Computer Networks 56 (2012) 3629–3638

Contents lists available at SciVerse ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Link quality estimation in wireless multi-hop networks using Kernel based methods

David Palma [a,*], Helder Araujo [b], Marilia Curado [a]

[a] Department of Informatics Engineering, Centre for Informatics and Systems, University of Coimbra, Coimbra, Portugal
[b] Institute for Systems and Robotics (ISR), University of Coimbra, Coimbra, Portugal

ARTICLE INFO

Article history:
Received 1 February 2012
Received in revised form 5 June 2012
Accepted 24 July 2012
Available online 1 August 2012

Keywords:
Ad hoc networks
Link quality
Quality estimation
Kernel Methods
Kernel Estimators

ABSTRACT

A new approach for link modelling in wireless multi-hop networks is described for portable devices, based on Kernel Regression Statistics. A non-parametric estimation of errors in the wireless medium provides an efficient and accurate model of link errors between any two nodes. This estimation results from the analysis of the inter-arrival time between any periodically sent packets. The obtained results prove that it is possible to infer on link quality without having unrealistic assumptions or additional overhead, by using Kernel Methods. Moreover, similar performances were achieved for different scenarios, without requiring model recalculations. The presented results show that the proposed link quality estimation can be used in order to improve wireless connectivity and ubiquity in future networks.

1. Introduction

The dissemination of new portable devices with enhanced communication characteristics has revolutionized the world in many aspects. Not only on the social side, where people are connected by their cell phones, personal digital assistants (PDAs) or laptops, but also on an economical and professional perspective, where these devices have introduced new ways of dealing with different situations. In fact, it is expected that in a near future, users will own several wireless enabled gadgets [1], demanding infrastructures or other connectivity alternatives.

Many works have been proposed for the creation of multi-hop wireless networks with different routing protocols. Despite providing some insights on how to handle these networks and find communication paths between different devices, these protocols usually disregard the environment behind wireless communication, ignoring, for instance link quality or even energy aspects. With the purpose of solving this issue, link metric extensions such as the Expected Transmission Time (ETT) among many others [2], have been added to these protocols. Furthermore, works more focused on modelling the wireless link specificities have been proposed, requiring some assumptions in order to correctly operate in this environment. However, many of these works' assumptions render them unrealistic in scenarios such as search and rescue, where information about mobility or position awareness is not available.

Taking into account that routing protocols benefit from knowledge about link quality, optimal route calculation should avoid poor quality links. Targeting the combination of the practical sense of multi-hop routing protocols, by avoiding strict assumptions with a profound and formal study of a wireless link quality model, will allow an efficient and realistic comprehension of the wireless environment. This understanding is fundamental for the creation and development of a new age of wireless interconnected devices and applications.

Bearing in mind the simplistic approach taken by common routing protocols, which periodically send routing probes to detect a wireless link, this work will present an analysis of the interval between routing messages sent,

* Corresponding author. Tel.: +351 965637055.
E-mail addresses: palma@dei.uc.pt (D. Palma), helder@isr.uc.pt (H. Araujo), marilia@dei.uc.pt (M. Curado).

1389-1286/$ - see front matter
http://dx.doi.org/10.1016/j.comnet.2012.07.012

as a link quality evaluation parameter. This will allow a practical and realistic approach for the link quality evaluation purpose, in conjunction with a thorough theoretical statistical analysis of a wireless link quality, leading to the definition of an accurate link quality estimator. A new approach, using Kernel Regression Estimators, is proposed for this task, as this method can provide the desired link quality evaluation without requiring unrealistic assumptions. Such estimator, which results from Kernel Regression Fitting presented by Wand and Jones [3], has been implemented and evaluated in the OPNET Modeler network simulator [4], revealing a significantly precise link quality estimation in real-time, simply by measuring the time interval between routing messages.

In Section 2 an analysis of related work regarding link modelling is presented. The specification of the proposed model for link quality estimation is introduced in Section 3. The required steps for the calculation of the defined Kernel Model, as well as the validation results for this model, are specified in Section 4. The final thoughts and insights on future work are discussed in Section 5.

2. Related work

The estimation of link quality and its availability in wireless networks is an important feature to consider in route establishment, in particular, it is more relevant in mobile ad hoc networks, where link quality variations are frequent. Several authors have proposed different approaches concerning the analysis of link availability.

The main drawback of most of the existing works is either the usage of unreliable parameters, which are prone to errors and variations, such as signal strength and available energy, or the requirement of unrealistic or complex assumptions such as positioning knowledge (for instance Global Positioning System, GPS coordinates), specific mobility models and characteristics (i.e. constant speed, known direction, known epochs), among many others. However, a relevant contribution from these works is the proposal of new routing protocols and thorough formal models which allow a better comprehension of link related aspects.

Regarding the analysis of link quality taking into account mobility aspects, Yu et al. [5] rely on the assumption that nodes are able to assess their own mobility parameters. For instance, knowledge about the nodes' average speed, pause time, direction and epoch time is necessary for predicting quality degradation, as well as the assumption of perfectly symmetric links. Moreover, this work's conclusions depend on the used mobility model, which must be the Random Waypoint Model with particular specificities such as independent and identically distributed (*i.i.d.*) speeds, epochs and directions.

Link lifetime (LLT) [6] estimation can be an extremely important feature to consider in route establishment. This aspect is more relevant in network scenarios that consider mobility where link breakages are frequent. The work presented by Huang and Bai [6] suggests an approach which uses a Markov Chain Model to determine the availability of a link between two nodes, by describing the relative movement of both, knowing the initial distance between them. A comparison of the proposed model with previous works shows that the Markov Chain Model outperforms other approaches that use the Rayleigh model [7] to predict node distribution, being able to increase stability in the construction of clustered networks [8]. However, this work relies on assumptions such as the knowledge of the distance between two nodes (either by using GPS or by analysing signal strength) or even assumptions on link characteristics considering them always bidirectional within a distance of R meters, not considering radio irregularity [9]. Additionally, assumptions on the mobility model, the Random Walk Mobility Model, are also required, such as a uniform distribution of speed and direction, as well as the same mean epoch length for each node.

