Impacts of Radio Irregularity on Duty-Cycled Industrial Wireless Sensor Networks

Mithun Mukherjee[1], Lei Shu[1(✉)], Likun Hu[1,2], and Der-Jiunn Deng[3]

[1] Guangdong Provincial Key Lab of Petrochemical Equipment Fault Diagnosis, Guangdong University of Petrochemical Technology, Maoming 525000, China
{m.mukherjee,lei.shu}@ieee.org

[2] College of Information and Computer Engineering, Northeast Forestry University, Harbin, China
likun.hu@outlook.com

[3] Department of Computer Science and Information Engineering, National Changhua University of Education, Changhua, Taiwan
djdeng@cc.ncue.edu.tw

Abstract. With rapid adoption of advanced wireless sensors in last decades, industrial wireless sensor networks (IWSNs) are increasingly deployed in the industries for various applications. Sleep scheduling is a common approach in IWSNs to overcome network lifetime problem due to energy-constrained sensor nodes. However, in real-environment, node's transmit power varies in different directions due to non-isotropic nature of electromagnetic transmission, path-loss, noise, and temperature. Thus, radio irregularity results in link asymmetry, thereafter, affects the performance of sleep scheduling in IWSNs. In this paper, we evaluate the impacts of radio irregularity on sleeping probability and lifetime performances of well-known connected k-neighborhood (CKN)-based sleep scheduling algorithms in duty-cycled IWSNs. We derive the upper-limit of sleep probability with radio irregularity variables. From the extensive simulations, we show that radio irregularity increases the number of awake nodes in duty-cycled sensor networks, therefore, network lifetime decreases with increasing values of link asymmetry parameters. Finally, an adverse impact of radio irregularity is observed in higher k-value in CKN-based algorithm due to more awake nodes to satisfy the k-connectivity in presence of link asymmetry.

Keywords: Industrial wireless sensor networks · Radio irregularity · Duty-cycled IWSNs · CKN-based sleep scheduling

1 Introduction

Recently, with the fast development of various emerging technologies in sensing devices and towards Industry 4.0 of traditional factories, industrial wireless sensor networks (IWSN) has become a global interconnection between management and factory products in large-scale industries [3,5]. Wireless sensor nodes

L.A. Maglaras et al. (Eds.): INISCOM 2016, LNICST 188, pp. 29–38, 2017.
DOI: 10.1007/978-3-319-52569-3_3

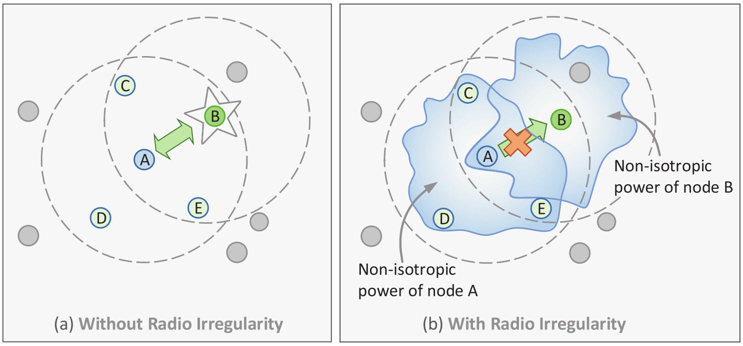

Fig. 1. Link asymmetry due to radio irregularity. (a) B, C, D, and E nodes are 1-hop neighbor of node. Node B decides to wake up at a given instance. (b) However, $\texttt{link}_{\mathrm{A}\rightarrow\mathrm{B}}$ is significantly different from $\texttt{link}_{\mathrm{B}\rightarrow\mathrm{A}}$ due to the link asymmetry.

are widely deployed to many applications, e.g., robotics, large-scale pipeline and equipment monitoring, fault diagnosis, and toxic gas leakage detection. Due to their advantage of low cost, ease of deployment, energy efficiency, and mobility compared to the traditional wired field-bus, an IWSN is a promising approach for manufacturers as well as plant designers.

