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Realistic Analysis of Energy Efficiency in Multihop Wireless Sensor Networks

Hui JING[†a)], ***Nonmember and*** **Hitoshi AIDA**[†b)], ***Member***

SUMMARY As one of the most widely investigated studies in wireless sensor networks (WSNs), multihop networking is increasingly developed and applied for achieving energy efficient communications and enhancing transmission reliability. To accurately and realistically analyze the performance metric (energy efficiency), firstly we provide a measurement of the energy dissipation for each state and establish a practical energy consumption model for a WSN. According to the analytical model of connectivity, Gaussian approximation approaches to experimental connection probability are expressed for optimization problem on energy efficiency. Moreover, for integrating experimental results with theories, we propose the methodology in multihop wireless sensor networks to maximize efficiency by nonlinear programming, considering energy consumptions and the total quantity of sensing data to base station. Furthermore, we present evaluations adapting to various wireless sensor networks quantitatively with respect to energy efficiency and network configuration, in view of connectivity, the length of data, maximum number of hops and total number of nodes. As the consequence, the realistic analysis can be used in practical applications, especially on self-organization sensor networks. The analysis also shows correlations between the efficiency and maximum number of hops, that is the multihop systems with several hops can accommodate enough devices in ordinary applications. In this paper, our contribution distinguished from others is that our model and analysis are extended from experiments. Therefore, the results of analysis and proposal can be conveniently applied to actual networks.

key words: *energy efficiency, multihop wireless sensor networks, optimization, realistic analysis, connectivity, nonlinear programming*

1. Introduction and Related Works

Wireless sensor networks (WSNs) have been made viable by the convergence of micro-electro-mechanical systems technology, wireless communications and digital electronics [1]. They are expected to consist of a number of sensor nodes (SNs) (few ten to thousands), each having sensing, data processing and communicating components with limited computational and communication power. To provide various measurements such as light, temperature, pressure and activity, these low-cost, low-power, multifunctional nodes have been widely deployed in a vast variety of environments for commercial, civil, and military applications such as surveillance, vehicle tracking, climate, etc..

Most of SNs are designed for battery power to reduce the size, which use limited power supply to support sensors, processor and radio. It allows for a range of different sensing modalities as well as an interface to external sensor via prototyping areas. It is always designed to equip several different environmental sensors for a wide variety of applications, such as weather station with humidity, temperature and pressure sensor, vehicle detection with accelerometer, and so on.

In most of applications, the radio with RF transceiver which is working for transmission and receiving messages, consumes much more energy than sensor board and microcontroller. In recent years, with the rapid development of embedded systems including energy efficient devices, hardware/software co-design and networking support, SNs have been smaller in size and more efficient in data processing and transmission. However, they are still limited in power, memory and computational capacities. As a result, the key challenge is to maximize the lifetime of SNs due to the fact that the battery is the main power source in a SN. Therefore, communication protocols are needed to be energy efficient to save energy.

Moreover, in view of the fact that a SN only covers a limited physical area and may produce noisy data by the quality of the hardware, data aggregation of the individual surveillance allows users to accurately and reliably monitor an environment. During data gathering, the combination data into high quality information on intermediate SN can reduce the number of packets to base station (BS) for energy conservation. Data aggregation is widely used and defined as the processing of aggregating data to eliminate redundant transmission and provide fusion information.

Due to restrictions on the channel in transmissions, TDMA scheduling is regularly applied for a large WSN. With the progress of hardware oscillator and lightweight time synchronization algorithms, the real network using two or more hops to convey information is available at present.

By recently developed wireless sensor networking techniques, a vast amount of applications is enabled. The areas also extend to underground [2] and underwater [3]. Under multiple circumstances, only theoretical analysis on WSNs cannot truly accommodate abundant developments and applications.

In order to maximizing energy efficiency in WSNs, we consider the optimization problem by nonlinear optimization. Nonlinearities are crucial for representing an application properly as a mathematical program. And nonlinear programming (NLP) (or nonlinear optimization) is the term used to describe an optimization problem when the objective or constraint functions are not linear [4].

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[†]The authors are with the Department of Electrical Engineering and Information Systems, The University of Tokyo, Tokyo, 113–8656 Japan.
a) E-mail: jh@aida.t.u-tokyo.ac.jp
b) E-mail: aida@aida.t.u-tokyo.ac.jp

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There are two types of solution. One is a global optimum, which is a solution to the overall optimization problem. Its objective value is as good as any other point in the feasible region. Another is a local optimum, which is optimal only with respect to feasible solutions close to that point. Points far removed from a local optimum play no role in its definition and may actually be preferred to the local optimum. Since every global optimum is also a local optimum, the overall optimization problem can be viewed as seeking the best local optimum.

In most of previous works [5]–[10], radio links are assumed ideal, that is, SNR is set at least a threshold value with no transmission errors. To fulfill this assumption, the receiver sensitivity should be high enough to guarantee that radio link has a low transmission error probability. As a consequence, all unreliable links are dismissed. However, from a practical point of view, connectivity is a prerequisite to providing reliable applications for WSNs.

