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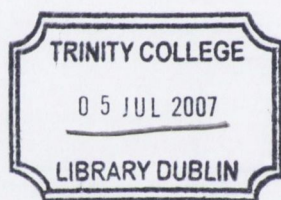
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THESIS
8102

Link Quality Prediction in Mobile Ad Hoc Networks

Gregor Gaertner

A thesis submitted to the University of Dublin, Trinity College

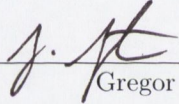
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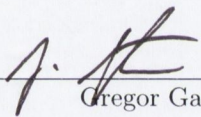


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Summary

Link quality prediction (LQP) is effective in masking topology changes in wireless mobile ad hoc networks (MANETs) as previously shown in reducing packet latency in proactive routing. However, most existing LQP algorithms have only been evaluated in simple simulations with basic radio propagation models. Therefore, we evaluated the accuracy of three existing LQP algorithms for an 802.11 MANET of nodes carried by pedestrians in two real-world, microcellular, urban environments. The best performing of these LQP algorithms failed to predict between 18% and 54% of the total observed packet loss for a prediction of two seconds ahead while between 12% and 43% of successfully received packets were falsely predicted to be lost. These results contrast sharply with the near-perfect accuracy of these algorithms shown in the standard NS-2 simulator. Our results show that LQP algorithms based on basic radio propagation models are not applicable to real-world environments. This thesis describes the design and evaluation of accurate LQP algorithms that are derived from a radio propagation model that closely resembles what is observed in microcellular, urban environments.

An initial study examined factors that potentially influence link quality in MANETs and make LQP difficult with off-the-shelf 802.11 cards. Our study did not identify any influence factor that makes accurate LQP impossible. Our work showed that obstructing objects, including the body of a person holding a node, have a significant influence on link quality. Accurate modelling, simulation and prediction of link quality must therefore consider this large-scale fading, which has been neglected in previous work on LQP.

The estimation of the large-scale fading signal requires the statistical description of its small-scale fading. While this latter phenomenon is very well researched in narrowband systems, it is much less understood in wideband systems such as 802.11. We showed that the cumulative distribution function of small-scale wideband signal envelope fading in microcells can be approximated with an average error of 1.65% and 1.78% by the Rice and Nakagami distributions, respectively, which are already known to describe the probability distribution of small-scale narrowband signal envelope fading. Additionally, we obtained an expression that maps the significant wideband propagation environment parameters

to their narrowband counterparts for different standards such as DSRC, WiMAX, UMTS and the family of 802.11 standards. Both discoveries enable important applications: the derivation of the appropriate averaging interval to estimate the large-scale fading signal in an 802.11 receiver and the fast simulation of wideband small-scale fading signals in packet-level simulators.

Based on our link quality model we derived the optimal link quality predictor (LQPR) whose parameters are estimated from signal-power and node-speed samples. We also proposed a fast estimator for these parameters whose computational complexity is three orders lower than the optimal estimator with only a slight loss in accuracy. Furthermore, a simplified LQPR is suggested for use when node-speed measurements are unavailable. These LQPRs were evaluated against the unachievable lower error bound on LQP obtained in this thesis. We showed in a major simulation study that the best LQPR predicts the packet reception probability for pedestrians in urban microcells on average with a mean absolute error of 13.09%, 15.55%, 16.71% and 17.52% for 1 s, 2 s, 3 s and 4 s ahead, respectively. This LQP accuracy resembles closely the lower error bound with, for example, a difference of 1.59% at 2 s ahead. We determined that these LQPRs are moderately more accurate in the Random Waypoint Mobility Model than in the Random Waypoint Mobility Model City Section that uses real-world maps. Furthermore, we demonstrated that longer packets are predicted more accurately than shorter packets, albeit that this effect levels off at large packet sizes. LQP accuracy was also shown to be independent of node density in the absence of collisions.

The large discrepancy in the accuracy of the evaluated LQP algorithms from the literature between NS-2 simulations and our real-world experiments showed the need to improve the realism of the NS-2 simulator. This improvement was achieved by simultaneously incorporating correlated large-scale fading, wideband small-scale fading and a bit error function that models the average performance of an 802.11 receiver in microcellular, urban environments. Excellent agreement was shown between the now improved simulations and measurements from the real-world experiments.

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Finally, I am grateful to my parents for their unconditional love and support over all my life. This thesis is dedicated to them.

Gregor Gaertner

University of Dublin, Trinity College

April 2007

We choose to ... do the other things, not because they are easy but because they are hard ...

John Fitzgerald Kennedy

*Four ducks on a pond,
A grass bank beyond,
A blue sky of spring,
White clouds on the wing—
What a little thing
To remember for years
To remember with tears.*

William Allingham

Publications Related to this Ph.D.

- Gaertner, G. & Cahill, V. (2004), ‘Understanding Link Quality in 802.11 Mobile Ad Hoc Networks’, *IEEE Internet Computing* **8**(1), 55–60.
- Gaertner, G., O Nuallain, E., Butterly, A., Singh, K. & Cahill, V. (2004), 802.11 Link Quality and Its Prediction—an Experimental Study, in ‘Personal Wireless Communications’, Vol. 3260 of *Lecture Notes in Computer Science*, Springer, Delft, The Netherlands, pp. 147–163.
- Singh, K., Nedos, A., Gaertner, G. & Clarke, S. (2005), Message Stability and Reliable Broadcasts in Mobile Ad-Hoc Networks, in ‘International Conference on Adhoc Networks and Wireless’, Vol. 3738 of *Lecture Notes in Computer Science*, Cancun, Mexico, pp. 297–310.
- Gaertner, G. & O Nuallain, E. (2007), ‘Characterising Wideband Signal Envelope Fading in Urban Microcells using the Rice and Nakagami Distributions’, *IEEE Transactions on Vehicular Technology*, to appear.

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Chapter 1

Introduction

Wireless mobile ad hoc networks (MANETs)(Schiller 2000, pp. 275–286) are self-organising communication networks without any infrastructure. Peer nodes work collaboratively to transport packets through the network in a store and forward fashion since the limited transmission radius of nodes necessitates multi-hop communication. MANETs are appropriate in scenarios in which an infrastructure is either not feasible due to economic constraints or not available due to physical constraints such as natural disasters or battlefield deployments. Applications range from the communication-enabled soldier, disaster recovery and Voice over IP to mobile gaming.

The mobility of nodes and radio propagation effects cause frequent changes in the topology of a MANET; link failures and link recoveries, which are infrequent events in wired networks, occur frequently in MANETs. Consequently, reliable high-bandwidth communication is a challenge that can only partially be addressed by existing methods for wired networks. One successful strategy to alleviate the impact of topology changes is to predict them such that corrective actions can be taken before the change occurs (e.g. Goff et al. 2001). In the literature the effectiveness of such proactive actions has been demonstrated in the area of multicast communications and routing, in which packet latency is significantly reduced by discovering new routes before links fail. Similar performance enhancements are envisioned for group communications with partition prediction. Link quality prediction (LQP) is the foundation for proactive actions and is therefore a

key technology for the efficient operation of MANETs. However, this topic has not been addressed adequately in the literature to date since the design and evaluation of existing LQP algorithms is typically based on overly-simplified, deterministic radio propagation models that do not resemble the physical reality sufficiently (see Chapter 2 and 3). Hence, these LQP algorithms are not applicable to real-world environments. This work addresses this gap.

1.1 Scope and Limitations of the Thesis

The goal of this thesis is to develop and realistically evaluate algorithms that accurately predict the link quality for communications between nodes carried by pedestrians in outdoor urban environments for 802.11 MANETs. By ‘realistic’ we mean that the evaluation is based on radio propagation and receiver models which correspond significantly better to real-world measurements than the models used to evaluate existing LQP algorithms¹ in 802.11 MANETs. Our models and evaluations are based on our own real-world measurements if feasible; otherwise we used measurement results from the literature and advanced stochastic simulations. The term ‘stochastic’ refers in this thesis to models or methods that involve the concept of probability. We focus in this work on short-term predictions (for up to 4 s ahead) that can be used to predict link failures and link recoveries. Such short-term predictions are required to alleviate the impact of network topology changes as shown or suggested in the literature for proactive routing, group communication and partition prediction. Link quality is defined in this thesis as being either the signal power or the probability of successful packet reception at the receiving node of a broadcast. This definition constitutes no limitation since higher-level link quality metrics such as throughput, packet latency or probability of successful packet reception of unicast transmissions with acknowledgement can be derived from our lower-layer metric.

We focus on urban environments since around half of the earth’s population is living in or around cities and 70% of the population are expected to reside in these environments by

¹We use the terms ‘link quality predictor’ and ‘link quality prediction algorithm’ interchangeably in this work.

the end of the next decade (Kumagai 2001). We restrict ourselves to LQP for pedestrians, for which diverse, important applications such as support for urban warfare (Kumagai 2001), disaster recovery (Pena-Mora et al. 2002) and mobile gaming (Reijers et al. 2002) are envisioned. However, the results in this thesis could also be applied to high-speed nodes such as cars. For example, the LQP accuracy that is determined for pedestrians at 4 seconds ahead in Chapter 6 corresponds to the accuracy for a car that is ten times faster than a pedestrian (around 50 km/h) at a prediction horizon of 0.4 seconds ahead. For comparison, the discovery of routes in proactive routing for 35 nodes took on average 0.1 seconds in Goff et al.'s (2001) study. Moreover, cars might also provide their locations that can be obtained, in contrast to pedestrians, by combination of Global Positioning System (GPS), inertial system and terrain maps. If LQP has such information available, improvements in prediction accuracy might be achieved for prediction horizons beyond 4 seconds.

We restricted most experiments in this thesis to MANETs with nodes that communicate by the original 802.11 standard. However, our methods are general and could be applied to other wireless standards and even infrastructure networks within urban microcells. For example, the extensions described in Chapter 5 for the NS-2 (McCanne & Floyd 2006) simulator can be adapted to most wireless standards by changing the performance model of the receiver. Our novel LQP algorithms from Chapter 6 could also be tailored to different wireless standards by deriving an appropriate averaging distance and by modelling the performance of the receiver for the standard in question.

In our real-world evaluation of LQP accuracy we restricted our study to LQP algorithms from the literature whose input is solely the measured signal power. Since we target pedestrians in urban environments, location information is too unreliable and too inaccurate to be useful (see Chapter 3). Furthermore, path loss varies with the urban environment (Goldsmith 2005, p. 47) and is additionally low even if pedestrians move apart at maximum speed for a few seconds. Therefore, location information is unlikely to add much value for short-term predictions of a few seconds. A detailed discussion on our selection criteria is given in Section 3.2.

The accuracy of our proposed LQP algorithms was evaluated in the absence of collisions. Collisions occur due to the hidden terminal problem (Tobagi & Kleinrock 1975). The frequency depends on the transmission pattern of nodes, the effectiveness of the 802.11 Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) mechanism and the Request to Send (RTS) & Clear to Send (CTS) mechanism if used. The number of collisions is a function of the coordination of node transmissions and their patterns and thus specific to the application that uses LQP. For example, a group communication system for ad hoc networks is likely to show a different transmission pattern than a real-time routing protocol. However, in both cases nodes achieve agreement and such agreement can ensure that few or no collisions due to transmissions occur. Due to the complexity of the agreement problem in MANETs, this topic is out of scope of this thesis, which focuses on modelling, simulating and prediction of link quality without considering this protocol-layer problem.

1.2 Key Contributions of the Thesis

In this section we outline the key contributions of this thesis. These contributions are ordered chronologically as they appear in this work.

First, we discovered that existing LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) for MANETs show high accuracy in basic simulations incorporating path-loss-only radio propagation models but low accuracy in real-world experiments or more realistic simulations that incorporate additional propagation effects. Our study suggests that stochastic LQP, which predicts the probability of successful packet reception, is more accurate than deterministic LQP that only predicts whether packets will be successfully received or not.

Secondly, we investigated systematically the factors that influence link quality in MANETs with an off-the-shelf 802.11 card in a real-world study. We concluded that some influence factors make accurate LQP difficult but we could not identify any influence factor that makes accurate LQP impossible. This study emphasised the importance of considering large-scale fading for modelling, simulation and prediction of link quality in 802.11 MANETs.

Thirdly, we discovered that the cumulative distribution and probability density functions (CDF and PDF respectively) of small-scale wideband signal envelope fading in microcells can be approximated very closely by both the Rice and Nakagami distributions that are already known to describe the probability distribution of small-scale narrowband signal envelope fading. While small-scale fading of narrowband signals is well researched and understood, fewer studies have examined small-scale fading of wideband signals and the probability distribution functions (CDF, PDF) of these signals were previously unknown. Our insight into the physical phenomenon of wideband small-scale fading allows the probability distribution of fading wideband signals to be described with closed-form expressions for the first time.

Fourthly, we obtained for small-scale fading an expression that maps the parameters of the wideband propagation environment for common wireless standards (e.g. UMTS, WiMAX, the 802.11 family) to their narrowband counterparts for the Rice and Nakagami distributions. Our results in the area of wideband small-scale fading have important applications. One application is the derivation of the appropriate sample spacing and averaging interval to estimate the large-scale fading signal accurately from the small-scale fading signal. The estimated large-scale fading signal is the basis for our proposed LQP algorithms. Furthermore, our results enable the simulation of small-scale wideband signal fading in packet-level simulators at low computational cost and with low implementation effort by adapting existing narrowband solutions. Moreover, the statistical description of small-scale fading allows for a complete model of link quality in wideband systems such as 802.11. Such a model allows the mathematical derivation of the optimal predictor for link quality.

Fifthly, we increased the realism of the NS-2 simulator by including additional propagation effects with realistic parameters at low computational cost. More specifically, we extended NS-2 by incorporating simultaneously correlated large-scale fading, wideband small-scale fading and a bit error function that models the average performance of an 802.11 receiver in microcellular urban environments. All models and parameters used are based on extensive measurement campaigns reported in the literature or our own measurements in real-world experiments. We also introduce the simple but novel concept of

parameter modification during simulations: since for most propagation parameters different studies measured different values for similar urban environments, the propagation parameters are pseudo-randomly chosen out of their measured range during simulation such that the simulation represents a variety of similar urban environments.

Sixthly, we derived a novel link quality predictor (LQPR) that optimally estimates the probability of successful packet reception. Since this predictor predicts the large-scale fading signal, we term it the ‘Distance Exponential Shadowing’ (DES) predictor. The DES predictor requires the estimation of its parameters from the sampled signal power and the nodes’ speed, which can be measured, in contrast to location, accurately and inexpensively by an accelerometer chip for pedestrians (Analog Devices 2002). We also derived the optimal parameter estimator although its cubic-time computational complexity with respect to the required number of parameter-estimation samples makes it impractical for use at runtime. Thus we derived an unbiased fast estimator, which is three orders computationally more efficient, while showing only a slight increase in estimation variance compared to the optimal estimator. For applications in which nodes are not equipped with accelerometers, we also designed a simple Last Local Mean (LLM) predictor, which is a special case of the DES predictor in which no speed measurements are required.

Seventhly, we investigated the accuracy of LQP in a major simulation study incorporating a wide range of scenarios. The simulation included path loss, correlated large-scale fading, wideband small-scale fading and the average bit error function of an 802.11 receiver and therefore covers more propagation effects than any LQP study that we surveyed in the literature. We compared the DES and LLM predictor with a theoretical (THEO) predictor that represents the lower error bound on LQP accuracy—one that can only be achieved by an external observer with perfect knowledge of the link quality model in the past but no knowledge of the future. The packet reception probability prediction accuracy of the DES predictor was, in the worst case, within 1.59% of the unachievable lower error bound for 2 s ahead. The theoretical predictor provides a much stronger benchmark than the LQP algorithms that were evaluated in our real-world study, since the latter algorithms were shown to perform as poorly in the extended NS-2 simulator as in the real-world

environments and they could not sensibly be adapted to an accurate stochastic rather than a deterministic prediction. We investigated the influence on the predictability of link quality for different mobility models, packet lengths, node densities and the influence of unidirectional vs. bidirectional communication links.

1.3 Road Map

This thesis covers four main topics that are related to 802.11 MANETs: the accuracy of existing algorithms for LQP and the factors that influence link quality, both evaluated in the real world; small-scale fading of wideband signals; simulation of link quality with a high degree of realism; and design and evaluation of novel LQP algorithms with high accuracy. Substantial contributions in all these areas were necessary to achieve the final goal of accurate LQP that is evaluated in simulations, which are more realistic than corresponding simulations in the MANET literature. Each chapter examines one of those topics in depth and provides a thorough evaluation. A separate chapter provides the reader with an overview of the literature relevant to this thesis.

In order to make the summary sections of each chapter and the conclusions self-contained, we introduce acronyms used therein once. The meaning of dispersed acronyms is sometimes recalled for convenience. References are only given the first time when a term, concept or product is introduced.

The thesis is structured as follows. The second chapter assesses and discusses critically the related work relevant to this thesis. The third chapter shows that existing LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) performed very well in basic simulations, which consider path loss as the sole propagation effect, but poorly in our real-world study. In the same chapter we investigate the factors that potentially influence link quality, make its prediction difficult and could account for the high discrepancy between the performance of the evaluated LQP algorithms in basic simulations and the real world. In the fourth chapter we propose probability distribution functions to characterise small-scale fading of wideband signals. This allows, for the first time, to describe this physical phenomenon with closed-form expressions such that important applications for

modelling, simulation and prediction of link quality are enabled. In the fifth chapter we describe improvements to the NS-2 simulator to enable more realistic simulations, i.e. by incorporation of correlated large-scale fading, wideband small-scale fading, propagation parameter modification and average bit error calculations for an 802.11 receiver. In the sixth chapter we derive novel LQPRs, compare their performance to an unachievable lower error bound and examine the factors that influence the prediction accuracy of link quality. In the last chapter we conclude our work. An overview over the notational conventions and principal symbols of this work is given in the Appendix A.1. A list of abbreviations and acronyms is given in the Appendix A.2.

Chapter 2

Related Work

In this chapter we discuss related work in the order in which the corresponding topics are addressed in this thesis. We begin with a comprehensive survey of LQP algorithms for MANETs. We then discuss real-world measurement studies that address link quality and which are related to our own measurements. We then present some key results in the area of small-scale wideband signal envelope fading that are used in this thesis. Following that we consider studies that examine the accuracy and methodology of MANET simulations. We conclude the chapter by summarising the state of the art in LQP algorithms.

2.1 Link Quality Prediction Algorithms

LQP algorithms can be classified using a variety of criteria. One criterion is the type of input that the algorithm uses to make predictions. The inputs can be signal-power measurements, location measurements, or other measurements such as the ratio of transmitted to received packets within some time interval. In fact, the type of input is the most significant criterion by which to classify LQP algorithms since it typically represents the focus of the algorithms' creators. Predictions based on signal-power measurements focus on the radio propagation model while predictions based on location measurements concentrate on the mobility model. Another criterion by which to classify existing algorithms is the output of the LQP. If the output is subset of a finite set of states, we classify the prediction

as being deterministic. Most deterministic prediction algorithms surveyed have only two possible output states; packets are predicted to be either lost or received for some time into the future. If the output of a LQP algorithm is a subset of an infinite set of states, we classify this prediction as stochastic since the output is in that case usually a probability. For example, an algorithm that estimates the probability of successfully receiving future transmitted packets is stochastic. Another possible classification criterion is the application of LQP. Successful applications are found in the area of routing, group communication, multicast communication and clustering. A final possible classification criterion is the radio propagation model on which a LQP algorithm is based. Since link quality is primarily dependent on the radio propagation model, even algorithms that focus on location measurements and mobility models are explicitly or implicitly derived with respect to a specific radio propagation model. In the literature we commonly found the use of the simple Radial Propagation Model, the Free Space Propagation Model (Rappaport 2002, pp. 107–109) and the Two-Ray Ground Propagation Model (Rappaport 2002, pp. 120–125). In the simple Radial Propagation Model a node i can communicate with a node j if the distance between i and j is less than or equal to a threshold; otherwise i does not receive packets that are sent by j and vice versa.

A graphical overview of the taxonomy of the surveyed literature based on these criteria is presented in Figure 2.1. Note that Roman et al.’s (2001) and Killijian et al.’s (2001) works are of a conceptual nature only such that we could only assess them with respect to their applications. Apart from these two studies all other works have been classified according to their input parameters, output parameters, radio propagation model and application area. Punnoose et al.’s (1999) study included two different radio propagation models as discussed later in this chapter. We found that LQP algorithms used various input parameters with signal power and location measurements being the most popular. Older LQP algorithms tend to provide deterministic predictions while newer algorithms favour stochastic predictions. The most important application area for LQP in the literature was found in routing. For a considerable number of LQP algorithms the radio propagation model, on which these algorithms were based and evaluated, was unspecified.

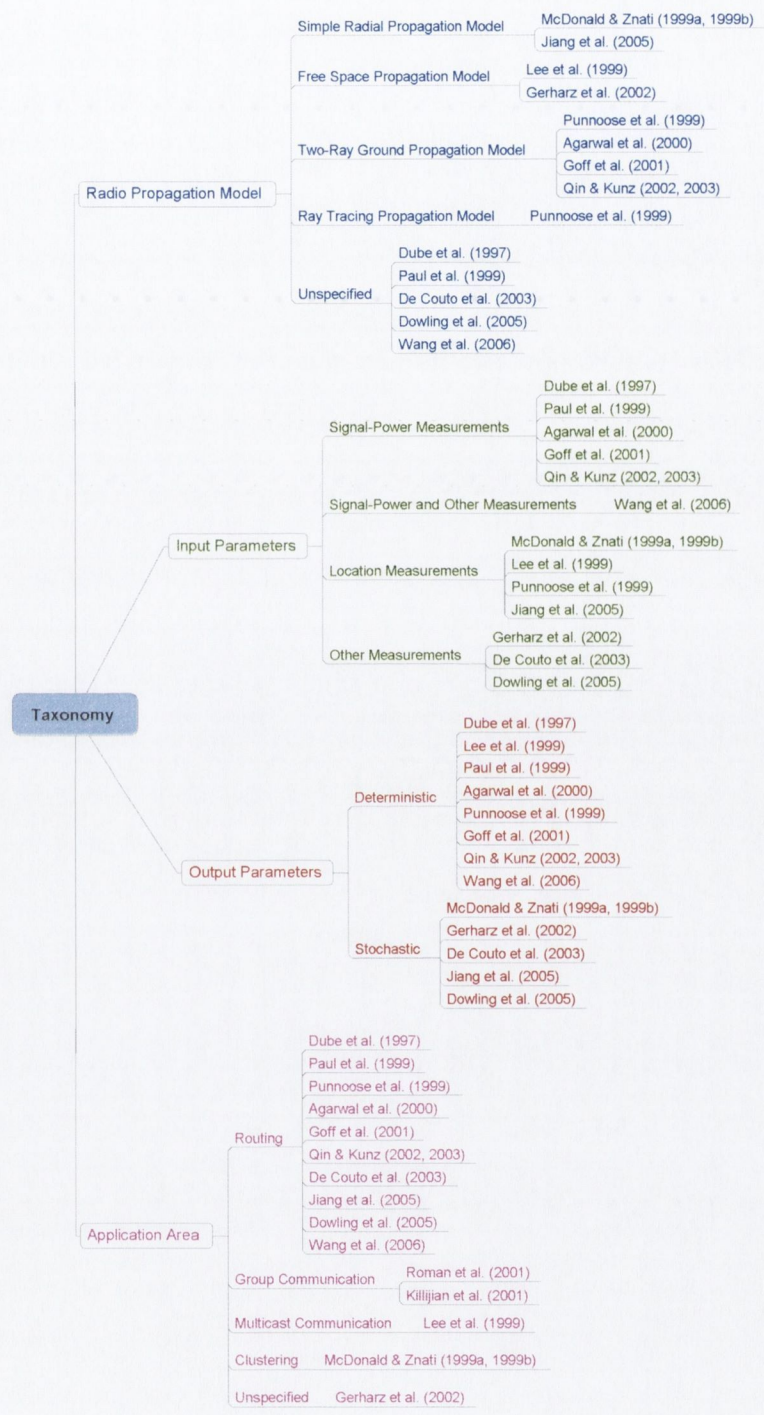


Figure 2.1: Taxonomy of LQP algorithms by different criteria. The surveyed algorithms use a variety of input parameters. Older LQP algorithms tend to provide deterministic predictions while newer algorithms focus on stochastic predictions. Routing has been by far the most important application area for LQP. The underlying radio propagation model is unspecified for a considerable number of algorithms.

All LQP algorithms are based on radio propagation models that characterise the propagation effect of path loss but do not account simultaneously for large-scale and wideband small-scale fading effects. However, the latter effects affect the radio propagation significantly (see, for example, Neskovic et al. 2000) and path-loss-only models do not consequently represent the real-world behaviour well. Therefore, none of these LQP algorithms are applicable to real-world environments as demonstrated by our own real-world measurements in Chapter 3. To avoid the detailed repetition of this crucial critique, we refer to LQP algorithms based on such radio propagation models as LQP algorithms being based on ‘path-loss-only’ radio propagation models.

In this chapter, we refer to ‘indirect’ and ‘direct’ evaluations of LQP algorithms. We refer to an indirect evaluation if the accuracy of a LQP algorithm is evaluated by demonstrating that some metric, which refers to a higher-layer protocol, has changed due to the use of LQP. A higher-layer protocol might be a routing protocol or a multicast protocol and typical metrics are packet latency, packet delivery ratio and data throughput. In contrast, an evaluation is direct if the accuracy of a LQPR is assessed by comparing its prediction of some quantity, such as the probability of receiving future transmitted packets, directly with future measurements of this quantity.

Notation and Nomenclature

In order to unify the various notations used to describe LQP algorithms, we introduce the following notation inspired by Harvey (1993, p. 33). Let t denote the variable that represents time and T represent the point in time at which a prediction is made. Then τ is the prediction horizon that represents the amount of time into the future for which this prediction is made. We call the interval $[T, T + \tau]$ the ‘prediction interval’ and the interval $[t_c, T]$ the ‘history interval’ where $t_c \leq T$ is some point in time. The data collected within the history interval is used at time T to predict a future value of a quantity at $T + \tau$. The probability of a transmitted packet being successfully received is symbolised by the packet reception probability (PRP) Φ with range $\Phi \in [0, 1]$. We denote a predictor for a quantity by a tilde over its symbol. A deterministic prediction of the PRP at time T for $T + \tau$ is

then defined as

$$\tilde{\Phi}_{T+\tau|T} = \begin{cases} 0 & \text{if packet is predicted at time } T \text{ to not be received at } T + \tau, \\ 1 & \text{if packet is predicted at time } T \text{ to be received at } T + \tau. \end{cases} \quad (2.1)$$

A stochastic PRP prediction is defined as the predicted probability that a packet will successfully be received at time $T + \tau$

$$\tilde{\Phi}_{T+\tau|T} \rightarrow \{0, \dots, 1\} \in \mathbb{R}. \quad (2.2)$$

It is important to discuss the interpretation of the time variables in the context of continuous real-world processes and the sampling by the computer. The stochastic processes of propagation effects investigated in this thesis are continuous. However, computers measure quantities of these processes from time to time, thus the stochastic process is discrete in the computer. Assume, for example, a continuous stochastic real-world process X that is sampled with a sampling interval of Υ between two samples. Hence, the sample x_t corresponds to the realisation of this process at time t . Assume that this sample has been taken at $t = 10 : 45 : 00$ h and that the sampling interval Υ is 0.5 seconds. If we now refer to a sample that was taken at x_{t+8} , this sample was not taken at 10:45:08 h but at 10:45:04 h since x_{t+8} corresponds in the discrete system to $t + 8\Upsilon$, which is 10:45:00 h plus $8 \cdot 0.5$ s. In general, the discrete samples x_{t+c} correspond to samples of the continuous system at the actual time $t + c\Upsilon$ while in the sampled computer representation t and c are some indices with the meaning explained above.

There are several other quantities that may be used or predicted by LQP algorithms. The location of a mobile node is represented by $\mathbf{o}$ and it is noteworthy that knowledge of successive locations allows for the derivation of the speed vector. The two quantities of speed v and its direction $\acute{v}$ can be calculated from the speed vector. The signal power of a received packet is denoted by R in watts and by $R_{(\text{dBm})}$ in dBm; the signal envelope is symbolised by r .

2.1.1 LQP Algorithms Based Solely on Signal-Power Measurements

In this section we present LQP algorithms that rely solely on signal-power measurements to predict link quality.

Dube, Rais, Wang & Tripathi (1997)

LQP in MANETs has been introduced in the context of routing by Dube et al. (1997). Their on-demand routing protocol uses two conditions for route selection that are based on signal-power measurements. These signal-power measurements are assumed to represent future link quality albeit that the prediction horizon is not specified. The first condition requires that signal-power measurements for each link on a route have higher exponential average power than a threshold. The second condition demands that the exponential average signal power for each link has been above its threshold for a specified period of time. The first condition is termed ‘signal stability’, the second one ‘location stability’. Applying both conditions leads to the selection of routes that have longer remaining lifetimes and therefore require less route maintenance. This was confirmed by simulations in which this routing protocol is compared to a simple, imaginary routing protocol that chooses the shortest route without considering signal-power measurements.

The LQPR used to select routes with higher remaining lifetimes is the exponential average

$$\tilde{R}_{T+1|T} = c_1 \tilde{R}_T + (1 - c_1) R_T \quad (2.3)$$

where c_1 is an experimentally determined constant, $\tilde{R}_T$ is the previously predicted signal power for some link, and R_T is the last signal power measured. If $\tilde{R}_{T+1|T}$ is higher than an experimentally determined threshold, the link between the transmitter and receiver of a packet is classified as being ‘strong’, otherwise as being ‘weak’. Since this prediction has only two possible outcomes we classify it as being deterministic. Routes with only strong links are preferred over routes that contain weak links. The expectation is that a route consisting of only strong links has a higher remaining lifetime than a route that also contains weak links. Older routes of strong links are preferred to younger routes.

A few observations are noteworthy. (2.3) is proposed without derivation or justification. The constant c_1 as well as all thresholds are chosen by experience. The performance evaluation is based on simulations with a radio propagation model that considers only the distance between nodes but is not further specified. Hence, we cannot assess the applicability of this LQP algorithm to real-world environments.

Paul, Bandyopadhyay, Mukherjee & Saha (1999)

Paul et al. (1999) propose an affinity metric that measures the strength of connection between two nodes. Based on this affinity metric a routing protocol for low volume data transmission and another for high volume data transmission are presented. The affinity metric is a value proportional to the predicted remaining lifetime of a link and is intended to identify routes with higher lifetime than without using such a predictive measure.

Let $\text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T])$ be the average signal-power trend at time T between two nodes for the samples $\mathbf{R}_{\mathbf{T}(\text{dBm})}$ over the last c_1 seconds. The affinity $g(T)$ is now defined as

$$g(T) = \begin{cases} \text{high} & \text{if } \text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T]) \text{ is positive,} \\ \frac{c_2 - R_{\mathbf{T}(\text{dBm})}}{\text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T])} & \text{if } \text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T]) \text{ is negative,} \\ \frac{c_2 - R_{\mathbf{T}(\text{dBm})}}{\text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T])} & \text{if } \text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T]) \text{ is negative} \end{cases} \quad (2.4)$$

where c_2 is the signal power at the maximum transmission range and $R_{\mathbf{T}(\text{dBm})}$ is the last signal-power sample. If the value of $\text{TAvg}(\mathbf{R}_{\mathbf{T}(\text{dBm})}, [T - c_1, T])$ is positive, the affinity between two nodes is increasing, given the authors' assumptions, since the nodes are moving closer to each other. In this case the affinity is classified simply as being 'high' since no link failure is predicted for the future. Otherwise, the affinity is calculated periodically using the above formula. A deterministic link failure can now be predicted by the following equation

$$\tilde{\Phi}_{T+\tau|T} = \begin{cases} 0 & \text{if } c_3 g(T) \leq T + \tau, \\ 1 & \text{otherwise,} \end{cases} \quad (2.5)$$

where c_3 is an experimentally determined constant that represents the proportionality factor between the affinity metric and the remaining link lifetime.

Paul et al. (1999) evaluated the accuracy of their proposed LQPR indirectly by showing that the number of route breaks can be significantly reduced in a variety of different scenarios when the affinity metric is used as a predictive measure to select routes with expected high remaining lifetimes.

The authors did not motivate or derive their LQPR. Therefore, we do not know what radio propagation model was used as the basis for its derivation and hence, we cannot judge its applicability to real-world environments. Nevertheless, the presented LQPR is interesting since it could provide accurate predictions at least for path-loss-only radio propagation models such as the Two-Ray Ground Propagation Model and the Free Space Propagation Model. These path-loss models are linear if the path loss is expressed in decibels versus the logarithmic distance. Consequently, the linear equations (2.4) and (2.5) are appropriate for these models, albeit with a certain prediction error if the signal power of nodes with constant speed vectors is measured in linear time intervals.

Agarwal, Ahuja, Singh & Shorey (2000)

Agarwal et al. (2000) built their Route-Lifetime Assessment Based Routing (RABR) protocol on Paul et al.'s (1999) LQPR discussed in the previous section. Since their work utilises the affinity metric without changes, we omit a discussion of it here. RABR introduces three new features compared to previous routing protocols. First, route selection for Transmission Control Protocol (TCP) traffic is extended to consider the throughput function of TCP as well as the affinity metric. Since the throughput of TCP traffic can be approximated by a function of the number of hops (Gerla et al. 1999), route selection is based on the product of the weakest link's affinity and the bandwidth of that route. Therefore, a route that has a lower predicted remaining lifetime but higher bandwidth can be more suited to a transmission than the route that has the longest predicted remaining lifetime but with much lower bandwidth. Secondly, the affinity metric is employed to increase the effectiveness of route cache maintenance. Route caching reduces the latency of route discovery in on-demand routing protocols since an intermediate rather than the destination node can answer the route discovery request from some source node, if a

suitable route exists in its cache. However, stale routes in the cache can increase latency considerably. Hence, a timeout that equals the expected lifetime of the route is assigned to each route cache entry such that no stale entries exist if the LQP is accurate. Thirdly, the authors introduce a power saving scheme that reduces the transmission power using the affinity metric. However, only between 3% to 5% of power was saved in their simulations.

The effectiveness of Paul et al.'s (1999) LQPR was demonstrated in simulations with NS-2. For a wide range of scenarios the performance of the RABR protocol was compared to other common routing protocols (Agarwal et al. 2000). For medium to large average node speeds the RABR protocol was shown to outperform its competitors in terms of TCP throughput and ratio of delivered to sent packets. However, the suggested LQP algorithm and its evaluation are based on a path-loss-only radio propagation model.

Goff, Abu-Ghazaleh, Phatak & Kahvecioglu (2001)

Goff et al. (2001) were the first to introduce the concept of proactive routing for on-demand routing protocols. On-demand routing protocols exhibit low traffic overhead since they only update active routes that have been used in the recent past. However, updates are only triggered after a link failure is detected in which case multiple retransmissions have been unsuccessful. Therefore, time passes while a new route is being discovered which results in high mean and variance of packet latency. Proactive routing, however, tries to minimise this latency by initiating route discoveries early enough to have discovered alternative routes by the time links fail. The efficiency of proactive route discovery relies on accurate LQP. If a link is falsely predicted to fail early, unnecessary route discoveries are initiated and a route with lower quality than currently used might be chosen. However, if a link failure is predicted too late or not predicted at all, the route discovery does not finish before the link fails; hence, packet latency is increased.

The authors rely on the concept of preemption for enabling proactive route discovery. A communication task (e.g. route discovery) is initiated preemptively such that it can be completed even if links between two nodes fail when these two nodes move apart at maximum speed. The preemptive region starts at the maximum distance at which two

nodes can be separated such that if they move apart at maximum speed, the communication task can still be completed. The preemptive region ends at the maximum transmission radius. The preemptive threshold is the signal power that corresponds to the begin of the preemptive region and this threshold is intended to determine whether a node has entered the preemptive region with respect to another node.

The proposed LQPR differs from previous ones in that it is more a protocol than a mathematical expression. The idea behind this approach is that a number c_1 of ‘ping-pong’ rounds are exchanged between two nodes if a packet is received whose signal power is below the preemptive threshold c_2 . If the signal power of c_3 or more of these c_2 packets are below the threshold or these packets are lost, the link is predicted to fail. The ‘ping-pong’ rounds are intended to reduce falsely predicted link failures that are caused by temporary fades due to small-scale fading. The preemptive threshold is calculated such that if two nodes move away from each other at maximum speed, the link failure is predicted early enough to allow a route discovery to complete before the link fails. Therefore, the threshold c_2 corresponds to the signal power at the beginning of the preemptive region that represents the difference between the maximum transmission distance and the product of the maximum relative speed between two connected nodes and the prediction horizon. For their evaluation Goff et al. (2001) set the number of ‘ping-pong’ rounds c_1 and the threshold c_3 to 3. The LQP algorithm was derived considering the Two-Ray Ground Propagation Model and small-scale fading.

Significant improvements due to proactive instead of on-demand routing were shown for the Dynamic Source Routing (DSR) (Johnson & Maltz 1996) and the Ad hoc On-demand Distance Vector (AODV) (Perkins et al. 2001) protocol in an augmented version of the NS-2 simulator. The simulator was augmented with an error model that assigns either a good or bad state to a link. In order to approximate small-scale fading, the signal power was decreased by division by a uniformly distributed random number between 2 and 100 when a bad state was assigned to a link. The mean length of staying in a state was set to 20 000 packets in the good state and to 2 packets in the bad state. It was shown for both routing protocols that the number of broken routes and the packet latency was significantly

reduced for constant-bit-rate traffic due to proactive route discovery. A similar reduction in packet latency was also demonstrated for TCP traffic.

This deterministic LQP algorithm relies critically on the assumption of bidirectional links since the ‘ping-pong’ mechanism to mitigate small-scale fading does not work otherwise. Furthermore, this algorithm only allows for LQP for one future point in time and not for a set of points (interval). For example, the algorithm can be used to predict link failure for 2 seconds ahead but not 0.5, 1.0, 1.5 and 2 seconds ahead simultaneously. This property is based on the protocol’s nature. Since the ‘ping-pong’ mechanism is triggered by the preemptive threshold that is a function of the prediction horizon, it cannot be triggered for a different threshold simultaneously. In terms of evaluation, the accuracy of the proposed approximation model for small-scale fading is questionable. Although small-scale fading affects the signal power of all transmitted packets, only deep fades, which occur very rarely with a probability of 1 in 10 000 packets in their model, are simulated. Goff et al. (2001) do not explain how this probability is obtained. Furthermore, the important propagation effect of large-scale fading has not been considered. For these reasons, the applicability of the proposed LQP algorithm to real-world environments is unclear.

Qin & Kunz (2002) and (2003)

Qin & Kunz (2002) add proactive route discovery to the DSR protocol similarly to Goff et al.’s (2001) work. However, Qin & Kunz (2002) use a different LQPR and they focus on reducing the number of dropped packets by means of LQP rather than improving the number of broken routes and the packet latency. Packets can be dropped during route discovery if no alternative route has yet been found. This loss of packets causes significant degradation in throughput as shown, for example, for TCP (Holland & Vaidya 2002). However, if alternative routes are discovered proactively before a link, and therefore a route, fails, no packets will be lost.

Qin & Kunz (2002) derive their LQPR trigonometrically using the same principle as Lee et al. (1999) and Jiang et al. (2005) whose works are discussed later in this chapter. However, the latter two approaches use location measurements to predict the time of link

failure, while this algorithm uses only signal-power measurements. These signal-power measurements are used to estimate the distance between two nodes by assuming that only the path loss as given by the Two-Ray Ground Propagation Model determines the signal power. The LQPR is derived from the Law of Cosines (Kay 2001, pp. 27–31) under the assumption that nodes maintain their speed and direction during the history and prediction intervals. Therefore, the time of link failure $\tilde{\phi}_{t>T|T}$ is predicted at time T by

$$\tilde{\phi}_{t>T|T} = \frac{\sqrt{g_2^2 - 4g_1g_3} - g_2}{2g_1} \quad (2.6)$$

where

$$g_1 = t_{T-1} \sqrt{R_{T-1} c_1} g_4 \quad (2.7)$$

$$g_2 = \sqrt{c_1} \left(\left(\sqrt{R_{T-2}} - \sqrt{R_{T-1}} \right) - t_{T-1}^2 \sqrt{R_{T-1}} g_4 \right) \quad (2.8)$$

$$g_3 = t_{T-1} \sqrt{R_{T-1} c_1} - t_{T-1} \sqrt{R_{T-2} R_{T-1}} \quad (2.9)$$

$$g_4 = \frac{\sqrt{R_{T-2} R_{T-1}} t_{T-1} + \sqrt{R_{T-1} R_T} T - \sqrt{R_{T-2} R_T} T - \sqrt{R_{T-1} R_T} t_{T-1}}{(t_{T-1} T^2 - T t_{T-1}^2) \sqrt{R_{T-1} R_T}} \quad (2.10)$$

and c_1 symbolises the signal-power threshold below which packets are lost, R_t represents the signal power measured at time t , and T , t_{T-x} denotes the times at which samples are taken. Equation (2.6) is only applied if three consecutive packets have decreasing signal power. Otherwise the nodes are assumed to be moving closer and the link is predicted not to fail. The deterministic PRP predictor is therefore defined as

$$\tilde{\Phi}_{T+\tau|T} = \begin{cases} 0 & \text{if } T + \tau \geq \tilde{\phi}_{t>T|T}, \\ 1 & \text{otherwise.} \end{cases} \quad (2.11)$$

Qin & Kunz (2002) also discuss how their LQPR can be made resilient against power fluctuations. They propose to preprocess the sampled signal power by linear regression and showed, for one example situation, that the accuracy of their link failure prediction increased compared to not using any preprocessing. This result stems from simulations in which the signal power varies by random noise of between 5% and 10% from its mean. However, there are a number of problems with this approach. First, Qin & Kunz (2002) do not define the cause of the power variations. Do these variations refer to measurement

noise or radio propagation effects? Secondly, the distribution and correlation structure of the noise process is not given. However, linear regression is only an unbiased estimator if the noise process is normally distributed and uncorrelated (Hines et al. 2002, pp. 409–414). These assumptions are invalid, for example, when the noise refers to small-scale and large-scale fading. Thirdly, the authors do not describe why the power varies only between the small values of 5% and 10% from its mean.

Qin & Kunz’s (2002) work is one of the few studies that directly evaluated the accuracy of the proposed LQPR. In a simulation with the NS-2 simulator it was shown that more than 90% of lost packets were successfully predicted for different mobility patterns. It was also demonstrated that the number of dropped packets in DSR due to unavailable routes was reduced by between 20% and 44.95% while the overhead of control messages increased by up to 33.5%. This increase in control messages, however, did not cause network congestion or other significant, negative side effects. However, these simulations, as well as the LQPR itself, are based on a ‘path-loss-only’ radio propagation model and even the previously discussed simple power variations were omitted.

2.1.2 LQP Algorithms Based on Signal-Power and Other Measurements

In this section we describe algorithms that use signal power as well as other types of measurements to predict link quality. These other measurements can be, for example, the average packet loss ratio or the hop count.

Wang, Martonosi & Peh (2006)

Wang et al. (2006) suggest the use of supervised learning to predict the quality of links in static wireless sensor networks. The term ‘prediction’ refers in this context more to estimation or classification of current link quality than to the forecast of link quality for a specific time into the future. Nevertheless, since Wang et al. (2006) assume similar to De Couto et al. (2003) and Dowling et al. (2005) justifiably that the current link quality represents the future link quality to some degree, we include this work in our survey. The proposed link quality estimator replaces the original link quality metric ETX (see Section

2.1.4 for details) in the MintRoute (Woo et al. 2003) routing protocol and its impact on different higher-layer metrics (e.g. packet delivery ratio and packet latency) in the original and augmented MintRoute protocol is assessed. The suggested link quality estimator intends to be more accurate in scenarios with high network traffic. In these situations snooping-based methods such as ETX can underestimate link quality due to high packet loss of probe packets that is caused by the hidden and exposed terminal problems as well as the unfairness of the 802.11 medium access control (MAC) protocol (Tobagi & Kleinrock 1975, Xu & Saadawi 2001).

Supervised learning establishes the mapping between an input and an output measure in an offline training phase. The input measure consists of a feature vector that contains features that can be measured by the system under consideration. These features are selected by humans at design time and they should have a meaningful relation to the desired output measure. If the output measure has a finite set of outcomes, the problem is called classification. In the training phase, the learning algorithm tries to minimise the classification error between the input measure and the given output measure. The output measure in Wang et al.'s (2006) work is the link state, which is assigned to be one of the three states 'bad', 'medium' and 'good'. Different metrics are suggested as the feature vector:

- The signal power of received packets.
- The usage of send and forward buffers to detect network congestion.
- The hop count of the sensor node from the base station.
- The average packet loss ratio, which is determined by a snooping-based method such as ETX, for the link in both directions.

Interestingly, the classification accuracy using all features was 80.8% and still around 70% for using the signal power or the average packet-loss ratio alone. Therefore, the classification was only moderately improved by using additional features.

Packet delivery ratio, packet latency and a fairness index were the metrics chosen to compare the performance of the original MintRoute protocol with its augmented version.

The fairness index is a summary statistic that captures the packet delivery ratio for all nodes of a network. It has a value between 0 and 1 and is 1 when all nodes have the same packet delivery ratio. The evaluation was conducted in a test bed of 30 wireless sensors nodes that were located across multiple offices in a building. The wireless nodes communicated over 802.15.4 (ZigBee) and the packet size for all experiments was set to 29 bytes. All nodes were static and the link quality in the network varied due to changes in the environment, radio propagation effects and different network loads. The new LQPR led to significantly higher packet delivery ratios, a comparable average packet latency and improved fairness of the MintRoute protocol.

The proposed supervised learning approach was shown to be effective for wireless networks with static nodes only. However, it is not clear if this method is also applicable to MANETs with node mobility. Moreover, the suggested LQPR is suitable for selecting routes in routing protocols leading to the reported performance improvements but is not able to predict link quality for a specifiable prediction horizon. Furthermore, all results were obtained for a small packet size. Since in many application scenarios longer and varying packet sizes can be expected, it is uncertain whether this learning approach will extend to these situations since the packet loss depends on the packet length, as it was, for example, observed in the work of De Couto et al. (2003).

2.1.3 LQP Algorithms Based Solely on Location Measurements

In this section we present LQP algorithms that rely solely on location measurements for their predictions. Location measurements are usually obtained by GPS in outdoor environments. However, GPS has a user-equivalent range error of 19.2 m (Grewal et al. 2001, pp. 128–130) and is therefore fairly inaccurate. The user-equivalent range error summarises the overall error experienced by a user from the various error sources of the GPS (e.g. transmission delays caused by the atmosphere, inaccuracy of satellite clocks, etc.). Furthermore, GPS requires a line-of-sight (LOS) connection to at least three satellites that are often not in view in dense urban environments.

Lee, Su & Gerla (1999)

Lee et al. (1999) presented a deterministic PRP predictor to enhance the performance of the On-Demand Multicast Routing Protocol (ODMRP) from Gerla et al. (1998). While the original ODMRP protocol uses a fixed refresh interval for periodic flooding to update each nodes' knowledge about the network topology, in the augmented ODMRP protocol the refresh interval is set to some time before the link with the shortest predicted remaining lifetime is assumed to fail. This anticipation of topology changes reduces latency by updating the network topology before it actually changes. LQP is also employed to select routes with longer remaining lifetimes such that route maintenance is reduced.

Lee et al.'s (1999) predictor is based on location measurements, the resulting speed vector and the Free Space Propagation Model. Although the authors do not give any mathematical derivation of their predictor, it is obvious from the expression that it is derived by trigonometry. If two nodes keep the same speed and direction within the prediction interval, the time until the link fails corresponds to the time at which the nodes are predicted to be further apart than the maximum transmission radius. Formally, let at time T (x_i, y_i) be the coordinates of mobile node i , v_i its speed and $\hat{v}_i$ its direction. Then the link failure time $\tilde{\phi}_{t>T|T}$ for the link between two nodes (i, j) is predicted by

$$\tilde{\phi}_{t>T|T} = \frac{-(g_1 g_2 + g_3 g_4) + \sqrt{(g_1^2 + g_3^2)c_1^2 - (g_1 g_4 - g_2 g_3)^2}}{g_1^2 + g_3^2} \quad (2.12)$$

where

$$g_1 = v_i \cos \hat{v}_i - v_j \cos \hat{v}_j \quad (2.13)$$

$$g_2 = x_i - x_j \quad (2.14)$$

$$g_3 = v_i \sin \hat{v}_i - v_j \sin \hat{v}_j \quad (2.15)$$

$$g_4 = y_i - y_j \quad (2.16)$$

and c_1 is the maximum transmission radius. If $v_i = v_j$ and $\hat{v}_i = \hat{v}_j$ then the link failure time is set to infinity without applying (2.12) since the nodes are maintaining a constant

distance. The deterministic PRP predictor is now defined by

$$\tilde{\Phi}_{T+\tau|T} = \begin{cases} 0 & \text{if } T + \tau \geq \tilde{\phi}_{t>T|T}, \\ 1 & \text{otherwise.} \end{cases} \quad (2.17)$$

The accuracy of the proposed LQPR was shown indirectly in the GloMoSim simulator (Bajaj et al. 1999) by comparing different aspects of the enhanced multicast protocol with the original one. It was shown that the packet delivery ratio of the enhanced ODMRP protocol was considerably higher than the original protocol, especially for high node speeds. Moreover, the packet latency was reduced significantly by anticipation of topology changes. However, the suggested LQPR and its evaluation are based on a ‘path-loss-only’ radio propagation model.

McDonald & Znati (1999b) and (1999a)

McDonald & Znati (1999b) suggest a stochastic PRP predictor for a cluster-based routing framework (McDonald & Znati 1999a). The idea behind this routing approach is to divide the mobile network into clusters that guarantee with certain probability for a certain length of time unbroken links for nodes within this cluster. The probability and length of time are specifiable. Table-driven routing is employed within a cluster; on-demand routing is used for inter-cluster routing. Table-driven routing protocols periodically update the routing information throughout the network for all possible routes. Therefore, for highly dynamic topologies the overhead is high while latency is still low since routes have been precomputed. On-demand routing protocols in contrast only maintain previously used routes. Hence, the traffic overhead is low but latency is high if a route between source and destination has to be discovered. Mixing these different routing schemes aims to balance the trade-off between table-driven and on-demand routing based on clustering nodes. The efficiency of this clustering relies on low effort for cluster maintenance that is achieved by LQP.

McDonald & Znati (1999b) derive their LQPR from their proposed mobility model and the simple Radial Propagation Model. Their mobility model assumes that each node’s

movements consist of a sequence of random length intervals called mobility epochs during which it moves in a constant direction at constant speed. The parameters of this mobility model are termed the ‘mobility profile’. Formally, for a node i the epoch length is assumed to be an exponentially distributed IID¹ random variable with mean $1/c_{1,i}$, the speed to be an IID random variable with mean $c_{2,i}$ and variance $c_{3,i}$ and the direction of movement to be an uniformly distributed IID random variable between 0 and 360 degrees. This mobility model is similar to the Random Walk Mobility Model (Polya 1921) and McDonald & Znati (1999b) do not explain how their model relates to the commonly used Random Waypoint Mobility Model (Johnson & Maltz 1996) or any other mobility model. The predicted PRP for a link (i, j) between two nodes is given by

$$\tilde{\Phi}_{T+\tau|T} \approx \frac{1}{2} \left(1 - I_0 \left(\frac{-2c_4^2}{g(T+\tau)} \right) \exp \left(\frac{-2c_4^2}{g(T+\tau)} \right) \right) \text{ with} \quad (2.18)$$

$$g(t) = 2t \left(\frac{c_{3,i}^2 + c_{2,i}^2}{c_{1,i}} + \frac{c_{3,j}^2 + c_{2,j}^2}{c_{1,j}} \right) \quad (2.19)$$

where I_0 is the modified Bessel function of the first kind and zero order, and c_4 is the maximum transmission radius. As evident from (2.19) the PRP is predicted based on the mobility profile (c_1, c_2, c_3) . However, McDonald & Znati (1999a) assume these values to be known by each node. Clearly, this assumption is valid for simulations only. Nevertheless, real-world use can be enabled when mobility profiles are estimated by each node using location measurements. We therefore classify this algorithm as being based on location measurements.

McDonald & Znati (1999b) evaluated the accuracy of their LQPR in a custom-built, discrete event simulator. On average, the LQP was accurate for longer prediction horizons but substantially underestimated link quality for shorter horizons as also observed by Jiang et al. (2005). The accuracy of the suggested LQPR was also assessed indirectly in McDonald & Znati (1999a) where it was shown that a proposed clustering algorithm, which uses (2.18) and (2.19), led to clusters that were stable and adaptive to node mobility.

¹Independent Identically-Distributed.

Again, these evaluation results and the design of the authors' LQPR stem from a 'path-loss-only' radio propagation model.

Punnoose, Nikitin, Broch & Stancil (1999)

Punnoose et al. (1999) propose a signal-power predictor for MANETs. Their approach uses location measurements from which the signal power is predicted by using a site-specific three-dimensional ray tracing propagation model with terrain map. The following components are suggested for their model:

- Non-location-based prediction. In the absence of location information this component predicts signal power by extrapolation of past signal-power samples.
- Mobility model. Probable future node locations are predicted using past location and speed measurements.
- Terrain map. The terrain map is used to provide the radio propagation model with necessary data about the environment and is updated when the environment changes.
- Radio propagation and communication model. This model predicts link quality by considering the predicted node locations, the terrain map and feedback about the accuracy of past predictions.
- Decision maker. The decision maker interacts with the network protocol to determine which links should be tracked and to provide LQP for the network.

While the above components have been suggested as a general architecture, these were only partly implemented and evaluated in the work of Punnoose et al. (1999). The non-location-based prediction was, for example, neither explained nor implemented. A terrain map was used for one evaluation scenario; however, it was not employed for a second scenario. The update of the terrain map was omitted. The mobility model for prediction was implemented and past information was used to increase prediction accuracy for cyclic mobility patterns. Nevertheless, the authors give no details about their algorithm for mobility

prediction such that we cannot assess this component. They used two different radio propagation models in their work. In one scenario, a three-dimensional “ $N+2$ ray+diffraction” propagation model (Punnoose et al. 1999) was employed that takes into account a direct ray, a ground reflected ray and rays reflected off N objects as well as diffraction from these objects. This propagation model relies on terrain maps that contain the shapes of buildings with reflection and diffraction coefficients of their materials. In order to reduce the computational cost of this ray tracing model, the search for all multipath sources was restricted. Specific details about this proposed enhancement such as the resulting computational effort and the reduction in accuracy were not given by Punnoose et al. (1999). In a second evaluation scenario the Two-Ray Ground Propagation Model with empirically determined, site-specific constants was employed for prediction. No explanation was given as to why two different radio propagation models have been chosen for the two scenarios. Furthermore, the suggested use of past locations was omitted from the prediction model implemented. The decision maker tracked the link quality for all nodes and interacted with the DSR protocol such that routes with higher predicted link quality were preferred.

The LQP accuracy was evaluated within an experimental outdoor test bed. In the first scenario, five mobile nodes in vehicles followed a looped course. Each mobile node was equipped with a differential GPS receiver. For a link between two nodes the predicted and measured signal power was displayed together with the packet loss as three separate graphs in Punnoose et al.’s (1999) paper. Unfortunately, these graphs use a large time scale that precludes a direct evaluation of the prediction accuracy in the order of seconds. Furthermore, the prediction horizon was not given such that the span of the prediction into the future is unknown. In the second scenario, one mobile node and two stationary nodes were used to show that the augmented DSR protocol chose routes with higher link quality due to the proposed LQPR. In summary, the results presented were not sufficiently detailed to allow us a full assessment.

Jiang, He & Rao (2005)

Jiang et al. (2005) present a stochastic LQPR that has some similarity to McDonald &

Znati's (1999b) approach. Both are based on the prediction of node mobility for exponential mobility models such as the Random Walk Mobility Model. Furthermore, both assume a simple Radial Propagation Model such that two nodes are connected if they are within a specified maximum transmission radius. Both approaches predict link quality to assess how reliable the connection between nodes is. While McDonald & Znati (1999b) use this information for clustering, Jiang et al. (2005) employ it for selection of routes in the context of on-demand routing. One major difference between both LQP approaches is that McDonald & Znati's (1999b) LQPR predicts at time T the PRP for $T + \tau$, while Jiang et al.'s (2005) approach predicts the probability that all packets, which will be sent between T and $T + \tau$, are received. However, this latter definition of link failure, which requires for an available link that every sent packet will be received, is restrictive. A link might experience brief periods of unavailability due to temporary packet loss, which is caused by small-scale fading, but is available for all times outside this brief period. Another considerable difference between both approaches is that for a link McDonald & Znati's (1999b) LQPR predicts the PRP probability for a specifiable time $T + \tau$ while Jiang et al.'s (2005) LQPR predicts first the link failure time and subsequently estimates the probability that the link will really last until the predicted link failure time.

More specifically, Jiang et al.'s (2005) LQPR works in the following two stages. First, a measurement-based approach predicts the time of link failure. The underlying assumption is that nodes will keep their past speed and direction within the prediction interval. Secondly, based on this link failure time the probability that the link will be available through the whole interval is calculated. For this prediction the situations are considered in which the speed and direction of the nodes do not change and in which one node or both nodes change their direction and speed.

