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# Optimal Energy Strategy for Node Selection and Data Relay in WSN-based IoT

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**Abstract** Data collection and dissemination in wireless sensor networks (WSN) for Internet of Things (IoT) require stable multi-hop networking path from source to sink. However, due to the limited energy capacity, relay nodes that run out of battery may cause disconnected path and result in failure of end-to-end data transmission in WSN-based IoT. Therefore, besides saving energy in itself, each sensor involved in the multi-hop transmission activity also needs a feasible strategy to select the relay nodes by leveraging their residual energy and multi-hop IoT network connectivity. In this paper, we first analyze energy consumption model and data relay model in WSN-based IoT, and then propose the concept of "equivalent node" to select relay node for optimal data transmission and energy conservation. A probabilistic dissemination algorithm, called ENS_PD, is designed to choose the optimal energy strategy and prolong the lifetime of whole network. Extensive simulation and real testbed results show that our models and algorithms can minimize energy consumption while guarantee the quality of communication in WSN-based IoT in comparison with other methods.

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## 1 Introduction

Recently, a variety of pervasive technologies, e.g. intelligent sensing [1, 2], low-power processing [3, 4], and wireless communication [5, 6], offer unprecedented opportunities to enable the creation of Internet of Things (IoT) [7]. Typical IoT applications include sustainable transportation, security surveillance, inventory tracking, mobile health and smart grid networks, where smart objects outfitted with sensors, actuators and radio frequency identification (RFID) interact with each other and cooperate with their neighbors for sensory data collection and control message delivery. In pervasive network and applications for IoT, wireless sensor network (WSN) [8–10] is a critical part of the information infrastructure in industrial control, logistics management, environmental monitoring, and civilian life.

As one of the most important parts of IoT, wireless sensor networks have been widely studied and deployed in wireless environments to collect and transmit data through the coordination among sensor nodes and sink nodes. However, the unique characteristics of sensor nodes and their wireless communication also pose significant challenges for the application of WSN-base IoT. One of complex and intriguing questions in WSN design is how to maximize the energy efficiency of whole network, because of the limited battery supply per node. As a data-centric multi-hop network, data relay is a fundamental operation in WSN to transmit data collected at sensor in the network towards a common sink, with the help of relay nodes. On one hand, these relay nodes present a flexible way to connect with each other to relay data to sink through hop-by-hop method. On the other hand, the lifetime of relay nodes affects the availability of connected multi-hop path to sink. Therefore, it is crucial to understand the energy consumption both from per-node and whole network aspects. A feasible energy strategy to select the relay nodes by leveraging their residual energy and multi-hop network connectivity is needed for the provision of such information.

In this paper, we study the energy consumption in WSN-based IoT by theoretic analysis on a particular kind of IoT deployment, called one-dimensional queue network. This deployment scheme is widely used in many industrial monitoring and management of IoT applications, e.g. street lighting, electrified railway, product pipeline, power grids, structural health, etc. Those IoT applications consist of many small sensors and control units, that need to collaborate with each other and relay spatial-temporal information to maintain the stability of whole system.

For example, as shown in Fig. 1, traditional street lighting consumes lots of electric power due to the absence of lighting management. We have observed that most street lighting systems are deployed in urban or rural area as one-dimensional queue network, and then we designed a corresponding WSN-based IoT solution for smart street lighting. In our solution, every street lamp is equipped with a motion sensor that can detect nearby object moving and relay sensing data. In the one-dimensional lighting network illustrated by Fig. 1, once the source node detects motion behavior in its sensing range, it will choose other motion sensors attached on other street lamps to relay the motion message to sink through multi-hop dissemination. When sink node obtains this motion message, it will send the message to control center by Internet, and then the control center can make intelligent decision and send back commands to turn on some lamps to light the street for moving object. Since not every street lamp is always chosen to turn on for lighting, this smart light solution can be used for energy saving and lamp maintenance.

In addition, to keep this WSN-based smart street lighting work in Fig. 1, we need an optimal energy strategy to guarantee the lifetime of per sensor node and whole sensor network, since relay node may run out of battery and then causes disconnection in the multi-hop IoT network. This potential problem could happen in other one-dimensional WSN-based IoT application as well. Therefore, it motivates us to design an algorithm to balance energy consumption in WSN-based IoT. Different from previous works that only focus on the maximal payoff of each sensor node, we also concern about optimal energy strategy for whole network, so that the practical one-dimensional queue network can achieve maximal efficient usage of energy to relay data in WSN-based IoT.

Each sensor node in our energy model selects appropriate energy strategy to relay data based on the source node of the data. To facilitate the study of the system and better plan of the optimal energy strategy for each sensor node, we apply the idea of opportunity routing theory [11–13] in our study and propose the concept of "equivalent node", namely EEN, to select relay node and minimize overall energy consumption. Source node locates virtual equivalent node at the optimal position in queue model, and then real neighbor nodes around the equivalent node will be chosen opportunistically with different probabilities to relay data to sink.

In addition, a probabilistic data dissemination algorithm, called ENS_PD (ENergy Saving via Probabilistic Dissemination), is designed to calculate equivalent node and select optimal relay node for data relay. Relay nodes are selected by our QoS (quality of service)-aware energy strategy and probabilistically relay the data, so that the calculated optimal power of transmission can be achieved.

The remainders of the paper are organized as follows. Section 2 reviews the related work. Section 3 introduces relevant network models and assumptions. Section 4 provides theoretical analysis of the optimal transmission power. Section 5 gives a general solution to calculate optimal energy strategy and describes the operation of ENS_PD algorithm. Section 6 presents the performance evaluation by simulation and real testbed experiments. Finally, Section 7 concludes our work with future directions.

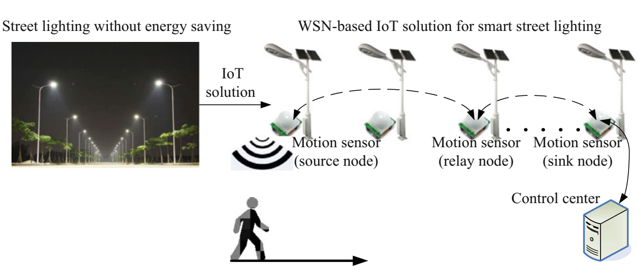


**Fig. 1** WSN-based IoT solution for smart street lighting

## 2 Related work

IoT refers to the concept of ubiquitous of the terminal devices and facilities. The core technology in IoT is the sensor network and computer information processing, for building an advanced and powerful information acquisition and processing platform. The growing interest in IoT technologies and applications is well demonstrated by a number of research initiatives arising worldwide. Milenkovic et al. [14] described some IoT implementation issues and proposed a IoT prototype for health monitoring based on wireless sensor networks. Patterson et al. [15] have set an IoT living environment where all objects are equipped with RFID tags, and residents wearing a glove with an RFID reader can sense and detect objects they have touched. Some IoT-centric programs, such as CASAGRAS2 and Auto-ID Lab, are greatly supported by international partners from Europe, the USA, China, Japan and Korea, focusing on the application of wireless sensor and RFID networks to enable future pervasive services [16].