A two-state Markov Chain Model is also proposed by Wu et al. [10] for the evaluation of a Single-Node Link Lifetime (S-LLT) using the Random Direction Mobility Model and assuming that the time duration of each epoch is denoted by a random variable that is exponentially distributed with a known parameter λ_m. Assumptions regarding bidirectional links, known mobility direction and speed are also taken, both being uniformly distributed between $[0, 2\pi]$ and $[v_{min}, v_{max}]$.

Link availability is a parameter often considered as a suitable metric for increasing routing performance in Mobile Ad hoc NETworks (MANETs). By assuming knowledge about nodes' direction and position while considering a constant speed within a Time Period (T_p) and independent movements, Jiang et al. [11] propose a link availability quantity estimation. This estimation is achieved by exploiting the instantly available velocity, reflecting the dynamic nature of the link status. The authors also propose a T_p estimation based on a mobility model that follows the assumption that terminal mobility is uncorrelated and that epochs are exponentially distributed with a known mean. In addition to the mobility related assumptions, all nodes are expected to know their positions by using GPS devices.

Shu and Li [12] consider node speed in a wireless network as being responsible for link failure and therefore poor network performance. A link quality estimation is achieved by using a simplified version of the Random Waypoint Mobility Model, where nodes move in an arbitrary large area with no obstacles (i.e. no boundaries). It is also assumed that all nodes constantly move at the same speed with no pause times and, similarly to other works, that every link is bidirectional within a radius of R meters.

Another work regarding link evaluation is presented by Manoj et al. [13], which estimates link lifetime by using a simple linear regression for path choice in a reactive routing protocol. However, this work relies on the used propagation model and link specificities such as the transmit power, channel and frequency, in order to obtain node positioning knowledge, which is required for the performed link estimates.

The work presented by Zhang et al. [14] has a slightly different perspective trying to consider LLT determination taking into account the energy drain rate and relative mobility estimation of wireless nodes. The presented estimation of route lifetime relies on the assumptions of no energy limitations in any of the observed nodes and of nodes moving in the same direction at a constant speed considering a short enough period of time. Moreover, it requires node positioning awareness, either by using GPS or by assuming that transmitted packets are sent with the same power level as perceived by the receiver, which then can apply the radio propagation model for distance calculation.

A comparison summary of the presented link modelling works is shown in Table 1, using as comparison parameters the assumptions of each proposal – which can be related with the mobility model, link characteristics or positioning knowledge. The accuracy of the used validation scheme and contribution with a correct formal model are also taken into account. This table confirms that most of the existing models have strong and unrealistic assumptions and, in addition, some fail to provide a proper validation and formal model.

Not directly related with link quality evaluation, but closely concerned with mobile networking modelling, an innovative work is presented by Saeed et al. [15] which consists on using Neuro-Fuzzy Modelling and Neural Network Modelling for analysing the behaviour of different routing protocols, namely the Dynamic Source Routing (DSR) [16], the Ad hoc On-Demand Distance Vector (AODV) [17] and the Optimized Link State Routing (OLSR) [18] Protocols in MANETs with variable and attainable parameters such as the number of nodes or mobility. This work provides Empirical Equation Models by analysing quantitative data using polynomial and multiple linear regressions. The authors use the network's context (node number and mobility) as inputs in conjunction with the network's performance (delay, routing delivery rate, routing packets delivery rate and routing load) as outputs for modelling. The modelled results are obtained by using simulation data for each parameter and routing protocol, showing the main differences between the empirical equations, neural networks and Neuro-Fuzzy Models. Despite not presenting validation results compared against the presented models, the proposed models (Neural Networks and Neuro-Fuzzy) are both efficient and accurate in representing wireless networks' features without requiring any simplifications of their complex and dynamic aspects. The main disadvantage of using these methods is that they require previous training.

In the following section a new link quality estimator is presented, using Kernel Methods to provide a feasible alternative to the existing models, without assuming known mobility patterns, positioning information nor link specific characteristics. Moreover, a formal model for this estimator and a proper validation are also presented.

3. An accurate model for link quality estimation

This work is focused on the usage of local polynomial Kernel Estimators for the determination of link quality. In fact, by simply analysing the time interval Δt reception of periodical routing messages, an accurate model for link quality estimation is derived. This technique allows an efficient model that does not considered unrealistic assumptions.

Kernel Estimators are applied by Kushki et al. [19] for positioning purposes in Wireless Local Area Networks, by creating "fingerprints" using the received signal strength (RSS). The results presented show that Kernel Regression is an efficient solution for such scenarios, thus motivating further usage of Kernel Methods in wireless modelling. Considering Link Quality, Kernel Methods will allow, through the use of existing routing or signalling messages, the determination of a link quality model estimator. The purpose is to analyse the interval between these periodically received messages and based upon them, estimate the quality of the used wireless link. These periodic messages can be obtained, for instance, from the routing protocol or from Layer-2 messages, such as beacons.

In particular, focusing on the OLSR protocol, it periodically sends *HELLO* messages with an interval of $2 \pm d$, $d \in X \sim U(0, 0.5)$ seconds, being d an added delay following a uniform distribution between 0 and 0.5 s. These messages are sent so that new links and lost links are regularly detected. The random factor is added in order to try to avoid nodes from sending routing packets at the same time, which would cause several collisions in the wireless medium. The expected average interval between *HELLO* messages in a perfect connection would be exactly $E(X = \widehat{\Delta t}) = 2$ s. However, as packet collisions and interferences exist, errors may occur, resulting in lost packets. Throughout this work, the Quality of a Link will depend on the number of lost packets, between two received *HELLO* messages, therefore, a link without packet losses has perfect link quality. The link quality is defined by the following equation:

$$Link\ Quality_{\Delta t} = \frac{1}{1 + \text{packets lost}}. \quad (1)$$

Even though this work focuses on the number of packet losses for the link quality assessment, other parameters could be considered. For instance the delay between a sent

Table 1
Wireless link modelling.