The time until link failure $\tilde{\phi}_{t>T|T}$ for two nodes is derived similarly to Lee et al. (1999) and Qin & Kunz (2002) by employing trigonometry. Therefore, $\tilde{\phi}_{t>T|T}$ is predicted at time T by

$$\tilde{\phi}_{t>T|T} = \frac{\sqrt{g_2^2 + 4c_1^2 - 4g_1g_3} - g_1}{2g_3} - T \quad (2.20)$$

where

$$g_1 = \frac{(d_{T-1}^2 T - d_T^2 t_{T-1}) - d_{T-2}^2 (T - t_{T-1})}{t_{T-1} T (t_{T-1} - T)} \quad (2.21)$$

$$g_2 = \frac{(d_{T-1}^2 T - d_T^2 t_{T-1}) - d_{T-2}^2 (T^2 - t_{T-1}^2)}{t_{T-1} T (T - t_{T-1})} \quad (2.22)$$

$$g_3 = d_{T-2}^2 \quad (2.23)$$

and c_1 denotes the maximum transmission range, d_t the distance between two nodes measured at time t , and T , t_{T-x} symbolises the times at which samples are taken. Jiang et al. (2005) stated that the distance could either be determined by location measurements or be approximated by signal-power measurements. However, since Jiang et al. (2005) used location measurements for their evaluation and they did not elaborate on how signal-power measurements can be employed, we classify this predictor as being based on location measurements. Note that Qin & Kunz (2002) proposed a very similar predictor that corresponds to Jiang et al.'s (2005) predictor with the distance being estimated by signal-power measurements using the Two-Ray Ground Propagation Model.

Let $g(\tilde{\phi}_{t>T|T})$ denote the predicted probability at time T that all future packets will be received successfully until the link is predicted to fail at $\tilde{\phi}_{t>T|T}$. Considering that the nodes might change their speed and direction, this probability is now predicted by

$$g(\tilde{\phi}_{t>T|T}) \approx (1 - e^{-2c_2\tilde{\phi}_{t>T|T}}) \left(\frac{1}{2c_2\tilde{\phi}_{t>T|T} + c_3} \right) + \frac{c_2\tilde{\phi}_{t>T|T}e^{-2c_2\tilde{\phi}_{t>T|T}}}{2} \quad (2.24)$$

where c_2^{-1} is the mean epoch length of the mobility model and c_3 is a constant that is updated at runtime. The mean epoch length c_2^{-1} is the amount of time in which, on average, the nodes do not change speed or direction and its value is dependent on the mobility model. In order to reduce the computational cost the predictor (2.24) is an approximation of the exact solution to the problem as defined by Jiang et al. (2005). More specifically, the predictor only considers changes of the nodes' speed and direction that lead to nodes moving further away but does not consider changes that lead to higher link quality as in the case of nodes moving closer. Consequently, the constant c_3 was introduced to correct for the difference between the approximate and exact solutions by comparing the predicted with the actual probability of link failure at run-time of the algorithm. Since

the determination of c_3 is complex, we refer the reader to Jiang et al.'s (2005) paper for further details.

The LQPR was evaluated in the OPNET (MIL 3 Inc. 2006) simulator. It was shown that (2.24) is, on average, a good predictor for remaining lifetime of links for exponential mobility models such as the Random Walk Mobility Model. However, the accuracy was significantly reduced for non-exponential mobility models such as the Random Waypoint Mobility Model. Furthermore, we noticed that the scale of the presented graphs emphasised long-term prediction horizons such that we cannot comment on the prediction accuracy for short-term horizons of the order of a few seconds. Jiang et al. (2005) also showed that packet latency, packet loss ratio and the ratio of received to delivered packets were all significantly improved for the DSR protocol when routes with longer remaining lifetimes were selected based on their LQPR. However, this improvement could only be observed for exponential mobility models and the improvement was only minor for the non-exponential Random Waypoint Mobility Model. All results and the proposed LQPR were derived by a 'path-loss-only' radio propagation model.

2.1.4 LQP Algorithms Based on Other Measurements

In this section we introduce LQP algorithms that use measurements other than signal power and location for their predictions. Possible measurement metrics are the link age or metrics that calculate ratios based on the number of transmitted and received packets in the recent past.

Gerharz, Waal, Frank & Martini (2002)

Gerharz et al. (2002) present two metrics that are intended to select the link with the highest remaining lifetime from a set of links. Both metrics are based on measurements of link age and its distribution. The first metric recommends choosing the link with the highest predicted average remaining lifetime. The second metric advocates choosing the link with the highest time at which this link is predicted to fail with 25% probability. Both metrics led in simulations to link choices that result in links with higher remaining lifetimes

than choosing links randomly. For most scenarios examined these metrics also led to links with higher remaining lifetimes than choosing the oldest link.

The proposed metrics for LQP are not intended to accurately predict the remaining lifetime of links; rather they help to select links that are likely to have the longest remaining life. Gerharz et al. (2002) derived their metrics empirically from the link age data that was obtained by conducting a number of simulations for different mobility models. All simulations, including those for evaluation, were done with the Free Space Propagation Model and a maximum transmission radius of 50 m. Therefore, the applicability of the proposed metrics is bound to this specific radio propagation environment and it is unclear if the metrics extend to more realistic radio propagation models or even the Free Space Propagation Model with a different maximum transmission radius. Furthermore, it was suggested that 30 minutes of link age data are required to use the proposed metrics. It was not explained how LQP can be provided within this initialisation interval, however. Moreover, Gerharz et al. (2002) assumed that the mobility patterns (e.g. the parameters of the mobility model) are static with respect to time. Due to all these severe shortcomings it is unclear whether Gerharz et al.'s (2002) method can successfully be applied in more realistic simulations or real-world deployments.

De Couto, Aguayo, Bicket & Morris (2003)

De Couto et al. (2003) introduce the expected transmission count metric (ETX) in order to find higher-throughput routes in multi-hop wireless networks than those given by the traditional minimum hop-count metric, which is the most common metric used in ad hoc routing protocols. The ETX metric is the expected number of transmissions, including possible retransmissions used in successfully making a unicast. It is assumed that the expected number of future transmissions corresponds to the estimated number of past transmissions. This estimation is realised by counting the number of transmitted and received packets with a subsequent calculation of their ratio. Metrics such as ETX, which use such counting mechanisms, are classified as being snooping-based.

The ETX metric was motivated by observations of link behaviour in a wireless test

bed of 29 nodes that were statically located on different floors in an office building. It was observed that the minimum hop-count metric often chooses routes with lower throughput than the optimal route. Furthermore, a high variance in packet reception ratios was perceived and around 20% of all links were asymmetric such that forward and reverse packet reception ratios differed by at least 25%. However, it should be noticed that a high degree of asymmetry was observed in an experiment in which all nodes had broadcast packets for 5 seconds consecutively. Therefore, the packet reception ratios of all possible node pairs were determined over a large time span (the worst case is a difference of 140 seconds), such that the degree of asymmetry could be overestimated due to a change of propagation characteristics in the environment during that time span. These observations led to the following definition of the ETX metric g_e for a link

$$g_e = \frac{1}{g_f g_r} \quad (2.25)$$

where g_f and g_r are the measured packet reception ratios for the forward and reverse links respectively. The ETX metric for a route is simply the sum of the ETX metrics of the links that constitute the route. The proposed metric has several desirable properties:

- ETX is based on packet reception ratios that are strongly correlated to the throughput.
- ETX considers the asymmetry of links by incorporating the packet loss in both directions.
- ETX penalises routes with higher hop counts that have naturally a lower throughput.

The snooping interval was set to 10 seconds for all trials. However, an explanation of this value is missing.

De Couto et al. (2003) confirmed the suitability of the ETX metric for routing in their wireless test bed of static nodes. It was demonstrated that the ETX metric leads to route selections with significantly higher throughput than the minimum hop-count metric in the DSDV protocol (Perkins & Bhagwat 1994). Furthermore, it was observed that the throughput of the DSR protocol was only slightly improved by employing the ETX

metric since DSR already includes link-layer transmission feedback and is therefore able to avoid links with high asymmetry. Moreover, the packet reception ratio was shown to depend on packet length. Since ETX determines this ratio via probe packets that are significantly longer than acknowledgements, it underestimates the reception probability for these acknowledgements, which leads to a biased estimation of the ETX metric as observed by the authors.

The ETX metric was evaluated in a static ad hoc network. Therefore, it is unclear how the above results translate to scenarios with node mobility, especially since large-scale and small-scale fading are spatial phenomena. Furthermore, the estimation of the ETX metric is representative for one packet length only since an influence of the packet length on the packet reception ratio was shown. Moreover, it is unclear how the ETX metric's performance, which was evaluated indoors, relates to the performance in an outdoor MANET. As we will discuss in Section 6.3.9, these problems can be eliminated by adapting the ETX metric to use one of the LQPRs proposed in this thesis. These LQPRs and the ETX metric are complementary concepts in which ETX is a higher-level metric.

Dowling, Curran, Cunningham & Cahill (2005)

Dowling et al. (2005) present a framework for collaborative reinforcement learning to solve optimisation problems in dynamic, distributed networks. As an example application for this framework, a routing protocol termed 'SAMPLE', which exploits online learning to minimise the cost of routing in MANETs, is proposed and evaluated. The learning goals are to maximise the overall network throughput, to minimise the ratio of delivered to undelivered packets and to minimise the number of transmissions for every packet sent.

Dowling et al. (2005) advocate a stochastic state transition model for links to model the cost of routes. This model predicts the probability of a successful unicast and is therefore a snooping-based method considering unicast packets as is the ETX metric of De Couto et al. (2003). The number of required transmissions for a successful unicast is given by

$$\mathbb{E} \left[\frac{g_s}{g_a} \right] = \frac{g_s + c_1 c_2 (g_r + g_b + g_p)}{g_a + c_2 (g_r + g_b + g_p)} \quad (2.26)$$

where g_s is the number of successful unicast transmissions, g_a is the number of attempted unicast transmissions, g_r is the number of received unicast transmissions, g_b is the number of received broadcast transmissions, g_p is the number of promiscuously received (overheard) unicast transmissions, and c_1 and c_2 are static constants. c_1 represents the belief in the successful transmission of a packet considering only received packets. c_2 controls the weight between received and transmitted packets. Equation (2.26) is based on snooping transmitted and received packets within a fixed time interval that was set by Dowling et al. (2005) to 10 seconds. c_1 and c_2 were set to 0.5 and 0.2 respectively.

The performance of the SAMPLE routing protocol was evaluated against AODV and DSR in the NS-2 simulator. Two scenarios were chosen with the first one representing the design assumptions of AODV and DSR in that a true ad hoc network without any fixed infrastructure was available. In the second scenario, these design assumptions were violated by including a subset of static nodes that provided a backbone. In the first scenario the packet delivery ratio of all routing protocols was high. However, when the NS-2 simulator was augmented such that links experienced random packet loss (without further details given about its statistical description), the SAMPLE protocol showed much better adaptivity. For packet loss of up to 20%, SAMPLE showed packet delivery ratios above 85% while AODV and DSR exhibited only 60% and 10% respectively. In the second scenario it was shown that SAMPLE outperformed its competitors in terms of throughput and packet delivery ratio since it better utilised the backbone. While the accuracy of the proposed LQPR was confirmed indirectly by these simulations, it is unclear how the obtained results relate to real-world radio links since the quality of links is not arbitrarily random but a complicated stochastic process that is governed by diverse propagation effects depending on the environment. Furthermore, the constants in (2.26) and the observation length were set to values without any further explanation.

2.1.5 Related Literature

In this section we discuss literature that does not suggest new LQP algorithms for MANETs but is related to LQP and its applications.

Roman, Huang & Hazemi (2001)

Roman et al. (2001) use the concept of announced disconnections to create a group communication system for MANETs that provides consistency. Consistency is defined such that all messages are sent and delivered in the same group view by all members and no message is lost under the assumption that no node fails and communication failures are announced in advance. These properties simplify the development of mobile applications greatly since even frequent changes in the network topology are masked from the application layer by the principle of transparency. The announcement of disconnection relies on LQP that is provided by Roman et al. (2001) by means of the principle of safe distance. This safe distance is defined as the maximum distance at which one can guarantee that any communication task between two nodes can still be completed before the link between them fails, even if the nodes move away from each other at maximum speed. This concept corresponds to the preemptive region from Goff et al. (2001) with the difference that Goff et al.'s (2001) communication task is the discovery of routes, while Roman et al.'s (2001) task is the delivery of messages to achieve consistency. The proposed group communication system consists of a group discovery and a reconfiguration protocol. The former uses location information to determine if new groups or group members are in the vicinity such that either groups or members join. The latter protocol merges and splits groups, handles joins and leaves of group members and ensures consistency of message delivery. Reconfigurations rely on the principle that all members of a group are within a safe distance such that consistency can be provided due to announcement of disconnections. If one or more group members move outside the safe distance with respect to other members, the group is split into multiple groups.

The work of Roman et al. (2001) focuses on the algorithms in their group communication system and does not provide any detailed LQPR. All the algorithms presented are only briefly outlined and no evidence of an implemented system is provided. Therefore, this work is of conceptual nature only. While we believe that LQP algorithms can be of great benefit for efficient group communication in MANETs, the practical feasibility of the proposed approach is questionable. Roman et al. (2001) assume perfect LQP as a

basis for providing consistency. In this way, Fischer et al.'s (1985) impossibility results for achieving consensus in an asynchronous distributed system, which experiences arbitrary link failures, is circumvented and the complicated task of achieving consensus in MANETs with restricted link failure patterns is greatly simplified. However, the assumption of perfect LQP is unrealistic and thus should not be the basis for providing consistency, since this property must be provided in all circumstances, even when the LQP is incorrect.

Killijian, Cunningham, Meier, Mazare & Cahill (2001)

Killijian et al. (2001) suggest a model for a location-aware group communication system. The key idea is that groups are defined not only by interest but also by proximity. A proximity group therefore consists of members that are within a defined space and that are interested in this group. The space is specified either absolutely or relatively to mobile nodes. For example, an absolute proximity might be defined for a traffic light that is to inform cars about its status. A proximity group around an ambulance, which informs nearby cars about its presence, requires in contrast a relative specification. The group membership management layer is supported by a partition prediction component. This component predicts the probability of a partition and is employed to guarantee consistency of group membership and message delivery. A failure predictor is recommended to predict link failures due to node crashes and battery status. A movement planner predicts mobility related link failures based on the notion of a safe distance (Roman et al. 2001). An environment evaluator is envisioned that infers knowledge from environmental conditions that have an influence on link quality.

While we like the idea of partition prediction, Killijian et al.'s (2001) work provides no details on how such partition prediction can be realised or how such a component integrates into the group membership management layer. Furthermore, only the prediction of link failures is envisioned. However, the prediction of a future network topology also requires a prediction of link recoveries since they also change the network topology. Moreover, Killijian et al. (2001) suggest LQP similar to Roman et al. (2001) for ensuring consistency. As discussed in previously, group communication systems provide consistency guarantees

that cannot be realised solely by imperfect LQP.

Handoff Algorithms

Handoff, which is also termed ‘handover’, is the process of transferring a connection with a mobile phone to a different base station than currently used in a cellular network. This transfer can be realised by switching the frequency band, time slot or codeword used or any combination of these. Handoff algorithms are specific to the structure of the infrastructure networks for which they are designed. For example, an algorithm that is designed to work in a macrocellular environment is unlikely to perform well in an overlay network of macro- and microcells. If the infrastructure network controls the handoff process, the handoff is centralised; otherwise it is decentralised. The goal of the handoff process is to maximise communication quality while minimising the number of handoffs. Handoff, admission control, channel allocation and power control are all resource management tasks that should be integrated to obtain better overall system performance. Most handoff algorithms are based on signal-power and noise-power measurements, which indicates that these criteria are well suited in determining link quality. An excellent survey article for handoff algorithms is given by Tripathi et al. (1998).

The handoff process is related to LQP in MANETs since both topics are concerned with link quality. However, these topics differ greatly in other respects. The handoff process switches between base stations in an infrastructure network. The infrastructure network is static with respect to mobility and therefore has well-defined properties such as certain coverage and fixed positions of the base stations. Furthermore, base stations are elevated, have more powerful transmitters and more sensitive receivers than mobile stations such that up- and down links have different properties. Moreover, base stations are connected by wired links and therefore have global knowledge about all mobile users and other base stations. All these properties are absent in MANETs that consists of mobile nodes, which act as peers only. Furthermore, the aim differs for both topics. The handoff process focuses on selecting the base station with the best communication quality and the accurate prediction of single link failures is of no particular concern. The mobile station

can also control the communication quality to a certain extent via the base station due to a feedback loop. The handoff problem is a global optimisation problem with global knowledge that aims to simultaneously maximise the communication quality and the capacity of the network. LQP in MANETs, however, aims to predict the probability of link failures without any global knowledge and without the possibility of influencing the communication quality. Furthermore, MANETs require multi-hop communication while cellular networks rely on single-hop wireless communication.

2.2 Real-World Measurement Studies Related To Link Quality in Outdoor 802.11 Networks

In recent years an increased number of measurement studies can be found in the literature due to the deployment of wireless networks, especially in universities. However, most of these measurements are concerned with higher-layer metrics in infrastructure networks and indoor studies are predominant. A comprehensive list of measurement studies is given by the ‘Community Resource for Archiving Wireless Data At Dartmouth’ project that intends to provide a wireless network data resource for the research community (Dartmouth College 2006). In this section we focus on some studies that measure link quality using low-layer metrics in outdoor 802.11 networks and that are related to our own measurements.

Anastasi, Borgia, Conti & Gregori (2004)

Anastasi et al. (2004) measured link quality in terms of the higher-level metrics of TCP and UDP throughput for an 802.11b network in ad hoc mode. All measurements were done outdoors with static nodes. The authors observed that the maximum transmission range is lower for higher data rates than for lower ones. This result confirms theory since with constant transmission power more energy per symbol is available for lower than for higher data rates. The maximum transmission range was estimated to be 30 m, 70 m, 90–100 m and 110–130 m for the data rates of 11 Mbps, 5.5 Mbps, 2 Mbps and 1 Mbps respectively. Therefore, Anastasi et al. (2004) conclude (erroneously) that the maximum

transmission range of 250 m, which is assumed in most MANET simulations, is 2–3 times higher than in a real-world, obstacle-free environment. Furthermore, it was demonstrated that the throughput is seriously degraded if a node height is below 1.20 m. This effect depends on the First Fresnel Zone that contains most of the radio energy. If nodes are too low, the First Fresnel Zone touches the ground such that a significant amount of radio energy is lost. Both reported results will be discussed comprehensively in Section 3.3.2 in relation to our own measurements.

Moreover, Anastasi et al. (2004) showed that the UDP and TCP throughput between two nodes was significantly reduced, if other nodes, which were placed further away than the maximum transmission range, transmitted on the same channel. However, the throughput increased in two steps with when the distance between the interfering nodes was increased. Therefore, the authors concluded that the maximum transmission range is smaller than the maximum physical carrier sensing range, which in turn is smaller than the maximum interference range. Consequently, Anastasi et al. (2004) suggest using different values for each of these ranges in simulations that traditionally use only one value for all ranges.

Aguayo, Bicket, Biswas, Judd & Morris (2004)

Aguayo et al. (2004) measured packet loss for a static mesh network of 38 nodes that were distributed over roofs in Cambridge, Massachusetts. Each node consisted of a PC with an 802.11b card with Intersil Prism 2.5 chipset in ad hoc mode and an omni-directional antenna. All measurements of signal power, noise power and packet loss were made with 1500-byte long packets at different data rates. The accuracy of the signal power and noise power measurements was shown to be within 4 dB for the type of 802.11 card used.

The ‘neighbour’ abstraction is commonly used in the design of MANET protocols and it expresses the idea that nodes can be grouped into partitions in which nodes can either communicate with 100% or 0% probability. However, Aguayo et al. (2004) demonstrated that a high number of nodes had packet loss ratios within the range of 10% to 90%. Therefore, the classical neighbour abstraction did not hold for this wireless test bed. This observation is consistent with our own findings in Section 3.2.2. Furthermore, it was

shown that the observed packet loss was only partly depending on the signal-to-noise ratio (SNR) or distance. In an experiment with a hardware channel emulator it was determined that a delay spread higher than a few hundred nanoseconds affected the packet loss negatively. This observation agrees with the 802.11 cards' specification which states that the RAKE receiver, which is the main receiver structure in an 802.11 card, and the channel equaliser only support delay spreads up to 250 ns. While this delay spread is appropriate for indoor environments, urban microcells exhibit delay spread often exceeding 1 ms (Aguayo et al. 2004). Moreover, it was shown that the packet loss typically varies by only a few per cent within a time frame of one second.

While Aguayo et al. (2004) present interesting results, it is not clear how general these are. All their measurements have been made with only one card type. However, as we will show in Section 3.3.2, different card types can show very different characteristics. Moreover, the propagation environment is over urban roofs in which diffraction is especially high. If the same observations would be made on the ground for moving nodes is open to question. Additionally, all measurements were made with very long packets of only one size and therefore it is open if the same results could be observed with different packet lengths.

Sridhara, Shin & Bohacek (2006)

Sridhara et al. (2006) examined signal-power variations due to pedestrians for an 802.11 network in infrastructure mode. Two nodes were placed at heights of 1.2 m and 4.3 m respectively and the signal power was simultaneously recorded for both transmitting nodes. It was observed that the signal power varied due to moving pedestrians albeit all nodes were static. This result corresponds to our measurements in Section 3.3.2 in which we show that people affect the signal power depending on the distance to the shadowed nodes. Sridhara et al. (2006) noticed further that with increasing density of pedestrians the variance of the signal power increased. Different node heights, however, only slightly affected the variance of the signal power. Moreover, it was demonstrated that the variations can be characterised well in the time domain by a one-dimensional diffusion process with four parameters. This statistical description allows a computationally inexpensive simulation

of the observed variations.

The proposed statistical description of signal-power variations, which are caused by pedestrians, is valid for stationary nodes only. Whether these results extend to mobile scenarios has not been explored yet. Furthermore, the authors do not investigate to what degree these signal-power fluctuations are caused by small-scale fading. Small-scale fading can also be experienced by static nodes if other objects move in the radio channel (Rappaport 2002, p. 178).

2.3 Small-Scale Wideband Signal Envelope Fading

In general the wideband signal envelope shows less severe small-scale fading than the narrowband signal envelope (Lee 1991). The reason for this is that wideband signals inherently exploit frequency diversity (Lee 1991, Kozono 1994, Yamaguchi et al. 1995). While the probability distributions of small-scale narrowband signal envelope fading, for which closed-form expressions exist, have been extensively studied (see, for example, Young 1952, Nakagami 1960, Jakes & Reudink 1967, Clarke 1968, Suzuki 1977), comparatively few such studies are reported for wideband systems (Kozono 1994, Yamaguchi et al. 1995, Yan & Kozono 1999, Oh et al. 2001) and closed-form expressions for the CDF and PDF of the small-scale fading envelope are unavailable.

Kozono (1994) and Yan & Kozono (1999)

Kozono (1994) and Yan & Kozono (1999) have proposed a wideband signal propagation model with which they investigated the small-scale fading of the received signal envelope of a mobile receiver. They verified their model with extensive measurements performed in the Tokyo region (Kozono 1994, Nakabayashi & Kozono 1998, Yan & Kozono 1999, Nakabayashi et al. 2001) and observed that the fading depth is strongly dependent not only on the ratio of the direct to indirect power of the wideband signal but also on what they term the ‘Equivalent Received Bandwidth’. They also observed that the distribution of the signal envelope is almost independent of the carrier frequency. Their results also

demonstrate that wideband signals in general exhibit shallower fades than narrowband signals and that small-scale wideband signal envelope fading in non-line-of sight (NLOS) conditions cannot in general be characterised using the Rayleigh distribution. They did not investigate however whether other known distributions can do this. Similar results to those given above were reported by Yamaguchi et al. (1995).

Yan & Kozono's (1999) model assumes that N_{Wv} multipath waves arrive at the receiver under the following conditions: each wave has an amplitude A_i , a path length L_i and an angle of arrival ϑ_i . A_i and L_i are independent of each other and are distributed uniformly over a given range. ϑ_i is distributed uniformly over 2π in the horizontal plane. A_0 and L_0 denote the amplitude and path length of the LOS wave. The ratio of the direct to indirect power is defined as

$$a = A_0^2 / \sum_{i=1}^{N_{Wv}-1} A_i^2, \quad (2.27)$$

giving $a_{(dB)}$ where

$$a_{(dB)} = 10 \log_{10} a. \quad (2.28)$$

The bandwidth of each arriving wave (assumed to have a flat power spectral density) is taken to be greater than the receiver bandwidth $2\Delta f$. The received signal power R in watts is then expressed by (Yan & Kozono 1999, (2))

$$R(2\Delta f) = 2\Delta f \left(\sum_{i=0}^{N_{Wv}-1} A_i^2 + \underbrace{\sum_{i=0}^{N_{Wv}-1} \sum_{\substack{j=0 \\ i \neq j}}^{N_{Wv}-1}} \frac{A_i A_j}{\frac{2\pi}{c} \Delta f \Delta L_{ij}} \cos \left(\frac{2\pi}{c} f_c \Delta L_{ij} \right) \sin \left(\frac{2\pi}{c} \Delta f \Delta L_{ij} \right) \right) \quad (2.29)$$

where ΔL_{ij} is the difference in the path lengths of the i th and j th arriving waves. As mentioned earlier Yan & Kozono (1999) also propose a propagation parameter termed the 'equivalent received bandwidth' which can be used to estimate the fading depth (Cardoso & Correia 2003). The equivalent received bandwidth is the product of the receiver bandwidth $2\Delta f$ and the maximum difference in path lengths $\Delta L_{\max}$ of the arriving waves (i.e. $\Delta L_{\max} = \max |L_i - L_j|$). In summary, the equivalent bandwidth and hence observed fading depth are dependent on the receiver bandwidth and the propagation environment.

Nakabayashi & Kozono (1998)

Two properties of the stochastic process of small-scale wideband signal envelope fading are important: the probability distribution of the process and its autocorrelation. The probability distribution is the summary of the amplitude structure of the process; the autocorrelation is the summary of the time structure (Yates & Goodman 2005, p. 353). Nakabayashi & Kozono (1998) investigated the autocorrelation properties of small-scale wideband signal envelope fading based on Kozono's (1994) wideband signal propagation model. It was shown that the normalised autocorrelation of the small-scale fading signal envelope r is independent of the receiver bandwidth and is described for both, narrowband and wideband signals, by (Nakabayashi & Kozono 1998, (2)), (Goldsmith 2005, pp. 73,74)

$$\rho_{rr}(\Delta_t) = J_0(2\pi f_D \Delta_t) \quad (2.30)$$

where f_D is the Doppler frequency, Δ_t is the time lag of the normalised autocorrelation, and J_0 is the zeroth-order Bessel function of the first kind. This result was derived analytically and also verified by measurements (Nakabayashi & Kozono 1998).

Oh, Lee, Choi & Kim (2001)

In their work on a statistical model of a W-CDMA receiver, Oh et al. (2001) showed that the distribution of the small-scale fading signal envelope can be described using the Nakagami distribution for a CDMA system. Though this simulation study was limited to only two receiver bandwidths deployed in two types of urban environment, namely, urban high-rise and urban residential, it suggested to us the possibility that the Nakagami and the closely related Rice distribution could be used as a general means with which to describe the distribution of the small-scale fading wideband signal envelope, albeit to a certain degree of approximation.

2.4 Accuracy and Methodology of MANET Simulations

Simulation is still the most popular means of evaluation in the MANET community (Kurkowski et al. 2005) since real-world measurements are expensive in terms of labour

and equipment. Simulations also allow the influence of parameters on evaluation metrics to be isolated and simulation experiments are easy to repeat. Nevertheless, the accuracy of current MANET simulators is debatable as some studies suggest. Furthermore, the methodology of MANET studies is often questionable and seems to be poorer than in more established fields (Kurkowski et al. 2005). Therefore, we discuss here some key studies that enabled credible evaluations in this work.

Cavin, Sasson & Schiper (2002)

Cavin et al. (2002) implemented a simple broadcast algorithm to compare the basic metrics of this protocol in three widely used MANET simulators, namely GloMoSim, NS-2 and OPNET without further assessment of these results in real-world experiments. The used broadcast algorithm floods the network by forwarding every message received for the first time to neighbouring nodes. This algorithm is simple enough to be implemented equally with the same parameters in all three simulators while also being relevant since broadcasting is an important building block in MANET protocols. Cavin et al. (2002) demonstrated that the evaluation results were quantitatively and qualitatively divergent. Not only did the absolute values of the evaluation metrics differ but also in some cases the general behaviour varied. They explained these observations by the different choice of models and different level of detail in the simulators used, especially in the physical layer. Similar results were obtained by Takai et al. (2001) who showed that the AODV and DSR routing protocols lead to different evaluation results in NS-2 than in GloMoSim, mainly due to differences in the physical layer. Both studies, as well as our own real-world measurements, lead us to the conclusion that the standard NS-2 simulator is unsuitable for credible evaluations such that we extended the physical layer as described in Chapter 5.

Gray, Kotz, Newport, Dubrovsky, Fiske, Liu, Masone, McGrath & Yuan (2004)

Gray et al. (2004) conducted a study in which they compared the performance of four ad hoc routing protocols in an outdoor trial, an indoor trial and simulations. The network

consisted of 33 laptops that were equipped with an 802.11 card and a GPS receiver each. In the outdoor trial, people moved randomly, similar to the Random Waypoint Mobility Model with no pauses, and the nodes would broadcast their GPS positions every three seconds. The locations were saved in files and a connectivity trace was derived that represents the network topology. Two nodes were modelled to be connected within the beacon interval, if they received a beacon; otherwise they were modelled to be disconnected. The experiment occurred on an athletic field that can roughly be divided into four flat, equally sized sections of which one was approximately 4 m to 6 m lower. This difference in height caused blockage in LOS paths. In the indoor trials, all laptops were located on the same tabletop and the GPS and connectivity traces were used to emulate mobility and connectivity. In the simulation experiment, six different combinations of radio propagation models and the connectivity trace were compared. The Free Space Propagation Model, the Two-Ray Ground Propagation Model and a single-slope path-loss model with an empirically derived path-loss exponent and large-scale fading were used either with or without the connectivity trace. If the connectivity trace was enabled, the simulator would first check that nodes were in range according to the trace file before the radio propagation model calculated the received power. If the power was higher than a threshold, a packet is received; otherwise it is lost. SWAN (Perrone & Nicol 2002) was the simulator of choice and the mobility was given by the GPS trace file.

Gray et al. (2004) demonstrated that the indoor experiments did not represent the outdoor behaviour despite relying on the outdoor connectivity trace. The performance metrics differed in values and even the relative ranking between the routing protocols varied. This observation was attributed mainly to interference that was caused by the 33 nodes all being located on the same tabletop. The comparison of simulations with outdoor measurements showed that the single-slope path-loss model with large-scale fading was fairly accurately predicting the outdoor performance while the other model combinations led to poorer representations of the real-world environment. This result indicated to us that stochastic radio propagation models with empirical constants for path loss and large-scale fading can lead to accurate outdoor simulations of MANETs, especially if these models are

extended with simulation of wideband small-scale fading.

Stepanov, Herrscher & Rothermel (2005)

Stepanov et al. (2005) compared the NS-2 simulator with a single-slope path-loss model (without any fading simulation) to an augmented NS-2 version that calculates the received power at nodes via a ray tracing based radio propagation model. The latter type of radio propagation model is known to describe the radio channel accurately when detailed geographical maps with building materials are used (Neskovic et al. 2000). Stepanov et al. (2005) demonstrated that the network topology differed significantly between simulations with the single-slope path-loss model with different constants and the ray tracing model. Additionally, it was shown that the packet delivery ratio, the routing packet overhead and the packet latency differed for simulations of the AODV protocol. Unfortunately, no comparison was made between the ray tracing model and a single-slope path-loss model with additional simulation of large-scale and small-scale fading.

For their study, Stepanov et al. (2005) precomputed the signal power for all possible transmitter-receiver positions in the city centre of Stuttgart with a commercial ray tracing based radio propagation simulator. This precomputed data was then fetched during simulations in NS-2. The signal power was precomputed for a 5 m by 5 m grid that leads to 32 billion position pairs for the city centre of Stuttgart. A finer sampling would have lead to significantly more position pairs. The precalculation step produced 120 GB of data and required the computing power of three days of a PC cluster of 50 machines. These required resources indicated clearly to us that ray traced based methods do not scale to ad hoc networks. While in infrastructure networks the position of base stations is fixed, every node in ad hoc networks is potentially mobile such that the problem of precomputing signal-power values increases by a whole dimension. Consequently, an improved stochastic simulation of the radio channel is better suited to the simulation of MANETs due to significantly lower resource requirements than using ray tracing based methods.

Kurkowski, Camp & Colagrosso (2005)

Kurkowski et al. (2005) investigated the methodology on which the MANET community performs evaluations. Their findings are derived by surveying all papers that have been published in the premier conference MobiHoc from 2000 to 2005. Four different criteria were identified for credible research. First, results should be repeatable. Secondly, results should be unbiased and not specific to an unrepresentative scenario. Thirdly, results should be rigorous and therefore scenarios and conditions of simulations should truly represent the aspects of the MANET protocol being studied. Fourthly, the results must be statistically sound. Based on these criteria, Kurkowski et al. (2005) concluded that the state of art in MANET simulations is poor and that most studies lack believability.

75.5% of all surveyed studies were based on simulations. Nevertheless, in 29.8% of all studies the simulator was not identified. NS-2, followed by GloMoSim, was by far the most popular MANET simulator and NS-2/GloMoSim were used in 43.8%/10.0% of all studies in which the simulator was identified. 57.9% of all studies did not state the type of simulation (e.g. termination or steady-state). Steady-state simulations represent the long-term behaviour of MANET protocols after the initialisation phase and they are the most common type of simulations since researchers are normally interested in the long-term behaviour of protocols. However, only 7.0% of all studies addressed the initialisation bias albeit using the unreliable method of arbitrarily discarding data from the beginning of the simulation. The number of simulation iterations was only published in 35.8% of all surveyed studies and confidence intervals were provided only in 12.5%. However, it is unclear how well results represent the population under study when the number of simulation iterations and confidence intervals are unknown.

We incorporated Kurkowski et al.'s (2005) recommendations into our evaluation of novel LQPRs as described in Section 6.5.1 to avoid the common shortcomings previously discussed.

PalChaudhuri, Boudec & Vojnovic (2005)

Steady-state simulations of MANETs require that the mobility distribution is in steady state within the whole simulation run since protocol performance varies significantly between the transient phase and the steady state as, for example, PalChaudhuri et al. (2005) showed for the packet reception ratio of the DSR protocol. Steady-state simulation of mobility, which is also called perfect simulation, is provided for the random trip model by a tool that was developed by PalChaudhuri et al. (2005) and is used for our simulations in Chapter 6. The random trip model is a generic model that includes the widespread Random Waypoint Mobility Model (Johnson & Maltz 1996) and also the Random Waypoint Mobility Model City Section (Saha & Johnson 2004). In the latter model the nodes move according to a geographical map that is often derived from the real world such that this mobility model is often considered to be realistic (Saha & Johnson 2004).

2.5 Summary

All the surveyed link quality prediction (LQP) algorithms are based on radio propagation models that only characterise path loss to various degrees of accuracy but fail to also consider large-scale and wideband small-scale fading effects. Consequently, neither these LQP algorithms themselves nor their performance evaluations are applicable to real-world environments in which these two propagation effects are pronounced (Neskovic et al. 2000, Kotz et al. 2004). Hence, novel LQP algorithms are required that incorporate these propagation effects and make the promise of accurate LQP in real-world urban environments a reality. Furthermore, the need for credible evaluations by real-world studies or advanced simulations, which account for the propagation effects of path loss, large-scale and small-scale fading, is evident.

A number of LQP algorithms rely on location measurements for their prediction. However, typical GPS measurements have a user-equivalent range error of 19.2 m and location information is often unobtainable in dense urban environments where a connection with at least three satellites cannot be continuously maintained. Therefore, location measurements

are currently impractical for these environments.

In the literature indirect evaluations of LQP algorithms prevail over direct ones. In these indirect evaluations the prediction accuracy of LQP algorithms is assessed by comparing the performance of communication protocols with and without LQP, typically by comparing metrics such as packet latency and data throughput. Since various studies use different communication protocols to evaluate their LQP algorithms, a direct comparison of LQP accuracy for different studies is difficult.

Chapter 3

Real-World Studies on Influence Factors and Prediction of Link Quality in 802.11 MANETs

The potential importance of link quality prediction for masking topology changes in MANETs has been shown in the literature. However, as described in Chapter 2, existing LQP algorithms are based on very basic radio propagation models whose applicability to real-world urban environments is questionable. Therefore, we conducted a real-world study in which we assessed the accuracy of three well-known LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) from the literature for a prediction horizon of two seconds ahead. The three LQP algorithms were selected because they seemed to be most likely to perform well in the microcellular urban environments under study (see Section 3.2 for the employed criteria). In order to ensure a fair evaluation of the algorithms, we chose a type of 802.11 card that reports signal-power levels with low errors due to measurement inaccuracies and discretisation. This low measurement error was verified for this type of off-the-shelf card by comparing the card's signal-power measurements with a wide range of reference powers.

The real-world study of LQP algorithms revealed that the accuracy of all the evaluated

algorithms was very poor in the urban environment under consideration and contrasted sharply with the excellent accuracy observed in corresponding simulations with the standard NS-2 simulator in its default configuration. The extent of this observed difference could not be explained by the measurement accuracy of the 802.11 cards that were used in our experiments. Therefore, we conducted a study that systematically investigated the factors that influence link quality in MANETs for an off-the-shelf 802.11 card. We especially tried to identify factors that make the prediction of link quality difficult and could account for the poor accuracy that was observed for the three LQP algorithms evaluated. For example, if changes in orientation due to small-scale movements, which inevitably occur with mobile nodes, have a strong effect on link quality, accurate prediction of link quality would be unlikely.

3.1 Signal-Power Measurement Accuracy of an Off-the-Shelf 802.11 Card

The 802.11 standard specifies that signal-power measurements are optional, although practically all 802.11 cards support them. More specifically, the 802.11 standard specifies (ANSI/IEEE Standard 802.11 1999, p. 150): “The receive signal strength indicator (RSSI) is an optional parameter that has a value of 0 through RSSI Max. This parameter is a measure by the PHY [physical] sublayer of the energy observed at the antenna used to receive the current PPDU [physical layer convergence protocol data unit]. RSSI shall be measured between the beginning of the start frame delimiter (SFD) and the end of the PLCP [physical layer convergence protocol] header error check (HEC). RSSI is intended to be used in a relative manner. Absolute accuracy of the RSSI reading is not specified.”

Since Bardwell (2002) observed that 802.11 cards from different manufacturers provide different resolutions and therefore different accuracies, we measured the accuracy of a ‘Lucent Orinoco PC Card Gold’ 802.11 card (henceforth called ‘Lucent Orinoco card’) that was employed for all measurements in this work unless stated otherwise. Since we had no access to a spectrum analyser or power meter with sufficient resolution bandwidth, we used

the measurement setup shown in Figure 3.1. Two Linux laptops (Knoppix 5.0.1, OpenSUSE 10.0) with Lucent Orinoco cards, whose data rate was set to 2 Mbps, were placed in separate rooms. The antennas of the wireless cards were disabled and the cards were connected via pig tails, a set of precision attenuators (Mini-Circuits N-Type Fixed Attenuators UNAT-Series (Mini-Circuits 2002)) and 10.5 m of shielded cable. The placement in separate rooms was required since the shielding of the pig tails was insufficient such that these pig tails would have allowed for an air connection when the two laptops had been placed next to each other on a tabletop. The following procedure was used to assess the accuracy of the card's signal-power measurements:

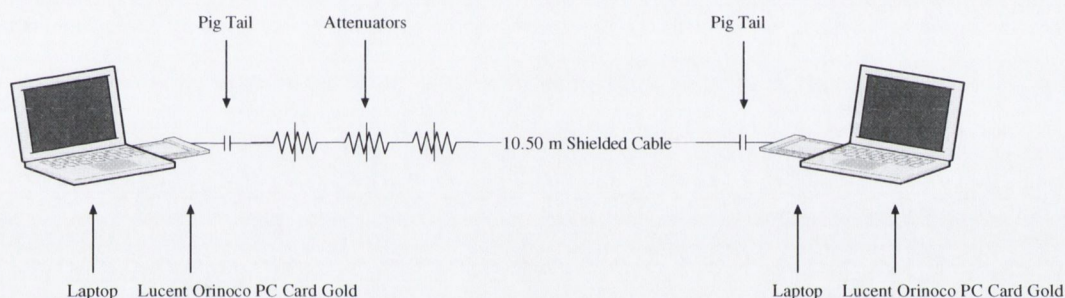


Figure 3.1: Setup to assess the signal-power measurement accuracy of a Lucent Orinoco card. The laptops were placed in different rooms and far enough apart to avoid air transmissions between the two pig tails that were less shielded than the connecting cable.

1. While continuously transmitting packets, we added attenuators until the receiver sensitivity of 91 dBm for a data rate of 2 Mbps was reached (Lucent Technologies 2000, p. A-6). This receiver sensitivity then acted as reference power.
2. We sent 10 packets and recorded the signal-power measurements at the receiving node. Based on this information the average signal power and the mean absolute error (MAE) of the power measurements were calculated.
3. We removed 5 dB attenuation by removing or exchanging attenuators. Since each attenuator had an uncertainty of ± 0.3 dB (Mini-Circuits 2002), any change in the number of attenuators led to a different measurement uncertainty.
4. We repeated Step 2 and 3 for the relevant measurement range of the card.

The average MAE of the signal-power measurements was 1.70 dBm, the average measurement uncertainty was 0.70 dBm. The MAE and uncertainty for different reference powers are shown in Figure 3.2. The power measurements showed good agreement with the reference powers. The MAE varied for different reference powers and tended to increase for powers above -71 dBm. Figure 3.3 shows the minimum, average and maximum of the signal-power measurements for different reference powers. The measurements varied about 1 dBm from their average signal power, which tended to be higher than the reference power. The maximum measurement error was 3 dBm.

Overall, we consider the measurement accuracy of a Lucent Orinoco card to be satisfactory for an off-the-shelf device and sufficient for our study. We are unaware of any similar study that has evaluated the accuracy of signal-power measurements of an off-the-shelf 802.11 card in such detail as presented here.

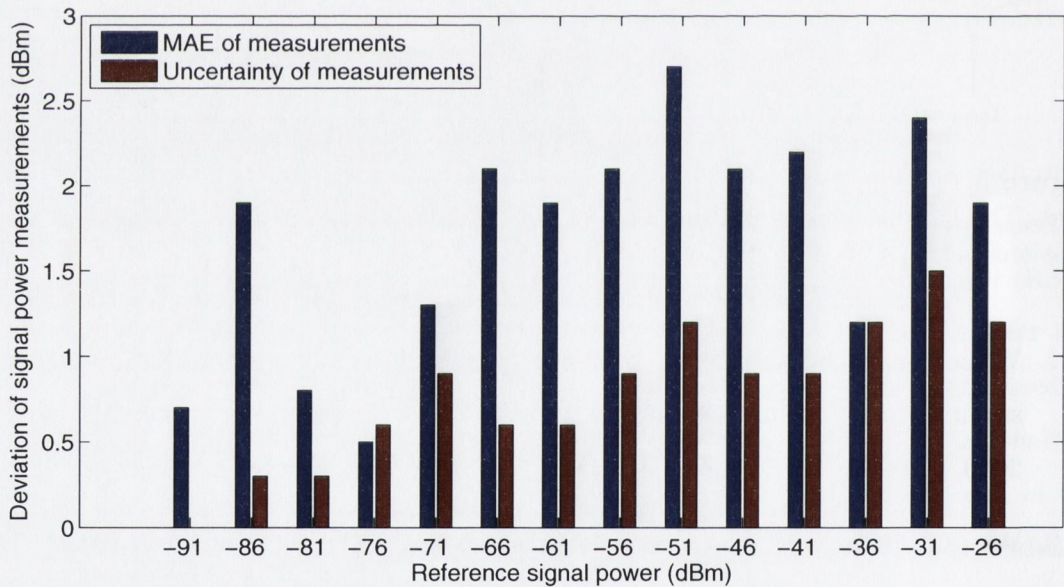


Figure 3.2: MAE of signal-power measurements of a Lucent Orinoco card for different reference powers. The measurements showed good accuracy.

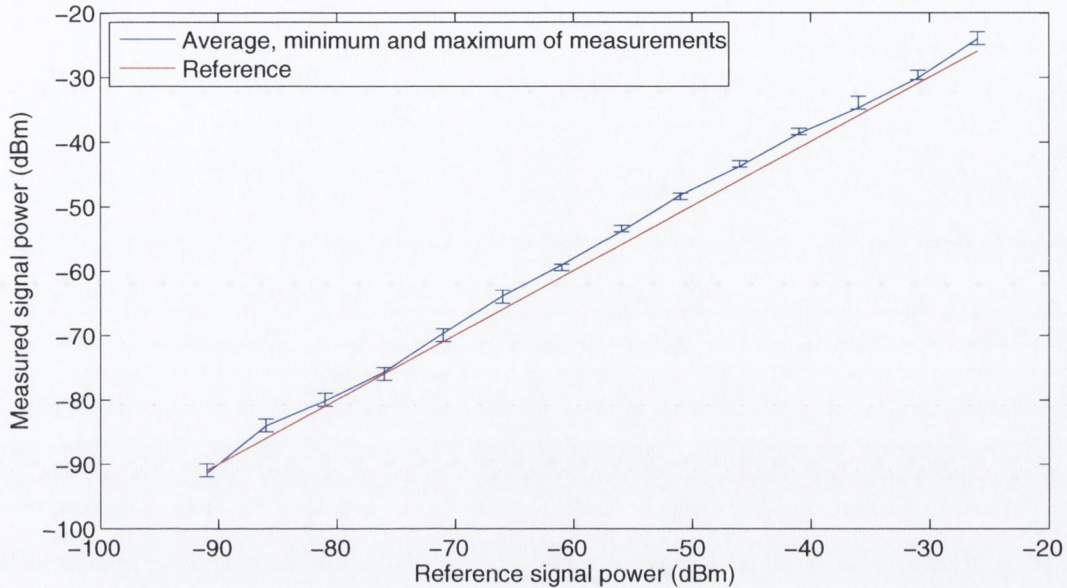


Figure 3.3: Minimum, average and maximum of signal-power measurements of a Lucent Orinoco card vs. reference powers; the red curve represents perfect measurements. The signal-power measurements tended to be higher than the reference power. The measurements typically varied 1 dBm about their averages.

3.2 Accuracy of Link Quality Prediction Algorithms

In order to investigate the performance of LQP algorithms from the literature, we specified the following criteria to select the most suitable algorithms:

1. The LQP algorithm predicts at time T either deterministically or stochastically the packet reception probability for $T + \tau$ where τ is set to 2 seconds.
2. The LQP algorithm should not rely on location measurements since location information is unsuitable for four reasons. First, GPS is often unreliable in urban environments (Nayak 2000, p. 1) since it requires a good view of the sky with at least three satellites in sight to obtain a location. This is confirmed by our own experience in which a GPS device was unable to obtain a location most of the time in the urban environment under test, despite the GPS device being pole mounted on a backpack. Secondly, the GPS accuracy with a user-equivalent range error of 19.2 m (Grewal et al. 2001, pp. 128–130) is much higher than the distance that a node

can move within a time of two seconds at walking speed. Thirdly, path loss mainly depends on the distance between two nodes but may also change due to variations of the path-loss exponent with respect to the urban environment (Goldsmith 2005, p. 47). However, all LQP algorithms, which have been reviewed in the previous chapter, assume that path loss depends solely on distance such that the underlying model and reality differ. Fourthly, Figure 3.4 shows that path loss affects link quality only moderately within a time frame of two seconds, even in the extreme case of nodes moving apart at maximum walking speed. The effect of path loss on link quality is especially low when nodes are located sufficiently far away from each other, which is the most important case for LQP, since the larger the distance between nodes, the higher the likelihood of packet loss. For all the above reasons we conclude that location information is unlikely to improve short-term LQP for pedestrians in urban environments (see also Section 6.3.4).

3. The LQP algorithm's design must rely on a path-loss model that is at least as accurate as a single-slope path-loss model with realistic path-loss exponent (Goldsmith 2005, p. 47) or the Two-Ray Ground Propagation Model (Rappaport 2002, pp. 120–125). These models do not account for the manifold propagation phenomena in urban environments such as large-scale and small-scale fading but are at least known to describe path loss well.
4. The LQP algorithm must have been presented in enough detail to allow an implementation.

Of the algorithms described in Chapter 2 the above criteria are only met by Paul et al. (1999), Goff et al. (2001) and Qin & Kunz (2002) which we therefore selected for our real-world study.

3.2.1 Experimental Setup

The urban environments we chose for our experiments include a variety of static (e.g. buildings, trees, etc.) and dynamic (e.g. people, cars) objects. The selected locations in

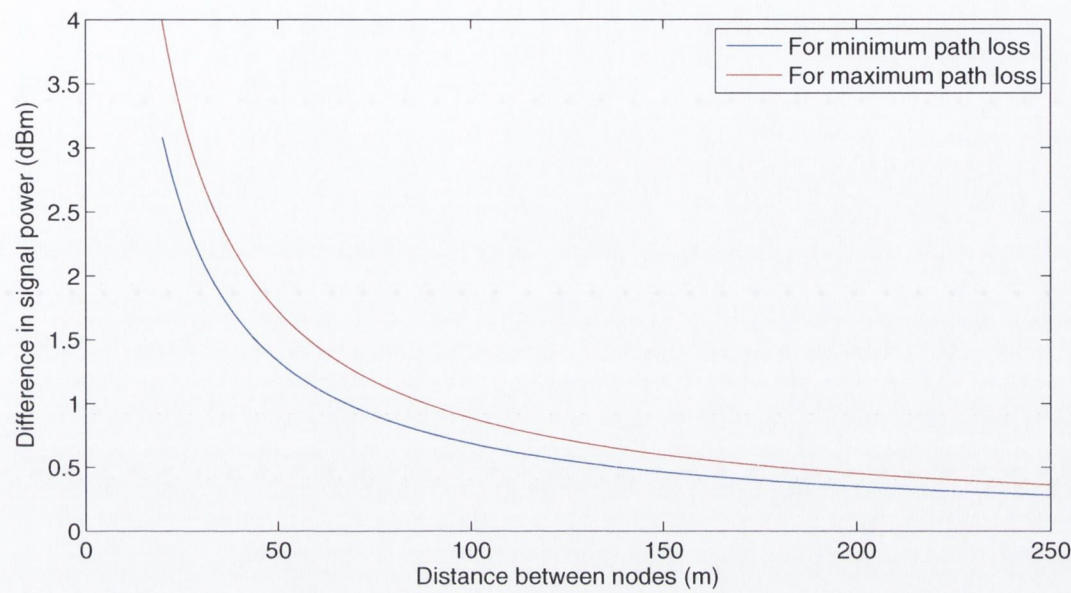


Figure 3.4: Minimum and maximum difference in signal power due to path loss between nodes that move apart from a starting distance with maximum walking speed for two seconds. The difference in signal power due to the environment-specific path loss is low, especially if nodes are sufficiently far apart; for example, if nodes are approximately further than 100 m away, the difference in path loss is below 1 dBm for a movement apart at maximum speed.

Dublin’s city centre are fairly typical of European cities. Grafton Street is a long narrow pedestrian precinct overshadowed by moderately high (three-storey) buildings. There is no vegetation and it is commonly quite full of people. The second location, O’Connell Street, is a wide avenue-like street. There are two lanes of traffic in both directions. These are separated by an island with some trees. Traffic is heavy throughout the day. On both sides of the street the foot paths are typically full of pedestrians. We conducted our experiments at busy times. We will refer to Grafton Street as ‘Street 1’ and O’Connell Street as ‘Street 2’ in this chapter.

Our study is based on two nodes that were carried by people. The bearers of both nodes moved between randomly chosen shops, their movement interspersed with pauses of about two seconds as might be expected of some pedestrians on these streets. This mobility pattern corresponds to the widely used Random Waypoint Mobility Model with a maximum walking speed of 1.5 m/s using pauses of two seconds. The nodes were confined

to the main street and its immediate precinct to ensure some degree of connectivity. Both nodes were broadcasting messages of 100-byte long payload at regular intervals (beaconing) directly over the MAC layer without using any higher-level protocol at a data rate of 2 Mbps. Since none of the LQP algorithms under exploration specified a required minimum sample rate, we chose 10 Hz that allowed for prediction in convenient 100 ms intervals. We conducted three trials of 30 minutes duration for each street. All received packets were recorded together with their associated signal power at the receiver.

Two Dell Latitude C400 laptops with Lucent Orinoco cards were used as the nodes. The transmission power was set to the maximum of 15 dBm with disabled power management. We used Redhat Linux 7.3 together with the `orinoco_cs` driver by David Gibson in version 0.12 (Gibson 2003), which we extended to send and receive packets directly over the MAC layer. During the experimental trials we attempted to record the current locations of each node with either a Magellan ‘GPS 315’ or a ‘Garmin ETrax’ GPS receiver. However, the number of satellites in view was mostly insufficient to obtain a location.

For the simulations NS-2 was configured according to the real-world study. The movements of the two nodes followed the Random Waypoint Mobility Model with a maximum speed of 1.5 m/s, 2 seconds pause and an area of 500 m². As propagation model the default Two-Ray Ground Propagation Model was employed. Our choice of mobility and propagation models corresponds to most MANET simulations (e.g. Takai et al. 2001, Agarwal et al. 2000, Goff et al. 2001, Qin & Kunz 2002).

3.2.2 Evaluation

In current MANET simulators link failures are implicitly modelled as being ‘sharp’ due to deterministic radio propagation models that consider path loss as the sole propagation effect. This contrasts with real-world behaviour, where a link typically oscillates between being available and unavailable over a transitional period as shown in Figure 3.5 before it eventually becomes unavailable. Since all three LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) are based on the implicit assumption that links fail sharply, we only determined their prediction accuracy when the link was stable. We define a link to

be stable in a system with a constant beaconing rate, if at least c_1 per cent of packets are received during a time span of c_2 seconds. Our results suggest that $c_1 = 70\%$ and $c_2 = 2$ s are reasonable values.

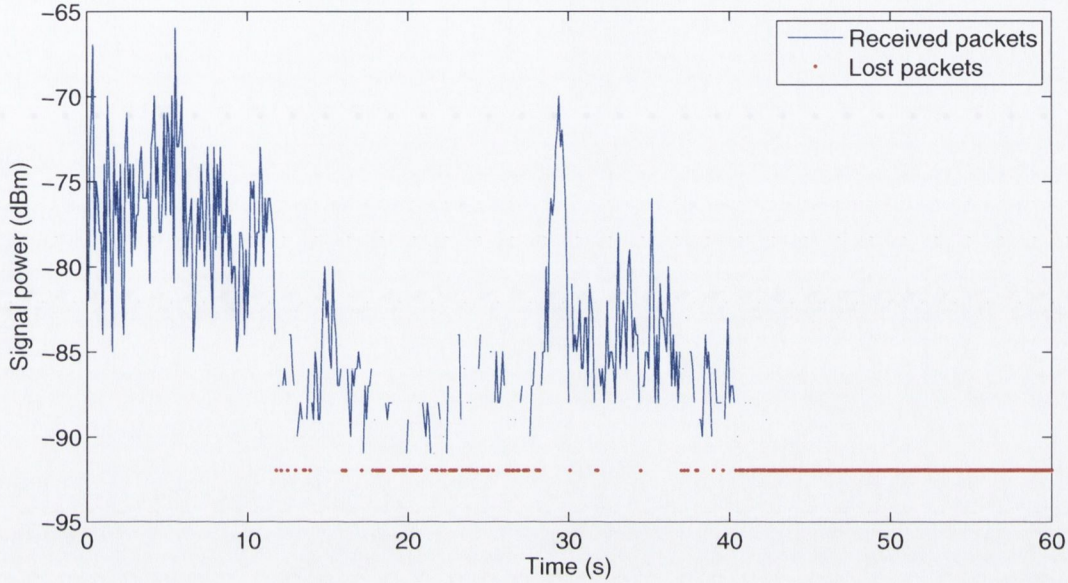


Figure 3.5: Example trace of received packets. The signal power of received packets is represented by the blue line, packets that were lost are symbolised by red dots that were placed at -92 dBm. The link did not fail ‘sharply’ but oscillated between being available and unavailable before it eventually failed completely.

All three LQP algorithms in our study were deterministic and were evaluated for a prediction horizon of two seconds ahead. We defined the LQP accuracy metrics by error statistics of ‘missed packet loss’ m

$$m = 100 \frac{\text{Number of lost packets while link is falsely predicted to be available}}{\text{Number of lost packets}}, \quad (3.1)$$

and ‘unnecessary packet loss’ u

$$u = 100 \frac{\text{Number of received packets while link is falsely predicted to be unavailable}}{\text{Number of received packets}}. \quad (3.2)$$

These metrics capture the fundamental trade-off in deterministic predictions: if the prediction is too pessimistic, the unnecessary packet loss is high but the missed packet loss is low. If the prediction is too optimistic the reverse is the case. Since both metrics have an

equal bearing on performance, an overall accuracy metric must include both. Therefore, we defined the degree of prediction inaccuracy i

$$i = m^2 + u^2 + (m - u)^2 \quad (3.3)$$

as the sum of the squares of missed packet loss m and unnecessary packet loss u with an additional term that requires these two equally important metrics to be balanced.

