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This is the accepted version of a paper published in *IEEE Journal on Selected Areas in Communications*. This paper has been peer-reviewed but does not include the final publisher proof-corrections or journal pagination.

Citation for the original published paper (version of record):

Du, R., Xiao, M., Fischione, C. (2018)

Optimal Node Deployment and Energy Provision for Wirelessly Powered Sensor Networks

IEEE Journal on Selected Areas in Communications, 37(2): 407-423

<https://doi.org/10.1109/JSAC.2018.2872380>

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Optimal Node Deployment and Energy Provision for Wirelessly Powered Sensor Networks

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Abstract—In a typical wirelessly powered sensor network (WPSN), wireless chargers provide energy to sensor nodes by using wireless energy transfer (WET). The chargers can greatly improve the lifetime of a WPSN using energy beamforming by a proper charging scheduling of energy beams. However, the supplied energy still may not meet the demand of the energy of the sensor nodes. This issue can be alleviated by deploying redundant sensor nodes, which not only increase the total harvested energy, but also decrease the energy consumption per node provided that an efficient scheduling of the sleep/awake of the nodes is performed. Such a problem of joint optimal sensor deployment, WET scheduling, and node activation is posed and investigated in this paper. The problem is an integer optimization that is challenging due to the binary decision variables and non-linear constraints. Based on the analysis of the necessary condition such that the WPSN be immortal, we decouple the original problem into a node deployment problem and a charging and activation scheduling problem. Then, we propose an algorithm and prove that it achieves the optimal solution under a mild condition. The simulation results show that the proposed algorithm reduces the needed nodes to deploy by approximately 16%, compared to a random-based approach. The simulation also shows if the battery buffers are large enough, the optimality condition will be easy to meet.

Index Terms—Wirelessly powered sensor networks, node placement, wireless energy transfer, sensing scheduling

I. INTRODUCTION

Wireless sensor networks (WSNs) are widely used for the long term monitoring of the natural environment [1] and infrastructures [2]. Therefore, the lifetime of WSNs is one metric. In the literature, there are different types of methods to improve energy-efficiency, such as routing, and sleep/awake mechanisms, to extend the network lifetime. Such approaches attempt to reduce the energy consumption rate of WSNs. However, no matter how low power a WSN consumes for the monitoring, the WSN will eventually expire if the batteries of sensor nodes are not recharged or changed.

The alternative approach consists in providing additional energy to a WSN. For example, the sensor nodes in the WSN can harvest energy from the ambient environment [3], [4], [5], and the nodes perform sensing and data transmission according to the amount of harvested energy. However, the

arrival of the ambient energy is in general hard to predict or even control [6]. It may make the monitoring performance of the WSN inconsistent overtime. Fortunately, such a problem can be potentially addressed by wireless energy transfer (WET) [6], [7].

The basic idea of WET is that we use dedicated energy transmitters to charge remote wireless devices [8] by electromagnetic waves. We call the energy transmitters energy base stations (eBSs) or wireless chargers throughout this paper. Then, the WSNs that are powered by the eBSs are wirelessly powered sensor networks (WPSNs). By using WET, we have a better controllability of how much power the sensor nodes in a WPSN can harvest [9]. However, it has some major drawbacks. One is that the energy suffers a great path loss in the energy transmission process. Additionally, due to the safety issue, the eBSs may not use a sufficiently large power. To address these problems, rather than broadcasting the energy, we can use energy beamforming [10], which concentrates the energy towards the targeted nodes.

In a WPSN with multiple sensor nodes, if the energy consumptions of the nodes are higher than the harvested energy, the lifetime of the WPSN will be still limited. Thus, to make the WPSN immortal, we need to provide each node with more energy than its consumed energy. This observation gives us the intuition to increase the harvested energy and to reduce the consumed energy of sensor nodes. A natural approach is that we deploy redundant nodes in the network, such that the nodes together may harvest more energy, meanwhile each node can consume less energy to fulfil the monitoring requirement. More specifically, assume that we need to monitor a specific location with a required sampling rate. If we deploy multiple nodes close to each other to monitor such a location, then the eBS can charge these nodes at the same time; whilst these nodes can save energy by taking turns to sense and transmit their measurement. In this case, the energy consumption of each node may be less than the energy it consumes. This observation motivates us to formulate a joint node deployment and wireless energy transfer scheduling problem to study how to deploy the sensor nodes and schedule the energy transmission and node sensing for a WPSN.

We consider a WPSN as shown in Fig. 1, where we have several regions of interest to monitor with sensor nodes. An eBS transmits energy to the sensor nodes to sense the environment and upload the measurements. We may deploy multiple sensor nodes in the same region to harvest the energy at the same time when the eBS transmits energy towards the region. Besides, the nodes in the same region take turns to work to reduce energy consumption. Therefore, the following problems naturally arise: 1) optimize the deployment

Manuscript received on March 14th, 2018; revised on July 6th, 2018; accepted on September 9th, 2018.

This work is supported by the Digital Demo Stockholm project IWater. The authors would like to thank the reviewers and the editors for their time and their valuable comments.

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Fig. 1. A wirelessly powered sensor network with one energy base station and multiple sensors. The sensors in a region take turn to make measurements and transmit the data.

of the sensor nodes, i.e., how many nodes we should deploy in each region, 2) the WET schedules, i.e., when the eBS should transmit energy to each region, and 3) the activation schedules of the nodes, i.e., when a node in a region has to be active to measure and to transmit. The problem couples energy provision and energy saving together, which makes the problem more challenging than the ones that consider either energy provision or energy saving.

To solve such a problem, we decouple the problem into two subproblems and establish a necessary condition to guarantee the network immortality. Then, we use greedy based algorithms to solve each subproblem. We show that such an approach achieves the optimal solution of the original problem under a mild condition. The contribution of the paper is summarized as follows:

- We propose a novel optimization problem that jointly considers sensor node deployment and WET scheduling for WPSNs, which to our best knowledge has never been studied before, except for our preliminary work [11];
- Given the complexity of the problem and the lack of existing solutions, we propose a novel solution approach based on two steps: 1) greedy based node deployment, 2) greedy scheduling;
- We provide the necessary condition on the sensor node deployment, such that the WPSN be immortal. Besides, we also prove that under a mild requirement on the battery size of sensor nodes, the proposed algorithm achieves the optimal node deployment, WET scheduling, and node activation, such that the WSN be immortal.

The rest of the paper is organized as follows. We present the related works in Section II. The WPSN system is modelled in Section III, where the necessary condition on node deployment for immortal WPSN is established. In Section IV, we provide the algorithm to achieve the optimal sensor node deployment. Then in Section V, the WET scheduling given the deployment is provided to guarantee the immortality of the WPSN. In Section VI, numerical results from simulations are given to show the performance of the proposed algorithm. The paper is concluded in Section VII, and the proofs can be found in Appendix B.

II. RELATED WORKS

Network lifetime is an important metric that one needs to consider. For a WSN used for monitoring purposes, it may fail to fulfil the monitoring requirement due to multiple reasons, such as the expiration of some or all the sensor nodes, and the

disconnection of the network. The time span beginning from when one deploy the network till the failure of the network can be defined as the lifetime of the WSN. In our work, we define that the network expires when the sampling rate of at least one region cannot meet the required rate. If one wants to have the WSN working as long as possible without replacing the nodes or the batteries, it is essential that the sensor nodes can get additional energy to recharge their batteries. The recharging methods can be roughly divided into two categories: energy harvesting and WET.

In energy harvesting, wireless devices can harvest energy from the environment, such as solar radiation [3], wind [4], vibrations [5], and the radio frequency (RF) power [9] that are transmitted from other wireless devices or TV towers. Due to that the energy sources are not controllable, the studies in energy harvesting mostly focus on the energy consumption side, i.e., how the nodes schedule their functioning based on the harvested energy [12], [13]. The basic idea is that, the nodes should transmit more data when they have more battery buffer, and they can harvest more energy [13]. The work in [14] studied the scheduling of the sensing time of sensor nodes. The authors achieved an algorithm that selects the nodes with the highest energy level to sense. In [15], the authors investigated a transmission scheme that a sensor uses all harvested energy to transmit all the data in its buffer. The authors provided the performance bound of such a scheme in terms of the distortion at the fusion centre. The authors of [16] analyzed the performance of a harvest-then-transmit scheme in terms of delay, and also proposed a transmission scheme based on the channel quality information of the sensor-to-sink link, to guarantee successful packet delivery.

Another method to charge the nodes is WET, where the energy comes from dedicated energy chargers. Compared to energy harvesting, WET has an additional degree of freedom, i.e., how to provide more energy to the nodes, to improve the network performance. In this case, the networks are called wirelessly powered communication networks (WPCNs), where base stations first transmit energy in the downlink to the nodes, and then the nodes use the received energy to transmit data in the uplink. For a single-user scenario, the work in [17] considered the optimization of the time duration of downlink energy transmission, such that the data rate in the uplink is maximized. However, it assumes that the charger has perfect channel information. This issue was studied in [18], where the authors investigated a time scheduling problem in a multi-user network and the nodes need to transmit energy pilots for channel estimation. When the energy receivers are sensor nodes, the WPCN is called WPSN, and the metrics in terms of lifetime and sensing performance are of more interest. The work in [19] studied a WSN that is charged by a vehicle with a wireless charger. The authors formulated a routing problem to find the path and the charging time of the vehicle, such that the WSN be immortal. For a static WPSN, our previous work [20] provided a necessary condition that the WPSN is immortal, and also studied a WET scheduling problem to maximize the network lifetime, when the condition is not met. In [21], the chargers form directional energy beam to charge the nearby sensor nodes. The authors investigated the charging radius of

the chargers to maximize the average received power of the sensor nodes.

Node deployment is also an important topic for WPSN. For example, the work in [22] studied a problem of deploying wireless chargers (RFID readers) to cover a region. The coverage ensures that every sensor node (wireless identification and sensing platform (WISP) tag) can have an average recharge rate that is no smaller than its consumption rate. The problem is related to a fundamental coverage problem in WSNs. The authors showed that the recharge power received by a tag from multiple chargers is additive, which enables them to use less number of chargers than the solution achieved by solving the traditional coverage problem. The authors also considered the mobility of sensor nodes. Such a mobility can improve the average recharge rate, and thus helps in reducing the number of chargers. Some similar problems that investigate the placement of chargers can be found in [23], [24]. Different to these studies, the problem studied in this paper considers the placement of sensor nodes. Thus, the solutions can not be applied directly in our problem.

Compared to the aforementioned studies that only consider how to provide more energy to the nodes, the problems that consider both energy transmission and energy consumption are more challenging and rewarding. For example, data routing is commonly studied together with WET. The work of [25], which is an extension of [19], studied a joint problem of the charging trajectory of the vehicle and the data routing of sensor nodes. In [26], a joint WET and data routing problem is formulated, and a solution algorithm is proposed based on a transformation to a semi-definite optimization problem. Besides data routing, the joint WET and node placement problem is also essential issue. The work in [27] investigated a two-hop relaying network, where the placement of the relay node and the splitting of data receiving and energy receiving of the destination node are jointly optimized. In [28], the authors studied the placement of chargers to charge some bottleneck sensor nodes based on resonant magnetic coupling, such that more data can be transmitted through these bottleneck nodes and the sink nodes can collect more data.

