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WNN-LQE: Wavelet-Neural-Network-Based Link Quality Estimation for Smart Grid WSNs

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ABSTRACT Wireless sensor networks (WSNs) are currently being used for monitoring and control in smart grids. To ensure the quality of service (QoS) requirements of smart grid applications, WSNs need to provide specific reliability guarantees. Real-time link quality estimation (LQE) is essential for improving the reliability of WSN protocols. However, many state-of-the-art LQE methods produce numerical estimates that are suitable neither for describing the dynamic random features of radio links nor for determining whether the reliability satisfies the requirements of smart grid communication standards. This paper proposes a wavelet-neural-network-based LQE (WNN-LQE) algorithm that closes the gap between the QoS requirements of smart grids and the features of radio links by estimating the probability-guaranteed limits on the packet reception ratio (PRR). In our algorithm, the signal-to-noise ratio (SNR) is used as the link quality metric. The SNR is approximately decomposed into two components: a time-varying nonlinear part and a non-stationary random part. Each component is separately processed before it is input into the WNN model. The probability-guaranteed limits on the SNR are obtained from the WNN-LQE algorithm and are then transformed into estimated limits on the PRR via the mapping function between the SNR and PRR. Comparative experimental results are presented to demonstrate the validity and effectiveness of the proposed LQE algorithm.

INDEX TERMS Smart grids, wireless sensor networks, quality of service, link quality estimation, wavelet neural network, radio link reliability.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have many advantages compared with traditional communication technology, such as ease of installation, maintenance, expansion, and integration. WSNs are also relatively inexpensive. Furthermore, as demonstrated by hundreds of projects and thousands of papers, WSNs include the following three advantages: (1) they can be deployed "off the grid" without a power supply or IT infrastructure; (2) they can be used on a small scale before being deployed in a wider area (e.g., in feasibility studies of new applications); and (3) they can be used in ad hoc and mobile environments. Because of the successes of WSN projects and recent advances in cyber-physical systems, WSN technology has attracted widespread attention in the power system community [1]–[3]. Recently, ZigBee, a specification for WSNs, has been listed as the recommended communication standard for smart grid technology by the National Institute of Standards and Technology of the United States [4]. However, innovative solutions are still needed to improve the reliability of WSNs, particularly to satisfy the strict Quality of Service (QoS) requirements of smart grids. One of the most important indicators of improved WSN reliability is link quality. Link quality must be estimated to guide the selection of a practical radio link that can reliably transmit data [5]. In this paper, we focus on developing a Wavelet-Neural-Network-based Link Quality Estimation (WNN-LQE) algorithm for WSN-based communication systems used in smart grid applications.

Because of electromagnetic influence on WSN nodes and internal circuits, radio link quality varies randomly over time and in space. Thus, Signal-to-Noise Ratio (SNR) is a link quality metric that can be considered as a random-time sequence that has both nonlinear and non-stationary random features. Several LQE methods [6]–[8] that have been used in WSNs attempt to filter some of the measurement noise and provide an accurate numerical estimate. However, from a statistical perspective, a deterministic number cannot effectively describe any random feature of link quality. In other words, because the link quality has random features, random error cannot be eliminated from numerical estimation results. Thus, even when the link quality is estimated to satisfy the reliability requirements, it is likely to fail in practice.

In this paper, before presenting the design of the proposed LQE algorithm, the time-varying nonlinear and non-stationary random characteristics of the link quality metric, the SNR, are analyzed according to the most common radio propagation model: the log-normal path-loss model. Based on this analysis, the SNR time series is designed to be decomposed into two parts: a time-varying nonlinear part and a non-stationary random part. Then, we design a novel WNN-LQE model to estimate the probability-guaranteed limits on the Packet Reception Ratio (PRR). This WNN-LQE model allows us to obtain a more reliable estimate of the radio link quality to judge whether it satisfies the stringent reliability requirements of smart grid applications. To the best of our knowledge, this study proposes the first LQE algorithm that can produce probability-guaranteed estimates of radio link quality.

We summarize the novelty and contributions of the work presented in this paper as follows:

1. The different characteristics of the link quality metric, the SNR, are decomposed and processed separately.
2. The probability-guaranteed estimation result can more comprehensively describe the performance range of a random dynamic radio link and is thus more useful for judging whether it satisfies the practical requirements for industrial applications.
3. We evaluate our LQE algorithm in a real-world outdoor smart grid environment.

The remainder of this paper is organized as follows. Section II presents a survey of the most interesting approaches related to our work. In Section III, we provide an analysis of the characteristics of the link quality metric. In Section IV, we introduce the WNN-LQE model. Section V reports a comparative experiment conducted in a real-world smart grid environment and analyzes the experimental results. Finally, we conclude the paper in Section VI.

II. RELATED WORKS

The purpose of Link Quality Estimation, also referred to as Link Quality Prediction, is to provide a basic description of the radio link quality in WSN protocols. Subsequently, this knowledge of the radio link quality is used to improve WSN performance. Many studies have proposed various algorithms for estimating radio link quality. The link quality metrics on which these LQE algorithms are based are commonly classified into three categories: hardware-based, software-based and score-based, as shown in Table 1.

Software-based LQE metrics are computed using transmission-based variables. The PRR, Required Number of Packet Transmissions (RNP), and Expected Transmission Count (ETX) are the most common software-based LQE metrics.

TABLE 1. The taxonomy of LQE applications.

	LQE metric	LQE algorithm
Software-based	PRR	WMEWMA [9]
	RNP	RNP [10]
	EXT	ETX [12] LEXT [13]
Hardware-based	RSSI	Wang [14] Weng [15]
	SNR	Kalman [7] Qin [6] XCoPred [8]
	LQI	Srinivasan [18] Qin [6]
Score-based	WER	Xu [20]
	Fuzzy metric	F-LQE [5]
	CSI	Halperin [21]
	Delivery probability	Cerpa [22]

PRR is the ratio of the number of successfully received packets to the number of transmitted packets. The PRR is also sometimes referred to as the Packet Success Ratio (PSR).

The PRR is a statistical metric computed within a given time window. It represents the average value of the link quality within the time window considered for the statistical computation. Thus, the PRR is not sensitive to rapid fluctuations in link quality. Woo and Culler [9] presented the Window Mean Exponentially Weighted Moving Average (WMEWMA) algorithm for smoothing the PRR using an EWMA filter to achieve a more stable and sufficiently agile estimation.

