A Novel Deployment Scheme for Green Internet of Things

Jun Huang, *Member*, *IEEE*, Yu Meng, Xuehong Gong, Yanbing Liu, and Qiang Duan, *Member*, *IEEE*

***Abstract*—The Internet of Things (IoT) has been realized as one of the most promising networking paradigms that bridge the gap between the cyber and physical world. Developing green deployment schemes for IoT is a challenging issue since IoT achieves a larger scale and becomes more complex so that most of the current schemes for deploying wireless sensor networks (WSNs) cannot be transplanted directly in IoT. This paper addresses this challenging issue by proposing a deployment scheme to achieve green networked IoT. The contributions made in this paper include: 1) a hierarchical system framework for a general IoT deployment, 2) an optimization model on the basis of proposed system framework to realize green IoT, and 3) a minimal energy consumption algorithm for solving the presented optimization model. The numerical results on minimal energy consumption and network lifetime of the system indicate that the deployment scheme proposed in this paper is more flexible and energy efficient compared to typical WSN deployment scheme; thus is applicable to the green IoT deployment.**

***Index Terms*—Deployment, energy efficient, green, Internet of Things (IoT).**

I. Introduction

THE INTERNET OF THINGS (IoT) has been envisioned as one of the most promising networking paradigms that bridge the gap between the cyber and physical world. The prevalence of IoT leads toward a new digital context for configuring novel applications and services. IoT consists of a variety of things or objects such as Radio Frequency Identification (RFID) tags, sensors, actuators, mobile phones, etc., which are interconnected through both wired and wireless networks to the Internet. Objects in IoT can sense the environment, transfer the data, and communicate with each other. They become powerful tools to understand physical world and to respond to emergent events and irregularities promptly. Thus, the IoT is seen by many as the ultimate solution for getting insights about real-world physical processes in real-time.

Manuscript received September 27, 2013; revised December 18, 2013; accepted January 10, 2014. Date of publication January 21, 2014; date of current version May 14, 2014. This work was supported in part by NCET, NSFC (Grants 61272400, 61309031), in part by Program for Innovation Team Building at Institutions of Higher Education in Chongqing (Grant KJTD201310), in part by Natural Science Foundation of Chongqing (Grant cstc2013jcyjA40026), in part by Scientific and Technological Research Program of Chongqing Municipal Education Commission (Grant KJ130523), and in part by CQUPT Research Fund for Young Scholars (Grant A2012-79).

J. Huang is with the Department of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing 400065, China (e-mail: xiaoniuadmin@gmail.com).

Y. Meng, X. Gong, and Y. Liu are with the Department of Computer Science and Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China (e-mail: liuyb@cqupt.edu.cn).

Q. Duan is with the Department of Information Science and Technology, The Pennsylvania State University, Abington, PA 19001 USA (e-mail: qduan@psu.edu).

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

Digital Object Identifier 10.1109/JIOT.2014.2301819

In parallel, the advancement of IoT brings some challenges to its implementation. Different from traditional wireless sensor networks (WSNs), IoT achieves a larger scale and becomes more complex [1]. This turns out that the schemes for deploying WSNs may not be transplanted in the IoT directly. On the other hand, since IoT consists of more objects that consume higher power, green issues should also be taken into consideration. Green networking plays a vital role in deploying IoT: they can reduce emission and pollution, exploit environmental conservation and surveillance, and minimize operational costs and power consumption [2]–[5]. Therefore, how to cost-effectively realize green deployment for IoT is a crucial issue, which is the research focus of this paper.

Although much exciting progress has been made in deploying energy-efficient WSNs, such as *exact* [6]–[8], *ad hoc* [9]–[11], *hierarchy* [12]–[14], and *hybrid* [13]–[15] schemes, these studies have not sufficiently investigated the deployment issue with green networking consideration in order to build a scalable and sustainable IoT. In response, we investigate how to cost-effectively arrange objects to form a green networked IoT in this paper and propose a novel deployment scheme. Specifically, we first give a hierarchical system framework for IoT deployment. The framework captures the scale feature of IoT and thus making it extensible. Then, we present an optimization model on the basis of the presented framework, where the model is constrained in terms of energy consumption, link flow balance, and system budget, which facilitate the IoT toward green. Finally, we devise a minimal energy consumption algorithm (MECA) by leveraging the clustering principle and a well-known *Steiner* tree algorithm to solve the optimization problem. We show that the proposed scheme can work more flexibly and energy-efficiently compared to typical WSN deployment scheme; thus is applicable to the green IoT deployment. The contributions of this paper are summarized as follows.

1) We present a hierarchical framework for placing network elements, i.e., objects/things in IoT. The framework captures the scale feature of IoT thus enables its extension. By allowing direct communications among relay nodes and not allowing communications among sensing nodes, the framework can migrate the traffic load from sensing nodes to relay nodes, thus prolonging the network lifetime.
2) Based on the presented framework, we model a green IoT by considering energy consumption, link flow balance, and system budget as an optimization problem. We then propose an MECA, which leverages the clustering principle and the *Steiner* tree algorithm to solve the optimization

problem. The proposed algorithm facilitates the deployed IoT to achieve green.

3) We conduct extensive numerical experiments on random networked IoT and compare our proposed scheme against a representative deployment scheme for WSNs. The obtained results show that our scheme is more preferable for green deployment of IoT.

The remainder of this paper is organized as follows. Section II describes the system framework for placing network elements in IoT. Section III formulates the problem of green IoT deployment and formally presents the optimization model. An MECA for solving the optimization problem is also proposed in this section. Section IV presents the experimental results to validate both the proposed model and algorithm. Section V concludes this paper.

II. Related Work

The topological structures for large-scale WSNs can be classified into four categories: mesh, plane, hierarchy, and hybrid. The corresponding deployment schemes for these four structure classes are *exact*, *ad hoc*, *hierarchy*, and $hierarchy + adhoc$, respectively. The *exact* deployment scheme [6]–[8] places sensors in a regularly distributed way where each sensor not only captures and disseminates its own data but also serves as a relay for other nodes; i.e., nodes must collaborate to propagate data in the network. Although this deployment scheme could increase network reliability and survivability, the nodes around the sink are more often to run out of power, which makes the lifetime of the whole network comparatively short. Therefore, this scheme may not be suitable for large-scale IoT deployment. The *ad hoc* deployment scheme [9]–[11] is widely used in many practical WSN scenarios, including battlefield surveillance and disaster relief operation as two representative applications. Networks deployed with this scheme also have a limited lifetime due to the same reason as the exact scheme. *Hierarchy* scheme [12] allows nodes to be placed in a tiered framework through some clustering algorithms. The sensor nodes are normally deployed in the lower layer and the relay nodes or base stations are placed in the upper layer. In this scheme, sensor nodes are only permitted to communicate with a relay node or base station and cannot communicate with each other directly. In this regard, the routing efficiency can be improved dramatically, thus making the network scalable and extensible well. The $hierarchy + adhoc$ scheme [14], [15] also deploys nodes in a tiered framework but allows sensor nodes in the lower layer to communicate directly with their neighbor nodes. Although this deployment scheme has better functionality in transmitting data, it suffers from the same problem as the exact and ad hoc schemes, and it needs the sensors to be equipped with more complex chips.

Therefore, in this paper, we adopt the philosophy of hierarchical deployment and present a three-layer system framework for large-scale IoT deployment. The proposed framework differs from the current hierarchical deployment scheme for WSNs in four ways. First, the hierarchical structure of WSNs is usually formed by configuring a certain clustering algorithm in sensing nodes; thus requiring the nodes to have relatively strong computing and storage capabilities. The proposed framework does not require a complex routing function at sensing nodes; thus significantly simplifying sensor implementation and reducing the network cost. Second, the relay nodes are deployed in advance instead of being elected by sensing nodes in each cluster. Third, the “cluster heads” in our model are the relay nodes which have more computing and storage capabilities, while the cluster heads in earlier studies are usually sensing nodes that are selected by a clustering protocol, such as LEACH [16], etc. Therefore, the network lifetime of previous protocols is comparatively short in the large-scale IoT since the sensing nodes are more likely to run out of power. Finally, the relay nodes in our architecture are allowed to communicate with each other, whereas communications among the cluster heads in most of the earlier works are not allowed. From a scalability perspective, our hierarchical architecture is more resilient to support large-scale IoT compared with the existing solutions.