Each LQP algorithm has parameters whose values in simulations are given by their authors (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002). However, these parameters are unknown for our real-world environments. In order to fairly evaluate these algorithms, we minimised the prediction inaccuracy i by optimisation for each environment such that each LQP algorithm showed the highest accuracy possible. This optimisation was, however, a difficult task since the inaccuracy function associated with a prediction algorithm and data set was not analytically differentiable and was also highly non-linear. The parameter space was cleft so that even classical direct search algorithms performed inadequately since they got stuck at local minima as a result of the greedy criterion. We resolved these problems using a robust evolutionary optimisation algorithm—The Differential Evolution Algorithm from Storn & Price (1997). We implemented all algorithms as described in Section 2.1.1.

Table 3.1 displays the performance of all the algorithms considered under different criteria. As mentioned earlier ‘ m ’ stands for the missed packet loss, ‘ u ’ for the unnecessary packet loss and ‘ i ’ for the overall inaccuracy. The table is divided into separate sections corresponding to real-world experiments and simulation. The experimental section is further partitioned into data sets on which the optimisation of the algorithm parameters was conducted. This distinction is required since the optimum parameters are environment-specific. Optimisation (Opt.) 1 and 2 refer to minimising the inaccuracy based on either the data set for Street 1 or Street 2 respectively. Since the optimum parameters are unknown a priori for a specific environment, Opt. 3 refers to minimisation of the inaccuracy over a compound data set for Street 1 and 2 that intends to find compromise parameter values for both environments. In the simulation study optimisation is not required since the parameters are given.

	Paul et al.'s (1999) algorithm			Qin & Kunz's (2002) algorithm			Goff et al.'s (2001) algorithm		
<i>Experimental trial—Street 1 (Grafton Street)</i>									
	Opt. 1	Opt. 2	Opt. 3	Opt. 1	Opt. 2	Opt. 3	Opt. 1	Opt. 2	Opt. 3
<i>m</i>	48.72%	49.63%	49.45%	58.17%	64.48%	58.17%	22.85%	53.71%	31.73%
<i>u</i>	34.73%	34.77%	34.77%	27.35%	22.71%	27.35%	28.07%	11.72%	22.62%
<i>i</i>	3775.53	3892.91	3869.76	5081.64	6418.15	5081.64	1337.30	4785.28	1601.45
<i>Experimental trial—Street 2 (O'Connell Street)</i>									
	Opt. 1	Opt. 2	Opt. 3	Opt. 1	Opt. 2	Opt. 3	Opt. 1	Opt. 2	Opt. 3
<i>m</i>	55.59%	54.19%	54.19%	61.75%	60.59%	61.75%	17.81%	28.39%	19.43%
<i>u</i>	36.89%	35.90%	35.91%	27.40%	24.62%	27.40%	43.40%	30.50%	39.06%
<i>i</i>	4800.81	4559.89	4560.24	5743.75	5571.13	5743.75	2855.60	1740.69	2288.55
<i>Simulation</i>									
<i>m</i>	0.00%			6.67%			0.00%		
<i>u</i>	0.00%			0.00%			0.00%		
<i>i</i>	0.00			44.44			0.00		

Table 3.1: Prediction accuracy in real-world urban environments and in simulations. Numbers explicitly mentioned in the text are displayed in bold for better readability. ‘*m*’ stands for the missed packet loss, ‘*u*’ for the unnecessary packet loss, ‘*i*’ for the overall inaccuracy, and ‘Opt.’ for the parameter optimisation based on Street 1/2 or a combination data set 3 of both streets. All algorithms showed poor accuracy in real-world environments but excellent accuracy in simulations. The signal-power-based algorithm from Goff et. al. (2001) surpasses the accuracy of the algorithms that rely on the trend of the signal power. However, Goff et. al.’s (2001) algorithm was highly sensitive to the values of its parameters.

The table shows that in our real-world measurements Goff et al.'s (2001) algorithm achieves the best accuracy by far. However, 22.85/28.39% of missed packet loss and 28.07/30.50% of unnecessary packet loss was measured in Street 1/2 despite optimal parameters having been used for each environment. This performance decreased with the use of non-optimum parameters that had been obtained in similar environments. For example, the inaccuracy of Goff et al.'s (2001) algorithm increased in Street 1 from 1337.30 to 4785.28 when the algorithm parameters used were the optimum parameters for Street 2. These results indicate that the parameters of LQP algorithms might benefit from adaptation to the current operating environment.

Paul et al.'s (1999) and Qin & Kunz's (2002) algorithms performed much more poorly on all counts than Goff et al.'s (2001) algorithm. Both algorithms failed to predict approximately half the packet loss while a quarter to one third of packets was unnecessarily predicted to be lost. We attribute this poor accuracy to these algorithms' reliance on signal-power trend data that seems highly sensitive to large-scale and small-scale fading effects. The mechanism of linear regression employed in Qin & Kunz's (2002) algorithms and the window size used in Paul et al.'s (1999) algorithm both seem to be ineffective in dealing with fading effects. Goff et al.'s (2001) algorithm showed a greater robustness in this regard since it uses the current signal-power values and not the trend. This observation demonstrates that signal power is a more powerful predictor of packet loss for short-term prediction horizons with nodes at walking speed since path loss is low under these conditions. This observation corresponds to our analytically derived conclusion about the insignificance of path loss in such scenarios in Section 3.2.

In simulations all algorithms showed near-perfect accuracy, both in terms of missed and unnecessary packet loss. Only Qin & Kunz's (2002) algorithm failed to predict some lost packets. This occurs in situations where the node speed changed during the sampling interval of the three consecutive packets used for prediction (as described by Qin & Kunz (2002) themselves). We would have liked to have compared the results of our simulations directly with those of the original authors. However, Paul et al. (1999) and Goff et al. (2001) assessed the prediction accuracy indirectly using metrics that show enhancement

of the routing protocol performance due to LQP. Qin & Kunz (2002), however, described direct prediction accuracies where it was reported that more than 90% of lost packets were predicted successfully for various mobility patterns. We observed a value of 93% in our simulation.

The near-perfect accuracy in simulations can be attributed to the fact that the LQP algorithms and simulation programs use the same deterministic radio propagation model, although it is well known that the propagation models used by such MANET simulators are simple and yield only to rough approximations of the real world (Gray et al. 2004, Kotz et al. 2004, Neskovic et al. 2000). Thus simulation accuracy is perceived as being optimistic (Qin & Kunz 2002). However, the large discrepancy between LQP accuracy given by MANET simulators with very basic radio propagation models and those obtained in real-world experiments has apparently not been appreciated in the literature to date. Our study demonstrated that current LQP algorithms are not applicable to real-world environments. The stochastic nature of small-scale and large-scale fading effects, neglected by these LQP algorithms, and our observation that links do not fail sharply, suggest that stochastic LQP is likely to be more accurate than deterministic LQP.

3.3 Assessing Influence Factors on Link Quality

The poor performance of prediction algorithms in urban environments motivated us to systematically examine the factors that influence link quality in MANETs and potentially make its prediction difficult, especially for an off-the-shelf 802.11 card. The signal power is a suitable metric to measure link quality since it reacts, in contrast to packet loss, which is only observable for low signal power, quickly to changes in link quality independently of its level. Since electronic sensors to precisely measure potential influence factors such as orientation and height were not available, we restricted our analysis to be qualitative and not quantitative. After introducing the experimental setup, we discuss every influence factor investigated in detail.

3.3.1 Experimental Setup

The variety of signal propagation phenomena observed in urban environments make the separation of potential and actual influence factors cumbersome in these environments. Hence, we chose a beach on a deserted island as a ‘benign’ obstacle-free environment in which to conduct our experiments. We used the same hardware as for the urban environment study that was discussed previously. Distance between nodes was determined accurately by markings that were made with a tape measure. The two nodes were typically facing each other.

Four types of experiments were designed to assess potential and actual influence factors on link quality:

Type I One node was motionless while the other node moved away at constant walking speed until returning after 300 m. This type of experiment exhibits path loss and is, for example, suitable for comparing different 802.11 card models.

Type II Both nodes were placed at a fixed distance. One node was motionless while the other node oscillated between being in motion (e.g. node was rotated, shaken, etc.) and motionless. The comparison of the signal power between the two different states reveals the influence of a factor.

Type III Both nodes were placed at a fixed distance and were motionless. An obstacle moved into line of sight between the nodes, paused and moved out. The difference in received signal power of the two states measures the influence.

All experiments were conducted three times and the mean was used for evaluation where possible. Both nodes transmitted messages periodically. All diagrams display the signal power that was measured at one node along the ordinate. If a packet was lost, no value is given for the signal power.

3.3.2 Evaluation

In the following we discuss the potential influence factors on link quality that are given in Table 3.2.

Factor	Influence
Model of wireless card	High
Type of ground	Low
Height of nodes	High
Orientation without shadowing body	Low
Orientation with shadowing body	High
Shadowing by person	High
Shadowing by car	High
Small-scale movements	None
Payload pattern	None
Communication load without collisions	None

Table 3.2: Influence of various factors on signal power.

Many simulations of MANETs (e.g. Goff et al. 2001, Qin & Kunz 2002) are based on the Two-Ray Ground Propagation Model with maximum node transmission radius of 250 m for a transmission rate of 2 Mbps at maximum transmission power. Nevertheless, a recent experimental outdoor study from Anastasi et al. (2003) claims that 250 m transmission range is far too optimistic and that the actual range would be 90–100 m in an open environment. These contradictory values can be attributed to the model of wireless card as shown in Figure 3.6 (Type I experiment), in which we compared a Lucent Orinoco with a Compaq WL100 card. Both cards comply with the same 802.11 specification and have the same transmission power but showed different behaviour. The maximum transmission range of the Compaq card was similar to Anastasi et al.’s (2003) measurements while the Lucent Orinoco card had a much larger maximum transmission range of approximately 250 m. The observed performance discrepancy of the cards may be caused by different chip sets, the design of the radio frequency components, different antennas and the signal processing algorithms of the cards’ onboard processors. Since the Lucent Orinoco card showed a much higher maximum transmission range, less signal-power variations and its measured path loss can be closely approximated by single-slope or dual-slope path-loss models (see Section 5.3.1 for details), we used this card model for all other measurements. While the 802.11 card model exhibited high influence on link quality, it does not affect predictability as long as the card’s characteristics (for example, the bit error probability

(BEP) function) are known to the node that is using the card.

In all our trials we noted the persistent occurrence of a single but substantial ‘dip’ in the signal power over approximately 10 m at distances ranging from 30 m to 50 m from the source (see, for examples, Figure 3.6 and Figure 3.7). This is most likely due to coupling between the ground and the source (antenna) (Janaswamy 1992).

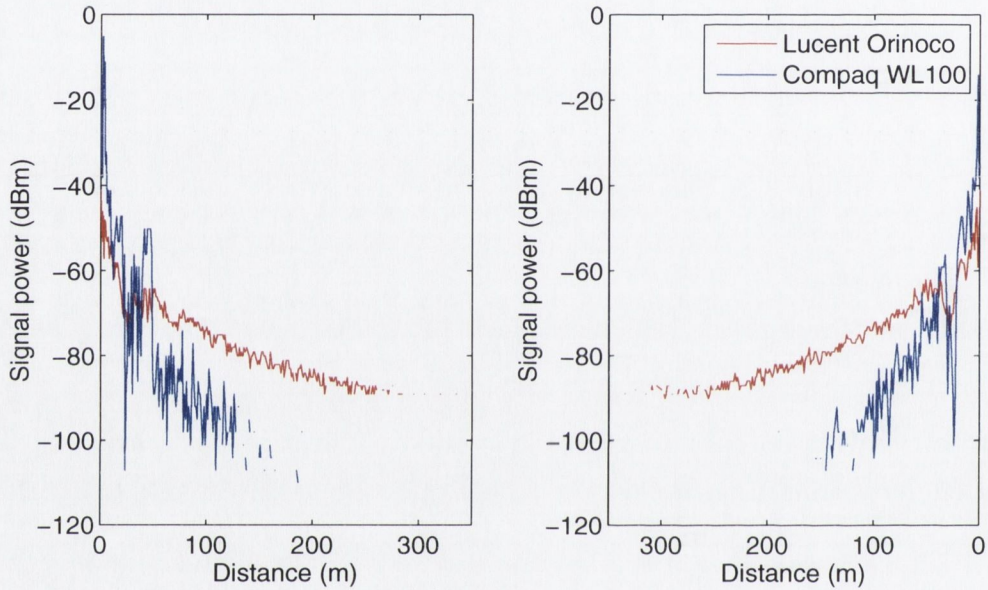


Figure 3.6: Signal power vs. distance for two 802.11 card models. The model of card had a high influence on the received signal power. However, this influence does not affect predictability of link quality when the card characteristics are known to the node that is using it.

In order to assess the influence of the type of ground, we compared measurements on sand with measurements on grass. The latter measurements were conducted in the Phoenix Park, Dublin, which provided a similar obstacle-free environment to North Bull Island. Figure 3.7 (Type I experiment) demonstrates that the type of ground had only low influence on link quality with sand having given slightly higher signal powers than grass.

The influence of node height above ground was assessed by placing two nodes 50 m apart while one node was stationary at navel height and the height of the other varied as shown in Figure 3.8 (Type II experiment). The signal power dropped significantly when one node was

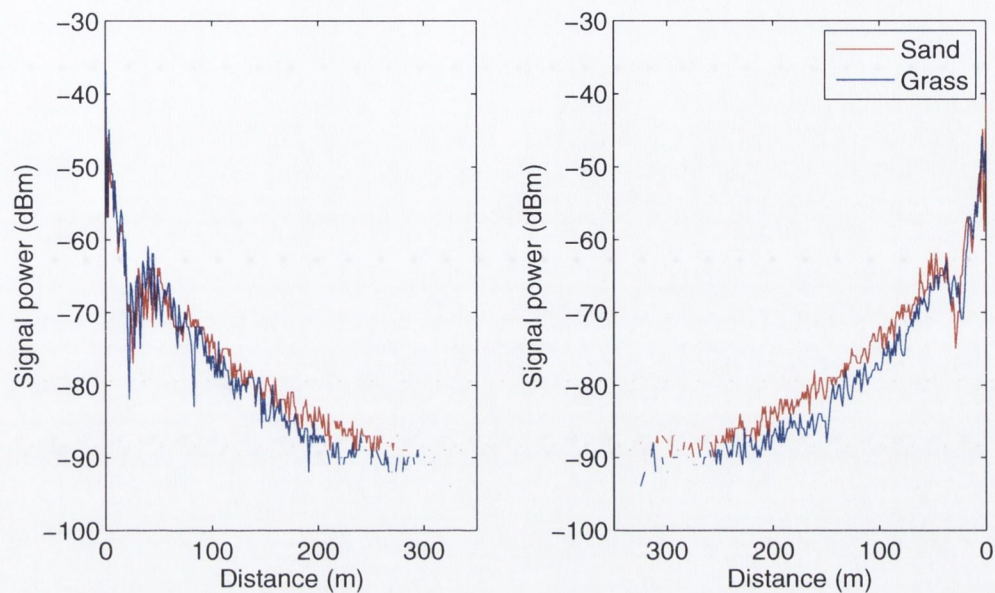


Figure 3.7: Signal power vs. distance measured on grass and sand. The type of ground had only a low influence on the signal power.

placed close to the ground and no relevant difference was observable between navel and head height. This observation was also made by Anastasi et al. (2003). When nodes are placed too low, the First Fresnel Zone, which contains most radio energy, touches the ground and a significant amount of radio energy does not reach the receiver. Nevertheless, since we assume that node heights change infrequently in ubiquitous computing and disaster recovery scenarios, we rate its importance for LQP in these applications to be low. However, link quality variations caused by varying node heights might pose a problem in military applications if the mobility patterns include changes in node heights.

In personal wireless networks, the orientation of nodes varies with the movements of the people who hold the nodes. While orientations between 0 and 360 degrees are relevant for the Z-axis due to people turning in different directions, only small variations in orientation relative to the X- and Y-axis are expected. If a typical 802.11 card has a truly omni-directional, cross-polarised antenna, varying orientations do not influence link quality. In order to assess the sensitivity to orientation, we kept one node stationary while the bearer of the second node varied the node's orientation. As evident from Figure 3.9

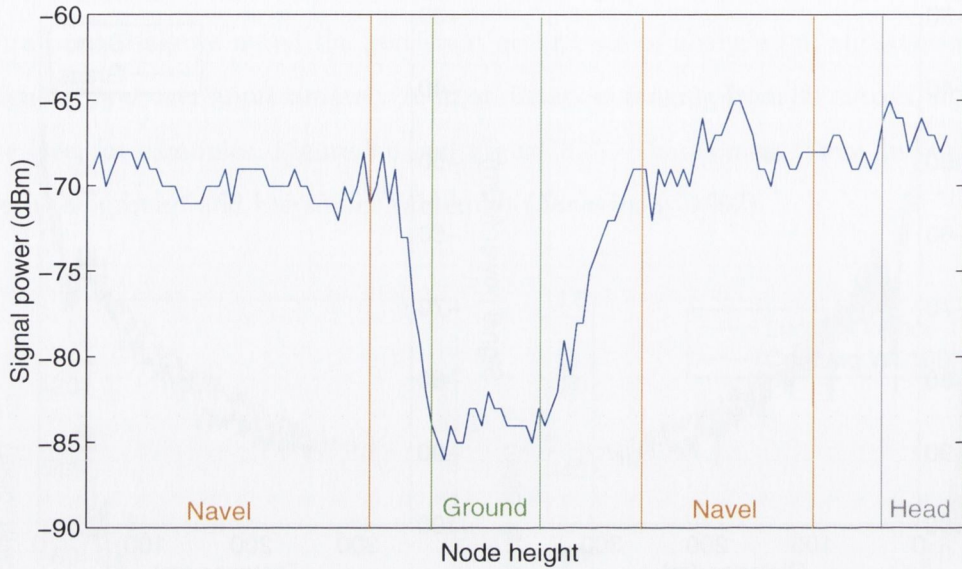


Figure 3.8: Signal power received at different node heights while one node was stationary. A sharp drop in signal power can be observed when the mobile node was placed close to the ground; no relevant difference was noted between navel and head height.

(Type II experiment), variations in orientation relative to the Z-axis influenced link quality only moderately in our experiments; comparable results were observed for variations in orientation relative to the X-axis and Y-axis. However, we realised that the body of a person holding a node, can shadow the link severely based on the node's orientation and position. This effect is illustrated at 150 m distance in Figure 3.10 (Type II experiment). At around 180 degrees the body's shadowing caused a significant drop in the signal power. This leads to a link failure although the node could potentially move 100 m further away at a different orientation without losing the connection. Since large-scale fading is caused by blockage from random objects in the radio channel (Goldsmith 2005, p. 48), large-scale fading accounts to some extent for blocking due to a person's body. Whether this latter effect is, however, fully addressed by the current models of large-scale fading is an open question since we are unaware of any study that investigates large-scale fading and its causes specifically in the context of MANETs, which have, in contrast to classical infrastructure networks, the same low antennae heights for all nodes.

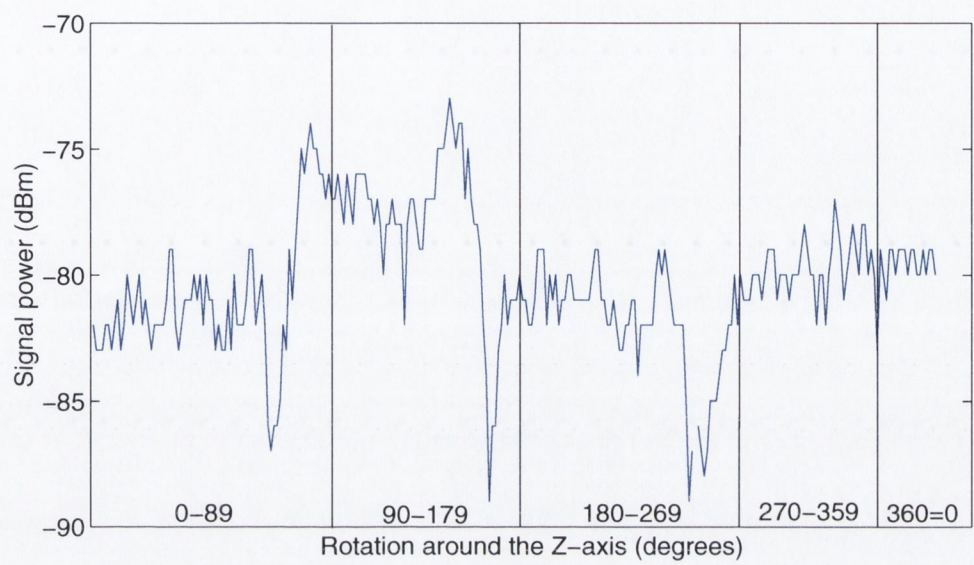


Figure 3.9: Signal power vs. varying node orientations. The influence of this effect was low as long as the body of a node’s bearer did not block the LOS path.

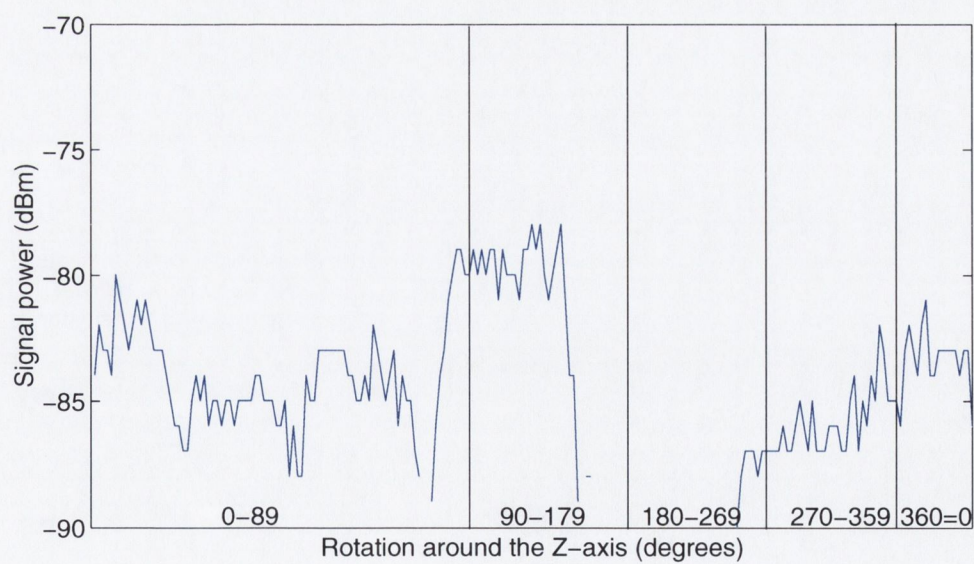


Figure 3.10: Signal power vs. varying node orientations. At around 180 degrees the person, who was holding the node, blocked the LOS path such that the signal power dropped significantly and packets were lost.

People and cars are common in urban environments. We evaluated their influence on link quality by moving a person or car into the LOS path between two nodes that were located 100 m apart (Type III experiment). Figure 3.11 and Figure 3.12 illustrate the influence of shadowing at different distances from the transmitter for a person and a car. At 20 m distance a person exhibited virtually no influence while a significant drop of link quality was noticed 1 m away. A person directly in front of a node, which is a common situation in crowded environments, led to a link failure at only 100 m distance between the nodes. Similar but stronger link quality degradations were observed for cars, where the connection was lost at a shadowing distance of 1 m. These observations emphasise again that large-scale fading, which describes the effect of blocking by random objects, must be considered in modelling, simulation and prediction of link quality.

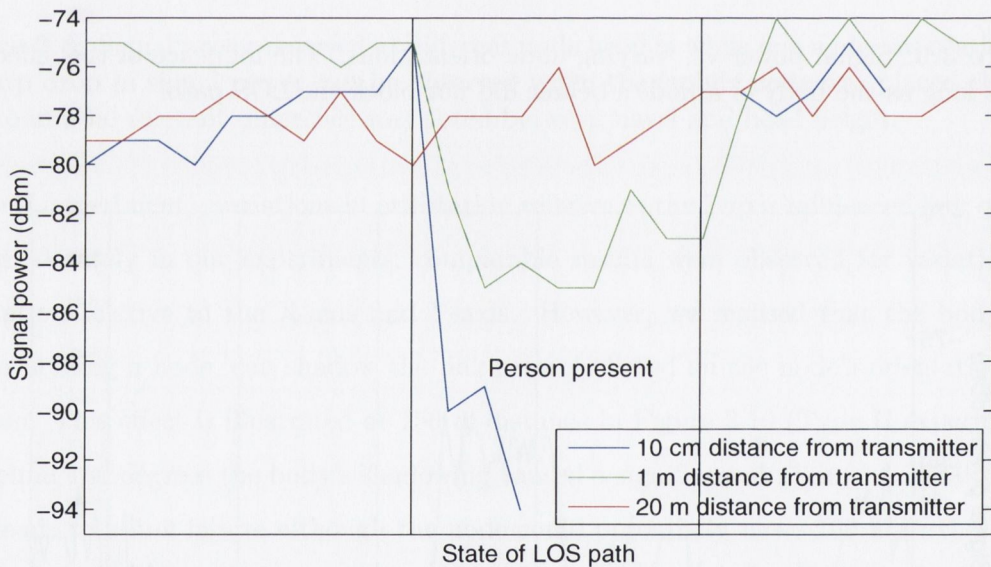


Figure 3.11: Signal-power measurements for a person in the LOS path at different distances. The closer the person to the transmitter, the stronger was the influence. At 20 m the presence of a person showed no influence on link quality.

The natural movement of people implies that the nodes, which they carry, experience small-scale movements. Therefore, we tested the resilience of the Lucent Orinoco card against small-scale movements by shaking one node for up to two 802.11 wavelengths

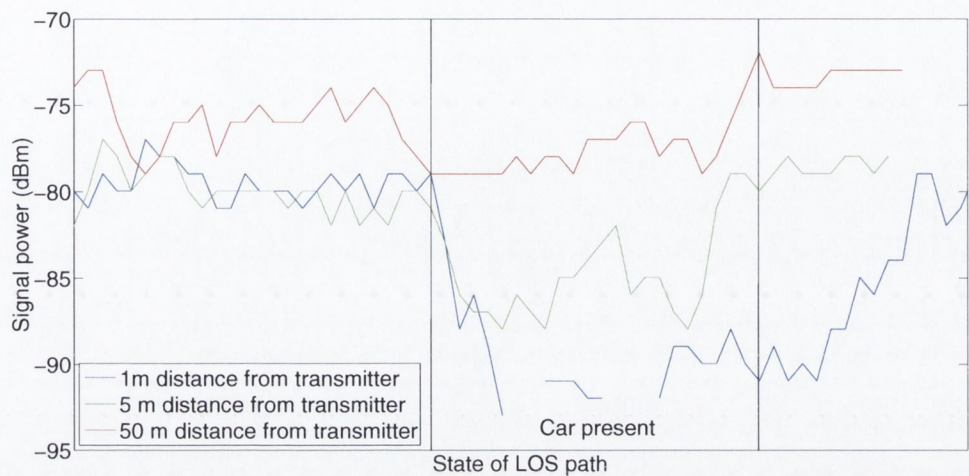


Figure 3.12: Signal-power measurements for a car in the LOS path at different distances. The closer the car to the transmitter, the stronger was the influence. As intuitively expected, shadowing by a car reduced link quality more strongly than shadowing by a person.

(roughly 25 cm) while the other node was stationary (Type II experiment). Figure 3.13 shows that small-scale movements had no observable effect on the received signal power. This resilience against small-scale movements is desirable since a strong influence of such movements on link quality in open space environments would have made accurate LQP difficult. However, small changes in position may lead to considerable signal variations in urban environments caused by small-scale fading due to multipath propagation as known from the literature, albeit that this effect is much less pronounced in wideband than in narrowband systems (for example, see Lee (1991), Kozono (1994) and Chapter 4).

An influence of communication patterns on link quality could also complicate LQP since we expect these patterns to vary widely with applications and times. Hence, we investigated two types of communication patterns (Type I experiments): the influence of payload pattern and the influence of communication load. Figure 3.14 demonstrates that the payload pattern, which was either random or an alternating bit stream of zeros and ones, did not affect the signal power. Similarly, varying degrees of communication load (one packet every 1 s, 200 ms or 80 ms), without collisions, did not affect the signal power as shown in Figure 3.15.

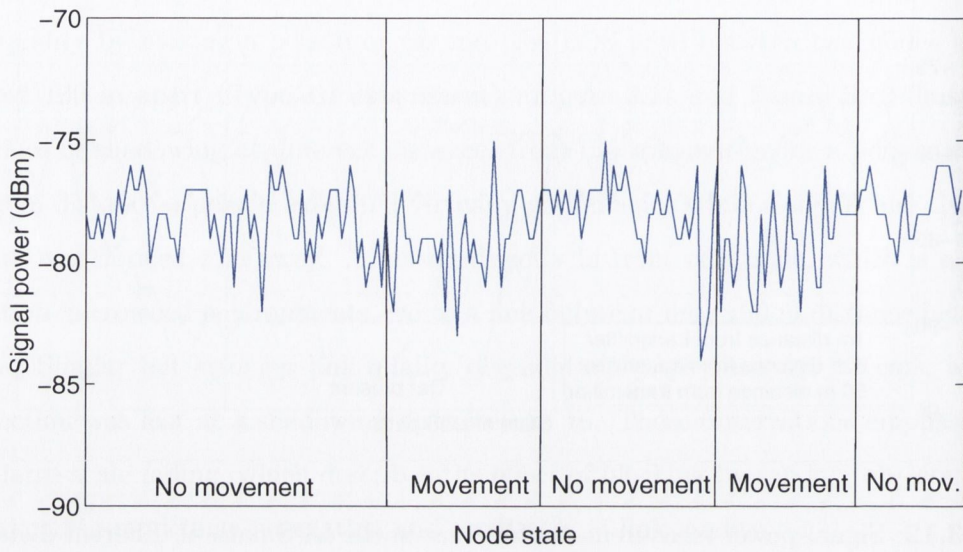


Figure 3.13: Influence of small-scale movements on signal power in an open space environment; no influence was observable.

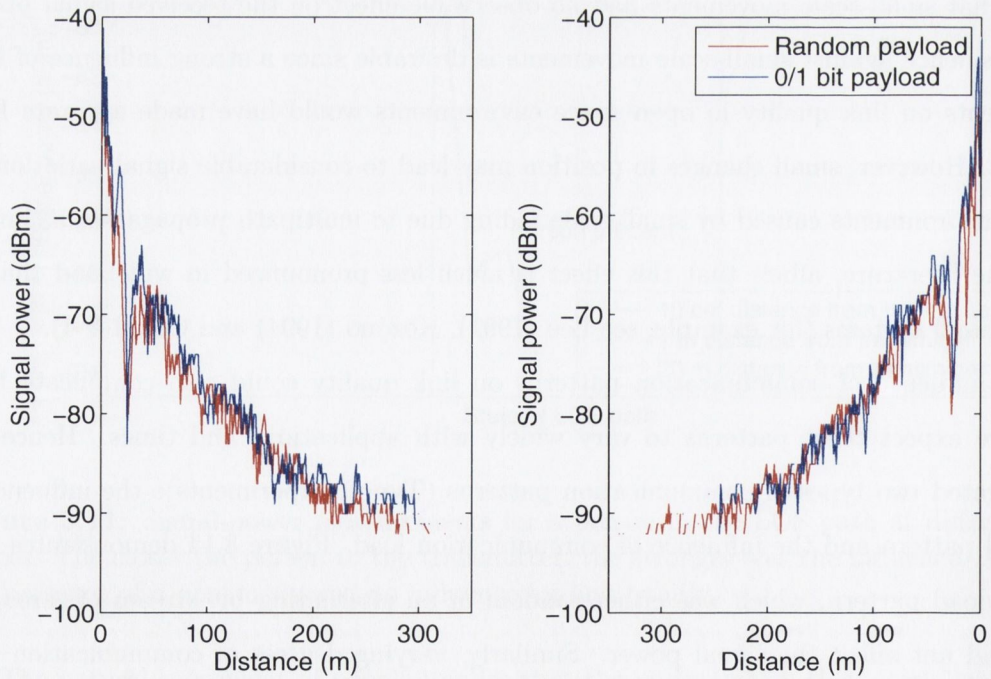


Figure 3.14: Signal power of received packets for different payload patterns; no influence was perceivable.

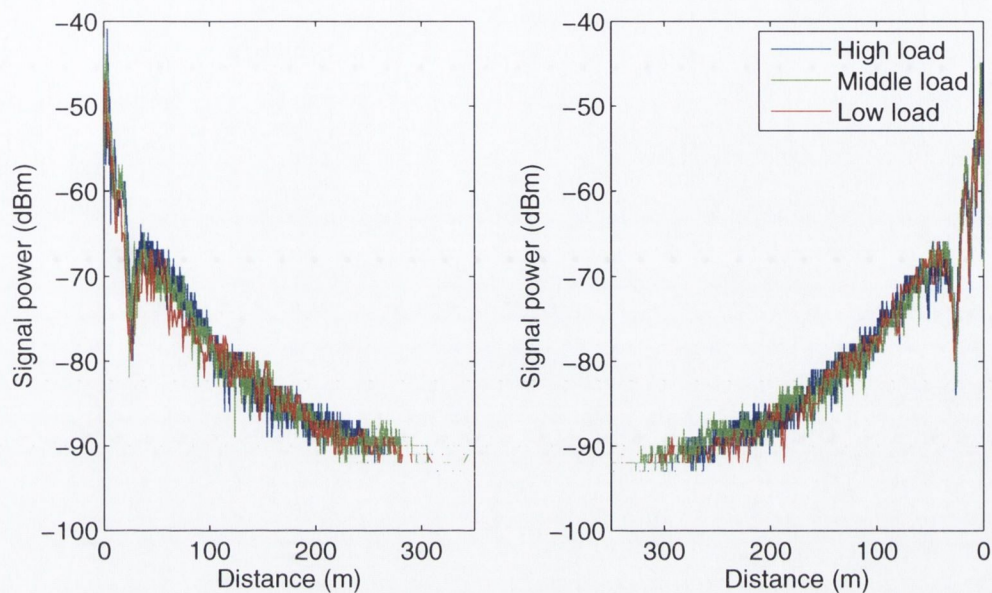


Figure 3.15: Signal power of received packets for low, middle and high communication loads; no influence was apparent.

Some MANET studies consider links as being symmetrical (e.g. Goff et al. 2001), others as being asymmetrical (e.g. Kotz et al. 2004, Aguayo et al. 2004). Clearly, when two nodes which constitute a link have different transmission powers, the link is asymmetrical. Moreover, our measurements with different 802.11 card models demonstrated that such cards can have significantly different characteristics such that a link with two different 802.11 card models is likely to show asymmetric behaviour. However, “the reciprocity principle states that a signal field strength is received the same at a base-station antenna from a mobile transmitter as it is received at the mobile-unit antenna from the base-station transmitter” (Lee 1993, p. 20). Clearly, this principle applies especially to MANETs since, in contrast to infrastructure networks, the node and therefore antennae heights in MANETs are similar such that even the noise characteristics, which are not covered by the reciprocity principle for infrastructure networks due to different antennae heights, are comparable. Consequently, if the transmission power and 802.11 card models of two nodes are identical, we expect a symmetric link. In order to assess this, we recorded the signal power of two nodes with identical transmission powers and identical 802.11 card models,

which were alternately transmitting and receiving packets, against distance (Type I experiment). Figure 3.16 illustrates that swapping the roles of transmitting and receiving did not influence the signal power significantly such that the link can be considered symmetrical under the above conditions. However, we expect that asymmetrical links in real-world MANETs exist since different transmission powers and card models can be assumed.

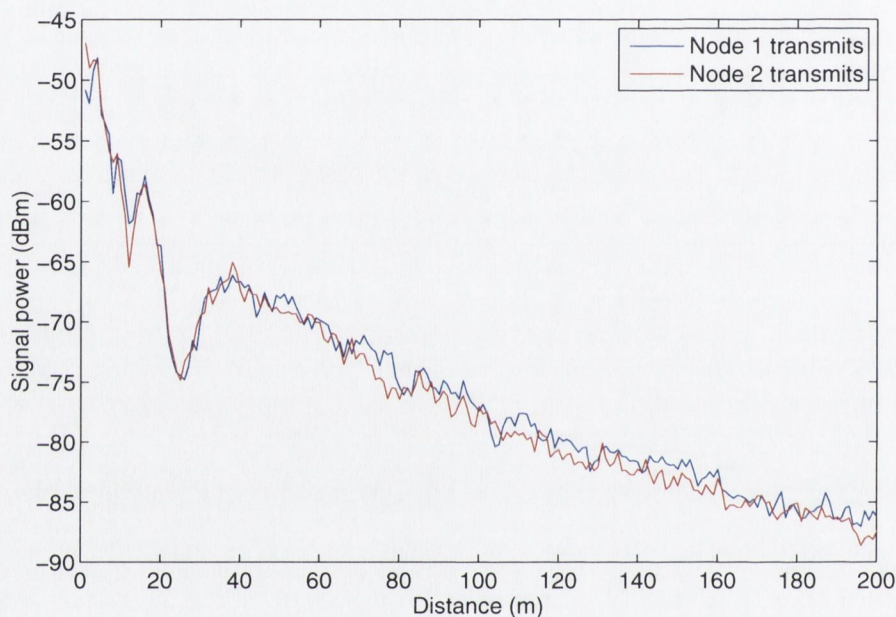


Figure 3.16: Signal power vs. distance for swapping the roles of transmitting and receiving for two nodes. The link between both nodes can be considered symmetrical as long as the 802.11 cards are of same model and use the same transmission power.

3.4 Summary

Using a set of high precision attenuators, together with the known receiver sensitivity of a Lucent Orinoco card, we determined the mean absolute error of signal-power measurements to be below 2 dBm on average over the evaluated measurement range for this type of 802.11 card. This acceptable measurement error made the evaluated card model suitable for our real-world study.

Since link quality prediction (LQP) algorithms from the literature are based on basic

radio propagation models that typically consider path loss as the sole propagation effect, we assessed the accuracy of three LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) for pedestrians in two real-world urban environments. This study showed that the best performing LQP algorithm from Goff et al. (2001) failed to predict between 18% and 54% of the total observed packet loss for two seconds ahead while between 12% and 43% of successfully received packets were falsely predicted to be lost. These results contrast sharply with near-perfect accuracy in simulations with the standard NS-2 simulator in its default configuration. We also observed in the study that signal power itself is a more accurate predictor for packet loss than the trend of signal power for short-term predictions and pedestrians in urban microcells. This observation may be explained by erroneous short-term trends that are caused by large- and small-scale fading. Since we also noticed in the study that links do not fail sharply but oscillate between being available and unavailable, we conclude that a stochastic prediction is likely to provide more accurate predictions than a deterministic one.

To account for the large discrepancy between simulations and real-world measurements, we performed an in-depth examination of factors that potentially influence link quality in MANETs and can make LQP difficult, especially for an off-the-shelf 802.11 card. Our investigation of these factors revealed that LQP is difficult but not impossible. Small-scale movements of a node and node heights over the belt showed no influence on link quality. Changes in orientation and the type of ground exhibited only a low influence. The 802.11 card model showed high influence on link quality but does not affect its predictability as long as the card's characteristics are known to the node that is using it. Different payload patterns and communication loads did not affect link quality. However, our experiments showed that shadowing due to objects in the radio channel and shadowing due to the body of a person carrying a node affected link quality significantly. Therefore, it is crucial that the resulting large-scale fading of the signal is considered in modelling, simulating and predicting link quality. Since an accurate large-scale fading signal can only be estimated by considering its small-scale fading, the latter effect is also of paramount importance to LQP.

Chapter 4

Characterising Small-Scale Wideband Signal Envelope Fading by Rice and Nakagami Distributions

802.11 signals are wideband signals in typical urban environments. Hence, modelling, simulation, and prediction of such 802.11 signals must consider their wideband nature and cannot rely on models and techniques that have only been shown to be appropriate for narrowband signals. Small-scale fading is an important propagation effect that shows different characteristics for narrowband and wideband signals and must therefore be modelled differently. In general, the wideband signal envelope shows less severe small-scale fading than the narrowband signal envelope since wideband signals inherently exploit frequency diversity. While small-scale fading of narrowband signals is well researched and understood, comparatively few studies are reported for wideband systems. Also, closed-form expressions are unavailable that describe the probability distribution of the small-scale fading wideband signal envelope. However, the knowledge of this probability distribution is required to completely model link quality, estimate the large-scale fading signal in 802.11 receivers and simulate efficiently small-scale wideband signal fading for MANET simulators which currently allow only for simulation of small-scale narrowband signal fading.

We show in this chapter that for a wide range of microcellular urban environments small-scale wideband signal envelope fading can be very closely approximated—and therefore characterised—by the Rice and Nakagami distributions. These characterisations provide, for the first time, closed-form expressions which describe the probability distribution of small-scale fading signals in wideband systems; these results not only apply to the family of 802.11 standards but also to DSRC, WiMAX and UMTS. While the Rice and Nakagami distributions characterise small-scale fading for both narrowband and wideband systems, the parameters of the probability distribution functions are different for the two types of systems. We therefore establish a mapping between the environmental parameters, which determine small-scale fading in wideband systems, and the parameters of the Rice and Nakagami distributions as they would traditionally be used in narrowband systems. In addition, we subsequently demonstrate two important applications of our findings. Firstly, our results enable the derivation of the appropriate averaging window size and sample spacing to accurately estimate the large-scale fading signal in an 802.11 receiver. This large-scale fading signal is essential for accurate LQP as discussed in the previous chapter. Secondly, these results are used to provide fast simulation of small-scale fading for wideband systems by reusing already available techniques for narrowband systems, as we will show in Section 5.3.3.

4.1 Methodology

Our study is based on the wideband propagation model of Kozono (1994) and Yan & Kozono (1999) that corresponds well with an extensive range of measurements (Kozono 1994, Yan & Kozono 1999, Nakabayashi & Kozono 1998, Nakabayashi et al. 2001), as was discussed in Section 2.3. To recapitulate some important notation, the wideband propagation environment is modelled by the maximum difference in propagation path lengths $\Delta L_{\max}$ of the arriving waves and the ratio of the direct to indirect power $a_{(\text{dB})}$; the receiver bandwidth is represented by $2\Delta f$. The observed degree of small-scale fading is dependent on the receiver bandwidth and the propagation environment.

To obtain the small-scale fading signal envelope we use Yan & Kozono's (1999) model

Parameter	Values
$a_{\text{(dB)}}$ (dB)	$\{\{-\infty\} \cup [1, 15]_{\text{step}=2}\} = \mathcal{S}_{a_{\text{(dB)}}}$
ΔL_{max} (m)	$\{\{0.1, 1\} \cup [5, 55]_{\text{step}=5}\} = \mathcal{S}_{\Delta L_{\text{max}}}$
$2\Delta f$ (MHz)	$\{[2, 34]_{\text{step}=2}\} = \mathcal{S}_{2\Delta f}$
Number of sample points per configuration	10,000
N_{Wv}	10
f_c (MHz)	2442

Table 4.1: Parameter values used in simulations of Yan & Kozono’s (1999) wideband signal propagation model.

to generate 10^4 samples, as suggested in (Cardoso & Correia 2003), for each propagation environment and receiver parameter tuple $(2\Delta f, \Delta L_{\text{max}}, a_{\text{(dB)}}) \in \mathcal{S}_{2\Delta f} \times \mathcal{S}_{\Delta L_{\text{max}}} \times \mathcal{S}_{a_{\text{(dB)}}}$. Since each tuple is dependent on properties of both the receiver and the propagation environment, we refer to each tuple $(2\Delta f, \Delta L_{\text{max}}, a_{\text{(dB)}})$ as a ‘configuration’. Due to the very large number of sample points taken we expect the empirical distribution function (EDF) will resemble the unknown exact CDF closely.

We chose the wideband power ratio $a_{\text{(dB)}}$ to range from $-\infty$ dB (NLOS) to +15 dB (strong LOS). This range was determined to be appropriate for microcellular environments in a major empirical study (Green 1990). The receiver bandwidth is chosen to range from 2 MHz to 34 MHz so that the results generated here will apply to current wideband standards (see Table 4.3 for examples of these standards and associated bandwidths). The maximum difference in propagation path lengths is estimated to range from 0.1 m to 55 m based on Cardoso & Correia’s (2003) model for urban microcells.

All data were generated using the IEEE 802.11 centre frequency f_c of 2442 MHz. Kozono (1994) has reported that the statistical distribution of a fading signal is practically independent of the centre frequency and so the inferences made regarding the distribution of this data will have general applicability for other wideband standards. As observed by Yan & Kozono (1999), the fading depth is practically independent of the number of arriving waves N_{Wv} for $N_{\text{Wv}} > 6$. As suggested by Yan & Kozono (1999) we use $N_{\text{Wv}} = 10$ for the purposes of this study. The list of parameters over which the data is generated is summarised in Table 4.1.

Various hypothesis tests and criteria are given in the literature to evaluate the goodness of fit of an EDF to a proposed CDF. It is important to note at this stage that if a hypothesis test indicates that a fading signal is not a strict realisation of the distribution under test, good agreement can however be of significant practical value. For this reason, we use the Kolmogorov-Smirnov (KS) test (Kotz & Johnson 1981, vol. 4, pp. 393-396, 398-402) throughout this study since this test statistic enables both hypothesis testing and easily comprehensible goodness-of-fit analysis where no strict realisation of the proposed CDF is given. The KS statistic gives the maximum error between the EDF and the proposed CDF.

The two-sided KS statistic for a data set $\mathcal{X} \subset \mathbb{R}$, is given by

$$\varepsilon_{\text{KS}} = \sup_{x \in \mathcal{X}} |\hat{F}(x) - F(x|\Theta)| \quad (4.1)$$

where $\hat{F}(x)$ is the EDF of the fading signal and $F(x)$ is the CDF of the proposed theoretical distribution. Θ is the Ricean K -factor or Nakagami shape factor depending on which distribution is being used, that is: $\Theta \in \{K, m\}$.

Throughout this study we also make use of the root mean squared error

$$\varepsilon_{\text{RMS}} = \sqrt{\frac{\sum_{i=1}^{|\mathcal{X}|} \left(\hat{F}(x_i) - F(x_i|\Theta) \right)^2}{|\mathcal{X}|}}, \quad x_i \in \mathcal{X}. \quad (4.2)$$

We use ε_{KS} for the formal goodness-of-fit tests and both ε_{KS} and ε_{RMS} in the subsequent analysis and discussion. Both error statistics are computed for each configuration $(2\Delta f, \Delta L_{\text{max}}, a_{\text{(dB)}})$. For better readability we express all error statistics—which are probabilities in this case—as percentages via multiplication by 100. In this way, for example, a certain event occurs in 100% of all trials and therefore has a percentage probability of 100%.

The parameter Θ is obtained by means of a maximum likelihood estimation (MLE) (Kotz & Johnson 1981, vol. 5, pp. 341–351). The Method of Moments (Kotz & Johnson 1981, vol. 5, pp. 467–473) is used to obtain the starting points for the MLE using the Simplex Search Method of Lagarias et al. (1998).

The following steps are taken to obtain the error statistics for each configuration $(2\Delta f, \Delta L_{\text{max}}, a_{\text{(dB)}})$:

1. Generation of signal envelope/power samples using Yan & Kozono's (1999) model.
2. Determination of the EDF of the signal envelope/power from the data obtained in Step 1.
3. MLE of the parameter Θ for the Rice/Non-Central Chi-Square and Nakagami/Gamma distributions.
4. Establishment, using the KS-test, of the formal goodness of fit between the proposed distributions using the parameter obtained in Step 3 and the EDF obtained in Step 2.
5. Calculation of ε_{KS} and ε_{RMS} using the data obtained in Steps 2, 3 and 4.

4.2 Probability Distribution of the Signal Envelope and Power

In this section we evaluate the goodness of fit of the Rice/Nakagami distributions to the EDF of the wideband signal envelope, r , over the range of propagation and receiver parameter configurations $\mathcal{S}_{2\Delta f} \times \mathcal{S}_{\Delta L_{\max}} \times \mathcal{S}_{a_{(\text{db})}}$ given in Table 4.1. The Rice distribution (Rice 1948) is given as follows (Stueber 2001, pp. 51–53):

$$f_r(x) = \frac{2x(K+1)}{\Omega_p} \exp\left(-K - \frac{(K+1)x^2}{\Omega_p}\right) I_0\left(2x\sqrt{\frac{K(K+1)}{\Omega_p}}\right), \quad x \geq 0 \quad (4.3)$$

where f_r denotes the PDF of the signal envelope, $\Omega_p = \text{E}[R]$ is the local mean power, K is the Ricean factor, x is the value of the signal envelope, and I_0 is the modified Bessel function of the first kind and zero order. Similarly, the Nakagami distribution (Nakagami 1960) is commonly used to describe the distribution of the small-scale fading narrowband signal envelope (Stueber 2001, pp. 53–55)

$$f_r(x) = \frac{2m^m x^{2m-1}}{\Gamma(m)\Omega_p^m} \exp\left(-\frac{mx^2}{\Omega_p}\right), \quad m \geq \frac{1}{2} \quad (4.4)$$

where m is the Nakagami shape factor and Γ is the Gamma function. Both distributions are related by the following approximate relationship between the Ricean factor and the

Nakagami shape factor (Stueber 2001, pp. 54)

$$m \approx \frac{(K + 1)^2}{(2K + 1)} . \quad (4.5)$$

As a first step in our evaluation, we test over how many configurations the fading signal envelope is a strict realisation of the Rice/Nakagami distributions. The KS test, set at a significance level of five per cent (Type I error), indicates a strict realisation of the Rice and Nakagami distributions in 50.53% and 43.89% of configurations respectively. To establish the practical relevance of these figures further investigation is required (DeGroot & Schervish 2001, pp. 529, 530). This is done by analysing the error statistics.

Figure 4.1 shows a histogram of $\varepsilon_{\text{KS}_r}$, the maximum difference between the empirical and proposed CDF of the signal envelope for each configuration. $\varepsilon_{\text{KS}_r}$ is less than 7.8% for all configurations and its values lie mostly in the range 0.5% to 2% for both the Rice and Nakagami distributions. It is noted that by this measure the Rice distribution is a somewhat better approximation to the EDF than is the Nakagami distribution but that the difference is marginal. The distribution of $\varepsilon_{\text{RMS}_r}$ is very similar to that of $\varepsilon_{\text{KS}_r}$ (see Table 4.2), tallying with the latter statement.

The numerical results are summarised in Table 4.2. The average $\varepsilon_{\text{KS}_r}$ over all configurations is 1.65% and 1.78% for the Rice and Nakagami distributions respectively. The 95th percentile of $\varepsilon_{\text{KS}_r}$ is less than 3.9% for both distributions, underlining the overall goodness of fit. The largest $\varepsilon_{\text{KS}_r}$ observed for a configuration is 7.8% using the Nakagami distribution. Again, the Rice distribution fares slightly better by this measure. However, since the observed differences in goodness of fit between both distributions are marginal, we conclude that the Rice and the Nakagami distributions are practically equally well suited to characterise the small-scale fading wideband signal envelope over the range of parameters chosen.

Important observations can be made about the ability of the Rice/Nakagami distribution to characterise the distribution of the wideband signal envelope by evaluating the dependence of the approximation error on the fading depth. The fading depth is taken to be the difference between the signal levels corresponding to 50% and 1% of the CDF. In Figure 4.2 the variation of $\varepsilon_{\text{KS}_r}$ with fading depth is shown for the Rice distribution. First,

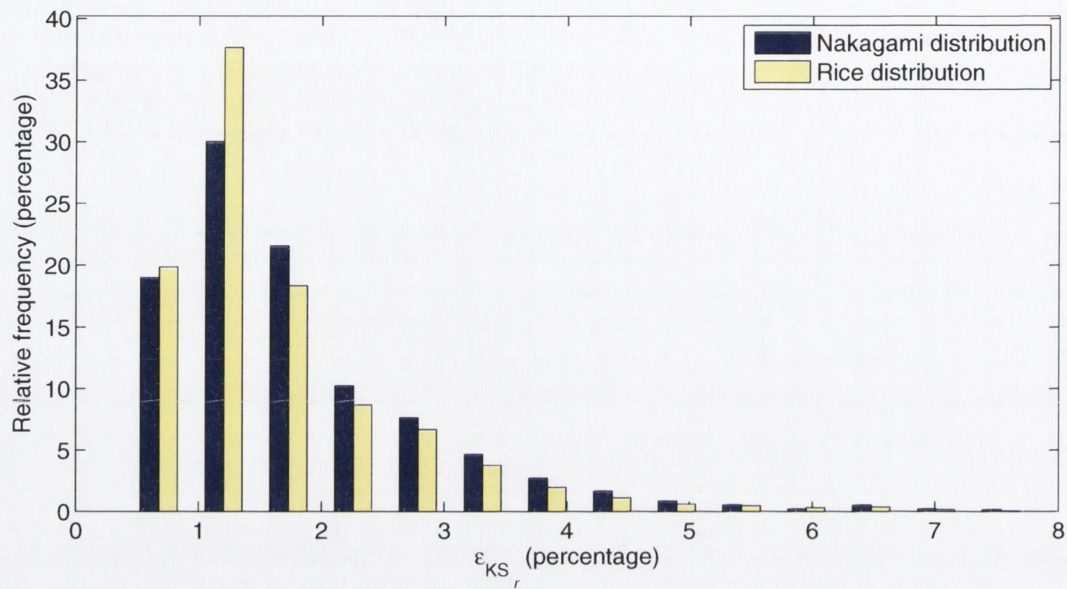


Figure 4.1: Distribution of ϵ_{KS_r} . Low approximation errors can be observed for both, the Rice and Nakagami distributions.

	Nakagami distribution	Rice distribution
Mean ϵ_{KS_r}	1.78%	1.65%
Mean ϵ_{RMS_r}	0.91%	0.85%
95th Percentile ϵ_{KS_r}	3.87%	3.58%
95th Percentile ϵ_{RMS_r}	2.13%	2.01%
Max. ϵ_{KS_r}	7.80%	7.61%
Max. ϵ_{RMS_r}	4.33%	4.30%

Table 4.2: Error statistics in the approximation of the distribution of the wideband signal envelope using the Rice and Nakagami distributions. The low error figures demonstrate the suitability of the Rice and Nakagami distributions to characterise wideband small-scale fading.

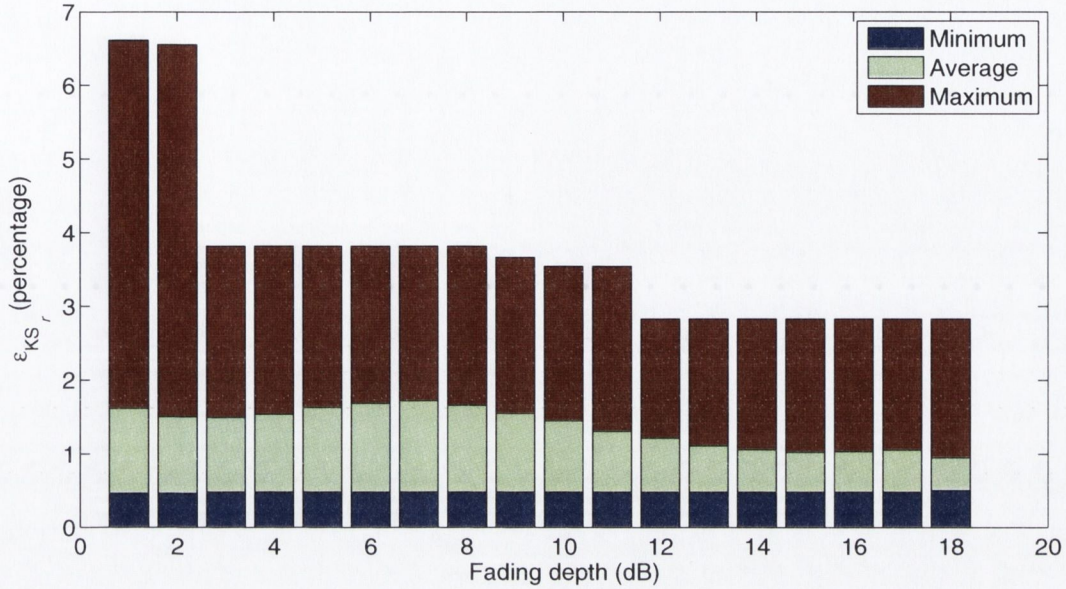


Figure 4.2: Dependence of ε_{KSr} from the fading depth. The approximation gets better with greater fading depth.

we observe that the minimum ε_{KSr} is virtually independent of the fading depth. Secondly, the average ε_{KSr} tends to be greater for shallower fading depth but starts to decrease for fading depths greater than about 8 dB and levels off for fading depths greater than about 13 dB. The maximum ε_{KSr} shows a sharp rise for fading depths less than 3 dB. These latter two observations indicate that the approximation gets better with greater fading depths. This is desirable since the stronger the fading the more important an accurate description of the phenomenon is. However, it also shows the limitation of characterising wideband fading signals by Rice/Nakagami distributions. Where there are small fading depths (< 3 dB) the approximation is still good on average, however sporadically higher approximation errors can be observed. Since the fading depth increases with a decreasing maximum difference in propagation path lengths, ΔL_{max} , we expect the approximation of the distribution of the wideband signal envelope by the Rice/Nakagami distributions to apply somewhat better in microcellular environments than in macrocellular environments where ΔL_{max} is typically greater.