In communication systems, information source is sent to the receiver through the antenna of the transmitter, after encoding, modulation. During signal transmission in the channel, a signal is distorted by the effect of distance, obstacle, and multipath shadow and so on. After received, the signal is demodulated and decoded to information sources. In realistic radio link, experiments show that channel seriously impacts a signal. During propagation in the channel, not only pass loss, but also fading and shadowing in simultaneous affect transmission signal.

Moreover, related researches [5]–[10] mainly focus on distance or received signal strength indication (RSSI) based signal propagation model. In the result of this model, it is difficult to build and apply the related proposal for a practical network, not to mention complex surroundings, for instance indoor system. Several investigations also neglect the fact that listening for an incoming packet consumes much more energy than settings in 2.4 GHz transceiver. Thus, as a result of multihop routing, the mechanism cannot receive assumed energy saving for WSNs.

Specifically, the multihop networking can be recognized as the clustering algorithm, when the maximum number of hops is 2. On studies of clustering algorithms, the prime opinion is to achieve energy efficient communications by balancing energy consumptions for cluster heads and other SNs. However, the quantity of data to BS is rarely considered at the same time in the system.

According to multifarious missions for WSNs, there are various options on multihop communications. Since the complete efficiency optimization problem for routing protocols is NP-hard, there is a great deal of research on multihop networks, which concentrate on optimizing each link for graph or tree based sensor networks. However, on account of the lack of realistic analysis of connectivity, these works suffer high computational complexity or difficult management for development and application. Therefore, in our research, we provide the analytic procedure for real networks, before performing specific routing protocols for establishing optimum network graph. With accurate and practical evaluations in circumstances, multihop protocols can be applied for energy efficient communication, which is targeted easy utilization and great accomplishment in the real world.

The rest of our paper is organized as follows: in Sect. 2, firstly we overview the system description of the packet format and the energy consumption model for real WSNs. Then, multihop networking is presented to achieve energy efficient data collections. The performance metric is optimized by convex optimization. Afterwards, in Sect. 3, we investigate the measurement and experiments. From the results, parameters and approximation functions for connectivity are described. Furthermore, we quantitatively analyze energy efficiency with output power, length of the payload, maximum number of hops and connection probability for practical networks in Sect. 4. Finally, we draw conclusions in Sect. 5.

2. Energy Efficient Multihop Network

In this section, the system description combined theory with experiment is provided. Afterwards, we concentrate on optimization of energy efficiency for multihop networks.

2.1 System Description

2.1.1 Packet Format

From IEEE 802.15.4 standard [11], packet format is defined as Fig. 1. The format is widely developed and applied in variable practical sensor networks. Due to the low power of SNs, header and footer of a packet are set to short size. The frame check sequence (FCS) is based on a cyclic redundancy check (CRC) of length 16 bit to detect corrupted frames. The length of the packet is denoted by l_{p}. And the maximum packet length is restricted by the transmitter frame buffer. In our research, we divide the data payload l_{d} into data information and several data blocks.

In practical WSNs, SNs mainly work for sensing data and transmitting data to BS. These data collected from sensor board should follow the user-defined structure. Otherwise, base station cannot interpret received messages. We define a data block as a serial data for a collection from sensor board. The data block is necessary to be operated and transmitted to BS for environment monitoring. Let l_{b} denote the length of a data block. And in the field of data information, the attributes of packet and data are recorded, such as

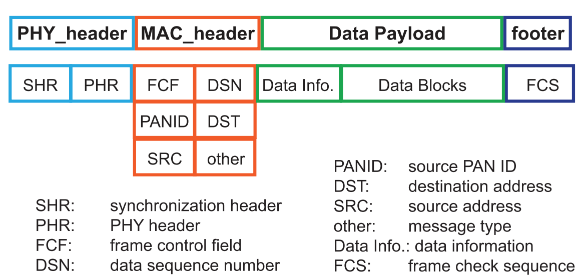


Fig. 1 Packet format for wireless sensor networks.

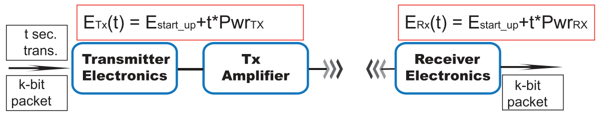


Fig. 2 Transceiver energy consumption model.

collection time, packet index, RSSI, voltage and so on. We define the length of data information as l_{inf}. Therefore, we get $l_{\mathrm{d}} = l_{\mathrm{inf}} + \beta l_{\mathrm{b}}$, where β is number of data blocks in a packet.

2.1.2 Energy Consumption Model

To examine the energy efficiency of a network, it is essential that energy consumption for each state should be revealed. We assume that a SN always powers on the microcontroller before exhausting battery. The sensor board and radio board are programmed enable power only in the working period to save energy consumption. From the experimental analysis in Sect. 3.1, we establish the practical energy consumption model as follows:

- Idle state: Compared with other states, the energy consumption is quite small in sleep mode.
- Sensing state: the energy consumption denoted by E_{sensing} is computed by the power pwr_{sensing} and the time t_{sensing}. The microcontroller receives the data acquired by sensors through analog-to-digital converter.
- Transceiver module: is shown in Fig. 2
  - Activated state: the energy consumption is denoted by $E_{\mathrm{power\_on}}$. Hardware/software synchronization is performed between microcontroller and radio transceiver.
  - Radio initial state: the energy consumption is denoted by $E_{\mathrm{radio\_initial}}$. After this state, a SN gets ready for RX or TX.
  - RX state: the energy dissipation for receiving denoted by E_{RX} can be calculated by the power consumption pwr_{RX} and message receiving time t_{RX}.
  - TX state: the energy dissipation for transmission defined as $E_{\mathrm{TX\_}\upsilon}$ is computed by the υth level output power $pwr_{\mathrm{TX\_}\upsilon}$ and message transmission duration t_{TX}.