Most of the WSNs applications in IoT right now are powered by battery which limits the lifetime of networks. Although the state of art of manufacturing techniques can improve capacity of battery and lower down the power consumption of hardware, it is equally important to maximize the energy efficiency on software level. Therefore, different types of relay node selection and power control schemes were proposed in the past few years for sensor networks and WSN-based IoT.

Many studies suggest proper selection of relay node with the concern of quality of communication [17, 19, 25]. The key idea of these works is to make a trade-off between energy consumption and desired SNR (signal to noise rate) with the knowledge of game theory. However, these methods only improve the payoff of each sensor node, which cannot guarantee the total energy saving in whole network and could even cause extra energy loss. In practice, each sensor node in WSN cannot only concern about optimizing its own energy strategy, but should take the lifetime prolongation of the whole network as its priority. Hence the non-cooperative game theoretic approach is not perfectly suitable to solve this energy problem in WSN-based IoT.

The energy consumption in WSN-based IoT is related to two factors. One is the transmission power of each communication and the other is the working rate of each sensor node. The energy consumption of a successful data transmission from source to sink should include the consumption of all the relay nodes on the selected routing path. Therefore, a proper planning of hop-count provides a solution by concerning about the two factors together to maximize the efficiency of energy usage.

Some studies [20, 21, 24] provide theoretical analysis and experiments to compare the consumed energy of single-hop transmission versus multi-hop transmission, and then calculate the suitable hop-count for the relay within the constant distance. [30] suggests that multi-hop communication can be more energy-efficient than single-hop communication. And a utility function is derived to show the advantage of N-hop transmission over single-hop transmission within the same distance. However, this model is somehow too simplified by its own placement of relay nodes, leading to favoring the multi-hop scenario and presenting it to be more energy-efficient. In reality, the position of sensor node is generally predetermined based on specific application. So these perfect energy strategies with oversimplified consumptions may not fit practical WSN-based IoT applications.

Other work in [18, 23] use transmission range adjustment to avoid overlapped sensing area but still maintain effective coverage. Their main objective is to minimize energy consumed by different sensing functions, which usually do not consider the effect of data communication.

Different from previous work, in our paper, practical models and algorithms are used to characterize multi-hop relay behavior in WSN-based IoT. Total energy consumption to transmit data from source to destination is analyzed. Then we leverage the residual energy of relay nodes and the connection of multi-hop network to design optimal energy strategy for whole network.

## 3 Network models and assumptions

Data collection and dissemination in wireless sensor networks require stable multihop networking links from source to sink. However, due to the limited energy capacity, relay nodes that run out battery may cause disconnected links and result in failed end-to-end data transmission in WSN-based IoT. Therefore, besides saving energy on itself, each sensor involved in the multi-hop transmission activity also needs a reasonable strategy to select the relay nodes by leveraging their residual energy and multi-hop network connectivity.

Without loss of generality, the relay node selection for multi-hop data transmission in WSN-based IoT is analyzed by one-dimensional queue model, as shown in Fig. 2. This model is quite common to relay sensory data in many IoT scenarios, such as street lighting system, bridge structural health, transmission line tower, and railway electrification system, where the WSN is used to detect different events to avoid infrastructural failure. Since WSN-assisted infrastructure maintenance is crucial to civil life and economic development, we address efficient data dissemination, based on following network models, to minimize energy consumption of relay nodes and prolong the lifetime of WSN-based IoT application.

### 3.1 Relay model

The one-dimensional queuing model is adopted to describe the relay behaviors among nodes in WSN-based IoT. As


**Fig. 2** The queuing model of relay with minimal transmission range of $d_{min}$ and maximum transmission range $Nd_{min}$

shown in Fig. 2, any two one-hop neighbor nodes in this model are with the equal distance $d_{min}$ by WSN deployment, and the total number of nodes with sensing and communication capability in this aligned network is $M$. The maximum transmission range of each node is $Nd_{min}$. Each node works under the same data collection rate $\beta$. With the help of relay nodes, the direction of data collection is oriented from data source and flowing towards sink node. Note that, in comparison with other oversimplified sensor deployment, the assumption of equal distance $d_{min}$ in our relay model is practical for many WSN-based IoT applications such as street lighting, product line, and electrified railway system.

### 3.2 Energy model

According to [22, 26], when sensor node is working, the energy consumption can be formulated as Eq. 1, where $\Phi$ is the basic energy consumption of sensor board to supply the running of MCU (micro-chip unit), a microprocessor used to monitor tasks such as collection and calculation. $p_i$ is the transmitted power strength of signal, with $\alpha$ as its correlation coefficient which is determined by electrical property of the RF (radio frequency) chip and antenna. $P_t$ denotes the energy consumption of transmitter.

$$P_t = \Phi + \alpha p_i \tag{1}$$

Correspondingly, the energy consumption of receiver $P_r$ can be expressed as Eq. 2, where $p_\wedge$ is a constant to indicate the radio power of receiver.

$$P_r = \Phi + p_\wedge \tag{2}$$

### 3.3 Propagation model

The path-loss by distance can be modeled in wireless communication as $pl = K(d_0/d)^\tau$ [27, 28], where $\tau$ is the path-loss exponent that satisfies $\tau > 1$. When $d > d_0$, $K$ can be empirically approximated as $K(dB) = 20\lg(\lambda/4\pi d_0)$, where $d_0$ is the reference distance, $d$ is the distance between transmitter and receiver, and $\lambda$ is the signal wavelength. According to this propagation model, the received power strength of signal $p_r$ can be defined as Eq. 3.

$$p_r = Kp_i(d_0/d)^\tau \tag{3}$$

The minimum power level of effective signal reception has been widely applied in energy conservation as a threshold for QoS-based data transmission [28, 29]. In our model, since the noise is viewed as a constant, the transmitter should adjust its transmission power to make receiving power on the receiver reach a minimum value. Here we define this minimum power level by a constant threshold value as $P_{TH}$.

## 4 Equivalent node for energy consumption analysis

In WSN application for IoT, data are delivered to sink through hop-by-hop connected relay nodes. A well chosen strategy of power control for each relay node can achieve per-node energy conservation for on-going and future transmission, and therefore prolong the network lifetime. To better analyze the transmission related energy consumption of relay nodes, we propose the concept of "equivalent node", namely EEN, to analyze energy consumption in WSN, and use it to select relay nodes.

**Definition 1** Equivalent node is a calculated virtual node that can equally function as selected one or several real nodes. The energy consumption of equivalent node equals to the energy consumption of these selected real nodes.