Constrained by limited physical sensor size, difficult access (e.g., heat exchange tube and rotating machines), and limited energy harvesting possibilities, IWSNs inherit limited lifetime problem of traditional WSNs. Sleep scheduling is one of the effective approaches to prolong network lifetime. Sleep scheduling allows a sub-set of deployed nodes to be awaken, while other nodes go to sleep for a certain amount of time to conserve their energy.

Among the extensive studies in duty-cycled WSNs [1,6], connected k-neighborhood (CKN) [4]-based approach has drawn a significant interest due to the following reasons: (1) each node have at least $\texttt{min}(N_u, k)$ awake neighbors in each epoch, where N_u is the set of 1-hop neighbors of node u and k is any positive integer, (2) all awake nodes will be connected, (3) every node (awake or sleep) has an awake neighbor, and (4) the set of awake nodes changes from epoch to epoch. The CKN algorithm efficiently reduces the number of active nodes while keeping the network k-connected. Recently, we proposed several CKN-based sleep scheduling schemes such as energy-consumption-based CKN (EC-CKN) [8], geographic routing-oriented sleep scheduling (GSS) [13], geographic-distance-based connected k-neighborhood for first path (GCKNF) [13] and geographic-distance-based CKN for all paths (GCKNA) [13], collaborative location-based sleep scheduling (CLSS) [11], and priority-based sleep scheduling (PSS) [12] in duty-cycled WSNs.

Since the low-power link quality in IWSNs strongly depends on the radio characteristics of the sensor nodes, radio irregularity [10] has a heavy impact on the performance of IWSNs. In the literature, several experimental studies have been presented in [2,7,9] to characterize the low-powered link through real-world

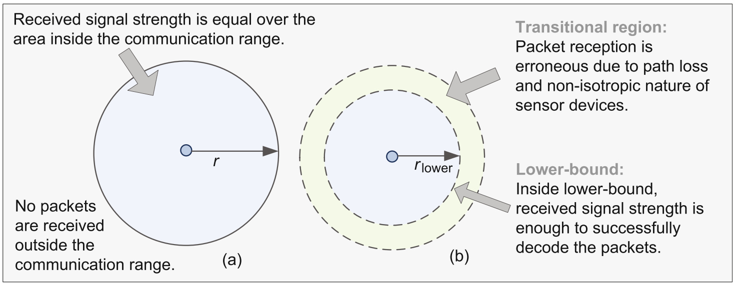

Fig. 2. (a) Example of binary perfect-reception within the transmission range. (b) However, the links are highly unreliable due to *transitional* region in real-deployment.

measurement with different assumptions and scenarios. However, apart from the cross-technology interference due to coexisting wireless devices with IEEE 802.11 b/g (WiFi), IEEE 802.15.1 (bluetooth), and IEEE 802.15.4 (ZigBee) standards, path loss, non-isotropic nature such as diffraction, scattering, and reflection of electromagnetic (EM) transmission, temperature, equipment noise are responsible for radio irregularity in low-powered IWSNs. This radio irregularity often results in link asymmetry as shown in Fig. 1. Link asymmetry is not always correlated with distance, rather is mainly located at the transitional region [14] where the received power is not good enough to correctly decode the packet. As shown in Fig. 2, a large number of links are unreliable in the transitional region in the dense deployments due to high-variance in reception rates and asymmetric connectivity. In addition, the transitional region of any nodes creates interference to its neighbor nodes, and leads to packet-error-reception (PER). Although the sleep scheduling algorithms [1,4,6,8,11–13] provide the efficient way to increase the network lifetime, however, none of them consider effects of the radio irregularity [2,9,10] in their schemes.

The focus of this paper is to investigate the effect of radio irregularity on the duty-cycled IWSNs. We evaluate the performance of sleeping probability with the link asymmetry and number nodes that have this asymmetric problem in the CKN-based sleep scheduling. We further derive the upper-limit of sleeping probability for the CKN-based sleep scheduling algorithms in presence of the radio irregularity.