Where the Rice distribution describes signal envelope fading, the distribution of the

signal power is described by the Non-Central Chi-Square distribution with two degrees of freedom (Stueber 2001, pp. 51–53)

$$f_R(x) = \frac{K+1}{\Omega_p} \exp\left(-K - \frac{(K+1)x}{\Omega_p}\right) I_0\left(2\sqrt{\frac{K(K+1)x}{\Omega_p}}\right), \quad x \geq 0. \quad (4.6)$$

Likewise, if the Nakagami distribution describes signal envelope fading then the distribution of the signal power follows the Gamma distribution (Stueber 2001, pp. 53–55)

$$f_R(x) = \left(\frac{m}{\Omega_p}\right)^m \frac{x^{m-1}}{\Gamma(m)} \exp\left(-\frac{mx}{\Omega_p}\right), \quad m \geq \frac{1}{2}. \quad (4.7)$$

Employing the same method used for the signal envelope we determined that the power distribution can be characterised by the Non-Central Chi-Square/Gamma distributions to a similar degree of accuracy as the signal envelope is characterised by the Rice/Nakagami distributions. The difference in accuracy is $\ll 10^{-2}\%$ by all measures used in Table 4.2.

4.3 Mapping Wideband Propagation Parameters to the Ricean K -Factor

In the previous section it was shown that wideband signal envelope fading can be characterised to a good approximation by the Rice and Nakagami distributions in urban microcells. In this section we obtain an approximate functional relationship between the wideband fading parameters $(2\Delta f, \Delta L_{\max}, a_{\text{(dB)}})$ and the Ricean K -factor using a curve-fitting approach. That is

$$g_k : \mathcal{S}_{2\Delta f} \times \mathcal{S}_{\Delta L_{\max}} \times \mathcal{S}_a \rightarrow \mathcal{S}_K, \quad \mathcal{S}_K \in \mathbb{R}. \quad (4.8)$$

This is done for a number of different wireless standards. The accuracy of this approach is then assessed. The Ricean K -factor is determined by MLE over a discrete range of wideband propagation parameters as described in Section 4.1 and the results tabulated. g_k is then determined by fitting an appropriate function to the value table. In the early stages of the curve fitting process we observed that no one function describes this mapping to a high degree of accuracy for all configurations. However, by fixing the bandwidth we

Wireless standard	System bandwidth (MHz)
UMTS	3.38 (Sharma 2002)
DSRC	8.13 (Yin et al. 2004)
802.11, 802.11b	9.68 (ANSI/IEEE Standard 802.11 1999, p. 195)
WiMAX (Europe)	14 (IEEE 802.16 WG 2001)
802.11a, HIPERLAN Type II	16.56 (van Nee et al. 1999)

Table 4.3: System bandwidths of various wireless standards.

obtain individual functions which fit the value table for the various wireless standards. The mapping is performed in linear instead of logarithmic space so that the problem of mapping a value of $-\infty$ dB in NLOS conditions is circumvented. The 3-dB bandwidths of some of the widely used wireless standards are displayed in Table 4.3. The bandwidths of DSSS-based systems are determined by (Dixon 1984, p. 21); the bandwidth of OFDM-based systems is determined by (Rodrigues 2002, p. 43, (2.35)).

We now detail the procedure to obtain the functional relationship g_k for the wireless standards given in Table 4.3, which can also be used to derive mappings for other wireless standards:

1. Determination of a value table for the wireless standard under consideration containing the wideband propagation parameters $\Delta L_{\max}$, a and the Ricean K -factor that is determined by MLE as described in Section 4.1.
2. Choice of a candidate function for curve fitting. If this function requires the wideband propagation parameters to lie within a specified range, as for example for the Chebyshev polynomial series, then the parameters must be scaled to that range.
3. Estimation of the constants in the candidate function by minimising the approximation error between the Ricean K -factor obtained in Step 1 and the approximate value of K as given by the candidate function.
4. Calculation of the mean, the 95th percentile and the maximum ε_{KS} for the approximation function that was determined in Step 3.

5. If the error statistics in Step 4 are satisfactory, terminate. Otherwise go back to Step 2.

The Chebyshev polynomial series is well known to be suitable for curve-fitting purposes. Its advantage lies in the fact that if the series is truncated to a polynomial of lower degree the consequent degradation in accuracy is graceful (Press et al. 1992, pp. 190–194). We found by using the above procedure that the following eighth degree Chebyshev polynomial approximates the Ricean K -factor well for all standards

$$g_k(a, \Delta L_{\max}) = c_{0,0} + \sum_{i=1}^7 \sum_{j=1}^i c_{i,j} g_{8-i}(x) g_j(y) + \sum_{i=1}^8 (c_{8,i} g_i(x) + c_{9,i} g_i(y)) \quad (4.9)$$

where

$$g_n(z) = \cos(n \arccos(z)), \quad (4.10)$$

$$x = \frac{a}{15.8115} - 1, \quad (4.11)$$

$$y = \frac{\Delta L_{\max} - 0.1}{27.45} - 1 \quad (4.12)$$

and the constants are given in Tables A.3 and A.4 in the Appendix. The Chebyshev polynomials require that their input parameters are in the range $[-1, 1]$ (Press et al. 1992, pp. 191–192) which is achieved via expressions (4.11) and (4.12). A similar curve fitting approach can also be taken to estimate the Nakagami shape factor.

The goodness of fit of the Rice distribution, where K has been obtained using the approximation function g_k , in describing the distribution of the small-scale fading wideband signal envelope is displayed in Table 4.4. It can be observed that the low average $\varepsilon_{\text{KS}_r}$ values indicate a very good fit. As in Section 4.1 we observe that the maximum values tend to increase with shallower fading depth. There is up to an 0.5% difference in Max. $\varepsilon_{\text{KS}_r}$ introduced due to the function approximation for K .

The relation between the wideband propagation parameters $\Delta L_{\max}$, a and the Ricean K -factor is illustrated in Figure 4.3 by graphing g_k for the 802.11 standard. The Ricean K -factor has, for very small values of $\Delta L_{\max}$, a value equal to a . The reason for this is that small-scale fading in such propagation environments is equally severe for wideband and narrowband signals; this phenomenon has also been reported by Yan and Kozono (Yan

Wireless standard	Mean $\varepsilon_{\text{KS}_r}$	95th Percentile $\varepsilon_{\text{KS}_r}$	Max. $\varepsilon_{\text{KS}_r}$
UMTS	1.74%	3.12%	3.89%
DSRC	1.66%	2.99%	4.81%
802.11, 802.11b	1.64%	3.05%	4.45%
WiMAX (Europe)	2.13%	4.56%	6.19%
802.11a, HIPERLAN Type II	2.36%	5.56%	7.70%

Table 4.4: Error statistics in the goodness of fit of the Rice distribution to the EDF where K has been obtained via g_k . The $\varepsilon_{\text{KS}_r}$ values indicate a very good fit.

& Kozono 1999). However, such small values of ΔL_{max} are rarely observed in microcells. As ΔL_{max} increases, the small-scale fading becomes less severe—as also observed by Yan and Kozono (Yan & Kozono 1999)—and consequently the Ricean K -factor increases. This increase is magnified for greater values of a .

4.4 Estimation of the Local Mean Power in 802.11 Systems

The stochastic process of small-scale signal envelope fading for narrowband and wideband systems is described by its probability distribution function and autocorrelation function. We have shown in Section 4.1 that the same probability distribution functions characterise small-scale signal envelope fading in narrowband and wideband systems in microcells, albeit with different parameters for which we provide a mapping between the two. These results allow, together with Nakabayashi and Kozono’s (Nakabayashi & Kozono 1998) result that the autocorrelation of small-scale signal envelope fading is independent of the bandwidth, adapting narrowband solutions for small-scale signal/power envelope fading to wideband solutions. One important application of these results is given in this section.

As previously discussed, the estimation of the large-scale fading signal, represented by its local mean power, is essential for accurate LQP. A well-known method (signal-power averaging over an appropriately chosen distance with appropriate sample spacing) for this task originated in the area of cellular networks with Lee (1985) and was later extended by Austin & Stueber (1994) for the Rice distribution. We first summarise some of Austin & Stueber’s (1994) and Stueber’s (2001, pp. 598–605) results for narrowband systems and

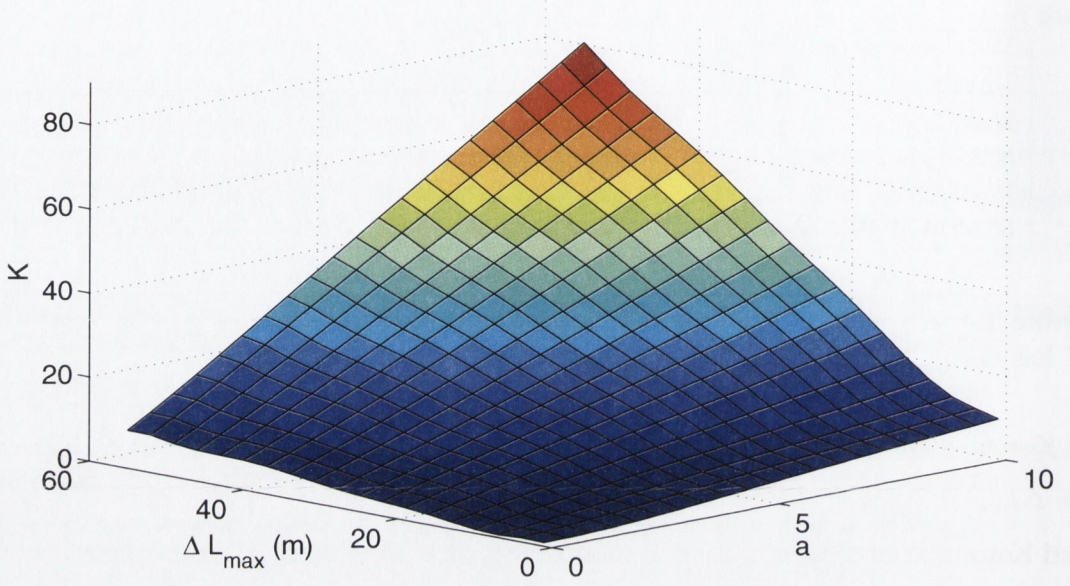


Figure 4.3: Relation between the wideband propagation parameters $\Delta L_{\max}$, a and the Ricean K -factor for the 802.11 standard. The higher the maximum difference in propagation path lengths $\Delta L_{\max}$ and the higher the power ratio a , the less severe the small-scale fading such that the Ricean K -factor increases.

then extend these results for an 802.11 system in an urban street with a maximum cell radius of 250 m. The received signal power at location $\mathbf{o}$ is given by (Austin & Stueber 1994, (5))

$$R(\mathbf{o}) = H(\mathbf{o}) \cdot \Omega_p(\mathbf{o}) \quad (4.13)$$

where $H(\mathbf{o})$ is the power of the small-scale fading signal and $\Omega_p(\mathbf{o})$ is the local mean power. In the regions where the local mean is constant the accuracy of the estimate can be expressed by the 1σ spread (Austin & Stueber 1994, (10)):

$$1\sigma \text{ spread} = 10 \log_{10} \frac{\Omega_p + \sigma_{\hat{\Omega}_p}}{\Omega_p - \sigma_{\hat{\Omega}_p}} \quad (4.14)$$

where $\sigma_{\hat{\Omega}_p}$ is the standard deviation of the estimated local mean power $\hat{\Omega}_p$. For analog

averaging, $\sigma_{\Omega_p}^2$ is given by (Austin & Stueber 1994, (9))

$$\sigma_{\Omega_p}^2 = \left(\frac{\Omega_p}{K+1} \right)^2 \frac{1}{\Delta_a} \cdot \int_0^{2\Delta_a} \left(1 - \frac{i}{2\Delta_a} \right) I_0 \left(\frac{2\pi i}{\lambda_c} \right) \left(I_0 \left(\frac{2\pi i}{\lambda_c} \right) + 2K \cos \left(\frac{2\pi i \cos(\vartheta_0)}{\lambda_c} \right) \right) di \quad (4.15)$$

and for digital averaging by (Austin & Stueber 1994, (14))

$$\sigma_{\Omega_p}^2 = \left(\frac{\Omega_p}{K+1} \right)^2 \left(\frac{1+2K}{N_H} + 2 \sum_{i=1}^{N_H-1} \left(\frac{N_H-i}{N_H^2} \right) I_0 \left(\frac{2\pi i \Delta_s}{\lambda_c} \right) \cdot \left(I_0 \left(\frac{2\pi i \Delta_s}{\lambda_c} \right) + 2K \cos \left(\frac{2\pi i \Delta_s \cos(\theta_0)}{\lambda_c} \right) \right) \right) \quad (4.16)$$

where Δ_a is the ‘window size’ or the distance over which the averaging is performed (measured in wavelengths), N_H is the number of samples taken over the interval, I_0 is the zero-order Bessel function of the first kind, λ_c is the carrier wavelength, ϑ_0 is the angle between the vector in the direction of propagation of the direct wave and the velocity of the receiver, and Δ_s is the sample spacing (measured in wavelengths).

The derivation of (4.15) and (4.16) only requires knowledge of the PDF and autocorrelation of the small-scale fading signal envelope. We have shown how to characterise the former for wideband signals while the latter has been shown to be bandwidth independent (Nakabayashi & Kozono 1998) and so these equations will apply to wideband systems where the appropriate value of K is used as has been described in this work.

The adaptation to an 802.11 system is straightforward. Only the Ricean K -factor has to be determined as described above via the function $g_k(a, \Delta L_{\max})$. The range of $\Delta L_{\max}$ is determined by the network type and the street geometry. We choose 250 m as the maximum cell range corresponding to our own measurements for an 802.11 network (Gaertner et al. 2004). Figure 4.4 shows the variation in the 1σ spread with $\Delta L_{\max}$ and Δ_a for analog averaging in NLOS conditions. The 1σ spread values, which correspond to a window size of $20\lambda_c$ and $40\lambda_c$ as suggested by Lee for narrowband systems, have been marked on the Z-axis as ‘Higher error bound’ and ‘Lower error bound’ respectively. Compared to the classical narrowband case, in which the result is independent of the

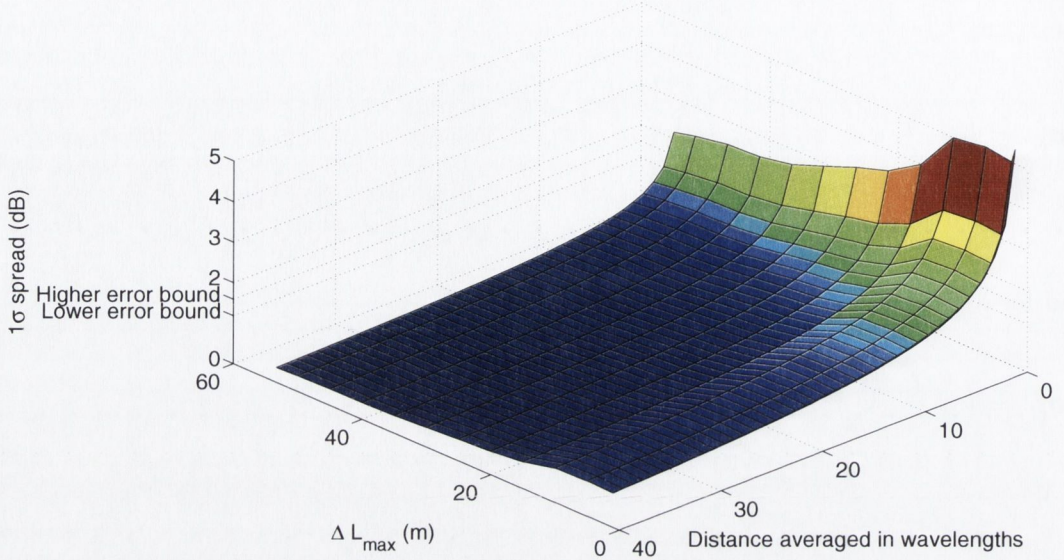


Figure 4.4: 1σ spread depending on the averaging distance and $\Delta L_{\max}$ in NLOS conditions. With higher maximum difference in path lengths $\Delta L_{\max}$ the 1σ spread decreases if the averaging distance stays constant.

maximum difference in propagation path lengths $\Delta L_{\max}$, it is clear that $\sigma_{\Omega_p}^2$ depends strongly on $\Delta L_{\max}$. However, for the propagation environment under consideration an averaging window size of between $13\lambda_c$ and $25\lambda_c$ guarantees to be within the desired error bounds. Since the autocorrelation of small-scale signal envelope fading is bandwidth independent, it follows from Stueber (2001, pp. 603, 604) that the sample spacing should be less than $0.5\lambda_c$ for wideband systems also.

The previously derived averaging window size of between $13\lambda_c$ and $25\lambda_c$ has to be rated conservative since it guarantees to be in the error bounds for the worst case, which corresponds to a wideband propagation environment with low $\Delta L_{\max}$ in NLOS conditions. However, urban environments are better represented by a range of values for $\Delta L_{\max}$ and $a_{\text{(dB)}}$ as given in Table 4.1 and not only by the worst case. Consequently, small-scale fading is less pronounced on average in these environments such that a smaller window size can be chosen. Therefore, we determined the 1σ spread for varying window sizes in all microcellular urban environments considered. Table 4.5 demonstrates that much smaller window sizes are suitable when all situations and not only the worst case is considered. A

Averaging window size	Percentage of situations with 1σ spread smaller than the lower classical error bound	Percentage of situations with 1σ spread smaller than the higher classical error bound
$25\lambda_c$	100.00%	100.00%
$20\lambda_c$	99.14%	100.00%
$15\lambda_c$	97.76%	100.00%
$13\lambda_c$	96.26%	100.00%
$8\lambda_c$	90.70%	97.75%
$6\lambda_c$	86.31%	94.76%
$5\lambda_c$	82.35%	92.51%
$4\lambda_c$	75.83%	89.41%

Table 4.5: Percentage of situations in which the 1σ spread is lower than the classical error bounds for different averaging window sizes. Smaller window sizes are appropriate when a certain percentage of errors higher than the classical error bounds is allowed.

smaller window size can lead to a more accurate local mean power estimation than a larger window size since the derivation of (4.15) is based on a simplification. This simplification, which was pointed out by Tepedelenioglu et al. (2001), is the assumption that the large-scale fading signal is constant during the averaging. However, with larger window sizes this assumption differs from reality. This must especially be considered in microcells where, as reported by Gudmundson (1991), the large-scale fading decorrelates considerably faster than in macrocells. Therefore, the window size should be chosen to be within the desired error bound but to be as small as possible (Tepedelenioglu et al. 2001). Consequently, we suggest a progressive window size of $5\lambda_c$ that still guarantees the 1σ spread to be within the higher classical error bound in over 90% of all situations while being considerably smaller than the conservative window size of $13\lambda_c$ for an 802.11 system.

4.5 Summary

In this chapter we showed that the cumulative distribution and probability density functions (CDF and PDF respectively) of small-scale wideband signal envelope fading in micro-cells can be approximated very closely by both the Rice and Nakagami distributions that

are already known to describe the probability distribution of small-scale narrowband signal envelope fading. Therefore, for the first time, link quality can be modelled for wideband systems with a closed-form expression that includes small-scale fading. This model can in turn be used to derive the optimal predictor of link quality. Our results were obtained by means of an extensive Monte Carlo based study of a wideband propagation model from the literature, which is itself supported by extensive measurements. The following error statistics were determined over a comprehensive range of microcell propagation parameters that include the common wideband standards: the 802.11 family, DSRC, WiMAX and UMTS. The average maximum error in the approximation of the small-scale fading signal envelope was 1.65% and 1.78% for the Rice and Nakagami CDFs respectively. The error in the approximation was 3.58% and 3.87% respectively for the 95th percentile and did not exceed 7.61% and 7.80% respectively in the worst case. Considering only the 802.11 standard, the approximation errors for the small-scale fading signal envelope were even lower. For example, the maximum approximation error for the worst case of the Rice CDF did not exceed 4.45%. We also determined that the probability distribution of the small-scale fading wideband signal power can be characterised by the Non-Central Chi-Square and Gamma distributions to a similar degree of accuracy as the signal envelope is characterised by the Rice and Nakagami distributions.

While small-scale fading of the signal envelope of narrowband and wideband systems can both be described by the same probability distribution functions, the parameters of these functions differ between the different types of systems. Therefore, we propose an expression that maps the significant small-scale wideband signal envelope fading parameters to their narrowband counterparts for different standards such as DSRC, WiMAX, UMTS and the family of 802.11 standards. This mapping enables techniques developed for small-scale fading narrowband signals to be readily adapted to deal with wideband signals. For example, we used this mapping to derive the appropriate averaging window size and sample spacing for estimation of the large-scale fading signal. Compared to the traditional rule of thumb of using a window size of 20 to 40 carrier wavelengths in narrowband systems for averaging, we propose for an 802.11 system a conservative window size

of 13 to 25 wavelengths and a progressive window size of only 5 wavelengths. This shorter window size reduces the communication load by requiring fewer samples and increases the accuracy of the estimation of the large-scale fading signal. An accurate estimation of this large-scale fading signal is essential for link quality prediction. Furthermore, we will use the proposed mapping in the next chapter to extend the NS-2 simulator to incorporate small-scale wideband signal fading at low computational cost.

Chapter 5

Extending the NS-2 Simulator to Support Realistic Simulations of 802.11 MANETs

The NS-2 simulator is the most popular simulator in the MANET community (Kurkowski et al. 2005) and is our current in-house choice for simulations due to the large community supporting this product. The accuracy of the NS-2 simulator, its open-source counterpart GloMoSim and its commercial rival OPNET has been discussed in the literature (Takai et al. 2001, Cavin et al. 2002) although none of them was identified as being more realistic than the others. As described in Section 3.2, we examined the accuracy of three LQP algorithms from the literature (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) and observed that simulations in the standard NS-2 simulator led to barely comparable results with the corresponding real-world experiments. In this chapter we extend the NS-2 simulator to improve its realism, especially for microcellular urban environments.

Extending the NS-2 simulator requires several contributions. First, we identified the major weaknesses of the NS-2 simulator that account for the observed differences in accuracy between its simulations and real-world measurements. These weaknesses led to requirements for improvements in the area of either radio propagation or 802.11 receiver

modelling. To address these requirements, we adapted, extended and added radio propagation and 802.11 receiver models to the NS-2 simulator that are based either on our own measurements or on the body of knowledge in the literature. The extensive number of available radio propagation and receiver models makes the selection of appropriate models—and their respective parameters for microcellular urban environments—a challenge. Typically, isolated models are presented in the literature, such that their application and mathematical integration into one model for an overall communication system poses significant difficulty. Finally, we evaluated the extended NS-2 simulator against the original version and real-world measurements.

5.1 Critique of the NS-2 Simulator

In this section we critically assess the radio propagation and 802.11 receiver model of the NS-2 simulator (version 2.28) to derive requirements for enabling more realistic simulations.

5.1.1 The Radio Propagation Model of the NS-2 Simulator

In the simulation of communication systems, the radio propagation channel is typically the most difficult part to model accurately (Tranter et al. 2003, p. 3). The NS-2 simulator ships with three radio propagation models (Fall & Varadhan 2005, Section 18.1, 18.2 and 18.3) where only one model can be used for simulation at a time.

- Free Space Propagation Model (RPM1) (Fall & Varadhan 2005, Section 18.1). This path-loss model is appropriate for unobstructed line-of-sight paths without ground reflections. Such paths can be observed for terrestrial communication, before the radio wave touches the ground, or, for example, in satellite communication systems.
- Combined Free Space Propagation Model and Two-Ray Ground Propagation Model (RPM2) (Fall & Varadhan 2005, Section 18.2). In this model, the Free Space Propagation Model is used up to a certain distance after which the Two-Ray Ground Propagation Model is used.

- Combined Free Space Propagation Model and single-slope path-loss model with large-scale fading (RPM3) (Fall & Varadhan 2005, 18.3). Path loss is simulated by the Free Space Propagation Model up to some reference distance after which a single-slope path-loss model with a specifiable path-loss exponent is used. Large-scale fading is simulated by adding a log-normally distributed random variable to each simulated signal-power value.

The Free Space Propagation Model and the Two-Ray Ground Propagation Model are single-slope path-loss models since the path-loss exponent, which describes the degree of path loss, is independent of the distance. The path-loss exponent is 2 and 4 (Goldsmith 2005, p. 47) for the Free Space Propagation Model and the Two-Ray Ground Propagation Model, respectively. If two models are combined, as in RPM2 and RPM3, the resulting models are dual-slope path-loss models (Goldsmith 2005, p. 44) since they have two different path-loss exponents, depending on the distance between the transmitter and receiver. It is generally accepted that RPM2 is a much more suitable model compared to RPM1 for path-loss simulation in unobstructed (open space) terrestrial environments (Goldsmith 2005, pp. 36, 37) (Feuerstein et al. 1994). However, different path-loss exponents are required to describe microcellular urban environments well (Rappaport 2002, pp. 138, 139). All simulations of LQP algorithms reviewed in Chapter 2 were based on the path-loss-only radio propagation models RPM1 or RPM2.

RPM3 simulates path loss with a single-slope path-loss exponent with specifiable exponent which can describe path loss accurately in urban environments given that the path-loss exponent is chosen properly. However, the implementation of the path-loss model in RPM3 is flawed. The path loss for RPM3 (Fall & Varadhan 2005, Section 18.3, (18.5)) is calculated depending on the term $-\log \frac{d}{d_0}$ where d is the distance between the transmitter and receiver and d_0 is the reference distance for measuring the reference path loss. If the distance d between the transmitter and receiver is much smaller than d_0 (the implementation does not impose a restriction on d), this leads to an unrealistic path loss that can result in a simulated power that is even higher than the transmission power. In the extreme case

this leads to

$$\lim_{d \rightarrow 0} -\log \frac{d}{d_0} = \infty \quad (5.1)$$

which is clearly an unintended side-effect. Besides this (easily rectifiable) problem of the path-loss simulation, we observed a more serious shortcoming for the large-scale fading simulation in RPM3 as did Kotz et al. (2004). While the simulation of large-scale fading of the signal power is well described by the log-normally distributed random variable used (Goldsmith 2005, pp. 48, 49), the important spatial correlation of the large-scale fading process (Stueber 2001, p. 99) is not considered. As discovered by Gudmundson (1991) the signal variations that are experienced due to large-scale fading are dependent on the distance that a node moves. If, for example, one node is stationary and the other node moves only a short distance of 0.5 m, the signal is nearly unchanged due to large-scale fading; however, if this node moves 10 m, large-scale fading leads to a considerable signal variation. In the RPM3 model the large-scale fading is independent of node movements so that even small movements can potentially lead to large signal variations. Furthermore, appropriate parameters for large-scale fading in microcellular urban environments are not given in the NS-2 documentation. In our experience, the RPM3 model has rarely been used in published MANET studies.

The NS-2 simulator ships without any support for simulation of small-scale fading although such a module exists from Punnoose et al. (2000) which simulates small-scale fading by means of the Rice distribution. Since prior to our work it was unknown that the Rice distribution can be used to characterise small-scale wideband signal envelope fading (but with a different value of the Ricean K -factor than in the narrowband case), this module is, unless modified, only applicable to narrowband systems. Hence, we introduce the necessary modifications to allow for an efficient simulation of wideband small-scale fading.

5.1.2 The 802.11 Receiver Model of the NS-2 Simulator

The 802.11 receiver model implemented in the NS-2 simulator is only very basic. Each received packet has a signal power associated with it. If this signal power is below a speci-

fiable threshold (typically the receiver sensitivity), the packet is assumed to be lost (Fall & Varadhan 2005, Chapter 18, p. 186). This overly-simplified model does not determine packet loss by calculation of the PRP, which depends on the packet length and the bit error probability (BEP). The BEP represents the performance of the 802.11 receiver for a packet that is received with a given signal-to-noise ratio (SNR). The PRP, BEP and SNR critically determine the performance of a communication system (Tranter et al. 2003, p. 49), although they are not simulated in the NS-2 simulator.

5.2 Requirements for Extending the NS-2 Simulator

In order to motivate the MANET community to adopt the extended NS-2 simulator, we specify the following general requirements.

1. Improvement of simulation accuracy. As we showed in Section 3.2, the accuracy of the evaluated LQP algorithms differed significantly between measurements in two microcellular urban environments and simulations in the NS-2 simulator. Therefore, the main goal of the extension is to reduce this discrepancy and provide extended NS-2 simulations that are closer to what is observed in real-world measurements in microcellular urban environments.
2. Ease of use. The extended simulator should be as easy to use as the original version to facilitate widespread use in the MANET community. For example, the extended simulator should not require terrain maps since these are typically expensive and unavailable to researchers.
3. Speed. An extension of the NS-2 simulator that simulates additional propagation effects naturally increases the computational cost. However, the increase in the computational cost should be moderate such that typically available computing resources can be used.

Our critique of the standard NS-2 simulator leads to the following specific requirements.

1. Path-loss modelling. Since various path-loss models are provided with the NS-2 simulator, we must identify the most accurate. Furthermore, a path-loss exponent suitable for microcellular urban environments must be determined.
2. Modelling of large-scale fading. As previously discussed, the NS-2 simulator ships with one radio propagation model that simulates path loss and large-scale fading (RP3) simultaneously. However, the important spatial correlation of large-scale fading, which is difficult to simulate, is not considered and must be supported. Suitable parameters for the large-scale fading process in microcellular urban environments must be chosen.
3. Modelling of small-scale fading. NS-2 does not ship with the capability of simulating small-scale fading albeit that an additional module supports this propagation effect for narrowband systems. Since an 802.11 system is wideband, we need to extend the NS-2 simulator for small-scale wideband signal fading with parameters appropriate in microcellular urban environments.
4. Parameter modifications. The NS-2 simulator allows for only one value per propagation parameter during a simulation although a range of parameters has been determined for similar microcellular urban environments. Therefore, current NS-2 simulations represent only a small subset of propagation characteristics that are experienced in urban environments. This limitation should be mitigated.
5. Signal-to-noise ratio modelling. Since the NS-2 simulator ships without any SNR calculations, these have to be added for the 802.11 receiver.
6. Bit and packet error modelling. Since neither bit errors nor packet errors are considered in the NS-2 simulator, both calculations must be added.

5.3 Extending the Radio Propagation Model of the NS-2 Simulator

Radio propagation modelling tries to accurately describe the varying dynamics of radio channels that are caused by three basic effects of electromagnetic wave propagation, namely reflection, diffraction and scattering (Rappaport 2002, pp. 113, 114). These three basic propagation effects lead to variations of the received signal in the radio channel that can be modelled by deterministic path loss, stochastic large-scale fading and stochastic small-scale fading (Goldsmith 2005, pp. 27, 28). As previously discussed, the NS-2 simulator shows deficiencies in the simulations of all these propagation effects for which we propose several enhancements in this section.

5.3.1 Augmenting the Path-Loss Model in the NS-2 Simulator

Various path-loss models have been proposed in the literature for different environments and antennae heights (for an overview see, for example, Goldsmith 2005, pp. 31–48). The most appropriate path-loss models for urban microcells, determined in a major empirical study by Feuerstein et al. (1994), are the single-slope and dual-slope path-loss models. The path-loss exponents of these models can either be empirically determined by minimisation of the mean-square error between model and measurements or they can be analytically determined as in the case of the Free Space and Two-Ray Ground Propagation Model for which the path-loss exponents are 2 and 4, respectively (Goldsmith 2005, p. 47).

The two-slope path-loss model for two nodes at distance d from each other is given by (Feuerstein et al. 1994)

$$B_{\text{(dBm)}}(d) = \begin{cases} -10\kappa_1 \log_{10} \frac{d}{d_0} + B_{0\text{(dBm)}} & \text{for } d_0 \leq d \leq d_f \\ -10\kappa_2 \log_{10} \frac{d}{d_f} + 10\kappa_1 \log_{10} \frac{d_f}{d_0} + B_{0\text{(dBm)}} & \text{for } d > d_f \end{cases} \quad (5.2)$$

where κ_1, κ_2 are the path-loss exponents, $B_{0\text{(dBm)}}$ is the reference path loss for the distance d_0 , and d_f is the distance at which the First Fresnel Zone touches the ground (First Fresnel Zone clearance). The reference path loss is the signal power measured at a short distance between transmitter and receiver, which we measured for our Lucent Orinoco

card to be $B_{0(\text{dBm})} = -28 \text{ dBm}$ at a distance of $d_0 = 1 \text{ m}$. It is customary to assume that the signal power is given by $B_{0(\text{dBm})}$ when two nodes are separated by less than d_0 (Goldsmith 2005, p. 36). The distance of the First Fresnel Zone clearance d_f was determined by (Rappaport 2002, p. 156) to be

$$d_f = \frac{1}{\lambda_c} \sqrt{16h_T^2 h_R^2 - \lambda_c^2 (h_T^2 + h_R^2) + \frac{\lambda_c^4}{16}} \quad (5.3)$$

where h_T and h_R describe the antenna height of the transmitter and receiver respectively, and λ_c symbolises the carrier wavelength. A one-slope path-loss model has only one path-loss exponent for all distances and this model is given by (Goldsmith 2005, p. 46)

$$B_{(\text{dBm})}(d) = -10\kappa_1 \log_{10} \frac{d}{d_0} + B_{0(\text{dBm})} \quad \text{for } d_0 \leq d. \quad (5.4)$$

Since Green & Obaidat (2002) recently suggested a path-loss model for 802.11 in LOS conditions (henceforth referred to as the ‘LOS 802.11 Path-Loss Model’), we evaluated the accuracy of this new model compared to our measurements and the classical models suggested in the literature. The authors assessed the accuracy of their model by comparing the measured distance at which packets got lost to the predicted distance of packet loss as given by the path-loss model. However, this evaluation was flawed since the agreement between this model and measurements was shown for only one particular distance (the distance of packet loss) and not for the whole range of distances.

In order to determine an accurate path-loss model for the NS-2 simulator, we compared the path-loss models that ship with the NS-2 simulator, the LOS 802.11 Path-Loss Model and a two-slope path-loss model (Feuerstein et al. 1994) with our own signal-power measurements that we conducted in the obstacle-free environment described in Section 3.3.1. While this comparison with our measurements identifies the most suitable model for path loss, it does not intend to identify parameters applicable to microcellular urban environments, which we will determine from the literature. Since the RPM1 model (Free Space Propagation Model) from the NS-2 simulator is known to be less accurate than the RPM2 model for describing path loss between terrestrial nodes (Fall & Varadhan 2005, Section 18.2, p. 187), we omitted RPM1 from our comparison.

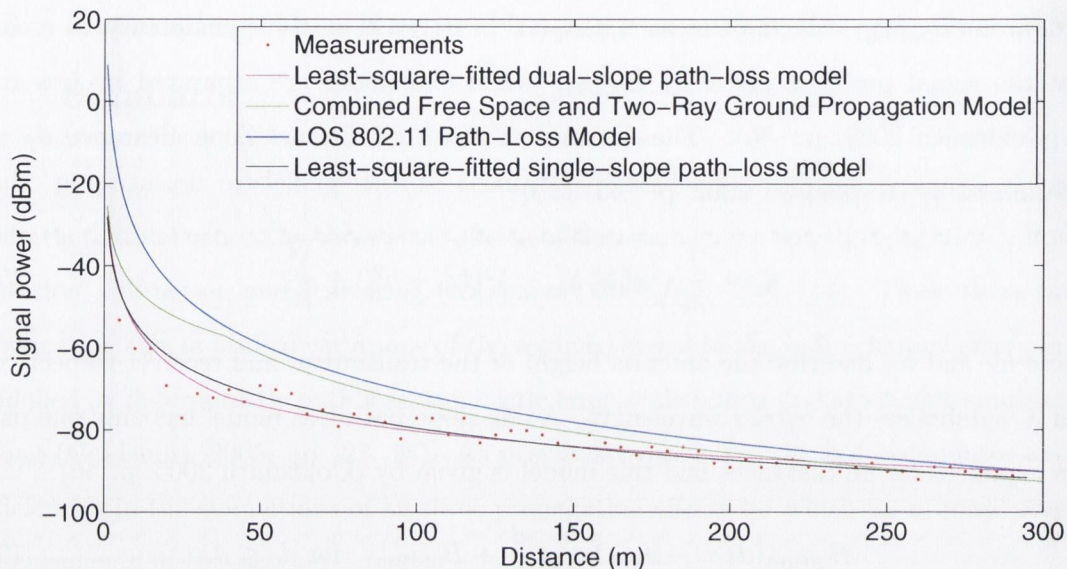


Figure 5.1: Comparison of various path-loss models with measurements. The least-square-fitted single-slope and two-slope path-loss models showed much closer agreement to our measurements than the LOS 802.11 Path-Loss Model and the combined Free Space and Two-Ray Ground Propagation Model.

Figure 5.1 shows that the single-slope (RPM3 in NS-2, large-scale fading disabled) and dual-slope (Feuerstein et al. 1994) path-loss models, whose path-loss exponents we determined by minimising the square of errors between model and measurements, agreed considerably better with our measurements than the LOS 802.11 Path-Loss Model and the RPM2 dual-slope path-loss model, whose path-loss exponents were given by the Free Space Propagation Model and the Two-Ray Ground Propagation Model. The MAE between model and measurements was 2.1 dBm for the least-square-fitted dual-slope path-loss model and 2.3 dBm for the least-square-fitted single-slope path-loss model. Since both path-loss models showed similar agreement to the measurements, we followed the advice of Goldsmith (2005, p. 46) and chose the simpler over the more complex model, i.e. the single-slope path-loss model.

We determined empirically a path-loss exponent of 2.58 for the single-slope path-loss model in our benign open space environment. Clearly, this value is environment-dependent and does not apply to microcellular urban environments, where path-loss exponents tend

to be higher due to attenuation by obstructions. Various studies have determined that path-loss exponents in the range of 2.7–3.5 are suitable for accurate modelling of path loss in microcellular urban environments (Goldsmith 2005, pp. 45, 46).

In summary, we exchanged the path-loss model in the NS-2 simulator by the single-slope path-loss model (5.4) with $B_{0(\text{dBm})} = -28 \text{ dBm}$, $d_0 = 1 \text{ m}$ and $\kappa_1 = [2.7, 3.5]$. We discarded the original single-slope path-loss model with large scale-fading (RPM3) from the NS-2 simulator since it contains the implementation and logical errors described in Section 5.1.1.

5.3.2 Adding Correlated Large-Scale Fading to the NS-2 Simulator

As previously mentioned, the NS-2 simulator includes one radio propagation model that describes the large-scale fading of the signal power by a log-normally distributed random variable (Fall & Varadhan 2005, pp. 187, 188), which is well known to describe large-scale fading accurately (see, for example, Goldsmith 2005, pp. 48, 49). However, the spatial correlation of the large-scale fading process, which is of great importance for simulation (Stueber 2001, p. 99), is not taken into account by the NS-2 simulator and must be added. The generally accepted correlation model (Stueber 2001, pp. 99, 100) (Goldsmith 2005, pp. 50, 51) for the large-scale fading process is due to Gudmundson (1991) and has been experimentally confirmed to accurately describe the correlation of signal power due to large-scale fading (Stueber 2001, pp. 99, 100) (Goldsmith 2005, pp. 48–51). The autocovariance function of the signal power in decibels due to large-scale fading of a node that has been moving from distance d by δ is given by (Gudmundson 1991) (Goldsmith 2005, p. 51)

$$\varrho_{S'_{(\text{dBm})}S'_{(\text{dBm})}}(d, \delta) = \text{E} \left[\left(S'_{(\text{dBm})}(d) - \text{E} [S'_{(\text{dBm})}(d)] \right) \right. \quad (5.5)$$

$$\left. \cdot \left(S'_{(\text{dBm})}(d + \delta) - \text{E} [S'_{(\text{dBm})}(d + \delta)] \right) \right] \\ = \sigma_S^2 \rho_{\text{dref}}^{\delta/d_{\text{ref}}} \quad (5.6)$$

where $S'_{(\text{dBm})}$ is the large-scale fading signal power with the mean given by the path loss, σ_S^2 is the variance of the large-scale fading process, and ρ_{dref} is the normalised autocovariance of the large-scale fading process separated by a reference distance of d_{ref} . Gudmundson (1991)

determined by empirical measurements that $\rho_{\text{dref}} = 0.3$ and $d_{\text{ref}} = 10$ m are appropriate values for urban microcells.

In MANETs, where all nodes are potentially mobile, the distance $\delta_{[t-x,t]}$ of movements for two mobile nodes between time $t - x$ and t is calculated by (Wang et al. 2004)

$$\delta_{[t-x,t]} = \|\mathbf{o}_{t-x,i} - \mathbf{o}_{t,i}\| + \|\mathbf{o}_{t-x,j} - \mathbf{o}_{t,j}\| \quad (5.7)$$

where $\|\mathbf{o}\|$ denotes the length of vector $\mathbf{o}$ in Euclidian space; $\mathbf{o}_{t-x,i}$, $\mathbf{o}_{t,i}$ are the positions of node i at time $t - x$ and t , respectively; and $\mathbf{o}_{t-x,j}$, $\mathbf{o}_{t,j}$ are the positions of node j at time $t - x$ and t , respectively. Note that the distance $\delta_{[t-x,t]}$ is therefore the sum of the independent distances that each of the two nodes moved between $t - x$ and t with respect to the origin of the coordinate system and not with respect to each other. Thus this distance δ differs from the distance d , which determines path loss, since d is the distance of one transmitter node with respect to a receiver node and not with respect to the origin of the coordinate system. For simplicity of notation, we typically omit the subscripts of δ if the time reference is not relevant or clear from the context.

The first-order autoregressive correlation model (5.6) can be simulated by first generating a white Gaussian noise process with variance σ_S^2 and then passing it through a first-order filter with the response $\rho_{\text{dref}}^{\delta/d_{\text{ref}}}$ (Gudmundson 1991) (Goldsmith 2005, p. 51) (Stueber 2001, pp. 99, 100). Thus the stochastic process of large-scale signal power fading at the discrete simulator index $t + 1$, in which δ has changed compared to index t , can be simulated by (Stueber 2001, p. 99)

$$S_{t+1(\text{dB})}(\delta) = \rho_{\text{dref}}^{\delta/d_{\text{ref}}} S_{t(\text{dB})} + (1 - \rho_{\text{dref}}^{\delta/d_{\text{ref}}}) M'_t \quad (5.8)$$

where $S_{(\text{dB})}$ describes the large-scale fading signal power with $S_{t=0(\text{dB})} = 0$ and M' is a normally distributed random variable (Stueber 2001, pp. 100)

$$M' \sim \mathcal{N}\left(0, \frac{1 + \rho_{\text{dref}}^{\delta/d_{\text{ref}}}}{1 - \rho_{\text{dref}}^{\delta/d_{\text{ref}}}} \sigma_S^2\right). \quad (5.9)$$

However, while (5.8) and (5.9) are well suited to simulate large-scale fading over a constant local mean power ($S_{t(\text{dB})}$ in (5.8) set to the local mean power), these equations are cumbersome to use when path loss varies with node movements. Therefore, Goldsmith (2005,

p. 51) suggests that path loss and large-scale fading should be simulated independently and then be superimposed, although she does not give the full details of this approach. Therefore, we have to fill this gap. The composite model that includes superimposed path loss and large-scale fading is defined by (Goldsmith 2005, p. 51)

$$S'_{t+1(\text{dBm})}(d + \delta) = B_{t+1(\text{dBm})}(d + \delta) - S_{t+1(\text{dB})}(\delta) \quad (5.10)$$

where $B_{t+1(\text{dBm})}$ is the path loss computed for simulation index $t + 1$. The autocovariance function of $S_{(\text{dB})}(t, t + 1(\delta))$, where the nodes moved by δ between simulator index t and $t + 1$, is given by (Stueber 2001, p. 100)

$$\varrho_{S_{(\text{dB})}S_{(\text{dB})}}(t, t + 1(\delta)) = \text{E} [S_{t(\text{dB})} S_{t+1(\text{dB})}(\delta)] = \sigma_S^2 \rho_{\text{dref}}^{\delta/d_{\text{ref}}}. \quad (5.11)$$

We can now show that the composite path loss and large-scale fading model (5.10) has the desired autocovariance function as given by (5.6). First, (5.10) is inserted in (5.5) which leads to

$$\begin{aligned} \varrho_{S'_{(\text{dBm})}S'_{(\text{dBm})}}(d, \delta) &= \text{E} \left[(B_{t(\text{dBm})}(d) - S_{t(\text{dB})} - \text{E} [B_{t(\text{dBm})}(d) - S_{t(\text{dB})}]) \right. \\ &\quad \cdot (B_{t+1(\text{dBm})}(d + \delta) - S_{t+1(\text{dB})}(\delta) \\ &\quad \left. - \text{E} [B_{t+1(\text{dBm})}(d + \delta) - S_{t+1(\text{dB})}(\delta)]) \right]. \end{aligned} \quad (5.12)$$

Subsequently, since $\text{E} [B_{t(\text{dBm})}(d)] = B_{t(\text{dBm})}(d)$ and $\text{E} [S_{t(\text{dB})}] = 0$ for any t , (5.12) can be simplified to

$$\varrho_{S'_{(\text{dBm})}S'_{(\text{dBm})}}(d, \delta) = \text{E} \left[(B_{t(\text{dBm})}(d) - S_{t(\text{dB})} - B_{t(\text{dBm})}(d)) \right. \quad (5.13)$$

$$\begin{aligned} &\quad \cdot (B_{t+1(\text{dBm})}(d + \delta) - S_{t+1(\text{dB})}(\delta) - B_{t+1(\text{dBm})}(d + \delta)) \Big] \\ &= \text{E} [S_{t(\text{dB})} S_{t+1(\text{dB})}(\delta)] = \sigma_S^2 \rho_{\text{dref}}^{\delta/d_{\text{ref}}} \end{aligned} \quad (5.14)$$

where the last step is given by (5.11). As claimed, (5.14) is equal to the desired autocovariance function (5.6).

Lastly, the simulation of correlated large-scale fading requires a value for its standard deviation σ_S appropriate for microcellular urban environments. Various studies (Rappaport & Milstein 1990, Berg et al. 1992, Marsan et al. 1990, Goldsmith &

Greenstein 1993, Goldsmith et al. 1994, Mogensen et al. 1991) determined a wide range of values for σ_S , as reported by Stueber (2001, p. 99), since the size of microcells (ca. 0.6–16 km) and antennae heights (5–93 m) varied widely between these studies. The study, whose settings most closely resemble MANETs in microcellular urban environments, was made by Berg et al. (1992) with an antenna height of 5 m and a cell size of up to 600 m. The authors recommend a range of 3.5–4 dB for σ_S to simulate large-scale fading in microcellular urban environments.

In summary, we implemented large-scale fading in the NS-2 simulator for urban microcells by (5.8), (5.10) and (5.7) with $\rho_{\text{dref}} = 0.3$, $d_{\text{ref}} = 10$ m and $\sigma_S = [3.5, 4.0]$.

5.3.3 Adding Wideband Small-Scale Fading to the NS-2 Simulator

As discussed previously, the standard NS-2 simulator does not support the simulation of small-scale fading. Yan & Kozono's (1999) signal propagation model, which we extensively used in Chapter 4, would be a candidate model for adding small-scale wideband signal envelope fading to the NS-2 simulator. However, while this signal propagation model is very suitable for studying the distribution of small-scale wideband signal envelope fading, it is unsuitable for simulations of MANETs. This signal propagation model simulates the propagation of multiple radio waves, which is computationally expensive, and contradicts the philosophy of any packet-level simulator, such as NS-2, which simulates only the statistical properties of the radio channel instead of multiple radio waves in order to significantly reduce the computational load. For each simulated packet, Yan & Kozono's (1999) signal propagation model is, as evident from (2.29), in the complexity class $\Theta(N_{\text{Wv}}^2)$ where N_{Wv} is the number of simulated radio waves.

An alternative way of extending the NS-2 simulator with small-scale fading is the use of Punnoose et al.'s (2000) module that simulates small-scale fading by means of the Rice distribution. This module creates small-scale fading signal envelopes in a computationally very efficient way by using a large precomputed lookup table such that the costly generation of correlated signal envelope samples from scratch at simulation time for each single packet is avoided. Hence, the simulation of small-scale fading is reduced to a single lookup

operation per packet with a simple scaling operation to account for the Ricean K -factor such that the computational complexity at simulation time is in $\Theta(1)$ per packet and is therefore independent of the number of radio waves (see the authors' original work for further details). However, while this module is computationally efficient, it has only been used to simulate small-scale fading for narrowband systems since prior to this work it was unknown that the Rice distribution can also be used to characterise small-scale wideband signal envelope fading albeit with a different value of the Ricean K -factor than in the narrowband case.

Our results from Chapter 4 allow the simple adaptation of Punnoose et al.'s (2000) module to simulate small-scale wideband signal envelope fading and take advantage of its low computational cost. The only required change is the replacement of the Ricean K -factor in the module with our equation (4.9), such that this module now simulates small-scale wideband signal envelope fading of an 802.11 system with an average accuracy ε_{KSR} of 1.64% as shown in Table 4.4. Consequently, the small-scale fading now depends on the wideband propagation parameters $\Delta L_{\text{max}}, a$ instead of the narrowband counterpart K . We implemented (4.9) as a lookup table to further reduce the computational cost since only one lookup operation per simulated packet is required for mapping the wideband propagation parameters to K . As previously discussed in Section 4.1, the wideband propagation parameters $\Delta L_{\text{max}} = [0.1, 55]$ and $a = [0, 31.62]$ characterise microcellular urban environments accurately.

Any stochastic process can be characterised by its amplitude and time structure (Yates & Goodman 2005, p. 353). In the previous paragraphs of this section, we discussed the amplitude structure of the small-scale wideband signal fading process, i.e. the probability distribution of this process. However, the simulation of the stochastic process of small-scale wideband signal fading also requires consideration of its time structure, which is summarised by its autocorrelation function (2.30), which was given in normalised form in Section 2.3. This autocorrelation function is identical for small-scale fading signals in narrowband and wideband systems as discovered by Nakabayashi & Kozono (1998).

The simulation of the time structure of the small-scale wideband signal fading process

requires an appropriate value for the Doppler frequency f_D in the autocorrelation function (2.30) that depends on the Doppler Effect. The Doppler Effect describes the apparent change in frequency of a wave that is received by a mobile node moving relative to a transmitter node (Serway & Jewett 2003, pp. 530–533). f_D is given for a wave of length λ_c and a mobile node moving at maximum speed v relative to a transmitter node by (Rappaport 2002, p. 224)

$$f_D = \frac{v}{\lambda_c} . \quad (5.15)$$

While the Doppler Effect can only be observed for mobile nodes, it is pointed out by Rappaport (2002, pp. 178, 179) that even static nodes experience small-scale fading due to multipath propagation that depends, among other factors, on surrounding mobile objects. For nodes carried by pedestrians in an microcellular urban environment with maximum walking speed (Wakim et al. 2004)

$$v = 1.4 \frac{\text{m}}{\text{s}}, \quad (5.16)$$

the Doppler frequency is given by (5.15) to be 11.45 Hz for an 802.11 system with the frequency and wavelength (Glover & Grant 2004, p. 940)

$$f_c = 2442 \text{ MHz} \quad (5.17)$$

$$\lambda_c = 0.12277 \text{ m}. \quad (5.18)$$

Thus we used $f_D = 11.45$ Hz in our simulations.

5.3.4 Adding Parameter Modifications to the NS-2 Simulator

As previously mentioned, the propagation effects of path loss, large-scale fading and small-scale fading are characterised by models for which empirical real-world studies have determined a range of values rather than a single value for each propagation parameter in similar microcellular urban environments. Moreover, even within a small geographical space in a microcellular urban environment the parameters sometimes vary considerably as was observed for small-scale fading by Green (1990). Unfortunately, we are unaware of real-world studies that have determined spatial models that associate changes in propaga-

tion parameters with geographical space although such models have been identified as an important research topic (see, for example, Prasad 1998, p. 43).

This situation suggests two options for conducting simulations. The first option is to choose one value for each propagation parameter and retain this value during a simulation as is currently done in typical MANET studies. However, this option leads to simulations that characterise the radio propagation channel only with respect to a small geographical space within an urban environment and therefore lack generality. The second option is to use a scheme that chooses values for each propagation parameter dynamically during simulations. This option has the advantage of reflecting the propagation characteristics of a range of geographical spaces within a microcellular urban environment and is therefore of higher generality. However, such a scheme has not been completely verified by measurements although the second option corresponds better with existing real-world measurements than the first. Assume one simulation is conducted with fixed radio propagation parameters and another one with dynamic parameters whose values are chosen from their respective range during simulation. If the propagation parameters are now determined by statistical analysis from the simulation data, each propagation parameter in the fixed-parameter simulation study would have only one value; clearly a result that is contradicted by the range of parameters determined in various real-world studies. However, the statistical analysis of the dynamic-parameter simulation would lead to a range of values for each propagation parameter that corresponds to the range observed in the real-world studies.

For the above reasons we chose the second option. The change of propagation parameters during simulation is controlled by the following rules:

- In the initialisation stage of a simulation the radio propagation parameters of all possible links are chosen pseudo-randomly uniformly from their respective range.
- The parameters of the radio channel for a link between two nodes are equal for both directions due to the principle of reciprocity (Lee 1993, p. 20).
- If no packet between two nodes has been received for at least c_1 seconds, the radio

propagation parameters of this link are re-initialised by choosing their values pseudo-randomly uniformly out of their respective range. Our experience suggests that $c_1 = 10$ seconds is an appropriate value.

The general idea behind this proposed scheme is that nodes, as long as they are connected to each other, share a similar geographical space and thus retain their parameters. Once these nodes have lost contact for a long enough period, they are assumed to have moved far enough such that their environmental characteristics and hence the radio channel has changed. While this model is reasonable and intuitive, it has the shortcoming that links between geographically close nodes can have different parameters and therefore have radio channels with different characteristics. For example, assume that three nodes are close to each other such that all nodes are connected. All three links may have different parameters associated with them, although, being in similar environments, the same parameters seem to be a more intuitive choice. However, in order to assign the same parameters to all links, the parameter values would be required to be associated with the simulated geographical space which leads to fundamental problems. First, the mapping of propagation parameters to geographical space is unknown and therefore an association between geographical space and propagation parameters is difficult to define. Secondly, when two connected nodes move from one region to another, where both regions have different sets of parameter values, the radio channel of this link would abruptly change albeit such a change should be gradual. Thirdly, a conflict would exist every time that two nodes are connected and are located in regions which have different propagation parameters associated with them. These problems suggested to us that the above simple scheme is a better choice than any model that associates the propagation parameters with simulated geographical space.

5.4 Extending the 802.11 Receiver Model of the NS-2 Simulator

As discussed in Section 5.1.2, the NS-2 simulator provides only a very basic 802.11 receiver model since received packets are modelled as being lost if their signal power is below a

specifiable threshold. In order to add a more detailed receiver model to the NS-2 simulator and meet the requirements outlined in Section 5.2, we first summarise the 802.11 physical layer. Subsequently we choose mathematical models from the literature that model a receiver that complies with this 802.11 physical layer.

5.4.1 Summary of the 802.11 Physical Layer

The 802.11 specification covers three different physical layer implementations, namely direct sequence spread spectrum (DSSS), frequency hopping spread spectrum and infrared (Crow et al. 1997). Since the latter two implementations never penetrated the market, we focus here on the DSSS implementation that is used in virtually all off-the-shelf 802.11 cards (for a description of the non-DSSS implementations see, for example, Schiller 2000, pp. 171, 173). A DSSS system spreads the modulated baseband signal in bandwidth before transmission and despreads it after reception. By using more bandwidth than required for the baseband signal, transmission resilience against narrowband interference is achieved since these interferences are attenuated in the despreading process (Gibson 1995, Chapter 11). In an 802.11 system the modulated baseband signal is spread by an 11-chip Barker sequence at 11 MHz (ANSI/IEEE Standard 802.11 1999, p. 195) such that the resulting 802.11 signal has a 3-dB bandwidth of 9.68 MHz as previously mentioned in Section 4.3. The baseband signal is modulated at a data rate of 1 Mbps with differential binary phase shift keying (DBPSK) and at 2 Mbps with differential quadrature phase shift keying (DQPSK) (Crow et al. 1997). Differential phase shift keying (DPSK) modulates the information by changing the phase of the baseband signal relative to the phase of the previously modulated symbol. In DBPSK a symbol consists of one bit while in DQPSK a symbol consists of two bits (Schiller 2000, pp. 45–48).