RNP is the average number of packet transmissions/retransmissions required before successful reception.

Cerpa *et al.* [10] introduced the RNP to describe the link quality of WSNs. However, the RNP has the disadvantage of being very unstable and it is unable to reliably estimate the success of link packet delivery, mainly because of link asymmetry [11].

ETX is the number of transmissions required to successfully send a packet.

De Couto *et al.* [12] introduced the ETX into WSN routing protocols to estimate the high-throughput paths that minimize the number of packet transmissions required for successful packet delivery. Gomez et al. [13] used the Link Quality Indicator (LQI)-based ETX (LETX) to identify high-quality links in the router decision process. However, the ETX-based approach fails in congested networks [11].

Hardware-based LQE metrics are obtained directly from the registers of radio transceivers (e.g., the TI CC2530) without any additional computation. Thus, they are more efficient than software-based LQE metrics. Generally, the Received Signal Strength Indicator (RSSI), Signal-to-Noise Ratio (SNR), and LQI are commonly used hardware-based LQE metrics.

RSSI: a measure of the power present in a received radio signal.

Wang *et al.* [14] adopted the RSSI, in combination with other WSN node features, such as buffer size and node depth, to determine link quality metrics. The sink node evaluates the link quality via a supervised learning algorithm; it classifies a link as either high or low quality for a given routing protocol. Weng *et al.* [15] used a nonparametric model to predict short-term link quality online by using the RSSI and one-way delay as model inputs. However, because the RSSI reflects only the power of the pure received signal at the receiver, it does not provide a measure of radio inference.

LQI is a characterization of the strength and/or quality of a received packet based on the IEEE 802.15.4 standard [16].

Currently, there is no consistent or standard definition of the LQI. In practice, different vendors calculate the LQI in different ways. For example, the ATMEL AT86RF231 determines the LQI by correlating quality with the packet error rate [6]. The TI CC2530 determines the LQI by correlating quality with the chip error rate, whereas Farzana and Neduncheliyan [17] used the RSSI to calculate the LQI. Srinivasan *et al.* [18] concluded that when the LQI is very high, a link has perfect quality. However, the variance in the LQI increases significantly as the link quality degrades. Thus, single LQI readings are considered insufficient to accurately describe link quality [6]. Qin *et al.* [6] used a Kalman filter algorithm to estimate link quality and introduced LQI into the calculation to correct the estimated result only when the LQI reading was high.

SNR is the difference, in decibels, between the received signal strength and the noise floor.

The SNR is a better metric than the RSSI because it considers both the strength of the received signal and the background noise. The SNR has been selected as the link quality metric in several LQE studies [6]–[8]. Senel *et al.* [7] presented a Kalman filter-based link quality estimation (KLE) algorithm. Qin *et al.* [6] presented a Kalman filter-based LQE algorithm that combines the SNR and LQI with minimal additional overhead. Farkas *et al.* [8] proposed XCoPred, a pattern-matching-based LQE scheme, to predict link quality variations based on the SNR. However, XCoPred is unsuitable for describing a random SNR using a fixed numerical value, as in [6]–[8]. Moreover, although these hardware-based LQE approaches are easy to implement, they are incapable of providing a sufficiently fine-grained description of the link quality [19].

In addition to the software- and hardware-based LQE algorithms introduced above, several LQE algorithms define score values rather than link properties to describe link quality. Xu and Lee [20] proposed the Weighted Regression Estimator (WRE) as an LQE metric. They used a complex-valued regression function to calculate the WRE based on an input vector containing a set of known node locations and link qualities. Baccour *et al.* [5] proposed the Fuzzy Link Quality Estimation (F-LQE) algorithm, which considered several important link properties to obtain a holistic characterization of a link; then, fuzzy logic was applied to estimate the link quality. Halperin *et al.* [21] normalized the RSSI and LQI and combined the two normalized values into a weighted sum called Channel State Information (CSI) to serve as the link quality metric. Liu and Cerpa [22] proposed the use of 4 separate metrics (the PRR, RSSI, SNR, and LQI) to estimate the probability that the next packet would be delivered successfully.

TABLE 2. The reliability requirements of smart grid applications.

Smart grid application	Reliability requirement
Substation	99.0–99.99%
Overhead transmission line monitoring	99.0–99.99%
Residential energy management	99.0–99.99%
Advanced measurement system	99.0–99.99%
Wide-area situational awareness system	99.0–99.99%
Demand response	95.0–99.0%
Outage management	95.0–99.0%
Power distribution system	99.0–99.99%
Distributed management & control	99.0–99.99%
Asset management	95.0–99.0%
Asset management	99.0–99.99%

III. LQE METRIC SELECTION AND ANALYSIS

A. LQE METRIC SELECTION

Several LQE metrics were introduced in Section II. However, not every metric is suitable for smart grid applications. Table 2 lists the communication reliability requirements for various smart grid applications [23]. The table clearly shows that each smart grid application has specific reliability requirements in the form of limits on the allowed PRR interval. However, as mentioned in Section II, the PRR is a statistical parameter calculated within a fixed window. Consequently, the accuracy of the PRR is proportional to the size of the window. Thus, there is a trade-off between accuracy and window size in PRR estimation. In addition, the PRR does not reflect the dynamic fluctuations in link quality within the chosen window.

In contrast, the hardware-based SNR metric reflects both the signal strength of an electromagnetic wave and the overall noise. Thus, in this study, we select the SNR as the link quality metric to be considered. The mapping function between the SNR and PRR introduced in [24] is adopted to transform SNR estimates into PRR estimates to verify whether the reliability of a radio link satisfies the smart grid SNR requirements listed in Table 2.

B. ANALYSIS OF THE SNR

According to the most commonly used radio propagation model, the log-normal path-loss model, the Received Signal

Strength (RSS) in units of dBm is as follows:

$$RSS = P_t - PL(d_0) - 10 \cdot n \cdot \log_{10}\left(\frac{d}{d_0}\right) - X_\sigma, \quad (1)$$

where P_t is the transmission power in dBm, $PL(d_0)$ is the path loss at a reference distance d_0 (commonly, $d_0 = 1$ m), n is the path-loss exponent, and d is the separation distance between the transmitter and receiver. The term X_σ, which represents shadow fading, is taken to be a Gaussian random variable with zero mean and a time-varying variance σ^2, i.e., $X_\sigma \sim \mathcal{N}(0, \sigma^2)$.

