Feasible Link Statistics for Adaptive Ad Hoc Networks

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***Abstract*— The dynamic nature of ad hoc networks advocates the use of adaptive schemes to optimize network performance. Such adaptive schemes require local observations of prevailing network conditions. This paper discusses the dependencies between locally observable metrics. The probability density functions for link statistic metrics are assessed, and the implications of the distribution model for parametric inference is investigated.**

I. Introduction and Motivation

A mobile ad hoc network is a collection of wireless mobile nodes that dynamically form a temporary network on an as needed basis without the use of any existing network infrastructure. The resulting network is a non-hierararchical distributed system. All nodes of the network act as routers and forward received packets to nodes within radio range. The network can grow, reduce in size or fragment in real-time without referencing any central authority [1].

Routing protocols facilitate peer-to-peer communication by routing packets according to a set of rules [2], [3], [4]. Parameters in the routing protocol define the exact protocol implementation. Routing in ad hoc networks is a challenge due to the dynamic topology, and so analysis of link statistics can reveal information about underlying characteristics.

A wide body of work exists in the area of ad hoc network routing and it is well established in the literature that adapting routing protocol parameters to the prevailing network conditions can optimize network performance [5], [6], [7], [8]. Existing algorithms use locally observable link statistics such as *link duration* (LD) or *link change rate* (LCR) to trigger adaptivity in the routing protocol. The importance of link statistics in adaptive schemes is discussed in Section II, and examples of existing work in the area are given. In Section III, the locally observable link statistics are defined. This paper investigates two important issues regarding the use of the LCR and LD metrics to infer link stability in an adaptive scheme. The dependence of the observed LCR metric on *node degree* (ND) is examined, and a maximum likelihood approach to the inference of link stability is proposed. The LD metric is implemented in a windowed analysis. Such an approach has been advocated in the literature [5], however remains unexplored until now. The LCR and LD distributions are discussed in terms of maximum likelihood estimation of their parameters. The role of both the observed ND and the distribution model are investigated in terms of adequately identifying the underlying p.d.f.. Section V discusses these points.

II. Background

Ad hoc network performance depends to a large extent on the routing protocol. Relative node movement causes the failure of existing communication links, and enables the creation of new communication links between nodes. Routing protocols must react to the changing topology to maintain communication.

Proactive protocols use periodic beacons to gather neighbourhood information and then disseminate topology information throughout the network either periodically or in response to observed local topology changes.

Reactive protocols generally differ quite significantly from proactive protocols in that they do absolutely nothing until there is a demand for a route from a node. These demand-driven protocols react to requests for a route by flooding the network with requests for routing information to the specified destination. Route requests are responded to with route replies. Replies may come from either the requested destination node or from an intermediate node that has routing information about the requested destination in its route cache. The means by which request and replies are generated and processed differs from protocol to protocol.

Boleng *et al* [5] suggest using the LD metric to proactively adjust the route request (RREQ) timeout parameter for the reactive DSR protocol. Gerharz *et al* [8] examine the LD metric to identify stable links for routing. In [6], Samar and Wicker adapt the frequency of routing updates in a proactive routing protocol in response to link change statistics.

As these examples show, there is a growing interest in the field of adaptive schemes, and adequate knowledge of the advantages, artefacts and dependencies of locally observable metrics is required to accurately infer network conditions.

III. Local Observations

The distributed environment of ad hoc networks presents challenges to adaptive schemes. Bandwidth resources limit the dissemination of control information, and therefore nodes must adapt to locally observable metrics. The available literature [9], [10], [11] and our own simulations indicate the major factors affecting ad hoc network performance are node mobility, node density and traffic conditions. This paper focuses on the relevance of node mobility and node density in an adaptive scheme.

In terms of network density, average ND is a local proxy measure. ND can be defined as the number of one-hop neighbors of a node. As per the OLSR and DSR specifications [4], [3], we make use of the option to rely on neighbour sensing capabilities of the underlying MAC layer. In this way we can assume knowledge of accurate link statistics.

Mobility in the ad hoc network causes link instability. Local link statistics such as LCR and LD can be used by a node to infer the stability of communication links. The LCR metric is defined as the number of communication links forming and breaking between nodes over a given time T_{lcr}. The LD metric describes the lifetime of communication links.