Although paper [17] gave a very similar three-layer hierarchical framework that allows relays to communicate with each other, the relays were connected in the tree structure by running Breadth-First-Search (BFS). The relays in our proposed framework are connected in a mesh mode; i.e., each relay node can communicate with all other relays within its transmission range. This is able to facilitate the proposed algorithm to find a better deployment solution.

Recently, energy saving for WSNs has also attracted a lot of interest from research community. Energy efficient strategies for WSNs can be classified into five categories: updating operating system [18], [19], controlling transmitting power [20]–[22], managing duty cycle [23], [24], routing with minimized power [25], [26], and clustering for data aggregation [14], [27]. The first strategy dynamically manages system resources by updating the operating system in sensor nodes to reduce power consumption. This kind of strategy requires high performance sensor nodes that lead to high system cost; therefore, may not be applicable to a large-scale IoT. The second type of approaches adjusts transmitting power via optimizing network topology in order to lower the overall network power consumption. However, unlimited adjustment in transmitting power would shorten network lifetime; therefore, network connectivity should be considered when adjusting sensor node transmitting power. Due to the complex network topology of IoT, applying this kind of strategy may cause a great amount of overheads for topology maintenance and path finding, which are not desirable for scalable IoT. The strategies based on managing duty cycle allow the smallest set of nodes to work, while putting the others in the sleep mode in order to minimize energy consumption. Although such techniques could prolong the network lifetime, the mechanism for discovering sleeping nodes is so complex that it is not suitable for IoT. Routing with minimized power employs data transmission power as one of the routing metrics in order to find network routes that minimize power consumption. Cluster-based energy saving schemes make use of some clustering algorithms to form a set of cluster heads and aggregate the data collected from sensors to cluster heads for saving power.

Compared to traditional WSNs, IoT must support effective and efficient data collection, process, and transmission in a much larger scale. In order to address the new challenges of energy saving in IoT, this paper presents a comprehensive, efficient, and simple optimization model, which differs from the previous studies in the following four aspects. First, this model considers the energy consumption of both transmitting and receiving data for communications among nodes in IoT. Second, the link traffic balance constraint is proposed for improving network load in order to address the problem caused by excessive pursuing energy consumption through limiting the maximum link traffic. Third, the optimization model examines change in network lifetime while minimizing energy consumption, which seeks the best node deployment solution to reduce system energy consumption and prolong network lifetime at the same time. Fourth, the optimization model reduces energy consumption and prolongs network lifetime by considering a system budget constraint, which leads to comprehensive optimization of the overall cost for IoT deployment.

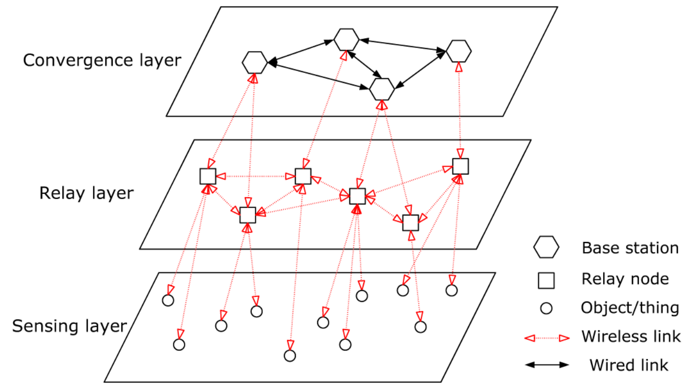

Fig. 1. Example of system framework for IoT deployment.

III. System Framework

IoT typically contains a large number of networked objects located in a wide area; thus having a larger scale and more complex networking scenario than regular WSNs. Our previous engineering practice in deploying large-scale WSNs [28] shows that WSN architecture with a dynamic routing mechanism is barely operable in wide area outdoor environments. Many factors such as electromagnetic interference, air humidity, and temperature, all have great impacts on sensor's data transmission; thus making such a network structure ineffective for large-scale networking. More importantly, WSNs configured with dynamic routing protocols require network nodes, which typically have low battery capacity, to perform power-consuming data processing for path computation. The power consumption of data processing increases significantly with network scale due to the complexity of dynamic routing protocols for a large number of nodes. In addition, dynamic routing requires network nodes to exchange route information among them regularly, which not only causes overhead traffic in network but also consumes node power for extra data communications. All these factors make such a network deployment scheme ineffective for building scalable green IoT. On the other hand, network elements deployed in IoT very often have low mobility and network topology remains relatively stable, which makes dynamic routing to gain little advantage over static routing configuration. Based on these observation and consideration, we argue that for large-scale IoT it is reasonable to adopt static routing for higher power efficiency in order to achieve better network scalability and longer lifetime. With above experience, we have installed more than 3000 nodes including temperature sensors, humidity sensors, ambient light sensors, etc., which are interconnected by a static routing protocol [28]. This IoT, at that time, was deemed as the largest IoT system in China. Following the design principle of this IoT, in this paper, we propose a tiered framework for IoT deployment, which places objects in a hierarchical network structure with static routing configuration.

Fig. 1 shows a paradigmatic example of system framework for IoT deployment that includes three layers, i.e., sensing layer, relay layer, and convergence layer from bottom to up. Sensing layer is used for placing objects and things (e.g., RFID etc.), Relay layer is formed by a collection of relay nodes, and convergence layer consists of several base stations that are connected to the Internet. With the purpose of energy saving and link load balancing, the objects/things (sensing nodes) in the sensing layer are not allowed to communicate with each other directly. Instead, the communication between any two objects must go through a relay node. That is, nodes in the sensing layer can only send data to a relay node in the upper layer. On the other hand, a sensing node receives a few signaling packets from its relay node. Such signaling packets are quite small, which can be neglected compared with data sending from sensing node. Nodes in the relay layer form a relay network where any two neighbor nodes can communicate with each other. The other major functionality of a relay node is to forward data from the sensing layer to a base station in the upper layer. In the convergence layer, base stations are also interconnected to form a network, which further uploads data to the Internet.

Note that in this work, we provide a general deployment scheme that facilitates building scalable and green IoT. We do not limit our scheme to any specific technical implementation in order to make the scheme applicable for various application scenarios. The typical network traffic or applications that can be expected under this framework include industrial control, environmental monitoring, etc.

By placing IoT elements in the above hierarchical framework, the proposed deployment scheme provides flexibility, promotes scalability, and promises increased manageability. One of the major benefits introduced by such a tiered paradigm is that equipments in IoT do not require sophisticated hardware and do not need to run complex routing mechanisms, and thereby significantly reduce the network cost.

In order to enable the tier-deployed IoT to be green, we first formally formulate the system framework as follows. Let x and y be the two points in Euclidean plane, $d(x, y)$ be the distance between x and y, denote $\mathbb{S}$ as the set of l sensing nodes (objects or things) in the sensing layer, $r > 0$ as the communication radius of each node. Also, denote $\mathbb{R}$ as the set of m relay nodes, $R \geq r$ as the communication radius of each relay node. Let $\mathbb{B}$ be the set of n base stations, and assume the communication radius of a base station be fairly large. Denote the entire network of IoT as $G(N, A)$ where N represents the node set and A represents the wireless link set, then the communication policy of any two nodes in IoT can be outlined as follows.