In WSN-based IoT, the equivalent nodes are composed of transmitters and receivers. Inspired from the probability-based opportunity routing approach, equivalent node is formed by jointly considering the distribution of real nodes and their transmission probabilities. Figure 3 presents a one-dimensional model to illustrate the probabilistic data dissemination in multi-hop WSN and corresponding formation scheme of the equivalent node.

In this one-dimensional model, node A is the transmitter and its transmission probabilities to node B and node C are $\eta$ and $(1-\eta)$ respectively. If the distance from node A to node B and node C are $d_1$ and $d_2$, respectively, and the received signal power meets the lowest QoS requirement, the position of equivalent node that represents B and C is given as Eq. 4, where $\tau$ is path-loss exponent.

$$l = [{d_1}^\tau \eta + {d_2}^\tau (1-\eta)]^{1/\tau} \tag{4}$$

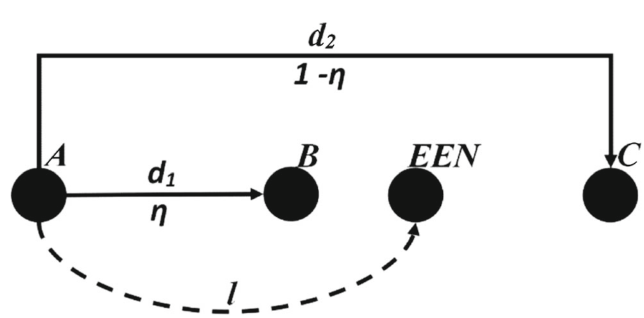


**Fig. 3** The formation of energy equivalent node (EEN)

Because the power threshold of effective signal reception is constant, we only concern about the energy strategy of transmitter for data relay in our model. Figure 4 illustrates a multi-hop WSN to relay data using one-dimensional queue model. For node $h$, there are $h-1$ nodes available for data relay. These nodes have same distance $d_{min}$ between neighbors. To find the optimal energy strategy for node h to relay data to other nodes, we converge real nodes to equivalent nodes and then minimize the overall relay energy consumption according to Theorem 1.

**Theorem 1** *In large-scale WSN where each node is equally distanced in a one-dimensional queuing model, if the energy consumption of transmitter is $P_t = \Phi + \alpha p_i$, and the energy consumption of receiver is $P_r = \Phi + p_\wedge$, and the optimal equivalent energy strategy of sensor node($h(h \gg 1)$) to relay data in the one-dimensional queue to sink is $P_t = [\phi(h\tau + 1) + p_\wedge]/(h\tau - 1)$.*

*Proof* Define the duration of each transmission as a unit interval. For the $h$th node in Fig. 3, the number of nodes ahead to sink is $h-1$, and the number of hops that relay data to sink is $n$. Therefore, the total energy consumption($C_h$) it takes to transmit the data to sink can be expressed as Eq. 5, where $p_i$ is the transmission signal power of the $i$th node.

$$C_h = \sum_{i=1}^{n} (\Phi + \alpha p_i) + (n-1)(\Phi + p_\wedge) \tag{5}$$

In order to save energy, each transmission only needs to satisfy the lowest QoS requirement (minimal tolerable SNR). Define the minimum power consumption of effective signal reception as $P_r = P_{TH}$. According to Eq. 3, we have

$$p_i (d_0/d_i)^\tau = const \tag{6}$$

We know that the distance between any two closest nodes is same as $d_{min}$. For $i$th hop during data relay, suppose the length of this one hop is $d_i$, we have

$$h = \sum_{i=1}^{n} (d_i/d_{min}) \tag{7}$$

The number of hops from node h to sink is given in Eq. 8, where $\overline{d_i} = \sum_{i=0}^{n} (d_i/n)$ represents the average length of each hop in the network.

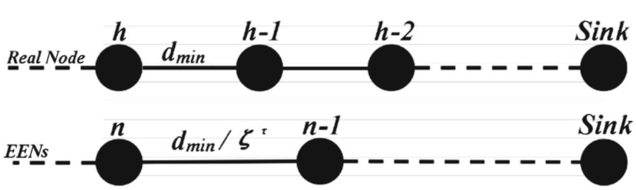


**Fig. 4** Real nodes and EEN in one-dimensional queue model

$$n = h/(\overline{d_i}/d_{min}) \tag{8}$$

We denote $p_{min}$ as the minimum transmission power in terms of $d_{min}$. Accordingly, we have following relation between hop number $n$ and transmission power $p_i$ as shown in Eq. 9, in which $\overline{p_i^{1/\tau}} = \sum_{i=0}^{n} p_i^{1/\tau}/n$.

$$n = h(p_{min}^{1/\tau}/\overline{p_i^{1/\tau}}) \tag{9}$$

$p_i$ can be transformed into Eq. 10, where $\zeta_i$ is a coefficient to reveal the connection between $p_i$ and $p_{min}$.

$$p_i = \zeta_i p_{min} \tag{10}$$

Combine Eqs. 5, 9 and 10 together, we reformulate the energy consumption of node $h$ as Eq. 11

$$C_h = (2\Phi + \alpha p_{min}\overline{\zeta_i} + p_\wedge)h/\overline{\zeta_i^{(1/\tau)}} - (\Phi + p_\wedge) \tag{11}$$

Where $\zeta_i$ can be expressed as Eq. 12, according to Eqs. 8 and 9.

$$\zeta_i = (d_i/d_{min})^\tau \tag{12}$$

Based on Eq. 7 we know the distance between node h and sink is determined, and for the given $n$ we can derive $\overline{d}_i$ in Eq. 8. Therefore, we can yield constant $\overline{\zeta_i^{1/\tau}}$, and derive (13), where $\zeta_1 = \zeta_2 = \cdots = \zeta_n = \overline{\zeta_i^{1/\tau}}^\tau = \zeta$.

$$C_h \geq (2\Phi + \alpha p_{min}\zeta + p_\wedge)h\zeta^{(-1/\tau)} - (\Phi + p_\wedge) \tag{13}$$

Accordingly, we can obtain the minimum value of $C_h$ with given $\overline{\zeta_i^{1/\tau}}$ as Eq. 14.

$$C_h{}^{min}(\zeta) = (2\Phi + \alpha p_{min}\zeta + p_\wedge)h\zeta^{(-1/\tau)} - (\Phi + p_\wedge) \tag{14}$$

In order to optimize the overall energy consumption during data relay, the first order derivative of $C_h{}^{min}$ need to satisfy following optimality condition as Eq. 16.

$$\begin{aligned} &\partial C^{min}/\partial\zeta \\ &= \alpha p_{min}(h-1)\zeta^{(-1/\tau)} - (1/\tau) \\ &\quad (2\Phi + \alpha p_{min}\zeta + p_\wedge)\zeta^{-(\tau+1)/\tau} \\ &= 0 \end{aligned} \tag{15}$$

Then we have result in Eq. 16 for either global maximum or minimum.