In many applications, after the transmission, SNs always change state to sleep to save energy and wait next wake-up. The system employs TDMA schedule for avoiding transmission collisions and reducing energy consumptions from other transceiver operations, such as clear channel assessment for CSMA in IEEE 802.15.4. Collisions between wireless transmissions are not considered with enough margin time of communication for TDMA scheduling in the paper. We use $E_{\mathrm{start\_up}}$ to present the sum of $E_{\mathrm{power\_on}}$ and $E_{\mathrm{radio\_initial}}$. Thus, radio start-up includes radio board and transceiver initialization. The TX dissipates energy E_{TX} to run the radio electronics and the power amplifier, and the receiver dissipates energy E_{RX} to run the radio electronics. In our research, we consider that a SN has limited output TX power. The difference with previous works is that TX power is ranged by levels not distances, which is credited and used in practical network.

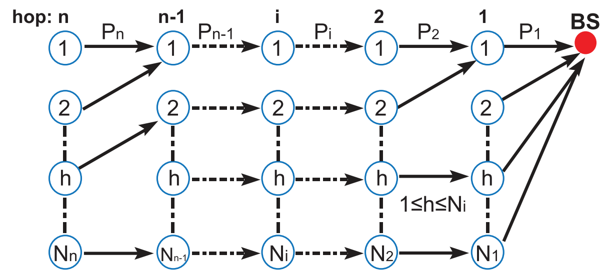


Fig. 3 Graph of multihop networking.

2.2 Multihop Networking and Optimization

In this section, we concentrate on establishing multihop networking and describing the optimization. Firstly, we define energy efficiency (eef) as the performance metric. Accordingly, in the network for data collections, eef can be expressed as the quantity of data (bits) received by BS per energy consumption. We use microjoule (μJ) as the unit of energy consumption. We consider practical application scenarios that a field of SNs sends data measurements to BS through intermediate nodes, which perform data aggregation to compress information. Then BS can receive data from intermediate nodes and terminal nodes. In most of the applications, BS is wired into the main source. After accomplishing β sensing tasks, each SN in the network transmits the sensing data once. Through time synchronization and TDMA scheduling, intermediate nodes can transmit messages after receiving without radio shutdown. Consequently, we have energy consumptions for a transmission:

$$E_{\mathrm{trans\_}\upsilon} = \beta E_{\mathrm{sensing}} + E_{\mathrm{start\_up}} + E_{\mathrm{TX\_}\upsilon}. \quad (1)$$

And the total energy consumption for each SN should also take a count on radio receiving consumption by the number of receiving.

Let W denote the total number of SNs. And we define the maximum number of hops as n, the number of SNs in the ith hop as N_i, respectively. Let $G = (V, E)$ be a multihop networking graph for a wireless sensor network, shown in Fig. 3. We use V to represent the set of all vertices including SNs and one BS, and E to represent the set of edges which are transmissions among vertices. We assume that each SN transmits once in each data collection. Consequently, we get G is a tree and $|V| = W + 1$, $|E| = W$. In realistic radio propagation, we should consider connectivity to express unreliable links during packet transmissions. Therefore, we denote P_i for unreliable transmission from ith hop to $(i-1)$th hop, which is defined as the average successful probability of packet transmission from a SN in ith hop to the receiver in $(i-1)$th hop. As the result of tree model, we can get energy consumptions for a data collection in a whole network by:

$$E_{\text{collection}} = \sum_{i=1}^{n} N_i E_{\text{trans\_}\upsilon\text{\_}i} + \sum_{i=1}^{n-1} N_{i+1} E_{\text{RX\_}i}. \tag{2}$$

$E_{\text{trans\_}\upsilon\text{\_}i}$ denotes mean transmission energy consumptions of a node in ith hop with υth output TX power; $E_{\text{RX\_}i}$ denotes average listening energy dissipation of a node in ith hop. According to experimental analysis of TX output power with connectivity in Sect. 4.1, we can get $E_{\text{trans\_}\upsilon\text{\_}i} = E_{\text{trans}}$, where all SNs in a network utilize maximum TX output power during transmissions. And E_{trans} denotes energy consumptions for one transmission by maximum TX power for a SN in our paper.