The studies above showed that, compared to the case where only WET is optimized, the network performance in terms of lifetime, sensing rate, and outage probability, achieved by jointly considering WET and energy consumption improves significantly. This result gives us the motivation to formulate a new problem that considers WET, node deployment, and also sleep/awake scheduling jointly. To the best of our knowledge, such a problem is novel and is only studied in our preliminary work [11]. Compared to our previous work, the major contributions and differences are as follows: 1) We consider a more realistic and general energy consumption model that contains the circuit consumption in the sleep mode of sensor nodes, which was neglected in the previous work. Therefore, we can consider that the problem in this paper is a general case of the one in [11]. Although the framework of the solution approach is the same as the one in our preliminary work, this new model makes the problem more complicated than before. We study the general problem and provide the corresponding new proofs and solutions, which

TABLE I
COMPARISONS OF THE LITERATURE ON WET FOR WSN

Paper	Deployment	WET scheduling	Other factors	Charger type
our work	Sensor nodes	✓	sleep-awake schedule	static, single
[6]	—	✓	data routing	mobile
[19]	—	✓	data routing	mobile
[20]	—	✓	—	static, single
[22]	Chargers	—	—	static, multi
[29]	Chargers	✓	—	static, multi
[28]	Chargers	—	data routing	static, multi

is one major contribution and difference. We also re-do the simulations due to the modification of the model; 2) We provide a more detailed discussion on our modelling of the relationship between the harvested energy and the number of nodes in a region in the manuscript, which is not provided in our previous work. We find out that the shadowing among the nodes is a key factor on the harvested energy of the nodes in the cases where the nodes are close to each other. We believe that our analysis and model will provide some insights for the people who are interested in a similar problem.

We provide some qualitative comparisons of our approach with other approaches that address either deployment problems or WET scheduling problems in the literature, as summarized in Table I. Most of the literature ([6], [19], [20]) considers the WET problems where the WSN deployment is given. The work in [29] considers the deployment of the WET chargers to cover a certain region. In fact, the deployment of the nodes, which relates to the total received energy and the energy consumption, is also important to network lifetime. As a result, it should be jointly considered in the WET problems, especially from the system design perspective. Although we only have one static charger in this work, we are interested in extending our solution approach to the cases with mobile chargers as formulated in [6], [19] in the future. In that case, the problem will be more complicated if the moving trajectories of mobile chargers also require to be determined.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we will first describe the considered WPSN model. Then, we will formulate the joint node deployment and WET scheduling problem. Due to the integer variables and non-convex constraints, solving such a problem is non-trivial. Therefore, we will also study a necessary condition for the optimality, which will be used to develop the solution. The major notation used in the paper is summarized in Table II.

We consider a WPSN as shown in Fig. 1. It consists of one eBS and several homogeneous sensor nodes to monitor N regions of interest. The distances from the eBS to the regions are in the order of tens of meters. The radius of a region are in the order of 1 meter, within which nodes will be naturally close to each other. The amount of data for sensor nodes to transmit is low, which is in the order of several bits per second. All these assumptions are not restrictive and are representative of many use cases of practical interest, such as smart agriculture [30]. The eBS provides energy to the sensor nodes wirelessly and collects the data from the nodes. Since

the energy is carried by RF, it suffers from high path loss. Therefore, the eBS uses energy beamforming to concentrate the energy towards the target [10]. Every sensor node uses a rectify antenna to harvest the RF energy from the eBS and store the energy to its rechargeable battery. The nodes use the harvested energy to make measurements and transmit them to a data sink, which could be the eBS.

We use $l_1, \dots, l_N$ to represent the N regions under monitoring. For each region l_i , we denote x_i the number of sensor nodes that are deployed in it, and $\mathbf{x} = [x_1, \dots, x_N]^T$ denotes the number of sensor nodes per region. We wish to find the optimal value for $\mathbf{x}$, i.e., the optimal number of nodes per region, such that the total number of nodes to deploy is minimized and the WPSN monitoring performance is guaranteed. Once the nodes are deployed, the WPSN starts making measurements. Time is divided into slots, each of which consists of two phases: energy transmission and data transmission.

During the energy transmission phase, the eBS forms a sharp energy beam to charge the nodes in one of the regions. Let binary variable $\mathbf{y}(t) = [y_1(t), \dots, y_N(t)]^T$ denote the WET of the eBS at timeslot t , where $y_i(t) = 1$ if the eBS transmits energy to l_i , otherwise $y_i(t) = 0$. Without loss of generality, we normalize the transmit power of eBS to be 1. Recall that multiple nodes are allowed to be deployed in the same region and the size of a region is in the order of 1 meter radius. We assume that the area of the nodes to deploy is not large compared to the width of the energy beam. Thus, all the sensor nodes in that region can harvest the RF energy, whilst the energy is too little to be harvested for the nodes in other regions. Recall that the sensor nodes in the same region are close to each other, the eBS is at 10-50 meters from it, and it transmits energy with carrier frequency 915MHz. Consequently, the wireless channel, averaged over the fast and slow fading statistics and including the path loss, is approximately constant over the region [31]. Therefore, the nodes in the same region have approximately the same averaged channel gain from the eBS to these nodes. Thus, when the eBS transmits energy to l_i , we use a term α_i to account for the averaged energy loss that is determined by the antenna gain at the eBS, the slow fading, and the RF-DC conversion loss at sensor nodes. Clearly, since the regions are at different locations, their path losses will be different and thus the term α_i will be different from region to region, i.e., the value of α_i depends on the region index i . Therefore, we call this term region-dependent. Besides α_i , the received energy for the nodes at l_i also depends on the number of sensor nodes in l_i . One reason is that, with less nodes in l_i , the eBS may use a more concentrated beam to cover all the nodes in l_i . Another reason is that, when more nodes are deployed, it is more likely that the additional node will partially shadow the energy beam to the existing nodes (or conversely the existing nodes shadow the energy beam partially). With more nodes, such a shadowing effect becomes more severe. Therefore, we use a function of the number of nodes, $g(x_i)$ to denote such a loss due to the node deployment. Then, the total energy that is harvested by the nodes in region i is $\alpha_i g(x_i) y_i(t)$. We assume that these nodes share the total energy equally. Therefore, each

node harvests $\alpha_i g(x_i) y_i(t) / x_i$ in average. In this paper, we assume that $g(x_i)$ exhibits the following properties: $g(1) = 1$ and $0 \leq g'(x_i) \leq 1, g''(x_i) \leq 0$ for all x_i larger or equal to 1. The first assumption that $g(1) = 1$ comes from that, when there is only one node, the eBS can use the sharpest beam, and only the region-dependent term accounts. The second assumption that $0 \leq g'(x_i) \leq 1, g''(x_i) \leq 0$ comes from that with more nodes, the total harvested energy is increasing, but the benefit is sub-additive, due to that the energy beam becomes wider and the nodes shadow each other. Notice that the total energy that are harvested by the nodes in the same region can not be larger than the transmitted energy. We have that $g(x_i)$ should be bounded. Based on the assumption, we can achieve that $g(x_i)/x_i$ is monotone decreasing with respect to x_i . It means that each individual sensor node harvests less power as more nodes are deployed in the same region. For more discussions on the term $g(x)$, please refer to Appendix A.

In the data transmission phase, the sensor nodes at the same region apply a sleep/awake mechanism to save energy. More specifically, in a timeslot t , only one node wakes up, senses, and transmits the measurement, whilst the other nodes in the same region are in the idle state. Denote v_{ij} the j -th node in l_i . Then, we denote $\mathbf{z}_i(t) = [z_{i,1}(t), \dots, z_{i,x_i}(t)]^T$ the activation of the nodes in l_i at timeslot t , where binary variable $z_{ij}(t)$ is the state of v_{ij} at timeslot t . Assume that the monitoring application requires a sampling rate λ_i for region l_i , then the energy consumption of a node in l_i is $c_i z_{ij}(t) + c$, where the first term c_i accounts for the energy spent on transmitting λ_i amount of data, and the second term c accounts for the static energy consumption of every sensor node, such as the timer and processor consumption. We assume that the sensor nodes use a TDMA or a CSMA/CA scheme for medium access. Moreover, the amount of data to transmit per node is little (several bits per second). Therefore, the transmission duration of each node is short. As a result, it is not likely that different nodes in different regions transmit simultaneously in a timeslot. Thus, we neglect the interference of the sensor nodes in the paper (although it is an important factors for other types of network, such as mobile networks). Let $E_{ij}(t)$ be the residual energy of node v_{ij} , and the battery size of all nodes is B . Then, the energy dynamic of the sensor nodes is

$$E_{ij}(t+1) = \min\{E_{ij}(t) + y_i(t) \frac{\alpha_i g(x_i)}{x_i}, B\} - z_{ij}(t) c_i - c. \quad (1)$$

We assume that the battery buffers are large, i.e., $B \gg c_i, \forall i$, i.e., a sensor node will not run out of energy in several timeslots, which is generally true for WSNs that are designed for long-term monitoring [32].

To summarize, we can model the WPSN as a tuple $(\mathbf{L}, \mathbf{c}, \boldsymbol{\alpha}, \mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{E}, B, g)$, where $\mathbf{L} = \{l_i\}$, $\mathbf{c} = [c, c_1, \dots, c_N]$, $\boldsymbol{\alpha} = [\alpha_i]$, $\mathbf{x} = [x_i]$, $\mathbf{y} = [y_i(t)]$, $\mathbf{z} = [z_{ij}(t)]$, and $\mathbf{E} = [E_{ij}(t)]$. Then, we define the immortality of a WSN as follows:

Definition 1. A WPSN $(\mathbf{L}, \mathbf{c}, \boldsymbol{\alpha}, \mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{E}, B, g)$ is immortal if and only if, in any timeslot t and any region l_i , the residual energy of any sensor node is non-negative, i.e., $E_{ij}(t) \geq 0$.

Remark 1. Correspondingly, the lifetime of a WPSN $(L, c, \alpha, x, y, z, E, B, g)$ is defined as the first timeslot t such that there exists a region l_i with $E_{ij}(t+1) < c_i + c, \forall 1 \leq j \leq x_i$.

Then, the *Joint Node Deployment and WET Scheduling Problem* is to find x, y , and z , such that the WPSN be immortal, as formulated below:

$$\min_{x, y, z} f(x) \triangleq \sum_{i=1}^N x_i \quad (2a)$$

$$\text{s.t. } E_{ij}(t) \geq 0, \forall i, j, t, \quad (2b)$$

$$E_{ij}(t+1) = \min\{E_{ij}(t) + y_i(t) \frac{\alpha_i g(x_i)}{x_i}, B\} - z_{ij}(t)c_i - c, \forall i, j, t, \quad (2c)$$

$$\sum_i^N y_i(t) = 1, \forall t, \quad (2d)$$

$$\sum_j^{x_i} z_{ij}(t) = 1, \forall j, t, \quad (2e)$$

$$x_i \in \mathbb{Z}^+, y_i(t) \in \{0, 1\}, z_{ij}(t) \in \{0, 1\}, \forall i, j, t, \quad (2f)$$

where the objective is to minimize the total number of sensor nodes to deploy, Constraint (2b) means that none of the nodes should run out of energy, Constraint (2d) means that the eBS charges the sensor nodes for a region in each timeslot, and (2e) means for each region, there should be one node awake to perform sensing and measurement transmission in a timeslot.