The rest of the paper is organized as follows. Section 2 presents the system model. The analysis of CKN-based schemes with radio irregularity is conducted in Sect. 3. The simulation results are presented in Sect. 4. Finally, conclusions are drawn in Sect. 5.

2 System Model

2.1 Network Model

We consider a multihop WSN with uniformly and randomly deployed sensor nodes in a large-scale 2-dimensional industrial sensing field. Let $G = (S, E)$ be a network graph, where $S = \{s_1, s_2, \dots s_N\}$ and $E = \{e(1,2), e(1,3), \dots, e(N,N)\}$ are the set of sensor nodes with total N number of sensor nodes and the set of edges between sensor nodes, respectively. Two sensor nodes $\{u, v\} \in S$ are called 1-hop neighbor if they are within the transmission region of each other and $e(u, v) \in E$. We assume bi-directional communication between 1-hop neighbors. It is assumed that MAC layer will mask the unidirectional links and pass the bidirectional links. Any two nodes $\{u, v\} \in S$ belong to 2-hop neighbor if $e(u, v) \notin E$, however, there exists a node $k \in S$ with $\{e(u, k), e(k, v)\} \in E$. The location of any sensor node along with its 1-hop neighbors can be obtained by possibly using the global positioning system (GPS) or other techniques such as triangulation or localization. The sink node knows the location and IDs of all nodes. We also do not consider the energy consumption aspect in this research work as we assume that the industrial sensor nodes can harvest energy from environment by using additional device, e.g., solar power panel. It is also assumed that each node has the same functionality and sensing capability. With a very large number of sensor nodes, we ensure a well-connected WSN in deployed area.

2.2 Radio Irregularity Model

We consider radio irregularity model (RIM) in [10]. Assume that each node u loses its unidirectional link $\texttt{link}_{u \to v}$ to any node v $\forall v \in N_u$ with a probability $\alpha(u)$ at each instant due to time-varying nature of radio irregularity. Since we assume RTS/CTS-based link scheduling, quality of the bi-directional link $l(u, v)$ strongly depends on $\alpha(u)$ and $\alpha(v)$ $\forall v \in N_u$. Let β be the ratio of the number of nodes with link asymmetry and the total number of deployed nodes in a given area $\mathcal{A}$. We observe that quality of bi-directional link depends on individual loosing connection, i.e., $\alpha(u)$ as well as number of nodes that suffer from link asymmetry, which is related to β. Without loss of generality, we denote $\alpha(u)$ and β as link asymmetry and node asymmetry, respectively. For the sake of simplicity, we drop u from $\alpha(u)$ in the rest of the paper.

3 Performance Analysis of CKN-Based Sleep Scheduling with Radio Irregularity Model

3.1 Sleep Probability Without Radio Irregularity

The probability that any node u has n neighbors in uniformly and randomly distributed WSNs with N nodes within an area $\mathcal{A}$ is given as

$$P(|N_u| = n) = \frac{\left(\rho \pi r^2\right)^n}{n!} \exp\left(-\rho \pi r^2\right), \tag{1}$$

where $\rho = N/\mathcal{A}$ is the node density. Thus, the expectation of the 1-hop neighbors of u is given as $\mathbb{E}\left[|N_u|\right] = \rho\pi r^2$. We denote N_u and N'_u are the set of the uth 1- and 2-hop neighbors, respectively. The probability that the graph G is k-connected is

$$P(G)_{\text{k-connected}} = \left(1 - \sum_{n=0}^{k-1} \frac{\left(\rho\pi r^2\right)^n}{n!} \exp\left(-\rho\pi r^2\right)\right)^N \quad (2)$$