Existing Approaches	Assumptions on Mobility	Assumptions on Link	Assumptions on Positioning	Proper validation	Formal model
Yu et al. [5]	✔	✔	×	✔	×
Huang and Bai [6]	✔	✔	✔	×	✔
Wu et al. [10]	✔	✔	✔	✔	✔
Jiang et al. [11]	✔	✔	✔	✔	✔
Shu and Li [12]	✔	✔	×	×	✔
Manoj et al. [13]	×	✔	✔	×	✔
Zhang et al. [14]	✔	✔	✔	✔	×

and received *HELLO* or even the number of Layer-2 retransmissions could be used to classify the quality of wireless link. However the delay between two neighbour nodes is very small, since they are directly connected, and Layer-2 retransmissions may not exist in several scenarios such as in real-time video streaming networks.

The time interval between a packet being sent and received depends not only on propagation characteristics, but also on the number of required packets sent until one is properly received, as depicted in Fig. 1. Fig. 1a represents a link quality of 100% for Δt_1, Δt_2 and Δt_3, while in Fig. 1b, Δt_1 has a link quality of 100% and in Δt_2 the link quality is only of 50%. These errors are more prone to occur when a poor link quality is registered. By measuring the interval between consecutive *HELLO* messages, an estimation of the link quality can be retrieved using Kernel Regression Estimation.

As previously mentioned, the estimators used in this work are from the class of Kernel-type regression, which allows the estimation of a least-squared weighted regression function $\hat{m}(x;p,h)$, that "locally" fits a pth degree polynomial, for a given data set (x,y) [3], where h is the smoothing or bandwidth parameter. In this work, the (x,y) data set consists of the tuple Δt and link quality respectively.

Kernel Methods and, in particular, Kernel Regression methods are also called *memory-based methods*, because they require keeping or storing the entire training set to estimate or compute future data points. In fact these methods fit a model separately at each data point x_i, and only data points close to x_i are used to fit the above mentioned model. This fitting process results in an estimated function smooth in $\Re$. In this work the training set is not required after the model calculation as no further data points need to be computed, thus solving the possible memory limitation.

Other regression functions related with Kernel Regression are the K-Nearest Neighbour (KNN) classification, State Vector Machines (SVMs), Neuro-Fuzzy Models and Radial Basis Functions (RBFs), which may not be so robust. For instance, on the classification RSS based fingerprints, Kushki et al. [19] do not consider the KNN approach, as it presents a poor performance when training vectors are nonconvex and multimodal. Also, previously used SVMs and RBFs have shown no resilience in scenarios with highly dynamic wireless settings, where MANETs should be included.

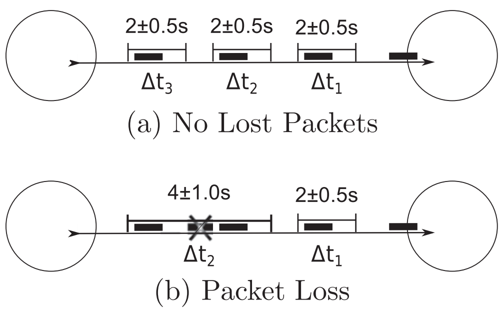

Fig. 1. Periodic routing message exchange.

Being m the true regression function of the real link quality observed, the random regression model can be written as $m(x) = E(Q|X = x)$, representing the conditional expectation of variable Q relative to a variable X. From this point forward, q will correspond to the link's quality observed between two nodes and x will be the Δt between measured routing messages (Q and X will be the estimated values).

The Kernel function K is a non-negative real-valued integrable function defined to be smooth with a maximum at 0 and with the following constraint:

$$\int_{-\infty}^{+\infty} K(x)\mathrm{d}x = 1 \quad \text{and} \quad K(-x) = K(x), \ \ \forall x \in \Re. \tag{2}$$

Two commonly used Kernels are the Epanechnikov Kernel and the Gaussian Kernel [3] presented in Eqs. (3) and (4) respectively.

$$K_h(x_i - x) = \frac{3}{4}\left(1 - \frac{|x_i - x|^2}{h}\right)_{\left\{\frac{|x_i - x|}{h} \leqslant 1\right\}}, \tag{3}$$

$$K_h(x_i - x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\frac{|x_i - x|^2}{h}}. \tag{4}$$

As previously mentioned, the Kernel Regression Fitting depends on a smoothing parameter h, usually referred to as bandwidth. The choice of a correct bandwidth is extremely important to prevent under or over fitted estimations. A bandwidth selector, as defined by Wand and Jones [3], is a method that uses the data $X_1, \ldots, X_n$ to produce a bandwidth $\hat{h}$. Typically, bandwidth selectors are divided in two different classes, the *quick and simple* and *hi-tech* selectors. The first class of selectors provide an acceptable bandwidth value, without any mathematical guarantees, thus being disregarded in this work. The *hi-tech* selectors are computationally more complex and aim at finding optimal bandwidth values, which will be presented later in this work.

With Kernel Regression, at point x the estimator $\hat{m}(x;p,h)$ is obtained through the fitting of $\beta_0 + \beta_1(\cdot - x) + \cdots + \beta_p(\cdot - x)^p$ to (x_i, Q_i) using the least squares with $K_h(x_i - x)$, which acts as a weighting function in the fitting, such that $\hat{\beta} = (\widehat{\beta_0}, \ldots, \widehat{\beta_p})^T$ minimises:

$$\sum_{i=1}^{n} \{Q_i - \beta_0 - \cdots - \beta_p(x_i - x)^p\}^2 K_h(x_i - x). \tag{5}$$

Considering $\hat{\beta} = \left(X_x^T W_x X_x\right)^{-1} X_x^T W_x Q$, as defined by Jones and Watson [3], it is the solution obtained by the standard weighted least squares theory, assuming that $X_x^T W_x X_x$ is invertible, where $Q = (Q_1, \ldots, Q_n)^T$ is the vector of responses,

$$X_x = \begin{bmatrix} 1 & x_1 - x & \cdots & (x_1 - x)^p \\ \vdots & \ldots & \ddots & \vdots \\ 1 & x_n - x & \cdots & (x_n - x)^p \end{bmatrix} \tag{6}$$

is an $n \times (p+1)$ matrix and $W_x = diag\{K_h(x_1 - x), \ldots, K_h(x_n - x)\}$ is an $n \times n$ diagonal matrix of weights.