Moreover, we use SN_{i_h} to denote the node as hth SN in the ith hop, and we can have $1 \leq h \leq N_i$. The aggregated data rate for SN_{i_h} is α_{i_h}. In our research, we consider a simple aggregation scheme, where data payload length l_{d} in each packet is invariable during data processing. Therefore, we can get $E_{\text{RX\_}i} = E_{\text{RX}}$ and $\alpha_{i\_h} = 1$. Furthermore, we assume that this aggregated data can completely exhibit all sources of information. Then, we can calculate eef by the following function:

$$eef = \frac{l_{\text{d}} \sum_{i=1}^{n} \prod_{j=1}^{i} N_i P_j}{W E_{\text{trans\_}\upsilon} + \sum_{i=2}^{n} N_i E_{\text{RX}}}, \tag{3}$$

The expression shows that energy efficiency is not linear. Consequently, in order to maximize energy efficiency, we use nonlinear programming as the solution tool. As one of the most widely applicable methods for the nonlinear programming problem, the local optimization method can manage the large-scale problem and requires differentiability of the objective and constraint functions. We adopt this method for our research for a large number of SNs and multihop networks. Next, we describe the optimization problem on energy efficiency. The solution can be obtained from differential equations including gradient of the objective function, Jacobian of the constraints and the Hessian of the Lagrangian function, which are derived by the differential and two-order differential of the objective and constraint functions.

In order to solve the optimization problem on energy efficiency, the Gaussian approximation model is used for fitting the curves of experimental results, which is not theoretic model based on wireless communications. The following proposed optimization of energy efficiency can be used from other approximation models, which are requested to be second order differentiable, even if Gaussian approximation is not applicable. From energy efficiency in Eq. (3), we describe the problem of getting an optimum energy efficiency estimate of parameter vector N as:

$$\begin{aligned} \text{maximize} &: eef; \\ \text{subject to} &: N; \\ \text{constraint} &: \sum_{i=1}^{n} N_i = W; \\ & \quad P_i \text{ from Gaussian approximation model.} \end{aligned} \tag{4}$$

Here, the vector $N = (N_1, N_2, \ldots, N_n)$ is the set of variables of the optimization problem, the function eef is the objective function and the approximate P_j from the Gaussian approximation model is represented in Sect. 3.2 from analysis of connectivity experiments. In first constraint function, the sum N should be equal to W. The other constraint functions is to calculate P_i for the objective function. We denote that N^* is a solution of the problem. Finally, we can get the N^* from $N^* = \arg\max eef$ by nonlinear programming.

3. Experimental Analysis

In this section, we show our experiments on energy measurements and connectivity of the WSN, which are developed in TinyOS [13]. The implements are IRIS motes with MTS400 sensor boards from Crossbow Technology. The mote operates on 2 AA batteries, and uses the Atmel RF230 radio frequency transceiver [14] integrated with an Atmega 1281 micocontroller, 8 KB RAM, 128 KB program memory and 512 KB flash memory. Moreover, the radio employs offset quadrature phase shift keying (O-QPSK), providing an effective data rate of 250 kbps in the 2.4 GHz unlicensed ISM band. The RF transmission power is programmable from 3 dBm to −17.2 dBm by 16 output power levels. Furthermore, the MTS400 sensor board offers five basic environmental sensors, which are humidity, temperature, barometric pressure, light and 2-axis accelerometer sensor. Applicable industries include agriculture, industrial, forestry, heating, ventilation, and air conditioning (HVAC) and more. The environmental sensor board utilizes energy efficient digital IC-based board-mount sensors. It also can be programmed enable and disable power to the individual sensor.

In measurements, we get the mean power consumption and average time for each state by the digital oscilloscope. Furthermore, connectivity results are analyzed to approximate functions of connection probabilities. The confidence of numerical analysis for statisticians is 0.975.

3.1 Measurements

Measurements of the energy consumption in each state are performed on 4 SNs from 4 channels simultaneously. The sampling rate is set to 0.2 μs/sample. The experiments on transceiver module are repeated 5 times for each TX power. On account of response delay of sensors, SNs execute sensing tasks during 1s and count number of sensing tasks. Then, the average period of a sensing task is about 8.8 ms from the results.

Shown in Fig. 4, it is essential to identify the following intervals for states. Moreover, the result of power consumption is presented in Table 1.

- T_1: A SN maintains a timer for waiting wake up and state-info LED in idle state.

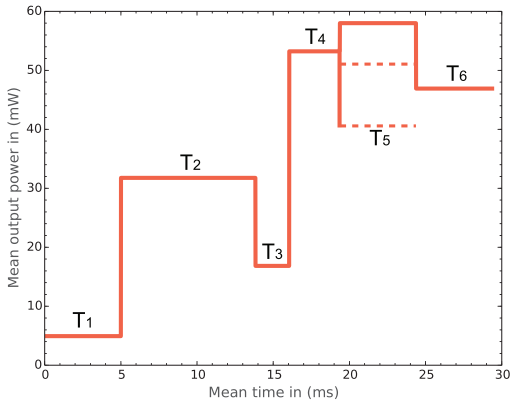


Fig. 4 Measurement of energy consumptions.

Table 1 Power consumption from measurements.