Similarly, we deduce the probability that the graph $G_{C_u+C'_u}$ is connected as follows

$$\text{Prob}_1 = P\left(G_{C_u+C'_u}\right)_{\text{1-connected}} = \Big(1 - \exp\left(-\rho'\pi r^2\right)\Big)^{\left(|C_u|+|C'_u|\right)}, \quad (3)$$

where $\rho' = |S'|/\mathcal{A}$, C_u, C'_u, and S' are the subset of N_u, N'_u, and S whose $\texttt{rank} \leq \texttt{rank}_u$, where $\texttt{rank}_u$ is the random rank that the senor node u picks randomly. Therefore, the probability that the graph G_{N_u} is k-connected in C_u is expressed as

$$\text{Prob}_2 = P\left(G_{N_u \sim C_u}\right)_{k\text{-connected}} = \left(1 - \sum_{n=0}^{k-1} \frac{\left(\rho'\pi r^2\right)^n}{n!} \exp\left(-\rho'\pi r^2\right)\right)^{|C_u|} \quad (4)$$

Therefore, the sleep probability of the node u in CKN-based sleep scheduling is expressed as $P_{\text{sleep}}(u) = \text{Prob}_1 \times \text{Prob}_2$, where Prob_1 and Prob_1 consider the two conditions of the CKN algorithm as (1) the graph $G_{C_u+C'_u}$ is connected and (2) the graph G_{N_u} is connected by C_u nodes, respectively.

3.2 Sleep Probability with Radio Irregularity

The probability that any node u with loosing neighbor connection probability $\alpha(u)$ has n neighbors with a uniformly and randomly distributed WSN in an area $\mathcal{A}$ is given as

$$\begin{aligned} P(|N_u| = n)^{\text{Irregular}} =& \frac{\left(\beta(1-\alpha)\rho\pi r^2 + (1-\beta)\rho\pi r^2\right)^n}{n!} \\ & \times \exp\big(-\beta(1-\alpha)\rho\pi r^2 - (1-\beta)\rho\pi r^2\big) \\ =& \frac{\left((1-\beta\alpha)\rho\pi r^2\right)^n}{n!} \times \exp\big(-(1-\beta\alpha)\rho\pi r^2\big) \end{aligned} \quad (5)$$

Thus, the probability that the graph G is connected in presence of radio irregularity is given as

$$P(G)^{\text{Irregular}}_{\text{k-connected}} = \left(1 - \sum_{n=0}^{k-1} \frac{\left((1-\beta\alpha)\rho\pi r^2\right)^n}{n!} \exp\big(-(1-\beta\alpha)\rho\pi r^2\big)\right)^N. \quad (6)$$

Table 1. Simulation parameters

Parameters	Values
Network size	$600 \times 600\,\mathrm{m}^2$
Number of sensor nodes	200 to 1000
k-value in CKN	1 to 10
Transmission radius	60 m
E_{elec}	50 nJ/bit
E_{amp}	$50\,\mathrm{nJ/bit/m}^2$
Initial energy	100000 mJ
Time epoch	1 min
Packet size	12 byte
Packet number	$1000 \times 32768^{32768}$

Using (3), (4), (5), and (6), the sleep probability of the node u with the link asymmetry becomes

$$P_{\mathrm{sleep}}(u)^{\mathrm{Irregular}} = \Big(1 - \exp\big(-(1-\beta\alpha)\rho'\pi r^2\big)\Big)^{\left(|C_u|+|C'_u|\right)} \times \left(1 - \sum_{n=0}^{k-1} \frac{\big((1-\beta\alpha)\rho\pi r^2\big)^n}{n!} \exp\big(-(1-\beta\alpha)\rho\pi r^2\big)\right)^{|C_u|}. \quad (7)$$

Note that the sleep probability in presence of radio irregularity is less than that without radio irregularity. Therefore, more number of nodes are awakened to satisfy the k-connectivity in duty-cycled WSNs with radio irregularity.

4 Simulation Results

In this section, we evaluate the impact of radio irregularity on sleeping rate and network lifetime of the CKN-based sleep scheduling in WSNs.

4.1 Simulation Setup

We conducted extensive simulation using the WSN simulator NetTopo[1]. For each number of deployed sensor nodes, we average the results over 100 network topologies with different seeds. The number of sensor nodes ranges from 200 to 1000 (each time increased by 100). The simulation parameters are summarized in Table 1. The network lifetime is defined as the instant from the network deployment to the instant when the first sensor node runs out of energy.

