Fuzzy Logic Based Multidimensional Link Quality Estimation for Multi-Hop Wireless Sensor Networks

Zhi-Qiang Guo, Qin Wang, Mo-Han Li, and Jie He, *Student Member, IEEE*

***Abstract*— In the applications of multi-hop wireless sensor networks, the effective evaluation of wireless link quality which can improve the network reliability is a crucial problem in the design of network protocols. The lossy and dynamic nature of the radio channel, however, makes link quality estimation a great challenge. First, we use data-driven modeling and statistical inference methods to model the burstiness of wireless link packet loss, which reflects the reliability of packet retransmission in the data link layer. Then, from a multidimensional view of characterizing the wireless link quality, we present the fuzzy logic based link quality indicator (FLI), which is a comprehensive reflection of single hop reliability of packet delivery, link volatility, and packet loss burst. Finally, we implement a wireless link quality estimator based on FLI in the collection tree protocol (CTP). Through the experimental comparison with the original link quality estimator in the CTP, the network performance with the new link quality estimator guarantees high end to end delivery reliability, while the average routing depth of the nodes and the dynamic changes of network topology are reduced.**

***Index Terms*— Wireless sensor networks, network reliability, link quality estimation, fuzzy logic, collection tree protocol.**

I. Introduction

THE basic idea of internet of things (IoT) is the pervasive presence of a variety of things or objects around us, which is a novel paradigm that is rapidly gaining ground [1]. Wireless sensor networks (WSN) play a crucial role in the IoT as a further bridge between physical and digital world. WSN consist of a certain number of sensing nodes with the short-range, low-power and multi-hop wireless communication. Usually nodes report the results of their sensing of the physical world to one of the special nodes called sinks. WSN have been proposed in several application scenarios, such as environmental monitoring, e-health, military, and industrial plant monitoring.

It has been experimentally shown that low-power radio is more prone to noise, interference, and multipath distortion [2]–[5]. The link quality can be degraded resulting from signal attenuation, interferences of various forms, etc. Time of link quality scales vary from milliseconds to days, and are often linked to human activity. The quality of the wireless links impacts network performance greatly, namely in what concerns topology control, routing and mobility management. Since changes in link quality can affect network connectivity considerably, link quality should be taken into account as a critical routing metric. In particular, routing protocols must overcome wireless link unreliability in order to maintain network performance efficiently.

Link quality estimation emerges as an important mechanism to select the most stable routes for communication [6]–[8]. Stable routes are built by selecting good quality links, which enable improving the network throughput, energy-efficiency, network topology stability and end to end probability of packet delivery. Therefore, adaptive link quality estimation is a prerequisite for efficient routing mechanisms that manage to overcome problems imposed by link unreliability.

Link quality estimation is seen as an essential tool for the computation of reliability-oriented route selection metrics. We should use different characteristics to design an adaptive and high-performance link estimator. It may be desirable to build gradient-based routing protocol with the goal to maximize reliability by using the link reliability metric to compute the "best" path, while maintain the stability of the network.

The contributions of this paper are introduced below. Firstly, the modeling for burstiness of wireless link packet loss is presented, which directly reflects the reliability of packet retransmission in the data link layer. Secondly, from the multidimensional view of characterizing the wireless link quality, a fuzzy logic based link quality indicator (FLI) is designed. Finally, we implement a wireless link quality estimator based on FLI, which finds the path that has the lowest cost with respect to the reliability metrics in the collection tree protocol (CTP) network. The results show that the CTP with a link estimator based on FLI guarantees a high end to end delivery rate, while reduces the routing depth and topology dynamic changes.

The rest of this paper is organized as follows. We briefly introduce the related work about wireless link quality estimation and some related gradient-based routing protocols in Section II. Section III describes the wireless link databases for our link quality estimation and modeling. Next, the modeling detail for the burstiness of packet loss is proposed in Section IV. In Section V, a fuzzy logic based link quality indicator is designed to characterize multidimensional link quality. Section VI gives the CTP network performance based

Manuscript received January 31, 2013; revised June 12, 2013; accepted June 27, 2013. Date of publication July 3, 2013; date of current version August 21, 2013. This work was supported in part by the National Natural Science Foundation of China under Grant 61003251, the National High Technology Research and Development Program of China ("863" Program) under Grant 2011AA040101, and the Doctoral Fund of Ministry of Education under Grant 20100006110015. The associate editor coordinating the review of this paper and approving it for publication was Dr. Mischa Dohler.

The authors are with the School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China (e-mail: guozhiqiang.ustb@gmail.com; wangqin@ies.ustb.edu.cn; lmhatgm@gmail.com; hejie1983@gmail.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JSEN.2013.2272054

on FLI compared with the original link estimator through practical experiments. Finally, we conclude this paper and discuss our future work plan in Section VII.

II. Related Work

Link quality estimation in the WSN is a challenging task due to the lossy and dynamic behavior of the wireless links, so it is important to correctly account for link characteristics. Here we briefly introduce most related work about link estimation method and multi-hop routing protocols.

The packet reception ratio (PRR), is computed as the ratio of the number of successfully received packets to the number of transmitted packets. The window mean with exponentially weighted moving average [9], the kalman filter based link quality estimator [10], and the packet success probability (PSP) [11], approximate the PRR mentioned above. Srinivasan *et al.* [12] tested the distribution of PRR over all links in their tested with different inter packet intervals (IPI). In short-term assessment, most links experience high temporal correlation in packets delivery. The increase of the IPI leads to the decrease in the temporal correlation in the packets reception, which means links may experience burstiness over short period.

In recent years, modeling for the measurement of link burstiness is researched. Munir *et al.* [13] defined Bmax as a metric that computes the maximum burst length for a link, which is the maximum number of consecutive packet delivery failures. Bmax is computed using an algorithm that takes the data trace as input and may change during the network operation due to environmental changes. Brown *et al.* [14] resolved the above problem through a mechanism for assessing link burstiness through the computation of Bmax during the network operation. Srinivasan *et al.* [15] employed a factor called β as a metric for modeling link burstiness, which is used to identify bursty links with long bursts of successes or failures. The β factor is computed using conditional probability distribution functions (CPDF), which determine the probability that the next packet will be received after N consecutive packet successes or failures. It requires a long data trace and might not be suitable for online link quality assessment. Willing *et al.* [16] presented the relative frequency histogram through statistics of burst size of link packet loss, and found that single packet loss accounts for 72%, and packet loss less than or equal to 3 accounts for 90%. However, statistics of burst size of link packet loss cannot effectively reflect the retransmission reliability affected by it.

Couto *et al.* [17] proposed expected transmission count (ETX) for link quality estimation, which shows that a reliability based metric can achieve better routing performance than the shortest hop-count. ETX estimates the number of transmissions needed to send a unicast packet by measuring the delivery rate of beacon packets between neighboring nodes. The 4 Bit link estimation proposed by Fonseca *et al.* [18] shows that combining information from the physical layer, link reliability information provided by ETX and routing information from network layer, 4Bit can achieve a better performance.

WSN routing protocols remain a fairly open issue and we only focus on gradient-based routing protocols, such as MintRoute [9], MultiHopLQI [19], Collection Tree Protocol (CTP) [20], and Routing Protocol for Low-power and Lossy Networks (RPL) [21].