$$\zeta = (2\Phi + p_\wedge)/[(h\tau - 1)\alpha p_{min}] \tag{16}$$

In addition, the second derivative of ${C_h}^{min}$ with respect to $\zeta$ at the point of Eq. 16 reveals that

$$\frac{\partial^2 {C_h}^{min}}{\partial \zeta^2}|_{\zeta=(2\Phi+p_\wedge)/[(h\tau-1)\alpha p_{min}]} = \frac{(2\Phi+p_\wedge)^{-(\tau+1)/\tau}}{\tau[(h\tau-1)\alpha p_{min}]^{-(2\tau+1)/\tau}} > 0 \tag{17}$$

Therefore, we can decide that (16) is the global minimum with respect to the energy consumption of node $h$. And the corresponding optimal distance to next node to relay data can be expressed as Eq. 18.

$$d^{op} = d_{min}\{(2\Phi + p_\wedge)/[(h\tau - 1)\alpha p_{min}]\}^{1/\tau} \tag{18}$$

Since the distance $hd_{min}$ from node $h$ to sink may not necessarily be the sum of multiple integral value $d^{op}$, (19) uses an integral value $n$ to describe their relation.

$$n(d^{op} + \varepsilon) = hd_{min} \tag{19}$$

When $h \gg 1$, we have $\varepsilon \to 0$ and can use Eq. 18 to select relay node for data transmission. Combine Eqs. 6 and 18, we can derive the optimal energy strategy as Eq. 20, according to the regulation in Eq. 1.

$$P_t = [\Phi(h\tau + 1) + p_\wedge]/(h\tau - 1) \tag{20}$$

□

This completes the proof of the theorem. Theorem 1 depicts an ideal situation which is only applicable when $h \gg 1$. The value $n$ in Eq. 19 indicates the position of relay node in our one-dimensional queue model. However, in reality as shown in Fig. 3, $n$ is unnecessarily equal to $h$, and the position of selected relay node by Theorem 1 would always end up to be somewhere between two real nodes. According to Eq. 4, equivalent node can reconcile this conflict for optimal data relay. We will further address the use of equivalent node for relay node selection and power control in following section.

## 5 Energy strategy for small-scale network

Theorem 1 for relay node selection can only be valid in a super large-scale queue model, which is not applicable in many WSN-based IoT scenarios. Certain IoT queue models, e.g. transmission line tower and electrified railway system, may deploy approximately infinite number of sensors queuing in a line. However, due to limited capacity of sink and robust requirement of data management in WSN, in reality for these applications, a large-scale queue model is usually divided into many small-scale queue models, and then organized by multiple sinks for data collection and dissemination. In this section, we study the optimal energy strategy for small-scale network. According to our theoretical results, an energy saving algorithm is specifically designed to select relay node through probabilistic data dissemination.

### 5.1 Condition of energy strategy

To save energy during data transmission in whole network, there must be an optimal energy strategy for each node. Unlike large-scale network where $h \gg 1$, the small-scale network cannot satisfy the condition $\varepsilon \to 0$ of Eq. 19 in most cases. In addition, the position of selected relay node by Theorem 1 may be EEN in one-dimensional queue model. Therefore, optimal energy strategy for small-scale network needs to be readdressed from Theorem 1.

In order to find out the optimal strategy, we illustrate two conditions needed to be satisfied in small-scale network.

**Condition 1** For node $h$, the selected EENs for data relay should have equal distance $d_\theta^{op}$ to their nearest neighbors. The selected EENs also need to satisfy that $hd_{min}$ is divisible by $d_\theta^{op}$.

From Condition 1, node $h$ converts the selection of relay node in small-scale network to be a similar problem in Eq. 19, and therefore selected EENs can be used to optimize energy consumption as the real node in Theorem 1.

**Condition 2** The optimal energy strategy for node $h$, according to Eq. 16, should satisfy (21) after selecting EENs.

$${C_h}^{min}({d_\theta}^{op}) \le {C_h}^{min}({d_j}^{op})|_{j \ne \theta} \tag{21}$$

Because $\zeta_i$ in Eq. 14 can be express by multiple $\zeta_i = (d_i/d_{min})^\tau$ as Eq. 12, condition 2 presents possible EENs as candidates to optimize energy consumption. Note that EENs in condition 2 need to first satisfy condition 1. From Eq. 21, node h can choose the candidate for the optimal strategy. The corresponding power of ${d_\theta}^{op}$ is thus the optimal strategy of each sensor node in the small-scale network. The specific algorithm to choose EEN is described in following section.

### 5.2 Energy equivalent node for optimal energy strategy

The two conditions above provide guidance for the selection of optimal energy strategy. However, since we need to calculate energy consumption for every relay node, it will result in large computing overhead. According to Theorem 1, we know that the energy consumption function (14) is convex with respect to distance variable $d$. We can achieve optimal energy strategy by choosing optimal strategy to determine

d. If the selected d is closer to estimated result in Eq. 18, then the network can achieve better energy usage.

According to the definition of EEN in Eq. 4, each EEN is determined by two close nodes: one before it and the other after it. If we can find the optimal strategy of choosing $d$, then we can locate the virtual relay node at position with distance $d$ from node $h$. By one-dimensional queue model, there will be two real nodes that closely locate before and after the EEN. Since these two real nodes are close to the optimal $d$, they can serve as desired relay nodes. The two real nodes choose their own optimal energy strategy for data relay, and then again each derives an EEN for next-hop data relay. If we continue this process, there will be many EENs generated after several hops. Therefore, here we propose that comparison of two candidates is good enough to obtain optimal energy strategy. That is, after the mentioned two relay nodes generate their next-hop EENs, we compare the two EENs and choose the one with better energy strategy as next hop.

Given $d^{op}$ from Theorem 1, the definition of these two candidates is expressed by ${d_1}^{op}$and ${d_2}^{op}$, respectively in Eqs. 23 and 24, where $\lfloor * \rfloor$ is to round off $*$ into integral. Accordingly, ${d_\theta}^{op}$ that meet Condition 1 and 2 is described as Eq. 24.

$$ {d_1}^{op} = (hd_{min})/[(hd_{min} + d^{op})/d^{op}] \quad d_{min} < d^{op} < Nd_{min} \tag{22} $$

$$ {d_2}^{op} = (hd_{min})/[(hd_{min})/d^{op}] \quad d_{min} < d^{op} < Nd_{min} \tag{23} $$

$$ {d_\theta}^{op} = \begin{cases} {d_1}^{op}, & {C_h}^{min}({d_1}^{op}) < {C_h}^{min}({d_2}^{op}) \\ {d_2}^{op}, & {C_h}^{min}({d_2}^{op}) \le {C_h}^{min}({d_1}^{op}) \end{cases} \tag{24} $$

In these definitions, there are mainly three relations between $d^{op}$ and $hd_{min}$, and therefore generate three cases to calculate different $d_\theta^{op}$ in terms of $d_1^{op}$ and $d_2^{op}$, as follows.