1 NetTopo (online at http://sourceforge.net/projects/nettopo/) is an open source software for simulating and visualizing WSNs.

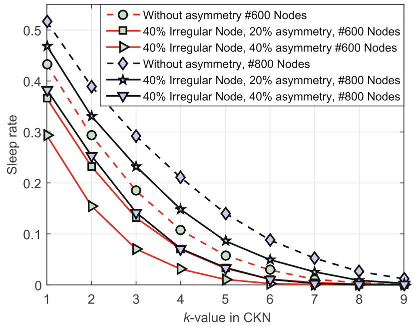

Fig. 3. Sleep rate with probability of link and node asymmetry in 600 and 800 numbers of deployed nodes with different k-value in CKN-based sleep scheduling.

4.2 Sleep Rate vs. k-Value with Different Node Density

To illustrate the impact of radio irregularity, Fig. 3 shows sleeping probability of CKN-based sleep scheduling with $\alpha = 0.4$, and $\beta = 0.2$ and 0.4. As observed in Fig. 3, the sleep-rate degrades with higher k-value due to more number of awaken node to satisfy the k-connectivity. Since less number of nodes are awaken to maintain k-value in CKN algorithm, the sleeping rate is higher in 800 node deployment compared to 600 nodes. The sleeping probability degrades with the irregularity parameter $\alpha = 0.4$ and $\beta = 0.2$ for both 600 and 800 node deployment. The reason is that more nodes have to be awaken to maintain k-connectivity due to link asymmetry nature. Furthermore, as β, which is the probability that how many nodes with asymmetric link, increases from 0.4 to 0.2, the impact is more compared to the previous value. To obtain a sleeping rate about 0.07, the maximum k-value can be satisfied upto 4 and 3 for $\{\alpha = 0.4, \beta = 0.2\}$ and $\{\alpha = 0.4, \beta = 0.4\}$, respectively with 600 nodes.

4.3 Sleeping Rate vs. Radio Irregularity Variable

Figure 4 illustrates sleep rate for CKN-based sleep scheduling with different probabilities of link and node asymmetry in duty-cycled IWSNs. From Fig. 4, we observe that sleep rate reduces with higher values of irregularity variables α and β. As observed in Fig. 4(a) and (b), sleep probability is 0.07 with $\alpha = 0.4$ and $\beta = 0.4$ with a number of node deployment of 200 with $k = 1$. We observe that almost all the nodes are awaken beyond $\alpha = 0.5$ and $\beta = 0.6$ for $k = 3$. Thus, the sleeping probability tends to zero as shown in Fig. 4(b). Accordingly, from the Fig. 4(c) and (d), we see that the sleeping rate is higher in 600 node deployment compared to 200 node deployment with $k = 1$ and $k = 3$, respectively, due to more number of sensor deployment. However, at higher k-value, the sleep rate degrades due to the increasing probabilities of link asymmetry and nodes with asymmetric nature. The performances of 1000 node deployment are shown in Fig. 4(e) and (f) with $k = 1$ and $k = 8$, respectively. The sleeping probability is