5.4.2 Adding Signal-to-Noise Ratio Modelling to the NS-2 Simulator

Since 802.11 is a DSSS system, the average SNR per bit γ_b is given by (Gibson 1995, Chapter 11, (11.1))

$$\gamma_b = \frac{\frac{R}{D}}{N_R + \frac{J}{2\Delta f}} \quad (5.19)$$

where R is the received signal power, D is the data rate, N_R is the receiver noise floor, J is the interference power, and $2\Delta f$ is the 3-dB bandwidth. If no interference power is present ($J = 0$), (5.19) simplifies to

$$\gamma_b = \frac{R}{N_R D}. \quad (5.20)$$

An 802.11 receiver has a noise floor that consists of the thermal noise floor N_0 and the receiver-specific noise figure N_f (Zyren & Petrick 1998). The thermal noise floor is caused by the temperature in the operating environment of the receiver and represents the lowest theoretical noise floor that can be achieved by a receiver. The performance penalty of actual receivers is captured in their noise figure that accounts for losses and internal noise and is assumed to be 7 dB for a typical 802.11 card (Zyren & Petrick 1998). Hence, we model the receiver noise floor N_R by (Zyren & Petrick 1998)

$$N_R = N_0 N_f \quad (5.21)$$

where N_0 is the thermal noise floor and N_f is the noise figure. The thermal noise floor is now calculated for an assumed temperature of 290 Kelvin (room temperature) as (Zyren & Petrick 1998)

$$N_0 = 1.38 \cdot 10^{-23} \frac{\text{Joules}}{\text{Kelvin}} \cdot 290 \text{ Kelvin}. \quad (5.22)$$

5.4.3 Adding Bit and Packet Error Modelling to the NS-2 Simulator

The evaluation of error-rate probabilities in digital communications over small-scale fading radio channels has been a very difficult and tedious task over the last forty years (Simon & Alouini 2005, p. XXV). However, this problem was greatly simplified by the recent discovery of the moment generating function (MGF) approach that unifies the calculations of error-rate probabilities and enables most of these error-rate expressions to be described by a single integral with finite limits and closed-form integrands (Simon & Alouini 1998). This unification is enabled by expressing the traditional error functions (Gaussian Q-Function, Marcum Q-Function) by alternative representations that are based on the MGF (Simon & Alouini 1998). The MGF of a probability distribution is a unique function that can

be used to obtain the moments of a probability distribution such as the mean or variance (Hines et al. 2002, pp. 65–67).

Assuming an 802.11 receiver with coherent DPSK modulation, we model the average bit error probability (BEP) P'_b for a radio channel with small-scale fading described by the Rice distribution by (Goldsmith 2005, p. 188, (6.70)) (Goldsmith 2005, p. 187, (6.64))

$$P'_b(\gamma_b, K) = \frac{1}{2} \frac{1 + K}{1 + K + \gamma_b} \exp\left(\frac{-K\gamma_b}{1 + K + \gamma_b}\right) \quad (5.23)$$

where γ_b is the average SNR and K is the Ricean factor. Assuming perfect channel equalisation, we now define the average BEP P_b for a wideband channel with small-scale fading as the mean of the average BERs over all configurations in a microcellular urban environment by

$$P_b(\gamma_b) = \sum_{\Delta L_{\max}=0.1}^{55} \sum_{a=0}^{31.62} \frac{P'_b(\gamma_b, g_k(a, \Delta L_{\max}))}{|\Delta L_{\max}, a|} \quad (5.24)$$

where $|\Delta L_{\max}, a|$ is the number of configurations and $g_k(a, \Delta L_{\max})$ is (4.9) that maps the wideband parameters $a, \Delta L_{\max}$ to the Ricean K -factor.

The average BEP for a wideband channel with small-scale fading is displayed by the magenta line for various SNRs in Figure 5.2. We also plotted the average BEP for a narrowband channel with small-scale fading described by the Rayleigh distribution (blue line) and a channel without any fading (red line, Additive Gaussian White Noise channel). As evident from this figure, the average BEP for the wideband channel is better than the Rayleigh channel, which characterises stronger narrowband small-scale fading and is worse than a channel without small-scale fading. Note that our BEP modelling of the wideband channel with small-scale fading was enabled by the results described in Chapter 4. We implemented (5.24) by a lookup table for fast simulations.

As suggested by Lee et al. (2005), we model the packet reception probability (PRP) for the 802.11 receiver as a sequence of Bernoulli trials. Therefore, the probability that a packet of q bits length is successfully received is given by (Hines et al. 2002, pp. 108, 109)

$$\Phi(\gamma_b, q) = \binom{q}{q} (1 - P_b(\gamma_b))^q (1 - (1 - P_b(\gamma_b)))^{q-q} \quad (5.25)$$

$$= (1 - P_b(\gamma_b))^q \quad (5.26)$$

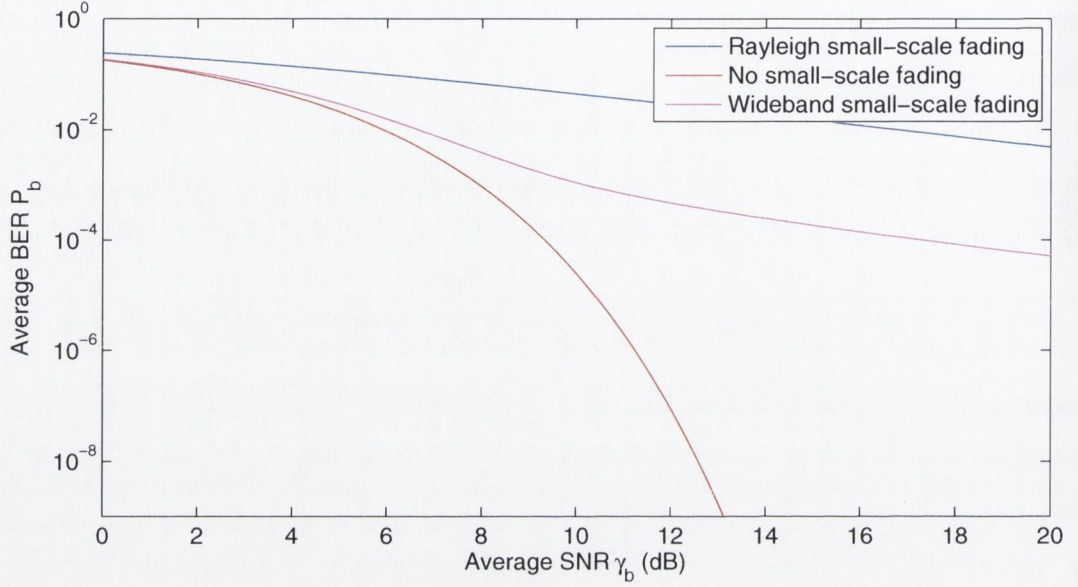


Figure 5.2: The average BEP for different channels vs. the average SNR. The BEP for a channel with wideband small-scale fading lies between the BEP given by a Rayleigh fading channel and a channel without small-scale fading.

where γ_b denotes the average SNR. Substituting (5.20) for γ_b allows (5.26) to be rewritten by

$$\Phi(R, q) = \left(1 - P_b \left(\frac{R}{N_R D}\right)\right)^q \quad (5.27)$$

where R is the received signal power, N_R is the receiver noise floor, and D is the data rate.

The 802.11 standard requires that the physical layer convergence procedure (PLCP) preamble and header are transmitted at 1 Mbps, while the MAC header and payload can be transmitted at higher data rates (Anastasi et al. 2004), which is in our case 2 Mbps as the highest data rate of the original 802.11 standard. The PLCP preamble and header together have a length of 192 bits (Schiller 2000, p. 171) and the MAC data, which is transmitted as PLCP payload, consists of a 224-bit long MAC header (Schiller 2000, p. 181) and a MAC payload of variable length. Therefore, the probability of successfully transmitting a packet is the probability that the PLCP data is successfully transmitted at 1 Mbps and the MAC data of q bits length is successfully transmitted at 2 Mbps

$$\Phi(R, q) = \left(1 - P_b \left(\frac{R}{N_R \cdot 1 \cdot 10^6}\right)\right)^{192} \left(1 - P_b \left(\frac{R}{N_R \cdot 2 \cdot 10^6}\right)\right)^q. \quad (5.28)$$

Inserting (5.21) with its constants in (5.28) leads to

$$\Phi(R, q) = \left(1 - P_b \left(\frac{R}{2.0058 \cdot 10^{-14}}\right)\right)^{192} \left(1 - P_b \left(\frac{R}{4.0116 \cdot 10^{-14}}\right)\right)^q \quad (5.29)$$

where $\Phi(R, q)$ is the PRP for a packet with MAC data of q bits in length, P_b is the average BEP of the wideband channel with small-scale fading (5.24), and R is the received signal power for a packet.

In summary, we extended the NS-2 simulator by implementing the packet and bit error calculations by (5.29) and (5.24).

5.5 Evaluation of the Extended NS-2 Simulator

All radio propagation models and their parameters that we used to extend the NS-2 simulator have been derived or verified by extensive measurement campaigns from the literature as previously discussed. The signal-power threshold, which NS-2 uses to decide if a packet is lost or received, was replaced by a more detailed 802.11 receiver model whose components were also derived from the literature. Since all extensions to the NS-2 simulator were evaluated in the literature, an additional evaluation by us is unnecessary. However, since we had real-world measurements from our LQP accuracy study available, we decided to use these measurements to further support our claim that the extended NS-2 simulator is more realistic than the original version.

In the real-world study we evaluated the accuracy of three LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) in two real-world microcellular urban environments. Additionally, we evaluated the accuracy of these algorithms in simulations with the standard NS-2 simulator and observed that these simulation results were barely comparable to the real-world experiments. We used the error statistics of missed packet loss m and unnecessary packet loss u as metrics that capture the LQP accuracy. In order to compare the extended NS-2 simulator with the real-world measurements, we applied the above LQP algorithms to the simulation data created by the extended NS-2 simulator with the mobility pattern given in Section 3.2.1 and the radio propagation parameters described in this chapter. The LQP algorithms' parameters were determined by optimisa-

tion exactly as in the case of the real-world measurements (see Section 3.2.2). Since the extended simulation was based on a 90-minute trial of two mobile nodes, as in the case of the real-world measurements and simulations with the standard NS-2, it did not cover all combinations of radio propagation parameters possible; thus the extended simulation represented the radio characteristics of a particular environment, as was the case in the real-world studies. Hence, we needed to calibrate the extended NS-2 simulator to closely represent the radio propagation environments encountered in the real-world studies. This calibration was realised by conducting 20 simulations with different random seeds and subsequently choosing simulations that led to LQP accuracy metrics that corresponded closest to those observed in the real-world measurements.

Table 5.1 compares the LQP accuracy metrics derived from real-world measurements with the metrics derived from the extended and standard NS-2 simulators. The LQP accuracy given by simulations with the extended NS-2 simulator showed excellent agreement to the accuracy determined for the real-world measurements while the latter was barely comparable to the accuracy observed in simulations with the standard NS-2 simulator. The mean difference between the accuracy metrics based on the real-world measurements and the extended NS-2 simulator was 1.16% for Street 1 and 2.06% for Street 2. If we had selected the next two best simulation data sets of the 20 simulations, the average difference would still only be 1.75/1.91% and 2.22/2.49% for the second/third best data sets for Street 1 and 2 respectively. These error statistics show that the extended NS-2 simulator gives much closer agreement than the standard simulator to real-world measurements. This observation was expected since our NS-2 extensions were based on models from the literature that have been verified by extensive real-world measurements.

Since the extended NS-2 simulator models more aspects of the radio propagation channel and of an 802.11 receiver, it is naturally slower than the standard simulator. In order to quantify the difference, we simulated all scenarios of the LQP accuracy study in the next chapter with the standard and extended NS-2 simulator on a Dell Precision PWS 380 machine with Pentium D 3.00 GHz, 2 GB RAM and SUSE Linux 9.3 Professional. On average, the extended NS-2 simulator was only 17.98% slower than the standard NS-2

Algorithm	Real world	Extended NS-2	Standard NS-2
<i>Experimental trial—Street 1 (Grafton Street)</i>			
Paul et al.'s (1999) algorithm, <i>m</i>	48.72%	47.59%	0.00%
Paul et al.'s (1999) algorithm, <i>u</i>	34.73%	36.08%	0.00%
Qin & Kunz's (2002) algorithm, <i>m</i>	58.17%	59.05%	6.67%
Qin & Kunz's (2002) algorithm, <i>u</i>	27.35%	28.13%	0.00%
Goff et al.'s (2001) algorithm, <i>m</i>	22.85%	24.40%	0.00%
Goff et al.'s (2001) algorithm, <i>u</i>	28.07%	29.37%	0.00%
<i>Experimental trial—Street 2 (O'Connell Street)</i>			
Paul et al.'s (1999) algorithm, <i>m</i>	54.19%	50.35%	0.00%
Paul et al.'s (1999) algorithm, <i>u</i>	35.90%	35.75%	0.00%
Qin & Kunz's (2002) algorithm, <i>m</i>	60.59%	57.77%	6.67%
Qin & Kunz's (2002) algorithm, <i>u</i>	24.62%	25.33%	0.00%
Goff et al.'s (2001) algorithm, <i>m</i>	28.39%	29.01%	0.00%
Goff et al.'s (2001) algorithm, <i>u</i>	30.50%	34.69%	0.00%

Table 5.1: Comparison of LQP accuracy in real-world urban environments with simulations in the standard and extended NS-2 simulator. While the LQP accuracy observed in real-world measurements and the extended NS-2 simulator was comparable, poor agreement was noticed between real-world measurements and simulations in the standard NS-2 simulator. The maximum difference in LQP accuracy between the extended NS-2 simulator and the real-world measurements was 1.55% and 4.19% for Street 1 and 2 respectively.

simulator. We attribute this low increase in computational load to the use of lookup tables, especially for the simulation of small-scale wideband signal envelope fading.

5.6 Summary

We identified that the standard NS-2 simulator only models some of the radio propagation effects experienced in real-world urban environments. In particular, the simulator accounts, in its default configuration, only for path loss and, in an extended configuration, also for large-scale fading albeit that the important correlation properties of the latter are not addressed. The simulator ignores small-scale fading entirely. Furthermore, bit and packet error calculations, which are based on 802.11 receiver models, are not implemented in the standard NS-2 simulator. These serious shortcomings have the consequence that existing MANET studies in NS-2 are based on overly-simplified radio propagation and receiver

models and hence their simulations show poor agreement with real-world experiments as, for example, shown in Section 3.2 for three LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002). Consequently, we suggested extensions that allow for more realistic, yet fast and easy-to-use simulations.

Since the field of radio propagation and receiver modelling is extensive, the selection of appropriate models with suitable parameters for microcellular urban environment is a challenge. We implemented a single-slope path-loss model for the NS-2 simulator that showed good agreement with our own measurements. Large-scale fading was incorporated by a model from the literature that takes its spatial correlation into account. An existing extension for NS-2 to simulate small-scale signal fading for narrowband systems was extended to wideband systems by employing our results from the previous chapter about the statistical properties of wideband small-scale fading. We also used these results in modelling the bit error probabilities of an 802.11 receiver in a small-scale fading wideband channel. Finally, models from the literature for calculation of signal-to-noise ratios and packet reception probabilities were added.

The choice of appropriate parameters for radio propagation models to describe microcellular urban environments is as important as choosing appropriate models themselves. However, in current MANET simulations only a constant value is used to represent each propagation parameter while measurements in similar geographic urban environments determined a range of values. Consequently, simulations based on a single value per radio propagation parameter lack generality since they only characterise the radio propagation environment well for small geographical spaces within an urban environment. To overcome this shortcoming, we introduce a simple but novel idea: instead of using a constant value for each parameter, the simulator chooses pseudo-randomly for each parameter a value from its measured range, thus leading to simulations that represent the full variety of microcellular urban environments. The simulator chooses new values for each pair of nodes when there has been no successful communication between them for a specifiable amount of time.

Our proposed extensions to the NS-2 simulator are entirely justified by relying on

models from the literature that have been derived or verified by extensive measurements. Nevertheless, we undertook an additional evaluation to support the claim that the extended NS-2 simulator leads to more realistic simulations than the standard simulator. We showed previously that the accuracy of three link quality prediction (LQP) algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) in simulations with the standard NS-2 simulator is barely comparable to the accuracy observed in real-world measurements. We now compared the accuracy of these LQP algorithms in the extended NS-2 simulator with the accuracy observed in the two real-world studies. The accuracy differed for the first environment by a maximum of 1.55% and for the second environment by a maximum of 4.19%. At the same time the extended simulator is as easy to use as the standard NS-2 simulator since it does not require any terrain maps.

Since we incorporate additional propagation effects such as large-scale and small-scale fading as well as error probability calculations into the simulations, the extended simulator is naturally slower than the standard NS-2 simulator in its default configuration that only incorporates path loss. However, for the wide range of scenarios considered in the next chapter's simulation study, the extended simulator was on average only 17.98% slower. This low increase in computational load was mainly achieved by use of lookup tables, especially for the simulation of small-scale wideband signal envelope fading.

Chapter 6

Derivation and Performance Evaluation of Novel Link Quality Predictors for 802.11 MANETs

In this chapter, we derive novel LQPRs that are based on a link quality model that includes path loss, large-scale and wideband small-scale fading. The obtained optimal predictor requires the runtime estimation of its parameters, for which we also derive the optimal estimator. However, it is known that no computationally inexpensive recursive solution exists for this class of estimation problems. Therefore, we propose a suboptimal but fast estimator that enables efficient runtime estimation of the parameters required for the predictor. We show rigorously that the accuracy of this fast estimator, represented by the parameter estimation variance, is only slightly reduced compared to the optimal estimator while being three orders computationally more efficient. Complementary to this fast predictor/estimator combination, termed the distance exponential shadowing (DES) predictor, we propose a simple beaconing protocol that uses Golay encoding to enable LQP in situations at very low SNR, in which previously no LQP has been possible. The DES predictor uses both signal-power and node-speed measurements, where the latter are required for a node mobility prediction algorithm that is also proposed in this chapter.

For applications in which sensors for node-speed measurements are unavailable, we suggest the simple Last Local Mean (LLM) predictor, which solely relies on signal-power measurements. This predictor is shown to be a special case of the DES predictor, in which nodes are assumed to be static due to the lack of available speed measurement sensors.

Since the necessary resources for an evaluation of our LQPRs by real-world experiments were unavailable, we assessed their accuracy by simulations in the extended NS-2 simulator for which good agreement with some real-world measurements was shown in Section 5.5. An assessment of the prediction accuracy of the LQPRs benefits from a comparison against a strong baseline. However, the three previously evaluated LQP algorithms from the literature are not suitable for that purpose due to their low LQP accuracy observed both—in real-world measurements and simulations in the extended NS-2 simulator for pedestrians in urban microcells—as well as due to the computational resources required to determine their parameters (see Section 6.5 for details). Therefore, we evaluated our LQPRs against a much stronger baseline which is given by a theoretical (THEO) predictor that is also derived in this chapter. The THEO predictor represents the LQP accuracy achievable by an external observer with perfect knowledge of the link quality model for the past but no knowledge of the future. While this LQP accuracy cannot be achieved by any actual implementation within the given link quality model and its assumptions, this lower error bound represents the strongest baseline possible against which to compare our LQPRs.

The performance of LQP in general and our LQPRs in particular might depend on various factors. However, apparently no comprehensive investigation of such influence factors has yet been conducted in the literature. Therefore, we assess the accuracy of our LQPRs in the extended NS-2 simulator in a wide variety of scenarios with respect to various potential factors that might influence LQP accuracy. We investigate the influence of two different mobility models, the length of packets for which predictions are made, the quality of links for which predictions are conducted, the density of nodes and the influence of having only bidirectional communication links. The statistical accuracy of our evaluation is demonstrated by means of the confidence intervals.

6.1 Assumptions

In this chapter we derive and evaluate three LQPRs that predict accurately the PRP of future transmitted packets in microcellular urban environments. We make the following assumptions:

- Location information is unavailable. As discussed comprehensively in Section 3.2, location measurements are highly unreliable in dense urban environments (Nayak 2000, p. 1) and with a user-equivalent range error of 19.2 m for GPS (Grewal et al. 2001, pp. 128–130) are very inaccurate. Both observations were also confirmed in our own real-world experiments.
- Node speed is available. In contrast to location information determined by GPS, the speed of nodes can be measured accurately for pedestrians by a cost effective accelerometer chip for approximately 10 Dollars (Analog Devices 2002, Analog Devices 2000). It is noteworthy that a typical accelerometer chip has sample rates of up to 6000 Hz (Analog Devices 2000) while a typical consumer grade GPS, such as the Magellan GPS 315, has a sample rate of only 0.5–1 Hz (Magellan 2000, p. 59).
- The speed of two nodes, for which a prediction is made, is constant within the history and prediction interval. In other words, the nodes' speed is assumed to be constant within the interval of making the measurements required for LQP and the time for which the link quality is predicted. Most LQP algorithms for mobile nodes implicitly or explicitly make this assumption (Lee et al. 1999, Paul et al. 1999, Punnoose et al. 1999, Agarwal et al. 2000, Qin & Kunz 2002) and typically require that nodes also maintain their directions.
- The LQPR should only rely on information that is available to the 802.11 MAC layer since lower-layer information from the 802.11 physical layer is typically card-specific and thus unavailable to higher layers. While the 802.11 cards that were available to us discard received corrupt packets and their associated signal power at firmware level, we assume that the payload with bit errors and the signal power

of corrupt packets is available at MAC level. Such behaviour does not violate the 802.11 specification (ANSI/IEEE Standard 802.11 1999) and the decision to dispose this valuable information at firmware level is made arbitrarily by the manufacturer. For example, this information could be discarded at driver level, from where it could be extracted for further use in LQP.

6.2 System Architecture

In the following we envision how the LQPRs, which have been developed in this thesis, might interact with other components within a middleware for mobile applications. Figure 6.1 displays the various components in the structure of the Open Systems Interconnection (OSI) Reference Model and their interactions:

- 802.11 Direct Spread Spectrum System (DSSS) Physical (PHY) layer (Crow et al. 1997). The 802.11 DSSS PHY is responsible for the digital transmission of data over the air as previously described in Section 5.4.1.
- 802.11 Medium Access Control layer (Crow et al. 1997). The 802.11 MAC controls access to the medium but also provides support for roaming, authentication and power conservation (Schiller 2000, p. 173). Three methods exist for accessing the medium, however, only the distributed coordination function based on carrier sense multiple access with collision avoidance (CSMA/CA) is used for broadcasts in MANETs (Schiller 2000, pp. 174–176) (for a detailed discussion of the other methods see, for example, Schiller 2000, pp. 177–180). In this method, a node *i*, trying to transmit data, senses the wireless medium for a specified time period termed ‘distributed inter-frame space’ (DIFS). If the medium is free for at least DIFS time units, this node *i* starts transmitting its data. However, if the medium is busy, node *i* waits for DIFS time units and enters a contention phase. In this contention phase, *i* randomly chooses a backoff time within a specified contention window and senses the medium during this backoff time. If the medium is idle until the backoff time elapses, *i* subsequently transmit its data. If during this waiting period another node

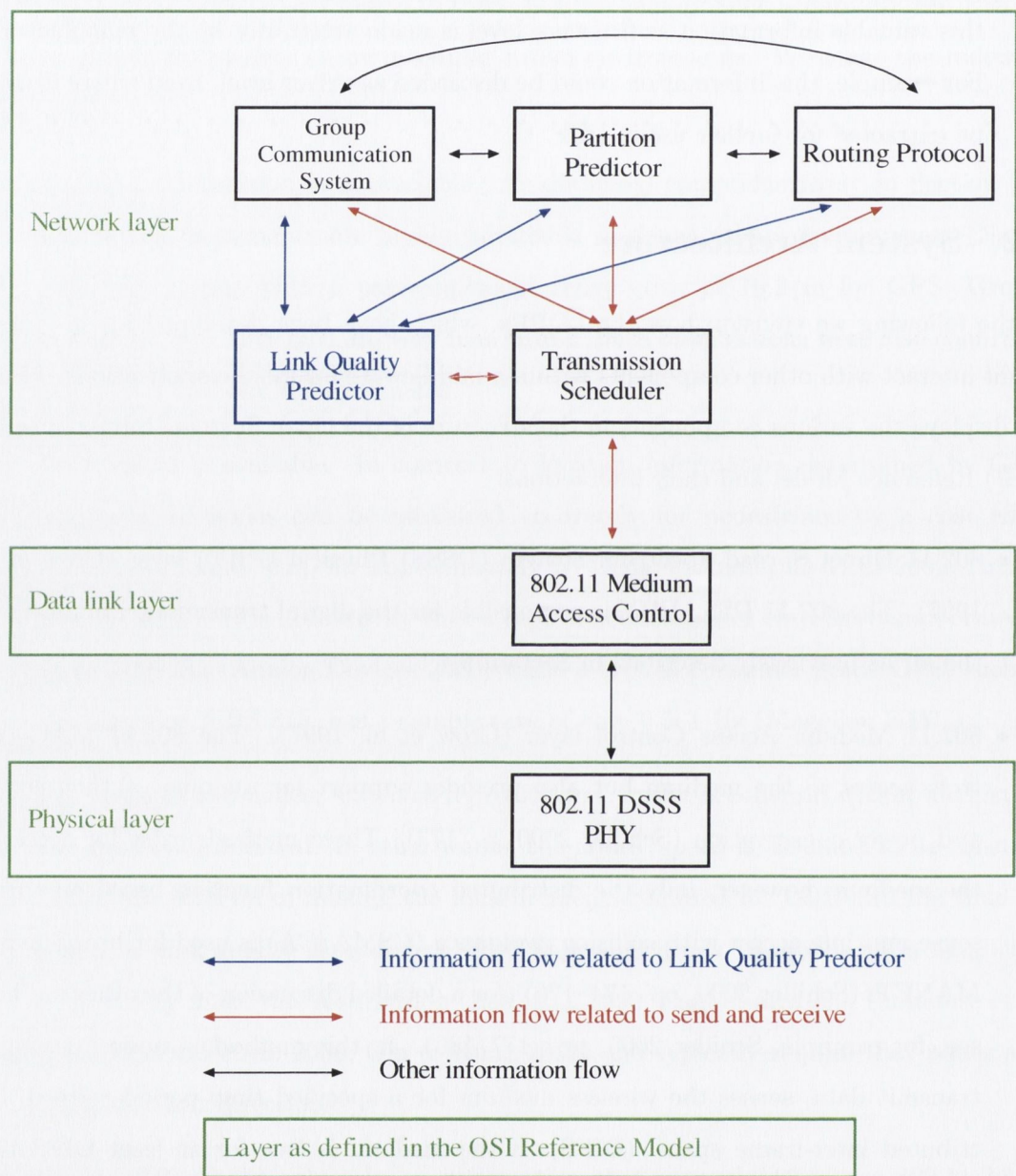


Figure 6.1: Middleware framework for mobile applications. The LQPR provides the group communication system, the partition predictor and the routing protocol with information about the future link quality.

$j \neq i$ transmits data, i stops its backoff timer and starts it again after the medium is idle for at least DIFS time units. This process repeats itself until the backoff timer of i elapses and the medium is free. The process of stopping and restarting the backoff timer at its previous value is called ‘exponential backoff’. It favours medium access for longer over shorter waiting nodes and intends to provide fair access to the wireless medium for all nodes. However, studies have shown that neither the fairness nor the collision avoidance of the 802.11 MAC protocol is perfect (see, for example, Xu & Saadawi 2001).

- **Link Quality Predictor.** The LQPR forms, in conjunction with the group communication system (GCS), the partition predictor (PP), the routing protocol (RP) and the transmission scheduler (TS), a framework for mobile applications. The LQPR predicts the PRP for packets that will be transmitted in the specifiable future. The LQPR requires periodic broadcasting (beaconing) of probe packets that are used to assess the condition of the radio channel. Since the GCS, PP, RP and applications are expected to also transmit beacons and other messages, the TS minimises the system-wide communication load by bundling multiple packets and by controlling the order among transmissions.

The LQPR predicts the PRP for broadcast packets, which do not use any acknowledgements or retransmissions, as the simplest transmission model. From this transmission model, the PRP of packets with acknowledgements and retransmissions, such as unicast packets, can be readily calculated, as will be shown in Section 6.3.9. The LQPR provides the following functionality. Let $\mathcal{J}$ denote the set of all one-hop communication partners of a node $i \notin \mathcal{J}$. Then the LQPR on node i predicts the future PRP of all links ($j \rightarrow i$) for every $j \in \mathcal{J}$, where i is the receiving node. Since the dissemination of the LQP information is specific to its use, the GCS, PP and RP may disseminate this information in their exchange of control packets which they use to build their global view of the multi-hop network. For example, the PP may require disseminating the LQP information of all links throughout the network since all nodes should have a view of the predicted global network. In contrast, proactive

routing does not require the distribution of LQP information throughout the network since a node can initiate a route discovery after having locally predicted a link failure.

- **Transmission Scheduler.** From the software engineering perspective it is desirable that all components of a wireless middleware can be developed and maintained independently in order to maximise reusability and lower maintenance costs. However, the lower reliability of communication in MANETs requires a higher degree of optimisation across layers to enable high-data-rate applications with low latency (Goldsmith 2005, p. 554). In order to balance these two conflicting requirements of component independence and cross-layer optimisation, we envision the use of a transmission scheduler. The TS gets transmission requests from all components including their required timeliness. For example, the LQPR might require that a beacon packet of 200 bytes is sent within the next 100 ms, the GCS may demand a transmission of 1200 bytes within 200 ms and the RP may require 900 bytes to be sent within the next second. The TS will then try to locally optimise the communication load by aggregating packets and scheduling their transmissions. In our example, the TS would aggregate the two packets from the LQPR and GCS into one packet: it would transmit this packet over the air as soon as possible and subsequently send the less time-critical packet for the RP. When packets are received, the TS preprocesses, splits and delivers them transparently to the components. However, the TS may not only optimise the communication locally but also globally within the network as suggested by Chockler et al. (2005a). They suggest that the TS (called ‘contention manager’ in their paper) may reduce contention and collisions by coordinating transmissions globally within the network. In summary, while the LQPR is able to work without a TS, we assume the latter component to be valuable for reducing the network-wide communication load.
- **Group Communication System.** A GCS provides reliable many-to-many communications within a network and it simplifies the development of applications with consistency requirements for wired (Birman 1993) and wireless networks (Singh et al. 2005).

Roman et al. (2001) suggest using LQP in MANETs to enforce the consistency properties of the GCS, albeit relying on 100% accurate LQP. Since LQP is not perfect, we suggest LQP to improve the performance of the GCS as opposed to guaranteeing consistency in all situations. Traditionally, if a link failure is detected, a GCS blocks progress until a new group membership view has been installed. This behaviour is appropriate for wired networks in which such link failures are rare but the behaviour is unsuitable for networks with a high number of topology changes. Therefore, analogous to proactive route discovery in routing protocols, we propose to use LQP to proactively reconfigure the group membership such that blocking is unnecessary when the prediction is correct. The effectiveness of proactive reconfiguration depends on the accuracy of LQP but an incorrect prediction leads to a performance penalty only; it does not affect consistency. A GCS may employ the LQPR directly and provide failure detection within its group membership protocol or use the PP that provides both of these functionalities.

- **Partition Predictor.** Killijian et al. (2001) suggest a PP component that predicts the future topology of a MANET by distributing and aggregating the LQP information from single links within the network. This predicted network topology can be used by the GCS for determining the group membership and also for flushing messages before partitioning occurs. If the GCS relies solely on the PP for membership determination, the PP must also provide the failure detection, otherwise provided by the GCS, for the cases in which the prediction is incorrect.
- **Routing Protocol.** While the GCS provides reliable many-to-many communications, the RP enables one-to-one communications. As discussed previously, routing profits from being proactive by initiating route discovery before predicted link failures occur such that packet latency is reduced. The required LQP can be either provided by the LQPR or, in systems in which a GCS with a PP is also present, by the PP.

6.3 Derivation of Novel Link Quality Predictors

The derivation of LQPRs for the radio propagation and receiver models, which were given in Chapter 5, is complicated. Hence, we start the derivation by presenting a high-level overview of the major steps first. Since the derivation requires several sometimes interwoven steps, we cannot present all the steps in a strictly linear order. Some expressions are given in different forms although only one form might be required at the time when the expression is presented; however, the other forms are required for later derivations.

6.3.1 Overview of the Derivation Process

We begin the derivation of the optimal LQPR by stating the generally accepted definition of an optimal predictor for a quantity (Harvey 1993, p. 33). Afterwards we define a complete link quality model that includes path loss, large-scale and wideband small-scale fading. Subsequently we simplify this link quality model by removing and approximating terms that do not contribute significantly to short-term LQP and thus make the problem tractable. Based on this model we derive the optimal LQPR and its parameters. If these parameters are known to an external observer with perfect knowledge of the link quality model in the past but no knowledge of the future, the optimal LQPR with perfect parameters is called the theoretical (THEO) predictor. Since the existence of an external observer cannot be assumed in real systems, the THEO predictor is only usable in simulations, where it represents the lowest error bound possible for LQP within the given link quality model.

The practical use of the optimal LQPR requires its parameters to be estimated from past signal-power and node-speed samples. We derive the optimal estimator for this purpose but this estimator is computationally so intensive that it is unsuitable for runtime use on current mobile computers. Thus we subsequently derive a fast but suboptimal parameter estimator for efficient computations at runtime that belongs to a computational complexity class that is three orders lower than the optimal estimator. Since the significant improvement in computational cost leads unavoidably to a reduction in estimation accuracy, we analytically derive the estimation accuracy and compare the fast and optimal

estimators. We term the combination of the optimal predictor and the fast estimator the distance exponential shadowing (DES) predictor. Since the DES predictor requires speed measurements of mobile nodes, we subsequently suggest a simple predictor without the need for such measurements, which is termed the last local mean (LLM) predictor. Note the difference between predictor and estimator: in the first part of this chapter, we derive an optimal predictor which determines future quantities based on some parameters; in the second part of this chapter we derive estimators, which estimate these parameters from past measurements.

Two of the three LQPRs presented in this work include a parameter that depends on the prediction of node mobility. Although mobility prediction is not the focus of this work, we propose a simple but reasonable mobility predictor for integration into the LQPRs. Subsequently we summarise all LQPRs in one section for convenience. Since we derive LQPRs that predict the PRP for packets without any acknowledgements and retransmissions, we afterwards underline the generality of our results by deriving expressions that predict the PRP for unicast 802.11 packets that may include both.

We conclude this section by suggesting a beaconing protocol that provides a LQPR with the information required for it to work. In this context we introduce a data encoding scheme for enabling LQP in situations at very low SNR where no LQP has been possible before.

6.3.2 Definition of an Optimal Predictor

Let X_t be a single sample of a stochastic process. Assume that all samples, which are realisations of this stochastic process until time T , are represented by the vector $\mathbf{X}_T = [X_{t=1} \dots X_{t=T}]^T$. Then the optimal predictor of X for the future time $T + \tau$, based on all information $\mathbf{X}_T$ available up to T , is given by the expectation conditional on this information (Harvey 1993, p. 33)

$$\tilde{X}_{T+\tau|T} = E[X_{T+\tau} | \mathbf{X}_T]. \quad (6.1)$$

Such a predictor is optimal in the sense that it has the minimum mean square error of all predictors.

6.3.3 Link Quality Model

The received signal power between two nodes is given by (Tepedelenlioglu et al. 2001)

$$R_{(\text{dBm})} = S'_{(\text{dBm})} + 10 \log_{10} h^2 \quad (6.2)$$

where $S'_{(\text{dBm})}$ is the large-scale fading process with its mean given by the path loss and h is the wideband small-scale fading envelope described by the Rice distribution. For notational convenience, we set $H_{(\text{dB})} = 10 \log_{10} h^2$. After separating the large-scale fading and path loss by inserting (5.10) into (6.2), the complete model of link quality is given by

$$R_{(\text{dBm})} = \underbrace{B_{(\text{dBm})}}_{\text{path loss}} + \underbrace{S_{(\text{dB})}}_{\text{large-scale fading}} + \underbrace{H_{(\text{dB})}}_{\text{small-scale fading}} \quad (6.3)$$

where $B_{(\text{dBm})}$ is the deterministic path loss, $S_{(\text{dB})}$ is a correlated normally distributed random variable with mean 0 and variance σ_S^2 , and $H_{(\text{dB})}$ is the power of the signal envelope h , which is a Ricean distributed random variable with $E[H_{(\text{dB})}] = 0$ (Tepedelenlioglu et al. 2001). Note that we replaced $-S_{(\text{dB})}$ with $+S_{(\text{dB})}$ after inserting (5.10) into (6.2) since $S_{(\text{dB})}$ is symmetrically distributed with a mean of 0.

The description of the stochastic processes of small-scale and large-scale fading requires information about their time structures, which is given by the normalised autocorrelation function for small-scale fading (2.30) and by the autocovariance function for large-scale fading (5.11). Note that the autocovariance function is equal to the autocorrelation function when the expectation of the stochastic process is zero (Yates & Goodman 2005, p. 371). To simplify the formula for the autocovariance function (5.11) for large-scale fading, we introduce the new constant

$$\rho_{\text{ref}} = \rho_{\text{dref}}^{1/d_{\text{ref}}} = 0.887 \quad (6.4)$$

that represents the empirically determined normalised autocovariance for urban microcells (Gudmundson 1991). Thus (5.11) becomes

$$\varrho_{S_{(\text{dB})}S_{(\text{dB})}}(\delta) = \sigma_S^2 \rho_{\text{ref}}^\delta. \quad (6.5)$$

6.3.4 Derivation of the Optimal Link Quality Predictor

We now derive the optimal predictor for the signal power of future received packets and subsequently map this power to the PRP. The future received signal power is predicted optimally, as defined by (6.1), at time T for the time $T + \tau$ by

$$\tilde{R}_{T+\tau|T}(\text{dBm}) = \text{E} [R_{T+\tau}(\text{dBm}) | \mathbf{R}_{\mathbf{T}}(\text{dBm})] . \quad (6.6)$$

The signal power is modelled by the deterministic path loss and the independent stochastic large-scale and small-scale fading processes. Therefore, the conditional expectation can be separated for both processes, resulting in

$$\begin{aligned} \tilde{R}_{T+\tau|T}(\text{dBm}) &= B_{T+\tau}(\text{dBm}) \\ &+ \text{E} [S_{T+\tau}(\text{dB}) | \mathbf{S}_{\mathbf{T}}(\text{dB})] \\ &+ \text{E} [H_{T+\tau}(\text{dB}) | \mathbf{H}_{\mathbf{T}}(\text{dB})] . \end{aligned} \quad (6.7)$$

This separation into three independent terms provides an opportunity to make this expression more tractable for further derivations by a simplification which is based on assessing the individual influence of the three propagation effects on short-term prediction.

Path Loss

As already discussed in Section 3.2 (see Figure 3.4), the difference in signal power due to path loss for two nodes, which in the worst case are moving apart at maximum walking speed for two seconds, is low. A more detailed analysis is enabled by Figure 6.2 in which the difference in signal power due to path loss between moving nodes is graphed. The nodes are initially located at a distance between 20 and 200 m from each other and move apart by a distance between 0 and 30 m. Two nodes can either move in the same direction, such that their relative separation does not change at all or they can move in the opposite direction such that the distance between them increases maximally depending on their speed. For example, if two collocated nodes move for two seconds at maximum walking speed, the distance between them will be between 0 and 5.6 m afterwards. Therefore, on average the power difference due to path loss can be expected to be considerably lower than

in the initial worst-case analysis from Section 3.2, where the difference was already shown to be low. Consequently, we approximate the path loss $B_{T+\tau}(\text{dBm})$ by the constant $C_{(\text{dBm})}$ eliminating the dependence on distance. Note that even if the difference in power due to path loss would generally be high and thus would be important for short-term LQP, it would be difficult to estimate the path loss since accurate location information for nodes is unobtainable in dense urban environments as repeatedly discussed in this thesis. Figure 6.2 also shows that a higher difference in power due to path loss is observed if the starting distance between the nodes is small. Although the approximation of the path loss being constant leads to higher signal-power prediction errors in these situations, the high level of signal power softens the impact of these errors on the PRP prediction since the link will still be predicted to be available¹.

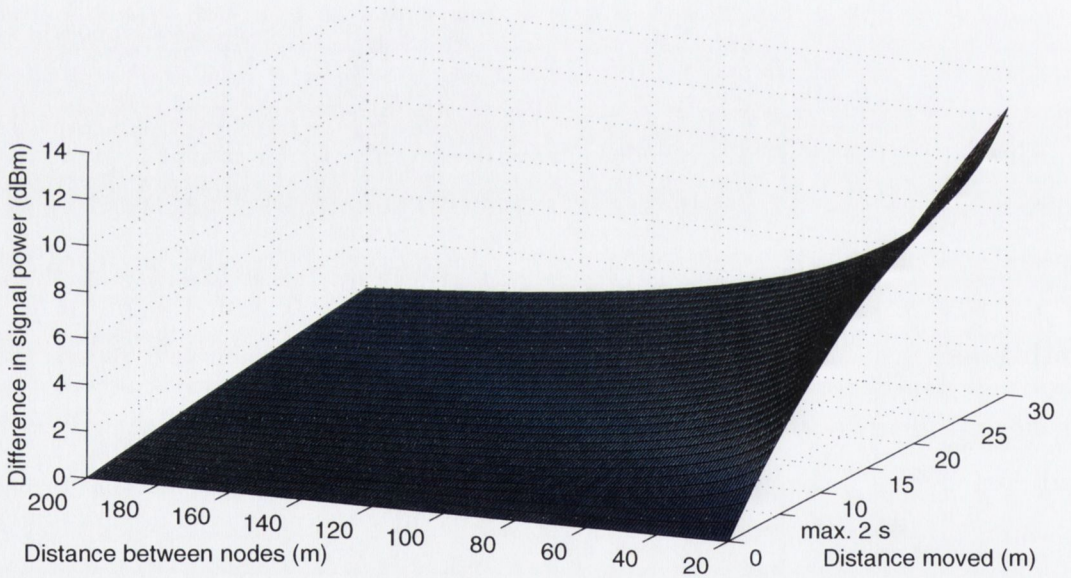


Figure 6.2: Difference in signal power due to path loss between nodes that move apart from a starting distance (X-axis) for a moving distance (Y-axis). The maximum possible power difference for nodes moving apart at maximum speed for two seconds is marked on the Y-axis. In general, the difference in power due to path loss is low for mobile nodes within a few seconds. The difference in power is displayed for a path-loss exponent of 3.1.

¹This analytical result is also confirmed by the empirical results in Section 6.5.2.2.

Small-Scale Fading

The predictability of the stochastic processes of large-scale and small-scale fading is dependent on how much current information about these processes at time T determines the future information at $T + \tau$. This relationship can be assessed by examining the autocorrelation or autocovariance functions of these processes, which illustrate their time structure. Figure 6.3 shows the normalised autocorrelation function (2.30) of the small-scale fading process. The graph shows that a current sample h_T has no predictive information beyond 0.03 s ahead for the Doppler frequency given for maximum walking speed. This corresponds to results from the literature which state that the received power of a mobile node due to small-scale fading, independent of the bandwidth of the signal, is uncorrelated beyond having moved for approximately 0.4 wavelengths (Goldsmith 2005, p. 74), which is approximately 5 cm for an 802.11 signal. Therefore, $E[H_{T+\tau}(\text{dB})|\mathbf{H}_T(\text{dB})]$ is identical to its unconditional expectation for $\tau > 0.03$ s and thus zero since $E[H_{(\text{dB})}] = 0$ (Tepedelenlioglu et al. 2001).

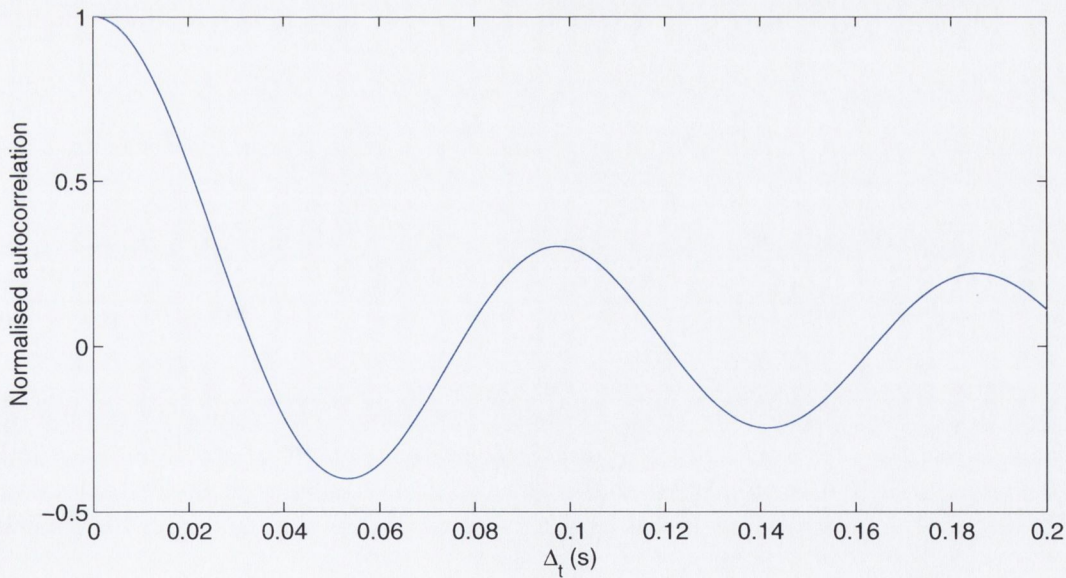


Figure 6.3: Normalised autocorrelation function for small-scale fading with a Doppler frequency given for maximum walking speed. The small-scale fading signal envelope decorrelates very quickly and a current signal-power sample has no predictive value beyond approximately 0.03 s.

Large-Scale Fading

Finally, we consider the case of large-scale fading. Figure 6.4 displays the normalised autocovariance function $\frac{\varrho_{S_{\text{(dB)}}}(\delta)}{\sigma_S^2}$, where $\varrho_{S_{\text{(dB)}}}(\delta)$ is given by (6.5). As is evident, there exists a high covariance of the large-scale fading signal power even for situations when nodes move at maximum walking speed for a few seconds. This covariance shows that a current sample of the large-scale fading signal is highly predictive of its future value within a few seconds and thus determines the future link quality significantly. Therefore, given this high correlation and also the considerable variance of the large-scale fading signal, we conclude that link quality within a prediction horizon of a few seconds is dominated by the large-scale fading propagation effect.

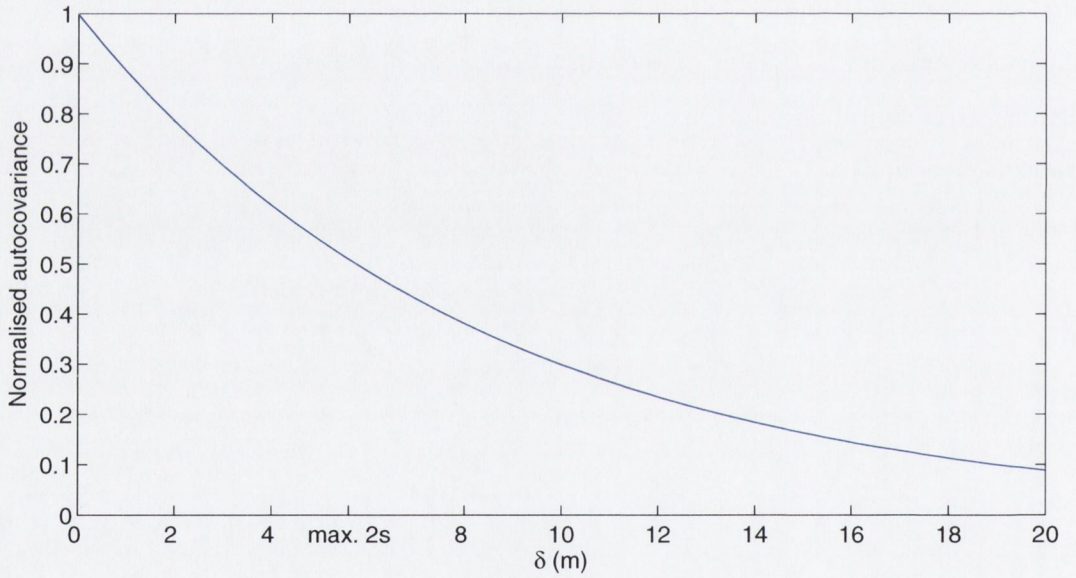


Figure 6.4: Normalised autocovariance function for large-scale fading. The large-scale fading decorrelates exponentially but slowly. A current sample of the large-scale fading signal power thus has a high predictive value for the link quality of nodes that move at walking speed for a few seconds. We marked on the X-axis the maximum distance that two nodes can move within two seconds.

Resulting Optimal LQPR

The above analysis allows us to simplify the optimal LQPR (6.7) to

$$\tilde{R}_{T+\tau|T}(\text{dBm}) = \underbrace{B_{T+\tau}(\text{dBm})}_{C_{(\text{dBm})}} \quad (6.8)$$

$$+ \text{E} [S_{T+\tau}(\text{dB}) | \mathbf{S}_{\mathbf{T}}(\text{dB})] \quad (6.9)$$

$$+ \underbrace{\text{E} [H_{T+\tau}(\text{dB}) | \mathbf{H}_{\mathbf{T}}(\text{dB})]}_0, \quad (6.10)$$

which is more conveniently given by

$$\tilde{R}_{T+\tau|T}(\text{dBm}) = C_{(\text{dBm})} + \text{E} [S_{T+\tau}(\text{dB}) | \mathbf{S}_{\mathbf{T}}(\text{dB})]. \quad (6.11)$$

From (6.11) the following approximated and simplified link quality model, derived for the purpose of LQP, results

$$R_t(\text{dBm}) = C_{(\text{dBm})} + S_t(\text{dB}). \quad (6.12)$$

The task is now to determine the conditional expectation $\text{E} [S_{T+\tau}(\text{dB}) | \mathbf{S}_{\mathbf{T}}(\text{dB})]$. The first-order autoregressive process of large-scale fading (5.8) with the normally distributed random variable (5.9) can be expressed with the simplified normalised autocovariance constant (6.4) by the equation

$$S_{t+1}(\text{dB})(\delta) = \rho_{\text{ref}}^{\delta} S_t(\text{dB}) + (1 - \rho_{\text{ref}}^{\delta}) M'_t \quad (6.13)$$

where M' is a normally distributed random variable

$$M' \sim \mathcal{N} \left(0, \frac{1 + \rho_{\text{ref}}^{\delta}}{1 - \rho_{\text{ref}}^{\delta}} \sigma_S^2 \right). \quad (6.14)$$

Recall that for two mobile nodes the distance δ is the sum of the distances that each of the two nodes moved independently between two points in time with respect to the origin of the coordinate system and not with respect to each other. Hence, the distance δ differs from the distance d , which determines path loss, since d is the distance between the transmitter and a receiver. Therefore, if we talk about distance in the context of large-scale fading, we always refer to the distance δ relative to the origin of the coordinate system, which was defined by (5.7). If we refer to path loss, we talk about d .

The normally distributed random variable M' is dependent on the lag of the autocovariance making the derivation of $E[S_{T+\tau}(\text{dB})|\mathbf{S}_T(\text{dB})]$ cumbersome. To remove this dependence, we employ the theorem that if X is a random variable $X \sim \mathcal{N}(0, \sigma_S^2)$ and c is a constant, then $Y = cX$ with $Y \sim \mathcal{N}(0, c^2 \sigma_S^2)$ (Zwillinger & Kokoska. 1999, Chapter 6, (6.18.3.5)). Thus we define

$$M \sim \mathcal{N}(0, \sigma_S^2). \quad (6.15)$$

and substitute M'_t in (6.13) with the IID random variable M_t resulting in

$$S_{t+1}(\text{dB})(\delta) = \rho_{\text{ref}}^\delta S_t(\text{dB}) + (1 - \rho_{\text{ref}}^\delta) \sqrt{\frac{1 + \rho_{\text{ref}}^\delta}{1 - \rho_{\text{ref}}^\delta}} M_t. \quad (6.16)$$

Basic term manipulations simplify (6.16) to

$$S_{t+1}(\text{dB})(\delta) = \rho_{\text{ref}}^\delta S_t(\text{dB}) + \sqrt{(1 - \rho_{\text{ref}}^\delta)^2 \frac{1 + \rho_{\text{ref}}^\delta}{1 - \rho_{\text{ref}}^\delta}} M_t \quad (6.17)$$

$$= \rho_{\text{ref}}^\delta S_t(\text{dB}) + \sqrt{(1 - \rho_{\text{ref}}^\delta)(1 + \rho_{\text{ref}}^\delta)} M_t \quad (6.18)$$

$$= \rho_{\text{ref}}^\delta S_t(\text{dB}) + \sqrt{1^2 - \rho_{\text{ref}}^{2\delta}} M_t \quad (6.19)$$

$$= \rho_{\text{ref}}^\delta S_t(\text{dB}) + \sqrt{1 - \rho_{\text{ref}}^{2\delta}} M_t. \quad (6.20)$$

Equation (6.20) now allows the simple derivation of the conditional expectation of the large-scale fading signal power by inserting (6.20) into (6.11) and thus the optimal predictor for signal power is given by

$$\tilde{R}_{T+\tau|T}(\text{dBm}) = C_{(\text{dBm})} + E \left[\rho_{\text{ref}}^{\tilde{\delta}_{T+\tau|T}} S_T(\text{dB}) + \sqrt{1 - \rho_{\text{ref}}^{2\tilde{\delta}_{T+\tau|T}}} M_T \right] \quad (6.21)$$

$$= C_{(\text{dBm})} + \rho_{\text{ref}}^{\tilde{\delta}_{T+\tau|T}} S_T(\text{dB}) + \sqrt{1 - \rho_{\text{ref}}^{2\tilde{\delta}_{T+\tau|T}}} \underbrace{E[M_T]}_0 \quad (6.22)$$

$$= C_{(\text{dBm})} + \rho_{\text{ref}}^{\tilde{\delta}_{T+\tau|T}} S_T(\text{dB}). \quad (6.23)$$

Given that the quantities $C_{(\text{dBm})}$ and $S_T(\text{dB})$ are typically estimated, the above equation can be also be written as

$$\tilde{R}_{T+\tau|T}(\text{dBm}) = \check{C}_T(\text{dBm}) + \rho_{\text{ref}}^{\tilde{\delta}_{T+\tau|T}} \check{S}_T(\text{dB}) \quad (6.24)$$

$$= \hat{C}_T(\text{dBm}) + \rho_{\text{ref}}^{\tilde{\delta}_{T+\tau|T}} \hat{S}_T(\text{dB}) \quad (6.25)$$

where $\tilde{C}_{T(\text{dBm})}$, $\tilde{S}_{T(\text{dB})}$ and $\hat{C}_{T(\text{dBm})}$, $\hat{S}_{T(\text{dB})}$ are estimated at time T by two different estimators, respectively, which will be introduced later in this chapter.

Since it is our goal to determine the optimal LQPR for the PRP, we now map the predicted signal power (6.23) to the PRP via (5.29). Since (5.29) refers to the power in watts, the predicted power in dBm is converted by (A.9). Thus the predicted PRP is given by

$$\tilde{\Phi}_{T+\tau|T}(\tilde{R}_{T+\tau|T}(\text{dBm}), q) = \Phi \left(10^{\frac{\tilde{R}_{T+\tau|T}(\text{dBm}) - 30}{10}}, q \right) \quad (6.26)$$

where q is the MAC-level bit length of the future packet for which the prediction is made and Φ is given by (5.29).

Given the assumptions in Section 6.1 and the link quality model (6.12), the signal-power predictor (6.23) and thus the PRP predictor (6.26) are optimal. Recall that optimality implies that no other predictor exists with lower minimum mean square error. However, these predictors cannot be used practically since the signal-power predictor and thus the PRP predictor both require the knowledge of $C_{(\text{dBm})}$ and $S_{(\text{dB})}$, which are not directly available from signal-power measurements. Hence, these quantities must be estimated for practical use². We term (6.26) to be the theoretical (THEO) predictor when used in conjunction with the optimal signal-power predictor (6.23) and when the quantities $C_{(\text{dBm})}$ and $S_{(\text{dB})}$ are known a priori. This knowledge can only exist in simulations, where the simulator has global ('god-like') knowledge that does not exist in real-world environments, such that the THEO predictor is non-realizable. In contrast, we call a LQPR realizable if it relies only on samples which could be made in real-world environments, independently of whether these samples originate from the real world or from simulations.

The THEO predictor represents the prediction of an external observer ('god') with perfect knowledge of the link quality model in the past but no knowledge of the future. It represents under the given assumptions the lower error bound on LQP that can never be achieved by any realizable predictor. Hence, the THEO predictor is the strongest baseline whether which to compare realizable predictors in simulations, since it shows how close a realizable predictor is to the unobtainable optimum.

²Both predictors also require the mobility prediction of $\tilde{\delta}_{T+\tau|T}$ which is given in Section 6.3.7.

6.3.5 Derivation of the Distance Exponential Shadowing Predictor

As just mentioned, the practical use of the optimal signal-power and PRP predictors requires knowledge of the unobservable quantities $C_{(\text{dBm})}$ and $S_{(\text{dB})}$. However, these quantities can be estimated from the composite power (6.3) of path loss, large-scale fading and small-scale fading that is measured with each received packet. Thus we suggest three estimation stages. In the first stage, the wideband small-scale fading is removed from the received signal power to obtain the sum of the power due to path loss and large-scale fading (6.12). In the second stage $C_{(\text{dBm})}$ is estimated from this quantity. We then derive two different estimators for $C_{(\text{dBm})}$. Thus the estimation of this quantity will be symbolised by either $\check{C}_{(\text{dBm})}$ or $\hat{C}_{(\text{dBm})}$ depending on its estimator. In the third stage, $S_{(\text{dB})}$ is estimated from the previously estimated quantities.

Link quality and its prediction in the short term are dominated by the large-scale fading effect with its autocovariance properties. Since the autocovariance decreases exponentially with distance and large-scale fading is also referred to as ‘shadow fading’, which was also the term used by Gudmundson (1991), who discovered its autocovariance function, we term the realisable optimal PRP predictor to be the distance exponential shadowing (DES) predictor.