Let BN represent the background noise in units of dBm. Then, the SNR is expressed as follows:

$$SNR = RSS - BN = P_t - PL(d_0) - 10 \cdot n \cdot \log_{10}\left(\frac{d}{d_0}\right) - X_\sigma - P_n, \quad (2)$$

where P_n represents the power of the background noise in dBm.

According to the experimental results presented in [25], P_n is a random variable whose distribution function is defined by a Gaussian distribution, and $\overline{P}_n$ and σ_n^2 are the time-varying mean and variance, respectively, of P_n. Thus, $P_n \sim \mathcal{N}(\overline{P}_n, \sigma_n^2)$. Let $X_n = P_n - \overline{P}_n$; then, we can obtain $X_n \sim \mathcal{N}(0, \sigma_n^2)$. Then, (3) can be deduced from (2) as follows:

$$SNR = P_t - PL(d_0) - 10 \cdot n \cdot \log_{10}\left(\frac{d}{d_0}\right) - \overline{P}_n - (X_\sigma + X_n). \quad (3)$$

According to Eq. (3), the SNR can be expressed as the sum of the following two components: a time-varying nonlinear part, $P_t - PL(d_0) - 10 \cdot n \cdot \log_{10}(d/d_0) - \overline{P}_n$, and a non-stationary random part, $X_\sigma + X_n$. The time-varying nonlinear part is mainly determined by the transmission power, the path-loss parameters, the separation distance and the mean background noise, any of which may vary over time in WSN communications. Meanwhile, the non-stationary random part is the difference between two Gaussian-distributed random variables. The total variance σ_t^2 of the non-stationary random part is obtained by (4):

$$\sigma_t^2 = \sigma^2 + \sigma_n^2. \quad (4)$$

IV. LINK QUALITY ESTIMATION ALGORITHM

To obtain a better estimation of the SNR, the time-varying nonlinear part and the non-stationary random part should be decomposed and processed separately, because they have different characteristics. Therefore, in the WNN-LQE algorithm, we first decompose the SNR time series into a time-varying nonlinear series and a non-stationary random series. After calculating the series of statistical variances of the non-stationary random series, we introduce the WNN model to estimate the time-varying nonlinear part and the variance of the non-stationary random part. Finally, we calculate the probability-guaranteed PRR range as our estimation result to better describe the reliability of a link with random quality features.

A. DECOMPOSITION ALGORITHM

Commonly used decomposition algorithms, such as empirical mode decomposition and local mean decomposition, are associated with high computational complexity, which has an adverse influence on the efficiency of an LQE algorithm. In this paper, we adopt the simpler and more efficient moving-average filter to decompose the SNR-based time series.

For a WSN node, we obtain the L most recent SNR readings, denoted by $S(L) = \{s_1, s_2, \ldots, s_L\}$, and use them to calculate the time-varying nonlinear series, $N(L) = \{n_1, n_2, \ldots n_L\}$, and the non-stationary random series, $R(L) = \{r_1, r_2, \ldots, r_L\}$, as follows:

$$\begin{cases} n_k = \dfrac{s_1 + s_2 + \cdots + s_k}{k} \\ r_k = s_k - n_k \quad for\ k = 1, 2, \ldots, L; \quad k < W;\ W < L \\ n_k = \dfrac{s_{k-W+1} + s_{k-W+2} + \cdots + s_k}{W} \\ r_k = s_k - n_k \quad for\ k = 1, 2, \ldots, L; \quad k \geq W; \quad W < L, \end{cases} \quad (5)$$

where W denotes the moving window size.

We then employ (6) to calculate the series of variances (denoted by $V(L) = \{v_1, v_2, \ldots v_L\}$) of the non-stationary random series $R(L)$.

$$\begin{cases} v_k = \dfrac{1}{k}\sum_{i=1}^{k}\left(r_i - \dfrac{r_1 + r_2 + \cdots + r_k}{k}\right)^2, \\ \qquad i = 1, 2, \ldots, k; \quad 1 \leq k \leq K;\ K < L \\ v_k = \dfrac{1}{K}\sum_{i=1}^{K}\left(r_{k-K+i} - \dfrac{r_{k-K+1} + r_{k-K+2} + \cdots + r_k}{K}\right)^2, \\ \qquad i = 1, 2, \ldots, k; \quad k > K;\ K < L, \end{cases} \quad (6)$$

where K denotes the window size used to calculate the variances.

B. WAVELET NEURAL NETWORK ESTIMATION MODEL

Because the random part of the link quality is non-stationary, its variance varies nonlinearly according to changes in the environment where the WSN nodes are located. Therefore, both the time-varying nonlinear part and its variance will vary in time and space at different scales. A WNN is a powerful tool for representing nonlinearities at different scales [26]. Therefore, in this paper, we adopt a WNN to estimate the time series of the decomposed data.

The WNN model we adopt is shown in Fig. 1. This model consists of an input layer, a hidden layer, and an output layer. The input data are the time-varying nonlinear series, $S(m) = \{s_{L-m+1}, s_{L-m+2}, \ldots, s_L\}$, and the variances of the non-stationary random series, $V(m) = \{v_{L-m+1}, v_{L-m+2}, \ldots v_L\}$ ($m \leq L$). The outputs of the WNN estimation model are s_{L+1} and v_{L+1}.

Let p_1, p_2, and p_3 represent the numbers of neurons in the input, hidden and output layers, respectively. From the input and output data of the model, we know that $p_1 = 2 \cdot m$ and

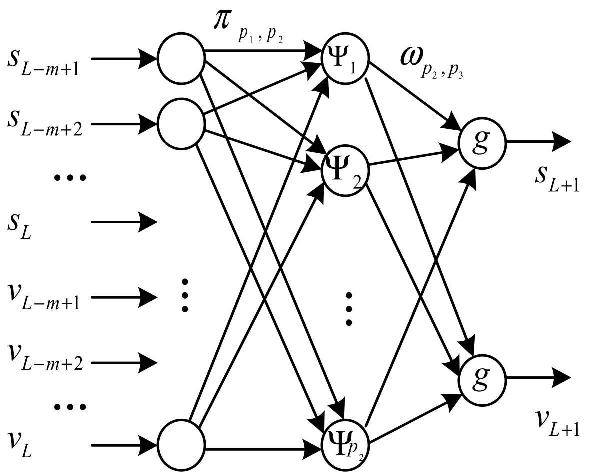


FIGURE 1. Wavelet neural network model structure.