CTP is a tree-based collection protocol intended to provide best effort routing. In the CTP, some nodes advertise themselves as tree roots of the network, and other nodes in the network form a set of routing trees to these roots. A particularity of CTP is that the network is address-free. Nodes implicitly choose a root by choosing a next hop, and best routes to the sink node are determined by using a gradient metric. Vilajosana *et al.* [22] proposed a combined approach at network and link layers to increase network lifespan while conserving reliability levels by means of probabilistic load balancing techniques, which is to cope with the "hot spot" problem in the CTP. In their work two metrics have been studied. The first one calculates distances between possible paths and assigns a probability proportional to them. The second technique uses a probability distribution function that assigns a probability to each possible path. Both techniques give more probability to the best route (i.e., represented by less ETX) in order not to compromise the reliability of the network heavily.

RPL is the standard protocol proposed by the Internet Engineering Task Force (IETF) for IPv6 routing over low power and lossy networks. The motivation of RPL is to construct a directed acyclic graph (DAG) rooted at the sink, which will minimize the cost of reaching the sink from any node as per the objective function (OF). The OF can minimize a particular metric, such as hop count or ETX. RPL improves CTP by enabling downstream communication from sink to the nodes. Tripathi *et al.* [23] presented a performance evaluation of RPL based on a simulator OMNET++. They pointed out potential areas of further study for RPL. In the simulation, packets are dropped randomly probability. However, they didn't consider the correlation distribution of packet loss, while we do in our research. Accettura *et al.* [24] found that further research should be required to optimize the RPL signaling in order to decrease the protocol overhead. They use the Contiki Cooja simulator to analyze the general behaviors of RPL under different conditions, and indicate that RPL is a very powerful technique, granting a very fast network set-up and its effectiveness can be further improved in terms of overhead.

III. Testbed and Wireless Link Databases

In contrast with theoretical models which may have assumptions not applicable to lossy links, we have gathered real link layer data traces from networks deployed on the field for our analysis of link estimation modeling. They are introduced briefly below.

TmoteDB wireless link database is built by ETH Zurich [25]. It contains many types of test configurations, which can set various parameters of the sending and receiving nodes. It also has several experiment modes, which are single sender mode, echo mode and polling mode.

Motelab is an integrated wireless link test platform in Harvard University for WSN [26]. Thirty MicaZ nodes are arranged in an office building. Through web-based interface,

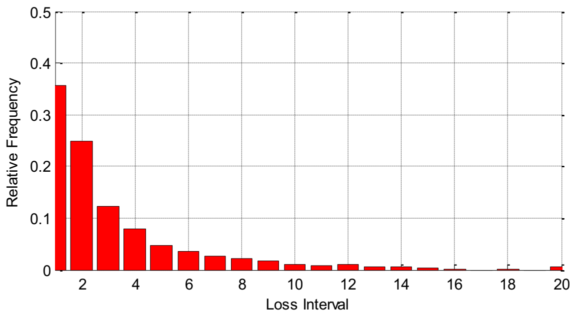


Fig. 1. Relative frequency of loss interval with PRR = 80%.

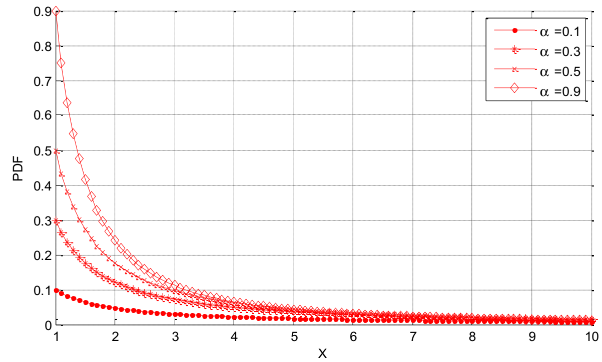


Fig. 2. Probability density function of Pareto distribution with different parameters.

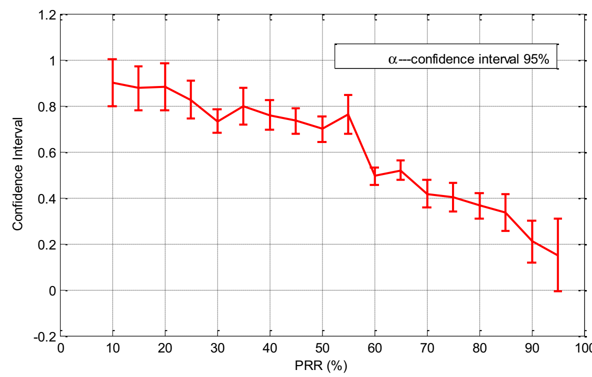


Fig. 3. The confidence interval of the distribution parameter for links with different PRRs.

we can access to each sensor node, and the experiment data can be collected and stored automatically. Motelab is an open platform for analyzing the wireless link quality.

Telosb-USTB is one of the wireless link quality test and evaluation platform designed by MICL laboratory in University of Science and Technology Beijing (USTB). It contains many sensor nodes, and the network connection can be in wired manner or wireless manner. PC client software is responsible for node programming, debugging, and experiment data collection and storage. We have formed a large database for wireless link quality estimation through network tests of many places, such as common offices, casting pilot plants in USTB, Anshan Iron and Steel Company, and so on [27]–[31].

In this paper, we use TmoteDB, Motelab and Telosb-USTB to represent three wireless link databases mentioned above.

IV. Modeling of Packet Loss Burst

We analyze the characteristics of packet loss in the wireless link and modeling the burstiness of it. Then a correlation distance is established to describe the burstiness of packet loss quantitatively and draw the relationship between the correlation distance and packet retransmission reliability.

A. Packet Loss Interval and Distribution

In each wireless link databases mentioned above, it stores the information of every probe packet, which forms a series of data tracks. The tracks record whether the packet is received correctly, and the physical information such as RSSI and LQI. Extracted from the tracks, a binary discrete sequence of a link denoted as $\{v_i\}_{i=1}^N$ is formed, which takes the value from the set $V = \{0, 1\}$, where 0 indicates data transmission fails, while 1 succeeds.

We define I_n the time interval of adjacent failed data packet, referred to as loss interval, which satisfies the condition below.

$$\{v_{m+n} = 0; v_m = 0; \forall k \in (m, m+1 \ldots, m+n), v_k = 1\}$$

and $m \in [1, N-n]$.

We draw a relative frequency histogram of I_n from the binary discrete sequence in the databases mentioned in Section III. All the histograms of the sample data have a certain statistical laws. Fig. 1 shows the distribution characteristics of I_n with PRR equal to 80% for one of the sample links. It can be seen from the figure that, as the loss interval increases, the relative frequency of it reduces with a power law style, and shows a long-tail effect. The loss interval less than 10 constitutes the majority proportion (more than 98%).

B. Statistical Inference

Pareto distribution is one of the power law distributions [32], and its probability density function is defined as follows.

$$P(x) = \alpha \frac{x_m^{\alpha}}{x^{\alpha+1}} \tag{1}$$

where $x \geq x_m$ and $x_m = 1$.

The Pareto distribution probability density curve of different distribution parameters is shown in Fig. 2.

We estimate the confidence interval of distribution parameters for loss interval with 95% confidence coefficient as shown in Fig. 3. It shows the average of distribution parameters is 0.15. The maximum is 0.3 when PRR is 95%. This indicates that for the entire sample space, the loss interval distribution can be considered as Pareto distribution. The confidence interval is bigger with PRR less than 20% and more than 90% of the sample data, while smaller between them, which indicate that the loss interval of the intermediate quality of the wireless link meets the Pareto distribution more suitably. Intermediate quality links play an important role in optimizing retransmission protocol in the data link layer, in particular with PRR between 50% and 90%.