Link statistics are used to infer the prevailing link stability, thus allowing a node to adapt protocol parameters accordingly. The framework requires a measure of link behaviour for the recent past. A *window* is defined as the period of time, T_w, in the recent past, within which measurements of link statistics are recorded. A windowed analysis of link statistics allows the observed metrics to respond to changing conditions, and limits their reliance on historical, out-of-date, link behaviour.

The LCR metric can easily be evaluated if the window time, T_w, is an integer multiple of the LCR period, T_{lcr}. The evaluation of the LD metric in a windowed analysis is more complicated, as it involves *censoring* of the lifetime data [12]. The average windowed LD is defined as the average duration of all links that either failed within the window period or that still exist. Censoring of data implies that the window size affects the observed p.d.f., and therefore the p.d.f. of link durations with an infinite window size is not representative of the data obtained in a windowed analysis.

The empirical probability density functions for the locally observable link statistics are analyzed for varying levels of mobility and node density. These empirical p.d.f.s characterize the link stability, and so the task of inferring the performance of a network in terms of link stability reduces to inferring the underlying link statistic p.d.f.. Approximations to the observed distributions of LCR and LD allow for maximum likelihood estimation (MLE) of the underlying distribution parameters, thus identifying the prevailing network scenario. Θ is the set of all possible parameters indexing a probability density function. Local observations are denoted by X. The MLE $\hat{\theta}$ is the $\theta \in \Theta$ that maximises the likelihood function $f(X|\theta)$. Notationally,

$$\hat{\theta} = \arg\max_{\theta} f(X|\theta) \tag{1}$$

ND information is often overlooked when implementing adaptive schemes. Link statistics yield information on the stability of links in the current ad hoc environment. ND information is required to assess the impact of link instability on the communication potential of the node. Furthermore, ND is also relevant to the correct analysis of LCR data, as shown in Section V-B.

IV. Experimental Design

Simulations are performed using a real ad hoc network, known as the Dublin Ad hoc Wireless Network (DAWN) [13]. DAWN was designed and created to facilitate research in the area of ad hoc networking. At the core of DAWN is a dynamic modular communication stack that runs on each of the nodes of the ad hoc network. Layers of the stack can be independently designed in a standalone fashion. A generic layer interface allows the dynamic assembly of these layers to form a network communication stack consisting of the relevant hardware and software elements. The inter-layer interface is very simple, consisting of primitives to send information upwards or downwards through the stack.

The physical medium is implemented in software, and models the movement of the nodes according to a *mobility model*. In all simulations, the random waypoint model on a torus [14] was used as the mobility model. This model ensures that the local observations of link statistics and average ND are spatially stationary. This is essential so that artefacts of the mobility model do not influence the results.

The global mobility is set by specifying node speed. Constant node speeds of 1m/s, 3m/s and 5m/s are used to simulate three different levels of mobility in the network. Specification of constant node speed eliminates transient behaviour in the simulations. The *pausetime* parameter of the mobility model is set to 0 seconds. Nodes are initially distributed randomly. The transmission range for all nodes is fixed at 250 metres, a figure commonly used and consistant with WLAN technology. Free space propogation is assumed.

Traffic is generated by constant bit-rate (CBR) sources that select a uniformly random destination for each packet. Packets are presented to the network layer every 5 seconds, and traffic density is dictated by the number of nodes acting as CBR sources. The DSR routing protocol [3] is used to route packets in the network. The number of nodes is fixed at 20, of which 5 are CBR sources. The density of the network is controlled via the simulation area. To create dense conditions a smaller simulation area is used. Each mobility level is simulated using 10 different simulation areas, thus yielding 30 unique network scenarios. For each scenario, 10 trials of 1000 seconds are performed and local statistics for LCR, LD and ND are analyzed.

V. Results and Discussion

The observation models for the LCR and LD statistics are proposed in Section V-A. The dependency of observed link statistics on ND is highlighted in Section V-B, and an important artefact of the observation models is given in Section V-C.

A. Observation Models for Link Statistics

The Kolmogorov-Smirnov (K-S) goodness-of-fit test is used to examine the *null hypothesis* that the p.d.f. for LCR can be approximated well by a Gaussian distribution. The cumulative density function (c.d.f.) of the empirical LCR and the proposed Gaussian c.d.f. are analyzed, and the maximum deviation in their values (D) is noted. D is compared to a table of Kolmogorov-Smirnov quantiles which accept or reject the null hypothesis at different critical values. The sample size is 39, therefore the critical value at a 5% significance level is $1.36/\sqrt{39} = 0.2178$. The D value for all 30 scenarios is below the critical value, and therefore the null hypothesis is not rejected and the Gaussian distribution is a plausible model. Fig. 1 shows a typical empirical p.d.f. of LCR data, superimposed on the Gaussian approximation to the data.