State	Power consumption (mW)
Idle	5
Sensing	31.8
Power_on	16.8
Radio_initial	53.2
RX	47
TX (3 dBm)	58
TX (1.1 dBm)	51
TX (−17.2 dBm)	41

- T_2: A SN executes one sensing task on all sensors of sensor board and voltage comparator of chip. And we get $T_2 = 8.8$ ms.
- T_3: The supply voltage is applied to the radio transceiver. The crystal oscillator gets activated and the master clock is provided to a clock source to the microcontroller after the crystal oscillator has stabilized. And we get $T_3 = 2.2$ ms.
- T_4: After the voltage regulator has been settled, the frequency synthesizer is enabled. To change RX state, the receiver is immediately enabled. For TX state, the message is written to the buffer. And we have $T_4 = 3.3$ ms.
- T_5: After transmission of the preamble and the start-of-frame delimiter (SFD), the frame buffer content is transmitted. The radio transceiver is configured to autonomously compute the FCS bytes and append it to the transmit packet. When the frame transmission is completed, the radio transceiver automatically turns off the power amplifier. The solid line and two dash lines denote results with different TX output power, which are maximum (3 dBm), 1.1 dBm and minimum (−17.2 dBm) TX output power, respectively.
- T_6: During this state, only the preamble detection of the digital signal processing is running. When a preamble and a valid SFD are detected, also the digital receiver is turned on. The radio transceiver enters the receiving state.

And TX period T_5 and RX period T_6 base on the packet length, which are equal to l_p/R_b. R_b is the bit rate of SNs.

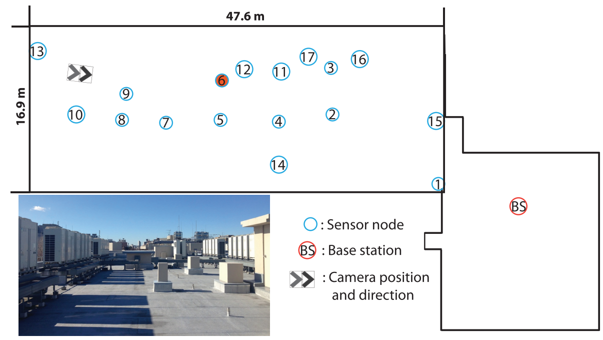


Fig. 5 Distribution of connectivity experiments.

3.2 Connectivity Experiments and Approximation

In order to characterize and quantify the connectivity for WSNs, we perform experiments on the roof of Engineering Building No.12, the University of Tokyo, shown in Fig. 5. Supposing that the location and height of BS are different with distributed SNs in the area, the characteristics of connection probability from a SN to the BS are different with those of connectivity probability from a SN to another SN. Therefore, connectivity from SNs to BS and connectivity between SNs are tested and investigated respectively. Moreover, we define connection probability as successful probability of packet transmission.

In experiments on connectivity to BS, we deploy a BS, a referenced BS and several SNs in the designated area. The BS has same TX/RX modular with SNs. The function of the referenced BS is to confirm messages disseminated by SNs, while the location is very close to the BS. Then the BS connects PC through USB interface to record received messages, and it is assigned to a height of 2.5 m. In connectivity experiment from SN to BS, 17 SNs are randomly distributed in 16.9m × 47.6m rectangular area shown in Fig. 5. On the roof, there are some cabins and outdoor parts of air conditioners, which are obstacles to the transmitted signal. In the experiment, a SN is scheduled for sending data to the BS by TDMA with the basic operating model for IEEE 802.15.4 applications [14]. Moreover, the transmission repeats 2000 times for each TX output power. The length of a packet is 1008-bit assumed as 5 data blocks, where l_d is 800 bits including all sensing data and current voltage data.

Next, we present characteristics of the distribution area, which can be a reference for outdoor applications. The mean distance from a SN to the BS is 32.8 m; the mean height of a SN is 0.8 m. The node distribution density ρ is about 0.02 node/m^2. Following Poisson point process theory of spatial data statistics, we can get that the expected nearest-neighbor distance in the distribution area is about 3.4 m. And in our research, the shadowing and fading channel affecting the transmission signal, should be concerned with connection probabilities of SNs in real WSNs.

In order to investigate connectivity between SNs, we let SNs transmit messages to the setting SN, which the ID

Table 2 Connectivity experiment results.

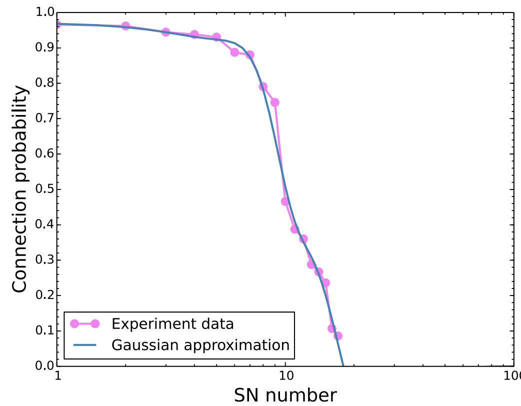
SN ID	Dis. to BS	CP. to BS	Dis. to SN 6	CP. to SN 6
01	9.5	0.966	27.0	0.910
02	22.9	0.466	13.5	0.972
03	25.9	0.931	12.2	0.0
04	29.7	0.236	7.0	1.0
05	35.0	0.107	4.2	0.948
06	36.2	0.791	/	/
07	40.1	0.388	7.4	0.961
08	45.6	0.746	11.9	0.967
09	45.5	0.267	10.7	0.983
10	50.4	0.288	16.4	0.887
11	31.8	0.888	5.8	1.0
12	34.6	0.881	3.0	1.0
13	55.6	0.086	19.8	0.329
14	28.0	0.361	11.1	1.0
15	13.2	0.938	25.4	0.957
16	24.7	0.945	16.7	0.865
17	28.8	0.962	11.5	0.950