**Case 1** $d^{op} > hd_{min}$

In this case, we have Eq. 25, where $Nd_{min}$ is the maximum transmission range

$$ {d_\theta}^{op} = \begin{cases} hd_{min}, & h < N \\ Nd_{min}, & h \ge N \end{cases} \tag{25} $$

**Case 2** $d^{op} < d_{min}$

In this situation the optimal strategy is $d^{op} = d_{min}$, because it is meaningless to set up the transmission range smaller than $d_{min}$.

**Case 3** $d_{min} \le d^{op} \le hd_{min}$

Under this circumstance, ${d_\theta}^{op}$ is calculated as Eq. 26.

$$ {d_\theta}^{op} = \begin{cases} {d_1}^{op}, & h < N; \\ & {C_h}^{min}({d_1}^{op}) < {C_h}^{min}({d_2}^{op}) \\ {d_2}^{op}, & d^{op} < Nd_{min}; h \ge N; \\ & {C_h}^{min}({d_2}^{op}) \le {C_h}^{min}({d_1}^{op}) \\ Nd_{min}, & d^{op} \ge Nd_{min}; h \ge N \end{cases} \tag{26} $$

The three cases provide a fast calculation of the optimal strategy for choosing $d$. Because of the relation between energy consumption and distance as Eq. 14, we use above optimal distance results to decide corresponding energy saving strategy, which is specifically achieved through following probabilistic dissemination algorithm, called ENS_PD.

### 5.3 ENS_PD algorithm

In ENS_PD, EEN is determined after formulation and calculation of ${d_\theta}^{op}$. E ach EEN functions by assigning different probabilities for close real nodes to relay data. For any node $h$, the transmitted data can be separated into two groups. One group is the sensor data of its own, and the other group is the relay data from other nodes.

From previous sections, we know that $hd_{min}$ indicates the distance from node $h$ to sink. The optimal strategy for choosing ${d_\theta}^{op}$ is dependent on $d_h$. In order to obtain value $h$ (source ID), when the data of second group arrive, each EEN needs to trace the ID of source by checking incoming data. And then it can calculate the optimal energy strategy to relay the data by case analysis as illustrated in Section III.

For a rapid selection of proper energy strategy according the source ID of the arrived data, we introduce ENS_PD algorithm for energy saving through probabilistic dissemination of the data. The ENS_PD algorithm for each EEN includes following steps:

(1) Calculate the optiaml transmission range based on Eq. 24, and get the optimal energy strategy of its own by Eqs. 23 and 24.
(2) Collect the sensor data and waiting for the incoming data.
(3) Check the source ID of the incoming data, and calculate the optimal transmission power strategy, according to the source ID.
(4) Update previous optimal transmission strategy, according to the source ID of incoming data, and probabilistically send out the data to two close-by real nodes which are before and after the EEN, respectively.

In addition, though above steps are designed for one-dimensional queue model, we can easily extend the ENS_PD algorithm for WSN with multiple sink and multiple relay queues, by checking the source ID and sink ID in each data. Since the two kinds of ID indicate unique information of each data flow, ENS_PD algorithm can direct the data on the right queue to corresponding sink.

Note that in previous sections we mainly address the strategy of EEN in the small-scale network. However, if there is a real node exactly located on the position of selected relay node by Theorem 1, we can simply replace EEN by the real node and let it follow the same operations to choose optimal energy strategy to relay data.

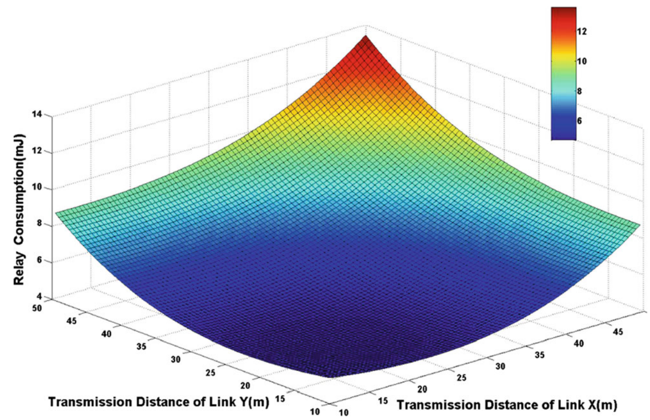


**Fig. 5** Energy strategies of two EENs according to total consumption spent on a successful delivery

## 6 Performance evaluation

We have evaluated our relay models and algorithms through extensive simulation results and real testbed experiments. The performance of END_PD algorithm has been verified by comparison with other methods. The energy strategy has been testified by data relay in multi-hop WSN-based IoT.

### 6.1 Simulation results

The simulation is implemented by Matlab in a scenario of queuing model to evaluate the performance of ENS_PD algorithm for data delay. Each node has the same collecting rate $\beta$=0.002, and firmware character $\phi$, $P_\wedge$, $\alpha$ in Eq. 1 is set as 200 mw, 10 mw and 2 respectively. Path-loss exponent of environment $\tau$ is 3.5. Considering (3), we set the lowest transmission power for communication at distance 12.5 m as 10 mw, and use it as as a standard reference to meet the minimum QoS requirement of receiver. The longest distance of a single hop is 50m and the stored energy is 3000mwh. During transmission, several offset channels are offered, thus the interference among the generated signals of each node is ignored.

#### *6.1.1 Evaluation of energy strategy*

Firstly, we evaluate the outcome of the network by the measuring consumption of a single packet delivery from the last node to sink at the distance of 100m with 10 nodes equally distanced to their adjacent neighbors among them. During relay, when the equivalent transmitters (ETs) of two different equivalent links change their transmission distances, the changed energy strategies of ETs will in turn affect the total energy consumption.

From Fig. 5, we see that there is an equilibrium energy strategy for both equivalent link X and link Y. According to the strategy, the total energy consumption of delivery is minimal. It can also infer that for each equivalent relay node the equilibrium is the same. Thus, the total consumption is decreased when nodes are all with equilibrium energy. The optimal energy strategy of each EEN, as shown in Fig. 5, is 51.8 mw with the transmission distance of about 22.5 m and collecting rate of $\beta$=0.002.

According to Eq. 1, $\Phi$ reveals the unique characters of MCU. Smaller $\Phi$ indicate slower consumption of MCU. Let $P_\wedge$ and $\alpha$ equal to 10mw and 2 respectively. The influence of path-loss exponent $\tau$ and sensor's firmware character $\Phi$ on the perfect transmission power is illustrated by Fig. 6. We can see that transmission power increases along with the increase of MCU consumption, and smaller pass-loss exponent results in sharper variation. So the transmission power is maximum when $\Phi$ is on its largest value while path-loss exponent is the lowest.