$p_3 = 2$. Then, p_2 can be determined using (7), as introduced in [27].

$$p_2 = \sqrt{p_1 \cdot p_2 + 1.6799 p_1 + 0.9298} \tag{7}$$

A Morlet wavelet function and a sigmoid function are chosen as the hidden-layer and output-layer functions (as shown in Fig. 1) and are defined in (8) and (9), respectively.

$$\Psi(x) = e^{-x^2/2} \cos(5x) \tag{8}$$

$$g(x) = \frac{1}{1 + e^{-x}}. \tag{9}$$

C. CONFIDENCE INTERVAL LIMITS ON THE PRR

The output data, s_{L+1} and v_{L+1}, are estimates of $S(L)$ and $V(L)$. They can be regarded as the mean and variance of the *SNR* expressed in (3). Hence, the limits of the probability-guaranteed interval of the *SNR* at a confidence level of α are given as follows:

$$\left[s_{L+1} - Z_{\alpha/2} \cdot \sqrt{v_{L+1}}, s_{L+1} + Z_{\alpha/2} \cdot \sqrt{v_{L+1}}\right], \tag{10}$$

where $Z_{\alpha/2}$ is the $(\alpha/2)$-th quantile of the standard Gaussian distribution.

The IEEE 802.15.4 standard adopts the O-QPSK modulation method. The mapping function between the SNR and PRR is defined as reported in [24]:

$$PRR = f(SNR) = \left(1 - Q\left(\sqrt{2 \times 10^{SNR \cdot B_N/R/10}}\right)\right)^l, \tag{11}$$

where B_N denotes the noise bandwidth of the WSN transceiver in kHz, R is the data communication rate in kbps, $Q(.)$ is the tail integral of a unit Gaussian probability density function, and l is the packet length in bits.

The limits of the probability-guaranteed interval of the PRR at a confidence level of α are given as follows:

$$\left[f\left(s_{L+1} - Z_{\alpha/2} \cdot \sqrt{v_{L+1}}\right), f\left(s_{L+1} + Z_{\alpha/2} \cdot \sqrt{v_{L+1}}\right)\right], \tag{12}$$

where the function $f(\cdot)$ is defined as shown in (10) and $Z_{\alpha/2}$ is the standard score of the Gaussian distribution for $\alpha/2$.

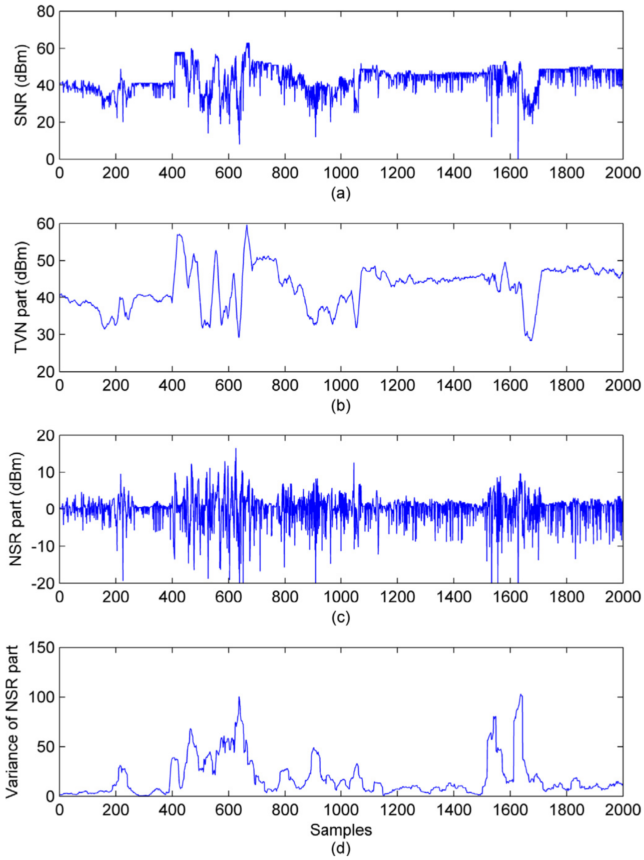


FIGURE 2. Measured SNR data for a 10 m inertial distance: (a) SNR series, (b) decomposed time-varying nonlinear series (TVN), (c) decomposed non-stationary random series (NSR), and (d) variance series for the NSR part.

V. EXPERIMENT

In this section, we evaluate the proposed WNN-LQE algorithm via real-world experiments performed at a power substation.

A. VERIFICATION OF THE ESTIMATION RESULTS

Ten TI CC2530 WSN transceiver nodes were used in the experiment. All the nodes operated on channel 26 in the 2.4 GHz ISM band, as defined in the IEEE 802.15.4 standard. A packet was sent from one node to another every 300 ms. Each packet was 20 bytes in size, which included 3 bytes for recording the packet serial number. When a receiver node received a packet, it recorded the received signal strength and the packet serial number (used to compute the software-based PRR for comparison purposes). Then, it measured the background noise (for calculating the SNR as expressed in (2)). All the data were recorded and decomposed; then, they were used to train the neural network and used for testing in MATLAB.

During the *SNR* data collection process, intentional obstructions were imposed to modify the radio link quality. Fig. 2(a) and Fig. 3(a) show the measured SNR data and the results computed using the decomposition algorithm for two WSN links (the separation distances for these radio links are