1) To any $i \in \mathbb{S}, j \in \mathbb{S}$, i and j cannot communicate with each other even $d(i, j) \leq r$;

2) To any $i \in \mathbb{S}$, $j \in \mathbb{R}$, if $d(i,j) \le r$, i can send data to j;
3) To any $i \in \mathbb{R}$, $j \in \mathbb{R} \cup \mathbb{B}$, if $d(i,j) \le R$, i and j can reach each other.

With these notations and symbols in hand, we herein make the following assumptions for the system framework.

1) All the nodes in the framework are in a fixed site.
2) Nodes in the same type have the same attribute, e.g., initial energy, energy consumption parameters, maximum sending power, minimal receiving power, and so on.
3) Nodes of the sensing layer can send data to a base station in a multi-hop manner.
4) Each node in both sensing and relay layers is energy constrained, while base station is not.
5) The whole network of IoT $G(N, A)$ represents a connected network; i.e, each node in the sensing layer has a path to a base station, so does each relay node.

In Section IV, we will model the IoT with green requirements based on the above assumptions of the system framework.

IV. Modeling the Green IoT

Given such a hierarchical system framework, the goal of deploying a green networked IoT is to determine the number and location of relay nodes while satisfying power-saving and budget constraints. In this section, we start with the variable and notation definitions used in the rest of the paper, then we formulate the system constraints according to the green requirements for IoT. Next, we address the IoT green deployment as an optimization problem. Finally, we propose an algorithm to solve such a problem. We also discuss the performance of our proposed algorithm in this section.

A. Variable Definition

Listed following are notations of variables and parameters used in this paper.

E_{tx}, E_{rx}	energy consumption at a node for data transmission and receiving, respectively;
E_{elec}	energy consumption of radio electronics;
ϵ_0, ϵ_1, ϵ_2	transmit amplifier of the node, sensing node, and relay node, respectively;
d_{ij}	the distance between node i and node j;
L	data length;
F_{ij}	data rate from node i to node j;
$F_{\max}$	maximum data rate of a link;
$C_{\mathbb{S}}$, $C_{\mathbb{R}}$, $C_{\mathbb{B}}$	monetary cost of a sensing node, relay node, and base station, respectively;
$\lvert \cdot \rvert$	cardinality of a set;
l, m, n	cardinality of set $\mathbb{S}$, $\mathbb{R}$, $\mathbb{B}$;
W_0	system budget;

B. System Constraints

A sensing node can only communicate with a relay node in the upper layer, whereas a relay node can send/receive data both to/from its neighbor relay nodes as well as a base station; therefore, $G(N, A)$ is a directed and connected graph. We call node i and node j neighbors, if i and j are able to communicate with each other. Let $\mathcal{N}(i)$ be the set of i's neighbors, $\mathcal{C}$ be the adjacency matrix of $G(N, A)$, then

$$\mathcal{C} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1|N|} \\ c_{21} & c_{22} & \cdots & c_{2|N|} \\ \vdots & \vdots & \ddots & \vdots \\ c_{|N|1} & c_{|N|2} & \cdots & c_{|N||N|} \end{bmatrix} \tag{1}$$

where $c_{ij} = 1$ if $j \in \mathcal{N}(i)$, otherwise $c_{ij} = 0$.

To address the green requirements, we consider the following system constraints.

1) Energy Consumption Constraints: From a system perspective, the energy consumption of IoT mainly comes from data communication because the energy expenditure in data sensing and processing is much less compared to data communication [29]. Thus, only the energy consumption of data communication, i.e., energy for sending and receiving data, is taken into account in this model. According to the Friis free space model [16], we have

$$E_{tx} = (E_{\text{elec}} + \epsilon_0 \cdot d^2) \cdot L \tag{2}$$
$$E_{rx} = E_{\text{elec}} \cdot L. \tag{3}$$

From the above two equations, the data length L from node i to node j in a time unit is equal to the data rate from i to j. Therefore, the energy consumption per time unit of each node can be calculated by

$$e_i = \sum_{j\in\mathbb{R}} c_{ij} \cdot F_{ij} \cdot (E_{\text{elec}}^{\mathbb{S}} + \epsilon_1 \cdot d_{ij}^2) \quad \forall i \in \mathbb{S} \tag{4}$$

$$e_j = \sum_{i\in\mathbb{S}\cup\mathbb{R}} c_{ij} \cdot F_{ij} \cdot E_{\text{elec}}^{\mathbb{R}} + \sum_{i\in\mathbb{B}\cup\mathbb{R}} c_{ji} \cdot F_{ji} \cdot (E_{\text{elec}}^{\mathbb{R}} + \epsilon_2 \cdot d_{ji}^2) \quad \forall j \in \mathbb{R} \tag{5}$$

$$e_k = \sum_{j\in\mathbb{R}} c_{jk} \cdot F_{jk} \cdot E_{\text{elec}}^{\mathbb{B}} \quad \forall k \in \mathbb{B} \tag{6}$$

where e_i, e_j, and e_k denote the consumption of sensing node, relay node, and base station, respectively. $E_{\text{elec}}^{\mathbb{S}}$, $E_{\text{elec}}^{\mathbb{R}}$, and $E_{\text{elec}}^{\mathbb{B}}$ are the energy consumption of radio electronics of sensing node, relay node, and base station, respectively.

Note that in (4), we only consider the case that sensing nodes send data to the upper layer, i.e., the energy of a sensing node for receiving data is ignored. This is due to the fact that the data received by a sensing node are usually signaling messages, the size of which is much smaller compared to sensing data (e.g., F_{ij}). Therefore, the energy consumption at sensing nodes for receiving data is omitted. Similarly, (5) excludes the energy consumption for receiving data from the base station and for transmitting data to the sensing node. Also, (6) omits the energy consumption when a base station sends data.

2) Link Flow Balancing Constraints: In the IoT, the base stations are usually interconnected by wired links, which have more bandwidth compared with relay and sensing nodes; therefore, the bandwidth is constrained at nodes except for base stations. For a relay node, it communicates with not only its neighbor relay nodes but also sensing nodes in the lower layer. Thus, the wireless links of a relay node should satisfy

$$c_{ij} \cdot F_{ij} + c_{ji} \cdot F_{ji} \leq F_{\max} \quad \forall i, j \in \mathbb{R}. \tag{7}$$

Likewise, the wireless links at each sensing node and base station need to meet the following constraint:

$$c_{ij} \cdot F_{ij} \leq F_{\max} \tag{8}$$

where $\forall i \in \mathbb{S}$, $j \in \mathbb{R}$ or $\forall i \in \mathbb{R}$, $j \in \mathbb{B}$.

It is interesting to note that, by placing a relay layer over the sensing layer in IoT, the relay nodes carry most of the network loads. Since relay nodes have relatively strong performance, one of the advantages of layering relay nodes in our proposed framework is that link flows can be balanced. In the ad hoc scheme, although each node is capable of transmitting data to its neighbors, nodes near to the sink or base station typically consume more energy due to the unbalanced flows that overload these nodes; thus suffering a short lifetime. Therefore, we advocate that the tiered framework is preferable for IoT deployment because it balances the flow loads, thus prolonging the network lifetime.

3) System Budget Constraint: Since relay nodes and base stations are comparatively expensive, the deployment of an IoT must be as cheap as possible. On the other hand, the number of base stations is fixed, consequently, the IoT deployment should meet the system budget constraint, i.e.,

$$0 < C_{\mathbb{S}} \cdot l + C_{\mathbb{R}} \cdot m < W_0. \tag{9}$$

With above system constraints, we are now ready to present the optimization model for green IoT deployment.