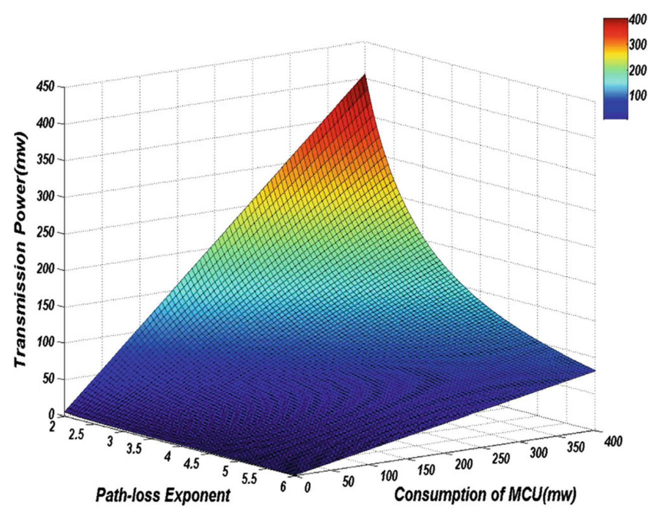


**Fig. 6** Transmission power of single node according to path-loss exponent and consumption of MCU

*6.1.2 Evaluation of relay algorithm*

To fully analyze the performance of ENS_PD, we compared it with the methods MADT (Maximum Distance Transmission) and SGHP (Single Hop Distance Transmission) [8], which represent the transmission power strategy with maximum and minimum transmission power, respectively, to satisfy QoS requirement of reception. The average power consumption of each node, the lifetime of the whole system, and packet loss rate are taken as criteria of evaluation.

Figure 7 shows the average power consumption of each node with collecting rate, when $\beta$=0.002 system is fully operation. The variables are total number of actual nodes in queuing model and the distance between two immediate neighbors. As we can see, ENS_PD can achieve the lowest consumption and is obviously better than MADT method.For MADT, when the minimum distance becomes larger, the original connected node may be out of transmission range, hence the transmitter has to decrease the power and select the furthest node within its transmission range. Therefore the energy consumption keeps changing and causes the performance fluctuation of MADT. At the distance more than 22.5 m, ENS_PD and SGHP result in similar energy consumption because both schemes can achieve optimal transmission distance, as illustrated in Fig. 5. For this case, both ENS_PD and SGHP only allow every node communicate to its nearest neighbor. No matter larger or smaller than this distance, ENS_PD always keeps the energy consumption at the lowest level.

The lifetime of a network is relevant to the maximum lifetime of relay nodes. Relay nodes should be capable to reach sink through multi-hop connection, no matter how much energy are left. And their energy indicate the transmission range. In Fig. 8, the result shows ENS_PD can have the longest lifetime. The life time of SGHP is shorter, and that of MADT is the shortest compared to ENS_PD. When the distance between two nearest nodes is extended to be more than 22.5 m, ENS_PD and SGHP have the same transmission distance, so they have the same lifetime as well. Thus, ENS_PD guarantees both the extensive lifetime and the largest conservation of energy.

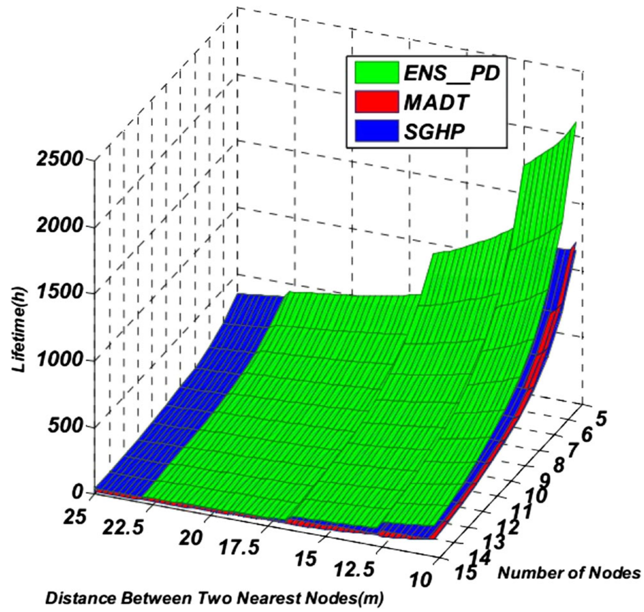


**Fig. 8** The comparison of lifetime referred to network scale and minimum distance between two nearest nodes

Suppose there is a constant packet loss rate for each link. The final arrival rate of sensor data is relevant to the number of hops. We set packet loss rate as 2 % for a single delivery. The result in Fig. 9 reveals that for the furthest node in queuing model, the packet loss rate is maximum if SGHP is used. MADT is the best option if we only concern about decreasing packet loss rate. The communication quality of ENS_PD is between SGHP and MADT. Consider that ENS_PD can

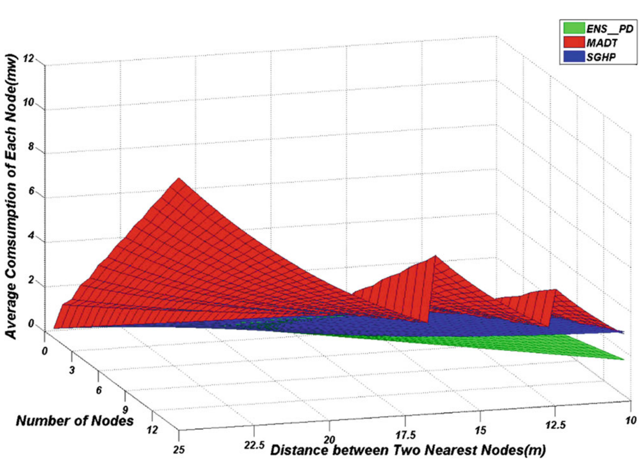


**Fig. 7** The comparison of average consumption according to network scale and minimum distance between two nearest nodes

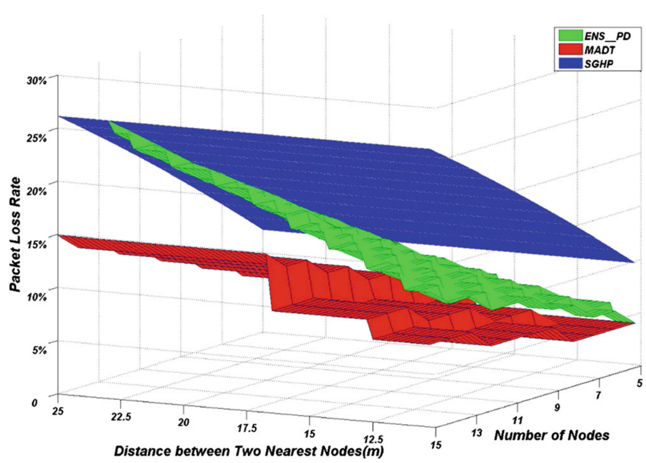


**Fig. 9** The comparison of packet loss rate according to network scale and minimum distance between two nearest nodes

extend network lifetime, it is still a fine option. Though minimal energy consumption, a promising packet loss rate can be satisfied by ENS_PD.