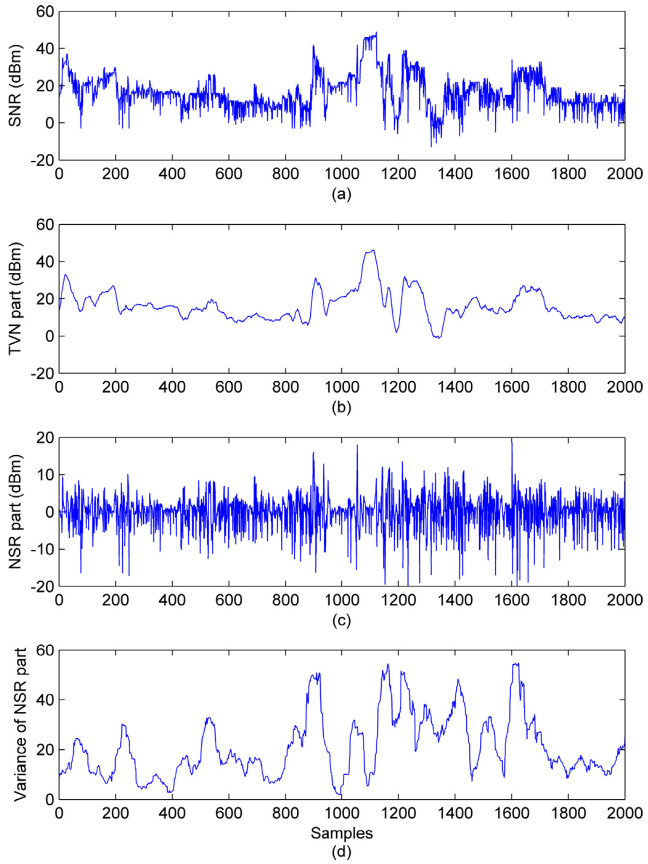


FIGURE 3. Measured SNR data for an 80 m separation distance: (a) SNR series, (b) decomposed time-varying nonlinear series (TVN), (c) decomposed non-stationary random series (NSR), and (d) variance series for the NSR part.

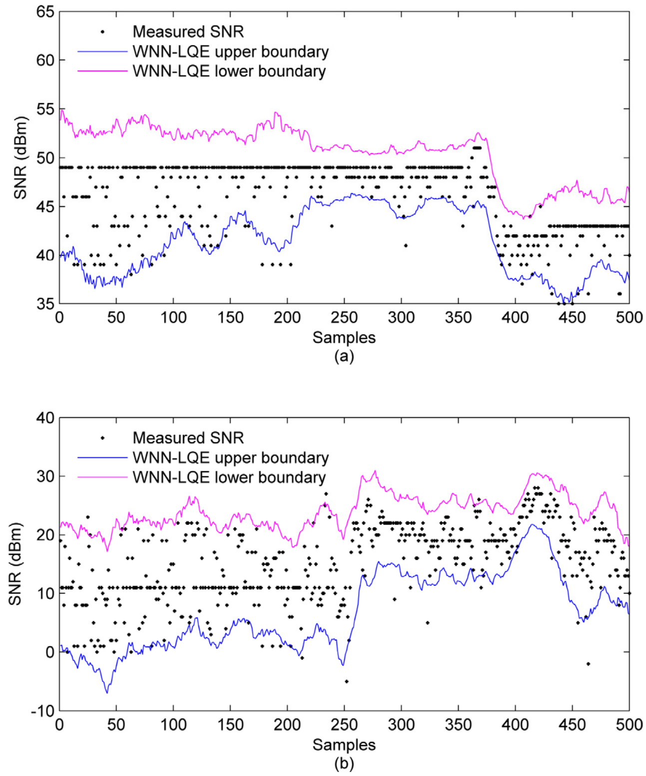


FIGURE 4. The estimated confidence interval limits on the SNR at a level of 0.95: (a) for the 10 m separation distance and (b) for the 80 m separation distance.

10 m and 80 m). Using (5), the measured SNR series (Fig. 2(a) and Fig. 3(a)) were decomposed into a time-varying nonlinear part and a non-stationary random part, where $W = 20$ and $L = 55$. As analyzed in Section III B, both time-varying nonlinear parts (Fig. 2(b) and Fig. 3(b)) vary over time and nonlinearly. The non-stationary random parts (Fig. 2(c) and Fig. 3(c)) are random with a mean of nearly zero. We further calculated the variances of the non-stationary random series using (6) for these two links ($K = 20$). The results are presented in Fig. 2(d) and Fig. 3(d), which show that in both cases, the variances vary over time, as expected. These results serve both to confirm the analysis in Section III B, which indicated that the SNR can be decomposed into two parts, and to verify the decomposition algorithm presented in Section IV A.

The measured and calculated data shown in Fig. 2 and Fig. 3 were used to train the weight coefficients $\pi p_1, p_2$ and $\omega p_2, p_3$ (Fig. 1) for the two radio links. The weight coefficients were then used to estimate the upper and lower limits on the estimated SNR at the 0.95 confidence level using our WNN-LQE algorithm. The measured SNR results are shown in Fig. 4(a) and (b) for the separation distances of 10 m and 80 m, respectively. The measured SNR results are integer values because the measurement resolution of the TI CC2530 is 1 dBm. As shown in Fig. 4, almost all the measured SNR values fall into the interval between the estimated upper and lower limits on the SNR. Quantitatively, 474 of the 500 measured SNR values fall within the estimated interval in Fig. 4(a), and the same is true for 473 of the 500 values in Fig. 4(b). The corresponding proportions are nearly equal to the prescribed confidence level of 0.95, thereby demonstrating that our WNN-LQE algorithm can produce probability-guaranteed limits on the link quality metric (the SNR) at a chosen confidence level.

B. COMPARISON OF LQE ALGORITHMS

We measured and estimated the SNRs for another link in the same 10-node network with a separation distance of 50 m. We compared the results of our WNN-LQE algorithm with those of four other link quality estimation algorithms, including the BP neural network-based LQE algorithm (BP) [28], the Kalman filter based LQE algorithm (Kalman) [7], the ARIMA-based LQE algorithm (ARIMA) [29] and XCoPred [8]. A total of 2,500 samples were collected for the experiments. The first 2,000 samples of the measured SNR data were used for training and to compute the parameters for all the algorithms, and the remaining 500 samples were used to compare the estimation results. The settings for each algorithm were as follows.