Problem (2) is hard, not only due to the integer and binary decision variables, but also the undetermined size of variables (see z as an example) and the non-convexity of the energy dynamic Constraint (2c). To solve Problem (2), we propose a solution method based on two steps: 1) We find the optimal deployment that satisfies the necessary condition of immortality, and 2) we find the WET scheduling y and the activation scheduling z given the deployment from step 1) such that the WSN be immortal.

Therefore, before we start describing the solution, we first present the necessary condition such that the WPSN is immortal in the following lemma.

Lemma 1. Let WPSN $(L, c, \alpha, x, y, z, E, B, g)$ be immortal. Then $\sum_{i=1}^N (c_i + cx_i)/(\alpha_i g(x_i)) \leq 1$.

In other words, if Problem (2) has a feasible solution, then there exists a positive x that satisfies $\sum_{i=1}^N (c_i + cx_i)/(\alpha_i g(x_i)) \leq 1$. To make it more concise, we define $h_i(x_i) \triangleq (c_i + cx_i)/(\alpha_i g(x_i))$. This lemma is used to formulate a deployment subproblem to solve Problem (2). More specifically, the deployment subproblem aims to find the minimum total number of sensor nodes to deploy while ensuring that this necessary condition holds.

Before we provide the solution algorithm for Problem (2), we present here another necessary condition such that Problem (2) has a feasible solution. This condition comes from Lemma 1 and will be used to determine whether Problem (2) has a feasible solution. The condition is given by the following lemma:

TABLE II
MAJOR NOTATIONS USED IN THE PAPER

Symbols	Meanings
$E_{ij}(t)$	Residual energy of node v_{ij}
N	Number of regions to be monitored
c	Static power consumption of the nodes
c_i	Energy consumption for data transmission of the nodes in l_i
$g(x_i)$	Deployment-dependent WET efficiency factor
l_i	The i -th region
x	Deployment of the nodes
y	WET scheduling
z	Node activation
α_i	Region-dependent WET efficiency term

Lemma 2. Consider a joint node deployment and WET scheduling Problem (2). The necessary condition that it has a feasible solution is

$$\sum_{i=1}^N \lim_{x_i \rightarrow x_i^{\min}} h_i(x_i) = \sum_{i=1}^N \lim_{x_i \rightarrow x_i^{\min}} \frac{c_i + cx_i}{\alpha_i g(x_i)} \leq 1, \quad (3)$$

where $x_i^{\min} \in \mathbb{Z}^+$ is defined as the positive integer that minimizes $h_i(x_i)$ in the positive integer domain, i.e.,

$$x_i^{\min} \triangleq \arg \min_{x_i \in \mathbb{Z}^+} h_i(x_i). \quad (4)$$

The proof is based on Lemma 1. For short, if Condition (3) does not hold, then there will be no feasible solution of x that satisfies $\sum_{i=1}^N (c_i + cx_i)/(\alpha_i g(x_i)) \leq 1$. Thus, Problem (2) has no feasible solution. We will use this lemma in the solution algorithm (see Algorithm 1 in Section IV). The value $x_i^{\min}$ is the upper bound of the number of nodes that we should deploy in region i .

Based on this necessary condition from Lemma 1, now we are ready to determine the deployment of the sensor nodes, as will be discussed in the next section.

IV. NODE DEPLOYMENT FOR IMMORTAL WSN

Based on Lemma 1, we will decouple the original problem into a node deployment problem and a WET scheduling problem. Therefore, in this section, we will first present the deployment problem. Then, we will provide the solution approach for such a deployment problem.

A. Node deployment sub-problem

Recalling that $\sum_i (c_i + cx_i)/\alpha_i g(x_i) \leq 1$ in Lemma 1 is the necessary condition for the immortality of the WPSN, we formulate the deployment problem to find the minimum number of nodes to satisfy such a necessary condition as follows:

$$\min_x \sum_{i=1}^N x_i \quad (5a)$$

$$\text{s.t. } \sum_{i=1}^N \frac{c_i + cx_i}{\alpha_i g(x_i)} \leq 1, \quad (5b)$$

$$x_i \in \mathbb{Z}^+, \forall i, \quad (5c)$$

where Constraint (5b) comes from the necessary condition (Lemma 1), and Constraint (5c) is the positive integer

constraint on the number of nodes to deploy in each region. Notice here that if Inequality (3) is not valid, then there is no feasible $\mathbf{x}$ that satisfies Constraint (5b). As a result, Inequality (3) is also the necessary condition by which Problem (5) has feasible solutions.

Before we propose the solution, we first analyse Constraint (5b), such that we can have a nice proposition for the solution of Problem (5). Recalling that $h_i(x_i) \triangleq (c_i + cx_i)/(\alpha_i g(x_i))$, we have the following lemma of $h_i(x_i)$:

Lemma 3. Consider $h_i(x_i) = (c_i + cx_i)/(\alpha_i g(x_i))$, where $c_i > 0, c > 0, 0 < \alpha_i < 1$, and the function $g(x)$ satisfies the assumption that $g(1) = 1$ and $0 \leq g'(x_i) \leq 1, g''(x_i) \leq 0$ for $x_i \geq 1$. Denote $r_i(x_i) = c\alpha_i g(x_i) - (c_i + cx_i)\alpha_i g'(x_i)$. Then, $h_i(x_i)$ achieves its minimum in domain $x_i \geq 1$ at x_i^{th} , where

$$x_i^{\text{th}} = \begin{cases} 1 & \text{if } r_i(1) \geq 0 \\ +\infty & \text{if } r_i(1) < 0, \lim_{x_i \rightarrow +\infty} h'_i(x_i) < 0 \\ \bar{x}_i^{\text{th}} & \text{otherwise,} \end{cases} \quad (6)$$

and $\bar{x}_i^{\text{th}}$ is the unique solution that satisfies $c\alpha_i g(\bar{x}_i^{\text{th}}) = (c_i + c\bar{x}_i^{\text{th}})g'(\bar{x}_i^{\text{th}})$. Furthermore, $h_i(x_i)$ is convex in region $[1, x_i^{\text{th}}]$.

The superscript ‘th’ means ‘threshold’ that $h_i(x_i)$ is monotone decreasing in $[1, x_i^{\text{th}}]$ and it is monotone increasing in $[x_i^{\text{th}}, +\infty)$. From the proof of Lemma 3, the first case in Equation (6) corresponds to the cases where $h_i(x_i)$ is monotone increasing for $x_i \in [1, +\infty)$; the second case corresponds to the cases where $h_i(x_i)$ is monotone decreasing for $x_i \in [1, +\infty)$; and the third case corresponds to the cases where $h_i(x_i)$ is first monotone decreasing for $x_i \in [1, \bar{x}_i^{\text{th}}]$, and then monotone increasing for $x_i \in [\bar{x}_i^{\text{th}}, +\infty)$. Based on this result, we can find $x_i^{\min}$ for Equation (4), as given by the following:

Remark 2. Recall that $x_i^{\min} \in \mathbb{Z}^+$ is defined as the positive integer such that $h_i(x_i)$ is minimized in the positive integer domain, whereas x_i^{th} minimizes $h_i(x_i)$ in the domain of positive integers. Lemma 3 gives us that

$$x_i^{\min} = \begin{cases} 1 & \text{if } r_i(1) \geq 0 \\ +\infty & \text{if } r_i(1) < 0, \lim_{x_i \rightarrow +\infty} h'_i(x_i) \leq 0 \\ \lceil x_i^{\text{th}} \rceil & \text{if } r_i(1) < 0, \lim_{x_i \rightarrow +\infty} h'_i(x_i) > 0, \\ & \text{and } h_i(\lceil x_i^{\text{th}} \rceil) < h_i(\lfloor x_i^{\text{th}} \rfloor) \\ \lfloor x_i^{\text{th}} \rfloor & \text{otherwise,} \end{cases} \quad (7)$$

and $\lceil x_i^{\text{th}} \rceil$ can be found by a simple binary search. The first and second case in (7) corresponds to the first and second case in (6), whereas the third and the fourth cases in (7) correspond to the third one in (6). The reason is that, although x_i^{th} minimizes $h_i(x_i)$, both cases of $h(\lceil x_i^{\text{th}} \rceil) < h_i(\lfloor x_i^{\text{th}} \rfloor)$ and $h(\lceil x_i^{\text{th}} \rceil) > h_i(\lfloor x_i^{\text{th}} \rfloor)$ may be valid.

Based on Lemma 3, the optimal deployment solution x_i lies in $[1, \lceil x_i^{\text{th}} \rceil]$. We call $\lceil x_i^{\text{th}} \rceil$ the maximum number of sensor nodes that are reasonable to be deployed in region i . This is because if we deploy more than $\lceil x_i^{\text{th}} \rceil$ nodes in region i , it is always worse than deploy $\lceil x_i^{\text{th}} \rceil$ nodes there. Thus, we have

the restricted node placement problem as follow:

$$\min_{\mathbf{x}} \quad \sum_{i=1}^N x_i \quad (8a)$$

$$\text{s.t.} \quad \sum_{i=1}^N \frac{c_i + cx_i}{\alpha_i g(x_i)} \leq 1, \quad (8b)$$

$$x_i \leq \lceil x_i^{\text{th}} \rceil, \forall i, \quad (8c)$$

$$x_i \in \mathbb{Z}^+, \forall i. \quad (8d)$$

Compared to Problem (5), Problem (8) introduces an additional Constraint (8c). However, it does not changes the optimal solution, as given by the following lemma:

Lemma 4. Consider the node deployment Problem (5). Its optimum is the same as the optimum of Problem (8).

From Lemma 4, the optimal solution of Problem (8) is also the optimal solution of Problem (5). This result allows us to solve the deployment Problem (5) by solving an easier one, i.e., Problem (8), as will be described in the next subsection.

B. Problem Solution

We will solve Problem (5) by solving Problem (8). Although Problem (8) is an integer optimization, we will develop an algorithm to find the optimal solution. We first provide the solution algorithm, and then we show its optimality.