6.3.5.1 Local Mean Power Estimation

In the first estimation stage the local mean power estimation removes small-scale fading from the received signal power, resulting in the estimated signal power due to large-scale fading and path loss only (Goldsmith et al. 1994). Recall that small-scale fading of an 802.11 wideband signal can be removed with good accuracy by signal power averaging over a distance of 5 wavelengths with a sample spacing below 0.5 wavelengths as shown in Section 4.4. Given the maximum walking speed of 1.4 m/s, for an 802.11 signal this distance corresponds to a sampling interval Υ of 0.04 seconds in the time domain with 11 samples ($N_H = 11$). The signal power can either be averaged in the logarithmic (decibel) or in the linear (watt) domain with similar accuracy (Goldsmith et al. 1994), albeit with a small accuracy advantage in the logarithmic domain (Goldsmith et al. 1994) (Goldsmith 2005,

p. 49). Hence, the signal power is averaged at time T by

$$\hat{R}_{T(\text{dBm})} = \frac{1}{N_H} \sum_{i=0}^{N_H-1} R_{T-i(\text{dBm})} \quad (6.27)$$

and from (6.12) follows for time T that

$$\hat{R}_{T(\text{dBm})} = C_{(\text{dBm})} + S_{T(\text{dB})}. \quad (6.28)$$

6.3.5.2 Optimal Parameter Estimator

The optimal predictor (6.23) requires that the quantities $C_{(\text{dBm})}$ and $S_{T(\text{dB})}$ are estimated from the sequence of signal-power measurements that are available at the time that a prediction is made. The quantity $C_{(\text{dBm})}$ is estimated first and subsequently $S_{T(\text{dB})}$.

An estimator is optimal if it attains the Cramer-Rao Lower Bound; thus it has minimum variance, is unbiased and it is impossible to find any unbiased estimator with lower variance (Kay 1993, p. 27). Since the link quality model (6.28) is a general linear model, $S_{T(\text{dB})}$ may be viewed in the estimation process of $C_{(\text{dBm})}$ as a normally distributed noise variable that is coloured by the autocovariance (6.5). For this class of models an optimal estimator exists (Kay 1993, pp. 83, 94–97) that will be given in the following.

Let $\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}$ denote the sequence of received signal-power samples, which where pre-processed by (6.27), as a vector of size $N_C \times 1$

$$\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})} = \begin{bmatrix} \hat{R}_{T-N_C+1(\text{dBm})} & \hat{R}_{T-N_C+2(\text{dBm})} & \cdots & \hat{R}_{T-1(\text{dBm})} & \hat{R}_{T(\text{dBm})} \end{bmatrix}^T \quad (6.29)$$

where N_C is the number of samples.

The optimal estimator $\check{C}_{(\text{dBm})}$ is given by (Kay 1993, pp. 94, 95)

$$\check{C}_{T(\text{dBm})} = \underbrace{\left[\underbrace{\begin{bmatrix} 1 & 1 & \dots & 1 & 1 \end{bmatrix}}_{1 \times N_C} \underbrace{\boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})}^{-1}}_{N_C \times N_C} \underbrace{\begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \\ 1 \end{bmatrix}}_{N_C \times 1} \right]}_{1 \times 1}^{-1} \cdot \underbrace{\left[\underbrace{\begin{bmatrix} 1 & 1 & \dots & 1 & 1 \end{bmatrix}}_{1 \times N_C} \underbrace{\boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})}^{-1}}_{N_C \times N_C} \underbrace{\begin{bmatrix} \hat{R}_{T-N_C+1}(\text{dBm}) \\ \hat{R}_{T-N_C+2}(\text{dBm}) \\ \dots \\ \hat{R}_{T-1}(\text{dBm}) \\ \hat{R}_T(\text{dBm}) \end{bmatrix}}_{N_C \times 1} \right]}_{1 \times 1} \quad (6.30)$$

where $\boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})}$ is the autocovariance matrix of the large-scale fading signal power. The autocovariance matrix is now given from the autocovariance function (6.5) by (Yates & Goodman 2005, pp. 370–371)

$$\boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} = \underbrace{\begin{bmatrix} \sigma_S^2 & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-N_C+1, T-N_C+2]}} & \dots & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-N_C+1, T-1]}} & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-N_C+1, T]}} \\ \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-N_C+2, T-N_C+1]}} & \sigma_S^2 & \dots & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-N_C+2, T-1]}} & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-N_C+2, T]}} \\ \dots & \dots & \dots & \dots & \dots \\ \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-1, T-N_C+1]}} & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-1, T-N_C+2]}} & \dots & \sigma_S^2 & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T-1, T]}} \\ \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T, T-N_C+1]}} & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T, T-N_C+2]}} & \dots & \sigma_S^2 \rho_{\text{ref}}^{\delta_{[T, T-1]}} & \sigma_S^2 \end{bmatrix}}_{N_C \times N_C} \quad (6.31)$$

Note that the estimator (6.30) can be implemented for real-world environments where the variance σ_S^2 is unknown, since (6.30) can also be used with the normalised covariance

matrix $\mathbf{Q}\mathbf{S}_{(\text{dB})}\mathbf{S}_{(\text{dB})}/\sigma_S^2$ in which the unknown constant scalar value σ_S^2 has been cancelled out of the equation. Recall that $\delta_{[t-x,t]}$ represents the sum of distances that two nodes in a link have moved with respect to the origin of the coordinate system within the time $t - x$ to t according to (5.7). Observe also that naturally $\delta_{[t-x,t]} = \delta_{[t,t-x]}$ and thus $\mathbf{Q}\mathbf{S}_{(\text{dB})}\mathbf{S}_{(\text{dB})}$ is symmetric. The estimator (6.30) is also termed a ‘weighted least-squares estimator’ where the weights are given by the covariance matrix (Madisetti & Williams 1997, Section 15.2).

After obtaining $\check{C}_{T(\text{dBm})}$, $S_{t(\text{dB})}$ is estimated by (6.28)

$$\check{S}_{T(\text{dB})} = \hat{R}_{T(\text{dBm})} - \check{C}_{T(\text{dBm})}. \quad (6.32)$$

This equation is obviously also valid if $\check{C}_{T(\text{dBm})}$ is estimated by another estimator, which will be derived in the next section, in which case (6.32) is given as

$$\hat{S}_{T(\text{dB})} = \hat{R}_{T(\text{dBm})} - \hat{C}_{T(\text{dBm})}. \quad (6.33)$$

Determination of N_C

The question remains how many N_C samples are required to accurately estimate $\check{C}_{T(\text{dBm})}$. It follows directly from the Cramer-Rao Lower Bound that the estimation accuracy of any efficient minimum variance unbiased estimator improves with increasing number of samples for estimation (Hines et al. 2002, p. 219). Therefore, we require to find a number of samples N_C for (6.30) that achieves an acceptable error bound on the estimation of $\check{C}_{T(\text{dBm})}$ for LQP. While such a bound and thus the required number of samples is easily derivable for an IID stochastic process, such derivation can be very difficult for stochastic processes with high covariance. Assume, for example, that $\check{C}_{T(\text{dBm})}$ is estimated by four samples of $\hat{R}_{(\text{dBm})}$ that were taken in one case where $\delta = 1$ m and in the other case where $\delta = 15$ m. Since the covariance of $S_{(\text{dB})}$ is high for 1 m, there is much less information in $\hat{R}_{(\text{dBm})}$ to estimate $\check{C}_{T(\text{dBm})}$ than if the samples were taken 15 m apart where the covariance of $S_{(\text{dB})}$ is low; hence, $\check{C}_{T(\text{dBm})}$ can be estimated more accurately by four samples when they are taken 15 m rather than 1 m apart. Consequently, the accuracy of the estimator is not only a function of the number of samples but also of the distances δ due to the covariance.

In our case an additional problem exists. The optimal LQPR has been derived by approximating the influence of path-loss on signal power to be constant for short-term prediction horizons. This approximation was shown to be accurate for the distance d that nodes can move with respect to each other within the prediction horizon as discussed previously in Section 6.3.4. However, the high covariance of $S_{(\text{dB})}$ requires the estimator of $\check{C}_{T(\text{dBm})}$ to sample over a larger distance δ_{max} than two nodes could move within the prediction horizon. Thus the accurate estimation of $\check{C}_{T(\text{dBm})}$ has to trade off that the spatial interval δ_{max} must be long enough to get a sufficient number of samples with low covariance and thus with high information about $\check{C}_{T(\text{dBm})}$ but short enough such that the approximation model (6.12) is still accurate. Referring back to Figure 6.2 that displays the difference in signal power due to path loss of moving nodes, it is evident that the approximation error due to treating the path loss as constant varies with node mobility patterns and thus the optimal spatial interval size δ_{max} for sampling also varies.

Overall, a suitable value for δ_{max} and thus N_C should allow, on average, for an accurate estimation of $\check{C}_{T(\text{dBm})}$ given the node mobility patterns that are observable for pedestrians in urban environments. Our discussion, however, showed that an analytical derivation of a suitable spatial interval δ_{max} is intractable. Our experience suggests that $\delta_{\text{max}} = 30$ m, in which the distance d between two nodes can change between 0 m and 30 m, is a reasonable value for an accurate estimation of $\check{C}_{T(\text{dBm})}$. Given that a signal-power sample is taken every 0.04 s to accurately estimate $\hat{R}_{(\text{dBm})}$ in the first estimation stage, $\delta_{\text{max}} = 30$ m corresponds to $N_C = 268$ samples.

Computational Complexity of the Optimal Estimator

The problem with the optimal estimator is its computational cost. As evident from (6.30), there is one unavoidable matrix inversion of the autocovariance matrix involved while the second inversion is a scalar operation. Although the complexity class of a matrix inversion has been shown to be of order $\Theta(N_C^{2.38})$ for very large matrices, practical numerically-stable algorithms are in the complexity class $\Theta(N_C^3)$ (Bailey & Gerguson 1998). Neither complexity class allows the optimal estimator (6.30) to be used at runtime since for each

new sample $\hat{R}_{T(\text{dBm})}$ the inverse for a 268×268 sample autocovariance matrix has to be computed. Since it is known that for the class of general linear systems with coloured noise, to which our link quality model belongs, no optimal estimator exists that can be implemented as a computationally inexpensive recursive solution (Kay 1993, p. 248), we have derived a fast but suboptimal estimator that trades estimation accuracy against computational cost.

6.3.5.3 Fast Parameter Estimator

The high computational cost of the optimal estimator necessitates finding a suboptimal estimator with good accuracy but lower computational requirements. The high computational cost arises from the autocovariance (6.5) of the large-scale fading process, which acts as coloured noise in the estimation. In order to reduce the computational cost, we neglect this autocovariance and assume the large-scale fading process to be driven by uncorrelated white noise. Under this assumption we propose an estimator, determine its computational complexity, derive its estimation bias and variance and compare these to the properties of the optimal estimator (6.30) to assess the impact of the above assumption.

We derive the fast estimator from the same link quality model (6.28) but assume that the large-scale fading process is uncorrelated. The following estimator (6.34), also known as ‘least-squares estimator’ (Kay 1993, p. 225), is unbiased and has minimum variance under the white-noise assumption (Kay 1993, p. 86)

$$\hat{C}_{T(\text{dBm})} = \underbrace{\left[\underbrace{\begin{bmatrix} 1 & 1 & \dots & 1 & 1 \end{bmatrix}}_{1 \times N_C} \underbrace{\begin{bmatrix} 1 \\ 1 \\ \dots \\ 1 \\ 1 \end{bmatrix}}_{N_C \times 1} \right]^{-1}}_{1 \times 1} \underbrace{\left[\underbrace{\begin{bmatrix} 1 & 1 & \dots & 1 & 1 \end{bmatrix}}_{1 \times N_C} \underbrace{\begin{bmatrix} \hat{R}_{T-N_C+1}(\text{dBm}) \\ \hat{R}_{T-N_C+2}(\text{dBm}) \\ \dots \\ \hat{R}_{T-1}(\text{dBm}) \\ \hat{R}_T(\text{dBm}) \end{bmatrix}}_{N_C \times 1} \right]}_{1 \times 1}. \quad (6.34)$$

(6.34) can be simplified in our case to

$$\hat{C}_{T(\text{dBm})} = \frac{1}{N_C} \mathbf{1}^T \hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})} \quad (6.35)$$

where $\mathbf{1}$ is a vector of ones with size $N_C \times 1$ and $\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}$ is the sequence of signal-power samples as given by (6.29) with size $N_C \times 1$. Note that (6.35) is the matrix form of

$$\hat{C}_{T(\text{dBm})} = \frac{1}{N_C} \sum_{i=0}^{N_C-1} \hat{R}_{T-i(\text{dBm})}, \quad (6.36)$$

which in this form is easily identifiable as the sample mean of $\hat{R}_{(\text{dBm})}$.

A naive implementation of (6.36) as a ‘for-loop’ would lead to an algorithm in the computational complexity class $\Theta(N_C)$ for each arriving signal-power sample. This is already a significant improvement over the computational complexity of the optimal estimator, which is in class $\Theta(N_C^3)$ for each arriving sample. However, the computational cost can be further reduced. As Tepedelenlioglu & Gao (2005) pointed out, any origin-moment based estimator can be computed recursively, which results in

$$\hat{C}_{T(\text{dBm})} = \frac{(N_C - 1) \hat{C}_{T-1(\text{dBm})} + \hat{R}_{T(\text{dBm})}}{N_C}. \quad (6.37)$$

This reduces the complexity of the fast estimator to be in $\Theta(1)$ for each new sample $\hat{R}_{T(\text{dBm})}$ such that this estimator belongs to the lowest possible order of complexity.

Bias of the Fast Estimator

In the following we determine whether the reduction in the computational cost results in a biased estimator. The estimator (6.36) (and its equivalent matrix form (6.35)) is unbiased if (Kay 1993, p. 16)

$$\mathbb{E} \left[\hat{C}_{T(\text{dBm})} \right] = C_{(\text{dBm})}. \quad (6.38)$$

In order to show that (6.35) is unbiased in the case of correlated large-scale fading, we start the derivation by inserting the estimator in its sum form (6.36) into (6.38), which

results in

$$\mathbb{E} \left[\frac{1}{N_C} \sum_{i=0}^{N_C-1} \hat{R}_{T-i}(\text{dBm}) \right] = C_{(\text{dBm})} \quad (6.39)$$

$$\frac{1}{N_C} \sum_{i=0}^{N_C-1} \mathbb{E} \left[\hat{R}_{T-i}(\text{dBm}) \right] = C_{(\text{dBm})}. \quad (6.40)$$

Taking the expectation of the link quality model (6.28) leads to

$$\mathbb{E} \left[\hat{R}_t(\text{dBm}) \right] = C_{(\text{dBm})} + \mathbb{E} \left[S_t(\text{dB}) \right], \quad (6.41)$$

which requires to derive the expectation of the large-scale fading variable using (6.20) such that

$$\mathbb{E} \left[S_t(\text{dB})(\delta) \right] = \rho_{\text{ref}}^{\delta} \mathbb{E} \left[S_{t-1}(\text{dB}) \right] + \sqrt{1 - \rho_{\text{ref}}^{2\delta}} \underbrace{\mathbb{E} \left[M_{t-1} \right]}_0 \quad (6.42)$$

$$= \rho_{\text{ref}}^{\delta} \mathbb{E} \left[S_{t-1}(\text{dB}) \right]. \quad (6.43)$$

The value of $\mathbb{E} \left[S_t(\text{dB}) \right]$ can be determined by induction. $S_{t=0}(\text{dB}) = 0$ (see (5.8)) implies that $\mathbb{E} \left[S_{t=0}(\text{dB}) \right] = 0$ (basis). Assume that $\mathbb{E} \left[S_{t=x}(\text{dB}) \right] = 0$ (inductive assumption). From (6.43) follows directly that $\mathbb{E} \left[S_{t=x+1}(\text{dB}) \right] = 0$ (inductive step) which shows that (Morash 1987, pp. 178–181)

$$\mathbb{E} \left[S_t(\text{dB}) \right] = 0. \quad (6.44)$$

Substituting (6.44) in (6.41) results in

$$\mathbb{E} \left[\hat{R}_t(\text{dBm}) \right] = C_{(\text{dBm})} \quad (6.45)$$

from which it follows that

$$\sum_{i=0}^{N_C-1} \mathbb{E} \left[\hat{R}_{T-i}(\text{dBm}) \right] = N_C C_{(\text{dBm})}. \quad (6.46)$$

Substituting (6.46) in (6.40) results in

$$\frac{1}{N_C} N_C C_{(\text{dBm})} = C_{(\text{dBm})} \quad (6.47)$$

$$C_{(\text{dBm})} = C_{(\text{dBm})}, \quad (6.48)$$

which shows that the estimator (6.36) (and (6.35)) is unbiased even when the large-scale fading is correlated.

The fast estimator is computationally much more efficient than the optimal estimator and both estimators are unbiased. Since the fast estimator can be implemented in a recursive form, which is not possible for the optimal estimator with coloured noise, the penalty for the fast estimator must lie in a less accurate estimation and thus in a higher estimation variance. Therefore, we now quantify this loss in estimation accuracy by deriving and comparing the estimation variances of both predictors.

Estimation Variance of the Fast Estimator

The variance of the fast estimator is given by (Hines et al. 2002, p. 58)

$$V[\hat{C}_{T(\text{dBm})}] = E[\hat{C}_{T(\text{dBm})}^2] - \left(E[\hat{C}_{T(\text{dBm})}]\right)^2. \quad (6.49)$$

Since we just showed that the fast estimator is unbiased, from (6.38) it follows that

$$V[\hat{C}_{T(\text{dBm})}] = E[\hat{C}_{T(\text{dBm})}^2] - C_{(\text{dBm})}^2, \quad (6.50)$$

which necessitates the determination of $E[\hat{C}_{T(\text{dBm})}^2]$. Since $\hat{C}_{T(\text{dBm})}$ is a scalar, $E[\hat{C}_{T(\text{dBm})}^2]$ can be expressed by

$$E[\hat{C}_{T(\text{dBm})}^2] = E[\hat{C}_{T(\text{dBm})}\hat{C}_{T(\text{dBm})}^T]. \quad (6.51)$$

Substituting the fast estimator (6.35) in (6.51) leads to

$$E[\hat{C}_{T(\text{dBm})}^2] = E\left[\frac{1}{N_C}\mathbf{1}^T\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}\frac{1}{N_C}\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T\mathbf{1}\right] \quad (6.52)$$

$$= E\left[\frac{1}{N_C^2}\mathbf{1}^T\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T\mathbf{1}\right] \quad (6.53)$$

$$= \frac{1}{N_C^2}\mathbf{1}^TE[\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T]\mathbf{1}. \quad (6.54)$$

$E[\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T]$ is the autocorrelation matrix of $\hat{R}_{T(\text{dBm})}$ and thus can be expressed by its autocovariance function as (Yates & Goodman 2005, p. 371)

$$E[\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T] = \boldsymbol{\varrho}_{\hat{\mathbf{R}}_{(\text{dBm})}} + \left(E[\hat{R}_{T(\text{dBm})}]\right)^2\mathbf{1}\mathbf{1}^T, \quad (6.55)$$

which under (6.45) is

$$\mathbb{E} \left[\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})} \hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T \right] = \boldsymbol{\varrho} \hat{\mathbf{R}}_{(\text{dBm})} \hat{\mathbf{R}}_{(\text{dBm})} + C_{(\text{dBm})}^2 \mathbf{1} \mathbf{1}^T. \quad (6.56)$$

It follows from (6.28) that the autocovariance matrices of $\hat{R}_{(\text{dBm})}$ and $S_{(\text{dB})}$ are equal (the mean of $\hat{R}_{(\text{dBm})}$ and $S_{(\text{dB})}$ differs only by $C_{(\text{dBm})}$)

$$\boldsymbol{\varrho} \hat{\mathbf{R}}_{(\text{dBm})} \hat{\mathbf{R}}_{(\text{dBm})} = \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})}, \quad (6.57)$$

which allows us to rewrite (6.56) as

$$\mathbb{E} \left[\hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})} \hat{\mathbf{R}}_{\mathbf{T}(\text{dBm})}^T \right] = \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} + C_{(\text{dBm})}^2 \mathbf{1} \mathbf{1}^T. \quad (6.58)$$

Inserting (6.58) into (6.54) results in

$$\mathbb{E} \left[\hat{C}_{T(\text{dBm})}^2 \right] = \frac{1}{N_C^2} \mathbf{1}^T \left(\boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} + C_{(\text{dBm})}^2 \mathbf{1} \mathbf{1}^T \right) \mathbf{1} \quad (6.59)$$

$$= \frac{1}{N_C^2} \mathbf{1}^T \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} \mathbf{1} + \frac{1}{N_C^2} \mathbf{1}^T C_{(\text{dBm})}^2 \mathbf{1} \mathbf{1}^T \mathbf{1} \quad (6.60)$$

$$= \frac{1}{N_C^2} \mathbf{1}^T \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} \mathbf{1} + \frac{1}{N_C^2} C_{(\text{dBm})}^2 \underbrace{\mathbf{1}^T \mathbf{1}}_{N_C} \underbrace{\mathbf{1}^T \mathbf{1}}_{N_C} \quad (6.61)$$

$$= \frac{1}{N_C^2} \mathbf{1}^T \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} \mathbf{1} + C_{(\text{dBm})}^2. \quad (6.62)$$

Substituting (6.62) back in (6.50) leads to the variance of the estimated quantity $\hat{C}_{T(\text{dBm})}$

$$\mathbb{V} \left[\hat{C}_{T(\text{dBm})} \right] = \frac{1}{N_C^2} \mathbf{1}^T \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} \mathbf{1} + C_{(\text{dBm})}^2 - C_{(\text{dBm})}^2 \quad (6.63)$$

$$= \frac{1}{N_C^2} \mathbf{1}^T \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})} \mathbf{1}, \quad (6.64)$$

which is simply $1/N_C^2$ times the sum of all elements of $\boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})}$.

In order to compare the estimation variance between the fast and the optimal predictor, the variance of the later requires being determined. This derivation was already done by Kay (1993, p. 95) yielding

$$\mathbb{V} \left[\check{C}_{T(\text{dBm})} \right] = \left(\mathbf{1}^T \boldsymbol{\varrho} \mathbf{S}_{(\text{dB})} \mathbf{S}_{(\text{dB})}^{-1} \mathbf{1} \right)^{-1}. \quad (6.65)$$

The comparison of estimation variance is given by the ratio

$$\frac{\mathbb{V} \left[\hat{C}_{T(\text{dBm})} \right]}{\mathbb{V} \left[\check{C}_{T(\text{dBm})} \right]} \quad (6.66)$$

and is independent of the large-scale fading variance since σ_S^2 is cancelled out of the fraction. For the worst case mobility scenario of both nodes moving with maximum walking speed, this ratio is only 1.13. Therefore, while the fast estimator is in a computational complexity class three orders lower than that of the optimal estimator, the penalty in accuracy is only a 13% difference in estimation variance.

To illustrate that the accuracy of both estimators is similar, we give an example using a Monte Carlo study. In this study, we investigate the performance of the optimal predictor with both estimators. Two nodes are located at a starting distance from which they either move towards or apart with respect to each other at maximum walking speed for 40 m with equal probability. The path-loss exponent and the variance of large-scale fading are randomly chosen from their range for microcellular urban environments. The experiment is repeated 200 times and two scenarios are investigated: the nodes start at 50 m or 150 m apart. The signal power consists of path loss and large-scale fading only since we are interested in the estimator performance without the influence of small-scale fading. Figure 6.5 shows the MAE of the signal-power predictor for various prediction horizons. Firstly, it can be observed that the combination of optimal predictor and fast estimator is only slightly worse in both scenarios than the combination of optimal predictor and optimal estimator, which illustrates the analytical result. Secondly, it can be noticed that the prediction accuracy at 50 m starting distance is lower than at 150 m since the approximation of the path loss being constant is less accurate if the nodes are closer as discussed previously.

Since the optimal estimator is computationally too expensive to be used at runtime for LQP and the fast estimator shows similar accuracy, we define the DES predictor to be the optimal PRP predictor (6.26), where the signal power is predicted by (6.25) using the mobility prediction in Section 6.3.7 and the required parameters are estimated by the fast predictor (6.36) with (6.33) and (6.27). All derived LQPRs of this chapter are also summarised in Table 6.1 in Section 6.3.8 for convenience.

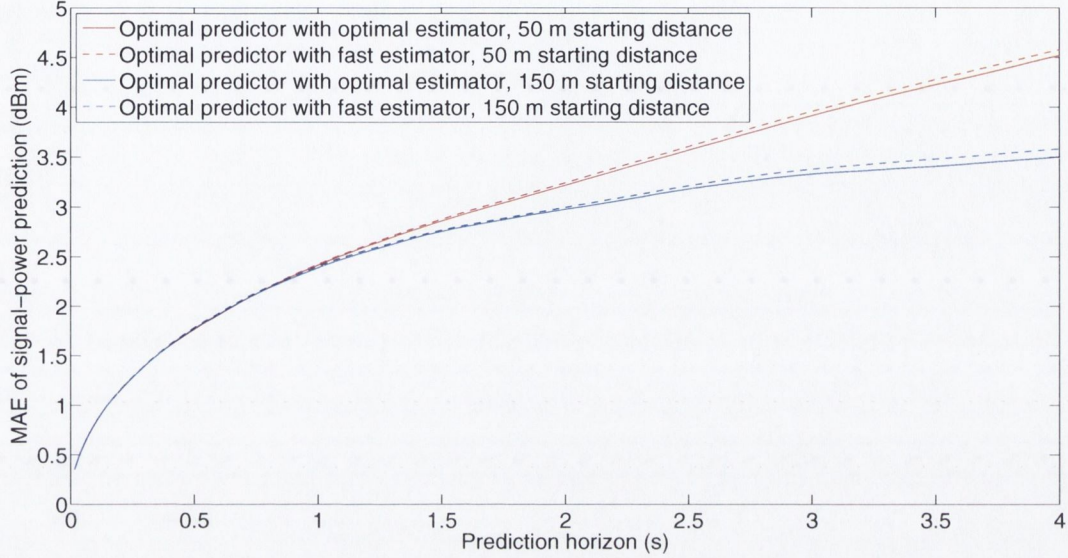


Figure 6.5: Accuracy of the optimal predictor with different estimators. The prediction with the fast estimator results in only a slightly reduced accuracy compared to the optimal estimator. The prediction accuracy is higher when nodes are further apart from each other since the approximation of the path loss being constant is more accurate.

6.3.6 Last Local Mean Predictor

The optimal LQPR requires that node-speed measurements are available to predict the future distance $\tilde{\delta}_{T+\tau|T}$. Although such measurements can easily be done with an inexpensive accelerometer (Analog Devices 2002), such a component might be unavailable. Therefore, we suggest a simple predictor that does not rely on such speed measurements. We observed in our real-world evaluation of LQP algorithms (Section 3.2.2) that LQP algorithms based on signal-power trend performed much worse than the algorithm that relied on the signal power itself. Therefore, we suggest to simply use the estimated last local mean power as signal-power prediction for the future. Thus we predict at time T the signal power for $T + \tau$ to be

$$\tilde{R}_{T+\tau|T}(\text{dBm}) = \hat{R}_T(\text{dBm}) \quad (6.67)$$

where $\hat{R}_T(\text{dBm})$ is given by (6.27). The PRP is then predicted by the mapping of the predicted signal power to the PRP (6.26). For obvious reasons, we term this PRP predictor the last local mean (LLM) predictor. Note that this predictor is fundamentally different from

Goff et al.'s (2001) LQPR that also uses signal power instead of signal-power trend values. The LLM predictor estimates $\hat{R}_{T(\text{dBm})}$ by (6.27) under consideration of the estimation bounds derived in Section 4.4 to mitigate the effects of wideband small-scale fading. Goff et al.'s (2001) LQPR in comparison uses ping-pong rounds to combat small-scale fading and this approach was shown to be ineffective in the Sections 3.2.2 and 5.5.

In the following we show that the intuitively motivated LLM predictor is a special case of the optimal DES predictor. Assume the DES predictor has estimated $\hat{C}_{T(\text{dBm})}$ by the fast estimator (6.36). Inserting the estimated $\hat{S}_{T(\text{dB})}$ from (6.33) into the optimal signal-power predictor (6.25) leads to

$$\tilde{R}_{T+\tau|T(\text{dBm})} = \hat{C}_{T(\text{dBm})} + \rho_{\text{ref}}^{\tilde{\delta}_{T+\tau|T}} \left(\hat{R}_{T(\text{dBm})} - \hat{C}_{T(\text{dBm})} \right). \quad (6.68)$$

Since no speed information is available, $\tilde{\delta}_{T+\tau|T}$ is assumed to be zero such that

$$\tilde{R}_{T+\tau|T(\text{dBm})} = \hat{C}_{T(\text{dBm})} + \rho_{\text{ref}}^0 \left(\hat{R}_{T(\text{dBm})} - \hat{C}_{T(\text{dBm})} \right) \quad (6.69)$$

$$= \hat{C}_{T(\text{dBm})} + \hat{R}_{T(\text{dBm})} - \hat{C}_{T(\text{dBm})} \quad (6.70)$$

$$= \hat{R}_{T(\text{dBm})}, \quad (6.71)$$

which is exactly the signal-power prediction as given by the LLM predictor. Hence, the LLM predictor corresponds to the DES predictor with the predicted distance $\tilde{\delta}_{T+\tau|T} = 0$. In other words, the LLM predictor corresponds to the DES predictor in the case of static as opposed to moving nodes. Therefore, at time T both predictors have the same performance since the nodes haven't moved yet. However, with increasing prediction horizon into the future, the accuracy advantage of the DES over the LLM predictor grows since the former predictor considers large-scale fading depending on the expected node mobility.

6.3.7 Mobility Prediction

Typical LQP algorithms from the literature (Lee et al. 1999, Paul et al. 1999, Punnoose et al. 1999, Agarwal et al. 2000, Qin & Kunz 2002) assume directly or indirectly that mobile nodes maintain constant speed and direction within the history and prediction interval. In other words, the speed and direction of the nodes are assumed to be constant

within the interval of taking the measurements required for LQP until the time for which the link quality is predicted. In this work we relax these assumptions and only assume that nodes maintain their speed but might change their directions. This is possible since the distance δ changes with respect to the origin of the coordinate system and not with respect to another node; hence, the distance δ is independent of nodes' directions. We only require the speed to be constant within $[T - (N_V - 1)\Upsilon, T + \tau]$, where N_V is the number of samples required to estimate the speed and Υ is the temporal sampling interval, which was determined in Section 6.3.5.1 to be 0.04 s. In order to alleviate possible measurement noise, the speed is averaged over N_V samples. For this work, we use $N_V = 3$. Since we investigate LQP accuracy for up to 4 s, the speed is assumed to stay constant within the interval $[T - 0.08 \text{ s}, T + 4 \text{ s}]$, which is a reasonable assumption for an interval length of 4.08 s.

Assume that at time t at each node $\mathbf{x}$ being carried by a pedestrian, a speed measurement $v_{t, \mathbf{x}}$ is available using an accelerometer (Analog Devices 2002). The displacement of a moving object with average speed $\bar{v}$ between time t_1 and t_2 is given by (Gibilisco 2001, p. 358)

$$\delta = (t_2 - t_1)\bar{v}. \quad (6.72)$$

Thus for a node $\mathbf{x}$ the predicted distance moved at time T for time $T + \tau$ is the average speed over N_V samples multiplied by the prediction horizon

$$\tilde{\delta}_{T+\tau|T, \mathbf{x}} = \tau \underbrace{\frac{1}{N_V} \sum_{w=0}^{N_V-1} v_{T-w, \mathbf{x}}}_{\bar{v}_{T, \mathbf{x}}} \quad (6.73)$$

where τ is the prediction horizon in seconds. For a link between two nodes (i, j) , the predicted distance at time T for time $T + \tau$ is then

$$\tilde{\delta}_{T+\tau|T, (i,j)} = \tilde{\delta}_{T+\tau|T, i} + \tilde{\delta}_{T+\tau|T, j}. \quad (6.74)$$

This equation can be calculated locally by both nodes i and j since each node includes its average speed when beaconing as explained in Section 6.3.10. For notational convenience we omit the subscripts for nodes from the expression $\tilde{\delta}_{T+\tau|T, (i,j)} = \tilde{\delta}_{T+\tau|T}$, when it is clear that we are referring to a link between two nodes (i, j) .

6.3.8 Summary of Link Quality Predictors

For convenience, Table 6.1 summarises the equations of all the LQPRs. This table not only gives a good overview of the computational steps, which are required by each LQPR, but also shows what steps are shared between the different LQPRs.

6.3.9 Link Quality Prediction for Unicast Transmissions

For unicast transmissions, 802.11 uses positive acknowledgements by means of 14-byte long packets at the MAC level (Gast 2005, Chapter 4, “Control Frames”) to inform a transmitter that a data packet was successfully received. If such an acknowledgement is not received, the transmitter assumes the data packet to be lost and retransmits it, independently of the data packet or the acknowledgement packet being lost (Gast 2005, Chapter 4, “Challenges for the MAC”). The number of retransmissions is specifiable with a default value of 7 (Gast 2005, Chapter 25, “Tuneable 802.11 Parameters”). Our LQPRs, which were derived for broadcast packets without any retransmissions, can conveniently be used for PRP predictions of unicast packets also.

The PRP of a unicast packet is the probability that both the data and the control packet are received successfully. This can be modelled as the probability of a success of a Bernoulli trial that might be repeated several times for retransmissions. The most convenient way to calculate this probability is as follows. First, calculate the probability that in a unicast transmission at least one of the two packets is lost. Secondly, calculate the probability that for all possible retransmissions the unicast transmissions are unsuccessful and subsequently take its complement.

Assume that node j wants to predict at time T the PRP of a unicast packet of MAC payload length q bits for time $T + \tau$ to node i , where node j is the transmitter. The retry limit is set to c_1 . Then this PRP $\tilde{g}_{T+\tau|T}(q, c_1)$ of a unicast packet is given by

$$\tilde{g}_{T+\tau|T}(q, c_1) = 1 - \left(1 - \tilde{\Phi}_{T+\tau|T, (j \rightarrow i)}(q) \tilde{\Phi}_{T+\tau|T, (i \rightarrow j)}(14 \cdot 8)\right)^{1+c_1} \quad (6.75)$$

where $\tilde{\Phi}_{T+\tau|T}$ can be any of the three LQPRs described earlier.

Another example of the general applicability of our LQPRs can be given by extending

Description	THEO predictor	DES predictor	LLM predictor
Summary	Lowest error bound on LQP; realisable only in simulations with knowledge of an external observer.	Optimal LQPR with fast parameter estimator; realisable; requires signal-power and node-speed measurements.	Suboptimal, intuitive LQPR; special case of the DES predictor; realisable; requires only signal-power measurements.
Estimation of $\hat{R}_T(\text{dBm})$	—	$\hat{R}_T(\text{dBm}) = \frac{1}{N_H} \sum_{i=0}^{N_H-1} R_{T-i}(\text{dBm})$	
Estimation of $\hat{C}_T(\text{dBm})$	Given by external observer	$\hat{C}_T(\text{dBm}) = \frac{1}{N_C} \sum_{i=0}^{N_C-1} \hat{R}_{T-i}(\text{dBm})$	—
Estimation of $\hat{S}_T(\text{dB})$	Given by external observer	$\hat{S}_T(\text{dB}) = \hat{R}_T(\text{dBm}) - \hat{C}_T(\text{dBm})$	—
Mobility prediction	$\tilde{\delta}_{T+\tau T} = \tau \underbrace{\frac{1}{N_V} \sum_{w=0}^{N_V-1} v_{T-w,i}}_{\bar{v}_{T,i}} + \tau \underbrace{\frac{1}{N_V} \sum_{w=0}^{N_V-1} v_{T-w,j}}_{\bar{v}_{T,j}}$		—
Signal-power prediction	$\tilde{R}_{T+\tau T}(\text{dBm}) = \hat{C}_T(\text{dBm}) + \rho_{\text{ref}}^{\tilde{\delta}_{T+\tau T}} \hat{S}_T(\text{dB})$		$\tilde{R}_{T+\tau T}(\text{dBm}) = \hat{R}_T(\text{dBm})$
PRP prediction	$\tilde{\Phi}_{T+\tau T}(q) = \Phi \left(10^{\frac{\tilde{R}_{T+\tau T}(\text{dBm}) - 30}{10}}, q \right)$, where Φ is given by (5.29).		
Variables	$R_t(\text{dBm})$ is the signal power measured at time t at node i associated with a packet sent by node j ; $v_{t,i}$, $v_{t,j}$ are the speeds measured at time t at node i and j , respectively; $\bar{v}_{T,i}$, $\bar{v}_{T,j}$ is the average speed at time T at node i and j , respectively; and q is the length in bits of the MAC-level payload for a packet for which the PRP is predicted.		
Constants	N_H is 11 samples, N_C is 268 samples and N_V is 3 samples.		

Table 6.1: Summary of LQPRs. In a link between the nodes j and i the link quality is predicted at node i for the direction ($j \rightarrow i$) at time T for time $T + \tau$. The table gives an overview of the required calculation steps for each LQPR.

a metric that is related to unicast transmissions. The ETX metric is the expected number of transmissions for a successful unicast and has been shown in the literature to facilitate the selection of higher-throughput routes in routing protocols in an ad hoc network of static nodes (De Couto et al. 2003) as previously discussed in Section 2.1.4. The extension of this metric to predictions for MANETs with mobile nodes follows immediately from its definition (2.25) since the ETX metric³ $\tilde{g}_{T+\tau|T}(q)$ for a packet with MAC payload length q bits predicted at time T for time $T + \tau$ at the transmitter node j is

$$\tilde{g}_{T+\tau|T}(q) = \frac{1}{\tilde{\Phi}_{T+\tau|T, (j \rightarrow i)}(q) \tilde{\Phi}_{T+\tau|T, (i \rightarrow j)}(14 \cdot 8)} \quad (6.76)$$

where $\tilde{\Phi}_{T+\tau|T}$ can be any of the three LQPRs described earlier. Note that in the original expression of the ETX metric the packet length is not included, since the authors use in their work fixed probe packets of 193 bytes.

6.3.10 Beacons Protocol

Any LQPRs based on signal-power measurements require the regular reception of packets in order to obtain signal-power samples that represent the channel condition. The sampling interval is determined to average out wideband small-scale fading and thus the sampling interval for a fixed estimation accuracy is determined by the physics of this propagation effect. For 802.11 MANETs of pedestrians in urban microcellular environments we determined in Sections 4.4 and 6.3.5.1 that a temporal sampling interval of 0.04 s is appropriate. We assume that beacon packets for LQP, control and other data packets are combined by the transmission scheduler as described in Section 6.2 to increase communication efficiency. Furthermore, we assume that nodes reach agreement such that every node sends approximately every $\Upsilon = 0.04$ s a beacon packet without collisions. In this section, we discuss a mechanism to enable LQP in situations at low SNR and we suggest a frame format of a beaconing protocol for LQP.

³Recall that $\tilde{g}$ is the general symbol in this thesis for prediction functions such that $\tilde{g}_{T+\tau|T}(q, c_1)$ for unicast transmissions is different from $\tilde{g}_{T+\tau|T}(q)$ for the ETX metric.

Golay Encoding

All reviewed LQPRs from the literature, which are based on the reception of packets, consider packets with at least one bit error to be lost although the arrival of such packets contains valuable information about weak links since the received signal power associated with them can still be obtained. Moreover, components such as a partition predictor require predicting not only link failures but also link recoveries, since both events determine the network topology; thus LQP is also important for weak links. Therefore, we suggest a method that allows LQP for weak links at low SNR when received packets are moderately corrupted. LQP requires a minimum of information from a received packet even when it is corrupt. First, its signal power must have been measured, which is independent of the number of bit errors in the packet. Secondly, it must be known which node transmitted the packet although the MAC address might have been corrupted in the MAC header. Thirdly, mobility prediction for the THEO and DES predictors requires the average speed of the node that transmitted the packet to be known. Our idea is to encode this vital information—the MAC address of the transmitting node and its average speed—with an encoding algorithm that uses extra bits to allow for data reconstruction in case of bit errors. An additional checksum ensures that the encoded information is correct after decoding. The encoded bits are transferred like any other MAC payload data such that the suggested scheme is fully 802.11 compliant. We refer to encoding/decoding in this section to our own encoding/decoding at MAC layer and do not refer to the encoding/decoding at the 802.11 DSSS physical layer.

A suitable encoding algorithm is the binary Golay code (Golay 1949) that transforms blocks of 12 unencoded message bits into 23 encoded bits and is able to correct up to 3 bit errors per block (Morelos-Zaragoza 2002, pp. 25–27). This code is optimal in the sense that it respects the Hamming bound (Hamming 1950) which places a lower bound on the extra bits required to correct a specified number of bit errors (in this case 3). Furthermore, Golay encoding and decoding can be implemented very effectively by a lookup table (Morelos-Zaragoza 2002, pp. 25–27). Since only the most important information required for LQP is encoded, the increase in packet length due to Golay encoding is moderate. However,

this encoding allows link quality to be predicted using corrupted beacon packets even in situations at low SNR where otherwise no LQP would be possible. This advantage is illustrated in Figure 6.6 where the probability of successfully receiving the LQP information is shown depending on the BEP of an 802.11 MAC packet with and without the information being Golay-encoded. In the situation of low SNR and thus high BEP, the LQP information has a much higher probability of being successfully received with Golay encoding than without it. For example, when the LQP information is transmitted in the MAC packet without any encoding, a high BEP of 0.015 leads to only a 19.53% probability of receiving this information correctly. Given the same BEP, the Golay-encoded information can be retrieved without error with 99.68% probability.

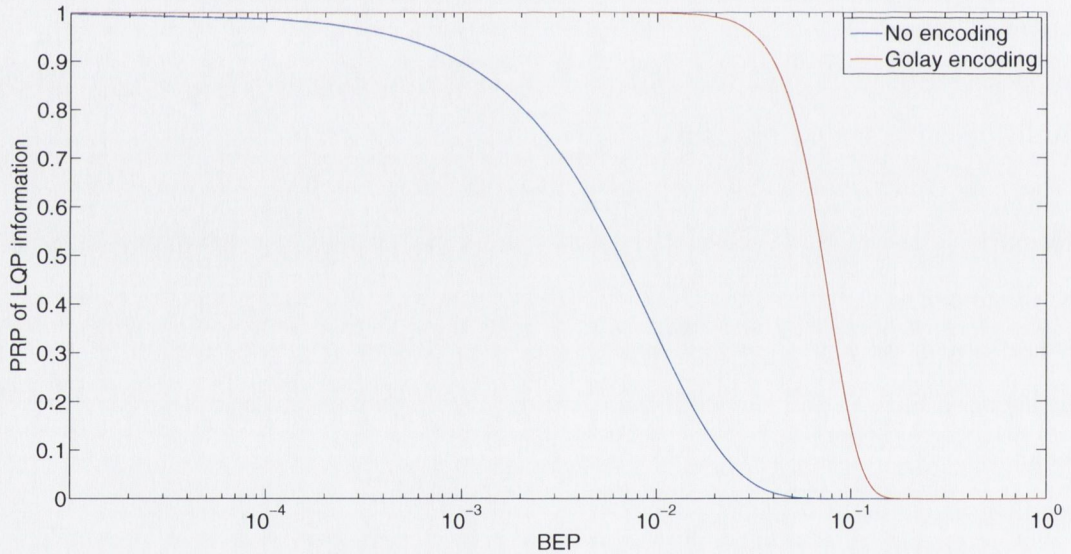


Figure 6.6: PRP of LQP information with and without Golay encoding. In cases of weak links with high BEP, Golay encoding increases the probability of receiving LQP information error-free significantly compared to no encoding.

Frame Format of the Beacons Protocol

We suggest the frame format given in Figure 6.7 for our LQPRs. The first field is a 16-bit long header identifier (HID). We chose a length of 16 bits since IP packets are encapsulated in 802.2 logical-link control packets (RFC 1042) that are identified by two bytes of value

0xAA (Gast 2005, Chapter 3, “Encapsulation of Higher-Layer Protocols within 802.11 (EHL)”)). Hence, if an uncorrupted packet is received, one comparison can determine if the received packet is a beacon or data packet such that in the later case the packet can be directly passed up the protocol stack. In case of a corrupted packet or a beacon packet, the LQP information is Golay decoded and its correctness is verified by CRC-28 error detection. If an error is detected, the packet is discarded since despite the knowledge of its signal power, it will not be certain from which node the packet was transmitted. If the checksum verification is successful, the signal power and the decoded LQP information are used to predict the quality for the link between the transmitter and the receiver node. In the protocol one zero bit is included after the Golay-encoded data to align the following fields to byte boundaries.

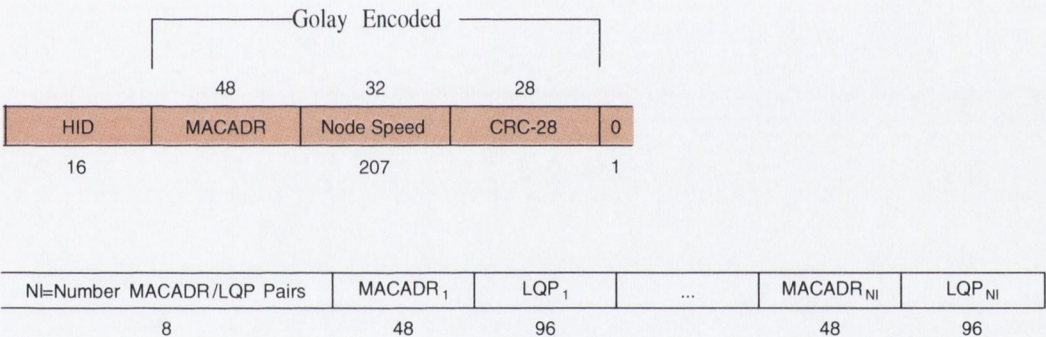


Figure 6.7: Frame format of the beaconing protocol, sizes are given in bits. The rose fields are mandatory; the other fields are a suggestion on distributing LQP-related knowledge via beacon packets. ‘HID’ is the protocol header; ‘MACADR’ is the MAC address of node i that transmits the beacon; ‘Node Speed’ symbolises the average speed $\bar{v}_{T,i}$ of node i ; ‘CRC-28’ is the checksum for the Golay-encoded information; N_i corresponds to the number of MAC address and LQP information pairs; MACADR _{x} is the MAC address of node x ; LQP _{x} is the LQP information ($\hat{C}_{T,x(\text{dBm})}$, $\hat{S}_{T,x(\text{dB})}$, $\bar{v}_{T,x}$) of node x that allows any receiver node of the beacon packet to predict the quality for the link ($x \rightarrow i$).

Although it is explicitly not the task of this work to address the problem of distributing LQP information within a MANET, we here sketch out a way to distribute this information within one-hop communication partners. Assume a node i received several beacons from neighbouring nodes, one of which is node j . Since node i can predict the quality for the link ($j \rightarrow i$) itself, it can include this information with the corresponding ID of node j in

the beacon packet. If node j can receive such a beacon packet (via a bidirectional link), it can predict the LQP for the link ($i \rightarrow j$) itself and it also can predict the opposite direction ($j \rightarrow i$) by using the information from node i 's beacon packets. The information included in a beacon packet allows the prediction for any prediction horizon and packet length using either the DES or the THEO predictor. In the case of the LLM predictor being used, the speed information would be omitted and $\hat{C}_{T, \times(\text{dBm})}$ and $\hat{S}_{T, \times(\text{dB})}$ would be replaced by $\hat{R}_{T, \times(\text{dBm})}$ since only the latter quantity is required for LQP. If a beaconing node i does not receive any packets from a node j with which it was previously connected, node i stops including LQP information of node j in its beacons after a threshold time (e.g. 1 s).

6.4 Implementation

While an overview of the LQPRs and their parameters has been given in Table 6.1, this section describes the details of how to implement these LQPRs efficiently. First, the network model, in which the algorithms are presented, is stated. Subsequently we present the details of the LQPR implementations.

6.4.1 Network Model

Recently, MIT's Theory of Distributed Systems research group has begun to extend their well-known synchronous network model (Lynch 1997, pp. 17–23) from wired to wireless multi-hop broadcast networks (Chockler et al. 2005b). Since this network model allows for a concise description of algorithms, which enables important algorithmic properties to be highlighted while abstracting unnecessary details, we use this network model to describe one possible implementation of our LQPRs. We augmented this model slightly to allow, for example, the reception of corrupted broadcast messages that was not considered in the original version. We assume a MANET with a fixed collection of NN nodes, whose identifiers, identical to their MAC addresses, range for simplicity from 1 to NN . "A node i broadcasts messages by invoking $\text{bcast}(msg)$, where msg is an arbitrary message, and receives messages by invoking $\text{rcv}()$. We assume that the system is synchronous: both the

nodes' clock skews and the inter-node communication delay are bounded by known constants. For simplicity, we assume that the processing is divided into synchronous rounds. In each round rd , each node i executes the following steps: (1) broadcasts at most one message, (2) receives a subset of messages that were broadcast by the nodes in round rd , and (3) performs a state transition based on its current state and the set of received messages" (Chockler et al. 2005b, symbols exchanged). The broadcast communication within each round guarantees that each message is received at each node at most once. Messages can be lost or corrupted by the radio communication channel. The function `delivmsg( $msg$ )` evaluates in round rd at node i if a message, which can either be correct or corrupted, has been delivered. "It is commonly assumed that the underlying communication layer supports collision-free communication when transmissions do not overlap (see e.g., ...)." (Chockler et al. 2005b). Nodes do not fail by crashing.

We present the algorithms in pseudo code that is inspired by the typeless programming language MATLAB, which is the heart of the commercial product Matlab (The MathWorks 2006), in which we evaluated the accuracy of our LQPRs based on simulations done in the extended NS-2 simulator. Arrays begin with an index of 1, in contrast to 0 in C, C++ or Java. Neither constants nor variables require any type declaration, memory allocation or deallocation. Functions are call-by-value only and can have multiple input as well as multiple output parameters. Constants are given in uppercase letters only. Global state information (global variables) begins with a capital letter while local state information (local variables) begins with a lower case letter. Constants and variables are displayed in italics, functions in a sans serif font and keywords are shown in bold.

6.4.2 Implementation

Listing 6.1 presents an implementation of the DES predictor that also contains the necessary functionality to implement the LLM or THEO predictors. Thus the implementation of the DES predictor can be viewed as a superset of the implementations of the two other LQPRs. In the listing, each node i predicts the link quality for a fixed prediction horizon (HZ) of 2 s for packets of 1000 bytes MAC payload length ($PKTLGTH$) in the direction

of $(x \rightarrow i)$ for each other node x of the network. The algorithm runs for 1 h (*RUNTIME*) after which it stops. These values are, of course, only examples. Listing 6.1 uses functions for the estimation and the prediction of link quality, which are given in Listing 6.2. Their helper functions, which are the basis for the efficient implementation, are shown in Listing 6.3.

Listing 6.1 is divided into three parts. In the first part, constants and variables are initialised. The second part implements broadcasting of beacon packets. In the third part, beacon packets are received and link quality is predicted.

The values for constants and variables are assigned in lines 1–5. *SMPLINT* is the sampling interval for beaconing that allows for accurate estimation of the local mean power. *NN* is the number of nodes, for which a prediction is made for packets of MAC payload length *PKTLGTH* for *HZ* seconds into the future. *NH*, *NC* and *NV* are the constants used for parameter estimation as summarised in Table 6.1 and *AUTREF* is the normalised autocovariance coefficient for urban microcells (Gudmundson 1991). Only the constants *RCVMIN* and *RCVSPAN* have not previously been discussed in this work. *RCVMIN* describes a threshold for the proportion of packets, which have been received in the time span *RCVSPAN* and whose protocol headers with their LQP-related information were successfully Golay decoded. If Golay decoding is unsuccessful, the packet does not reveal the node ID of its transmitter and thus cannot be used for LQP. A link for which the prediction is not possible due to a lack of useable packets has long been broken for data transfer, which was hopefully predicted. Since in such situations the stored information about the past link quality is stale, this information is discarded by reinitialising the global state, which is done by invoking the *initialisevars()* function. This reinitialisation is the reason why the assignments of variables are split: the average speed queue *SpdQ* of node i is constantly updated without discarding information while the variables in *initialisevars()* in the lines 42–45 are reset in case of broken links. *RcvratQ*, *RhatQ* and *ChatQ* are specialised FIFO queues that are discussed later with respect to the Listings 6.2 and 6.3. *RcvratQ* holds the average rate of received packets suitable for LQP while *RhatQ* and *ChatQ* hold the estimated parameters for LQP. All three queues store their respective values for each

node pair (i, x) of the network. Finally, the constants *HID* and *RUNTIME* describe the header ID and the runtime of the algorithm, respectively.

Since each node of the network beacons every *SMPLINT* seconds, a round is defined to occur every $\frac{SMPLINT}{NN}$ seconds and $\lceil \frac{RUNTIME}{SMPLINT} \rceil \cdot NN$ rounds are required for the algorithm to run for at least *RUNTIME* seconds (line 7). The LQPR itself is executed between the lines 8 and 39.

The LQPR starts with broadcasting its identifier (ID) and average speed in the lines 8–11. First, the node tests whether it is due to beacon or to wait for a packet. If the node is due to transmit in the current round, it determines its current speed for round *rd* by invoking *speed(rd)* and subsequently calculates its average speed *spdi*. Note that we do not update the global state of the queue *SpdQ*, indicated by using the local variable *unused*, since the formal network model allows for global state transitions only after receiving a packet⁴. The beacon packet *msg* is then composed as described in Section 6.3.10, where the ID and node speed is safeguarded by a CRC calculated by the function *makecrc()* and Golay encoded by *encode()* before being broadcasted.

Since only one node per round is broadcasting, resulting in collision-free broadcasts, a node only waits for packet reception when it is not beacons (line 13). If the node is in receive mode (line 14), invoking *recv()* results either in an empty set to indicate that no packet was received or a packet which is either correct or corrupted. In either case, the average speed of the node is updated (line 15) since the formal network model allows for the global state to change now, which is in this case the queue *SpdQ* that calculates and holds the average node speed. If a packet has been received (line 16), the header is Golay decoded (line 17); otherwise the local flag *nomsg* is set to indicate that no packet was received (line 34). If the CRC is correct (line 18), the LQP calculation begins; otherwise the packet is considered to be lost since no reliable information could be extracted (line 32). In the former case, the local flag, which indicates that a packet was successfully decoded, is set and the relevant information for LQP is extracted from the protocol header of the packet (lines 19–20). Subsequently the packet reception ratio *rcvrat* and its queue

⁴Since we are here not conducting formal proofs of this algorithm, we could have also relaxed the model.

$RcvratQ$ for node j , whose ID is now known, is updated (line 21). Afterwards a test is conducted to determine whether enough signal-power samples are available to have reliably estimated the packet reception ratio and whether this ratio is equal or above the specified threshold (line 22). If one of these two conditions fails, no prediction can be made since an insufficient number of recent power-samples is available and this round is finished.

Otherwise, the parameters for LQP are updated by invoking `estimate()` in the lines 23–24, where `pow()` is the received signal power of the packet and $RhatQ[j]$ and $ChatQ[j]$ are the data structures that hold the past parameter estimates for the link with node j . The function `estimate()` returns the updated global data structures for parameter estimation, the current parameter estimates themselves ($rhat_rd$, $chat_rd$, $shat_rd$) and the type of prediction $ptype$ that is possible with the available information at this time. As previously discussed, the DES predictor requires three parameters to be estimated that necessitate a different number of samples. The estimation of $rhat_rd$ requires $NH=11$ signal-power samples, the estimation of $chat_rd$ and $shat_rd$ require $NC=268$ samples of $rhat_rd$. Therefore, the DES predictor can make its first prediction if at least $NH + NC - 1$ recent signal-power samples are available, which takes approximately 11 s at the given sample interval when no previous samples were available. This situation arises when nodes come into contact. Since an early prediction is desirable, we enable this using the following solution. Until enough signal-power samples are available for the DES predictor to work, the LLM predictor is employed instead since it requires only 11 signal-power samples and thus can start its prediction after 0.44 s. Hence, within the first 11 s of nodes coming into contact we prefer the reduced accuracy of the LLM predictor compared to the DES predictor, rather than having no LQP at all. Therefore, the estimation function returns the $ptype$ variable, which indicates that either a DES prediction, an LLM prediction or no prediction is possible; the latter case indicates that less than 11 recent signal-power samples are available and thus no prediction is possible. Otherwise, if the DES predictor is available, the function `predictpow()` predicts the future signal power (line 26) which in turn is mapped to the PRP (line 27). If the number of signal-power samples is only sufficient to use the LLM predictor, the local mean power $rhat_rd$ corresponds to the prediction of

the future signal power (line 29) which is subsequently mapped to the PRP (line 30). The mapping from the predicted signal power *rpred_hz* and the packet length *PKTLGTH* to the PRP is done for both predictors by the function **mappowprp()**, which implements the expressions (6.26), (5.29) and (5.24) where the latter expression is given by a lookup table.