C. An Optimization Model for Green IoT Deployment

The main purpose of this paper is to reduce energy consumption to achieve a green IoT. Hence, the optimization model for green IoT deployment is defined as

$$\begin{aligned}
&\min \left[\sum_{i \in \mathbb{S}} e_i + \sum_{j \in \mathbb{R}} e_j + \sum_{k \in \mathbb{B}} e_k \right] \\
&\text{s.t.} \\
&e_i = \sum_{j \in \mathbb{R}} c_{ij} \cdot F_{ij} \cdot \left(E_{\text{elec}}^{\mathbb{S}} + \epsilon_1 \cdot d_{ij}^2\right) \quad \forall i \in \mathbb{S} \\
&e_j = \sum_{i \in \mathbb{S} \cup \mathbb{R}} c_{ij} \cdot F_{ij} \cdot E_{\text{elec}}^{\mathbb{R}} \\
&\qquad + \sum_{i \in \mathbb{B} \cup \mathbb{R}} c_{ji} \cdot F_{ji} \cdot \left(E_{\text{elec}}^{\mathbb{R}} + \epsilon_2 \cdot d_{ji}^2\right) \quad \forall j \in \mathbb{R} \\
&e_k = \sum_{j \in \mathbb{R}} c_{jk} \cdot F_{jk} \cdot E_{\text{elec}}^{\mathbb{B}} \quad \forall k \in \mathbb{B} \\
&c_{ij} \cdot F_{ij} + c_{ji} \cdot F_{ji} \leq F_{\max} \quad \forall i, j \in \mathbb{R} \\
&c_{ij} \cdot F_{ij} \leq F_{\max} \quad \forall i \in \mathbb{S}, j \in \mathbb{R} \quad \text{or} \quad \forall i \in \mathbb{R}, j \in \mathbb{B} \\
&0 < C_{\mathbb{S}} \cdot l + C_{\mathbb{R}} \cdot m + < W_0.
\end{aligned} \tag{10}$$

Theorem 1: Problem (10) is NP-hard.

Proof: The key step to resolve problem (10) is to map the transmitting/receiving energy for the node pair to a weight on each edge. As such, the problem of finding the minimum energy consumption for the entire system reduces to a *Steiner* tree problem where the base stations and partial relay nodes (cluster heads) are the destinations, the remainder relay nodes are *Steiner* points. Since the *Steiner* tree problem is NP-hard, problem (10) is NP-hard.

D. A Minimal Energy Consumption Algorithm

Algorithm I MECA

Input:

$\mathbb{S}, \mathbb{R}, \mathbb{B}, R \geq r > 0$

Output:

Minimal Energy Consumption $\min(e)$

1: Apply K-means clustering algorithm to obtain a single-cover set $\mathbb{S}_1 \subseteq \mathbb{S}$, choose the closest relay $i \in \mathbb{R}$ to replace the $j \in \mathbb{S}_1$ forming the set $\mathbb{R}_1$.
2: **for** $i \in \mathbb{R}$, $j \in \mathbb{R} \cup \mathbb{B}$, $i \neq j$ **do**
3:   Calculate the distance d_{ij} between i and j;
4:   **if** $d_{ij} \leq R$ **then**
5:     Add the node i and j to a candidate set RN for placement, set $c_{ij} = 1$ in G;
6:   **end if**
7: **end for**
8: Assign edge weight for G in terms of (4), (5), and (6) on each edge;
9: Apply a well-known *Steiner* Tree algorithm to compute a minimal energy consumption *Steiner* tree G^T of $G = (\mathbb{S} \cup RN \cup \mathbb{B}, A)$ spanning the node set $\mathbb{B} \cup \mathbb{R}_1$.
10: **for** each edge in G^T **do**
11:   Sum the total weight on each edge, denoted as $\min(e)$;
12: **end for**
13: **return** $\min(e)$.

We devise an MECA as shown in Algorithm I in order to solve problem (10). The basic idea behind MECA is to first apply canonical K-means clustering algorithm to select the relays, then construct a graph to associate each edge a weight through mapping the transmitting/receiving energy of the connected node pair. Finally, MECA employs a well-known *Steiner* tree algorithm to solve the problem. Specifically, MECA works in the following four steps.

In the first step (line 1), MECA applies K-means clustering algorithm [30] in the sensing layer to find a set of clusters, and then the closest relay from each cluster is selected to form the set $\mathbb{R}_1$, where K-means clustering is a method of cluster analysis which aims to partition n observations into K clusters in which each observation belongs to the cluster with the nearest mean. Set $\mathbb{R}_1$ is essentially the minimal single-cover set due to the minimal clusters found by K-means.

The second step (lines 2–8) establishes the graph connecting relays and base stations. It also assigns the weight on each edge.

In the third step of MECA (line 9), it employs a well-known *Steiner* tree algorithm [31] to compute a minimal energy consumption tree. Note that the *Steiner* tree algorithm used in this paper is similar to that used in [15] and [32]. The major difference is that MECA exploits the energy consumption as the link weight instead of the weight as defined in [15] and [32]. In such a way, the number and location of relay nodes can be determined by the *Steiner* tree algorithm, which guarantees the entire network to be energy-efficient.

The forth step obtains the solution $\min(e)$ for optimization problem (10) by summing the total weight on each edge, where

$$\min(e) = \min\left[\sum_{i\in\mathbb{S}} e_i + \sum_{j\in\mathbb{R}} e_j + \sum_{k\in\mathbb{B}} e_k\right]$$

the total weight here means the multiples of the weight on the common links, which transmits data to base stations for two or more sensing nodes.

It is worthwhile noticing that MECA is a deployment algorithm that runs offline before the IoT is formed. Thus, there is no information distribution required among the nodes during network operation. The traditional sensor network-based works are usually configured with dynamic routing protocols requiring network nodes to exchange route information among them regularly, which not only causes overhead traffic in network but also consumes node power for extra data communications. Therefore, we present a static network based on MECA to restrain the networking overhead. On the other hand, since MECA runs in an offline computation mode, dealing with link failures after the IoT has been formed is not a function of the algorithm. How to handle the link failures is beyond the scope of the paper, which is an important problem for study in the next stage.

Now we show the worst-case time complexity of MECA by the following theorem.

Theorem 2: The worst-case time complexity of MECA is $\mathcal{O}(\mathcal{T}_\mathcal{A} + m\cdot(m+n) + \mathcal{T}_\mathcal{B})$. $\mathcal{T}_\mathcal{A}$ and $\mathcal{T}_\mathcal{B}$ are the time complexities of K-means clustering and Steiner tree algorithm.

Proof: The first line in MECA leveraging K-means algorithm to select clusters takes $\mathcal{O}(\mathcal{T}_\mathcal{A})$ time. The first for-loop from line 2 to line 7 spends $\mathcal{O}(m\cdot(m+n))$ time to establish the graph. Line 8 consumes $\mathcal{O}(|A|)$ time for assigning edge weights. Line 9 takes $\mathcal{O}(\mathcal{T}_\mathcal{B})$ to generate the *Steiner* tree, while the for-loop from lines 10 to 12 consumes $\mathcal{O}(|A|)$ time at most. Therefore, the worst-case time complexity of MECA is $\mathcal{O}(\mathcal{T}_\mathcal{A}+m\cdot(m+n)+2\cdot|A|+\mathcal{T}_\mathcal{B}) = \mathcal{O}(\mathcal{T}_\mathcal{A}+m\cdot(m+n)+\mathcal{T}_\mathcal{B})$.

Theorem 3: The approximation ratio of MECA is $2\cdot(1-\frac{1}{m+|\mathbb{R}_1|})$.

Proof: Since the approximation ratio of MECA depends on that of *Steiner* tree algorithm used in this paper, according to [31], the approximation ratio of the *Steiner* tree algorithm used is $2\cdot(1-\frac{1}{h})$ where h represents the number of leaf nodes in the *Steiner* tree. Then in the MECA, the number of leaf nodes is $m+|\mathbb{R}_1|$, therefore, the approximation ratio of MECA is $2\cdot(1-\frac{1}{m+|\mathbb{R}_1|})$.