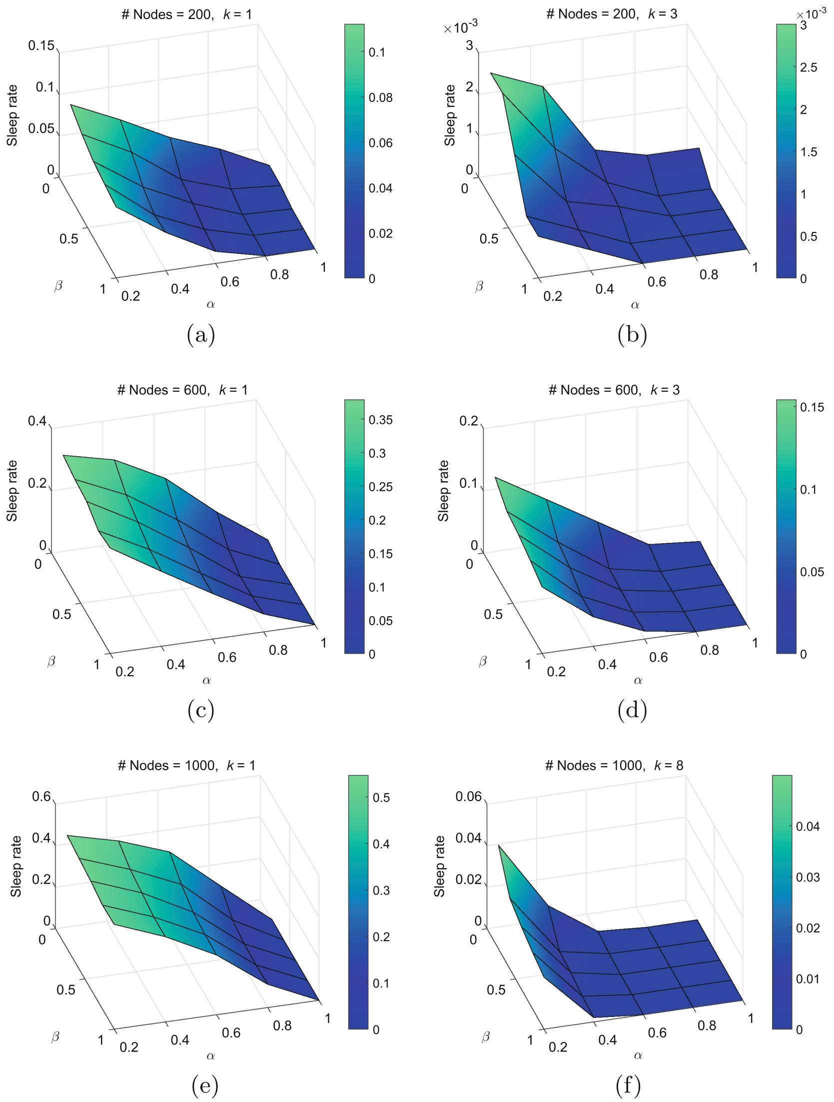

Fig. 4. Sleep rate with probability of asymmetric node and different link asymmetry at various numbers of deployed nodes with k value in CKN-based sleep scheduling.

higher compared to the previous node density, however, at a high deployment cost. We also observe that the k-value can be maintained upto 8 with $\alpha = 0.4$ and $\beta = 0.8$ with 1000 nodes. From the results we confirm that impact of radio irregularity is more in higher k-value in CKN algorithm since more number of deployed nodes are awaken to maintain k-connectivity in asymmetric nature of the radio link.

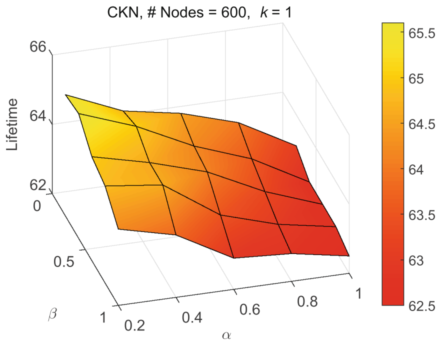

Fig. 5. Network lifetime with the probability of asymmetric node and different link asymmetry in the CKN-based sleep scheduling.

4.4 Life Time vs. Irregularity Variables

In order to see the relationship between the network lifetime and radio irregularity variables, we present the simulation results in Fig. 5. The network lifetime decreases with the increasing values of radio irregularity parameters α and β. As the link asymmetry becomes more serious with higher α value with more number of asymmetric nodes, i.e. β, the round of duty cycle decreases due to more number of awake nodes.

5 Conclusion

In this paper, we investigated the impact of radio irregularity on sleep probability for CKN-based duty-cycled IWSNs. We observed that more number of deployed nodes are awakened to satisfy higher k-constraint in presence of radio irregularity. The extensive simulation results further support the adverse impact of link asymmetry of the nodes as well as the number of nodes that have link asymmetry. In addition, our analysis shows that sleeping probability decreases when the radio links become more asymmetric in duty-cycled IWSNs.