In this work, a 1st degree polynomial estimation was used, so the local linear estimator $\hat{m}(x;1,h)$ is defined by the following equation:

$$n^{-1}\sum_{i=1}^{n}\frac{\{\hat{s}_2(x;h)-\hat{s}_1(x;h)(x_i-x)\}K_h(x_i-x)Q_i}{\hat{s}_2(x;h)\hat{s}_0(x;h)-\hat{s}_1(x;h)^2}$$

where

$$\hat{s}_r(x;h)=n^{-1}\sum_{i=1}^{n}(x_i-x)^rK_h(x_i-x),\quad \forall r\in 0,1,2. \tag{7}$$

In order to guarantee the quality of the obtained Kernels, some of the most commonly used optimality *hi-tech* criteria for selecting a bandwidth matrix will be considered. These are, for instance, the Mean Integrated Squared Error (*MISE*) and the Averaged Squared Error (*ASE*), which is used in this work.

$$ASE(h)=\hat{m}_h=\frac{1}{n}\sum_{j=1}^{n}\{\hat{m}_h(X_j)-m(X_j)\}^2w(X_j). \tag{8}$$

The *ASE* is a discrete approximation of the Integrated Squared Error (*ISE*) which has been shown by Marron and Härdle [20] to lead asymptotically to the same level of smoothing as the *ISE* and *MISE*. Therefore, without significant loss of performance and knowing that it is the easiest to calculate and handle [21], the *ASE* is clearly an appropriate bandwidth selector.

4. Model parametrisation and validation

Having defined the main theoretical aspects of the proposed link quality estimator model, this section aims at presenting the necessary steps to obtain traces generated by simulation until the final link quality estimation results are reached. Moreover, an implementation of the proposed Kernel Estimator in the OPNET Modeler Wireless Suite® [4] network simulator is also presented with the purpose of validating the estimated link quality values.

4.1. Link quality estimator calculation

With the purpose of obtaining data traces for the pair (x,q) required by the previously defined model, x being time interval Δt between routing messages and q the link quality, several simulations were performed using the OPNET simulator. These traces were gathered from two nodes placed at several fixed distances (60 m, 65 m, ..., 120 m). The Kernel Based Model is calculated using the traces and its robustness is presented in the next section.

For each measured distance, 10 h of routing traffic were simulated using the OLSR Protocol with a total of 50 runs, using different seed values. The physical layer of the wireless nodes follows the IEEE 802.11 g (54 Mbit/s), uses a transmit power of 3.6×10^{-4} W and a packet reception-power threshold of −95 dBm, which results in a theoretical maximum range of 100 m [22]. The actual range may vary as the OPNET simulator implements by default an accurate radio model where asymmetric links or even unidirectional links may occur, as well as channel errors and multi-path interferences.

The *R* statistical language [23] was used together with the "locpol" package [24] in order to perform the required bandwidth computations and regression fitting. The obtained bandwidths and *ASE* errors are presented in Table 2. Both Epanechnikov and Gaussian Kernels were used in order to analyse the main differences between them. Figs. 2 and 3 depict these two Kernels and their main characteristics. The two figures include the time intervals up to a maximum of 6*s*, corresponding to the OLSR maximum hold time for a link, such that the registered link error percentages are always bellow 100%.

Table 2
Obtained Kernels.

	Epanechnikov	Gaussian
Bandwidth	0.3217648	0.1557449
ASE	0.0006754408	0.0006754788

Fig. 2 presents the Regression obtained by using the Epanechnikov Kernel. The density of values obtained for each time interval, x density, is depicted in Fig. 2b. It is clear that the density is higher for lower time intervals, between 1.5 and 2.5 s, as they correspond to a better link quality with less errors and therefore more delivered packets. On the other hand, for higher time intervals, density variations occur due to the physical layer specific operations, such as transmission retries, which influence the final packet delivery. Moreover, as it would be expected, at larger distances higher time intervals are registered and there is a steep increase of the number of losses [25,26].

In order to better illustrate the significance of the provided estimation, Fig. 2c and d depicts respectively the calculated variance for each estimated value as well as a 95% confidence interval, showing that the chosen bandwidth value, obtained by minimising the *ASE*, provides good final estimations.

Fig. 3 depicts the obtained results using a Gaussian Kernel for the same trace values. It is possible to verify that the Gaussian Kernel Estimation provides a smoother regression, while keeping similar estimated values throughout the x-axis. This aspect is particularly noticeable in Fig. 3c and d, which show a slightly better estimation when compared with the Epanechnikov Kernel, despite both having used the same method for bandwidth calculation.

4.2. Model validation

While a formal model is itself a contribution for the representation of a reality, its final application in a realistic scenario is also important, as well as its precision. The proposed Link Estimation model has no unrealistic assumptions, requiring only the measurement of the time elapsed between receiving two consecutive routing messages, disregarding the protocol itself. Having this in mind, the obtained Kernel Estimators were implemented in the OPNET simulator and link quality estimations were performed in real time in two different mobility scenarios, presented next. It is important to note that any other scenario and mobility models could be used without requiring any recalculation of the obtained models, as long as the wireless physical layer specifications are maintained. Despite having used traces from static nodes to perform the Kernels Calculation, they are still suitable for any scenarios with or without mobility.