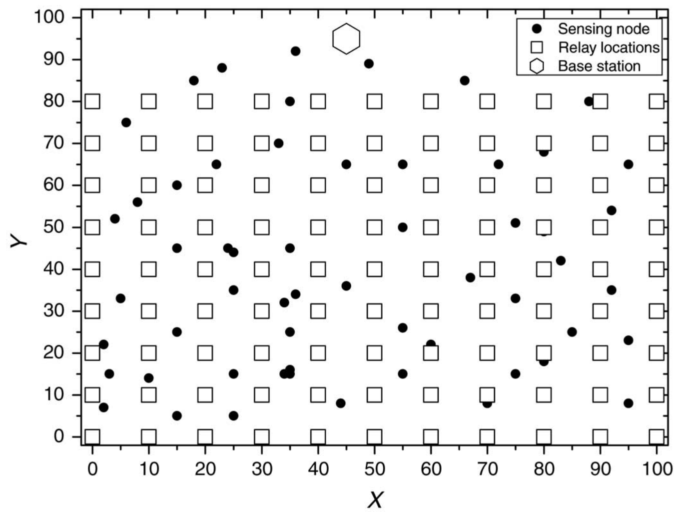

Fig. 2. Illustrative generated topology.

On the basis of MECA, it is easy to calculate the network lifetime [33]–[35]. The network lifetime is defined as the time spans from when a network starts its operation to when energy depletion occurs at the first node [36]. Using such a definition, we can examine the worst-case network lifetime, which offers an in-depth insight for entire IoT performance. The network lifetime of entire IoT is

$$T^L = \min\left\{\frac{E_1}{e_i}, \frac{E_2}{e_j}\right\} \tag{11}$$

where E_1 and E_2 are the initial energies of sensing and relay nodes.

Here, we defined network lifetime as the time to the first node death so that we can examine the worst-case network lifetime, which offers an in-depth insight for entire IoT performance. More network lifetime metrics, such as [37], could also be used for examining energy efficiency of the proposed deployment scheme.

Through calculating the *Steiner* tree in MECA, the number and location of relay nodes are thus determined: assume that the set of *Steiner point* in the tree G^T is $\mathbb{R}_2$, then the minimal connected single-cover is $\mathbb{R}_1 \cup \mathbb{R}_2$. In other words, the green networked IoT can be eventually deployed according to such a single-cover set.

V. Performance Evaluation

A. Experiment Setup

In this section, we validate the effectiveness of the deployment scheme presented in this paper through numerical experiments. The nodes in each topology are distributed in a 100×100 m^2 region. Fig. 2 shows randomly generated topology where $l = 57$, the number of candidate locations for placing relay node is 99, and $m = 1$. The detailed topology settings used in our experiments can be found in [38]. The

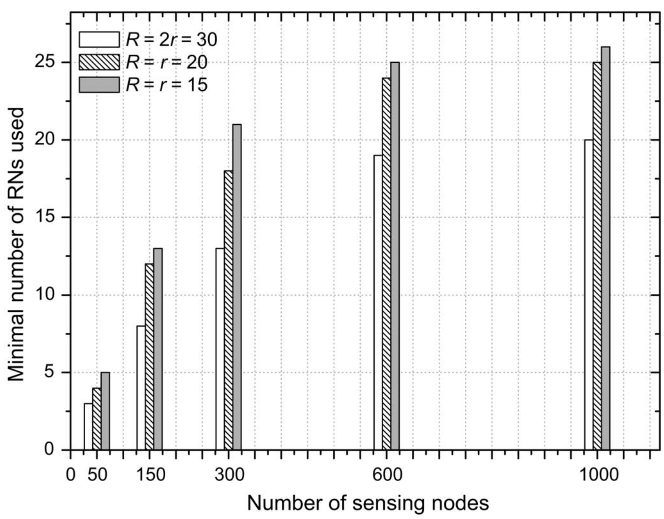

Fig. 3. Number of relay nodes used for five topologies with different communication radii.

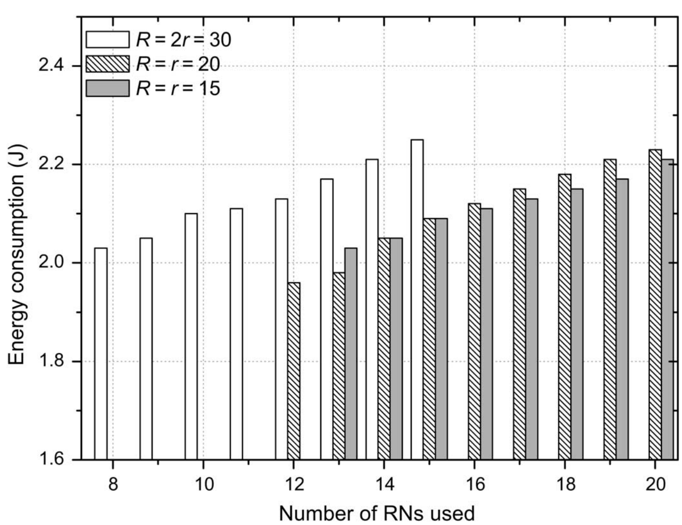

Fig. 4. Energy consumption of deployed IoT ($l = 150$) versus the number of relay nodes with different communication radii.

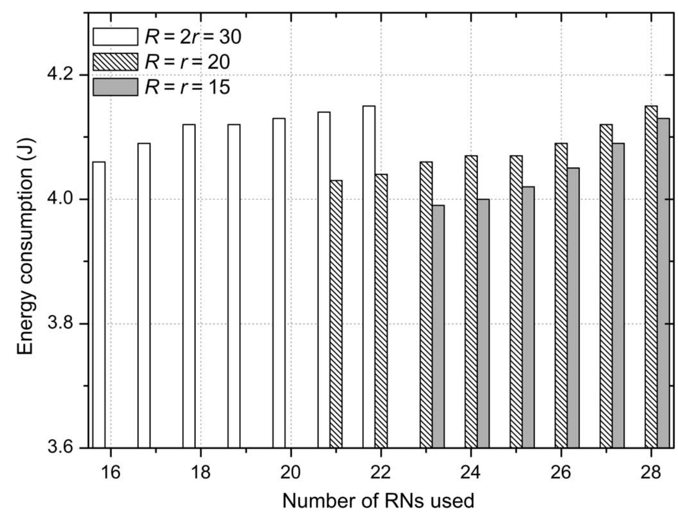

Fig. 5. Energy consumption of deployed IoT ($l = 300$) versus the number of relay nodes with different communication radii.

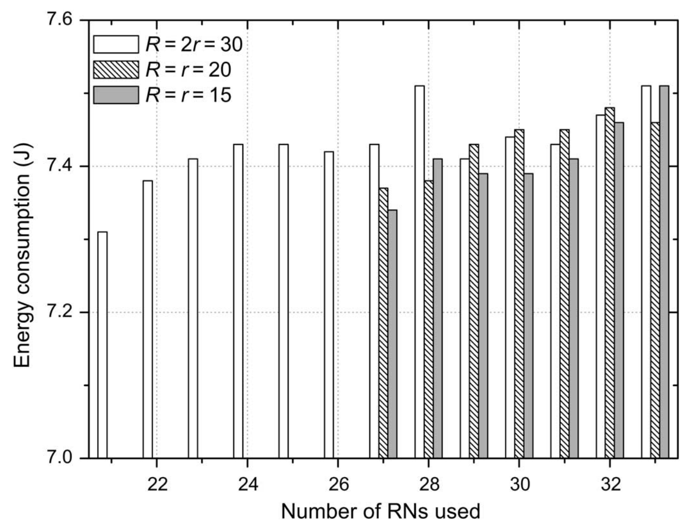

Fig. 6. Energy consumption of deployed IoT ($l = 600$) versus the number of relay nodes with different communication radii.

parameters are configured as follows. We set $E_{\text{elec}} = 50\ \text{nJ/bit}$, $E^{\mathbb{B}}_{\text{elec}} = 2E^{\mathbb{R}}_{\text{elec}} = 4E^{\mathbb{S}}_{\text{elec}} = 4E_{\text{elec}}$, $\epsilon_1 = \epsilon_2 = 100\ \text{pJ/bit/m}^2$, $F_{ij} = 100\ \text{kbps}$ for sensing nodes, $F_{ij} = 200\ \text{kbps}$ for relay nodes, and $F_{\max} = 400\ \text{kbps}$. We examine the variation of IoT energy consumption and network lifetime with parameters such as communication radius and the number of sensing nodes.