Fitting error of Pareto distribution parameter reflects the accuracy of the distribution fitting, which can be described

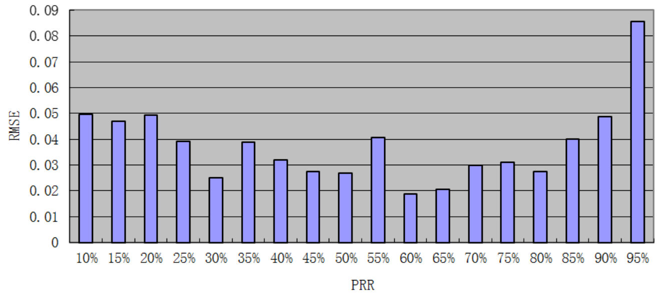


Fig. 4. The root-mean-square histogram of parameter estimation.

through the root mean square error (RMSE) under the distribution parameters. RMSE, also known as fitting standard deviation of the regression, is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)} \tag{2}$$

where n is the capacity of the sample set, y_i is the real sample value and $\hat{y}_i$ is the inferred value.

As shown in Fig. 4 which illustrates the RMSE of distribution parameter estimation with different PRRs, Pareto distribution is suitable for intermediate quality links (PRR = 30%∼80%), with low PRR followed and high PRR worst. This is because the wireless link of high PRR is very good with rare packet loss. This type of good link quality is unnecessary for retransmission of the data packet at the most time, and will not affect the performance of retransmission reliability in the data link layer heavily.

C. Distribution Correlation and Retransmission Reliability

In order to characterize the burstiness of wireless link packet loss quantitatively, we define D_α using the difference of Pareto distribution parameters between the actual link and the link satisfying the independent and identically distribution (I.I.D) with the same PRR, also known as distribution correlation. It is shown in equation below.

$$D_\alpha = \alpha_{sample} - \alpha_{iid}. \tag{3}$$

D_α is the quantitative description of packet loss burst. In particular, the distribution parameter of actual link is always bigger than link with I.I.D characteristic.

If wireless link packet loss is assumed to satisfy I.I.D characteristic, the packet retransmission reliability can be expressed as follow.

$$\begin{aligned} P_{retransmission} &= Pr(S1) + Pr(S2 \cdot E1) \\ &= 1 - (1 - PRR)^2 \end{aligned} \tag{4}$$

where S denotes data transmission succeed and E fail.

In order to analyze how retransmission interval affects reliability in the actual sample data, we use data-driven simulation to reproduce the packet retransmission process with sample data from 3 link databases mentioned in Section III.

Through the simulation above, retransmission reliability of the real link data is different with the link satisfying I.I.D characteristic. Real link data shows greater burstiness, and retransmission reliability with small interval is lower than the theoretical value.

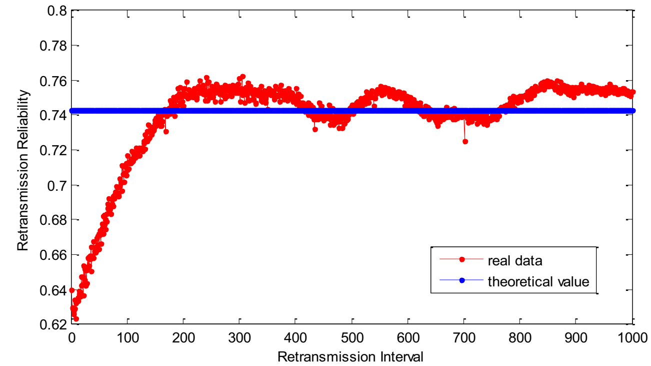


Fig. 5. Retransmission reliability of real links with PRR = 49%.

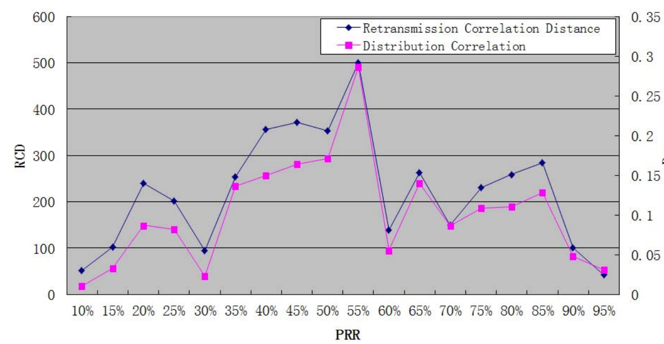


Fig. 6. The RCD and correlation distance with different PRR.

Fig. 5 shows the retransmission reliability versus retransmission interval for an actual link with PRR 49%. We can see that with retransmission interval increasing from 1 to 200, reliability linearly tends to the theoretical value of corresponding link with I.I.D. characteristic. Then as the retransmission interval increases, reliability varies slightly around its theoretical value.

As show in Fig. 5, we define the retransmission interval when retransmission reliability reaches the theoretical value of corresponding link with I.I.D as Retransmission Correlation Distance (RCD). RCD reflects the time scope in which retransmission interval affects data retransmission reliability. Once exceeding RID, the retransmission reliability reaches the theoretical value. It is obvious that the RCD of link with I.I.D characteristic is 0.

We test the data retransmission reliability of a large number of sample data in a data-driven trace manner and find that the D_α of link samples has the same trend of RCD, which means link layer retransmission reliability can be quantitatively portrayed by D_α. Fig. 6 shows the curves of D_α and RCD under different PRR of wireless link from link databases. We can draw an approximately linear relationship between them as follows.

$$RCD/D_\alpha = C. \tag{5}$$

Through a linear regression method, we can derive the optimal value of the constant C. C reflects the influence of the environment. As for characterizing wireless link packet

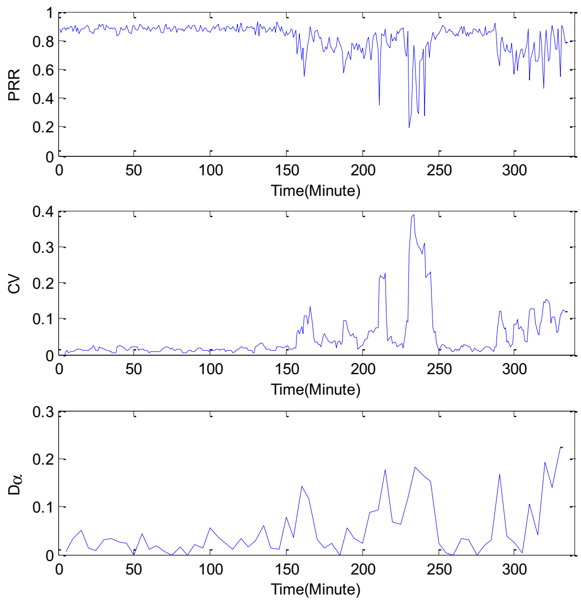


Fig. 7. Multidimensional metric of wireless link quality.

loss bursty, simple PRR fails to reflect characteristics of the link on the time correlation, while D_α takes into account the underlying distribution of packet loss. Besides, D_α is an indicator of link retransmission reliability under the same retransmission mechanism.

V. Fuzzy Logic Based Link Quality Indicator (FLI)

With respect to the reliability of the wireless sensor network, it seems an infeasible approach to only apply a single dimension when evaluating link quality. Therefore we use fuzzy logic and synthesize multiple dimensions of link features into a comprehensive metric FLI.