The input of the algorithm is the energy consumption model (i.e., c_i and c) and the energy transmission model (i.e., α_i and the function $g(x)$). We define the marginal contribution of deploying an additional node in l_i with x_i nodes to be $\Delta h_i(x_i^{(k)}) \triangleq h_i(x_i^{(k)}) - h_i(x_i^{(k)} - 1)$. The algorithm uses a greedy improvement, i.e., it greedily deploys one sensor node into the region after another, until Constraint (8b) is satisfied, or the marginal contribution for every region is non-positive. Recalling that $x_i \in \mathbb{Z}^+$, we have that $x_i \geq 1, \forall i$. Thus, initially we set $x_i^{(0)} = 1, \forall i$, and let $\mathcal{L} = \{i | \Delta h_i(x_i^{(k)}) > 0\}$ as the set of regions whose marginal contribution is positive. In each iteration k , if $\mathbf{x}^{(k)} = [x_1^{(k)}, \dots, x_n^{(k)}]^T$ does not satisfy Constraint (8b), we find the region with the largest marginal benefit to deploy an extra sensor node, i.e.,

$$l^{(k)} = \arg \max_{i \in \mathcal{L}} \Delta h_i(x_i^{(k)}). \quad (9)$$

Then, we do the following update:

$$x_i^{(k+1)} = \begin{cases} x_i^{(k)} + 1 & \text{if } i = l^{(k)}, \\ x_i^{(k)} & \text{otherwise,} \end{cases} \quad (10)$$

and update $\mathcal{L}$. The complete algorithm is shown in Algorithm 1. We call the algorithm Greedy Based Deployment (GBD) algorithm, and we denote the output of the algorithm by $\mathbf{x}^{\text{GBD}}$.

In the following, we analyze the performance of the GBD algorithm. We first show that $\mathbf{x}^{\text{GBD}}$ is a feasible solution for Problem (8) by the following lemma:

Lemma 5. Consider a feasible Problem (8). The solution achieved by the GBD algorithm, $\mathbf{x}^{\text{GBD}}$, is a feasible solution of Problem (8).

Algorithm 1 Greedy-based deployment (GBD) algorithm

Input: $c, \alpha, g(\cdot)$

Ensure: Deployment x for Problem (5).

- 1: Set $x_i^{(k)} = 1, \forall i, k = 0, \mathcal{L} = \{i | \Delta h_i(x_i^{(k)}) > 0\}$
- 2: Find $x_i^{\min}$ according to (7)
- 3: **if** $\sum_{i=1}^N \lim_{x_i \rightarrow x_i^{\min}} h_i(x_i) \leq 1$ **then**
- 4: **while** $\sum_{i=1}^N h_i(x_i^{(k)}) > 1$ **do**
- 5: **if** $\mathcal{L} = \emptyset$ **then**
- 6: **return** The problem has no feasible solutions
- 7: **else**
- 8: Find $l^{(k)}$ according to (9).
- 9: Update $x_i^{(k+1)}$ according to (10), set $k \leftarrow k + 1$, and update $\mathcal{L}$
- 10: **end if**
- 11: **end while**
- 12: Set $x = x^{(k)}$.
- 13: **return** x .
- 14: **else**
- 15: **return** The problem has no feasible solutions
- 16: **end if**

Recall that Problem (8) is a restricted version of Problem (5). We can directly achieve that the solution achieved by the GBD algorithm is also a feasible solution of Problem (5). Then, the remaining problem is whether the solution achieved by the GBD algorithm is also an optimal solution of Problem (5). The optimality of the GBD algorithm is described in the following theorem.

Theorem 1. *Consider feasible optimization Problem (5). Then, the GBD algorithm achieves an optimal deployment in terms of the number of deployed sensor nodes. That is, there exists no other deployment x , such that $\sum_{i=1}^N x_i < \sum_{i=1}^N x_i^{\text{GBD}}$.*

Theorem 1 shows that our GBD algorithm achieves an optimal solution of the deployment Problem (5), and the WPSN is immortal for networking purposes¹. Based on the deployment achieved by the GBD algorithm, if we can find the WET scheduling y and sensing scheduling z , such that Constraints (2c)- (2e) are satisfied, then the deployment is the optimal deployment. We will describe the problem that finds the WET scheduling and sensing scheduling under the GBD deployment in the next section. Before that, we provide more discussions on the deployment subproblem and the GBD algorithm in the following subsection.

C. Performance Analysis and Discussions

In this subsection, we will first provide a lower bound of the optimum of Problem (5), which will be used for comparison in the simulation section. We also analyze the time complexity of the algorithm, and discuss the cases where we have additional

¹In reality, this deployment is a lower bound of the nodes to deploy for the immortality of the WSN. The reason is that node failures and uncertainty in the parameters should be also considered. Thus, we need to deploy more nodes in each region in general to be more robust. It could be one of our future works.

constraints on the total number of nodes that can be deployed in a region.

1) *Lower bound of the optimum:* The basic idea of the lower bound is integer variable relaxation. In details, observing that the integer constraints in Problem (5) make the problem non-trivial, we relax these constraints to non-negative constraints, such that a lower bound can be achieved. The relaxed problem is as follows:

$$\min_x \sum_{i=1}^N x_i \quad (11a)$$

$$\text{s.t.} \quad \sum_{i=1}^N \frac{c_i + cx_i}{\alpha_i g(x_i)} \leq 1, \quad (11b)$$

$$1 \leq x_i, \forall i. \quad (11c)$$

Problem (11) is achieved by relaxing the positive integer Constraint (5c) of Problem (5) to be the positive Constraint (11c). Recall from Lemma 3 that $h_i(x_i)$ is convex in region $[1, x_i^{\text{th}}]$, and its convexity is not certain in region $[x_i^{\text{th}}, +\infty)$. Therefore, we can not ensure that Problem (11) is a convex optimization problem. However, according to Lemma 3 and the arguments for Lemma 4, the optimal solution of Problem (11) must lie in $x_i \in [1, x_i^{\text{th}}], \forall i$. Thus, we can rewrite Problem (11) to the following one without changing the solution:

$$\min_x \sum_{i=1}^N x_i \quad (12a)$$

$$\text{s.t.} \quad \sum_{i=1}^N \frac{c_i + cx_i}{\alpha_i g(x_i)} \leq 1, \quad (12b)$$

$$1 \leq x_i \leq x_i^{\text{th}}, \forall i. \quad (12c)$$

The convexity of the relaxed problem (8) is given by the following lemma:

Lemma 6. *Consider Problem (12) where $c_i, \alpha_i > 0$ for all i , $g'(x_i) \geq 0, g''(x_i) \leq 0$ for all $x_i \geq 1$, and $g(1) = 1$. It is a convex optimization problem.*

Proof: From Lemma 3 it follows that $h_i(x_i) = (c_i + cx_i)/(\alpha_i g(x_i))$ is convex in the region $[1, x_i^{\text{th}}]$. Thus, Constraint (12b) and Constraint (12c) are convex. In addition, the objective function is convex. This result gives us that Problem (12) is convex. ■

According to Lemma 6, we can efficiently achieve the optimal solution of Problem (11), denoted by x_i^{re} , by solving the convex Problem (12). Denote $f^{\text{re}} = \sum_{i=1}^N x_i^{\text{re}}$, and f^* the optimum of Problem (5). Then, from the fact that Problem (12) is a relaxation of Problem (5), we have that f^{re} is a lower bound of f^* . Besides, one may achieve a feasible solution of Problem (5) based on x_i^{re} . One way is taking $\lceil x_i^{\text{re}} \rceil$ as a solution (please refer to previous work [11] for more details). This solution is suboptimal, and we will use it in the simulation for comparison purpose.

2) *Complexity of the GBD algorithm:* We are also interested in the complexity of the GBD algorithm. Notice that if Problem (5) has a feasible solution, then the algorithm runs f^* number of iterations. In each iteration, the complexity

comes from Line 8 of the algorithm, whose complexity is $\mathcal{O}(N)$. Thus, the remaining is to find the number of iterations the GBD algorithm will have. Notice that $g(x)$ should be bounded. The reason is that, if it is not bounded, then the total energy that is harvested by the nodes in the same region will be larger than the transmitted energy, which contradicts to the conservation of energy. Therefore, for each region i , the maximum number of nodes that is reasonable to be deployed at the region, $\lceil x_i^{\text{th}} \rceil$, is also bounded. Then, from Constraint (8c) we have that the optimum should satisfies $f^* = \sum_{i=1}^N x_i^* \leq \sum_{i=1}^N \lceil x_i^{\text{th}} \rceil$, where x_i^* is the optimal solution. Notice that $\lceil x_i^{\text{th}} \rceil$ is independent to the number of regions N . Consequently, we have that f^* is bounded by $\mathcal{O}(N)$. Together with the complexity of each iteration ($\mathcal{O}(N)$), we have that the time complexity of the GBD algorithm is $\mathcal{O}(N^2)$. We can conclude that the GBD algorithm is an efficient algorithm to achieve the optimal solution of Problem (5).

3) *Extension for realistic cases:* In realistic scenarios, it may have a constraint of the total number of nodes that can be deployed in a region. Denote x_i^{max} the total number of nodes that can be deployed in region i . In this case, we can still apply the GBD algorithm by some simple modifications. More specifically, if x_i^{max} is larger than x_i^{min} , then such a constraint does not affect the deployment in region i . Otherwise, no more nodes will be deployed in that region when $x_i = x_i^{\text{max}}$. Based on this, we can revise the feasible checking step (Line 3) of the GBD algorithm to be $\sum_{i=1}^N \lim_{x_i \rightarrow \min\{x_i^{\text{min}}, x_i^{\text{max}}\}} h_i(x_i) \leq 1$, and the set $\mathcal{L}$ in (9) to be $\mathcal{L} = \{i | \Delta h_i(x_i^{(k)}) > 0 \wedge x_i^{(k)} < x_i^{\text{max}}\}$. With these modifications, the performance of the algorithm in terms of complexity and optimality will not change. The proofs are similar to the ones we present in the paper. Due to the limited space, we skip the proofs here.

Besides of the constraint mentioned above, we should mention that the actual harvested and consumed energy of a sensor node in a timeslot may be different to the averaged value we used in the modelling, for example, due to fast fading of channels. Such a dynamic may make the WSN that is achieved by the proposed algorithm run out of energy at some timeslot. However, before the deployment of the sensor nodes, it is impossible for us to know these exact dynamics of the network in advance. The possibility that our WSN fails due to such dynamics depends on how large the variation of the actual dynamics to the averaged/expected value is, and how large battery capacity the sensor nodes have. In general, with larger battery capacity, and the smaller variation, the WSN achieved by our algorithms is less-likely to run out of energy. Therefore, to make the WSN more robust against the dynamics, we can equip the nodes with a battery of larger capacity, or maybe deploy more sensor nodes. We will also see whether our solution algorithm is robust against network dynamics in the simulations.

V. WET SCHEDULING AND NODE ACTIVATION

In the previous section, we have presented the solution algorithm for the node placement problem. Based on such a deployment, we will describe the solution of the WET scheduling problem, and show that, under certain requirement

Algorithm 2 Max-Activation algorithm

Input: $E_{ij}(t), \forall j$.

Ensure: Activation $z_{ij}(t)$ for region i .

- 1: Find $k \leftarrow \arg \max_j \{E_{ij}(t)\}$
 - 2: Set $z_{ik}(t) = 1$ and $z_{ij} = 0, \forall j \neq k$.
 - 3: **return** $z_{ij}(t), \forall j$.
-

Algorithm 3 W-scheduling algorithm

Input: $E_{ij}(t), \forall i, j, c_i$.