Acknowledgments. This work is supported by Guangdong University of Petrochemical Technology through Internal Project 2012RC106, 2013 Special Fund of Guangdong Higher School Talent Recruitment, Educational Commission of Guangdong Province, China Project 2013KJCX0131, Guangdong High-Tech Development Fund 2013B010401035, and National Natural Science Foundation of China Grant 61401107. Lei Shu is the corresponding author.

References

1. Berman, P., Calinescu, G., Shah, C., Zelikovsky, A.: Power efficient monitoring management in sensor networks. In: Proceedings of the IEEE WCNC, pp. 2329–2334. Atlanta, Georgia USA, April 2004

2. Cerpa, A., Wong, J.L., Kuang, L., Potkonjak, M., Estrin, D.: Statistical model of lossy links in wireless sensor networks. In: Proceedings of the IEEE IPSN, pp. 81–88. Los Angeles, California, April 2005
3. Evans, P.C., Annunziata, M.: Industrial internet: pushing the boundaries of minds and machines. Technical report, November 2012. www.ge.com/docs/chapters/Industrial_Internet.pdf
4. Nath, S., Gibbons, B.: P.: Communicating via fireflies: geographic routing on duty-cycled sensors. In: Proceedings of the IEEE/ACM 6th International Symposium on Information Processing in Sensor Networks (IPSN), Cambridge, MA, pp. 440–449, April 2007
5. Sasajima, H., Ishikuma, T., Hayashi, H.: Future IIoT in process automation − Latest trends of standardization in industrial automation. In: Proceedings of the IEEE 54th Annual Conference on Social Instrumentation Control Engineers of Japan (SICE), Hangzhou, China, pp. 963–967, July 2015
6. Tian, D., Georganas, N.: A coverage-preserving node scheduling scheme for large wireless sensor networks. In: Proceedings of the ACM International Workshop on Wireless Sensor Networks and Application, Atlanta, Georgia, USA, pp. 32–41 (2002)
7. Wang, L., Washington, W., Gilmore, K., Liu, C.: Impact of radio irregularities on connectivity of wireless networks with log-normal shadowing. In: Proceedings of the 11th IEEE International Conference on Mobile Ad-hoc and Sensor Networks (MSN), Shenzhen, pp. 250–257, December 2015
8. Wang, L., Yuan, Z., Shu, L., Shi, L., Qin, Z.: An energy-efficient CKN algorithm for duty-cycled wireless sensor networks. Int. J. Distrib. Sensor Netw. **2012**, 1–15 (2012)
9. Zhao, J., Govindan, R.: Understanding packet delivery performance in dense wireless sensor networks. In: Proceedings of the ACM Sensor System, Los Angeles, California, pp. 1–13, November 2003
10. Zhou, G., He, T., Krishnamurthy, S., Stankovic, J.A.: Models and solutions for radio irregularity in wireless sensor networks. ACM Trans. Sensor Netw. **2**(2), 221–262 (2006)
11. Zhu, C., Leung, V.C.M., Yang, L.T., Shu, L.: Collaborative location-based sleep scheduling for wireless sensor networks integratedwith mobile cloud computing. IEEE Trans. Comput. **64**(7), 1844–1856 (2015)
12. Zhu, C., Sheng, Z., Leung, V.C.M., Shu, L., Yang, L.T.: Toward offering more useful data reliably to mobile cloud from wireless sensor network. IEEE Trans. Emerg. Topics Comput. **3**(1), 84–94 (2015)
13. Zhu, C., Yang, L.T., Shu, L., Leung, V.C.M., Rodrigues, J.P.C., Wang, L.: Sleep scheduling for geographic routing in duty-cycled mobile sensor networks. IEEE Trans. Ind. Electron. **61**(11), 6346–6355 (2014)
14. Zuniga, M., Krishnamachari, B.: Analyzing the transitional region in low power wireless links. In: Proceedings of the IEEE SECON, Santa Clara, California, pp. 517–526, October 2004