A. Multidimensional Analyses for Link Quality

A number of link reliability metrics could be defined reflecting several reliability aspects. We choose three different perspectives of link quality to analyze wireless links considering their influences on network reliability of data delivery.

Over short time spans, links may experience high temporal correlation in packet reception, so PRR is a basic metric of wireless link quality. We firstly use it to determine the reliability of packet reception for one hop.

We use the coefficient of variance (CV) of PRR to indicate the link dynamics which affects the network topology stability. It is defined as the ratio of the standard variance and the mean of a given time window of PRRs, as computed in the following equation.

$$CV = \sigma_{PRR}/\mu_{PRR} \tag{6}$$

where σ_{PRR} is the standard variance and μ_{PRR} is the mean of PRRs. It is very suitable for describing link dynamics where PRR varies in a great range. Also CV serves as a valuable perspective to analyze the reliability of wireless links.

In Section IV we design a metric called the distribution correlation denoted as D_α, which describes the burstiness of packet loss. At the link layer, packet retransmission for reliability is always used. D_α is an indicator of link reliability under the same retransmission mechanism, and higher D_α means lower retransmission reliability. Thus we use it as a third metric to describe link reliability.

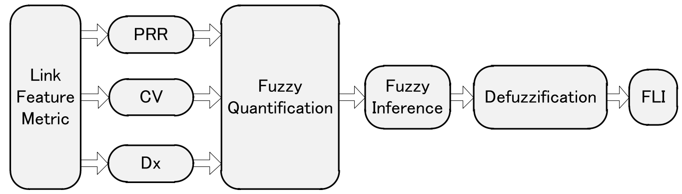


Fig. 8. Fuzzy inference system structure diagram for FLI.

Fig. 7 shows the multidimensional metric of the wireless link from the link databases whose average PRR is 81%. Such link shows a significant feature of time variability and dynamics. Before the 150 minute, the link has a high PRR, low link variance and low packet loss burst. Then the link begins to vary in a large range. Especially between the 220 minute and the 240 minute, PRR varies drastically around 50%, which is shown by the CV metric. In the meantime, D_α shows that the packet loss of the link is highly burst. After the 290 minute, we may not conclude that the link has fairly good quality as it has a high PRR of 81%. However, we should take D_α into consideration which affects retransmission reliability, and at that time D_α has a relative high value.

We give different paces at which link quality metrics change for link estimator in order to preserve network routing stability. When using a dynamic link estimator, we should make use of a multi-threshold scheme reflecting multidimensional link quality change rather than single individual metric, which avoids spurious and unnecessary routing changes. We use different reporting frequency for each metric mentioned above, and the update time for each metric is represented below,

$$T_p > T_c > T_d \tag{7}$$

where Tp denotes the update time of PRR, Tc the update time of CV, and Td the update time of D_α.

B. FLI Design Process

Traditional wireless link quality evaluation solely stress a certain angle of link feature, regardless of the fact that the quality of wireless link is vulnerable to various factors such as link dynamics and packet loss burstiness, let alone many specific concerns relevant to application scenarios. Consequently, wireless link quality should be measured and evaluated in a multidimensional manner. In this paper we regard wireless link quality as a fuzzy concept.

Without losing generality, we define two fuzzy sets of wireless link quality: High Quality Links (HQ) and Low Quality Links (LQ). The link metric includes PRR, CV and D_α as described above. Then we design a fuzzy inference system as shown in Fig. 8.

Firstly we design the membership function for each metric. In order to lower the computational complexity, we use linear membership functions suitable for sensor nodes. There are two

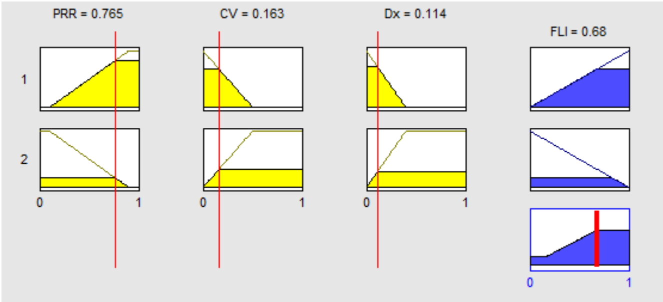


Fig. 9. Instance diagram of fuzzy inference system.

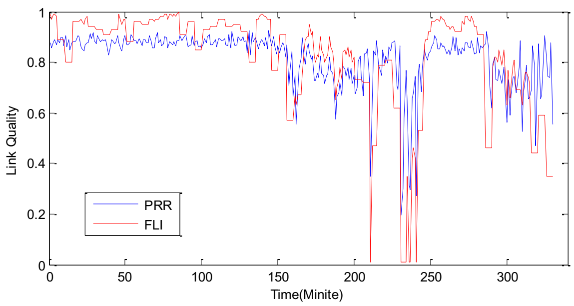


Fig. 10. Time-varying diagram of comprehensive link quality FLI.

criterions when choosing the proper membership function. One is that the degree of membership should agree with general sense. The other is that the inferred FLI should keep the linear cumulative probability, which guarantees the evenness and fine grain of the link quality estimation.

After quantification of each link feature using membership function, the fuzzy inference rules are designed as follows:

(1) *IF "PRR is HQ" and "CV is HQ" and "D_α is HQ", THEN "FLI is HQ".*

(2) *IF "PRR is LQ" and "CV is LQ" and "D_α is LQ", THEN "FLI is LQ".*

The result of fuzzy inference needs defuzzification. There are many principles that can be used as guidance. In order to generate FLI that keeps a linear cumulative probability, we can apply Smallest of Maximum (SOM), Middle of Maximum (MOM) or Largest of Maximum (LOM) methods for defuzzification [33].

Fig. 9 shows an instance to generate FLI through a fuzzy inference system. The four subfigures of the first row indicate the degree of membership to HQ generated based on rule (1). Similarly, the four subfigures of the second row indicate the degree of membership to LQ generated based on rule (2). The subfigure at the lower right corner shows the process of using SOM method for defuzzification and generating FLI.

A time-varying diagram of comprehensive link quality FLI is depicted in Fig. 10 for wireless link corresponding to the link in Fig. 7. We can observe that FLI has synthesized multiple features of link quality, including the single hop delivery reliability, link variance and the burstiness of packet loss. Before the 150 minute, FLI is stable around 0.9. After that time the link quality begins to degrade, and considerable packet loss is observed. Therefore FLI drops correspondingly and sometimes goes down below 0.1. When the link quality returns stable for a short period and starts varying again. FLI varies accordingly around 0.5 in the last 50 minutes.

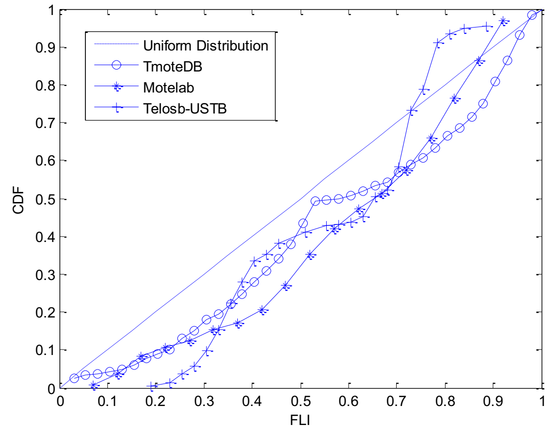


Fig. 11. The cumulative distribution probability of FLI.