For the last group of simulation, we set the distance between two adjacent neighbors as 10m, the network scale is of 10 nodes and the rest parameters are the same in a multi-hop WSN. If the longest distance of single hop is 50m, the number of nodes that can directly access to sink is 5, which is based on the standard reference mentioned above. Without those 5 nodes, the network will be disconnected and failed to transmit to sink. Thus, we look at the first 5 nodes from sink, measure their energy consumption and evaluate their performance.

Figure 10 shows the energy consumption of the 5 sensor nodes which are capable of communicating to sink directly. We again evaluate the three relay methods with collecting rate $\beta$=0.002. As we can see, ENS_PD can achieve lower average energy consumption compared with MADT and SGHP, because of its probabilistic dissemination and small-scale network schemes. And due to the lower consumption, a longer lifetime can be achieved as well by ENS_PD method.

From simulation results, we can conclude that ENS_PD scheme, based on equivalent node, is more robust than other schemes on choosing next-hop data relay, by balancing energy and lifetime from both per node and whole network aspects.

### 6.2 Real testbed experiments

To analyze the performance of our models and algorithms in real life, a SOC solution tailored for IEEE 802.15.4/Zigbee applications, called CC2530, is used to implement our algorithm for real testbed experiments. Because the transmission power in practice cannot be quantized into levels as

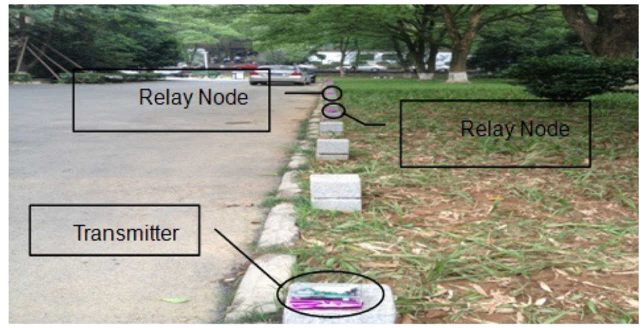


**Fig. 11** Network topology for real testbed experiments

many as the theoretic analysis does, we use 20 available levels of transmission power in the RF front-end, CC2591, for evaluation.

We choose an area that will be used for future street lighting deployment, and set the WSN-based IoT for smart street lighting application, as illustrated by the example of one-dimensional lighting network in Fig. 1. The network is composed of 10 sensor nodes with wireless communication capability. These nodes are placed in a line, as shown in Fig. 11. Any adjacent node is of 10m away from each other. The maximum transmission power is 20 dbm, the minimum interval of the transmission power is 1dbm, and the bandwidth is $5 \times 10^6$ HZ . Each node is working in the same channel, and message is delivered with three mechanisms: one-hop, random-hop and equivalent-hop.

In each mechanism, we calculate the energy consumption for one packet transmitted from the first node to the sink in the line. The transmission power level can be set through serial port. For one-hop mechanism, we let each node only communicate with the next hop node, and calculate the energy consumption by Eq. 1. For random-hop mechanism, each node transmits the packet randomly

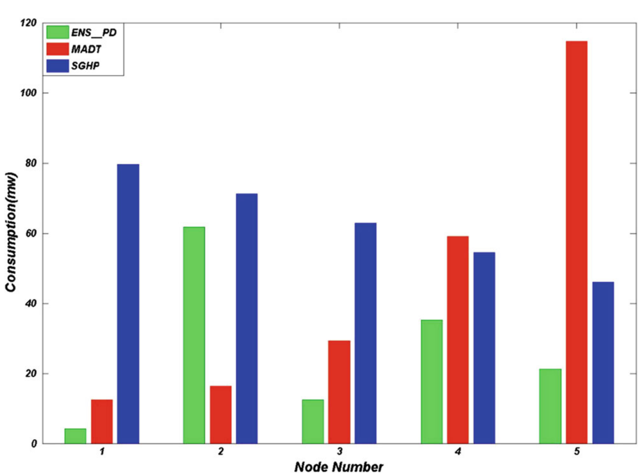


**Fig. 10** Energy consumption of first 5 nodes from the sink by different relay methods

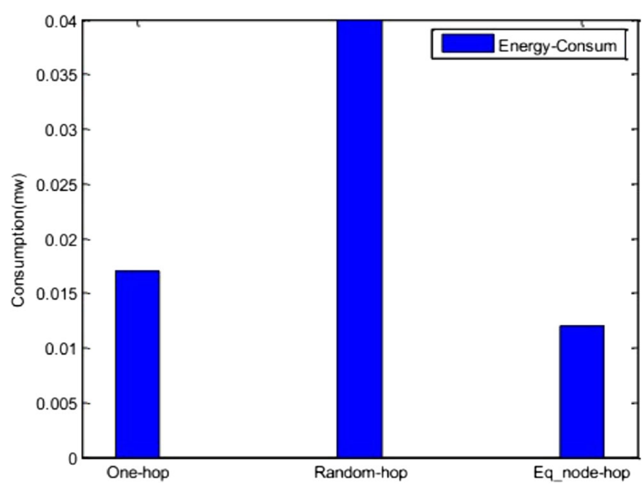


**Fig. 12** Energy consumption per unit time of three different delivery mechanisms

to the node in the line. And when the sink gets the packet, we calculate the overall energy consumption. For equivalent-hop mechanism, we first use the equivalent node for data relay according to Eq. 5. Then we line the 10 node with the distance same as the distance calculated by equivalent node, and let each node communicate with the next hop node. When sink gets the packet, we calculate the whole energy consumption of this mechanism.Then, energy consumption per unit time is calculated by dividing between whole energy consumption and time consuming.

Figure 12 shows the average energy consumption per unit time (ms) of the three different mechanisms. Random hop mechanism has the highest energy consumption per unit time as 0.040mw. However, there is a plunge for one-hop and equivalent-hop mechanisms. The energy consumption per unit time of equivalent-hop mechanism is 0.012 mw, which is the lowest value among the three mechanisms. The energy consumption of one-hop mechanism is 0.017 mw, which is much higher than equivalent-hop mechanism. These results meet our analysis in Theorem 1., which is the basis of our scheme to present the optimal energy strategy.

Through evaluation of smart street lighting as one application of realistic one-dimensional IoT network, we can verify that the equivalent-hop mechanism and corresponding node relay scheme can present an efficient way to save the energy and prolong network lifetime, for the multi-hop WSN-based IoT both in simulation and real testbed.