For the BP algorithm, the structure introduced in [28] was adopted. The number of input neurons of the BP neural

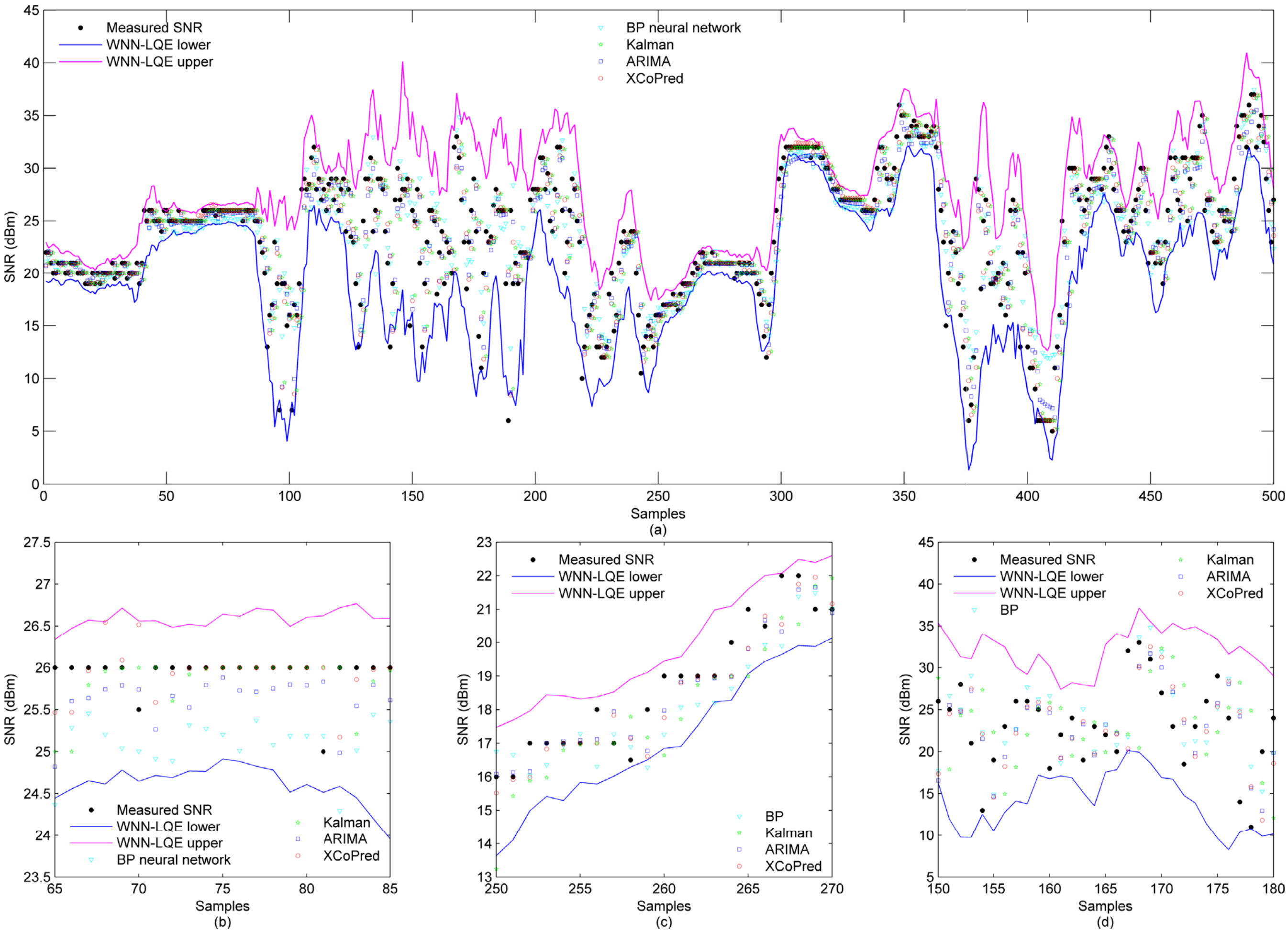


FIGURE 5. Measured SNR data and estimated results of the WNN-LQE, BP, Kalman, ARIMA and XCoPred algorithms: (a) overall estimation results, (b) zoomed-in view of samples 65 to 85, (c) zoomed-in view of samples 250 to 270, and (d) zoomed-in view of samples 150 to 180.

network was 8, the number of output neurons was 1, and the number of neurons in the hidden layer was 10. The 2,000 training samples were used to train the weight coefficients of the BP neural network. The trained parameters were then used to estimate the SNR based on the 500 test samples.

For the Kalman algorithm, the state space model introduced in [7] was adopted. The 2,000 training samples were used to compute the process noise covariance matrix and the measurement noise covariance matrix. The initial values of the estimate covariance and the Kalman gain matrixes were set equal to those of the identity matrix.

For the ARIMA algorithm, we used the 2,000 training samples to compute the best values of the orders of the autoregressive part and the moving-average part, using the minimum Akaike Information Criterion (AIC), to construct the corrected ARIMA model. Then, the ARIMA model was used to estimate the link quality in one step.

For the XCoPred LQE algorithm, the 2,000 training samples were used as the training data. The covariance of the Kalman filter in XCoPred was also computed based on the training data. The query order and training data order were both set to 20. The match threshold was set to 0.95. The prediction order was 1.

Fig. 5(a) shows the link quality estimation results for each tested method, from which we can generally observe that almost all the estimated results of the BP, Kalman, ARIMA and XCoPred algorithms and the measured SNRs are within the interval calculated by our WNN-LQE algorithm. Fig. 5(b), (c) and (d) show zoomed-in views of Fig. 5(a) to provide more details. From these figures, we can make the following observations:

(1) When the link quality remains stable, as shown in Fig. 5(b) (samples 65 to 85 in Fig. 5(a)), the Kalman and XCoPred algorithms obtain better estimates (with average estimation errors of approximately 0.25 dBm). The BP and ARIMA algorithms also perform well, with average estimation errors of less than 0.8 dBm.

(2) When the SNR is increasing stably, as shown in Fig. 5(c) (samples 150 to 180 in Fig. 5(a)), the ARIMA and XCoPred LQE algorithms have lower average estimation errors than the BP and Kalman