From the analysis above, our approach comprehensively evaluate wireless link quality from multiple features and should be beneficial when applied in route choosing. Furthermore, FLI is more human-readable, serving as a better guidance when applied.

C. Prior Probability of FLI

The inference rules described in previous part are human-readable and can be extended to more rules in order to get a finer grain of fuzzy inference. However, more rules result in more resource usage of computation and storage in resource-constrained WSN nodes. The main criteria for evaluating the adequacy of the fuzzy inference rules is whether the resulting link quality indicator has a fine grain in our applications. That is to say, we should check whether FLI keeps the cumulative probability linearly, which guarantees the FLI a fine grain estimation metric.

Fig. 11 is the overall cumulative distribution function (CDF) of the link samples from three separate databases mentioned in Section III. We can observe that in comparison to uniform distribution, the CDFs of FLI are basically linear. FLI provides reasonable link quality estimation and neither overestimates nor underestimates link quality heavily. Therefore, FLI is fine grain link quality estimation and two inference rules are sufficient for the design of FLI.

VI. Verification in Multi-Hop Routing Protocol

In this section, we test and verify the performance of our link estimator in the scenario of static multi-hop wireless sensor networks. We choose the original link estimator in CTP to be our opponent. For differentiation, we denote them FLI-CTP and 4Bit-CTP respectively.

A. Collection Tree Protocol

Collection Tree Protocol (CTP), as the name suggests, is a tree-shaped, multi-hop data collection protocol [34]. It has

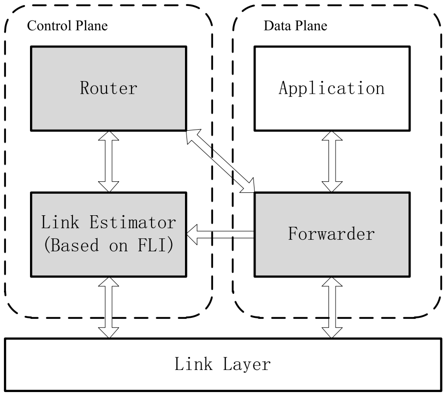


Fig. 12. Schematic diagram of CTP.

three main components: Link Estimator, Router Engine and Forwarder Engine.

The Link Estimator is responsible for determining the inbound and outbound quality of 1-hop communication links. The Router Engine is responsible for sending and receiving beacons as well as creating and updating the routing table. The Forwarder Engine, as the name says, is in charge of forwarding data packets which may either come from the application layer of node itself or from neighboring nodes. In this paper we design and implement a new link quality estimator based on FLI as depicted in Fig. 12.

The link estimator in CTP combines information both from the beacon packets of the Control Plane and the data packets of the Data Plane. There are several differences between unicast and broadcast link properties, so it is difficult to precisely estimate unicast link properties via those of broadcast. The estimation based on beacon packets runs in the initial period of the network and helps to form neighbor information. After the network becomes stable, estimation based on data packets plays a major role and is proportional to the data collection rate. Our link estimator based on FLI not only considers PRR, but also takes link dynamics and packet loss burstiness into account. FLI helps the Router Engine choose the best path that has the lowest cost with respect to above metrics.

B. FLI Implementation in CTP

Original CTP uses ETX as its routing gradient. A root has an ETX of 0. The ETX of a node is the ETX of its parent node plus the ETX of its link to its parent node. Given a choice of valid routes, CTP chooses the one with the lowest ETX value. A perfect link has an ETX of 1.

The ETX in the original CTP is computed according to the formula depicted below,

$$ETX = \frac{1}{D_f \times D_r} \tag{8}$$

where $\mathrm{D_f}$ is the measured probability that a packet is received by the neighbor and $\mathrm{D_r}$ is the measured probability that the acknowledgment packet is successfully received.

The link estimator in the original CTP uses the acknowledgement information to refine link estimates, combining broadcast and unicast ETX estimates into a hybrid value. The result is a hybrid data/beacon windowed-mean EWMA estimator. When there is heavy data traffic, unicast estimates dominate. When the network is quiet, broadcast estimates dominate

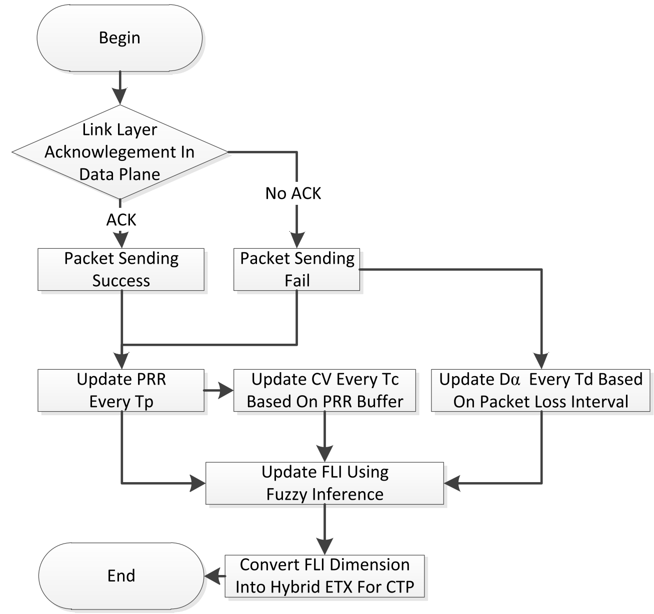


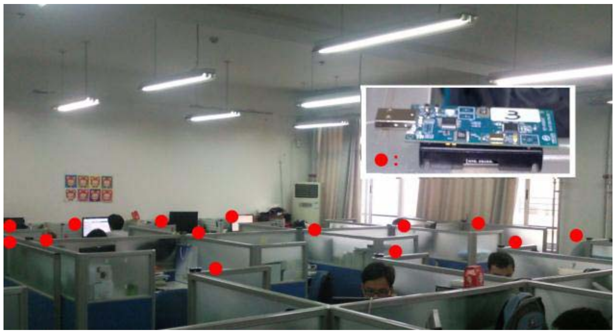
Fig. 13. Flowchart of aggregating FLI into the CTP.

FLI designed in this paper is used to quantify the link reliability using a continuous value, from 0 to 1. The mechanism used to aggregate FLI into the CTP is described in Fig. 13 below.

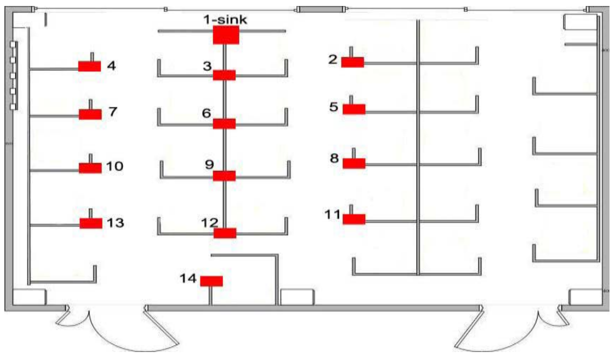
From the link layer acknowledgement in the data plane, we can compute the PRR every Tp period, and fill the new PRR into PRR buffer to compute CV every Tc period. When packet sending fails, packet loss interval can be recorded. After a period of Td, statistics is made on the relative frequency of packet loss interval. We use the relative frequency of the loss interval equal to 1 to approximate the distribution parameter α, and easily get the Dα by subtracting distribution parameter of I.I.D packet trace of the same average PRR. Every link quality above updates periodically based on their own demand, and invokes the update of FLI using fuzzy inference method mentioned in section V. When practical, low-pass filtering is used to avoid rapid fluctuations of these values. When making use of FLI in the CTP, we should convert FLI's dimension to the same as ETX, and aggregate the result into the hybrid ETX replacing the data-driven estimation in original CTP link estimator.