Dis.: Distance in meter; CP.: Connection probability.

is 6 in Fig. 5 and the height is 1.1 m. Then, we collect data from 15 SNs to dissect connection probability of the intra-area distribution, except SN 3 totally blocked to SN 6 by obstacles. The experiment settings are similar with the experiment on connectivity to BS.

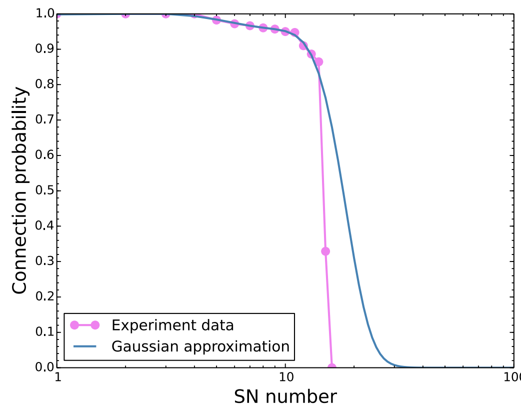
The results of experiments on connectivity are shown in Table 2. Figure 6 and Fig. 7 show the connection probability in the descending order. In view of energy efficient multihop networking, a SN in ith hop has one transmission link to its receiver in $(i-1)$th hop, which has higher connection probability than that of links to the other SNs in $(i-1)$th hop. SN number (τ) denotes the τth highest connection probability to BS and between SNs in Fig. 6 and Fig. 7, respectively. In Fig. 6, considering optimization of energy efficiency, if the τth SN is the first hop node, the other SNs with higher connection probabilities to BS will be in the first hop. The average connection probability of first hop P_1 should be the average value of connection probabilities from the first SN to the τth SN. In Fig. 7, if the SN in $(i-1)$th hop is the τth highest connection probability node of the SN in ith hop and the connection probability is higher than that to other SNs in $(i-1)$th hop, the SN in $(i-1)$th hop will be as a receiver. The average connection probability from a SN in ith hop to a SN in $(i-1)$th hop can be calculated by expected number of neighbors for a SN in ith hop. In general, connection probability decreases with the rise in distance between transmissions due to the path loss. However, from effect of obstacles to signal, the connection probability may violently change such as SN 2 to BS in Table 2. Accordingly, the SN 2 with low connection probability would transfer messages to the BS through other intermediate SN.

In order to accurately formulate connectivity to the model, we use the Gaussian approximation model to fit for our experimental curves with a minimum sum of the squares of the errors. Gaussian peaks [15] can be matched our results of connectivity better than other mechanisms. We have the equation for a Gaussian model is:



SN number (τ): the τth highest connection probability to BS

Fig. 6 Connectivity from SNs to BS.



SN number (τ): the τth highest connection probability to SN

Fig. 7 Connectivity between SNs.

$$y = \sum_{i=1}^{m} a_i \exp\left[-\left(\frac{x-b_i}{c_i}\right)^2\right], \tag{5}$$

where a is the amplitude, b is the centroid, c is related to the peak width, m is the number of peaks to fit, and $1 \leq m \leq 8$. From this model, we can get approximation of P_i shown as blue lines in Fig. 6 and Fig. 7:

$$\begin{aligned} P_1 &= \sum_{j=1}^{m} a_{\mathrm{bs\_}j} \exp\left[-\left(\frac{N_1 - b_{\mathrm{bs\_}j}}{c_{bs\_j}}\right)^2\right], \text{where } m = 2; \\ P_i &= \sum_{j=1}^{m} a_{\mathrm{sn\_}j} \exp\left[-\left(\frac{\frac{WN_i}{N_{i-1}^2} - b_{\mathrm{sn\_}j}}{c_{\mathrm{sn\_}j}}\right)^2\right], \text{where } m = 2; \end{aligned} \tag{6}$$

From Poisson point process, $\frac{N_i}{N_{i-1}}$ represents the average number of links for a SN in ith hop to a SN in $(i-1)$th hop. We can calculate $\frac{WN_i}{N_{i-1}^2}$, which is the expected value of number of neighbors for a SN in ith hop as SN number, when the average number of links is $\frac{N_i}{N_{i-1}}$. Furthermore, SNs are chosen for the first hop by connectivity order. We can get a series of parameters for constraint functions in optimization from the Gaussian fitting processing, including sets of $\{a_{\mathrm{bs\_}j}, b_{\mathrm{bs\_}j}, c_{\mathrm{bs\_}j}\}$ $(j = 1, 2)$ and sets of $\{a_{\mathrm{sn\_}j}, b_{\mathrm{sn\_}j}, c_{sn\_j}\}$

(j = 1, 2). Finally, we get {0.9698, −0.1058, 24.75}, {0.04434, 8.126, 3.066} for connectivity to BS and {0.9885, 1.245, 12.83}, {0.4641, 13.83, 6.581} for connectivity between SNs, respectively. These parameters are applied to our experimental results and provided for a reference in the outdoor system.