The execution continues at line 35 if either no packet was received or the CRC check of the Golay-encoded header failed. The round number allows the determination of the ID of the node whose packet was either too damaged to be useful or was lost (line 36). Subsequently the packet reception ratio for this node is updated (line 37). If enough signal-power samples were available to determine the packet reception ratio and this ratio is below its threshold (line 38), the information about the link is stale and thus the global state is reset (line 39). It might now be argued that the ID of the node, whose packet was lost or from which no information could be extracted, could only be known in the synchronous network model in which the algorithm is presented and thus the packet reception ratio could not have been updated in an implementation in the timed asynchronous network model (Cristian & Fetzer 1999) which describes typical computers well. However, this argument is wrong. Assume an implementation in the latter network model and assume that node *i* has received from node *j* one packet at time $t_1 = 1$ s and one at $t_2 = 1.16$ s. When node *i* updates its packet reception ratio for node *j*, it knows from its local clock that due to the constant beaconing it should have received a packet from node *j* at time $t_{1b} = 1.04$ s, $t_{1c} = 1.08$ s and $t_{1d} = 1.12$ s such that three packets were lost. Thus the packet reception ratio can be updated accordingly.

The above description covered the full algorithm that executes all rounds of the for-loop until it finally halts (line 40). As mentioned before, the implementation of the DES predictor in Listing 6.1 can easily be augmented to provide the LLM or THEO predictor. The LLM predictor is implemented if the **estimate()** function in lines 23–24 returns the *pptype* of either ‘LLM’ or ‘NONE’, depending on whether or not enough samples for estimation of the local mean power are available. The THEO predictor is implemented if the **estimate()** function in lines 23–24 returns always ‘DES’ and provides the true values of the variables *rhat_rd*, *chat_rd*, *shat_rd* instead of their estimates. The true value is given by an external

observer that retrieves them from a log file in which the extended NS-2 simulator recorded them.

Listing 6.1: Implementation of the DES predictor

```

1  SMPLINT  $\leftarrow$  0.04 s, NN  $\leftarrow$  5, RUNTIME  $\leftarrow$  3600 s, HID  $\leftarrow$  0x00FF
2  RCVMIN  $\leftarrow$  0.1, RCVSPAN  $\leftarrow$  1 s, NH  $\leftarrow$  11, NC  $\leftarrow$  268, NV  $\leftarrow$  3, AUTREF  $\leftarrow$  0.887
3  PKTLGTH  $\leftarrow$  1000 bytes, HZ  $\leftarrow$  2 s
4  SpdQ  $\leftarrow$  initq(NV)
5  initialisevars()
6
7  for rd  $\leftarrow$  1 to  $\lceil \frac{RUNTIME}{SMPLINT} \rceil \cdot NN$ 
8      if mod(rd, NN) = i-1
9          (unused, spdi)  $\leftarrow$  updateq(SpdQ, speed(rd))
10         msg  $\leftarrow$  (HID, encode(i, spdi, makecrc(i, spdi)), 0)
11         bcast(msg)
12
13     if mod(rd, NN)  $\neq$  i-1
14         msg  $\leftarrow$  rcv()
15         (SpdQ, spdi)  $\leftarrow$  updateq(SpdQ, speed(rd))
16         if delivmsg(msg) = true
17             msg  $\leftarrow$  decode(msg)
18             if crcgood(msg) = true
19                 nomsg  $\leftarrow$  false
20                 (unused, j, spdj, unused2, unused3)  $\leftarrow$  msg
21                 (RcvratQ[j], rcvrat)  $\leftarrow$  updateq(RcvratQ[j], 1)
22                 if fullq(RcvratQ[j]) = true and rcvrat  $\geq$  RCVMIN
23                     (rhat_rd, chat_rd, shat_rd, ptype, RhatQ[j], ChatQ[j])
24                          $\leftarrow$  estimate(pow(msg), RhatQ[j], ChatQ[j])
25                     if ptype = 'DES'
26                         rpred_hz  $\leftarrow$  predictpow(chat_rd, shat_rd, spdi, spdj, HZ, AUTREF)
27                         prppred_hz  $\leftarrow$  mappowprp(rpred_hz, PKTLGTH)
28                     elseif ptype = 'LLM'
29                         rpred_hz  $\leftarrow$  rhat_rd;
30                         prppred_hz  $\leftarrow$  mappowprp(rpred_hz, PKTLGTH)
31                     else
32                         nomsg  $\leftarrow$  true;
33                 else
34                     nomsg  $\leftarrow$  true;
35                 if nomsg = true
36                     j  $\leftarrow$  mod(rd, NN)+1
37                     (RcvratQ[j], rcvrat)  $\leftarrow$  updateq(RcvratQ[j], 0)
38                     if fullq(RcvratQ[j]) = true and rcvrat  $\leq$  RCVMIN
39                         initialisevars()
40  halt
41
42  initialisevars()
43  for each node j  $\leq$  NN, j  $\neq$  i
44      RcvratQ[j]  $\leftarrow$  initq( $\lceil \frac{RCVSPAN}{SMPLINT} \rceil$ )
45      RhatQ[j]  $\leftarrow$  initq(NH), ChatQ[j]  $\leftarrow$  initq(NC)

```


Listing 6.2 shows the estimation and prediction functions that are invoked from the main program. The function `estimate()` implements the three estimation stages as given by the equations (6.27), (6.36), (6.33). These equations differ from their implementations by being batch calculations while the implementation is based on sequential updates to reduce the computational complexity. In other words, with each new signal-power sample parameter estimates are not updated by calculating them from all the past samples but only by updating them with the new sample. The detailed sequential update procedure, leading to a very efficient implementation, will be described when the helper functions of `updateq()` and `fullq()` are discussed with respect to Listing 6.3.

The estimate function retrieves all variables as call-by-value parameters, assigns updates to the local variables of the same name, which are subsequently assigned to the output variables that were specified when invoking the function. For example, when the main algorithm invokes $(..., RhatQ, ...) \leftarrow \text{estimate}(..., RhatQ, ...)$, the global state variable $RhatQ$ of the main algorithm is updated by `estimate()`. However, invoking $(..., RhatQ2, ...) \leftarrow \text{estimate}(..., RhatQ, ...)$ assigns to $RhatQ2$ an updated copy of $RhatQ$ and does not change $RhatQ$ in the main algorithm, since the latter was passed to the function as call-by-value.

In line 47, a new local mean power $rhat_rd$ is estimated and the specialised FIFO queue is updated. If enough samples of the local mean power are available (line 48), $chat_rd$ and $ChatQ$ are updated with respect to the newly estimated local mean power (line 49). If enough samples are available to have estimated $chat_rd$ reliably (line 50), $shat_rd$ is estimated from the current estimates of $rhat_rd$ and $chat_rd$ (line 51). Finally, depending on the available number of samples and thus available parameter estimates, the best possible prediction type is returned as previously explained (lines 52–56).

The signal-power prediction of the DES prediction is obtained for HZ seconds ahead by the function `predictpow()` from the current parameter estimates (lines 58–59). This function is a literal implementation of the expressions (6.23) for signal-power prediction and (6.73), (6.74) for mobility prediction and thus no further explanations are necessary.

Listing 6.2: Estimation and prediction functions of the DES predictor

```

46 ( rhat_rd , chat_rd , shat_rd , ptype , RhatQ , ChatQ ) ← estimate ( msgpow , RhatQ , ChatQ )
47 ( RhatQ , rhat_rd ) ← updateq ( RhatQ , msgpow )
48 if fullq ( RhatQ ) = true
49   ( ChatQ , chat_rd ) ← updateq ( ChatQ , rhat_rd )
50   if fullq ( ChatQ ) = true
51     shat_rd = rhat_rd - chat_rd ;
52     ptype = 'DES'
53   else
54     ptype = 'LLM'
55   else
56     ptype = 'NONE'
57
58 rpred_hz ← predictpow ( chat_rd , shat_rd , spdi , spdj , HZ , AUTREF )
59 rpred_hz ← chat_rd + AUTREF(HZ · (spdi + spdj)) · shat_rd

```

The computational efficiency of the estimation part of the DES predictor is based on its sequential update procedure that is shown in Listing 6.3. As pointed out previously, the mean of a variable X with N_X samples can recursively be calculated by sequential update (Tepedelenlioglu & Gao 2005)

$$\bar{X}_T = \frac{(N_X - 1) \bar{X}_{T-1} + X_T}{N_X}, \quad (6.77)$$

since

$$\bar{X}_T = \frac{1}{N_X} \sum_{i=0}^{N_X-1} X_{T-i} = \frac{1}{N_X} \left(\underbrace{\sum_{i=1}^{N_X-1} X_{T-i}}_{(N_X-1) \bar{X}_{T-1}} + X_T \right). \quad (6.78)$$

(6.77) is only suitable to sequentially update the mean of a random variable in which all samples from time $t = 1$ to $t = T$ are considered. However, our estimator requires sample mean estimation over a maximum window size N_W , where N_W can be smaller than N_X , such that only the mean over the samples from time index $t = T - N_W + 1$ to $t = T$ and not over $t = 1$ to $t = T$ have to be calculated. We solve this problem by introducing a FIFO queue which allows us to discard samples that are outside the window. Assume that the previous mean $\bar{X}_{T-1}$ has been calculated by N_W samples and that now an additional sample is available such that $N_X = N_W + 1$. The sample mean over the

window $[t = T - N_W + 1, t = T]$ can be written as

$$\bar{X}_T = \frac{1}{N_W} \sum_{i=0}^{N_W-1} X_{T-i} = \frac{1}{N_W} \left(\underbrace{\sum_{i=1}^{N_W} X_{T-i}}_{N_W \bar{X}_{T-1}} - X_{T-N_X+1} + X_T \right) \quad (6.79)$$

$$= \frac{N_W \bar{X}_{T-1} - X_{T-N_X+1} + X_T}{N_W} \quad (6.80)$$

where $\bar{X}_{T-1}$ is the previous sample mean and X_{T-N_X+1} is the oldest sample that has to be removed since it is outside the window $[t = T - N_W + 1, t = T]$. The retrieval of the oldest sample X_{T-N_X+1} can easily be implemented by a FIFO queue that always stores the most recent N_W samples.

The above calculations are implemented in the `update()` function of the specialised FIFO queue in the lines 82–91. If fewer samples are available than specified by the queue size (line 83), the sequential update (6.77) is employed in line 85. Otherwise, the oldest sample (line 88) is fetched and discarded when the sample mean is calculated over the new window by (6.80) in line 90. In either case, the new sample is added to the tail of the queue (line 84, 89) and the current mean, which will be the previous mean in the next invocation of the `update()` function, is stored (lines 86, 91).

The function `initq()` initialises the queue (lines 60–64), `fullq()` tests if the queue is full (lines 66–70), `getq()` gets the oldest element from the queue (lines 72–75) and `putq()` adds a new element to the tail of the queue (lines 77–80). The arrays are one element larger compared to the number of elements that can be held in the FIFO queue, since this allows adding of error checks to the implementation (Sedgewick 2002, Chapter 4.7, “FIFO Queues and Generalized Queues”). Since the implementation of the abstract data type FIFO queue (henceforth called ‘normal FIFO queue’) is well described in (Sedgewick 2002, Chapter 4.7, “FIFO Queues and Generalized Queues”), we just point out the differences between the normal and our specialised FIFO queue data type. In the specialised FIFO queue, we added a field that holds the previous mean (line 64) to allow for the sequential update (6.80) when an element has to be removed. We also added a counter for the stored elements (line 61) since this number is required for the sequential update (6.77) when less samples than specified by the window size are available.

Listing 6.3: Queue functions

```

60 queue ← initq(size)
61 queue.size ← size+1, queue.count ← 0
62 queue.head ← size+1, queue.tail ← 1
63 queue.el ← emptyarray[size+1]
64 queue.elprevmean ← 0
65
66 res ← fullq(queue)
67 if queue.count = (queue.size-1)
68   res ← true
69 else
70   res ← false
71
72 (queue, el) ← getq(queue)
73 queue.head ← mod(queue.head, queue.size)+1
74 el ← queue.el[queue.head]
75 queue.count ← queue.count-1
76
77 queue ← putq(queue, el)
78 queue.el[queue.tail] ← el
79 queue.tail ← mod(queue.tail, queue.size)+1
80 queue.count ← queue.count+1
81
82 (queue, meanel) ← updateq(queue, el)
83 if fullq(queue) = false
84   queue ← putq(queue, el)
85   meanel ←  $\frac{(queue.count-1) \cdot queue.elprevmean + el}{queue.count}$ 
86   queue.elprevmean ← meanel
87 else
88   (queue, oldestel) ← getq(queue)
89   queue ← putq(queue, el)
90   meanel ←  $\frac{queue.count \cdot queue.elprevmean - oldestel + el}{queue.count}$ 
91   queue.elprevmean ← meanel

```

It is straightforward to determine the computational complexity class, depending on the number of received signal-power samples, to which the implemented LQPRs belong. An algorithm with associated complexity function $g(x)$ belongs to the complexity class $\Theta(g(x))$ if it belongs to the complexity classes given by the asymptotically lower bound $\Omega(g(x))$ and the asymptotically higher bound $\mathbf{O}(g(x))$ (Neapolitan 2003, Chapter 1.4, “Order”). We claim that all our LQPRs belong to $\Theta(N)$ where N is the number of received signal-power samples. We start the analysis by considering the DES predictor. First, for each received signal-power sample at least one instruction is carried out (e.g. `decode()` in line 17 in Listing 6.1), such that the lower bound is $\Omega(N)$. Secondly, for each signal-power sample

neither a recursion nor a for-loop⁵, which depends on the number of received signal-power samples, is executed (see lines 8–39 in Listing 6.1; Listing 6.2 and 6.3 itself). Thus, a finite number of computational steps are executed which are independent of the number of available signal-power samples. Hence, the higher bound is $\mathbf{O}(N)$ and consequently the complexity class is $\Theta(N)$. Since the LLM and THEO predictor differ from the DES predictor only by the estimation function `estimate()` (lines 23–24 in Listing 6.1), in which case this function still has a finite number of computational steps that are independent of the number of received signal-power samples, both LQPRs belong to the same complexity class as the DES predictor.

6.5 Evaluation

The objective of the evaluation is to determine the accuracy of the LQPRs in a wide variety of scenarios involving pedestrians in urban environments. While the accuracy of the LQPRs is our main focus, we are also interested in what factors exist that affect the predictability of link quality by these predictors. The following high-level decisions were made in order to achieve these objectives:

- **Evaluation criteria.** The primary metric that determines the quality of any network-layer service is the proportion of successfully received to transmitted packets, represented by the PRP. Therefore, we use the difference between the predicted and actual PRP as the primary evaluation metric for LQP. The signal power, associated with packets, is also an indicator of link quality, although it does not necessarily affect the PRP and thus the data throughput (e.g. when the SNR is very high). Therefore, we consider this metric as being secondary and focus our evaluation on the PRP.
- **Evaluation baseline.** With an increasing power of its baseline, there is a corresponding improvement in the relevance of an evaluation. However, the LQP algorithms that we evaluated (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) have shown

⁵The for-loop in line 7 executes only the rounds of the network model. Since the computational complexity analysis for the number of received signal-power samples is conducted inside and thus independently of this for-loop, this for-loop is of no relevance to the complexity analysis.

a poor accuracy in their deterministic LQP both in real-world measurements and in simulations with the extended NS-2 simulator. Furthermore, the best performing algorithm (Goff et al. 2001), which intends to mitigate the effects of small-scale fading by exchanging ‘ping-pong rounds’ (see Section 2.1.1 for details), relies critically on the assumption that links are bidirectional. Since this assumption is only valid in very restrictive circumstances (see Section 3.3.2 for a detailed discussion), our evaluation includes unidirectional links for which this algorithm is not applicable. Moreover, since these algorithms are based on deterministic path-loss-only radio propagation models and neglect other important stochastic radio propagation effects, they cannot benefit from being extended to a stochastic prediction (e.g. by mapping a predicted link failure to a PRP of 0% and a predicted available link to a PRP of 100%). Furthermore, a meaningful evaluation of these algorithms in real-world experiments and in simulations in the extended NS-2 simulator was enabled by determining their parameters via optimisation of the LQP accuracy, since the parameters given by the authors are valid for path-loss-only radio propagation models. However, this optimisation took approximately one night per algorithm on the employed PC for the data representing one link between two nodes, where this data was acquired either by real-world measurements or simulations in the extended NS-2 simulator. Since the evaluation of our LQPRs covers many different scenarios, mostly with five nodes, leading to possibly 20 links per scenario and experiment, a determination of the parameters for these LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) is beyond the available computing resources. In summary, the use of these LQP algorithms as baseline for evaluation is neither sensible given their accuracy nor feasible given the required computing resources for parameter optimisation. Thus we decided to compare the realisable DES and LLM predictors against the THEO predictor. The latter predictor places a lower bound on LQP, which cannot be improved on within our link quality model and its assumptions, such that the THEO predictor is the strongest possible baseline against which to evaluate.

- Evaluation environment. A real-world evaluation is, of course, the most convincing,

but it can be very difficult to achieve repeatability in complex real-world environments. For example, when a comparison is to be made as to whether the PRP is more predictable for packets of 500 or 1000 bytes, it might be very difficult to conduct real-world experiments in which the environments are equal for both trials, such that only the packet length and not, for example, the number of uninvolved people in the radio channel and their movement patterns change. Moreover, for the available 802.11 cards we have no knowledge of their BEP function that is crucial for determining the PRP. Furthermore, these cards discard packets with at least one bit error at firmware level such that even at driver level we have been unable to obtain this valuable information. Additionally, the required amount of sample data is much higher for a stochastic prediction and its evaluation than for a deterministic one since the PRP cannot be measured directly in the real world but needs to be estimated, while for a deterministic prediction whether a packet is received or lost is observable. In summary, the required resources for a real-world evaluation were for the above reasons not available. Therefore, we use the extended NS-2 simulator, whose agreement to real-world measurements was shown in Section 5.5, as a credible alternative to real-world measurements. Note that the realism of the extended NS-2 simulator is also justified by using radio propagation models and their parameters from the literature which have been obtained by extensive real-world measurements.

- Influence factors on LQP. The accuracy of LQP might depend on various factors which could also change the order of accuracy among the LQPRs. Interesting factors are the influence of the mobility model, the length of the packet for which to predict the PRP, the node density and the directionality of links (bidirectional only links vs. a combination of bidirectional and unidirectional links).

6.5.1 Methodology

According to Kurkowski et al. (2005), a “poor state of simulation based studies in the network community” exists and “in general, results published in MANET simulation studies lack believability”. These conclusions were drawn in a study, which we discussed in Section

2.4, that surveyed all papers of the premier conference MobiHoc from 2000 to 2005. In our methodology, we address the weaknesses identified by Kurkowski et al. (2005) as outlined below.

The evaluation of our LQPRs is rigorous and unbiased since they were evaluated in a wide range of different scenarios. In order to achieve statistical soundness, we use long simulation runs of 3600 s duration, typically with 5 nodes, and each experiment is repeated by 4 independent trials. This effort resulted in approximately 100 million received packets, for which 50 predictions were made and evaluated from 0.08 s to 4 s into the future for every LQPR. Consequently, our evaluation achieved narrow confidence intervals as will be shown in Section 6.5.2.4. However, this statistical accuracy resulted in a modern standard desktop PC requiring approximately two weeks for this task. The size of LQP-relevant data stored in log files, which is mainly a function of the number of nodes and the simulation time, was required to be within the limits of the main memory of the available computing resources. Otherwise, the time for I/O processing would have increased dramatically and evaluation would have been impractical with the available computing resources. In summary, the high evaluation effort required for unbiased results and high statistical accuracy necessitated a careful selection of scenarios.

We selected two mobility models for evaluation: the Random Waypoint Mobility Model (RWP) and the Random Waypoint Mobility Model City Section (CITY). We chose the former model since it is the most commonly used mobility model in MANET studies (PalChaudhuri et al. 2005) and we selected the latter model since it is considered to be a more realistic model (PalChaudhuri et al. 2005). In the RWP model, a node randomly chooses a speed from its range, a random destination point within the simulation area and moves at this speed to the destination point. It then pauses for a randomly chosen time within its bounds and the cycle repeats. The CITY model operates in a similar way with the following differences. Nodes can move only on pathways, which are given by a real-world map, and only the intersections of these pathways can be chosen as destination points. Nodes can change their speed and directions frequently but they have to stay within the pathways when they travel towards their destination points.

For both models, we choose the node speed to lie within 1.2 m/s [Chapter 4, page 4L1](U.S. Department of Transportation 2003) and 1.4 m/s (Wakim et al. 2004), which are appropriate values for pedestrians. The pause time of the RWP model was chosen from the range 5 to 15 s. The simulation area had a size of 500 by 500 m for most scenarios, which corresponds to the area size of our real-world study from Section 3.2. The same parameters were used for the CITY model, which additionally employed a map of 500 by 500 m representing an area of the West University, Houston, TX, USA, which has been given and previously been used by Saha & Johnson (2004). The pathway width was set to 2 m and every 15 seconds the direction changed randomly within the pathways and a new speed was selected.

As pointed out by Kurkowski et al. (2005) it is of vital importance to conduct steady-state simulations when the true long-term behaviour of an algorithm in a MANET is to be studied. Therefore, no evaluation should be made during the transitional period in the beginning of the simulation until it reaches its steady state. Some authors try to achieve this goal by removing an arbitrary amount of simulation data from the beginning (Kurkowski et al. 2005). In this work we chose a more elegant way. The LQPRs operate solely in their steady state since no prediction and thus no evaluation is conducted until enough signal-power samples are available. Hence, we only need to address the problem that the node distribution, depending on the mobility model, approaches its steady-state distribution over a transitional period in the beginning of the simulation. However, this problem was solved for both mobility models by PalChaudhuri et al. (2005), who developed a tool that provides mobility traces which exhibit steady-state node distributions from the beginning of the simulation. Therefore, we used their tool to ensure that our evaluation is based on steady-state simulations.

We decided to evaluate the accuracy of all LQPRs for all possible combinations of both mobility models and packet lengths of 100, 500, 1000 and 1500 bytes covering a wide range of scenarios. In all these scenarios we used five nodes, which is the maximum number of nodes possible that can send packets of up to 1500 bytes within the sampling interval without collisions. Note that in an actual deployment of the LQPRs small beacon

packets would be used that allow for a much higher number of nodes. In this evaluation, however, the LQP accuracy is assessed depending on various and thus sometimes large packet lengths, which can only be done by transmitting packets of such lengths so that the actual PRP can be compared to the predicted PRP. Thus the maximum number of nodes in a network is restricted by the evaluation requirements and not by the LQPRs themselves. From the five nodes used, we chose three nodes to transmit at maximum transmission power of 15 dBm while two others had a 1 dBm reduced power to include unidirectional links in the study. As determined in Section 3.3.2, unidirectional links can be expected in real-world MANETs in which the transmission power and 802.11 card models can vary between different nodes. These scenarios allowed us to evaluate the difference in accuracy between all LQPRs, the influence of packet length and the influence of the mobility model on the LQP accuracy.

Furthermore, we included scenarios in the evaluation with 3 and 10 nodes for 500-byte long packets to study the impact of node density on LQP accuracy by varying the number of nodes. Moreover, we added one scenario in which the simulation area was reduced to 300 by 300 m to vary the node density by changing the size of the simulation area. Finally, we consider a scenario in which all nodes have the same transmission power such that only bidirectional links exist. A summary of all scenarios is given in Table 6.2.

Our primary evaluation criterion is the MAE of the actual and the predicted PRP for all nodes and times of a scenario. Formally, we define this error by first considering the PRP prediction (PRPP⁶) error for one fixed link at one fixed time and later extend this definition to all links and times of a scenario. Thus the absolute error of the actual and the predicted PRP at time $T + \tau$ for a packet of MAC payload length q bits in a link ($j \rightarrow i$) is

$$\varepsilon_{\Phi_{T+\tau, (j \rightarrow i)}}(q) = |\tilde{\Phi}_{T+\tau|T, (j \rightarrow i)}(q) - \Phi_{T+\tau, (j \rightarrow i)}(q)|. \quad (6.81)$$

Since we refer in these evaluation sections exclusively to packets at the MAC level, we omit this qualification from now on. The MAE of the actual and the predicted PRP for a

⁶In this section we use the abbreviated term ‘PRPP’ in the text while using the term ‘PRP prediction’ in all graphs, their captions and in section headings.

ID	Mobility model	Packet length (bytes)	Number of nodes	Simulation area (m^2)
SC1	RWP	100	5	500 · 500
SC2	RWP	500	5	500 · 500
SC3	RWP	1000	5	500 · 500
SC4	RWP	1500	5	500 · 500
SC5	CITY	100	5	500 · 500
SC6	CITY	500	5	500 · 500
SC7	CITY	1000	5	500 · 500
SC8	CITY	1500	5	500 · 500
SC9	RWP	500	3	500 · 500
SC10	RWP	500	10	500 · 500
SC11	RWP	500	5	300 · 300
SC12	RWP	500	5 (bidirectional links only)	500 · 500

Table 6.2: Simulation scenarios. The LQP accuracy was determined over a wide range of scenarios. Each scenario was simulated for 3600 s in four independent trials.

packet of length q for a complete scenario with N_{Rd} rounds and N_N nodes is now given by

$$\bar{\varepsilon}_{\Phi_\tau}(q) = \frac{1}{N_{\text{Rd}}(N_N^2 - N_N) - N_e} \sum_{\text{rd}=1}^{N_{\text{Rd}}} \sum_{j=1}^{N_N} \sum_{i=1}^{N_N} \varepsilon_{\Phi_{\text{rd}+\tau}, (j \rightarrow i)}(q), \quad i \neq j \quad (6.82)$$

where N_e is the number of times at which no LQP is done (in which case $\varepsilon_{\Phi_{\text{rd}+\tau}, (j \rightarrow i)}(q)$ is set to zero) since the link $(j \rightarrow i)$ does not exist or not enough signal-power samples are available to allow LQP for this link. For better readability we express the error statistic $\bar{\varepsilon}_{\Phi_\tau}(q)$ —which is a probability in this case—as percentage via multiplication by 100. In this way, for example, a certain event occurs in 100% of all trials and therefore has a percentage probability of 100%. Since the MAE of the signal-power prediction can similarly be defined via the individual errors of the signal-power predictions, we omit a formal definition.

The simulation of all scenarios was conducted with the extended NS-2 simulator with all extensions and parameters described in Chapter 5. The simulations were executed on a Dell Precision PWS 380 machine with Pentium D 3.00 GHz, 2 GB RAM under SUSE Linux 9.3 Professional. The evaluation was done with Matlab R14 SP3, executed on various

machines⁷.

6.5.2 Results

In this section, we present the evaluation results grouped by different aspects. Since LQP accuracy is dependent on the prediction horizon and thus dependent on a time scale, we use graphs as the main means of presenting the evaluation results. All empirical results originate from simulations of the different scenarios described in the previous section. When appropriate, we support these empirical results by analytical results to further strengthen the generality of the former.

6.5.2.1 Accuracy of Signal-Power Predictions

We begin the evaluation by assessing the accuracy of signal-power predictions. As evident from the expressions of the LQPRs (e.g. see Table 6.1), signal-power prediction is independent of the length of the packets for which predictions are made. Figure 6.8 (SC2) displays the MAE of signal-power prediction for all three LQPRs depending on the prediction horizon for the RWP model. As expected, the THEO predictor performs best since it represents the lower error bound that cannot be achieved by realisable predictors. Furthermore, the DES predictor, which is the optimal realisable predictor, shows higher prediction accuracy than the LLM predictor. For very short prediction horizons the accuracy of the LLM and DES predictor is approximately equal, which was explained by our analysis in Section 6.3.6 since the LLM predictor is a special case of the DES predictor in which the nodes are assumed to be static. However, with increasing prediction horizon the difference in accuracy between the DES and LLM predictor grows since the nodes move further within this larger time span and the effect of these movements on link quality due to large-scale fading is only considered by the DES predictor. Nevertheless, the difference in accuracy between both predictors is generally small for signal-power predictions. The above results are also observed in the CITY model, for which the MAE of signal-power prediction is displayed in Figure 6.9 (SC6). The prediction errors are moderately higher

⁷Matlab code is platform and machine independent.

in this mobility model since nodes vary their speed more frequently, leading to a higher variance of node mobility and thus less precise mobility prediction.

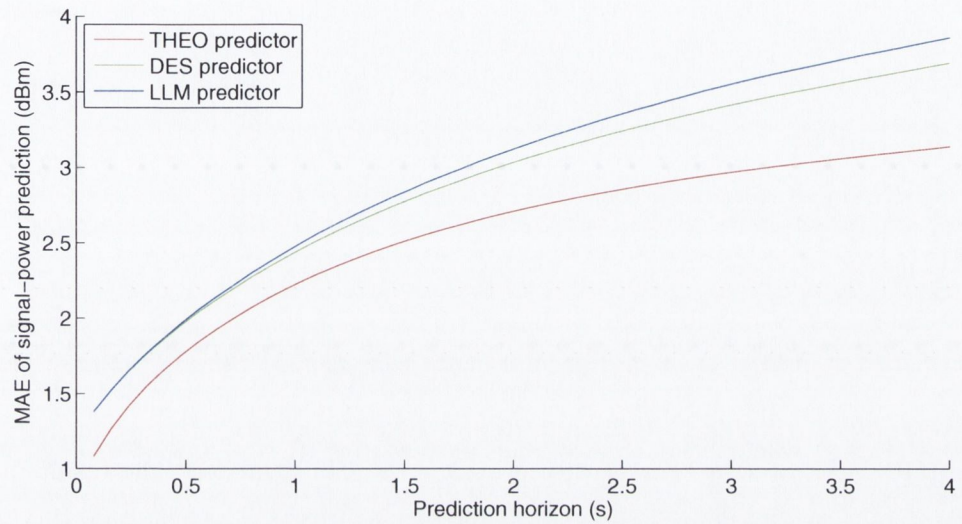


Figure 6.8: MAE of signal-power prediction for the RWP model. As expected, the lower bound of the THEO predictor is not achieved by either of the realisable predictors. The DES predictor shows for very short prediction horizons only slightly better accuracy than the LLM predictor but its accuracy advantage magnifies with increasing prediction horizon.

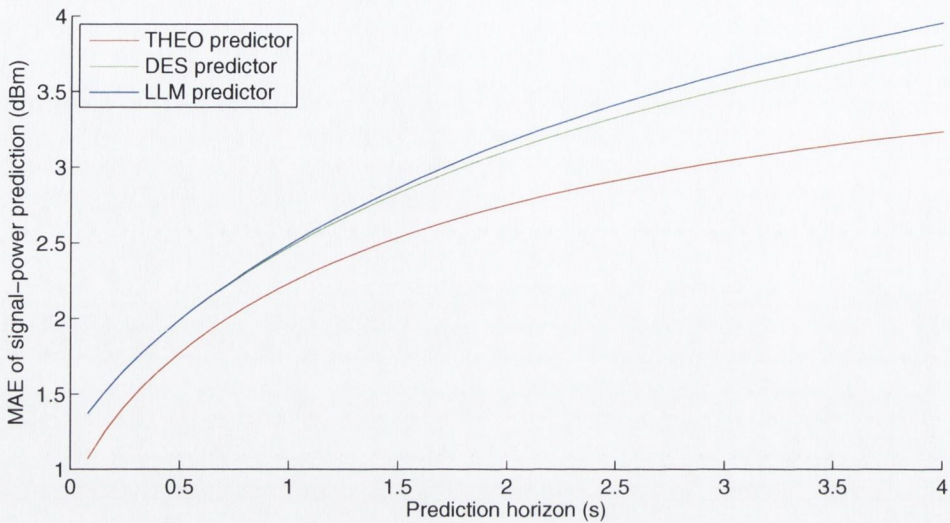


Figure 6.9: MAE of signal-power prediction for the CITY model. The results are very similar to the corresponding results observed for the RWP model except that slightly higher prediction errors are noted since the node speed changes more frequently in the CITY compared to the RWP model.

6.5.2.2 Accuracy of PRP Predictions

The main evaluation criterion for LQP is the prediction accuracy of the PRP since this metric has a direct impact on the communication quality that an application experiences. This prediction accuracy is given by the MAE of the actual and the predicted PRP. We show in Figure 6.10 the MAE of PRPP for the same scenario (SC2) as was displayed in Figure 6.8 for signal-power prediction. As expected, the accuracy order among the LQPRs did not change since the PRPP accuracy is a function of the predicted signal power and the length of the packet for which a prediction is made. Thus the order in decreasing accuracy is THEO, DES and LLM predictor. However, it is evident that the DES predictor predicts the PRP considerably better than the LLM predictor while a much smaller accuracy advantage was observed for signal-power prediction. The same observations can be made in Figure 6.11, where the MAE of the PRPP is displayed for scenario SC7—the CITY model with a packet size of 1000 bytes. The increased relative accuracy in PRP prediction over signal-

power prediction is a desirable property of the DES predictor since the former directly influences the communication quality experienced in a network. This property is a direct consequence of the varying estimation accuracy of $\hat{C}_{T(\text{dBm})}$ as discussed in Sections 6.3.5.2 and 6.3.5.3. The link quality model for the derivation of the LQPRs was approximated by assuming a constant path loss since the signal power changes only slightly within the prediction horizon due to path loss. However, the quantity $\hat{C}_{T(\text{dBm})}$ is estimated over a larger time and space interval in the past such that this approximation is less accurate when nodes are very close with respect to each other, which was illustrated in Figure 6.2. Therefore, when nodes are very close to each other, the signal-power prediction of the DES predictor is expected to be considerably less accurate than if nodes are further away, which was illustrated in an example in Figure 6.5. However, this property leads primarily to a higher prediction error of the signal power but affects the prediction error of the PRP only moderately as is illustrated in Figure 6.12. When nodes are very close, the SNR is high and the PRPP error is insensitive to signal-power prediction errors since the link is far from experiencing packet loss. At medium to lower SNR ($\approx 20\text{--}11$ dB), however, the sensitivity to signal-power prediction errors is high but the approximation of path loss being constant is accurate and thus the DES predictor outperforms the LLM predictor by a higher relative margin for PRPPs compared to signal-power predictions.

In summary, the order of PRPP accuracy among the THEO, DES and LLM predictors (decreasing accuracy) remains invariant for every combination of mobility model and packet length evaluated. The DES predictor is the best realisable predictor and its accuracy gets considerably better than the LLM predictor's with increasing prediction horizon. These results are expected from our derivations since the THEO predictor represents the non-realizable lower error bound, the DES predictor is the optimal realisable predictor with fast parameter estimator and the LLM predictor is a special case of the DES predictor in which large-scale fading due to node mobility is not considered. All three LQPRs show good accuracy and the practical significance of these results for applications is discussed in Chapter 7.

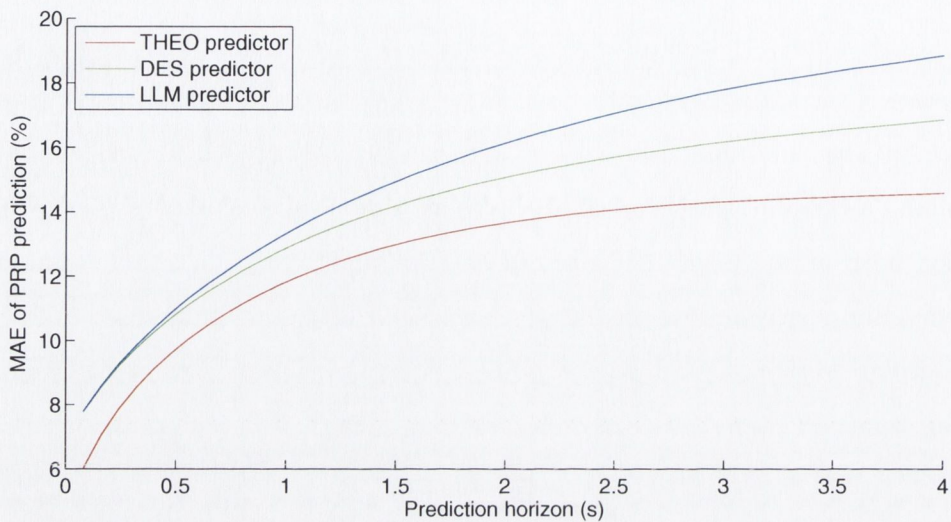


Figure 6.10: MAE of PRP prediction for the RWP model with 500-byte long packets. The THEO predictor is most accurate, followed by the DES and then the LLM predictors. It can be noticed that the DES predictor outperforms the LLM predictor for PRP predictions by a higher relative margin than for signal-power predictions.

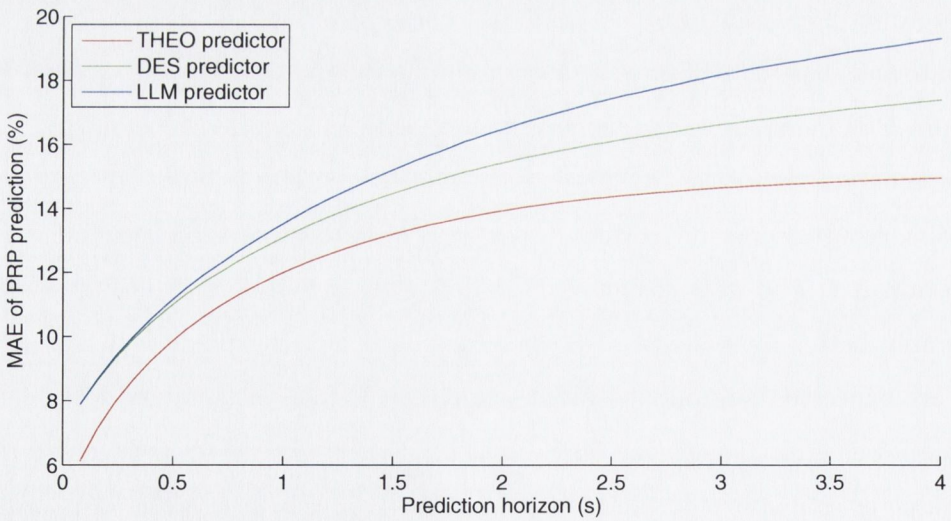


Figure 6.11: MAE of PRP prediction for the CITY model with 1000-byte long packets. As in the previous scenario of the RWP model, the DES predictor outperforms the LLM predictor for PRP predictions by a higher relative margin than for signal-power predictions. This property is observed for all combinations of mobility models and packet lengths evaluated.

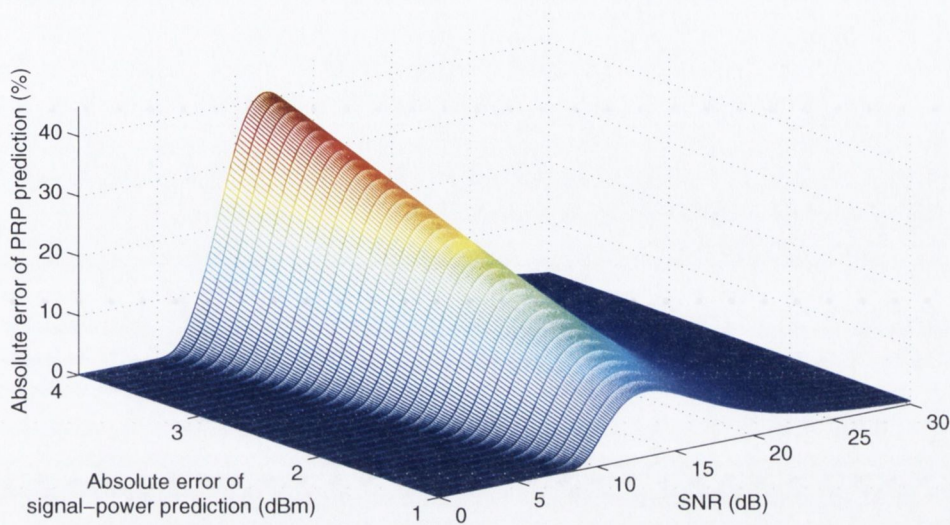


Figure 6.12: Sensitivity of PRP prediction error depending on the signal-power prediction error and the SNR for 500-byte long packets. At high SNR, where the approximation of the link quality model is less accurate than at lower SNR, signal-power prediction errors have a low impact on the PRP prediction error.

6.5.2.3 Dependence of PRP Prediction Accuracy on the Mobility Model

The accuracy order among the LQPRs was shown to be independent of the mobility model in all our experiments. However, the prediction accuracy of all LQPRs between RWP and CITY model was observed to differ moderately. Figure 6.13 shows the MAE of the PRPP for the DES predictor with very short and very long packets for the CITY and RWP models⁸. As evident, the PRPP accuracy is moderately lower for the CITY than for the RWP model. The difference in accuracy is small for short packets but increases with packet length. The LQP accuracy is lower in the CITY than in the RWP model since in the former model the speed of nodes changes more frequently. Therefore, the difference in prediction accuracy between both mobility models is slightly higher for the DES and THEO predictor compared to the LLM predictor since the former two LQPRs rely on mobility prediction that is less accurate in the CITY model. These properties hold for all combinations of mobility model and packet length.

⁸The dependence of LQP accuracy on packet length will be assessed in Section 6.5.2.5.

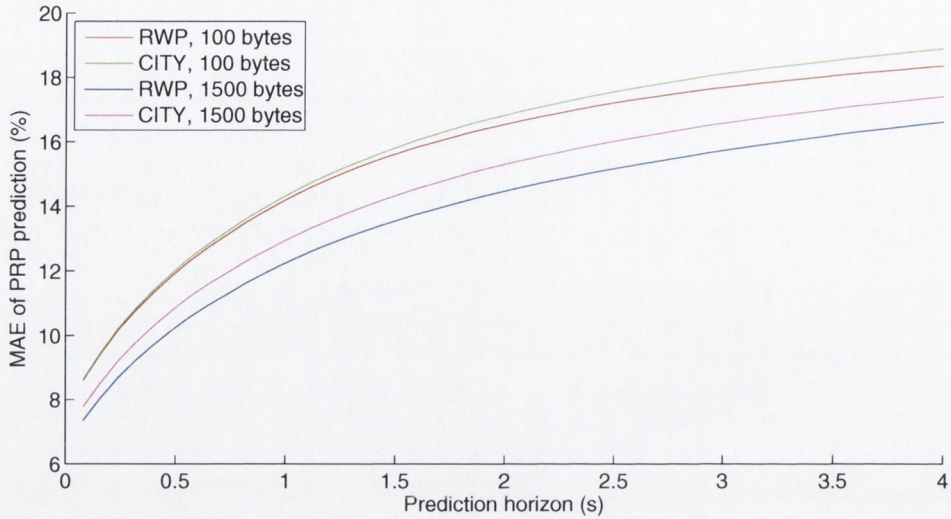


Figure 6.13: PRP prediction accuracy of the DES predictor for the CITY and RWP models. The DES predictor is more accurate for the RWP compared to the CITY model since in the latter the speed of nodes changes more frequently. The difference in PRP prediction accuracy between these two mobility models increases with packet length.

6.5.2.4 Confidence Intervals for PRP Prediction Accuracy

A credible evaluation requires that its statistical accuracy is shown, which has typically been omitted in most MANET studies (Kurkowski et al. 2005). Here, we employ confidence intervals to support the credibility of our evaluation. Figure 6.14 shows the 95% confidence interval for scenario SC2—the RWP model and 500-byte long packets, which has been used frequently in the evaluation section. For comparison with a very different scenario, we also show the confidence intervals in Figure 6.15 for scenario SC8, in which the simulation is based on the CITY model with long packets of 1500 bytes. Both figures show narrow 95% confidence intervals that are nearly independent of the prediction horizon, the packet length and the mobility model. The 95% confidence intervals are typically within ± 0.6 – 0.7% probability. Since narrow confidence intervals can be observed for all mobility model and packet length combinations, we typically present graphs without them to increase readability.

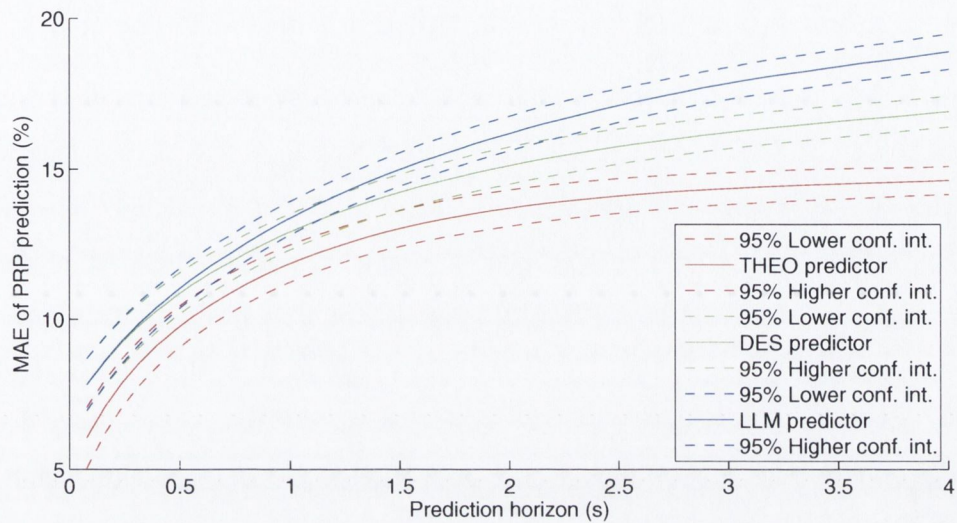


Figure 6.14: 95% Confidence intervals for PRP prediction errors for 500-byte long packets and the RWP model. All LQPRs have confidence intervals of small and similar length.

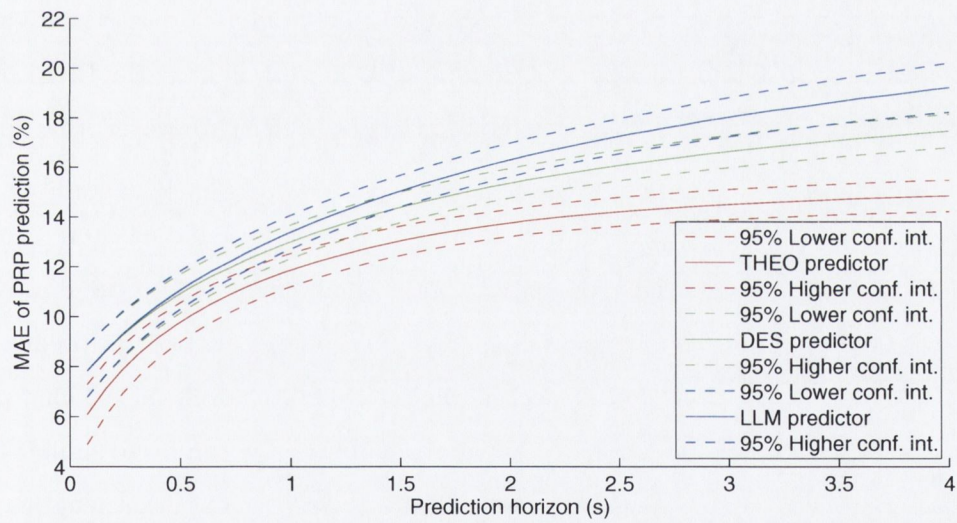


Figure 6.15: 95% Confidence intervals for PRP prediction errors for 1500-byte long packets in the CITY model. The confidence intervals are similarly narrow compared to the scenario with much shorter packets (500 bytes) and the RWP model.

6.5.2.5 Dependence of PRP Prediction Accuracy on Packet Length

Figure 6.13 suggests that the LQP accuracy is moderately dependent on the mobility model but considerably more dependent on packet length, where packet length is the size of the MAC payload of the packets for which the PRP is predicted. Therefore, we explore the influence of packet length on LQP accuracy by graphing the MAE of the PRPP for all evaluated packet lengths for the RWP model (SC1–4) in Figure 6.16 and for the CITY model (SC5–8) in Figure 6.17. It is noticeable that in both mobility models the prediction accuracy increases with longer packets but the difference in accuracy decreases. This property has also been observed for the THEO and LLM predictors and thus is independent of the LQPR. This generality must be the consequence of the signal-power prediction to PRPP mapping since the signal-power prediction is independent of packet length. Therefore, using the mapping (5.28) between signal power and PRP, we displayed the difference of absolute PRPP errors for packets of 100 and 1500 bytes in Figure 6.18 and for packets of 1000 and 1500 bytes in Figure 6.19. In both figures, the PRPP error at low to medium SNR is higher for shorter than for longer packets. However, this difference is much greater for packets that differ considerably in length than for packets of similar length. Although both figures show that shorter packets are predicted more accurately at high SNR than longer packets, this advantage is small compared to the disadvantage of higher predictor errors at low to medium SNR. Therefore, all LQPRs predict longer packets more accurately than shorter packets albeit this effect levels off for long packets, where the accuracy between packets of 1000 and 1500 bytes size can be so similar that for some prediction horizons the accuracy order varies with respect to packet length.

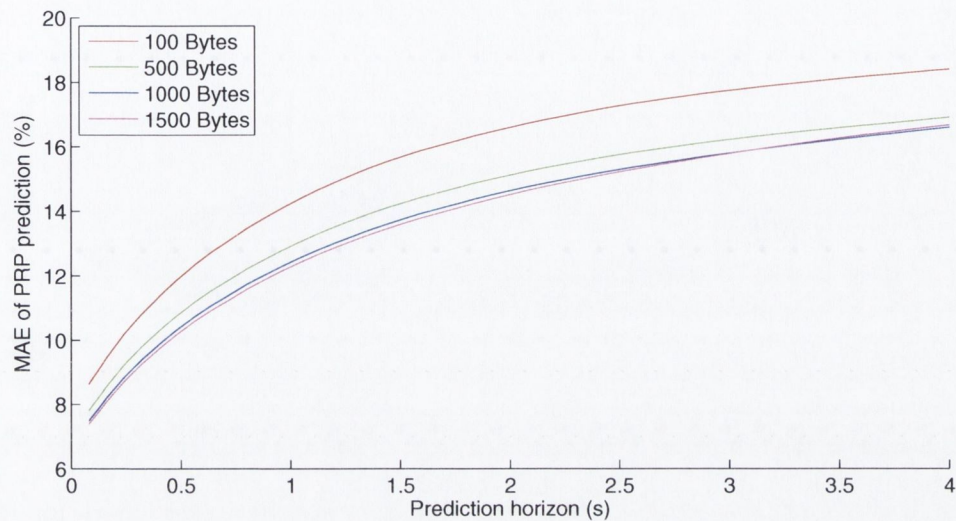


Figure 6.16: MAE of PRP prediction for various packet lengths and the RWP model for the DES predictor. The prediction accuracy increases with longer packets but the difference in accuracy levels off for longer packets. Thus the difference in prediction accuracy for 1000- and 1500-byte long packets is very low, such that at different prediction horizons the accuracy order with respect to packet length can even vary.

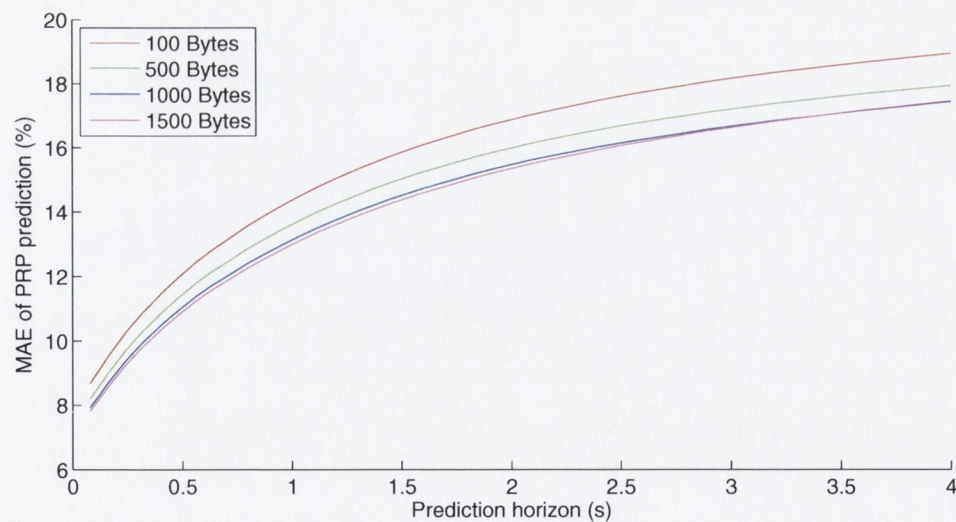


Figure 6.17: MAE of PRP prediction for various packet lengths and the CITY model for the DES predictor. The longer the packets are, the higher the prediction accuracy is, although this effect decreases with increasing packet length.

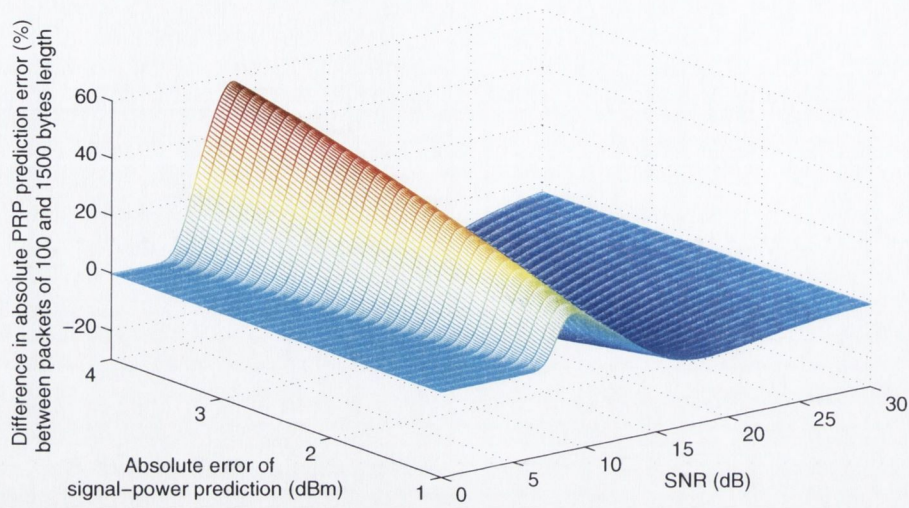


Figure 6.18: Dependence of absolute PRP prediction error on packet length for 100- and 1500-byte long packets. The graph shows the difference of the absolute PRP prediction error between packets of 100 and 1500 bytes depending on various parameters. Assuming a fixed signal-power prediction error, the absolute PRP prediction error of short packets is much higher than for longer packets at low to medium SNR. While at high SNR shorter packets are predicted with lower error than longer packets, this difference is only small compared to the difference in PRP prediction accuracy observed at low to medium SNR.

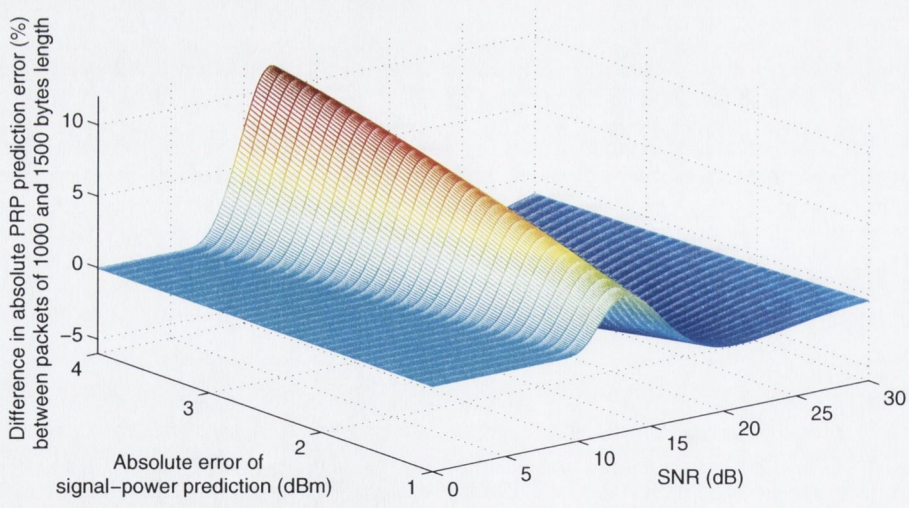


Figure 6.19: Dependence of absolute PRP prediction error on packet length for 1000- and 1500-byte long packets. The graph shows the difference of the absolute PRP prediction error between packets of 1000 and 1500 bytes depending on various parameters. While the same characteristics are observed than in Figure 6.18, the difference in PRP prediction accuracy between 1000- and 1500-byte packets is much lower than for 100- and 1500-byte packets.

6.5.2.6 Dependence of PRP Prediction Accuracy on Link Quality

It is interesting to examine if the accuracy of PRPP is dependent on the quality of links for which predictions are made. For example, a trivial LQPR, which always predicts a PRP of 100%, shows high accuracy when it is only used in situations in which nodes are so close that there is virtually no risk of losing packets. Therefore, we investigated the accuracy of all LQPRs depending on the quality of links for which predictions are made. Figure 6.20 shows the LQP accuracy measured as MAE of PRPP for the DES predictor in scenario SC2. In this scenario the DES predictor shows similar prediction accuracy for links with PRP between 0% and 75% but considerably better results for strong links with PRP greater than 75%. The better predictability for strong links is a consequence of the insensitivity of the PRPP to signal-power prediction errors at high SNR which has previously been shown in Figure 6.12. Thus this property was observed for all LQPRs in all scenarios.

The THEO predictor typically shows a similar behaviour to the DES predictor. However, we noticed that the LLM predictor differs in one respect from the other two predictors as illustrated in Figure 6.21 for the same scenario (SC2) for which the prediction accuracy of the DES predictor was shown. The LLM predictor predicts the PRP of links in the range between 25% and 75% with similar accuracy, strong links considerably more accurately than other links but it differs from the DES and THEO predictors by having a lower prediction accuracy for weak links in the 0% to 25% range.