C. Experiment Setup

We aim to investigate whether the new link estimator based on FLI can improve the whole network performance. The experiments were conducted using 15 Telosb nodes. They are deployed statically on the joint of office tables in our lab, consisting of 1 sink node and 14 common nodes showed in Fig. 14. There exist many WiFi hot spots and people moving



(a)



(b)

Fig. 14. Experiment layout pictures. (a) Office environment and nodes picture. (b) Office structural representation.

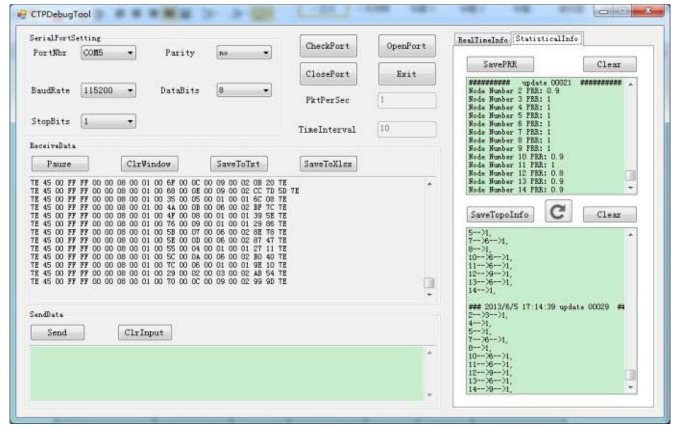


Fig. 15. Software interface of CTP debug tool in the PC.

around sometimes. All these factors are regarded as sudden interference to the whole network.

The Telosb nodes are equipped with a TI MSP430 MCU and a CC2420 RF transceiver. We make use of TinyOS as an operating system. Link estimator based on FLI has been implemented with TinyOS.

In order to debug the CTP network performance, we encapsulate the information we need into the payload field of CTP data packets. As sink node gathers all the information from other common sensor nodes, we connect the sink node to a PC and use the CTP debug tool we have designed to analyze the data from each node. The software interface is showed in Fig. 15. With the help of CTP debug tool, we can easily get the information about the real-time original packet, PRR of every node, and network topology change.

Several studies confirmed that the temporal variation of link quality is due to changes in the environment characteristics, such as climate conditions, human presence, interference, and obstacles [2], [5], [12], [35]. In order to minimize influence of the environment for our contrast experiment, we run 4 bit-CTP and FLI-CTP alternatively with each period of 20 minutes. We run average 12 hours for each contrast experiment with different network configurations and gather sufficient data for the analysis afterwards. We set three different network configurations to test the performance of CTP for comparison. Configuration details are given in the table I.

D. Performance Analyses

First, we give the contrast memory usage between 4Bit-CTP and FLI-CTP. Table II gives the detail about ROM and RAM usage for CTP with TinyOS, which shows FLI-CTP uses 3.3% ROM and 8.7% RAM more than 4Bit-CTP.

TABLE I
NETWORK CONFIGURATIONS

Configuration Index	Transmit Power	Packet Sending Interval
1	-22dBm	1 Second
2	-22dBm	1.5 Second
3	-15dBm	1.5 Second

TABLE II
MEMORY USAGE FOR CTP WITH DIFFERENT LINK ESTIMATOR

Link Estimator	ROM	RAM
4Bit-CTP	30230 bytes	2300 bytes
FLI-CTP	31252 bytes	2500 bytes

Next, we compare the performance of CTP using different link estimator from three aspects as follows:

1) End to End Delivery Rate: It is defined as the ratio of the number of packets received at sink to that of packets sent at the source node.
2) Path Length: It is defined as the number of hops a packet travels from the source node to the sink. It indicates the route depth of the source node and has great implication on end-to-end latency and network energy consumption.
3) Network Stability. It is defined as the number of changes of network topology in a given period.

From the comparison chart of end-to-end delivery rate, as shown in Fig. 16, we can see that at different packets sending intervals and transmission power, FLI-CTP shows a high End to End Delivery Rate similar to 4Bit-CTP.

We can draw these conclusions below from the comparison chart of path length as shown in Fig. 17. When the transmission power is higher, both FLI-CTP and 4Bit-CTP have shorter path length. This is because the signal coverage of a node increases as a consequence of higher power. Under 3 different network configurations, FLI-CTP shows better performance of evaluating the quality of links from neighbors and chooses the

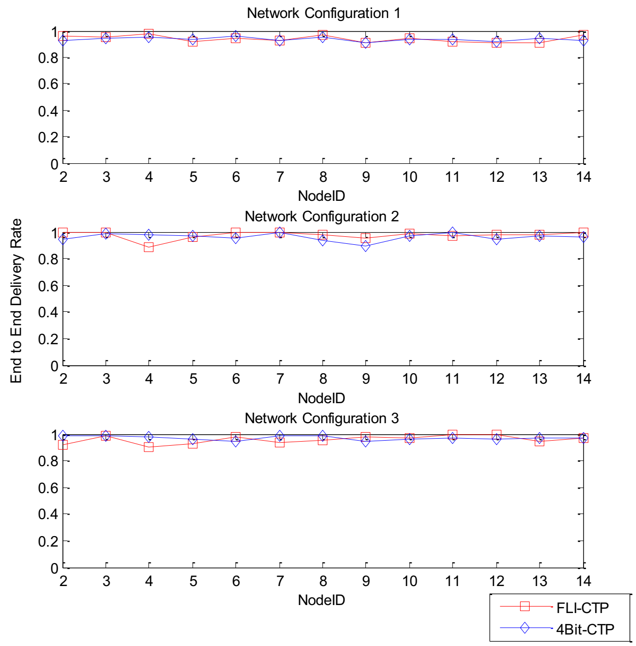


Fig. 16. The performance comparison for end-to-end delivery rate in 3 network configurations.

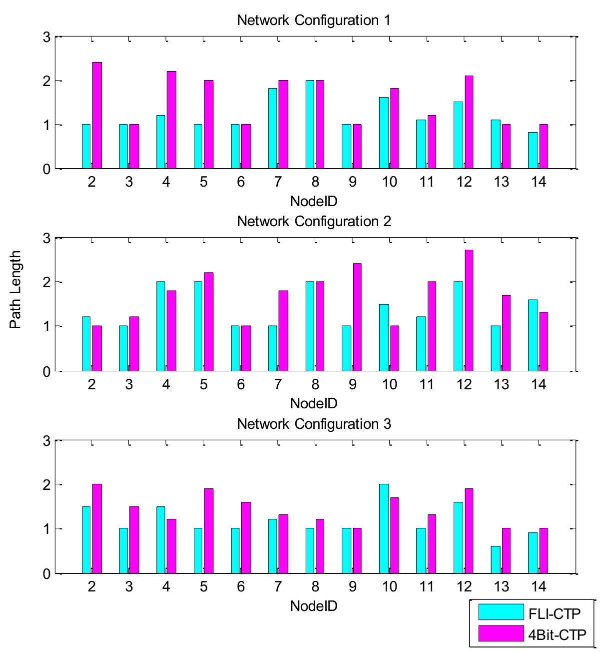


Fig. 17. The performance comparison for path length in 3 network configurations.

best neighbor, which usually guarantee shorter path to the sink. As a result, the average route depth is reduced accordingly.