4. Evaluation

We present evaluations based on experiments in this section. Due to variable applications for WSNs, there are different performance metrics in current research. However, considering that the main usage of SNs is to sense data and transfer data to the BS, the energy efficiency of our definition is functional and practical in WSNs.

4.1 On Elementary Transmission

First of all, we investigate the elementary transmission, which is known as direct communication to the BS. According 16 channels supported by 2.4 GHz band, this kind of protocols can apply for a small network, not only short range to the BS but also a small number of SNs. Moreover, the elementary transmission is a unit for every network algorithm. We assume that a SN achieves β sensing job, and transfer the l_d-bit message as data payload. The reference probability of successful transmission for 1008-bit packet is changed from 0.1 to 0.9, with different TX output power levels to model multifarious distribution environments. The energy efficiency can be calculated by Eq. (3) assuming $n = 1$. Then we can get optimization results in Fig. 8 and Fig. 9.

Both results show that energy efficiency is greatly influenced by connection probability. The first figure shows that the length of a packet is restricted by probability of successful transmission to achieve optimum energy efficiency. Accordingly, suffering adverse circumstances in channel, SN should choose a short packet to avoid wasting energy by massive transmission failure. Another figure shows that comparing TX power, connectivity almost completely determines energy efficiency. Therefore, TX power level should be settled by connectivity. For example, when the connection probability is much more than the threshold value (0.88) with the TX power, a SN can level down the power and simultaneously guarantee the threshold probability to achieve energy efficient communications. Consequently, we believe that the connection probability is presented and measured with 3dBm TX output power, which is the maximum transmitting power for energy efficient communication in most application cases of multihop WSNs.

4.2 On Multihop Networking

In multihop WSNs, we utilize experiments on connectivity in Eq. (6) to optimize energy efficiency for similar networks. And the proposed methodology can be exploited for other applications. In order to extend the evaluations on larger WSNs, we consider consistent node distribution density with the experiment for the addition of SNs. We assume that the user-defined packet structure is used, where $l_p = 1008$ bits. In consideration of connection probability in the environment, direct communication is quite energy inefficient for a large system. Thus, SNs transmit sensing data hop by hop with data aggregation. Connectivity is approximated by provided Gaussian models. Furthermore, we can get the solution N^* of the optimization problem on eef in Expression (4) by NLP. From these results, we make study of energy efficient communications for multihop networks.

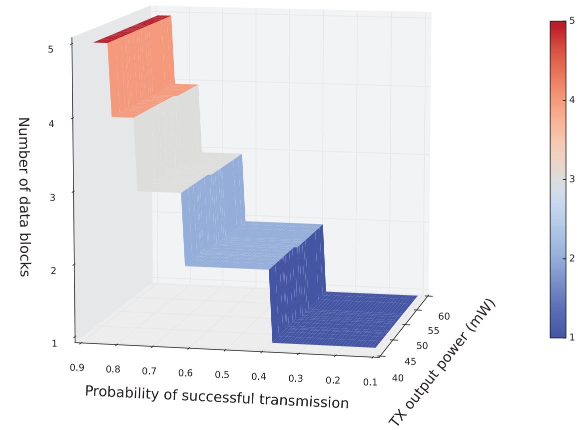


Fig. 8 Number of data blocks for optimum eef.

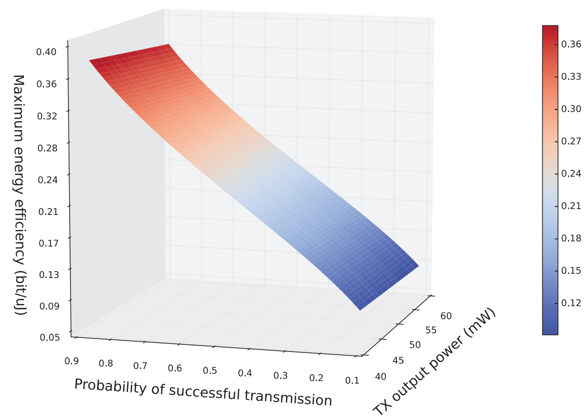


Fig. 9 Optimum energy efficiency with variable length of packet.

The results of eef for multihop networking are shown from Figs. 10 and 11, where results provide analysis on maximum eef with a total number of SNs, maximum number of hops by same node density as our connectivity experiments. Figure 12 provides the network structure to achieve optimum energy efficiency for two settings on node distribution density.