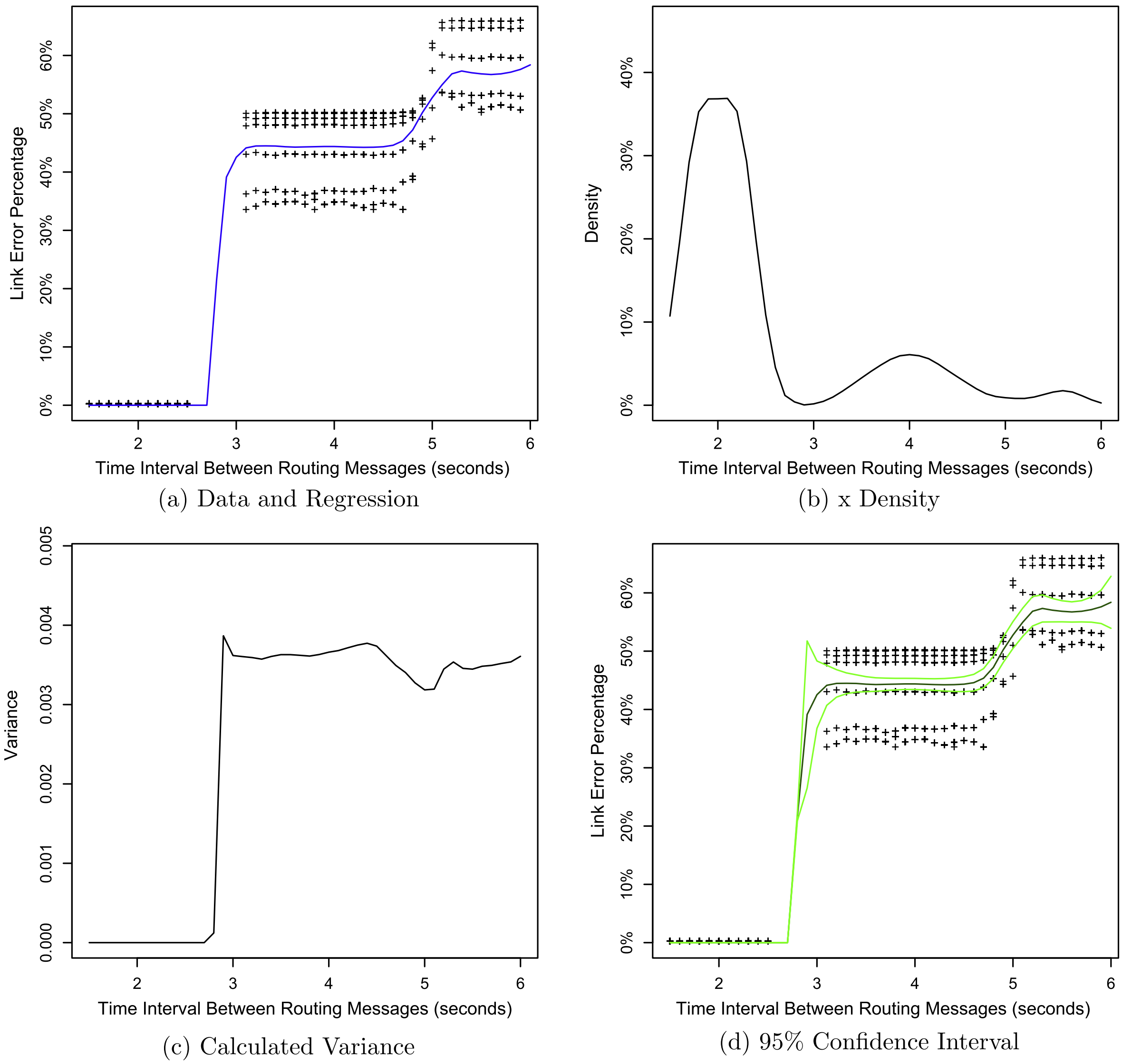

Fig. 2. The Epanechnikov Kernel Regression results.

An exhaustive evaluation was performed, where each Link Quality Kernel Estimation was ran 50 times, using different seed values, with a total time of 10 simulated hours per run for each scenario. The two used scenarios are representative of different circumstances where mobile ad hoc networks can be found, using two distinct mobility models.

4.2.1. High density scenario

For the validation process, a scenario was created with ten nodes moving freely in an area that exceeds more than twice the area covered by the nodes' maximum range (240×240 m). The nodes follow the Random Waypoint Mobility Model with a uniform speed between 3 and 30 km/h, corresponding to pedestrians' walking speed or moderate driving [27] with a pause time of 100 s. This scenario represents a dense area which is prone to have more packet collisions and therefore errors. While it is a more academic scenario, it allows a thorough validation of the obtained Kernel Estimators.

4.2.2. Oulu scenario

A more complex scenario was also created using Synthetic Map-based Mobility Traces [28] allowing the definition of mobility traces according to real-world locations. This was obtained using the Bonnmotion tool [29] and the Random Street Model specifying a total area of 3000×3500 m, with 30 moving nodes in Oulu, Finland. Again, the used speed corresponds to pedestrian walking or moderate speed driving (uniform speed between 3 and 30 km/h with a pause time of 100 s), creating a fairly realistic scenario. The obtained trajectories are depicted in Fig. 4.