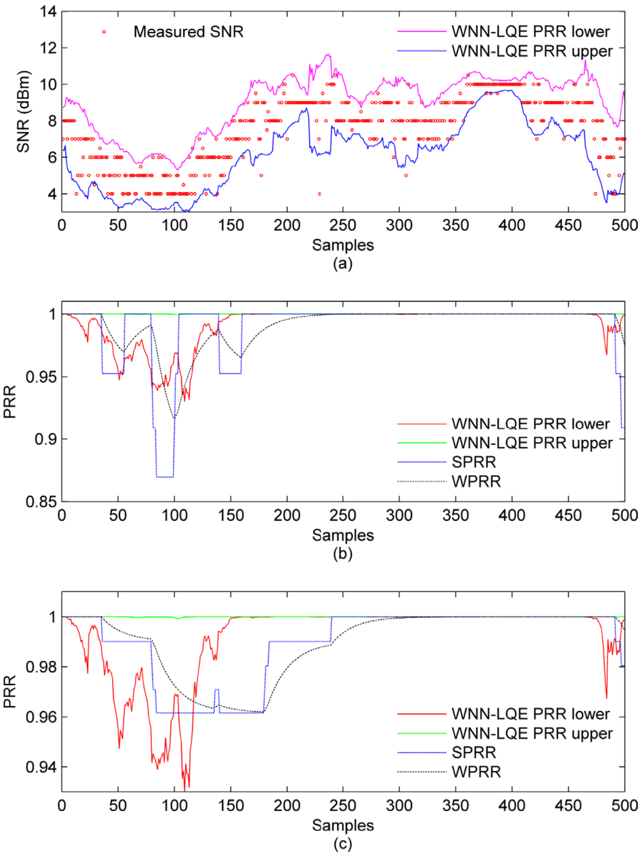


FIGURE 6. **SNR and PRR estimates vs. software-based PRR calculations: (a) estimated SNR vs. measured SNR, (b) software-based PRR computed for the last 20 packets, and (c) software-based PRR computed for the last 100 packets.**

algorithms, and all the average estimation errors are below 1 dBm.

(3) When the link quality fluctuates strongly, as shown in Fig. 5(d) (samples 150 to 170 in Fig. 5(a)), although the BP algorithm performs best, its average estimation error is still large (4.4 dBm). The Kalman algorithm is the worst, with an average estimation error of 5.9 dBm. Moreover, with respect to the deviations from the average estimation error, the variances of the estimation error for the BP, Kalman, ARIMA and XCoPred LQE algorithms are 27.8, 54.5, 26.3, and 29.2, respectively. These results indicate that the estimation results of these LQE algorithms are unreliable when there are strong fluctuations in the link quality.

As seen from Fig. 5(a)-(d), almost all the measured SNRs fall between the upper and lower limits estimated using our WNN-LQE algorithm; thus, we can conclude that our algorithm yields more useful results than those of the other LQE algorithms. Considering that WSN protocols require link quality information to make decisions (such as routing decisions) regarding important communication traffic (for example, control commands) in smart grids and other industrial applications, the practical usefulness of estimation results for such purposes is more important than their accuracy.

C. COMPARISON OF THE PRR ESTIMATION RESULTS

In this experiment, we estimated the SNR (Fig. 6(a)) with a 0.95 confidence level and transformed it into the PRR via (11). We compared the results with software-based PRR measurements (SPRR) and the results of the WMEWMA PRR algorithm [9] (WPRR). Because the software-based PRR depends on the window size used for the statistical calculations, we computed the SPRR results for the previous 20 and the previous 100 packets based on the packet serial numbers. The WPRR results were also computed for sliding windows of 20 and 100 packets. The weight coefficient α was set to 0.9.

Comparisons of the WNN-LQE PRR estimates with the SPRR and WPRR results are shown in Fig. 6(b) and (c). We can draw the following conclusions from Fig. 6:

(1) When the link quality degrades (samples 50 to 150 in Fig. 6(a)), the estimated PRR determined by the WNN-LQE algorithm can update rapidly to reflect the changes in link quality.

(2) According to the serial numbers of the received packets, we computed the SPRR based on the last 20 packets (Fig. 6(b)). The results reflect the change in link quality only after a packet is dropped, which adds a slight lag to the change. The WPRR calculation can smooth the SPRR results but cannot eliminate the lag. The same phenomenon is also observed at sample 480. For the 20-packet SPRR, the minimum resolution is 1/20, which is obviously not accurate.

(3) To increase the minimum resolution to 1/100, we computed the SPRR and WPRR results for the last 100 packets (Fig. 6(c)). The figure clearly shows that the SPRR and WPRR results for 100 packets are much smoother than those calculated using only 20 packets, but the lag also increases (see samples 180 to 250 in Fig. 6(b) and (c)).

(4) If we disregard the lag, the SPRR and WPRR results for 100 packets lie within the PRR interval estimated by the WNN-LQE algorithm. This demonstrates the practical usefulness and validity of our WNN-LQE algorithm.

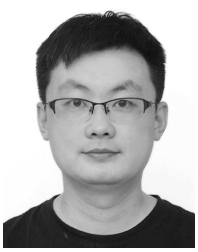
VI. CONCLUSION AND FUTURE WORK

The tendency to adopt wireless communications in smart grids has led to the emergence of new ideas and techniques for improving QoS according to communication specification requirements. More practically useful estimates of radio link quality are required to enable the optimization of WSN protocol designs. In this paper, through an analysis based on the commonly used log-normal path-loss model, we show that the radio link quality represented by the SNR can be decomposed into two parts with different characteristics. Then, a new link quality estimation method called WNN-LQE is developed by separately processing the two parts to obtain probability-guaranteed limits on the link quality. The probability-guaranteed limits are more suitable than state-of-the-art link quality estimation/prediction algorithms for describing the random features of a radio link and determining whether the link satisfies the requirements of smart grid communication standards. Our study is expected to lead to the development of protocols that can provide an end-to-end reliability guarantee for smart grid applications. To this end, we anticipate performing further research on the following topics:

(1) Estimation of communication reliability for multi-hop radio links in a mesh network
(2) Control of the transmission power of WSN nodes according to the estimated results to guarantee reliability
(3) Reduction of the computational complexity of the estimation algorithm to make it easier to implement in WSN nodes.