Similarly, the K-S test is used to examine the null hypothesis that the p.d.f. for LD can be approximated well by a gamma distribution. The sample size is 51, therefore the critical value at a 5% significance level is $1.36/\sqrt{51} = 0.1904$. The D value for all 30 scenarios is below the critical value, and therefore the gamma distribution can be used as an efficient approximation to the LD distribution. Fig. 2 shows a typical empirical p.d.f. of LD data, superimposed on the gamma approximation to the data. The gamma distribution is commonly used to model lifetime data [12] and indeed is used by Zonoozi and Dassanayake in [15] to model cell residence time in a cellular environment.

It should be noted that the form of the p.d.f.s is dependent on the mobility model used to dictate movement in the network. The model used in these experiments guarantees spatial stationarity of link statistics throughout the simulation space. Real ad hoc networks may not be spatially stationary however, and the locally observed link statistic p.d.f. may change from region to region. Additionally, in a real ad hoc network the local observations may include data from regions exhibiting different mobility conditions. This data should be regarded as noise in the inference process, as inference of the predominant mobility level is required.

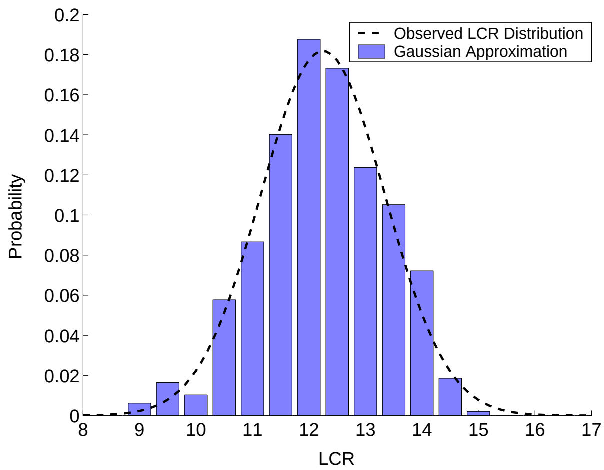

Fig. 1. Empirical LCR distribution and corresponding Gaussian approximation for scenario with $500 \times 500m^2$ area and $5m/s$ node speed.

B. Observation Metric Dependence

A thorough analysis of the dependencies between observable metrics is required for effective maximum likelihood estimation. In particular, the dependency between link statistics

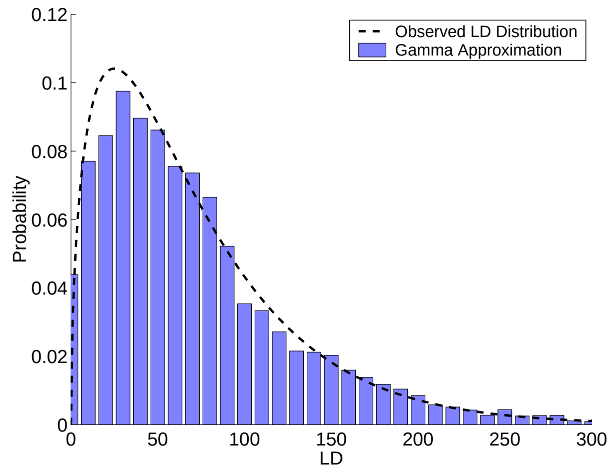

Fig. 2. Empirical LD distribution and corresponding Gamma approximation for scenario with $550 \times 550m^2$ area and $3m/s$ node speed.

and ND is analyzed. Observations of ND are denoted X_{nd}, yielding the likelihood function $f(X_{lcr}|\theta_{lcr}, X_{nd})$ for the LCR metric and $f(X_{ld}|\theta_{ld}, X_{nd})$ for the LD metric. θ_{lcr} and θ_{ld} are used to denote the realisation of LCR and LD distribution parameters respectively.

The observation of the LD metric is found not to depend on node degee. For each mobility level of $1m/s$, $3m/s$ and $5m/s$ the expected LD is plotted for the expected ND and shown in Fig. 3. Error bars show one standard deviation about the expected value. Thus the p.d.f. of observed LD is given by $f(X_{ld}|\theta_{ld}, X_{nd}) = f(X_{ld}|\theta_{ld})$.

