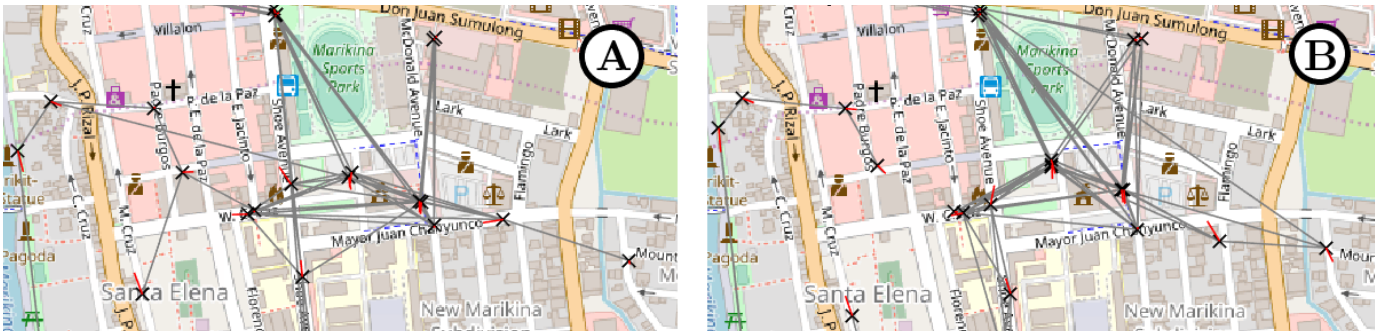

Fig. 1. Two successive instantiations of connectivity in the measurements. Red lines indicate the movement since previous instance. Grey lines indicate connectivity and crosses indicate the devices. Note that some links appear from A to B

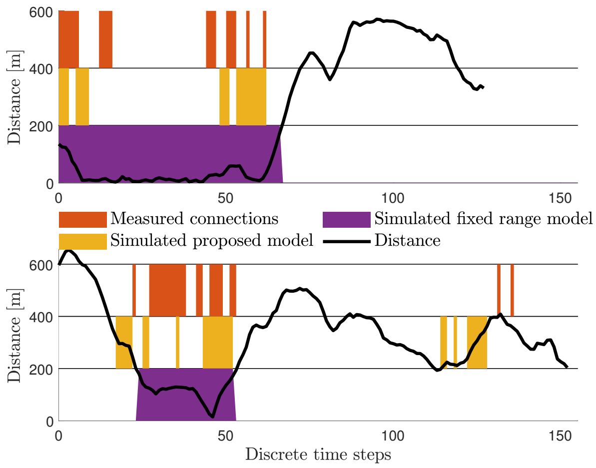

Fig. 2. Link distance and connectivity for two selected links. The black line indicate the link distance. The underlay of colored bars illustrate the connection of three connectivity traces: One based on the data, one based on simulation of the proposed model and one based on simulations of the fixed range model. Both models were parameterized by the data.

TABLE I
MAXIMUM LIKELIHOOD ESTIMATES OF PARAMETER VALUES

Parameter	Value	Estimator standard deviation (relative to value)	
$\hat{\alpha}$	$4.6 \cdot 10^4$	580	(1.3%)
$\hat{\beta}$	10.2	0.25	(2.5%)
$\hat{p}_{10}$	0.2	$2.5 \cdot 10^{-3}$	(1.3%)

the measurements; connectivity is intermittent at short link distances and interrupted at medium distances. Conversely, the fixed range model provides continuous connectivity when links are shorter than 180 m.

A. Validation and Discussion

From the data, the empirical stationary probability of link connection versus distance is calculated as the ratio between connected links and total number of links using a kernel smoothing function. Let C be the set of data where the links are connected and D the set of data where the links are disconnected, such that the union of C and D is the complete data set. The empirical stationary probability of link connection versus distance can be estimated as

$$\hat{\pi}_1(d) = \frac{\hat{f}_C(d) \cdot |C|}{\hat{f}_{C \cup D}(d) \cdot |C \cup D|} \tag{8}$$

where $|\cdot|$ denotes set cardinality and $\hat{f}_{\bullet}(d)$ is the probability density estimate calculated by kernel smoothing with a normal kernel function. The resulting estimate, $\hat{\pi}_1$, is illustrated in Figure 3. For comparison we plot the model of (2) where $\hat{\alpha}$ and $\hat{\beta}$ are estimated based on the data, and the simple model of having a fixed communication range, $\ddot{\pi}_1(d)$

$$\ddot{\pi}_1(d) = \begin{cases} 1, & \text{if } d < 180\,\text{m} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

The proposed model produces stationary connection probability with far better fit to the data when compared to the common fixed communication range model. The proposed model overestimates slightly the connection probability at large link distances. However, at the shortest link distances, due to the model assuming disconnection at zero length links, the model underestimate the connection probability.