Ensure: WET schedule at $t, y_i(t)$.

- 1: Set $E_i(t) \leftarrow \min_j \{E_{ij}(t)\}, \forall i$.
 - 2: Find $k \leftarrow \arg \min_i \{E_i(t)x_i/(c_i + cx_i)\}$.
 - 3: Set $y_k(t) = 1$ and $y_i(t) = 0, \forall i \neq k$.
 - 4: **return** $y_i(t), \forall i$.
-

of the battery size of the nodes, the deployment and the scheduling can ensure that the WPSN be immortal. More specifically, given the node deployment, we need to find the WET scheduling and node activation scheme, to make sure that $E_{ij}(t) \geq 0$ for all i, j, t .

We first provide the activation scheme $z_{ij}(t)$ in each region as follows. The principle is that, we activate the node with the maximum residual energy $E_{ij}(t)$ in region l_i at timeslot t , i.e., $z_{ij}(t) = 1$ if and only if j is the smallest index such that $E_{ij}(t) \geq E_{ik}(t)$ for all $k \neq j$. We call such an activation scheme *Max-Activation*, as shown in Algorithm 2. Recall the assumption that every node in the same region has the same energy consumption rate and charging rate. We use a virtual node $\tilde{v}_i$ to represent the sensor node with the minimum residual lifetime in l_i . Then, the residual energy of $\tilde{v}_i$ is $E_i(t) \triangleq \min\{E_{ij}(t)\}$, and the dynamic of $\tilde{v}_i$ is the lower envelope of the energy dynamics of the nodes in l_i . As long as the virtual node does not run out of energy, all the sensor nodes in that region do not run out of energy. Recalling that, in any timeslot, only the sensor node with the maximum residual energy among the nodes in the same region consumes energy $c_i + c$, and the other nodes consumes c , we have that the virtual energy consumption rate² of $\tilde{v}_i$ is $c_i/x_i + c$. Then, the minimum lifetime of l_i is $E_i(t)x_i/(c_i + cx_i)$, and we also call it the lifetime of the region.

Based on the concept of the virtual node, and the lifetime of the region, we provide the WET scheduling at the eBS. The idea is to charge the region with the minimum lifetime, i.e., $y_i(t) = 1$ if and only if i is the minimum index that satisfies $E_i(t)x_i/(c_i + cx_i) \leq E_j(t)x_j/(c_j + cx_j)$ for all $j \neq i$, as shown in Algorithm 3. For simplicity, we call such a WET scheduling *W-scheduling*.

Then, we are going to show that, under a mild requirement, Condition (5b) is sufficient so that the WPSN is immortal, as shown in the following theorem.

Theorem 2. Consider a WPSN $(L, c, \alpha, x, y, z, E, B, g)$.

²This rate corresponds to the case where all the sensor nodes in l_i have the same residual energy. Thus, they take turns to activate with period x_i . Then, in every x_i timeslots, the residual energy of all the sensor nodes reduces by $c_i + cx_i$, which means that, averagely the virtual node $\tilde{v}_i$ consumes $c_i/x_i + c$ in a timeslot.

If the WPSN satisfies $E_{ij}^b \leq E_{ij}(0) \leq B$ for all i, j , $\sum_{i=1}^N h_i(x_i) \leq 1$, where $E_{ij}^b = \max\{(c_i/x_i + c) \sum x_i, \alpha_i\}$ is a bound of initial battery of node v_{ij} , and $\mathbf{y}, \mathbf{z}$ is achieved by W-scheduling algorithm and Max-Activation algorithm respectively, then Condition (5b) is sufficient for immortality.

Theorem 2 gives us that the proposed algorithms achieves a feasible solution for Problem (2) if the battery size of the nodes satisfies a certain requirement. Therefore, we can design the battery size of the nodes based on such a requirement, and we will show in the simulation that this requirement is easy to satisfy. We will also show that, under this condition, the solution achieved by the proposed algorithm is an optimal solution of Problem (2), by the following theorem:

Theorem 3. Consider the Joint Node Deployment and WET Scheduling Problem (2). If the battery capacity of the sensor nodes satisfies $E_{ij}^b \leq E_{ij}(0) \leq B$ for all i, j , then the deployment $\mathbf{x}$ achieved by GBD algorithm, the $\mathbf{y}$ achieved by W-scheduling, and the $\mathbf{z}$ achieved by Max-Activation is an optimal solution of the problem.

As sensor nodes are generally designed for long term monitoring, they usually are low power consumption devices. Thus, it is not difficult to have the battery of sensor nodes satisfies the requirement of $\max\{(c_i/x_i + c) \sum x_i, \alpha_i\} \leq B$. Furthermore, if the initial energy of the sensor nodes in the same region is the same, then with the Max-Activation scheme, these nodes activate periodically one by one. Thus, it is a simple enough activation scheme. We conclude that, the GBD algorithm, the W-scheduling, and the Max-Activation can be used in practice to efficiently solve the joint node deployment and WET scheduling problem.

VI. SIMULATIONS

We present the results of numerical simulations to illustrate our analysis and discuss the performance of the proposed algorithms. The WSN consists of one base station and N sensor nodes with a star topology. The network parameters are set as follows by default³: The base station is located at the origin. It transmits RF energy with 3 Watts, with an energy carrier in the frequency 915 MHz. The centres of N regions are randomly located within an annulus region with inner radius 15 meters and outer radius 50 meters. Each region i requires a sampling rate λ_i bits per second. The energy consumption of transmitting a unit bit is 10^{-6} Joules/bit. Then, we have $c_i = 10^{-6} \lambda_i$. The static power consumption of a sensor node is $c = 10^{-6}$ Watts. For each node, α_i is determined by two factors: path loss and RF-DC conversion rate. The path loss from the base station to a sensor node is determined by the Friis equation, and the RF-DC conversion rate of each sensor node is 0.5. The function $g(x)$ is set to be $g(x) = (1 - q^x)/(1 - q)$, with $q = 0.9$. The dynamic of the

node's battery follows Eq. (1), where $y_i(t)$ is determined by the algorithm used in the base station.

First, we evaluate the probability that the WSNs be immortal under different number of regions and required sampling rates, if only one sensor node is deployed at each region. The number of regions to be monitored, ranges from 1 to 30. For each test case, we examine the immortality of the WSN according to Lemma 1. We simulate 200 times with different locations of the regions, and then take the average as the results, which are shown in Fig. 2(a). The lines with circles, squares, and crosses represent that the required sampling rate of each region, λ , are uniform randomly chosen from $[7, 10]$, $[3, 7]$, $[1, 3]$ bits/s, respectively. It is shown that, even when λ is low, i.e., in average 2 bits/s, the WSNs is hard to be immortal under WET when there are more than 26 regions to monitor and only one node is deployed at each region. The probability of immortality of the WSNs drops dramatically when λ increases. This result shows that, the idea of deploying only one node at each region does not scale with the network size. Thus, for a WSN of large size, we need to deploy additional nodes in each region, such that the WSN can be immortal.

Next, we evaluate the node deployment algorithm, i.e., GBD algorithm, in terms of the number of total sensor nodes to be used. The performance of GBD algorithm (square marks), as shown in Fig. 2(b), is compared with that of the relaxation approach (circle marks) and a random deployment approach (square marks). For the random deployment, we deploy sensor nodes one by one in a region that is independently and randomly chosen, until the network becomes immortal according to Lemma 1. We also compare the total number of sensor nodes of the GBD algorithm to the lower bound (cross marks) achieved by the relaxed optimization Problem (11). Fig. 2(b) shows the total number of sensor nodes achieved by different algorithms with different field size N , where λ_i are uniform randomly chosen from $[7, 10]$ bits/s. The results show that, due to the sub-additive behaviour of $g(x)$, the number of required sensor nodes grows superlinearly with N . Furthermore, we can see that, the required number of sensor nodes achieved by GBD algorithm is very close to the lower bound, which can be explained by the optimality of the GBD algorithm according to Theorem 1. Compared to the relaxation approach and the random approach, the GBD algorithm saves approximately 9% and 16% of the total required nodes. For $N = 20$, in average 5 nodes per region is needed, such that the WSN be immortal for the networking purpose. It shows that it is cost-effective to deploy multiple nodes in the same region to receive enough energy for sensing and data uploading.

Then, we examine that, if the battery buffer sizes of the sensor nodes satisfy the requirement in Theorem 2, the WSN becomes immortal with the use of GBD algorithm to deploy the nodes, the use of W-scheduling for WET at the base station side, and Max-Activation scheme described in Section V. For a WSN deployment given by GBD algorithm, we determine the energy transmission $y_i(t)$ and the activation $z_{ij}(t)$, and update the nodes' residual energy based on (1). In each timeslot t , we find the sensor node with the minimal percentage of residual energy, i.e., $E_{ij}(t)/B$, and denote it by the minimal percentage of residual energy among all the sensor nodes at that timeslot.

³For the energy consumption model, the value is in the scale of the ones in the datasheet of MicaZ (it is approximately 3×10^{-6} Watts in sleep mode, and in the transmission mode it is 42 mW for data rate 250kbps, which results in approximately 4×10^{-6} Joule/bit), and the TI CC2420 transceiver [28] (approximately 2.2×10^{-7} Joules/bit for data transmit).

Fig. 2. (a) The probability of wirelessly powered sensor networks to be immortal with different number of regions N and sampling rates λ ; (b) Comparison of the required number of sensor nodes achieved by different algorithms.

Fig. 3. (a) The dynamic of the minimum percentage of residual energy; (b) The comparison of our scheme with non optimal deployment and non optimal energy transmission.

In the simulation, $N = 30$, and λ is uniform randomly chosen from $[7, 10]$ bits/s. Fig. 3(a) shows an example of the dynamic of the minimal percentage of residual energy among all the sensor nodes (blue solid line), and the dynamic of the residual energy of a sensor node in region l_1 (red dotted line). We can see that, none of the sensor node depletes its battery, and the minimum percentage of residual energy remains at approximate 75%. Moreover, since the minimum residual energy of each node is above approximately 75% of its battery buffer, we can see that the bound $E_{i,j}^b$ is quite loose. In the simulation, the value of such a bound is at the scale of 10^{-4} Joules, which is much smaller than the capacity of a rechargeable battery. Therefore, we conclude that, the battery buffer requirement is easy to meet, and thus under the node deployment by GBD algorithm, W-scheduling at the base station side, and Max-Activation scheme in each region, the WSNs can be immortal.

Next, we compare our scheme with the two other suboptimal cases. One is that the deployment of sensor nodes is not optimal (its deployment is the same as the GBD deployment except that one less sensor node is deployed in the first region) whilst the WET scheduling and node activation are the same as our scheme. The other one is that we deploy nodes by GBD algorithm and the nodes use Max-Activation whilst the eBS charges a random region in a timeslot. The result is shown in Fig. 3(b). The X-axis represents the timeslots, and the

Y-axis represents the minimal percentage of residual energy among all the sensor nodes at that timeslot. The blue, red, and green lines correspond to our scheme, the scheme where node deployment is not optimal, and the scheme where the WET scheduling is not W-scheduling. For our scheme, the residual energy of the nodes are always positive, as expected. For the non-optimal node deployment case, we can see the trend of residual energy of the nodes is decreasing. It means that, even the difference is just one node, the non-optimal node deployment results in a finite network lifetime. For the non-optimal WET scheme, we can see that the nodes run out of battery at around 246 timeslots. Even with the optimal node deployment, the network lifetime is very short due to the bad WET scheduling. Therefore, the scheduling of the WET also plays an important role to make the WPSN immortal. That is why we should jointly consider the placement and the WET scheduling.