Under the same network configuration, our test shows no necessary relevance between the path length and the physical distance between the source node and sink, as shown in Fig. 17. The reason behind is the multipath effect which makes some remote node may have lower route depth than that near the sink.

The stability of network topology is fundamental to higher layer protocol behaviors such as resource scheduling and data collection. In the CTP, each node has only one parent at a given time. Therefore, after a node changes its parent, the whole network topology will change accordingly. The table III below shows the average times of topology change of 4Bit-CTP and FLI-CTP respectively under the 3 network configurations mentioned above.

TABLE III
TOPOLOGY CHANGES UNDER DIFFERENT CONFIGURATIONS

Configuration Index	Routing Protocol	Topology Change
1	4Bit-CTP	26times
1	FLI-CTP	21times
2	4Bit-CTP	37times
2	FLI-CTP	23times
3	4Bit-CTP	22times
3	FLI-CTP	17times

Under the 3 network configurations, the average number of topology changes of FLI-CTP is lower than that of 4Bit-CTP. In other words, under the same network environment, 4Bit-CTP shows certain bias on link estimation causing nodes switching their parent nodes frequently. Such changes in network topology will increase energy consumption and reduce network stability. On the other hand, FLI-CTP uses multidimensional link estimation and is robust against the influence of any single feature such as link dynamics and packet loss burstiness, while 4Bit-CTP cannot. Thus FLI-CTP achieves great immunity against environmental interference and can choose the stable and reliable links at its best effort.

As already pointed out, dynamically calculated metrics are important in many circumstances for routing protocol. This is mainly because a variety of metrics change on a frequent basis, thus implying the need to adapt the routing decisions. The attributes of link quality metric should change according to their own time scales. Controlled adaptation of the routing metrics and rate at which paths are computed are critical to avoid undesirable routing instabilities resulting in increased latencies and packet loss. Furthermore, excessive route changes will impact the traffic and power consumption in the network.

The ultimate reason behind the different performances of 4Bit-CTP and FLI-CTP is that they have distinct estimation methods. 4Bit-CTP describes link quality through the metric ETX, regardless of other factors that will severely affect network reliability. In contrast to 4Bit-CTP, FLI-CTP not only considers PRR, approximately the reciprocal of ETX, but also takes link dynamics and packet loss burst into account. FLI comprehensively reflects the influence of the three factors above on link qualities. Therefore, FLI-CTP reduces average path length and frequency of topology change, while maintaining a high end-to-end delivery rate similar to 4Bit-CTP.

VII. CONCLUSION AND FUTURE WORK

The lossy and dynamic nature of wireless channels poses great challenges on effective wireless link quality estimation in WSN. In this paper we first model the burstiness of wireless link packet loss which is a direct reflection of link layer packet retransmission reliability. Then a fuzzy logic based link quality indicator FLI is presented, which synthetically reflects one-hop reliability of wireless link, link dynamics and packet loss burst. Finally we implement our new link quality estimator based on FLI in the routing protocol CTP. Through the comparison of the performances between 4Bit-CTP and FLI-CTP, we conclude that the FLI-CTP reduces the average path length and the topology changes in different network configurations. At the same time, it maintains a high end to end delivery rate, paying the cost of more memory usage than 4Bit-CTP.

An open issue is how to validate link quality estimation and tune it to be optimally used by higher-layer protocols. The design of a link-quality-based routing metric is a crucial and challenging problem. The effectiveness of a routing protocol depends not only on the link quality estimation process, but also on how to use the estimate as a routing metric for path selection. This was addressed in the widely used CTP, but is still to be resolved for RPL.

As a future work, we will aggregate the link quality estimation method based on fuzzy inference to the PRL, especially for the design of objective function (OF). Some directions have been already shown in this paper. Besides, when designing the link quality estimator, we will also take some node characteristics into account as routing metrics, such as residual energy.

ACKNOWLEDGMENT

The authors would like to thank the editor and anonymous reviewers for their valuable comments to improve the quality of this paper.

REFERENCES

[1] A. Luigi, A. Iera, and G. Morabito, "The internet of things: A survey," *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, Oct. 2010.

[2] L. Tang, K. C. Wang, Y. Huang, and F. Gu, "Channel characterization and link quality assessment of IEEE 802.15.4-compliant radio for factory environments," *IEEE Trans. Ind. Inf.*, vol. 3, no. 2, pp. 99–110, May 2007.

[3] V. C. Gungor and G. P. Hancke, "Industrial wireless sensor networks: Challenges, design principles, and technical approaches," *IEEE Trans. Ind. Electron.*, vol. 56, no. 10, pp. 4258–4265, Oct. 2009.

[4] N. Baccour, A. Koubaa, L. Mottola, M. A. Zúñiga, H. Youssef, C. A. Boano, and M. Alves, "Radio link quality estimation in wireless sensor networks: A survey," *ACM Trans. Sensor Netw.*, vol. 8, no. 4, p. 34, Sep. 2012.

[5] J. Ortiz and D. Culler, "Multichannel reliability assessment in real world wsns," in *Proc. 9th ACM/IEEE Int. Conf. Inf. Process. Sensor Netw.*, Apr. 2010, pp. 162–173.

[6] V. C. Gungor and M. K. Korkmaz, "Wireless link-quality estimation in smart grid environments," *Int. J. Distrib. Sensor Netw.*, pp. 1–10, Feb. 2012.

[7] D. Palma, H. Araujo, and M. Curado, "Link quality estimation in wireless multi-hop networks using Kernel based methods," *Comput. Netw.*, vol. 56, no. 16, pp. 3629–3638, Nov. 2012.

[8] S. Kim, O. Lee, S. Choi, and S. J. Lee, "Comparative analysis of link quality metrics and routing protocols for optimal route construction in wireless mesh networks," *Ad Hoc Netw.*, vol. 9, no. 7, pp. 1343–1358, Sep. 2011.

[9] A. Woo, T. Tong, and D. Culler, "Taming the underlying challenges of reliable multihop routing in sensor networks," in *Proc. 1st Int. Conf. Embedded Netw. Sensor Syst.*, 2003, pp. 14–27.

[10] M. Senel, K. Chintalapudi, D. Lal, A. Keshavarzian, and E. J. Coyle, "A kalman filter based link quality estimation scheme for wireless sensor networks," in *Proc. IEEE Global Telecommun. Conf.*, Nov. 2007, pp. 875–880.

[11] M. Zuniga and B. Krishnamachari, "Analyzing the transitional region in low power wireless links," in *Proc. 1st Annu. IEEE Commun. Soc. Conf. Sensor Ad Hoc Commun. Netw.*, Oct. 2004, pp. 517–526.

[12] K. Srinivasan, P. Dutta, A. Tavakoli, and P. Levis, "An empirical study of low-power wireless," *ACM Trans. Sensor Netw.*, vol. 6, no. 2, p. 16, Feb. 2010.

[13] S. Munir, S. Lin, E. Hoque, S. M. Shahriar Nirjon, J. A. Stankovic, and K. Whitehouse, "Addressing burstiness for reliable communication and latency bound generation in wireless sensor networks," in *Proc. 9th ACM/IEEE Int. Conf. Inf. Process. Sensor Netw.*, Apr. 2010, pp. 303–314.

[14] J. Brown, B. McCarthy, and U. Roedig, "BurstProbe: Debugging time-critical data delivery in wireless sensor networks," in *Wireless Sensor Networks*. Berlin, Germany: Springer-Verlag, 2011, pp. 195–210.