To illustrate the effect of the model parameters, variations of the estimated parameters $\hat{\alpha}$ and $\hat{\beta}$ are plotted in Figure 4. The parameter β is seen to control the connection probability at short distances, while α adjusts the decay of connection probability.

The ecdf of the contiguous time steps a link remains in a connected state (connection duration), $F_{\hat{X}}(x)$, is estimated based on the data and plotted in Figure 5. We simulate connectivity states on links based on the link distances from the data and the model parameters described in Table I. To observe the spread, the cdfs of all 100 realizations are plotted in Figure 5 along with the combined cdf from all simulations, $F_{\bar{X}}(x)$. In addition, we plot the cdf obtained from simulation with the fixed length communication range model, $F_{\ddot{X}}(x)$. The connection duration cdf produced by simulation

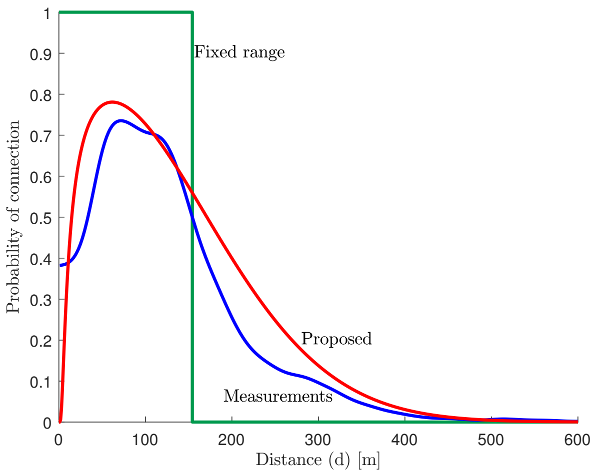

Fig. 3. Stationary probability of connection from the data, $\hat{\pi}_1(d)$, proposed model (2) with parameters estimated based on the data, $\check{\pi}_1(d)$, and a fixed communication range model, $\ddot{\pi}_1(d)$.

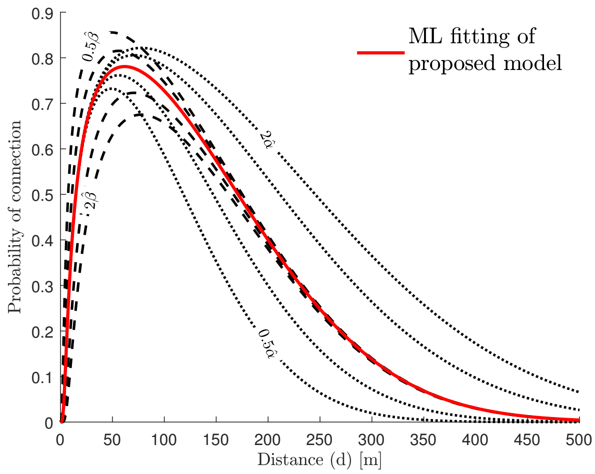

Fig. 4. Variations to the estimated parameters $\hat{\alpha}$ and $\hat{\beta}$ in the model for stationary probability, $\check{\pi}_1(d)$, are plotted in dotted and dashed lines, respectively.

with the proposed model has a negligible bias towards longer connection durations compared to the data and produce a much closer fit than the fixed range model. The implications of varying the transition probability, $\hat{p}_{10}$, can be seen in Figure 6, where the cdf of contiguous connection duration is obtained from simulation with various values of $\hat{p}_{10}$. The ecdf obtained through simulations relies on the mobility data from the measurement campaign, in which some devices suffered from sporadic loss of GPS signal, i.e. absence of link length and therefore undefined connection state. This effect explains the slight variation from the theoretical cdf. As expected, a lower transition probability from connected to disconnected state results in longer link connections. By halving p_{10}, the cdf approaches that produced by the fixed communication range model.