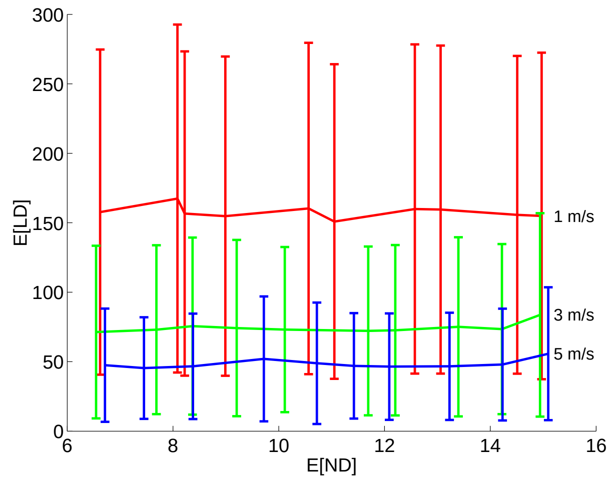

Fig. 3. Expected Link Duration versus Expected Node Degree for mobility levels of $1m/s$, $3m/s$ and $5m/s$

The observation of LCR is found to depend on the node degee. Intuitively, the more neighbours a node has, the more link changes can occur in a mobile environment. For each mobility level of $1m/s$, $3m/s$ and $5m/s$ the expected LCR is plotted for the expected ND and shown in Fig. 4. Error bars show one standard deviation about the expected value. The dependency of LCR on ND is shown to be linear, and the slope of the relationship is dictated by the mobility of the scenario. Thus the LCR metric must be used in conjunction with observed ND to accurately assess the link stability of the network.

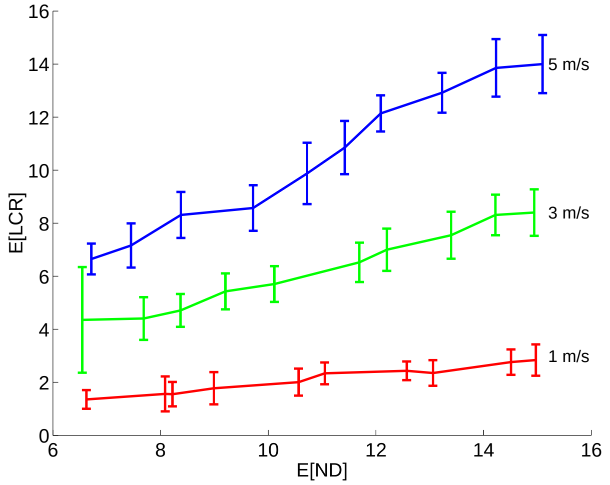

Fig. 4. Expected Link Change Rate versus Expected Node Degree for mobility levels of $1m/s$, $3m/s$ and $5m/s$

C. Observation Models and the Implications for Parametric Inference

It is shown in Section V-A that the LCR and LD data can be modelled with Gaussian and gamma distributions respectively. This section highlights the advantage of using the LCR metric rather than the LD metric due to the difference in distributional shape of the probability density functions.

Recall that the ultimate aim is to reliably infer the parameters of the LCR or LD p.d.f. using local observations. Maximum likelihood estimation involves evaluating the set of possible p.d.f.s at points dictated by the locally observed data. A p.d.f. is identified with greater certainty when it is unique among the entire set of possible p.d.f.s. As the probability density functions become more similar, the ability of the inference model to correctly identify the underlying distribution in the face of noise is diminished.

The Kullback-Leibler (K-L) divergence [16] is used to measure the average distance between observed distributions for both LCR and LD metrics. Three mobility levels of $1m/s$, $3m/s$ and $5m/s$ are analyzed. Probability density functions for the LCR and LD metrics in a $500 \times 500m^2$ simulation area are shown in Fig. 5. The average divergence between the LCR distributions for the three mobility levels is 106.6 while the average divergence between the LD distributions for the three mobility levels is 1.13. The values for the K-L divergence are an accurate reflection of the K-L values obtained in repeated tests using different node densities. The underlying LCR p.d.f. can therefore be inferred more accurately that the underlying LD p.d.f.. The results demonstrate an important advantage in using the LCR metric to assess link stability in ad hoc networks.