## 7 Conclusion

The energy consumption is a big concern in WSN because of the limited energy supply per node. To achieve efficient data relay and prolong network lifetime in multi-hop WSN-based IoT, this paper focuses on the pursuit of optimal transmission energy strategy. Theoretic results about calculation of optimal energy strategy are given in ideal large-scale WSN. After that, a modified calculation of this optimality for practical small-scale network is demonstrated with the help of equivalent nodes. Finally, the ENS_PD algorithm is designed to select relay node and choose optimal energy strategy to prolong the lifetime of whole network. Extensive simulation and real testbed results show that our models and algorithms can minimize energy consumption while guarantee the quality of communication in comparison with other methods

This work mainly studies one-dimensional queuing model for one kind of IoT applications, e.g. street lighting, electrified railway, and product line. In the near future, we will extend the concept of equivalent node to other more universal and higher dimensional models. Corresponding optimal energy strategies are also needed to be readdressed for other practical queuing model of WSN-based IoT applications, such as inventory tracking, health care, home appliances, smart grids, etc.

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## References

1. Olaru A, Magda Florea A, Seghrouchni A (2013) A Context-Aware Multi-Agent System as a Middleware for Ambient Intelligence. Mob Netw Appl 18(3):429–443
2. Deng R, Chen J, Cao X, Zhang Y, Maharjan S, Gjessing S (2013) Sensing-Performance Tradeoff in Cognitive Radio enabled Smart Grid. IEEE Trans. on Smart Grid 4(1):302–310
3. Chen X, Zhao Z, Zhang H (2013) Stochastic power adaptation with multiagent reinforcement learning for cognitive wireless mesh networks. IEEE Trans Mob Comput 12(11):2155–2166
4. Wang S, Wang Y, Coon JP, Doufexi A (2012) Energy-Efficient Spectrum Sensing and Access for Cognitive Radio Networks. IEEE Trans Veh Technol 61(2):906–912
5. Wu D, Bao L, Liu CH (2013) Scalable Channel Allocation and Access Scheduling for Wireless Internet-of-Things. IEEE Sensors J 13(10):3596–3604
6. Niu J, Cheng L, Gu Y, Shu L, Das SK (2014) R3E: Reliable Reactive Routing Enhancement for Wireless Sensor Networks. IEEE Trans Ind Inform 10(1):784–794
7. Atzori L, lera A, Morabito G (2010) The Internet of Things: A Survey. Comput Netw 54(15):2787–2805
8. Akyildiz IF, Weilian S, Sankarasubramaniam Y, Cayirci E (2002) A survey on sensor networks. IEEE Commun Mag 40:102–114
9. Wei Y, Heidemann J, Estrin D (2002) An energy-efficient mac protocol for wireless sensor networks. IEEE 21st conference comput commun 3:1567–1576
10. Chen JM, Cao XH, Cheng P, Xiao Y, Sun YX (2010) Distributed collaborative control for industrial automation with wireless sensor and actuator networks. IEEE Trans Ind Electron 57(12):4219–4230
11. Mao X, Tang S, Xu X, Li X, Ma H (2011) Energy-Efficient Opportunistic Routing in Wireless Sensor Networks, Parallel and Distributed Systems. IEEE Trans Parallel and Distrib Syst 22(11):1934–1942
12. Zhuang YY, Pan JP, Cai L (2010) Minimizing Energy Consumption with Probabilistic Distance Models in Wireless Sensor Networks. IEEE INFOCOM:1–9
13. Luo J, Hu J, Wu D, Li R (2015) Opportunistic routing algorithm for relay node selection in wireless sensor networks. IEEE Trans Ind Inform 11(1):112–121
14. Milenkovic A, Otto C, Jovanov E (2006) Wireless sensor networks for personal health monitoring: Issues and an implementation. Comput Commun 29(13-14):2521–2533
15. Patterson D, Fox D, Kautz H, Philipose M (2005) Fine-grained activity recognition by aggregating abstract object usage. 9th IEEE Int Symp on Wearable Comput:44–51

16. Gubbi J, Buyya R, Marusic S, Palaniswami M (2013) Internet of Things (IoT): A vision, architectural elements, and future directions. Future Generation Comp. Syst 29(7):1645–1660
17. Long CN, Zhang Q, Li B (2007) Non-Cooperative Power Control for Wireless Ad hoc Networks with Repeated Games. IEEE J on Sel Areas in Commun 25(6):1101–1112
18. Wu D, Bao L, Li R (2010) A holistic approach to wireless sensor network routing in underground tunnel environments. Comput Commun 33(13):1566–1573
19. Papavassiliou S, Katsinis GK, Tsiropoulou EE (2012) Distributed Uplink Power Control in Multi-Service Wireless Networks via a Game Theoretic Approach with Convex Pricing. IEEE Trans on Parallel and Distrib Syst 23(1):61–68
20. Fedor S, Collier M (2007) On the problem of energy efficiency of multi-hop vs one-hop routing in Wireless Sensor Networks. 21st Int Conf Adv Inf Netw and Appl Workshops 2:380–385
21. Kakitani MT, Brante G, Souza RD, Munaretto A (2011) Comparing the Energy Efficiency of Single-Hop, Multi-Hop and Incremental Decode-and-Forward in Multi-Relay Wireless Sensor Networks. IEEE 22nd Int Symp Pers Indoor and Mob Radio Commun:970–974
22. Raghunathan V, Schurgers C, Park S (2002) Energy-Aware Wireless Microsensor Networks. IEEE Signal Proc Mag 19(2):40–50
23. Zalyubovskiy V, Erzin A, Astrakov S, Choo H (2009) Energy-efficient area coverage by sensors with adjustable ranges. Sensors 9(4):2446–2460
24. Ramaiyan V, Kumar A, Altman E (2011) Optimal Hop Distance and Power Control for a Single Cell, Dense, Ad hoc Wireless Network. IEEE Trans Mob Comput 11(11):1601–1612
25. Zhou Z, Zhou SL, Cui JH Cui (2008) Energy-efficiency Cooperative Communication Based on Power Control And Selective Relay in Wireless Sensor Network. IEEE Trans Wirel Commun 7(8):3066–3078
26. Karl H, Willig A (2005) Protocols and Architectures for Wireless Sensor Networks, Wiley. Sons Ltd, England
27. Goldsmith A (2005) Wireless Communications. Cambridge, England
28. Luo J, Pan C, Li RF, Ge F (2012) Power Control in Distributed Wireless Sensor Networks Based on Noncooperative Game Theory. International J Distrib Sensor Netw 2012:1–10
29. Rasti M, Sharafat AR, Seyfe B (2009) Pareto-efficient and goal-driven power control in wireless networks: a game-theoretic approach with a novel pricing scheme. IEEE/ACM Trans Netw 17(2):556–569
30. Zhao F, Leonidas G (2004) Wireless Sensor Networks: An Information Processing Approach. Morgan Kaufmann, San Francisco