Last, we check how robustness our solution is against the variations of the consumed power and harvested power of the nodes. In the simulation, N is 30, and the λ is uniform randomly chosen from $[2, 10]$ bits/s. We consider that the actual consumed power and harvested power of a node in a timeslot is the averaged value plus a noise. For the consumed power, the noise follows a zero mean Gaussian distribution whose standard deviation is 0.05 times of the averaged consumed power. For the harvested power, the noise

Fig. 4. (a) The dynamic of the minimum percentage of residual energy with different standard deviation of the harvested power; (b) The comparison of the minimum percentage of residual energy with additional sensor nodes.

is also a zero mean Gaussian distribution whose standard deviation is σ times of the average harvested power. We set σ to be 0, 0.01, and 0.02 respectively, to see how the robustness of the proposed algorithm is. The result is shown in Fig. 4(a), where the X axis is the timeslot, and Y axis is the minimal percentage of residual energy among all the sensor nodes at that timeslot. The blue curve, red curve, and the green curve corresponds to the case where $\sigma = 0$, $\sigma = 0.01$, and $\sigma = 0.02$, respectively. We can observe that, for all the cases, the WSN does not run out of energy. Therefore, our solution of deployment and energy transmission is robust against some variations of the network. We also consider the cases where the variation is large, whose result is shown in Fig. 4(b). In the simulation, we set $\sigma = 0.2$. In this case, the WSN runs out of energy at around 30000 timeslots, due to the actual network dynamics, as shown by the red curve. However, if we deploy one more node for every region, the WSN does not run out of energy, as shown by the blue curve. This result shows how we can improve the robustness of the network system by deploying additional nodes.

In summary, the proposed algorithms are effective to make the WPSN immortal and outperform other suboptimal schemes.

VII. CONCLUSIONS AND FUTURE WORKS

In this paper, we studied the joint problem of the node deployment and the scheduling of the wireless energy transfer in wirelessly powered sensor networks, such that the network lifetime be infinite. We analyzed the necessary condition on the deployment for the network immortality. This condition allows us to decouple the original problem into a node deployment problem and a scheduling problem. To satisfy such a necessary condition, we developed an algorithm to achieve the optimal node deployment. Finally, we proposed greedy algorithms for energy transmission at the base station side and for the sensor node activation. We proved that, if the initial energy of sensor nodes is above a threshold, the sensor network becomes immortal with the proposed deployment and the scheduling algorithm. Our analysis and simulation results showed the effectiveness of the proposed algorithm, and it outperforms the cases where the placement and the WET scheduling is not jointly considered.

In the future, we plan to study the problem with time varying charging efficiency. Also, we will consider the cases with multiple energy base stations or mobile chargers.

APPENDIX A DISCUSSION ON $g(x)$

Here, we provide two motivating examples. These examples give us the intuition in modelling the function $g(x)$ that represents the relationship of the expected total harvested energy of the sensor nodes in a same region with respect to the number of nodes in the region. In general, when we deploy additional nodes in a region, the eBS may need to change its energy beamforming, such that the additional nodes are also charged with a certain power. The change of energy beamforming may affect the harvested energy by the existing nodes. In addition, due to the shadowing effect, the additional nodes may also affect the channels from the eBS to the existing nodes. Therefore, the expected total harvested energy depends on the channel fading and the energy beamforming of the eBS. It motivates us to understand how $g(x)$ behaves under the change of energy beamforming and channel fading due to the change of number of nodes. Consequently, we take such two factors into account in our motivating examples.

In the first example, we consider the case where the eBS optimizes the energy beamforming based on the channel to each sensor node in a region. We apply a commonly used model as follows. Recall that each sensor node has one rectenna to harvest energy. Given a region with n nodes, we denote the channel from the eBS to the i -th node by $\mathbf{h}_i \in \mathbb{C}^{M \times 1}$, where M is the number of antenna of the eBS. If the eBS steers an energy beam $\mathbf{w} \in \mathbb{C}^{M \times 1}$, then the received power of node i is $P_i^r = \mathbf{w}^H \mathbf{h}_i \mathbf{h}_i^H \mathbf{w} = \text{tr}[\mathbf{H}_i \mathbf{W}_i]$, where $\mathbf{H}_i = \mathbf{h}_i \mathbf{h}_i^H$ and $\mathbf{W}_i = \mathbf{w} \mathbf{w}^H$. The total energy that is harvested by the nodes is $\sum_{i=1}^n P_i^r = \text{tr}[(\sum_{i=1}^n \mathbf{H}_i) \mathbf{W}] = \text{tr}[\mathbf{H}(n) \mathbf{W}]$, where $\mathbf{H}(n) \triangleq \sum_{i=1}^n \mathbf{H}_i$ is defined as the equivalent channel covariance from the eBS to all the sensors in the region. To maximize the total harvested energy, we can achieve the optimal beamforming vector as the eigenvector corresponding to the largest eigenvalue of $\mathbf{H}(n)$. With it, we can analyze the behaviour of $g(n)$ with respect to n by simulation as follows.

Fig. 5. The difference of $g(x)$ with respect to x under the model of the first motivating example.

We place the eBS at the origin, and set the center of a square region of interest at $(10, 0)$ where the unit is expressed in terms of meters. The side length of the square is 2 meters. We deploy n sensor nodes uniform randomly in the region. Based on the locations of the eBS and each sensor node i , we use Rician fading to model the channel h_i according to [33]. Then, we calculate the equivalent channel covariance $\mathbf{H}(n)$, optimize the beamforming, and achieve the sum of energy that is harvested by the n sensor nodes. We divide the sum of energy by the averaged harvested energy when $n = 1$ to be $g(n)$. We vary n from 1 to 10. For each value we make 50000 different deployment cases, and the final result $g(n)$ is the average of these 50000 cases. To make it easier to observe the behaviour of $g(n)$ with respect to n , we plot $\Delta g(n) \triangleq g(n) - g(n-1)$ with respect to n , as shown in Fig. 5.

We observe that, $\Delta g(x)$ drops from 1 to 0.97 when x increases from 1 to 2, and it remains almost constant when x is larger or equal to 2. Therefore, we can say that $\Delta g(x)$ is monotone decreasing. It follows that the gain $g(x)$ in this example can be considered as concave. However, under this modelling, we will have that $g(x)$ is not bounded, which is counter-intuitive. The main reason is that the nodes in the model are considered as a perfect node with no size, and therefore the deployment of a new node does not affect the channel of the other existing nodes.

Notice that, when we deploy a new node in a region, the new node may partially shadow some existing nodes, or it may be shadowed by some existing nodes. Therefore, we consider such a shadowing effect here in the second example. To capture such a shadowing effect, we use a simplified but effective example as follows. Consider the case where the eBS steers a sharp energy beam towards region i , as shown in Fig. 6. Recall that the size of the region is comparatively much smaller than the distance from the eBS to the region. We model the energy beam as a group of parallel rays, and each ray carries a same amount of the energy. To model the shadowing effect, we assume that each sensor node has a certain size, which will shadow other nodes. The energy a node can harvest is proportional to the area that is exposed to the energy ray. We project the sensor nodes onto an axis that is orthogonal to the energy rays. Shadowing occurs when the projections of two or more nodes overlap. For example, if the projection of the first node on the axis is $[1, 5]$, and the projection of the second node is $[3, 7]$. Then, the part $[3, 5]$ of the second node

Fig. 6. The second motivating example, with the consideration of shadowing of nodes.

Fig. 7. The difference of $g(n)$ with respect to n under the model of the second motivating example.

is shadowed by the first node. The total harvested energy is proportional to the sum of the length of the projections that are exposed to the rays. In the example above, the total length is 6 (because the segment $[1, 7]$ is exposed to the rays); whereas if the two nodes do not shadow each other, the total length of the projections that are exposed to the rays is 8.

Based on this model, we can analyze the function $g(n)$ with respect to the number of nodes in the region by simulation. More specifically, we set the width of energy arrays to be 1 meter, and let the length of each sensor node be 5 centimeters. We uniform randomly deploy n nodes in the region, where n ranges from 1 to 30. We measure the length of the projections that is exposed to the energy ray with different n , and divide it by 5 centimeters (the length of projections that is exposed to the energy beam when there is only one node) to be $g(n)$. For each value of n , we make 50000 different deployment cases, and the final result is the average of these 50000 cases. We plot $\Delta g(n) \triangleq g(n) - g(n-1)$ with respect to n , as shown by the blue line with square marks in Fig. 7. As we can see, $\Delta g(n)$ is monotone decreasing and positive, therefore, $g(n)$ is monotone increasing and concave. We find out that the curve can be well fitted by a geometric progression of ratio $q = 0.949$ (as shown by the red line with cross marks), and q depends on the ratio of the size of a node and the size of the region. Therefore, $g(n)$ is well fitted by a geometric series. As $g(1) = 1$, we have that $g(n) = (1 - q^n)/(1 - q)$. We can examine that, such a $g(n)$ satisfies all the assumptions we made in Section III. This model of $g(n)$ is also used in the simulation section.

Although the above model is simple, we observe that the shadowing effect of the sensor nodes in a region is similar

to coverage. In many coverage problems, a submodularity property usually exists [34], i.e., the additional benefit, in terms of coverage area, of deploying an additional node to a group of nodes is less than or equal to the additional benefit to deploy that node to a subset of the group of the nodes. This property gives us the intuition to assume that $g(x)$ is monotone increasing and concave, which allows us to derive general analytical results.