In practice, the accuracy of inference is also dependent on the number of samples indexing the p.d.f.. The number of samples available to index the LCR p.d.f. is T_w/T_{lcr}. The number of samples available to index the LD p.d.f. is equal to the number of links that either failed within T_w or that still exist. Therefore, the accuracy of the inference of LD is dependent on the number of links (ND).

VI. Conclusion

Local observations are crucial to the success of an adaptive ad hoc networking scheme. This paper has analyzed the probability distributions for the locally observable LD and LCR statistics. In a spatially staionary simulation space, the LCR distribution is found to be approximated well by a Gaussian p.d.f. while the LD is distributed according to a gamma p.d.f.. The dependence of link stability metrics on ND is described. While LD is independent of ND, LCR exhibits dependence on ND. Inference techniques using the LCR metric must take account of this dependency. The p.d.f.s of LCR and LD reveal an inherent advantage of the LCR metric in efficiently inferring link stability in the network. This artefact of the LD metric is subtle, yet it can have a major impact on the adaptive ability of the ad hoc network. This further highlights the importance of adequate research in the area of locally observable metrics.

As noted in Section V-A, a real ad hoc network may exhibit spatial non-stationarity of link statistics. This leads to noisy local observations of the LCR and LD metrics. Future work aims to investigate the effect of such scenarios on the observed LCR and LD distributions, with a view to modelling the noise and improving the accuracy of the inference process.

Acknowledgment

This work is funded by the Irish Research Council for Science, Engineering and Technology (IRCSET)

References

[1] C. E. Perkins, *Adhoc Networking*. Addison-Wesley, 2001.

[2] C. E. Perkins and E. M. Royer, "Ad-hoc on-demand distance vector routing," in *MILCOM '97 panel on Ad Hoc Networks*, 1997.

[3] D. B. Johnson and D. A. Maltz, "Dynamic source routing in ad hoc wireless networks," in *Mobile Computing*, Imielinski and Korth, Eds. Kluwer Academic Publishers, 1996, vol. 353, pp. 153–181.

[4] P. Jacquet, P. Mhlethaler, T. Clausen, A. Laouiti, A. Qayyum, and L. Viennot, "Optimized link state routing protocol," in *IEEE INMIC'01, 28-30 December 2001, Lahore, Pakistan*, IEEE. IEEE, December 2001.

[5] J. Boleng, W. Navidi, and T. Camp, "Metrics to enable adaptive protocols for mobile ad hoc networks," *In Proceedings of the International Conference on Wireless Networks (ICWN'02)*, pp. 293–298, 2002.

[6] P. Samar and S. B. Wicker, "On the behavior of communication links of a node in a multi-hop mobile environment," *Fifth ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, May 2004.

[7] C. Gomez, D. Garcia, and J. Paradells, "Improving performance of a real ad hoc network by tuning olsr parameters," in *10th IEEE Symposium on Computers and Communications (ISCC'05)*, June 2005, pp. 16–21.

[8] M. Gerharz, C. de Waal, M. Frank, and P. Martini, "Link Stability in Mobile Wireless Ad Hoc Networks," *In Proceedings of the 27th Annual IEEE Conference on Local Computer Networks*, pp. 30–42, 2002.

[9] S. R. Das, C. E. Perkins, and E. E. Royer, "Performance comparison of two on-demand routing protocols for ad hoc networks," in *INFOCOM (1)*, 2000, pp. 3–12.