B. Experimental Results

Fig. 3 shows the number of relay nodes deployed to achieve the green networked IoT in different communication radii. In this experiment, the number of sensing nodes was set to be 50, 150, 300, 600, and 1000 to represent different scales of IoT. From this figure, we can see that the minimal number of relay nodes increases with network scale. This is natural because the larger the network scale is, the more relay nodes are needed for covering all the sensing nodes. Another interesting observation we obtained from this figure is that when the number and positions of sensing nodes and base stations are stable, the minimal number of relay nodes decreases as the communication radius of relay nodes increases. This is because larger communication radius allows a relay node to cover more sensing nodes; thus reducing the number of relays required for deploying. In addition, we also find that a small variation in communication radius has little impact on the minimal number of relay nodes. In particular, Fig. 3 gives similar minimum numbers of relay nodes for the cases of 600 and 1000 nodes. Since the nodes are randomly distributed in a $100 \times 100\ \text{m}^2$ region, the nodes' density is relatively high. Therefore, the minimal number of relay nodes for IoT deployment would be affected by not only communication radius but also the node density.

Figs. 4–7 give the relationship between energy consumption of deployed IoT and the number of relay nodes with different communication radii. It can be seen from these figures that the

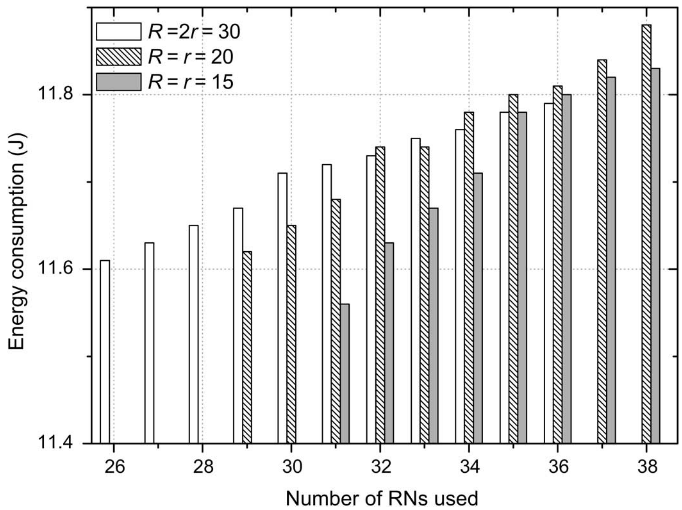

Fig. 7. Energy consumption of deployed IoT ($l = 1000$) versus the number of relay nodes with different communication radii.

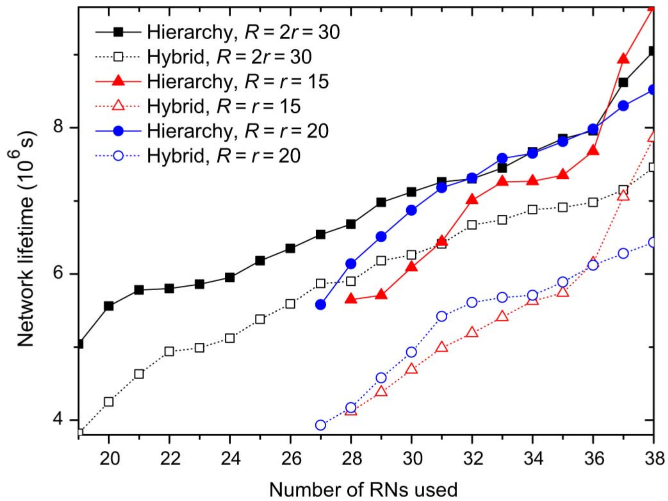

Fig. 9. Network lifetime comparisons for the topology $l = 600$, $m = 111$, $n = 1$.

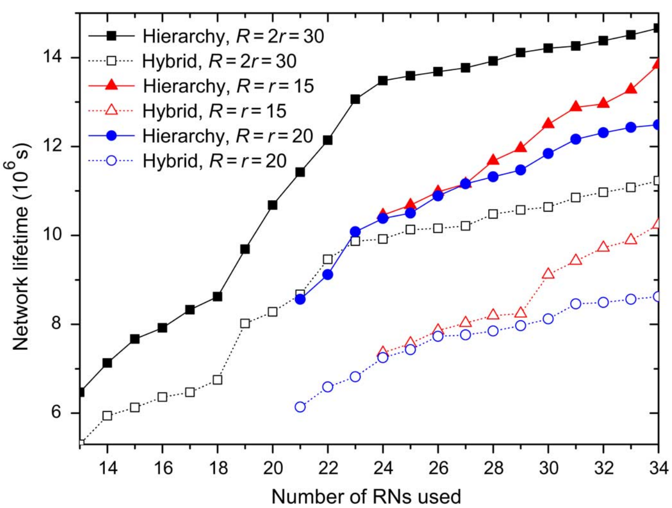

Fig. 8. Network lifetime comparisons for the topology $l = 300$, $m = 83$, $n = 1$.

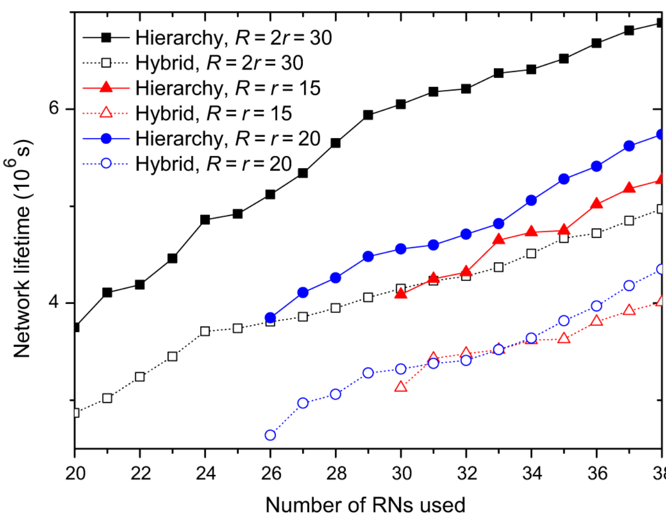

Fig. 10. Network lifetime comparisons for the topology $l = 1000$, $m = 111$, $n = 1$.

network energy consumption per unit time increases with the number of sensing nodes. Specifically, Fig. 4 shows the energy consumption for another topology where $l = 150$ and $n = 1$. We observe that the energy consumption tends to be high while the communication radius of relay nodes increases. It turns out that the minimal number of relay used in this topology is reached when $R = 2$ and $r = 30$. In addition, we can also see that the IoT is unconnected when $R = r = 20$ or $R = r = 15$, and $m < 12$ or $m < 13$, which leads to zero network energy consumption. Note that we assume the network energy consumption be zero if the graph is unconnected. Since the goal of deploying a green networked IoT is to place as few relay nodes as possible in the IoT, we only need to consider the energy consumption for the scenario with the least relay used. Therefore, it is not necessary to consider the case of $m > 15$, $R = 2r = 30$, and we assume that the energy consumption is also zero in this setting. Figs. 5–7 give the data of energy consumption for the network when $l = 300$, $l = 600$, and $l = 1000$, respectively. These figures provide the same insight as Fig. 4 does, which proves the proposed algorithm's robustness.