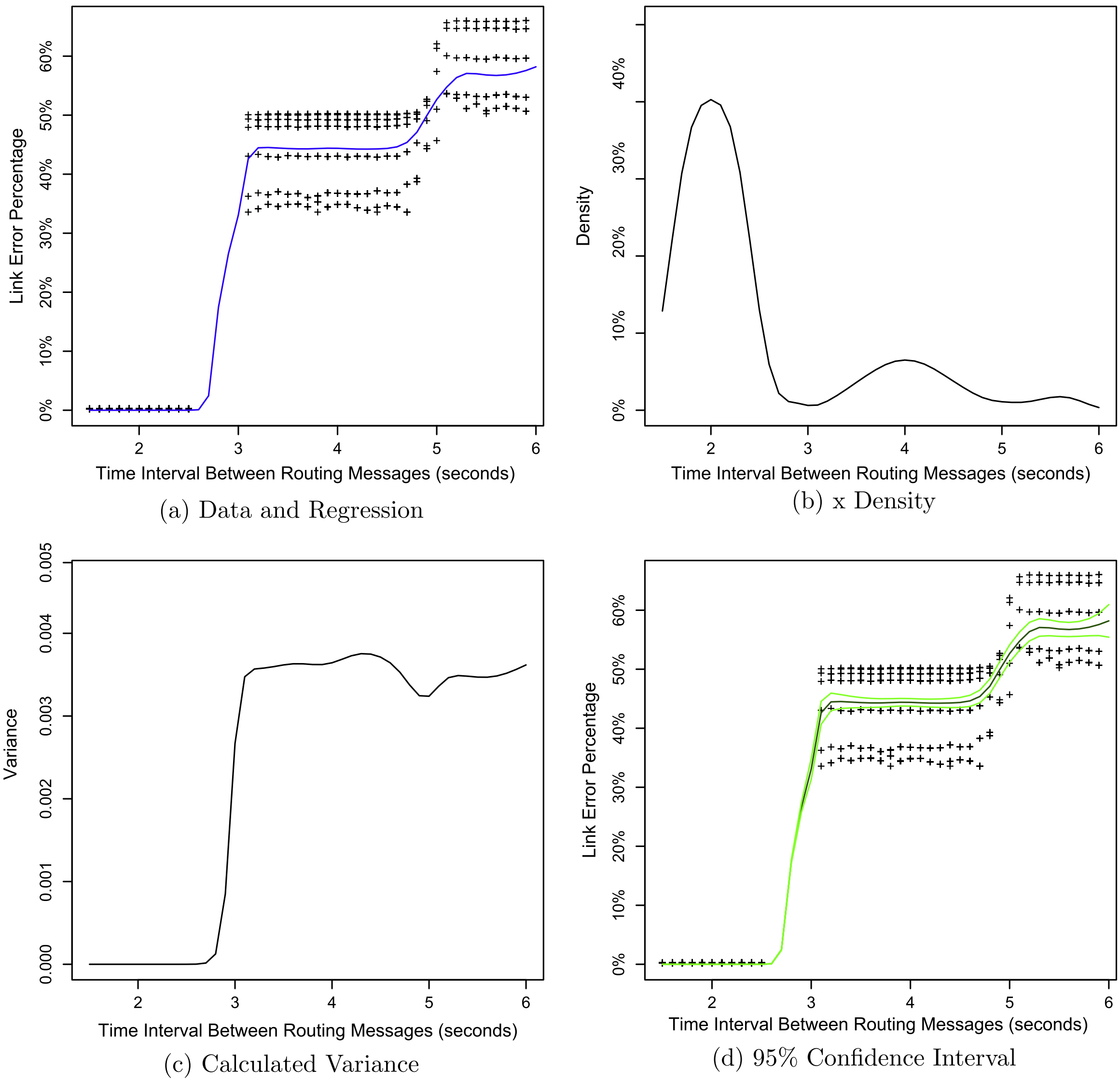

Fig. 3. The Gaussian Kernel Regression results.

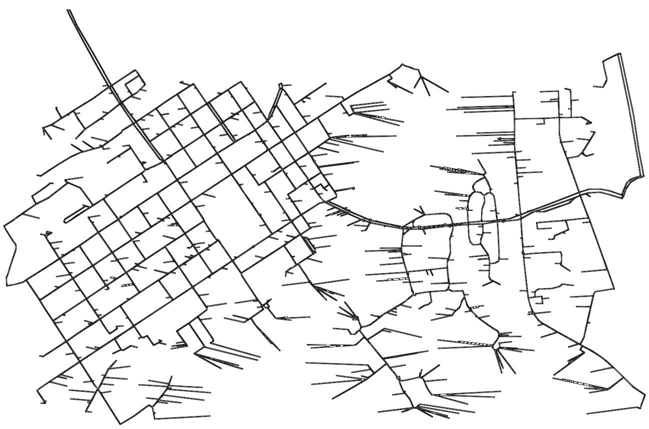

Fig. 4. Oulu mobility trajectories.

Table 3
Combined results (50 runs).

	Random waypoint			Random street		
	Average link errors	Standard deviation	Total difference	Average link errors	Standard deviation	Total difference
Real values	0.0198374	0.00254325	–	0.0190814	0.0211598	–
Epanechnikov	0.0193507	0.00234906	0.0004867	0.0184662	0.0196664	0.0006152
Gaussian	0.0195183	0.00234445	0.0003191	0.0186297	0.0195614	0.0004517

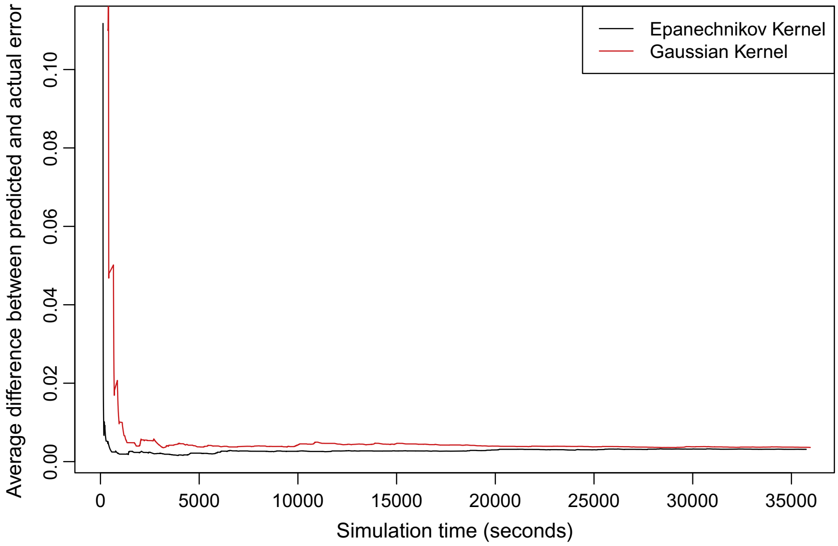

Fig. 5. High density scenario-real-time performance.

4.2.3. Validation results

The wireless link quality is influenced by the amount of errors that may occur when transmitting a packet. For each simulated run, all the generated packets have been registered, as well as all the link quality estimations made by the used models. By comparing, per link, the amount of packets with errors (i.e. not received) and the determined link quality, it is possible to assess the performance of the estimators.

Comprising all the validation results (from 50 runs), Table 3 shows the overall link error percentage for both Kernel Based Estimations and real values. This table

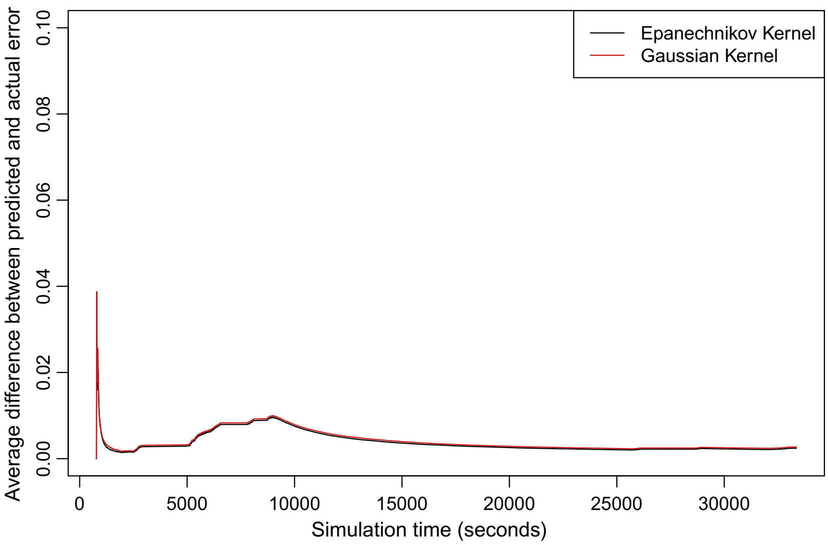

Fig. 6. Oulu scenario-real-time performance.