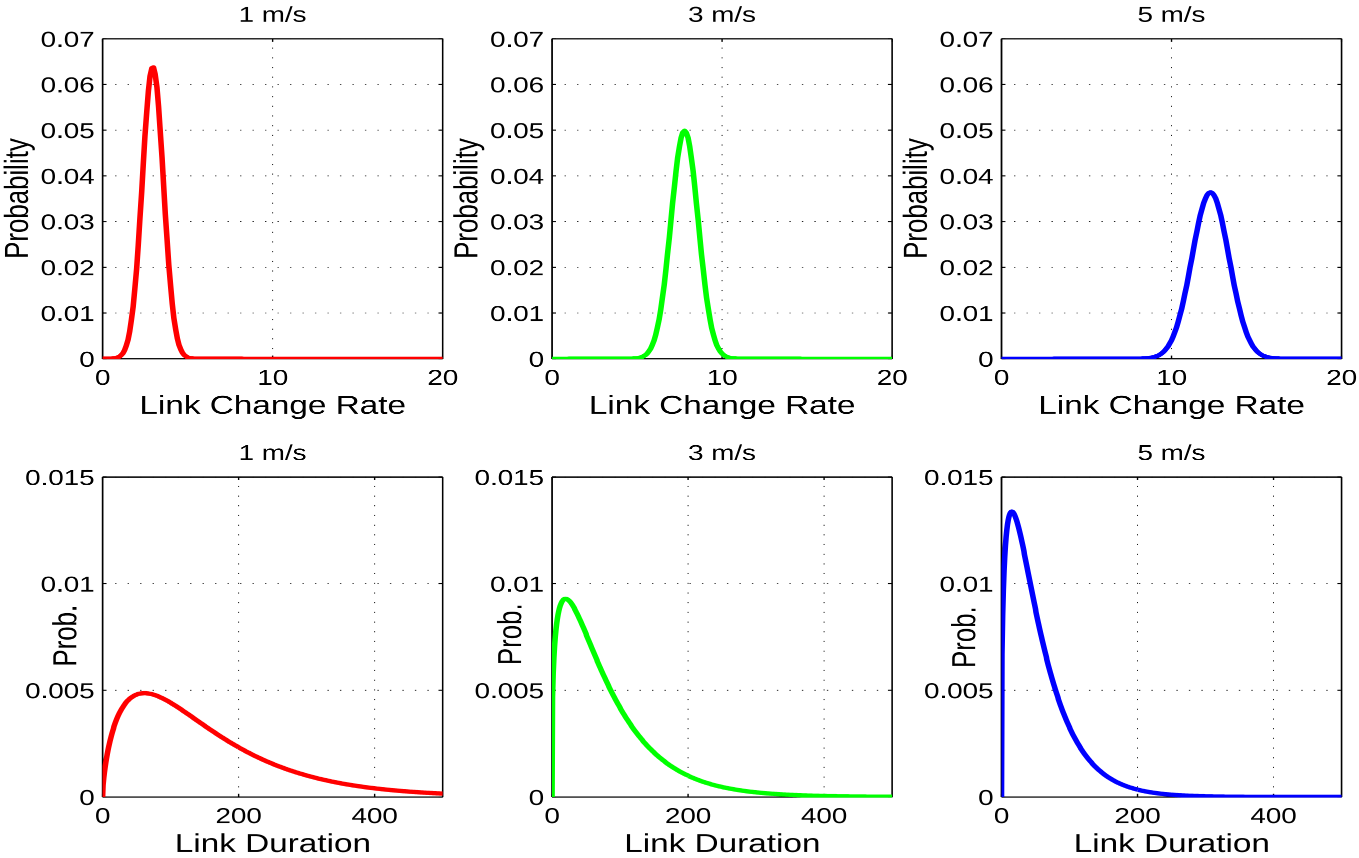

Fig. 5. Link Change Rate and Link Duration p.d.f.s for mobility levels of $1m/s$, $3m/s$ and $5m/s$ in a simulation area of $500 \times 500m^2$

[10] D. Perkins, H. D. Hughes, and C. B. Owen, "Factors Affecting the Performance of Ad Hoc Networks," *Proceedings of the IEEE International Conference on Communications*, vol. 4, pp. 2048–2052, 2002.

[11] T. Clausen, P. Jacquet, and L. Viennot, "Analyzing control traffic overhead versus mobility and data traffic activity in mobile ad-hoc network protocols," *ACM Wireless Networks journal (Winet)*, vol. 10, no. 4, July 2004.

[12] J. F. Lawless, *Statistical Models and Methods for Lifetime Data, 2nd Edition*. Wiley, New York, 2002.

[13] D. O'Mahony and L. Doyle, "An adaptable node architecture for future wireless networks," in *Mobile Computing: Implementing Pervasive Information and Communication Technologies*. Kluwer series in Interfaces in OR/CS, Kluwer Academic Publishers, 2002, pp. 77–92.

[14] G. Lin, G. Noubir, and R. Rajaraman, "Mobility models for ad hoc network simulation." in *INFOCOM*, 2004.

[15] M. Zonoozi and P. Dassanayake, "User Mobility Modeling and Characterization of Mobility Patterns," *IEEE Journal on Selected Areas in Communications*, vol. 15, no. 7, September 1997.

[16] S. Kullback and R. A. Leibler, "On information and sufficiency," *Annals of Mathematical Statistics*, vol. 22, no. 1, pp. 79–86, March 1951.