APPENDIX B PROOFS

A. Lemma 1

Proof: As the WSN is immortal, there exists a corresponding WET scheduling. Given a large enough duration T , we denote β_i the percentage of timeslots that the base station transfers energy to region l_i . Then, we have

$$\sum_{i=1}^N \beta_i = 1. \quad (13)$$

Also, we have that, for each region l_i , the total energy consumption should be less than or equal to the charged energy (otherwise the energy of the nodes in l_i will eventually run out). Recalling that only one node is active in a timeslot, we have that the total energy consumption is $c_i T + x_i c T$. For the charged energy, it is $\alpha_i g(x_i) \beta_i T$. Thus, we have that $\alpha_i g(x_i) \beta_i \geq c_i + x_i c$ for all i . It gives us that

$$\beta_i \geq \frac{c_i + c x_i}{\alpha_i g(x_i)}, \forall i. \quad (14)$$

We replace β_i in (13) by (14) and achieve that

$$\sum_{i=1}^N \frac{c_i + c x_i}{\alpha_i g(x_i)} \leq 1,$$

which completes the proof. ■

B. Lemma 2

Proof: It can be proved by contradiction. We know from Lemma 1 that, if Problem (2) has a feasible solution, then there exists a $x_i \in \mathbb{Z}^+$ that satisfies $\sum_{i=1}^N h_i(x_i) \leq 1$. Notice that $x_i^{\min}$ is defined as the positive integer that minimizes $h_i(x_i)$. Therefore, we have that for all $x_i \in \mathbb{Z}^+$

$$\sum_{i=1}^N h_i(x_i) \geq \sum_{i=1}^N \lim_{x_i \rightarrow x_i^{\min}} h_i(x_i).$$

If Inequality (3) does not hold, we have that for all $x_i \in \mathbb{Z}^+$, $\sum_{i=1}^N h_i(x_i) > 1$, which is contradicted to that Problem (2) has a feasible solution according to Lemma 1. Therefore, if Problem (2) has a feasible solution, Inequality (3) must hold. ■

C. Lemma 3

Proof: The derivative of $h_i(x_i)$ is given as follows:

$$h'_i(x_i) = \frac{dh_i}{dx_i} = \frac{c \alpha_i g(x_i) - (c_i + c x_i) \alpha_i g'(x_i)}{\alpha_i^2 g^2(x_i)} = \frac{r_i(x_i)}{\alpha_i^2 g^2(x_i)}.$$

Note that the denominator is positive for $x_i \geq 1$. We have that $h_i(x_i)$ is increasing (decreasing) in the region of x_i where $r_i(x_i)$ is positive (negative). Then, we check the derivative of $r_i(x_i)$ as follows:

$$\begin{aligned} r'_i(x_i) &= c \alpha_i g'(x_i) - c \alpha_i g'(x_i) - (c_i + c x_i) \alpha_i g''(x_i) \\ &= -(c_i + c x_i) \alpha_i g''(x_i) \geq 0, \end{aligned}$$

where the inequality comes from $c \geq 0, c_i > 0, x_i \geq 1$, and $g''(x_i) \leq 0$. Therefore, if $r_i(1) \geq 0$, i.e., $c g(1) - (c_i + c) g'(1) \geq 0$, $h_i(x_i)$ is monotone increasing in $[1, +\infty)$. If $r_i(1) < 0$, and $\lim_{x_i \rightarrow +\infty} h'_i(x_i) \leq 0$, then $h_i(x_i)$ is monotone decreasing in $[1, +\infty)$. Otherwise, there is one $\bar{x}_i^{\text{th}}$ such that $c \alpha_i g(\bar{x}_i^{\text{th}}) = (c_i + c \bar{x}_i^{\text{th}}) \alpha_i g'(\bar{x}_i^{\text{th}})$, and thus $h_i(x_i)$ is monotone decreasing in $[1, \bar{x}_i^{\text{th}}]$, and monotone increasing in $[\bar{x}_i^{\text{th}}, +\infty)$. To summarize, Equation (6) holds and $h_i(x_i) (x \geq 1)$ achieves its minimum at x_i^{th} .

For the convexity of $h_i(x_i)$, we find its second derivative as follows:

$$h''_i(x_i) = \frac{r'_i(x_i) \alpha_i^2 g^2(x_i) - 2 \alpha_i^2 r_i(x_i) g'(x_i) g(x_i)}{\alpha_i^4 g^4(x_i)} \geq 0,$$

where the inequality comes from $r'_i(x_i) \geq 0, g(x_i) \geq 1, g'(x_i) \geq 0$, and $r_i(x_i) \leq 0$ in $[1, x_i^{\text{th}}]$. Consequently, $h_i(x_i)$ is convex in $[1, x_i^{\text{th}}]$, which completes the proof. ■

D. Lemma 4

Proof: Denote the optimal solution for Problem (8) by $\mathbf{x}^{\text{res}}$. Note that the difference of Problem (5) and Problem (8) is the additional Constraint (8c), which restricts the solution into a smaller region. Thus, the optimum of the minimization Problem (5) is not larger than the optimum of the restricted Problem (8). Therefore, what we need to prove is that the optimum of Problem (5) is also not smaller than the optimum of Problem (8)

Suppose that there exists an integral point $\mathbf{x} = [x_1, \dots, x_N]^T$, which contains an index i , such that $x_i > \lceil x_i^{\text{th}} \rceil$. If $\sum_{j=1}^N (c_j + c x_j) / (\alpha_j g(x_j)) \leq 1$, then we have that

$$\sum_{j=1, j \neq i}^N \frac{c_j + c x_j}{\alpha_j g(x_j)} + \frac{c_i + c \lceil x_i^{\text{th}} \rceil}{\alpha_i g(\lceil x_i^{\text{th}} \rceil)} \leq \sum_{j=1}^N \frac{c_j + c x_j}{\alpha_j g(x_j)} \leq 1,$$

where the first inequality comes from that $h_i(x_i)$ is monotone increasing in region $[x_i^{\text{th}}, +\infty)$. Therefore, we can modify $\mathbf{x}$ by reducing x_i to $\lceil x_i^{\text{th}} \rceil$ such that the resulting point satisfies Constraint (5b) and the objective value does not increase.

Based on this result, if $\mathbf{x}$ is an optimal solution of Problem (5) with some indexes i such that $x_i > \lceil x_i^{\text{th}} \rceil$, we can set all such x_i to be $\lceil x_i^{\text{th}} \rceil$, such that the objective value decreases, and the resulting solution is also feasible for Problem (8). Consequently, the optimum of Problem (5) is no smaller than the optimum of Problem (8), which completes the proof. ■

E. Lemma 5

Proof: We will show that $\mathbf{x}^{\text{GBD}}$ satisfies all the constraints of Problem (8).

For Constraint (8b), according to Lemma 2, if Problem (5) is feasible, $\sum_{i=1}^N \lim_{x_i \rightarrow x_i^{\min}} h_i(x_i) \leq 1$. Thus, the algorithm will go into the branches from Line 4 to 13. If the algorithm outputs a solution $\mathbf{x}^{\text{GBD}}$, Line 4 of the algorithm gives us that $\sum_{i=1}^N h_i(x_i^{\text{GBD}}) \leq 1$. Thus, it satisfies Constraint (8b).

For Constraint (8c), we will show that $x_i^{\text{GBD}} \leq \lceil x_i^{\text{th}} \rceil$ for all i . The reason is that, according to Lemma 3, $h_i(\lceil x_i^{\text{th}} \rceil) \leq h_i(x_i^{\text{th}})$. It means that $\Delta h_i(\lceil x_i^{\text{th}} \rceil) \leq 0$. Thus, when there is a k such that $x_i^{(k)} = \lceil x_i^{\text{th}} \rceil$, then $i \notin \mathcal{L}$ any more. Therefore, according to (9), $l^{(k')} \neq i$ for all $k' \geq k$. As a result, $x_i^{\text{GBD}} \leq \lceil x_i^{\text{th}} \rceil$.

Last, it is easy to know that x_i^{GBD} is positive integer. Thus, it satisfies Constraint (8d).

To summarize, $\mathbf{x}^{\text{GBD}}$ satisfies Constraints (8b)-(8d). Thus, it is a feasible solution for Problem (8). ■

F. Theorem 1

To prove this theorem, we first show the following lemma.

Lemma 7. Consider feasible optimization Problem (5). The deployment achieved by the GBD algorithm at the k -th iteration is $\mathbf{x}^{(k)} = [x_1^{(k)}, \dots, x_N^{(k)}]^T$. Then, for any other deployment $\tilde{\mathbf{x}} = [\tilde{x}_1, \dots, \tilde{x}_N]^T$ with $\tilde{x}_i \leq \lceil x_i^{\text{th}} \rceil$ for all i , such that $\sum_{i=1}^N \tilde{x}_i = \sum_{i=1}^N x_i^{(k)}$, we have that $\sum_{i=1}^N h_i(\tilde{x}_i) \geq \sum_{i=1}^N h_i(x_i^{(k)})$.

Proof: Since $\tilde{\mathbf{x}} \neq \mathbf{x}^{(k)}$ and $\sum_{i=1}^N \tilde{x}_i = \sum_{i=1}^N x_i^{(k)}$, there exists an index pair j and m , such that $\tilde{x}_j < x_j^{(k)} \leq \lceil x_j^{\text{th}} \rceil$ and $x_m^{(k)} < \tilde{x}_m \leq \lceil x_m^{\text{th}} \rceil$. Then, we first show that, we can modify $\tilde{\mathbf{x}}$ to be $\tilde{\mathbf{x}}' = [\tilde{x}_1', \dots, \tilde{x}_N']^T$ by the following operation

$$\tilde{x}_i' = \begin{cases} \tilde{x}_i + 1 & \text{if } i = j \\ \tilde{x}_i - 1 & \text{if } i = m \\ \tilde{x}_i & \text{otherwise,} \end{cases} \quad (15)$$

such that

$$\sum_{i=1}^N h_i(\tilde{x}_i) \geq \sum_{i=1}^N h_i(\tilde{x}_i'). \quad (16)$$

To show (16), it is equivalent to show

$$h_j(\tilde{x}_j) + h_m(\tilde{x}_m) \geq h_j(\tilde{x}_j + 1) + h_m(\tilde{x}_m - 1). \quad (17)$$

Recall Equation (9) that the index of the region with the largest marginal benefit to deploy a sensor node in the k -th iteration is $l^{(k)}$. Notice that $\tilde{x}_j < x_j^{(k)}$, i.e., the $\tilde{x}_j$ -th node that is deployed at region j by Algorithm 1 is deployed earlier than the k -th iteration. Denote that the $\tilde{x}_j$ -th node that is deployed at region j by Algorithm 1 is at the k' -th iteration ($k' < k$), i.e., $l^{(k')} = j$ and $x_j^{(k')} = \tilde{x}_j$. Then, we have that

$$\begin{aligned} h_j(\tilde{x}_j) - h_j(\tilde{x}_j + 1) &= h_{l^{(k')}}(x_{l^{(k')}}^{(k')}) - h_{l^{(k')}}(x_{l^{(k')}}^{(k')} + 1) \\ &\geq h_{l^{(k)}}(x_{l^{(k)}}^{(k')}) - h_{l^{(k)}}(x_{l^{(k)}}^{(k')} + 1) \\ &\geq h_{l^{(k)}}(x_{l^{(k)}}^{(k)}) - h_{l^{(k)}}(x_{l^{(k)}}^{(k)} + 1), \end{aligned} \quad (18)$$

where the first inequality comes from the fact that $k' < k$ and the greedy behaviour of Algorithm 1 that deploy a node to the location with the largest marginal benefits at each iteration, and the second inequality comes from that $x_{l^{(k)}}^{(k)} > x_{l^{(k)}}^{(k')}$ and $h'_{l^{(k)}}(x) \leq 0, h''_{l^{(k)}}(x) \geq 0$ for $x \in [1, x_{l^{(k)}}^{\text{th}}]$ (according to Lemma 3). Similarly, as $\tilde{x}_m > x_m^{(k)}$, we have that

$$\begin{aligned} h_{l^{(k)}}(x_{l^{(k)}}^{(k)}) - h_{l^{(k)}}(x_{l^{(k)}}^{(k)} + 1) &\geq h_m(x_m^{(k)}) - h_m(x_m^{(k)} + 1) \\ &\geq h_m(\tilde{x}_m - 1) - h_m(\tilde{x}_m), \end{aligned} \quad (19)$$

where the first inequality comes from the greedy behaviour of Algorithm 1, and the last inequality holds due to that $\tilde{x}_m - 1 \geq x_m^{(k)}$, and $h'_m(x_m) \leq 0, h''_m(x_m) \geq 0$ for $x_m \in [1, x_m^{\text{th}}]$. Consequently, from (18) and (19), we have that

$$h_j(\tilde{x}_j) - h_j(\tilde{x}_j + 1) \geq h_m(\tilde{x}_m - 1) - h_m(\tilde{x}_m),$$

which is equivalent to (17), and thus (16) holds. It means that Operation (15) does not increase $f(\mathbf{x})$.