In summary, we found that strong links are predicted by all LQPRs considerably more accurately than links with a PRP between 0% and 75%. All LQPRs predict links within the PRP range of 25% and 75% with similar accuracy, although this accuracy is different for each predictor. The LLM predictor often shows higher prediction errors for weak links in the PRP range of 0% to 25% than for links outside this PRP range. The THEO and DES predictors typically show similar relative behaviour. The mobility model has only a minor influence on the LQP accuracy with respect to link quality.

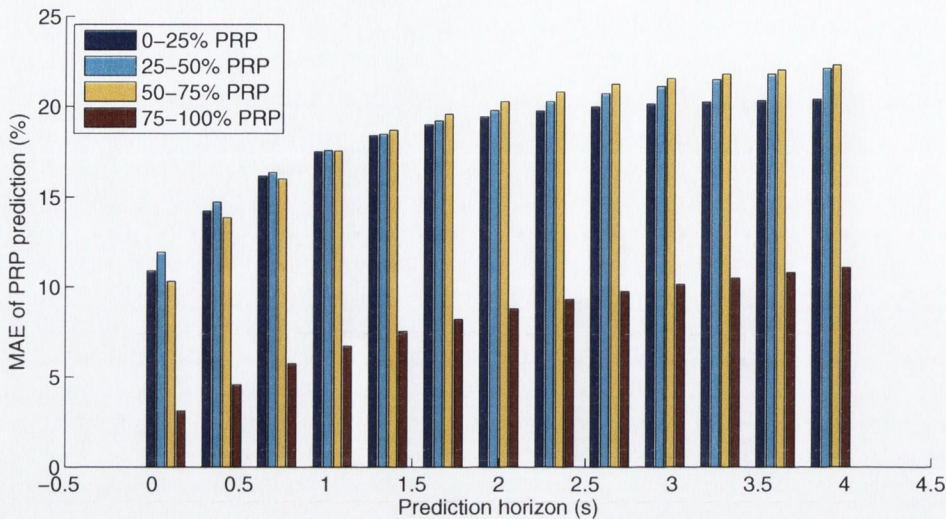


Figure 6.20: Prediction accuracy of the DES predictor depending on link quality for 500-byte long packets and the RWP model. Within the PRP range of 0% to 75% the prediction accuracy is very similar, for strong links the accuracy is considerably better.

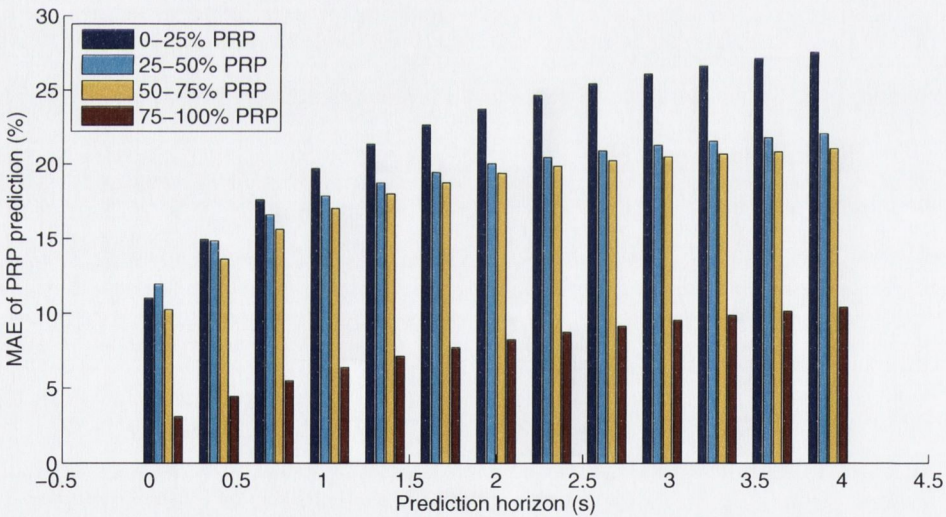


Figure 6.21: Prediction accuracy of the LLM predictor depending on link quality for 500-byte long packets and the RWP model. The LLM predictor shows similar behaviour to the DES predictor, except for weak links in which it performs worse.

6.5.2.7 Dependence of PRP Prediction Accuracy on Node Density

The previously reported evaluation results have been derived from simulations in which the number of nodes and the simulation area were invariant. It is evident from the LQP model that the accuracy of the LQPRs must be independent of the number of nodes since node links are independent of each other and, due to our beaconing pattern, no collisions occur. However, a change in the number of nodes or in the size of the simulation area changes the node density, which is defined as the number of nodes divided by the simulation area (Kurkowski et al. 2005). Since a change in node density might influence the distribution of quality among the links (e.g. to have more strong or weak links), the accuracy of LQP could be affected.

Figure 6.22 shows the LQP accuracy for the DES predictor for 3 nodes (SC9), 5 nodes (SC2) and 10 nodes (SC10) with an identical size of simulation area (500 by 500 m), which led to node densities of $1.20 \cdot 10^{-5}$, $2.00 \cdot 10^{-5}$ and $4.00 \cdot 10^{-5}$, respectively. It can be noticed that the LQP accuracy of the two most different node densities are nearly identical, while the medium node density shows a noticeable difference to the others. Since the scenarios with the two most diverse node densities show similar LQP accuracy, there seems to be no observable relationship between them and thus the difference for one scenario is likely to be random. This possibility is illustrated by the same diagram with confidence intervals shown in Figure 6.23. First, we notice the large size of the confidence intervals for the scenario with only 3 nodes. This observation is caused by having far less prediction data available for evaluation due to a lower number of links than in the scenarios with 5 or 10 nodes. Secondly, it can be observed that all confidence intervals overlap by a significant margin such that the noticeable difference in LQP accuracy for one scenario is most likely caused by chance, especially since no relationship between node density and LQP accuracy is observable. To strengthen our argument, we simulated an additional scenario (SC11), in which we reduced the node density by keeping the number of nodes constant but reduced the simulation area to 300 by 300 m, which led to a node density of $5.56 \cdot 10^{-5}$. Figure 6.24 compares the LQP accuracy for this scenario with our default scenario SC2 and the accuracy is nearly identical. Thus we conclude from the above evidence that LQP accuracy

is independent of node density in the absence of collisions since the above observations apply also to the two other LQPRs.

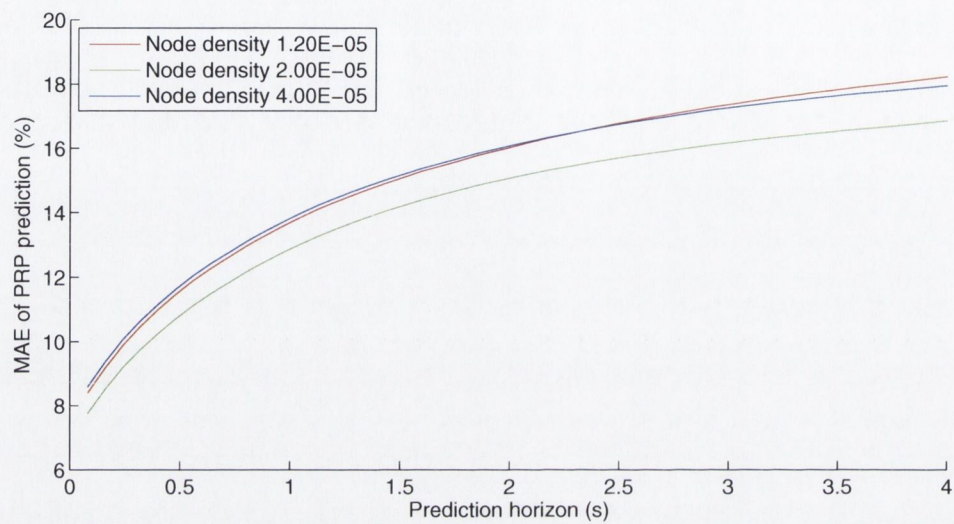


Figure 6.22: Dependence of prediction accuracy on node density. The two most diverse scenarios have nearly identical LQP accuracy while the scenario with medium node density shows a noticeable difference in PRP prediction accuracy to the other two scenarios.

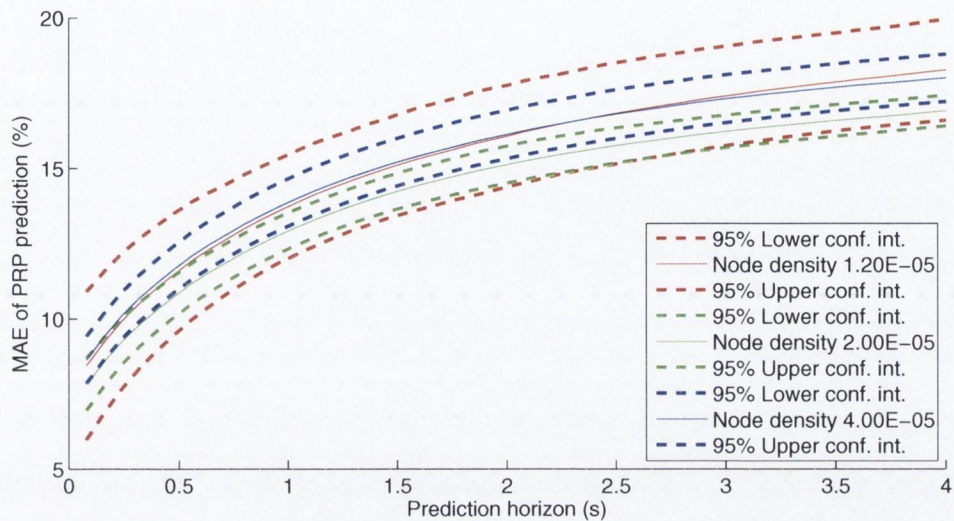


Figure 6.23: Dependence of prediction accuracy on node density with confidence intervals. The confidence intervals for the PRP prediction accuracy of all three scenarios overlap considerably. Therefore, the noticeable difference in LQP accuracy for one scenario is most likely due to chance. The confidence interval of the scenario with the lowest node density is large since considerably less LQP data is available for 3 nodes compared to 5 or 10 nodes.

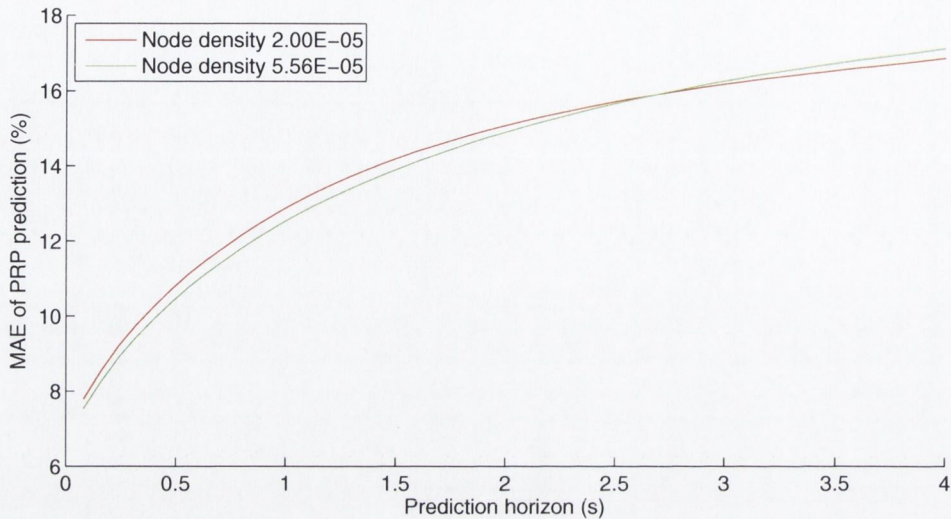


Figure 6.24: Dependence of prediction accuracy on node density varied by changing the size of the simulation area. Despite the high difference in node densities, the LQP prediction accuracy is nearly identical for both scenarios.

6.5.2.8 Dependence of PRP Prediction Accuracy on Link Directions

As we have shown in Section 3.3.2, the assumption of bidirectional links between a node pair is valid as long as both nodes have the same 802.11 card model and transmission power. However, in real-world MANETs various 802.11 card models and transmission powers are expected. Therefore, in all previous scenarios some nodes had a 1 dBm higher transmission power than other nodes, leading to some unidirectional links in all these simulations. In order to assess the influence of link directionality on LQP, we simulated a scenario (SC12) in which all nodes had the same transmission power and thus bidirectional links only. Figure 6.25 shows for the DES predictor that the existence of only bidirectional links had no influence on the PRPP accuracy as it was also observed for the other LQPRs. This result is expected since the quality of a link between two nodes is predicted independently for each direction and thus is unaffected by the link being uni- or bidirectional. However, unidirectional links are important to consider for the development of protocols that use LQP, since such links make the distribution of knowledge, including LQP-related information, more difficult than if only bidirectional links exist.

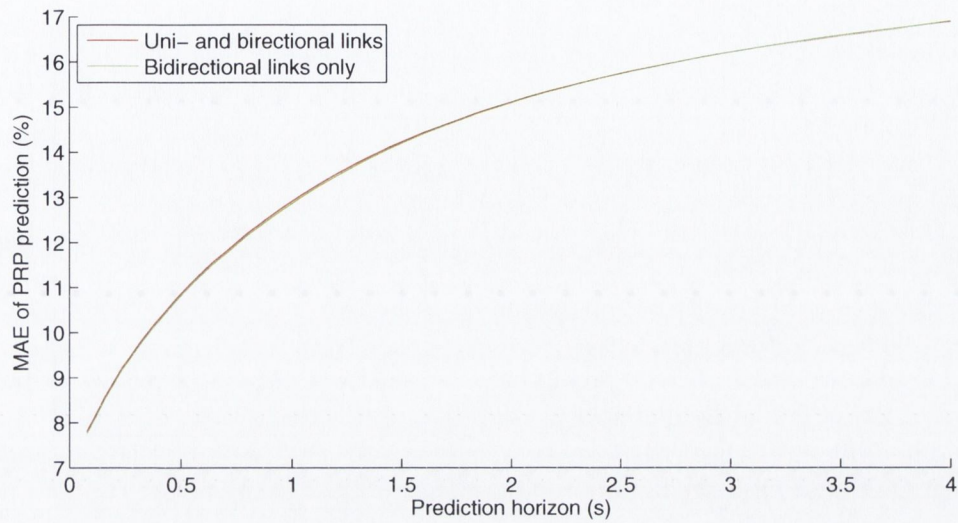


Figure 6.25: Dependence of PRP prediction accuracy on link directionality in the RWP model for 500-byte long packets. The existence of bidirectional links only caused no observable difference in PRP prediction accuracy compared to having a combination of uni- and bidirectional links.

6.5.2.9 Numerical Analysis of PRP Prediction Accuracy

In the following, we present various statistics for the MAE of PRPP for all the LQPRs and the main scenarios (SC1–SC8). As previously discussed, the ascending accuracy order among the LQPRs is LLM, DES and THEO predictors as expected from the derivation of the LQPRs. In general, link quality can be predicted with good accuracy for pedestrians in microcellular urban environments within a prediction horizon of a few seconds. For example, at one and two seconds ahead the DES predictor shows on average an MAE of PRPP of 13.09% and 15.55%, respectively. While the accuracy of the LLM and DES predictors are both close to the lower unachievable error bound of the THEO predictor, the difference between the DES and THEO predictors is especially low. At two seconds ahead, the DES and THEO predictors showed a maximum difference of 1.59% PRPP accuracy and at four seconds ahead this maximum difference was 2.61%. Although the LLM predictor differs more strongly from the theoretical optimum with 2.57% and 4.62% at two and four seconds, respectively, it also shows good PRPP accuracy. The advantage

Prediction horizon	1 s	2 s	3 s	4 s
Mean MAE of PRP prediction for THEO predictor	12.00%	14.07%	14.77%	15.087%
Mean MAE of PRP prediction for DES predictor	13.09%	15.55%	16.71%	17.52%
Mean MAE of PRP prediction for LLM predictor	13.47%	16.54%	18.21%	19.38%
Max difference of MAE of PRP prediction between DES and THEO predictor	1.15%	1.59%	2.11%	2.61%
Max difference of MAE of PRP prediction between LLM and THEO predictor	1.54%	2.57%	3.65%	4.62%
Mean difference of MAE of PRP prediction between LLM and DES predictor	0.39%	1.00%	1.50%	1.89%

Table 6.3: Numerical PRP prediction accuracy for all LQPRs.

of the DES over the LLM predictor ranges on average from 0.39% to 1.89% and is 1.00% for two seconds ahead. Hence, in simulations and pervasive computing applications, where speed measurement equipment for nodes is available, the DES predictor is the preferred option. However, the moderate accuracy advantage of the DES over the LLM predictor does not justify the additional installation of acceleration sensors, when they are either not integrated in an 802.11 card by the manufacturer or they are not required for additional purposes.

6.6 Summary

In this chapter, we derived from our link quality model a novel and optimal link quality predictor (LQPR) which is the predictor with minimum mean square error. This predictor requires the estimation of its parameters from signal-power and node-speed samples from the recent past. We derived the optimal estimator for this problem which has a computational cubic-time complexity with respect to the number of samples used for parameter estimation. This high computational requirement makes this optimal estimator unsuitable for real-world application. Thus a fast estimator is derived whose complexity is independent of the number of samples used for estimation and is thus three orders computationally

more efficient than the optimal estimator. The fast estimator is also unbiased and its accuracy is very close to the optimal estimator as shown by a low increase in the parameter estimation variance. The combination of optimal predictor and fast estimator is termed the distance exponential shadowing (DES) predictor, which is the best realisable predictor. For situations in which no node-speed measurements are available, we propose the simple last local mean (LLM) predictor that is a special case of the DES predictor in which nodes are assumed to be static. Both LQPRs require regular beaconing and we suggest a beaconing protocol with Golay encoding that enables link quality prediction (LQP) at very low signal-to-noise ratio in which previously no LQP has been possible.

We evaluate both LQPRs in a major simulation study in the extended NS-2 simulator whose close agreement to real-world measurements was shown in the previous chapter. The previously investigated LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) have shown poor performance in real-world measurements and in the extended NS-2 simulator. This and other shortcomings, which have been discussed in this chapter, necessitate the determination of a stronger baseline to evaluate our LQPRs against. This baseline is given by the previously derived optimal predictor, whose parameters are now provided by an external observer with perfect knowledge of the link quality model in the past but no knowledge of the future. This theoretical (THEO) predictor represents a lower error bound on LQP that cannot be achieved by any realisable predictor in the given link quality model. Over a wide range of scenarios we demonstrated that the mean absolute error (MAE) of the packet reception probability (PRP) prediction for the DES predictor is in the worst case within 1.59% of the unachievable lower error bound of the THEO predictor for 2 s ahead. Furthermore, the DES predictor outperforms the LLM predictor in all scenarios although the accuracy difference is moderate. The MAE of PRP prediction for the DES predictor is on average over all scenarios 13.09%, 15.55%, 16.71% and 17.52% for 1 s, 2 s, 3 s and 4 s ahead, which shows that accurate LQP is possible for pedestrians in microcellular urban environments within short prediction horizons. The generality of our LQP study is not only demonstrated by the wide range of scenarios on which it is based but also by the narrow confidence intervals for LQP accuracy that have been achieved.

The study determined that link quality is predicted with higher accuracy in the Random Waypoint Mobility Model than in the Random Waypoint Mobility Model City Section, since in the latter model the speed of nodes changes more frequently. Furthermore, it was demonstrated that longer packets are more accurately predicted than shorter packets, albeit this effect levels off at larger packet lengths. The predictability of link quality was shown to be independent of node density in the absence of collisions. LQP was equally accurate in scenarios with only bidirectional links compared to scenarios that also include unidirectional links.

Chapter 7

Conclusions

In the first section of this chapter, we highlight the specific contributions of this work. We then assess their potential impact with respect to the field of MANETs and wireless communications. Finally, we propose extensions to this work for further research.

7.1 Specific Conclusions

Existing link quality prediction (LQP) algorithms for MANETs are typically based on very basic radio propagation models that consider path loss as the sole propagation effect. We selected the three potentially best performing LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) from the literature for a real-world study of an 802.11 MANET of pedestrians in two microcellular urban environments. The best performing LQP algorithm (Goff et al. 2001) failed to predict between 18% and 54% of the total observed packet loss for two seconds ahead while between 12% and 43% of successfully received packets were falsely predicted to be lost. These results differ greatly from the near-perfect accuracy observed in simulations with the standard NS-2 simulator in its default configuration. It was noted that signal power is a better short-term predictor of link quality than its trend for pedestrians in urban microcells. Furthermore, it was observed that links oscillate between being available and unavailable such that a stochastic prediction of link quality is more likely to provide accurate results than a deterministic one.

Our real-world investigation of factors that potentially influence link quality and its prediction showed that LQP is difficult but not impossible. Small-scale movements of nodes in benign free-space environments and node heights over the belt showed no influence on link quality. The 802.11 card model influenced link quality considerably but does not affect its prediction when the card's characteristics are known to the node that is using it. Various payload patterns and communication loads did not influence link quality. However, our experiments showed that shadowing due to objects in the radio channel and shadowing due to the body of a person carrying a node affected link quality significantly. Therefore, the resulting large-scale fading of the signal must be considered in modelling, simulating and predicting link quality.

A large-scale fading signal can only be accurately estimated by considering its small-scale fading. While the latter effect is well understood in narrowband systems, its probability distribution functions were previously unknown for wideband systems. We showed in a major Monte Carlo study based on a wideband propagation model from the literature, which is itself supported by extensive measurements, that the probability distribution of small-scale wideband signal envelope fading in microcells can be approximated very closely by both the Rice and Nakagami distributions that are already known to describe the probability distribution of small-scale narrowband signal envelope fading. Over a comprehensive range of microcell propagation parameters, the average error in the approximation of the small-scale fading signal envelope was shown to be 1.65% and 1.78% for the Rice and Nakagami cumulative distribution functions (CDFs) respectively. The error in the approximation was 3.58% and 3.87% respectively for the 95th percentile and did not exceed 7.61% and 7.80% respectively in the worst case. Considering only the 802.11 standard, the approximation errors for small-scale wideband signal envelope fading were even lower. For example, the approximation error for the worst case of the Rice CDF did not exceed 4.45%. We also demonstrated that the probability distribution of the signal power can be characterised by the Non-Central Chi-Square and Gamma distributions to a similar degree of accuracy as the signal envelope is characterised by the Rice and Nakagami distributions. While small-scale fading of the signal envelope in narrowband and wideband systems can

both be described by the same probability distribution functions, the parameters of these functions differ between the different types of systems. Therefore, we provided an expression that maps the significant wideband small-scale signal envelope fading parameters to their narrowband counterparts for different standards such as DSRC, WiMAX, UMTS and the family of 802.11 standards. Using both of these results, we found that signal-power averaging over 5 wavelengths results in an accurate estimate of the large-scale fading signal for 802.11 in urban microcells.

The standard NS-2 simulator in its default configuration only models path loss while an extended configuration also models large-scale fading albeit that the important correlation properties of the latter are not addressed. Small-scale fading as well as bit error and packet error calculations for an 802.11 receiver are not considered. Consequently, existing MANET studies using the NS-2 simulator show poor agreement with real-world measurements as, for example, shown in our study of LQP algorithms. Therefore, we extended the NS-2 simulator with models for correlated large-scale fading, wideband small-scale fading as well as bit and packet error calculations for 802.11. The simulation of small-scale wideband signal envelope fading and the determination of the bit error probabilities of an 802.11 receiver were enabled by our results concerning the probability distribution of wideband small-scale fading and the mapping of its parameters to narrowband systems. The choice of appropriate parameters for radio propagation models to describe microcellular urban environments is as important as choosing appropriate models themselves. Since real-world measurements from the literature determined a range of values for each radio propagation parameter, we introduce the simple idea of the simulator choosing for each parameter pseudo-randomly a value from its measured range: this mechanism leads to simulations that represent the full variety of microcellular urban environments as opposed to a particular subspace of these. Although our proposed extensions to the NS-2 simulator are entirely justified by relying on models and parameters from the literature, which have been derived or verified by extensive measurements, we undertook an additional evaluation to support the claim that the extended NS-2 simulator leads to more realistic simulations than the standard simulator. While the accuracy metrics of the LQP algorithms (Paul et al. 1999,

Goff et al. 2001, Qin & Kunz 2002) from the real-world study were barely comparable to simulations in the standard NS-2 simulator, close agreement was shown to simulations in the extended NS-2 simulator with a maximum difference of 4.19% in LQP accuracy metrics between measurement and simulation. Despite the significant improvement in realism, the extended NS-2 simulator is as easy to use as the standard version and was on average only 17.98% slower than the latter.

Based on a comprehensive stochastic link quality model that includes path loss, large-scale and wideband small-scale fading, we derived a novel optimal link quality predictor (LQPR) that has the minimum mean square error among all LQPRs. This predictor requires the estimation of its parameters from past signal-power and node-speed samples. Although we determined the optimal estimator for these parameters, its computational cubic-time complexity with respect to the number of samples used makes it unsuitable for use at runtime. Consequently, we propose an unbiased fast estimator that is three orders computationally more efficient than the optimal estimator while showing only a slight increase in the parameter estimation variance. The combination of optimal predictor and fast estimator is termed to be the distance exponential shadowing (DES) predictor. Additionally, for applications where node-speed measurements are unavailable, we suggest the simple last local mean (LLM) predictor that is a special case of the DES predictor in which nodes are assumed to be static. We introduce a protocol for regular beaconing, which is required by both of these LQPRs, that uses Golay encoding to enable LQP in situations at very low signal-to-noise ratio (SNR) in which no LQP has previously been possible.

Both LQPRs were evaluated in a major simulation study in the extended NS-2 simulator. The previously investigated LQP algorithms (Paul et al. 1999, Goff et al. 2001, Qin & Kunz 2002) have shown poor performance in real-world experiments and in this simulator. Since the parameters of these algorithms are unknown for such environments, in which not only path loss but also large-scale and wideband small-scale fading are experienced, they had to be determined by computationally very expensive optimisations. For both reasons, these LQP algorithms are neither suitable nor feasible for an evaluation of LQP accuracy

such that we had to determine a stronger baseline against which to compare our LQPRs. This baseline is given by the optimal predictor, whose parameters in simulations, in contrast to the DES predictor, can be determined by an external observer with perfect knowledge of the link quality model in the past but no knowledge of the future. This theoretical (THEO) predictor places a lower error bound on LQP that cannot be achieved by any realisable predictor in the given link quality model. The mean absolute error (MAE) of the packet reception probability (PRP) prediction for the DES predictor was shown to be close to the THEO predictor with, for example, an average difference of 1.59% for 2 s ahead. While the DES predictor outperformed the LLM predictor in all scenarios, the accuracy advantage was moderate with a maximum difference of 2.61% at 4 s ahead. Thus while acceleration sensors could be integrated into standard 802.11 cards due to their low costs, the effort of installing such sensors cannot be justified for the sole purpose of LQP. We determined that accurate LQP is possible for pedestrians in microcellular urban environments within short prediction horizons by both the LLM and DES predictors. For example, the MAE of PRP prediction (PRPP) for the DES predictor was shown on average over all scenarios to be 8.75%, 13.09%, 15.55%, 16.71% and 17.52% for 0.16 s, 1 s, 2 s, 3 s and 4 s ahead. These prediction horizons allow proactive applications to react generously to predicted topology changes since, for example, the discovery of routes in proactive routing took on average only 0.1 s for a MANET of 35 nodes as reported in Goff et al.'s (2001) study. Link quality was predicted in our work with higher accuracy in the Random Waypoint Mobility Model than in the Random Waypoint Mobility Model City Section, since in the latter model the speed of nodes changes more frequently. Longer packets were predicted more accurately than shorter packets, albeit that this effect levelled off at large packet sizes. LQP accuracy was unaffected by node density in the absence of collisions and was also independent of the directionality of links.

7.2 General Conclusions

The accuracy of LQP in MANETs has previously been studied in the context of very basic radio propagation models that typically consider path loss as the sole propagation effect.

However, our measurements demonstrated that LQP algorithms based on these assumptions and their accuracy are neither applicable to nor representative of real-world 802.11 MANETs of pedestrians in microcellular urban environments. Hence, two major consequences follow. First, LQP algorithms applicable to real-world environments are required to consider the previously neglected radio propagation effects of large-scale and wideband small-scale fading. Such algorithms have been derived in this work for 802.11 MANETs of pedestrians and good LQP accuracy, close to the theoretical optimum, has been shown for a wide range of scenarios. Secondly, LQP accuracy in real-world environments is lower than in simulations with deterministic path-loss-only radio propagation models. Hence, the large LQP-based improvements in higher-layer metrics of routing protocols, such as the reduction in packet latency and the selection of links with high remaining lifetime, shown in the literature by such simulations are likely to be optimistic. Consequently, a re-evaluation of these higher-layer metrics in more realistic simulations or in real-world experiments is required with LQP algorithms, such as those derived in this thesis, that are designed to work in such environments. We still expect significant improvements in higher-layer metrics for these environments, since especially good accuracy was shown to be achievable for very short prediction horizons that are practically relevant for applications (e.g. less than 9% MAE of PRPP for the DES predictor for 0.1 s ahead). However, we envision these improvements to be less pronounced than previously determined in the literature.

Originally, the scope of this thesis was restricted to the investigation of LQP and its accuracy in 802.11 MANETs of pedestrians in urban microcells. However, we identified that the characterisation and simulation of link quality had not been adequately addressed previously in the MANET area such that significant contributions were required by us to lay the foundation for developing and assessing credible LQP. We rate these contributions to be as important as addressing LQP for MANETs itself and we envision that our results have a considerable sustainable impact in the area of MANETs (simulation of link quality) and to some degree for wireless communications in general (determination of the probability distribution functions of small-scale fading wideband signals).

Our study confirmed previous results from the literature which indicated that current MANET simulations, which typically consider path loss as the sole propagation effect, do not represent real-world urban environments well. In contrast to these studies, however, we suggest a solution to this problem that does not require large additional resources as, for example, needed for real-world experiments or ray-tracing simulations. Our extension of the NS-2 simulator improves the realism of its simulations by incorporating additional stochastic models for correlated large-scale fading, wideband small-scale fading as well as bit and packet error calculations for an 802.11 receiver while requiring only slightly more computational resources. Although we restricted these extensions to microcellular urban environments for 802.11 MANETs, they are more general and can easily be adapted to different situations. For example, a HIPERLAN system might be simulated by the same means as suggested in this thesis but with different parameters for small-scale wideband signal envelope fading and a different receiver model.

While the probability distribution of small-scale signal envelope fading has previously only been known for narrowband systems, we showed that this phenomenon can be characterised in microcellular urban environments by the same probability distribution functions but with different parameters for wideband systems. Since we also provided a mapping for these parameters between the two types of systems, solutions and results for small-scale fading in narrowband systems can now be readily adopted to wideband systems. Such adaptation has been shown in this work for the important areas of local mean power estimation, efficient simulation of small-scale wideband signal envelope fading and bit error probability derivations of an 802.11 receiver. However, our results might also be applicable to other areas, some of which might not even have been identified yet. For example, methods to estimate the Ricean K -factor, which were originally developed for narrowband systems, can also be applied to wideband systems in urban microcells and can be used to estimate at runtime the unavoidable LQP error that is caused by the small-scale fading of the wideband signal envelope.

7.3 Future Work

In this thesis we laid the foundation to enable credible LQP in MANETs, derived novel LQP algorithms for 802.11 MANETs of pedestrians in microcellular urban environments and assessed the accuracy of these algorithms in a wide range of scenarios depending on different factors. We consider the problem of LQP under such circumstances to be comprehensively treated and solved. Building on these new results, the use and application of LQP in MANETs should be revisited and extended. As previously mentioned, the improvements in higher-layer metrics in proactive routing protocols such as packet latency should be re-evaluated under more realistic conditions than previously. Furthermore, we envision significant performance improvements for group communication systems (GCS) in MANETs since such systems typically block progress after a change in the network topology occurs until a new group membership has been established. Since the network topology can change frequently in MANETs, proactive adaptation of the group membership could reduce the latency of packet delivery analogously to proactive route discovery in routing protocols by avoiding such blocking. The potential of this approach has not yet been explored in the literature. Additionally, previous work suggested the use of a partition predictor (PP) that predicts the future network topology and could be employed, for example, in a GCS for proactive group membership adaptation. However, such a component has only been sketched in the literature and has never been built to the best of the author's knowledge. Thus the realisation of a PP that extends LQP from single links to a whole MANET by distributing relevant knowledge throughout the network poses an interesting challenge. In the context of all mentioned applications their individually required minimum prediction horizon should be subject to further investigation. Little research has been conducted in that topic to the best of our knowledge. We are only aware of Goff et al.'s (2001) study which determined that route discovery took on average 0.1 s for a MANET of 35 nodes. This result suggests that a slightly higher prediction horizon than 0.1 s should be sufficient to enable proactive routing in MANETs of similar size. Given this outcome and the high processor and communication speeds of current computers, we believe that the maximum prediction horizon of 4 s, which was used in this thesis, is considerably higher than required

for proactive applications of LQP.

The frequency of collisions in 802.11 is a function of the effectiveness of the employed CSMA/CA mechanism and the pattern and coordination of transmissions which are made by network-layer protocols and applications. In this work we evaluated LQP accuracy in the absence of such collisions. This was achieved in our simulations by transmitting beacon packets regularly in an a priori fixed pattern such that only one node could transmit a packet at any time and thus the node transmissions are perfectly coordinated. Such a scheme can be implemented in real-world MANETs with, for example, the help of globally synchronised clocks for which synchronisation protocols with much tighter than required deviation bounds (e.g. a maximum clock offset of 50 micro seconds for a 500-node MANET (Zhou & Lai 2005)) exist. However, even without clock synchronisation network-layer protocols are expected to coordinate their transmission patterns with or without explicit node agreement to minimise collisions since uncontrolled transmissions are well known to cause collisions and contention in MANETs as has already been shown in the early work of Ni et al. (1999). Thus we assume that typically only a small number of collisions occur, decreasing LQP accuracy only slightly. However, we see the need for further research to develop a component that coordinates not only transmissions between different nodes but also transmissions of different network-layer protocols (e.g. GCS, routing protocol) that currently operate independently of each other. Thus multiple beacons and control packets are transmitted ineffectively by various protocols. While cross-layer design addresses this problem, we believe that a future transmission scheduler component addresses the above problem better since it reduces communication load while maintaining the independence of the various protocols. If the impact of collisions on LQP accuracy is to be studied in the NS-2 simulator as future research, significant changes to its software architecture are required to obtain meaningful results. Currently, the NS-2 simulator models collisions by comparing the signal power of simultaneously received packets pairwise (Takai et al. 2001). If the difference in signal power between two simultaneously received packets is above a threshold, the packet with higher signal power is modelled as being successfully received; otherwise both packets are modelled as being lost. However, collisions are realistically

modelled by summing up the signal power of all interfering nodes first and subsequently considering this power in the SNR calculation to determine the success probability for packet reception (Takai et al. 2001). Since the current architecture of the NS-2 simulator allows only for pairwise comparisons in which, in a premature decision, at least one packet is internally discarded, the summation of the signal power of all interfering nodes is difficult to achieve and expensive to implement.

We investigated in this thesis LQP and its accuracy for pedestrians in microcellular urban environments for prediction horizons of up to 4 s. We determined that signal power predicts link quality better than its trend for nodes with walking speed since the influence of path loss is low in these circumstances. Our results apply also to higher-speed nodes such as cars albeit being restricted to shorter prediction horizons. For example, a car at 50 km/h, the typical speed limit in European cities, is about ten times faster than a pedestrian. Thus the LQP accuracy for pedestrians for 4 s ahead corresponds to the LQP accuracy for cars at 50 km/h for 0.4 s ahead. Since some results in the literature suggest that prediction horizons as short as 0.1 s are valuable to applications, our LQP algorithms are likely to be of practical use for higher-speed nodes also. However, if applications require longer prediction horizons, the proposed LQP algorithms are envisioned to provide better LQP accuracy when they are tailored towards use with higher-speed nodes. Since such nodes can travel considerably longer distances than pedestrians within the same prediction horizon, path loss and thus the trend of signal power are likely to be an important factor for prediction horizons in the order of a few seconds. Since the path loss depends strongly on the distance between nodes, location measurements would be highly beneficial. While accurate location measurements for pedestrians cannot realistically be made in urban environments, such measurements are feasible in cars where a combination of GPS, inertial systems and street maps is available. Thus the optimal predictor (6.23) from this work can be extended to consider path loss. Its parameters can be estimated by a linear estimator, using the same approach (Kay 1993, pp. 83, 94–97) as used for pedestrians, in which case the signal power is now regressed in the presence of coloured noise with respect to the nodes' distances. Since the consideration of coloured noise leads to a computationally expensive parameter

estimator, a fast estimator for cars would need to be given analogous to ours for pedestrians by, for example, assuming white noise for which a computationally inexpensive sequential linear regression can be employed (Kay 1993, pp. 242–251). However, while this white-noise assumption led in this work to a fast parameter estimator for pedestrians with only a slightly increased estimation variance compared to the optimal estimator, it is a subject for further research as to whether the same assumption leads to an accurate fast parameter estimator for LQP with cars.

Appendix A

A.1 Notational Conventions and Principal Symbols

Linear algebra	
$\mathbb{R}$	$\mathbb{R}$ is the set of real numbers
$\mathbf{X}$	$\mathbf{X}$ is a matrix or vector
$\mathbf{X}^T$	Transpose of matrix $\mathbf{X}$
$\mathbf{X}^{-1}$	Inverse of matrix $\mathbf{X}$
$\mathcal{X}$	$\mathcal{X}$ is a set
$\mathbf{1}$	Matrix of ones
Probability calculus and statistics	
$E[X]$	Expectation of random variable X
f_X	Probability density function of random variable X
F_X	Cumulative distribution function of random variable X
$\hat{F}_X$	Empirical distribution function of random variable X
$X \sim \mathcal{N}(\mu, \sigma)$	X is a normally distributed random variable with mean μ and variance σ
$\hat{X}$	Estimation of random variable X by some $g_1(X)$
$\tilde{X}$	Estimation of random variable X by some $g_2(X)$
$V[X]$	Variance of random variable X
ε_{KS}	Kolmogorov-Smirnov statistic

ε_{RMS}	Root-mean-square error
Θ	Unknown parameter to be estimated
ρ_{XX}	Autocorrelation of random variable X
ϱ_{XX}	Autocovariance of random variable X
$\varrho_{\mathbf{X}\mathbf{X}}$	Autocovariance matrix of random variable X
Time-computational complexity measures	
$\mathbf{O}(g(x))$	The complexity class $\mathbf{O}$ places an asymptotically higher bound on $g(x)$
$\Theta(g(x))$	$g(x)$ is in the asymptotic complexity class Θ
$\Omega(g(x))$	The complexity class Ω places an asymptotically lower bound on $g(x)$
Time and prediction	
$\tilde{X}_{T+\tau T}$	Tilde symbolises the prediction of a quantity (typically a random variable) X at time T for time $T + \tau$
t	Variable to denote time
T	Time at which a prediction is made
τ	Prediction horizon
Node and node movements	
i	i is a node and is displayed in the font sans serif
(i,j)	Link between node i and j
$(i \rightarrow j)$	Link between node i and j , where i is transmitter and j is receiver
d_t	Distance between two nodes with respect to each other at time t
N_N	Number of nodes
N_V	Number of samples to estimate the average node speed
$\mathbf{o}_{t,i}$	Position of node i at time t

$v_{t,i}$	Speed of node i at time t
$\delta_{[t-x,t]}$	Aggregated distance that two nodes have moved between $[t - x, t]$ with respect to the origin of an Euclidian coordinate system
Principal symbols	
a	Ratio of direct to indirect power for small-scale fading wideband signals in linear space
$a_{\text{(dB)}}$	Ratio of direct to indirect power for small-scale fading wideband signals in dB
$B_{\text{(dBm)}}$	Power in dBm given by a path-loss model
$c, c_1, c_2, \dots$	Constants
$C_{\text{(dBm)}}$	Constant that approximates the local mean power as given by a path-loss model in dBm
$g, g_1, g_2, \dots$	Functions
g_k	Function that maps the wideband propagation parameters $a, \Delta L_{\text{max}}$ for small-scale fading wideband signals of different wireless standards to the Ricean- K factor.
h	Small-scale fading signal envelope in V
H	Small-scale fading signal power in W
K	Ricean K -factor, usually ratio of direct to indirect power for small-scale fading narrowband signals
m	Nakagami shape factor
N_C	Number of samples to estimate $C_{\text{(dBm)}}$
N_H	Number of samples to estimate the local mean power
N_{Wv}	Number of radio waves
P_b	Average bit error probability
q	Packet length in bits
r	Received signal envelope in V
R	Received signal power in W

$R_{\text{(dBm)}}$	Received signal power in dBm
$S_{\text{(dB)}}$	Large-scale fading signal power with the mean of 0 dB
$S'_{\text{(dBm)}}$	Large-scale fading signal power with the mean given by a path-loss model in dBm
γ_b	Average signal-to-noise ratio
ΔL_{max}	Maximum difference in propagation path lengths in m
Δ_s	Spatial distance between signal-power samples for local mean power estimation in m
κ	Path-loss exponent
λ_c	Carrier wavelength in m
ρ_{dref}	Normalised autocovariance coefficient for large-scale fading determined at a reference distance dref
σ_S	Standard deviation of large-scale fading
Υ	Sampling interval in a discrete system
ϕ	Time of link failure
Φ	Packet reception probability
Ω_p	Local mean power in W; path loss and large-scale fading are assumed to be constant
$2\Delta f$	Receiver bandwidth in Hz

A.2 Abbreviations and Acronyms

AODV	Ad hoc On-demand Distance Vector (routing protocol)
BER	Bit Error Rate
BEP	Bit Error Probability
CDF	Cumulative Distribution Function
CITY	random waypoint mobility model CITY section
CRC	Cyclic Redundancy Check
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance

CTS	Clear To Send
DBPSK	Differential Binary Phase Shift Keying
DES	Distance Exponential Shadowing
DIFS	Distributed Inter-Frame Space
DPSK	Differential Phase Shift Keying
DQPSK	Differential Quadrature Phase Shift Keying
DSDV	Destination-Sequenced Distance-Vector (routing protocol)
DSR	Dynamic Source Routing (routing protocol)
DSRC	Dedicated Short Range Communication (standard)
DSSS	Direct Sequence Spread Spectrum
EDF	Empirical Distribution Function
ETX	Expected Transmission Count
FIFO	First In First Out (queue)
GCS	Group Communication System
GPS	Global Positioning System
KS	Kolmogorov-Smirnov (statistic or test)
IBSS	Independent Basic Service Set
ID	IDentifier
IID	Independent Identically-Distributed (random variable)
LOS	Line-Of-Sight
LQP	Link Quality Prediction
LQPR	Link Quality PredictoR
MAC	Medium Access Control
MAE	Mean Absolute Error
MANET	Mobile Ad hoc NETwork
MGF	Moment Generating Function
Mbps	Mega bits per second
MHz	Mega Hertz
MLE	Maximum Likelihood Estimation

NLOS	Non-Line-Of-Sight
ODMRP	On-Demand Multicast Routing Protocol
OFDM	Orthogonal Frequency Division Multiplexing
OSI	Open Systems Interconnection
PP	Partition Predictor
PDF	Probability Density Function
PHY	Physical (layer)
PLCP	Physical Layer Convergence Procedure
PRP	Packet Reception Probability
PRPP	Packet Reception Probability Prediction
RABR	Route-lifetime Assessment Based Routing (protocol)
RFC	Request For Comment
RP	Routing Protocol
RTS	Request To Send
RWP	Random WayPoint mobility model
SNR	Signal-to-Noise Ratio
TCP	Transmission Control Protocol
TS	Transmission Scheduler
UDP	User Datagram Protocol
UMTS	Universal Mobile Telecommunications System (standard)
WiMAX	Wireless interoperability for Microwave ACCess (standard)

A.3 Constants of Expression (4.9)

Con- stant	UMTS	DSRC	802.11, 802.11b	WiMAX	802.11a, HIPERLAN type II
$c_{0,0}$	$2.65638 \cdot 10^1$	$5.73860 \cdot 10^1$	$6.59047 \cdot 10^1$	$8.76270 \cdot 10^1$	$1.13186 \cdot 10^2$
$c_{1,1}$	$1.37812 \cdot 10^1$	$4.23944 \cdot 10^1$	$5.26263 \cdot 10^1$	$7.48435 \cdot 10^1$	$9.38172 \cdot 10^1$
$c_{1,2}$	$2.86887 \cdot 10^0$	$2.20801 \cdot 10^0$	$2.68786 \cdot 10^0$	$1.81718 \cdot 10^0$	$9.27280 \cdot 10^{-1}$
$c_{1,3}$	$-7.25628 \cdot 10^{-1}$	$-2.68774 \cdot 10^0$	$-2.07149 \cdot 10^0$	$-2.56708 \cdot 10^0$	$-2.93542 \cdot 10^0$
$c_{1,4}$	$-5.55885 \cdot 10^{-1}$	$7.24910 \cdot 10^{-1}$	$1.28425 \cdot 10^0$	$1.47843 \cdot 10^0$	$1.36397 \cdot 10^0$
$c_{1,5}$	$-5.08939 \cdot 10^{-2}$	$-2.74460 \cdot 10^{-1}$	$-5.48678 \cdot 10^{-1}$	$-8.57421 \cdot 10^{-1}$	$-1.20001 \cdot 10^0$
$c_{1,6}$	$4.94091 \cdot 10^{-2}$	$1.14778 \cdot 10^{-1}$	$6.47051 \cdot 10^{-2}$	$1.98571 \cdot 10^{-1}$	$1.04618 \cdot 10^0$
$c_{1,7}$	$2.51037 \cdot 10^{-1}$	$7.59186 \cdot 10^{-1}$	$4.26026 \cdot 10^{-1}$	$5.78706 \cdot 10^{-3}$	$3.93874 \cdot 10^{-1}$
$c_{2,1}$	$-3.28653 \cdot 10^{-1}$	$1.62175 \cdot 10^{-1}$	$7.30515 \cdot 10^{-1}$	$-2.20253 \cdot 10^0$	$1.15162 \cdot 10^0$
$c_{2,2}$	$-1.72785 \cdot 10^{-1}$	$-1.15478 \cdot 10^{-1}$	$3.74852 \cdot 10^{-2}$	$-9.96457 \cdot 10^{-1}$	$6.37858 \cdot 10^{-2}$
$c_{2,3}$	$-3.11678 \cdot 10^{-1}$	$-1.84657 \cdot 10^{-1}$	$-2.16077 \cdot 10^{-1}$	$-1.06276 \cdot 10^0$	$-1.26930 \cdot 10^{-1}$
$c_{2,4}$	$-3.57024 \cdot 10^{-2}$	$1.21763 \cdot 10^{-1}$	$-1.55779 \cdot 10^{-1}$	$-7.02574 \cdot 10^{-1}$	$4.46329 \cdot 10^{-2}$
$c_{2,5}$	$-1.88604 \cdot 10^{-2}$	$-1.40336 \cdot 10^{-1}$	$-3.45822 \cdot 10^{-1}$	$-6.53393 \cdot 10^{-1}$	$4.56496 \cdot 10^{-2}$
$c_{2,6}$	$2.50330 \cdot 10^{-1}$	$-9.47594 \cdot 10^{-2}$	$-1.81959 \cdot 10^{-2}$	$-3.01985 \cdot 10^{-1}$	$5.04646 \cdot 10^{-1}$
$c_{3,1}$	$-1.48940 \cdot 10^{-1}$	$2.45746 \cdot 10^{-1}$	$3.78772 \cdot 10^{-1}$	$-1.10417 \cdot 10^0$	$3.14616 \cdot 10^{-1}$
$c_{3,2}$	$-1.42424 \cdot 10^{-1}$	$-2.70189 \cdot 10^{-2}$	$-2.57752 \cdot 10^{-2}$	$-9.16816 \cdot 10^{-1}$	$3.40990 \cdot 10^{-1}$
$c_{3,3}$	$1.26737 \cdot 10^{-2}$	$-7.43703 \cdot 10^{-2}$	$8.94587 \cdot 10^{-2}$	$-8.15853 \cdot 10^{-1}$	$1.24125 \cdot 10^{-1}$
$c_{3,4}$	$8.78986 \cdot 10^{-2}$	$-3.30148 \cdot 10^{-1}$	$-7.63737 \cdot 10^{-2}$	$-5.66470 \cdot 10^{-1}$	$-2.44335 \cdot 10^{-1}$
$c_{3,5}$	$1.34503 \cdot 10^{-1}$	$-3.09275 \cdot 10^{-1}$	$-1.95375 \cdot 10^{-1}$	$-3.76809 \cdot 10^{-1}$	$1.47865 \cdot 10^{-3}$
$c_{4,1}$	$-4.86988 \cdot 10^{-2}$	$-1.30967 \cdot 10^{-1}$	$1.77666 \cdot 10^{-1}$	$4.80351 \cdot 10^{-1}$	$-7.77204 \cdot 10^{-1}$
$c_{4,2}$	$3.94004 \cdot 10^{-2}$	$2.00451 \cdot 10^{-1}$	$2.17075 \cdot 10^{-1}$	$-2.30076 \cdot 10^{-1}$	$1.26390 \cdot 10^{-2}$
$c_{4,3}$	$1.44729 \cdot 10^{-1}$	$-6.33639 \cdot 10^{-2}$	$1.83147 \cdot 10^{-1}$	$-3.15561 \cdot 10^{-1}$	$-1.81383 \cdot 10^{-1}$
$c_{4,4}$	$1.43865 \cdot 10^{-1}$	$-2.38714 \cdot 10^{-1}$	$1.52262 \cdot 10^{-1}$	$3.35545 \cdot 10^{-2}$	$-4.05003 \cdot 10^{-1}$
$c_{5,1}$	$2.17622 \cdot 10^{-1}$	$-1.44119 \cdot 10^{-1}$	$-5.02657 \cdot 10^{-2}$	$1.85959 \cdot 10^0$	$-1.36030 \cdot 10^0$
$c_{5,2}$	$9.43872 \cdot 10^{-3}$	$3.80796 \cdot 10^{-1}$	$4.36697 \cdot 10^{-1}$	$1.96556 \cdot 10^{-1}$	$4.25680 \cdot 10^{-2}$
$c_{5,3}$	$1.22688 \cdot 10^{-1}$	$1.42236 \cdot 10^{-1}$	$3.29747 \cdot 10^{-1}$	$2.83263 \cdot 10^{-2}$	$3.43354 \cdot 10^{-2}$

Table A.3: Constants of Expression (4.9) part I

Con- stant	UMTS	DSRC	802.11, 802.11b	WiMAX	802.11a, HIPERLAN type II
$c_{6,1}$	$2.66421 \cdot 10^{-1}$	$5.29977 \cdot 10^{-2}$	$-1.44150 \cdot 10^{-1}$	$2.15135 \cdot 10^0$	$-1.01214 \cdot 10^0$
$c_{6,2}$	$6.35142 \cdot 10^{-2}$	$2.97995 \cdot 10^{-1}$	$3.39882 \cdot 10^{-1}$	$2.53135 \cdot 10^{-1}$	$2.33021 \cdot 10^{-1}$
$c_{7,1}$	$1.95478 \cdot 10^{-1}$	$5.41460 \cdot 10^{-2}$	$-1.37397 \cdot 10^{-1}$	$9.79141 \cdot 10^{-1}$	$-4.11092 \cdot 10^{-1}$
$c_{8,1}$	$2.45464 \cdot 10^1$	$5.55525 \cdot 10^1$	$6.25894 \cdot 10^1$	$7.87694 \cdot 10^1$	$1.10503 \cdot 10^2$
$c_{8,2}$	$-9.70984 \cdot 10^{-1}$	$2.36040 \cdot 10^0$	$1.30470 \cdot 10^0$	$-4.46444 \cdot 10^0$	$6.27350 \cdot 10^0$
$c_{8,3}$	$-3.47196 \cdot 10^{-1}$	$4.92801 \cdot 10^{-1}$	$3.67036 \cdot 10^{-1}$	$-1.48506 \cdot 10^0$	$1.07976 \cdot 10^0$
$c_{8,4}$	$5.87212 \cdot 10^{-1}$	$-1.13974 \cdot 10^0$	$-7.74282 \cdot 10^{-2}$	$2.05396 \cdot 10^0$	$-3.18989 \cdot 10^0$
$c_{8,5}$	$1.10683 \cdot 10^0$	$-2.43033 \cdot 10^0$	$-8.28685 \cdot 10^{-1}$	$4.60730 \cdot 10^0$	$-6.66513 \cdot 10^0$
$c_{8,6}$	$1.36636 \cdot 10^0$	$-2.44872 \cdot 10^0$	$-9.42947 \cdot 10^{-1}$	$5.27685 \cdot 10^0$	$-7.11342 \cdot 10^0$
$c_{8,7}$	$9.04447 \cdot 10^{-1}$	$-1.68777 \cdot 10^0$	$-6.69374 \cdot 10^{-1}$	$3.21195 \cdot 10^0$	$-4.59178 \cdot 10^0$
$c_{8,8}$	$3.41023 \cdot 10^{-1}$	$-4.90294 \cdot 10^{-1}$	$-1.13625 \cdot 10^{-1}$	$8.92708 \cdot 10^{-1}$	$-1.27969 \cdot 10^0$
$c_{9,1}$	$1.54564 \cdot 10^1$	$4.59253 \cdot 10^1$	$5.66118 \cdot 10^1$	$8.23151 \cdot 10^1$	$1.00352 \cdot 10^2$
$c_{9,2}$	$3.06967 \cdot 10^0$	$2.27811 \cdot 10^0$	$2.76990 \cdot 10^0$	$2.30991 \cdot 10^0$	$1.21875 \cdot 10^0$
$c_{9,3}$	$-5.02265 \cdot 10^{-1}$	$-2.58672 \cdot 10^0$	$-1.93193 \cdot 10^0$	$-2.00708 \cdot 10^0$	$-2.64205 \cdot 10^0$
$c_{9,4}$	$-4.57437 \cdot 10^{-1}$	$5.98170 \cdot 10^{-1}$	$1.41196 \cdot 10^0$	$1.81532 \cdot 10^0$	$1.25771 \cdot 10^0$
$c_{9,5}$	$7.25653 \cdot 10^{-2}$	$-1.92815 \cdot 10^{-1}$	$-3.22624 \cdot 10^{-1}$	$-4.95736 \cdot 10^{-1}$	$-1.18167 \cdot 10^0$
$c_{9,6}$	$-1.81167 \cdot 10^{-1}$	$1.12025 \cdot 10^{-1}$	$3.30403 \cdot 10^{-2}$	$3.81488 \cdot 10^{-1}$	$5.99549 \cdot 10^{-1}$
$c_{9,7}$	$2.40094 \cdot 10^{-1}$	$9.12304 \cdot 10^{-1}$	$4.47269 \cdot 10^{-1}$	$1.46104 \cdot 10^{-1}$	$3.43866 \cdot 10^{-2}$
$c_{9,8}$	$-1.66003 \cdot 10^{-1}$	$-6.86901 \cdot 10^{-2}$	$-3.36637 \cdot 10^{-1}$	$-8.67049 \cdot 10^{-2}$	$-3.38656 \cdot 10^{-1}$

Table A.4: Constants of Expression (4.9) part II

A.4 Conversion between Decibel and Watt

Decibel (dB) is the ratio x_{dB} of a power x to a reference power x_{ref} (White 2004, p. 35) and thus is defined as

$$x_{\text{dB}} = \frac{x}{x_{\text{ref}}}(\text{db}) = 10 \log_{10} \left(\frac{x}{x_{\text{ref}}} \right). \quad (\text{A.1})$$

Applying $10^{\frac{(\cdot)}{10}}$ to (A.1) results in

$$10^{\frac{x_{\text{dB}}}{10}} = 10^{\frac{x}{10x_{\text{ref}}}} = \frac{x}{x_{\text{ref}}} \quad (\text{A.2})$$

and thus it follows that

$$x_{\text{ref}} 10^{\frac{x_{\text{dB}}}{10}} = x \quad (\text{A.3})$$

where x_{ref} determines the unit of x .

Here are some expressions for typical reference powers:

(White 2004, p. 37)

$$x_{(\text{dBm})} = 10 \log_{10} \frac{x_{(\text{mW})}}{1 \text{ mW}} \quad (\text{A.4})$$

(White 2004, p. 37)

$$x_{(\text{dBm})} = 10 \log_{10} \frac{x_{(\text{W})}}{0.001 \text{ W}} \quad (\text{A.5})$$

(White 2004, p. 37)

$$x_{(\text{dBW})} = 10 \log_{10} \frac{x_{(\text{W})}}{1 \text{ W}} \quad (\text{A.6})$$

(Saunders 1999, p. 89)

$$x_{(\text{dBW})} = x_{(\text{dBm})} - 30 \quad (\text{A.7})$$

From (A.7) follows that

$$x_{(\text{dBm})} = x_{(\text{dBW})} + 30. \quad (\text{A.8})$$

Since this thesis requires the conversion from $x_{(\text{dBm})}$ to $x_{(\text{W})}$, this conversion can be expressed by using (A.3), (A.6) and (A.7) as

$$x_{\text{W}} = 10^{\frac{x_{\text{dBW}}}{10}} = 10^{\frac{x_{(\text{dBm})} - 30}{10}}. \quad (\text{A.9})$$

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