REFERENCES

[1] M. Yigit, V. C. Gungor, E. Fadel, L. Nassef, N. Akkari, and I. F.Akyildiz, "Channel-aware routing and priority-aware multi-channel scheduling for WSN-based smart grid applications," *J. Netw. Comput. Appl.*, vol. 71, pp. 50–58, Aug. 2016.
[2] S. Ma, Y. Yang, Y. Qian, H. Sharif, and M. Alahmad, "Energy harvesting for wireless sensor networks: Applications and challenges in smart grid," *Int. J. Sensor Netw.*, vol. 21, no. 4, pp. 226–241, 2016.
[3] A. N. Alvi, S. H. Bouk, S. H. Ahmed, M. A. Yaqub, M. Sarkar, and H. Song, "BEST-MAC: Bitmap-assisted efficient and scalable TDMA-based WSN MAC protocol for smart cities," *IEEE Access.*, vol. 4, pp. 312–322, 2016.
[4] *NIST Framework and Roadmap for Smart Grid Interoperability Standards*, U.S. Nat. Inst. Standards Technol., Gaithersburg, MD, USA, 2014.
[5] N. Baccour *et al.*, "F-LQE: A fuzzy link quality estimator for wireless sensor networks," in *Proc. Eur. Conf. Wireless Sensor Netw.*, 2010, pp. 240–255.
[6] F. Qin, X. Dai, and J. E. Mitchell, "Effective-SNR estimation for wireless sensor network using Kalman filter," *Ad Hoc Netw.*, vol. 11, no. 3, pp. 944–958, May 2013.
[7] 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. (GLOBECOM).*, 2007, pp. 875–880.
[8] K. Farkas, T. Hossmann, F. Legendre, B. Plattner, and S. K. Dasc, "Link quality prediction in mesh networks," *Comput. Commun.*, vol. 31, no. 8, pp. 1497–1512, May 2008.
[9] A. Woo and D. Culler, "Evaluation of efficient link reliability estimators for low-power wireless networks," Univ. California, Berkeley, Berkeley, CA, USA, Tech. Rep. UCB/CSD-03-1270, Nov. 2003, pp. 1–20.
[10] A. Cerpa, J. L. Wong, M. Potkonjak, and D. Estrin, "Temporal properties of low power wireless links: Modeling and implications on multi-hop routing," in *Proc. ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2005, pp. 414–425.
[11] N. Baccour *et al.*, "Radio link quality estimation in wireless sensor networks: A survey," *ACM Trans. Sensor Netw.*, vol. 8, no. 4, 2012, Art. no. 34.
[12] D. S. J. De Couto, D. Aguayo, J. Bicket, and R. Morris, "A high-throughput path metric for multi-hop wireless routing," in *Proc. 9th Annu. Int. Conf. Mobile Comput. Netw.*, 2003, pp. 134–146.
[13] C. Gomez, A. Boix, and J. Paradells, "Impact of LQI-based routing metrics on the performance of a one-to-one routing protocol for IEEE 802.15.4 multihop networks," *EURASIP J. Wireless Commun. Netw.*, vol. 2010, no. 1, pp. 1–20, 2009, Art. no. 205407.
[14] Y. Wang, M. Martonosi, and L.-S. Peh, "Predicting link quality using supervised learning in wireless sensor networks," *ACM SIGMOBILE Mobile Comput. Commun. Rev.*, vol. 11, no. 3, pp. 71–83, Jul. 2007.
[15] L. Weng, P. Zhang, Z. Feng, H. Cheng, H. Lian, and B. Fu, "Short-term link quality prediction using nonparametric time series analysis," *Sci. China Inf. Sci.*, vol. 58, no. 8, pp. 1–15, 2015.
[16] *IEEE Standard for Local and Metropolitan Area Networks—Part 15.4: Low-Rate Wireless Personal Area Networks (LR-WPANs) Amendment 1: MAC Sublayer*, IEEE Standard 802.15.4e-2012, 2012, pp. 1–225.
[17] A. H. F. Farzana and S. Neduncheliyan, "Ant-based routing and QoS-effective data collection for mobile wireless sensor network," *Wireless Netw.*, vol. 23, no. 6, pp. 1697–1707, Mar. 2016, doi: 10.1007/s11276-016-1239-6.
[18] K. Srinivasan, P. Dutta, A. Tavakoli, and P. Levis, "An empirical study of low-power wireless," *ACM Trans. Sensor Netw.*, vol. 6, no. 2, Feb. 2010, Art. no. 16.
[19] R. Fonseca, O. Gnawali, K. Jamieson, and P. Levis, "Four-bit wireless link estimation," in *Proc. HotNets VI*, 2007, pp. 1–7.
[20] Y. Xu and W.-C. Lee, "Exploring spatial correlation for link quality estimation in wireless sensor networks," in *Proc. 4th Annu. IEEE Int. Conf. Pervasive Comput. Commun. (PERCOM)*, 2006, pp. 200–211.
[21] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Predictable 802.11 packet delivery from wireless channel measurements," in *Proc. ACM SIGCOMM Conf.*, 2010, pp. 159–170.
[22] T. Liu and A. E. Cerpa, "Data-driven link quality prediction using link features," *ACM Trans. Sensor Netw.*, vol. 10, no. 2, Jan. 2014, Art. no. 37.
[23] V. C. Gungor *et al.*, "A survey on smart grid potential applications and communication requirements," *IEEE Trans. Ind. Informat.*, vol. 9, no. 1, pp. 28–42, Feb. 2013.
[24] M. Z. Zamalloa and B. Krishnamachari, "An analysis of unreliability and asymmetry in low-power wireless links," *ACM Trans. Sensor Netw.*, vol. 3, no. 2, Jun. 2007, Art. no. 7.
[25] N. B. Sarr, H. Boeglen, B. L. Agba, F. Gagnon, and R. Vauzelle, "Partial discharge impulsive noise in 735 kV electricity substations and its impacts on 2.4 GHz ZigBee communications," in *Proc. Int. Conf. Select. Topics Mobile Wireless Netw. (MoWNeT)*, Apr. 2016, pp. 1–7.
[26] A. K. Alexandridis and A. D. Zapranis, "Wavelet neural networks: A practical guide," *Neural Netw.*, vol. 42, pp. 1–27, Jun. 2013.
[27] X. Li, J. Ouyang, T. Jiang, and B. Yang, "Integration modified wavelet neural networks for solving thin plate bending problem," *Appl. Math. Model.*, vol. 37, no. 5, pp. 2983–2994, Mar. 2013.
[28] L. Liu, Y. Fan, J. Shu, and C. Zhao, "A link quality prediction method for WSNs based on BP artificial neural network," *J. Comput. Res. Develop.*, vol. 48, no. S, pp. 212–215, Sep. 2011.
[29] S. Yao, C. Chen, and H. Zhang, "Research on the link quality prediction mechanism based on ARIMA model for multi person cooperative interaction," in *Proc. Int. Conf. Ind. IoT Technol. Appl.*, 2016, pp. 231–239.



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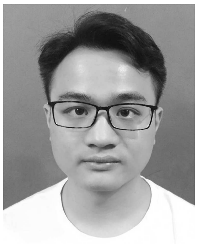

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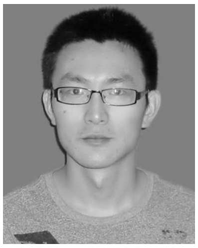

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