presents the actual average link quality and standard deviation registered by analysing all the generated packets next to the results obtained by both the presented link quality estimator models for both scenarios. As it can be seen, both Kernel Estimators performed extremely well in a realistic implementation in two different scenarios. It is worth noting that the difference between real and estimated errors is small, proving the quality of Kernel Methods as estimators and highlighting their generalisation properties. Furthermore, it has been shown that the proposed model does not require traces obtained with mobility for a good performance, further proving its quality and applicability.

Being able to determine the amount of link errors in real-time is an important feature of link quality estimators. All the presented results were obtained instantaneously during the performed simulations, as no recalculation is needed for any scenario. For example, in the high density scenario, the average difference between the real link errors and the estimated errors is represented in Fig. 5. This figure shows the performance of both the Epanechnikov and Gaussian Kernel Estimators and, despite being quite small even at the beginning of the simulation (less than 0.12%), the difference between the estimated and true error percentage gets even smaller through time, for both Kernels.

Similar results are presented in Fig. 6, showing that for a more realistic scenario the performance is maintained. However, despite being very small, a fluctuation is registered, suggesting that the dynamic characteristic of this scenario may present different link behaviours that the used model estimators were still able to cope with.

5. Conclusion

A new model for link quality estimation has been proposed, without requiring any unrealistic assumptions. This model was derived from Kernel Regression Estimation techniques, which resulted in an accurate estimation of the wireless link quality obtained through the statistical analysis of routing packets' inter-arrival times, using Kernel Methods. Such results are extremely relevant for future wireless communications, allowing routing protocols to choose the best available links without additional messages overhead or imposed limitations.

The presented results prove that any routing protocol or periodically sent messages (e.g. Layer-2 messages) can be used with the presented model. This was demonstrated by using two different Kernel Regression Estimators, which were able to successfully determine, in real-time, the quality of wireless ad hoc links, being the Gaussian Kernel the most accurate.

A major contribution of the defined model is that its adaptable approach is capable of providing accurate estimations for any given scenario. This property has been shown by using two distinct mobility models, without recalculating the Kernel Estimators. Therefore the inclusion of Kernel Regression Estimators has proved itself as a suitable option for link quality modelling in wireless networks.

An important conclusion is that both the resulting Kernel Estimators were able to provide realistic estimates in scenarios with different types of mobility and node density. This suggests that in a real scenario the required traces can easily be obtained and used in a myriad of situations. In addition to this, Kernel Methods do not require any training (supervised or not), being therefore more efficient than other techniques such as neural networks.

Acknowledgements

This work was supported by the Portuguese National Foundation for Science and Technology (FCT) through a PhD Scholarship (SFRH/BD/43790/2008) and by the National Project MORFEU (PTDC/EEA-CRO/108348/2008). The authors thank the OPNET University Program for the licenses provided for the OPNET Modeler Wireless Suite®.

References

[1] A. Cimmino, P. Donadio, Overall requirements for global information multimedia communication village 10th strategic workshop, Wireless Personal Communications 49 (3) (2009) 311–319, http://dx.doi.org/10.1007/s11277-009-9686-3. <http://dx.doi.org/10.1007/s11277-009-9686-3>.

[2] V.C.M. Borges, M. Curado, E. Monteiro, Cross-layer routing metrics for mesh networks: current status and research directions, Computer Communications 34 (6) (2011) 681–703.

[3] M. Wand, M. Jones, Kernel Smoothing, first ed., Chapman and Hall/CRC, 1994. ISBN 0412552701.

[4] O.T. Inc.'s, OPNET Simulator, 2012. <http://www.opnet.com/, http://www.opnet.com/>.

[5] M. Yu, A. Malvankar, W. Su, S.Y. Foo, A link availability-based QoS-aware routing protocol for mobile ad hoc sensor networks, Computer Communications 30 (18) (2007) 3823–3831, http://dx.doi.org/10.1016/j.comcom.2007.09.009. ISSN 0140-3664.

[6] J. Huang, Y. Bai, A novel approach of link availability estimation for mobile ad hoc networks, in: Vehicular Technology Conference, 2008. VTC Spring 2008. IEEE, 2008, pp. 26–30. ISBN 1550-2252. http://dx.doi.org/10.1109/VETECS.2008.18.

[7] M. Qin, R. Zimmermann, L.S. Liu, fSupporting multimedia streaming between mobile peers with link availability prediction, in: Proceedings of the 13th annual ACM international conference on Multimedia, MULTIMEDIA '05, ACM, New York, NY, USA, 2005, pp. 956–965. ISBN 1-59593-044-2. http://doi.acm.org/10.1145/1101149.1101350.

[8] Y. Bai, J. Huang, Q. Han, D. Qian, Link availability based mobility-aware max–min multi-hop clustering (M^4C) for mobile ad hoc networks, IEICE Transactions on Communications 92 (2009) 3132–3142, http://dx.doi.org/10.1587/transcom.E92.B.3132.

[9] Y. Bai, L. Gong, Link availability prediction with radio irregularity coverage for mobile multi-hop networks, IEEE Communications Letters 14 (6) (2010) 518–520, http://dx.doi.org/10.1109/LCOMM.2010.06.100238. ISSN 1089-7798.

[10] X. Wu, H. Sadjadpour, J.G. luna aceves, Link dynamics in MANETS restricted node mobility: modeling and applications, IEEE Transactions on Wireless Communications 8 (9) (2009) 4508–4517, http://dx.doi.org/10.1109/TWC.2009.070309. ISSN 1536-1276.

[11] S. Jiang, D. He, J. Rao, A prediction-based link availability estimation for routing metrics in MANETs, IEEE/ACM Transactions on Networking 13 (6) (2005) 1302–1312, http://dx.doi.org/10.1109/TNET.2005.860094. ISSN 1063-6692.