In Fig. 10, we investigate optimum eef with the maximum number of hops. Efficiency is maximized at 6 hops for 50 SNs and 80 SNs, 7 hops for 100 SNs in networks, respectively. When the total number of SNs is large, the greater total number of hops achieves more efficient, especially shown in the 100-SN network. Considered complexity of communication protocols and energy efficiency, a 5-

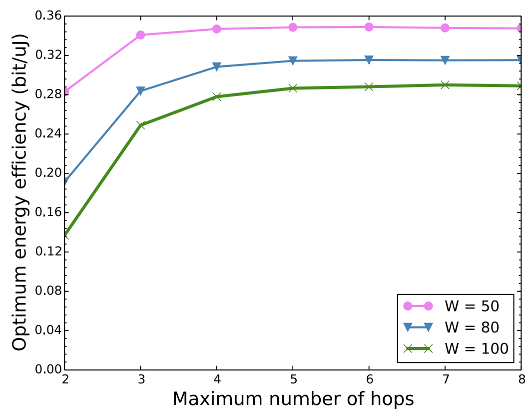


Fig. 10 Optimum energy efficiency with variable maximum number of hops.

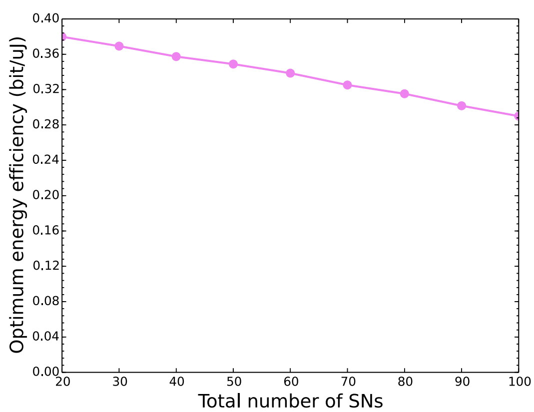


Fig. 11 Optimum energy efficiency with variable total number of SNs.

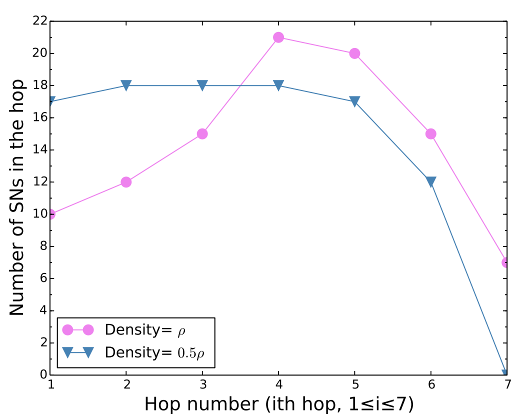


Fig. 12 Energy efficient multihop networks for 100 SNs.

hop network can accommodate enough devices in normal applications, which is close to the optimum total number of hops. And, regarding applications, 100 SNs can be admitted in a 3-hop network with 86 percent optimum eef of 7-hop network. Moreover, raising the maximum number of hops cannot achieve more efficient than optimum eef according to constitute of WSNs.

We present optimum eef with a total number of SNs for a network in Fig. 11. Due to the constant node distribution density, the eef of networks decreases with increasing the total number of SNs. In other words, a SN consumes more energy for transferring data to BS in a larger WSN, even with more hops. Generally, transmitting data would consume energy with long distance in a large network. Therefore, increasing the number of BSs or making movable BS is one of recent technologies for large WSNs.

After analysis on eef, we show multihop structure for WSNs in Fig. 12. Double distribution densities are considered for 100-SN networks to achieve maximum energy efficiency. We show the average number of SNs in each hop from the solution of multihop networking optimization. Low node distribution density brings small connection probability between SNs by path loss. And we can see the multihop network with 0.5ρ density achieves optimum eef at 6 hops less than that in the ρ network. Because connectivity between SNs in the 0.5ρ network is smaller. And much more SNs in first two hops are chosen to increase connectivity for other SNs.

During the network organization, SNs with high connection probabilities to BS would be chosen as nodes in the first hop, according to the solution of multihop networking optimization N^*. In intra-area, nodes in ith hop (where $i > 1$) would be determined by $(i-1)$th hop with high connection probabilities. And the average number of SNs in ith hop should be N_i from N^*.

5. Conclusion

In this paper, in order to quantitatively analyze energy efficiency in multihop networking, we firstly develop a practical model for energy consumptions from our measurements, and present statistics of power consumption in operation states. Moreover, we establish a multihop networking model for a WSN, and optimize the performance metrics by nonlinear programming. From experiments on connectivity, we investigate the connection probability and formulate it to the model by Gaussian approximation. Finally, after simplifying and modeling, we provide evaluations to express optimum energy efficiency of elementary transmission and multihop networking. As one of the studies on WSNs, our proposal is extended from experiments. Therefore, it provides not only accurate analysis of theory, but also reliable applications to real WSNs.

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Hui Jing received the M.E. Degree from University of Tsukuba, Japan in 2007. Now he is enrolled in the University of Tokyo as Ph.D. candidate. His research interests include the communication area of wireless sensor networks.

Hitoshi Aida was born in 1957. He graduated from The University of Tokyo in 1980, and received Doctor of Engineering in 1985. After joining the University of Tokyo, he stayed two years at SRI International in California as an international fellow from 1988 to 1990. He has been a professor of the University of Tokyo since 1999. His current research interests include computer networks, distributed processing, wireless network applications, and disaster resilient networks. He is a senior member of IEEE and a member of ACM, IEICE, IPSJ, JSSST, JSAI and IEIEJ.