In order to validate the effectiveness of our proposed hierarchical deployment structure, we implement a hybrid deployment scheme for comparing the network lifetime of the two frameworks. The main difference between the hybrid scheme and our proposed hierarchical framework is that the sensor nodes in the lower layer of the hybrid structure are allowed to communicate directly with their neighboring nodes. Figs. 8–10 show the comparing results of network lifetime for different numbers of nodes with various communication ranges.

From these figures, we find that the network lifetime of IoT deployed in the hierarchical structure is longer than that of IoT deployed in the hybrid scheme. This is due to the fact that in the hybrid scheme, the sensing nodes near to relay nodes may be overloaded, therefore, consume more energy than other nodes, which causes a shorter network lifetime. While in the hierarchical scheme, sensing nodes send information to their neighbor relay nodes, then the relay nodes forward such information to a base station. In this way, the hierarchical scheme balances the network load of the nodes; thus balancing node energy consumption and extending the network lifetime. As shown in Figs. 8–10, the more the relay nodes are deployed, the longer the network lifetime is. In addition, increasing communication radius of relay nodes would also prolong the network lifetime. Another important fact we can see from these figures is that the network lifetime becomes shorter when the number of sensing nodes increases. Since more sensing nodes result in more network traffic, which leads to a shorter network lifetime, the proposed hierarchical deployment scheme is better than the hybrid scheme with respect to the network lifetime. Therefore, we claim that the proposed hierarchy scheme is more preferable for green deployment of IoT.

VI. Conclusion

The prevalence of IoT lowers the barrier from real world to the Internet, which leads toward a new digital context for novel applications and services. Developing green deployment schemes for IoT plays a vital role in its massive implementation. In this paper, we have investigated the problem of cost-effectively arranging network objects to form a green IoT and proposed a novel deployment scheme. Specifically, we first gave a hierarchical system framework for IoT deployment, which captures the scale feature of IoT and thus making it extensible. Then based on this framework, we have presented an optimization model that is constrained by energy consumption, link flow balance, and system budget, which facilitate green IoT deployment. Finally, we have devised an MECA leveraging the clustering principle and a *Steiner* tree algorithm to solve the optimization problem. Through extensive numerical experiments, we show that the proposed scheme can achieve much longer network lifetime compared to the typical WSN deployment scheme; thus is preferable for green deployment of IoT. As future work, we will consider applying the compressed sensing technique [12], [27]in the proposed hierarchical framework and address the other energy consumption models [39] to achieve a more energy-efficient IoT. Further, study on both coverage and connectivity [40] in the IoT is also an interesting topic for investigation.

References

[1] L. Atzori, A. Iera, and G. Morabito, “The Internet of Things: A survey,” *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, 2010.

[2] L. Xiang, J. Luo, C. Deng, A. Vasilakos, and W. Lin, “Deca: Recovering fields of physical quantities from incomplete sensory data,” in *Proc. 9th Annu. IEEE Commun. Soc. Conf. Sensor Mesh Ad Hoc Commun. Netw.* (SECON), Jun. 2012, pp. 182–190.

[3] V. Jelicic, M. Magno, D. Brunelli, G. Paci, and L. Benini, “Context-adaptive multimodal wireless sensor network for energy-efficient gas monitoring,” *IEEE Sensors J.*, vol. 13, no. 1, pp. 328–338, Jan. 2013.

[4] S. Lee and M. Younis, “Eqar: Effective qos-aware relay node placement algorithm for connecting disjoint wireless sensor subnetworks,” *IEEE Trans. Comput.*, vol. 60, no. 12, pp. 1772–1787, Dec. 2011.

[5] X. Sun and E. J. Coyle, “Quantization, channel compensation, and optimal energy allocation for estimation in sensor networks,” *ACM Trans. Sensor Netw.*, vol. 8, no. 2, pp. 1–25, Mar. 2012.

[6] C. Liu and G. Cao, “Distributed critical location coverage in wireless sensor networks with lifetime constraint,” in *Proc. IEEE INFOCOM,* Mar. 2012, pp. 1314–1322.

[7] L. Yan, W. Pan, B. Luo, X. Li, and J. Liu, “Modified energy-efficient protocol for wireless sensor networks in the presence of distributed optical fiber senor link,” *IEEE Sensors J.*, vol. 11, no. 9, pp. 1815–1819, Sep. 2011.

[8] V. Kapnadak and E. Coyle, “Optimal non-uniform deployment of sensors for detection in single-hop wireless sensor networks,” in *Proc. 8th Annu. IEEE Commun. Soc. Conf. Sensor Mesh Ad Hoc Commun. Netw.* (SECON), Jun. 2011, pp. 89–97.

[9] P. Wei, S. Chu, X. Wang, and Y. Zhou, “Deployment of a reinforcement backbone network with constraints of connection and resources,” in *Proc. IEEE 30th Int. Conf. Distrib. Comput. Syst.* (ICDCS), Jun. 2010, pp. 10–19.

[10] F. Li, J. Luo, S.-Q. Xin, W.-P. Wang, and Y. He, “Laacad: Load balancing k-area coverage through autonomous deployment in wireless sensor networks,” in *Proc. IEEE 32nd Int. Conf. Distrib. Comput. Syst.* (ICDCS), Jun. 2012, pp. 566–575.

[11] W. Shen and Q. Wu, “Exploring redundancy in sensor deployment to maximize network lifetime and coverage,” in *Proc. 8th Annu. IEEE Commun. Soc. Conf. Sensor Mesh Ad Hoc Commun. Netw.* (SECON), Jun. 2011, pp. 557–565.

[12] X. Xu, R. Ansari, and A. Khokhar, “Power-efficient hierarchical data aggregation using compressive sensing in WSN,” in *Proc. IEEE Int. Conf. Commun.* (ICC), Budapest, Hungary, Jun. 2013.

[13] J.-S. Lee and W.-L. Cheng, “Fuzzy-logic-based clustering approach for wireless sensor networks using energy predication,” *IEEE Sensors J.*, vol. 12, no. 9, pp. 2891–2897, Sep. 2012.

[14] M. Xu and H. Leung, “A joint fusion, power allocation and delay optimization approach for wireless sensor networks,” *IEEE Sensors J.*, vol. 11, no. 3, pp. 737–744, Mar. 2011.

[15] D. Yang, S. Misra, X. Fang, G. Xue, and J. Zhang, “Two-tiered constrained relay node placement in wireless sensor networks: Computational complexity and efficient approximations,” *IEEE Trans. Mobile Comput.*, vol. 11, no. 8, pp. 1399–1411, Aug. 2012.

[16] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, “An application-specific protocol architecture for wireless microsensor networks,” *IEEE Trans. Wireless Commun.*, vol. 1, no. 4, pp. 660–670, Oct. 2002.

[17] A. A. Abbasi and M. Younis, “A survey on clustering algorithms for wireless sensor networks,” *Comput. Commun.*, vol. 30, no. 14–15, pp. 2826–2841, Oct. 2007.

[18] J. Zhang, S. Iyer, P. Schaumont, and Y. Yang, “Simulating power/energy consumption of sensor nodes with flexible hardware in wireless networks,” in *Proc. 9th Annu. IEEE Commun. Soc. Conf. Sensor Mesh Ad Hoc Commun. Netw.* (SECON), Jun. 2012, pp. 112–120.

[19] D. Bol, J. De Vos, F. Botman, G. de Streel, S. Bernard, D. Flandre *et al.*, “Green socs for a sustainable internet-of-things,” in *Proc. IEEE Faible Tension Faible Consommation* (FTFC), 2013, pp. 1–4.