[15] K. Srinivasan, M. Jain, J. I. Choi, T. Azim, E. S. Kim, P. Levis, and B. Krishnamachari, "The κ factor: Inferring protocol performance using inter-link reception correlation," in *Proc. 16th Annu. Int. Conf. Mobile Comput. Netw.*, 2010, pp. 317–328.

[16] A. Willing and R. Mitschkei, "Results of bit error measurements with sensor nodes and casuistic consequences for design of energy-efficient error control schemes," in *Wireless Sensor Networks*. Berlin, Germany: Springer-Verlag, Feb. 2006, pp. 310–325.

[17] D. Couto, D. Aguayo, J. Bicket, and R. Morris, "A high-throughput path metric for multi-hop wireless routing," *Wireless Netw.*, vol. 11, no. 4, pp. 419–434, Jul. 2005.

[18] R. Fonseca, O. Gnawali, and K. Jamieson, "Four-bit wireless link estimation," in *Proc. 6th Workshop Hot Topics Netw.*, 2007, pp. 1–7.

[19] (2004). *MultiHopLQI* [Online]. Available: http://www.tinyos.net/tinyos-1.x/tos/lib/MultiHopLQI

[20] O. Gnawali, R. Fonseca, K. Jamieson, D. Moss, and P. Levis, "Collection tree protocol," in *Proc. 7th ACM Conf. Embedded Netw. Sensor Syst.*, 2009, pp. 1–14.

[21] T. Winter and P. Thubert, "RPL: IPv6 routing protocol for low power and lossy networks," in *Networks and Distributed Systems Seminar*. New York, NY, USA: Springer-Verlag, Mar. 2010.

[22] X. Vilajosana, J. Llosa, J. C. Pacho, I. Vilajosana, A. A. Juan, J. L. Vicario, and A. Morell, "ZERO: Probabilistic routing for deploy and forget wireless sensor networks," *Sensors*, vol. 10, no. 10, pp. 8920–8937, 2010.

[23] J. Tripathi, J. C. de Oliveira, and J. P. Vasseur, "A performance evaluation study of RPL: Routing protocol for low power and lossy networks," in *Proc. 44th Annu. CISS*, Mar. 2010, pp. 1–6.

[24] N. Accettura, L. A. Grieco, G. Boggia, and P. Camarda, "Performance analysis of the RPL routing protocol," in *Proc. IEEE ICM*, Apr. 2011, pp. 767–772.

[25] M. Dyer, J. Beutel, and T. Kalt, "Deployment support network wireless sensor networks," in *Wireless Sensor Networks*. Berlin, Germany: Springer-Verlag, 2007, pp. 195–211.

[26] G. Werner-Allen, P. Swieskowski, and M. Welsh, "MoteLab: A wireless sensor network testbed," in *Proc. 4th Int. Symp. Inf. Process. Sensor Netw.*, 2005, p. 68.

[27] Q. Wang, Y.-D. Wan, L. Li, S.-H. Duan, "Multi-channel reliability modeling and analysis for IEEE802.15.4 in industrial enviroment," *J. Comput. Res. Develop.*, vol. 46, no. 12, pp. 1971–1984, 2009.

[28] J. He, K. Pahlavan, S. Li, and Q. Wang, "A test-bed for evaluation of the effects of multipath on performance of TOA-based indoor geolocation," *IEEE Trans. Instrum. Meas.*, vol. 62, no. 8, pp. 2237–2247, Aug. 2013.

[29] Y. D. Wan, L. Li, J. He, X. Zhang, and Q. Wang, "Anshan: Wireless sensor networks for equipment fault diagnosis in the process industry," in *Proc. 5th Annu. IEEE Commun. Soc. Conf. Sensor, Mesh Ad Hoc Commun. Netw.*, Jun. 2008, pp. 314–322.

[30] J. He, Y. S. Geng, and K. Pahlavan, "Modeling indoor TOA ranging error for body mounted sensors," in *Proc. IEEE 23nd Int. Symp. PIMRC*, Sep. 2012, pp. 9–12.

[31] Z. Q. Guo, Q. Wang, Y.-D. Wan, and M.-H. Li, "A classification prediction mechanism based on comprehensive assessment for wireless link quality," *J. Comput. Res. Develop.*, vol. 50, no. 6, pp. 1227–1238, 2013.

[32] M. Newman, "Power laws, Pareto distributions and Zipf's law," *Contemp. Phys.*, vol. 46, no. 5, pp. 323–351, 2005.

[33] S. Greenfield, F. Chiclana, and S. Coupland, "The collapsing method of defuzzification for discretized interval type-2 fuzzy sets," *Inf. Sci.*, vol. 179, no. 13, pp. 2055–2069, 2009.

[34] (2009). *Collection Tree Protocol* [Online]. Available: http://www.tinyos.net/tinyos-2.x/doc/html/tep123.html

[35] S. Lin, G. Zhou, K. Whitehouse, Y. Wu, J. A. Stankovic, and T. He, "Towards stable network performance in wireless sensor networks," in *Proc. IEEE Real-Time Syst. Symp.*, Dec. 2009, pp. 227–237.

Zhi-Qiang Guo received the B.E. and M.E. degrees from the Ocean University of China, Qingdao, China, in 2007 and 2010, respectively. He is currently pursuing the Ph.D. degree in computer science and engineering at the School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing, China, under the guidance of Dr. Q. Wang. His current research interests include industrial wireless sensor networks, intelligent instrument, and embedded system on programmable chips.

Qin Wang is a Professor with the School of Computer and Communication Engineering, University of Science and Technology Beijing (USTB), Beijing, China, and a Visiting Professor with BSAC, U.C. at Berkeley, Berkeley, CA, USA. She received the B.S., M.S., and Ph.D. degrees in computer science and engineering from USTB in 1982, Peking University, Beijing, in 1985, and USTB in 1998. She joined USTB in 1985, became a Full Professor in 2000. He was a Visiting Scientist with the EECS Department, Cornell University, Ithaca, NY, USA, from 2005 to 2006, and a Visiting Researcher with the EECS Department, Harvard University, Cambridge, MA, USA, from 2006 to 2007. Her research and contributions focused on wireless sensor network technology and related power consumption modeling from both device and network system perspective. She has focused on low power wireless sensor networks and multiprocessor system-on-chip technology in communications and networking systems. Since January 2012, she has been working on OpenWSN project in U.C. at Berkeley as a Visiting Professor. She has been involved in international wireless network standard development since 2007, including ISA100.11a, IEEE 802.15.4e, and industrial wireless standard WIA-PA proposed to IEC from China.

Mo-Han Li received the B.E. degree from the University of Science and Technology Beijing, Beijing, China, in 2013. He has been pursuing the Ph.D. degree in computer science at Washington University in St. Louis, MO, USA, since 2013. His current research interests include wireless sensor network protocol design and simulation, embedded system design, and computer architecture.

Jie He (S'11) received the B.E. and Ph.D. degrees from University of Science and Technology Beijing, Beijing, China, in 2005 and 2012, respectively. He began to work in the field of wireless indoor location system in 2007. From 2011 to 2012, he was a Visiting Student, involved in research on body area networks, with the Center for Wireless Information Network Studies, Department of Electrical and Computer Engineering, Worcester Polytechnic Institute, Worcester, MA, USA. His current research interests include indoor location system, wireless sensor networks, and body area network.