[12] X. Shu, X. Li, Link failure rate and speed of nodes in wireless network, in: International Conference on Wireless Communications, Networking and Mobile Computing, 2007, WiCom 2007, pp. 1441–1444. http://dx.doi.org/10.1109/WICOM.2007.365.

[13] B. Manoj, R. Ananthapadmanabha, C. Murthy, Link life based routing protocol for ad hoc wireless networks, in: Proceedings of the Tenth International Conference on Computer Communications and Networks, 2001, pp. 573 –576. http://dx.doi.org/10.1109/ICCCN.2001.956324.

[14] X.M. Zhang, F.F. Zou, E.B. Wang, D.K. Sung, Exploring the dynamic nature of mobile nodes for predicting route lifetime in mobile ad hoc

networks, IEEE Transactions on Vehicular Technology 59 (3) (2010) 1567–1572, http://dx.doi.org/10.1109/TVT.2009.2038708. ISSN 0018-9545.
[15] N. Saeed, M. Abbod, H. Al-Raweshidy, Modeling MANET utilizing artificial intelligent, in: Second UKSIM European Symposium on Computer Modeling and Simulation, 2008. EMS '08, 2008, pp. 117–122. http://dx.doi.org/10.1109/EMS.2008.8.
[16] D.B. Johnson, D.A. Maltz, Y.C. Hu, The Dynamic Source Routing Protocol for Mobile Ad Hoc Networks (DSR), Tech. Rep., IETF MANET Working Group, 2007. <http://tools.ietf.org/html/rfc4728>.
[17] C.E. Perkins, E.M. Belding-Royer, S.R. Das, Ad hoc On-Demand Distance Vector (AODV) Routing, RFC Experimental 3561, Internet Engineering Task Force, 2003. <http://www.ietf.org/rfc/rfc3561.txt>.
[18] T. Clausen, P. Jacquet, Optimized Link State Routing Protocol (OLSR), RFC 3626, Internet Engineering Task Force, 2003. <http://www.ietf.org/rfc/rfc3626.txt>.
[19] A. Kushki, K.N. Plataniotis, A.N. Venetsanopoulos, Kernel-based positioning in wireless local area networks, IEEE Transactions on Mobile Computing 6 (6) (2007) 689–705, http://dx.doi.org/10.1109/TMC.2007.1017. ISSN 1536-1233.
[20] J.S. Marron, W. Härdle, Random approximations to some measures of accuracy in nonparametric curve estimation, Journal of Multivariate Analysis 20 (1) (1986) 91–113, http://dx.doi.org/10.1016/0047-259X(86)90021-7. ISSN 0047-259X.
[21] W. Härdle, M. Müller, S. Sperlich, A. We1atz, Nonparametric and Semiparametric Models, Springer, 2004. ISBN 3540207228.
[22] S. Ortiz, IEEE 802.11n: the road ahead, IEEE Computer 42 (7) (2009) 13–15, http://dx.doi.org/10.1109/MC.2009.224. ISSN 0018-9162.
[23] R Development Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2010. ISBN 3-900051-07-0. <http://www.R-project.org/>.
[24] J.L.O.C., Locpol: Kernel Local Polynomial Regression, R Package Version 0.4-0, 2009. <http://CRAN.R-project.org/package=locpol>.
[25] G. Anastasi, E. Borgia, M. Conti, E. Gregori, IEEE 802.11 ad hoc networks: performance measurements, in: Proceedings of 23rd International Conference on Distributed Computing Systems Workshops, 2003, pp. 758–763. http://dx.doi.org/10.1109/ICDCSW.2003.1203643.
[26] D. Pham, Y. Sekercioglu, G. Egan, Performance of IEEE 802.11b wireless links: an experimental study, in: TENCON 2005 2005 IEEE Region 10, 2005, pp. 1–6. http://dx.doi.org/10.1109/TENCON.2005.300898.
[27] 3GPP, Spatial Channel Model for Multiple Input Multiple Output (MIMO) Simulations, Technical Specification Group Radio Access Network., Tech. Rep. 7, 3rd Generation Partnership Project, 2008.
[28] N. Aschenbruck, M. Schwamborn, Synthetic map-based mobility traces for the performance evaluation in opportunistic networks, in: Proceedings of the Second International Workshop on Mobile Opportunistic Networking, MobiOpp '10, ACM, New York, NY, USA, 2010, pp. 143–146. ISBN 978-1-60558-925-1. http://doi.acm.org/10.1145/1755743.1755769.
[29] N. Aschenbruck, R. Ernst, E. Gerhards-Padilla, M. Schwamborn, BonnMotion: a mobility scenario generation and analysis tool, in: Proceedings of the 3rd International ICST Conference on Simulation Tools and Techniques, SIMUTools '10, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), ICST, Brussels, Belgium, Belgium, 2010, pp. 51:1–51:10. ISBN 978-963-9799-87-5. http://dx.doi.org/10.4108/ICST.SIMUTOOLS2010.8684.

David Palma is a PhD student in the Doctoral Program in Information Science and Technology at the Department of Informatics Engineering of the University of Coimbra, Portugal. His research interests are on Ad hoc Networks, Scalable Routing, Mobility, and Resilience. He has participated in the IST FP6 Integrated Projects, EuQoS and WEIRD.

Helder Araujo is a Professor in the Department of Electrical and Computer Engineering of the University of Coimbra, Portugal. He is also a researcher at the Institute for Systems and Robotics-Coimbra. His research interests include computer and robot vision, robot navigation and localisation, and sensor modelling for robot navigation and localisation. He has publications on topics related to Computer Vision, Mobile Robotics, Navigation and Control.

Marilia Curado is an Assistant Professor at the Department of Informatics Engineering of the University of Coimbra, Portugal, from where she got a PhD in Informatics Engineering on the subject of Quality of Service Routing, in 2005. Her research interests are Quality of Service, Mobility, Routing, and Resilience. She has participated in several projects, in Networks of Excellence from IST FP5 and FP6, in the IST FP6 Integrated Projects, EuQoS and WEIRD, and on ICT FP7 STREPs MICIE and GINSENG.