[20] J.-M. Liang, J.-J. Chen, H.-H. Cheng, and Y.-C. Tseng, “An energy-efficient sleep scheduling with qos consideration in 3gpp lte-advanced networks for internet of things,” *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 3, no. 1, pp. 13–22, Mar. 2013.

[21] S. Abdullah and K. Yang, “An energy-efficient message scheduling algorithm in internet of things environment,” in *Proc. 9th Int. Wireless Commun. Mobile Comput. Conf.* (IWCMC), 2013, pp. 311–316.

[22] S. Panichpapiboon, G. Ferrari, and O. Tonguz, “Optimal transmit power in wireless sensor networks,” *IEEE Trans. Mobile Comput.*, vol. 5, no. 10, pp. 1432–1447, Oct. 2006.

[23] Y. Zhao, J. Wu, F. Li, and S. Lu, “Vbs: Maximum lifetime sleep scheduling for wireless sensor networks using virtual backbones,” in *Proc. IEEE INFOCOM,* Mar. 2010, pp. 1–5.

[24] T. La Porta, C. Petrioli, and D. Spenza, “Sensor-mission assignment in wireless sensor networks with energy harvesting,” in *Proc. 8th Annu. IEEE Commun. Soc. Conf. Sensor Mesh Ad Hoc Commun. Netw.* (SECON), Jun. 2011, pp. 413–421.

[25] A. Ben Nacef, S. Senouci, Y. Ghamri-Doudane, and A. Beylot, “Ecar: An energy/channel aware routing protocol for cooperative wireless sensor networks,” in *Proc. IEEE 22nd Int. Symp. Pers. Indoor Mobile Radio Commun.* (PIMRC), Sep. 2011, pp. 964–969.

[26] I. Amadou, G. Chelius, and F. Valois, “Energy-efficient beacon-less protocol for WSN,” in *Proc. IEEE 22nd Int. Symp. Pers. Indoor Mobile Radio Commun.* (PIMRC), Sep. 2011, pp. 990–994.

[27] L. Xiang, J. Luo, and A. Vasilakos, “Compressed data aggregation for energy efficient wireless sensor networks,” in *Proc. 8th Annu. IEEE Commun. Soc. Conf. Sensor Mesh Ad Hoc Commun. Netw.* (SECON), Jun. 2011, pp. 46–54.

[28] J. Huang, (2013). *IoT News* [Online]. Available: https://code.google.com/p/greeniot/downloads/list.

[29] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, “Wireless sensor networks: A survey,” *Comput. Netw.*, vol. 38, no. 4, pp. 393–422, 2002.

[30] M. Li, M. Ng, Y.-M. Cheung, and J. Huang, “Agglomerative fuzzy k-means clustering algorithm with selection of number of clusters,” *IEEE Trans. Knowl. Data Eng.*, vol. 20, no. 11, pp. 1519–1534, Nov. 2008.

[31] L. T. Kou, G. Markowsky, and L. Berman, “A Fast Algorithm for Steiner Trees,” *Acta Inform.*, vol. 15, no. 2, pp. 141–145, 1981.
[32] E. Lloyd and G. Xue, “Relay node placement in wireless sensor networks,” *IEEE Trans. Comput.*, vol. 56, no. 1, pp. 134–138, Jan. 2007.
[33] H. Karkvandi, E. Pecht, and O. Yadid-Pecht, “Effective lifetime-aware routing in wireless sensor networks,” *IEEE Sensors J.*, vol. 11, no. 12, pp. 3359–3367, Dec. 2011.
[34] I. S. AlShawi, L. Yan, W. Pan, and B. Luo, “Lifetime enhancement in wireless sensor networks using fuzzy approach and a-star algorithm,” *IEEE Sensors J.*, vol. 12, no. 10, pp. 3010–3018, Oct. 2012.
[35] F. Wang, D. Wang, and J. Liu, “Traffic-aware relay node deployment: Maximizing lifetime for data collection wireless sensor networks,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 22, no. 8, pp. 1415–1423, Aug. 2011.
[36] W. Liang and Y. Liu, “Online data gathering for maximizing network lifetime in sensor networks,” *IEEE Trans. Mobile Comput.*, vol. 6, no. 1, pp. 2–11, Jan. 2007.
[37] Z. Cheng, M. Perillo, and W. Heinzelman, “General network lifetime and cost models for evaluating sensor network deployment strategies,” *IEEE Trans. Mobile Comput.*, vol. 7, no. 4, pp. 484–497, Apr. 2008.
[38] J. Huang, (2013). *Topologies Used* [Online]. Available: https://code.google.com/p/greeniot/downloads/list.
[39] N. Pantazis, S. Nikolidakis, and D. Vergados, “Energy-efficient routing protocols in wireless sensor networks: A survey,” *IEEE Commun. Surveys Tuts.*, vol. 15, no. 2, pp. 551–591, May 2013.
[40] K. Han, L. Xiang, J. Luo, and Y. Liu, “Minimum-energy connected coverage in wireless sensor networks with omni-directional and directional features,” in *Proc. 13th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.* (MobiHoc), Jun. 2012, pp. 85–94.

Jun Huang (M’12) received the B.S. degree in computer science from Hubei University of Automotive Technology, Shiyan, China, in 2005; M.S. degree (with honor) in computer science from Chongqing University of Posts and Telecommunications, Chongqing, China, in 2009; and Ph.D. degree (with honor) from Institute of Network Technology, Beijing University of Posts and Telecommunications, Beijing. China, in 2012.

Currently, he is an Associate Professor with School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China. His current research interests include network optimization and control, Quality-of-Service, etc.

Dr. Huang was a Visiting Researcher at Global Information and Telecommunication Institute, Waseda University, Tokyo, from September 2010 to September 2011. He was a best paper award winner of AsiaFI 2011. He has published more than 30 refereed journal/conference papers.

Yu Meng received the B.E. degree in information and computing science from North China University of Water Resources and Electric Power, Zhengzhou, China, in 2010. Now, he is a master student in the School of Computer Science, Chongqing University of Posts and Telecommunications, Chongqing, China.

His current research interest includes green IoT deployment.

Xuehong Gong received the B.E. degree in computing science from Chongqing University of Posts and Telecommunications, Chongqing, China, in 2011. Now, she is a master student in the School of Computer Science, Chongqing University of Posts and Telecommunications.

Her current research interest includes IoT security.

Yanbing Liu received the M.S. degree in computer science and technology from Beijing University of Posts and Telecommunications, Beijing, China, in 2001; and Ph.D. degree from University of Electronic Science and Technology of China, Chengdu, China, in 2007.

He is currently a Professor with Chongqing University of Posts and Telecommunications (CQUPT), Chongqing, China. His research interests include Cloud computing, network virtualization, Internet of things, and system performance evaluation.

Dr. Liu is the recipient of National Science and Technology Award and several Chongqing Science and Technology Awards. He is an executive director of Chongqing Youth Federation of Science and Technology, a panelist of Chongqing Science and Technology Award, a member of the Chongqing General Bid Evaluation Committees, and an academic leader of CQUPT. He has published more than 60 refereed papers.

Qiang Duan (M’03) received the B.S. degree in electrical and computer engineering and M.S. degree in telecommunications and electronic systems in 1992 and 1995, respectively. He received the Ph.D. degree in electrical engineering from the University of Mississippi, Oxford, MS, USA, in 2003.

He is an Assistant Professor of information science and technology with the Pennsylvania State University Abington College, Abington, PA, USA. His research interests include data communications and computer networks, network virtualization and the next generation Internet, the service-oriented architecture, Cloud computing, and networking system hardware/software design and analysis. He has published over 50 journal articles, conference papers, and book chapters.

Dr. Duan is an Associate Editor for *International Journal of Network Protocols and Algorithms* and *International Journal of Internet and Distributed Computing Systems*.