Observe also that Operation (15) does not change the total number of deployed sensor nodes in the field. Thus, we have that for any deployment $\tilde{\mathbf{x}}$ other than $\mathbf{x}^{(k)}$, there exists a sequence of Operation (15) to achieve $\mathbf{x}^{(k)}$, such that

$$\sum_{i=1}^N h_i(\tilde{x}_i) \geq \sum_{i=1}^N h_i(x_i^{(k)}),$$

which completes the proof. ■

Thanks to Lemma 7, we are now in the position of proving Theorem 1:

Proof of Theorem 1: Clearly, when the optimal solution is $x_i = 1$ for all i , the GBD algorithm will terminate at $k = 0$ and also achieve such a solution. Because $x_i \geq 1$, there is no other deployment $\mathbf{x}$, such that $\sum_{i=1}^N x_i \leq \sum_{i=1}^N x_i^{\text{GBD}}$. Therefore, in the following, we consider the cases where the algorithm terminates at $k \geq 1$.

The proof is by contradiction.

Suppose there exists another feasible solution $\tilde{\mathbf{x}}$, such that $\sum_{i=1}^N \tilde{x}_i < \sum_{i=1}^N x_i^{\text{GBD}}$. Then, we have that $\sum_{i=1}^N h_i(\tilde{x}_i) \leq 1$. According to Lemma 3, if $\exists i$ such that $\tilde{x}_i > \lceil x_i^{\text{th}} \rceil$, we can update $\tilde{x}_i \leftarrow \lceil x_i^{\text{th}} \rceil$, such that it is still a feasible solution, and $\sum_{i=1}^N h_i(\tilde{x}_i) \leq 1$. Therefore, in the following, we assume that $\tilde{x}_i \leq \lceil x_i^{\text{th}} \rceil$ for all i .

Assume that GBD algorithm takes k iterations to achieve the final deployment $\mathbf{x}^{\text{GBD}}$. Denote the deployment achieved by GBD algorithm at the $(k-1)$ -th iteration is $\mathbf{x}^{(k-1)}$. Then, Line 4 of the algorithm gives us that

$$f(\mathbf{x}^{\text{GBD}}) \leq 1 < f(\mathbf{x}^{(k-1)}) < \dots < f(\mathbf{x}^{(0)}).$$

According to that $\sum_{i=1}^N \tilde{x}_i < \sum_{i=1}^N x_i^{\text{GBD}}$, there is a $\tilde{k} \leq k-1$, such that $\sum_{i=1}^N x_i^{(\tilde{k})} = \sum_{i=1}^N \tilde{x}_i$. From Lemma 7, we have that

$$1 < f(\mathbf{x}^{(\tilde{k})}) \leq f(\tilde{\mathbf{x}}),$$

which contradicts to the assumption that $\tilde{\mathbf{x}}$ is a feasible deployment. As a result, there is no other feasible solutions $\tilde{\mathbf{x}}$, such that $\sum_{i=1}^N \tilde{x}_i < \sum_{i=1}^N x_i^{\text{GBD}}$. This completes the proof. ■

G. Theorem 2

To prove Theorem 2, we first need to prove the following lemma.

Lemma 8. Consider a WPSN where in each timeslot the eBS transmits energy according to W-scheduling, and the sensor nodes in each region activate according to Max-Activation algorithm. Suppose the batteries of the nodes are large enough such that no energy overcharge happens. Then, once the eBS selects a region l_i to charge, the number of timeslots that the eBS employs to charge again region l_i is upper-bounded as

$$T_i^{\max} = \sum_{j \neq i} \frac{\alpha_i(c_j + cx_j)g(x_i)}{\alpha_j(c_i + cx_i)g(x_j)}.$$

Proof: The WET procedure can be considered as the WET to the virtual nodes $\tilde{v}_i$ at region l_i for all i , where the WET efficiency in l_i is $\alpha_i g(x_i)/x_i$, and the energy consumption rate is $c_i/x_i + c$. Note that, the WET scheduling is not changed if we multiply the WET efficiency, the energy consumption rate, the battery buffer, and the initial energy of every virtual nodes $\tilde{v}_i$ by a factor $x_i/(c_i + cx_i)$. In this case, every virtual node consumes a unit energy in each timeslot, and receives $\alpha_i g(x_i)/(c_i + cx_i)$ unit of energy if the eBS transmits to it.

For virtual node $\tilde{v}_i$, when it is selected for charging, its lifetime is not greater than the lifetime of the other virtual nodes. After the charging, the virtual node $\tilde{v}_i$ has at most $\alpha_i g(x_i)/(c_i + cx_i)$ energy units more than $\tilde{v}_j$ for all $j \neq i$. Then, as the eBS charges $\tilde{v}_j$ with $\alpha_j g(x_j)/(c_j + cx_j)$ units energy per timeslot, it takes at most $(\alpha_i g(x_i)/(c_i + cx_i))/(\alpha_j g(x_j)/(c_j + cx_j))$ timeslots to charge node $\tilde{v}_j$ such that $\tilde{v}_j$ has more energy units than $\tilde{v}_i$. Thus, in total, it takes at most $\sum_{j \neq i} \alpha_i g(x_i)/(c_i + cx_i)^{-1}/(\alpha_j g(x_j)(c_j + cx_j)^{-1})$ timeslots such that all the other virtual nodes have more energy units than $\tilde{v}_i$. Thus $\tilde{v}_i$ will be charged again. This completes the proof. ■

Based on Lemma 8, Theorem 2 is proved as follows:

Proof of Theorem 2: The proof consists of two stages: 1) Transition stage: we will prove that, if the condition holds, i.e., $E_{ij}(0) \geq (c_i/x_i + c) \sum x_i$ for all i, j , $\sum_{i=1}^N h_i(x_i) \leq 1$, and $\mathbf{y}, \mathbf{z}$ is achieved by W-scheduling algorithm and Max-Activation algorithm respectively. Then every sensor node will always have enough energy before every node has been charged by at least once; 2) Stable stage: if the condition holds, every node will not run out of energy between any consecutive charges.

Transition stage: Since $E_{ij}(0) \geq (c_i/x_i + c) \sum_i x_i$ for all i, j , we have that $E_{ij}(0)/(c_i/x_i + c) \geq \sum_i x_i$ for all i, j . It means that when the charging is achieved by W-scheduling algorithm, and the nodes are activated according to Max-Activation algorithm, each sensor node has large enough initial energy such that it will not run out of energy before every other nodes has been charged once.

Stable stage: Observe that the immortality of a WSN is equivalent to that the virtual nodes be immortal. Thus, in the following arguments we use the virtual nodes to represent the sensor nodes in each region of the WSN.

Recall that the base station uses W-scheduling. For any region l_i , suppose at a time when it is selected for charging,

then the next time that it will be charged is at most $T_i^{\max}$ later, as shown in Lemma 8. Denote E_i^{out} the energy consumption of $\tilde{v}_i$ during two consecutive chargings, then we have

$$\begin{aligned} E_i^{\text{out}} &\leq \frac{c_i + cx_i}{x_i} (T_i^{\max} + 1) \\ &= \frac{c_i + cx_i}{x_i} \left(\sum_{j \neq i} \frac{\alpha_i g(x_i)(c_j + cx_j)}{\alpha_j g(x_j)(c_i + cx_i)} + 1 \right) \\ &= \frac{c_i + cx_i}{x_i} + \sum_{j \neq i} \frac{\alpha_i(c_j + cx_j)g(x_i)}{\alpha_j x_i g(x_j)} \\ &= \frac{\alpha_i(c_i + cx_i)g(x_i)}{\alpha_i x_i g(x_i)} + \sum_{j \neq i} \frac{\alpha_i(c_j + cx_j)g(x_i)}{\alpha_j x_i g(x_j)} \\ &= \frac{\alpha_i g(x_i)}{x_i} \sum_{j=1}^N \frac{(c_j + cx_j)}{\alpha_j g(x_j)} \leq \frac{\alpha_i g(x_i)}{x_i}, \end{aligned}$$

where $\alpha_i g(x_i)/x_i$ is the charged energy of $\tilde{v}_i$, and the last inequality comes from Constraint (5b), namely $\sum_{i=1}^N (c_i + cx_i)/(\alpha_i g(x_i)) \leq 1$. Such a result means that the averaged energy consumption of a sensor node is less than or equal to the charged energy. Thus, if the buffer size of each sensor node is larger or equal to the charged energy, i.e., $B_i \geq \alpha_i g(x_i)/x_i$, then the node will not run out of energy during the stable stage. Jointly consider both the transition stage and the stable stage, we have that the initial energy should larger or equal to $\max\{(c_i/x_i + c) \sum x_i, \alpha_i g(x_i)/x_i\}$. Recall that $g'(x) \geq 0, g''(x) \leq 0$ for all $x \geq 1$. Therefore, $g(x_i)/x_i \leq 1$, and we have $E_{i,j}^b \geq \max\{(c_i/x_i + c) \sum x_i, \alpha_i g(x_i)/x_i\}$. Thus, if $E_{i,j}^b \leq E_{ij}(0) \leq B$ for all i, j , $\sum_{i=1}^N h_i(x_i) \leq 1$, and $\mathbf{y}, \mathbf{z}$ is achieved by W-scheduling algorithm and Max-Activation algorithm respectively, then Condition (5b) is sufficient for the immortal WSN. ■

H. Theorem 3

Proof: According to Theorem 1, $\mathbf{x}$ achieved by GBD algorithm is the optimal solution for Problem (5). Thus, it satisfies $\sum_{i=1}^N (c_i + cx_i)/(\alpha_i g(x_i)) \leq 1$. Then, according to Theorem 2, $\mathbf{x}$ achieved by GBD algorithm, $\mathbf{y}$ achieved by W-scheduling, and $\mathbf{z}$ achieved by Max-Activation algorithm, is a feasible solution to Problem (2).

Regarding the optimality, let us suppose that there is another deployment $\mathbf{x}'$ such that the WSN be immortal and $\sum x'_i < \sum x_i$. Then, we have $\mathbf{x}'$ is a feasible solution of Problem (5) due to Theorem 1, which is contradicted to Theorem 1 as $\sum x'_i < \sum x_i$. This completes the proof. ■

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