Multi-hop connectivity is a key target in mobile ad hoc networks. Therefore, we plot in Figure 7 the cdf of 2-hop connection duration obtained from measurements, and simulations with the fixed range and proposed models. Even though our model is not explicitly designed to consider multi-hop connectivity we observe a close agreement of the proposed model with the measurements. In contrast, the fixed range model overestimates the the 2-hop connection duration.

IV. Conclusion

Link connectivity in a mobile ad hoc network is modeled based on a two state Markov chain. The stationary connection probability is specified to depend on distance between transmitter and receiver. The maximum likelihood estimator is available and model parameters are estimated based on data from a mobile ad hoc network measurement campaign. Our proposed model, unlike the fixed range connectivity model, accurately reproduce the connection lengths of both 1- and 2-hop connections and connection probabilities observed in the data, despite its simplicity and three parameter design.

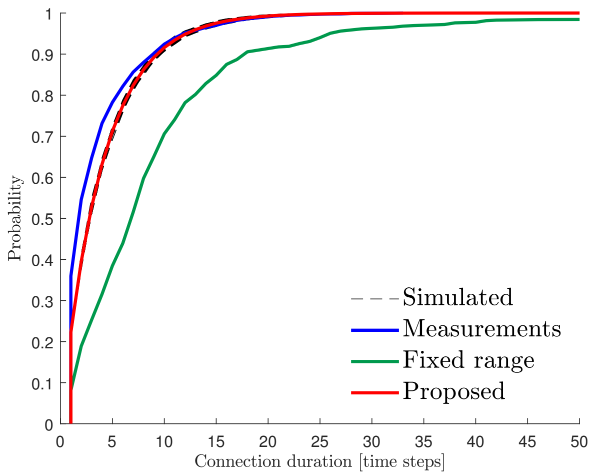

Fig. 5. Cdfs of connection duration as obtained from measurement data ($F_{\hat{X}}(x)$), simulations with the fixed range model ($F_{\ddot{X}}(x)$), simulations with proposed model ($F_{\bar{X}}(x)$) and the spread observed in 100 simulated realizations.

Parameter estimation and especially simulation with the model is computationally efficient.

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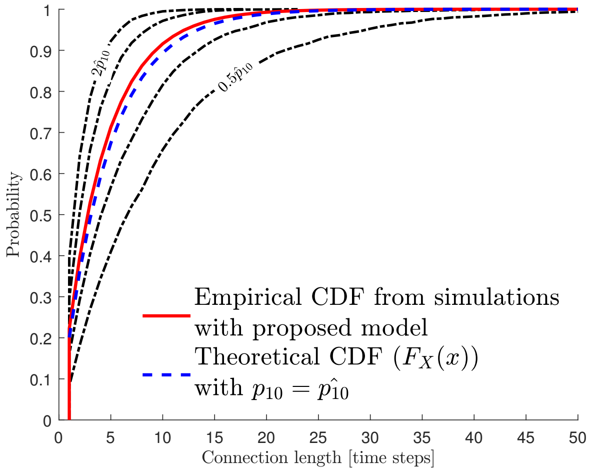

Fig. 6. Variations to the estimated parameter $\hat{p}_{10}$ in simulations of $F_{\tilde{X}}(x)$ are plotted in dotted lines.

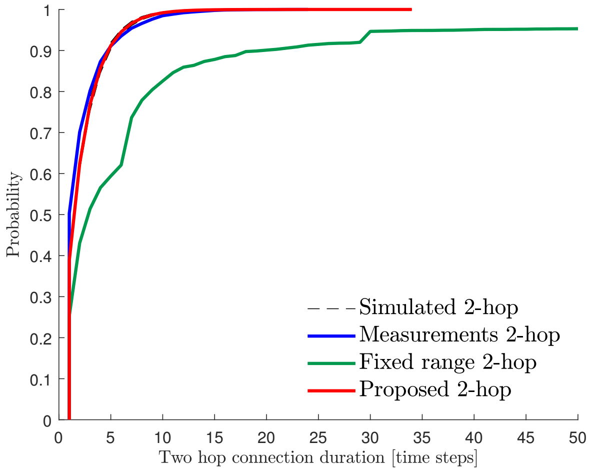

Fig. 7. Cdfs of 2-hop connection duration as obtained from measurement data, simulations with the fixed range model, simulations with proposed model and the spread observed in 100 simulated realizations for both 1- and 2-hop connections.

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