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How Wireless Power Charging Technology Affects Sensor Network Deployment and Routing

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***Abstract*—As wireless power charging technology emerges, some basic principles in sensor network design are changed accordingly. Existing sensor node deployment and data routing strategies cannot exploit wireless charging technology to minimize overall energy consumption. Hence, in this paper, we (a) investigate the impact of wireless charging technology on sensor network deployment and routing arrangement, (b) formalize the deployment and routing problem, (c) prove it as NP-complete, (d) develop heuristic algorithms to solve the problem, and (e) evaluate the performance of the solutions through extensive simulations. To the best of our knowledge, this is the first effort on adapting sensor network design to leverage wireless charging technology.**

I. Introduction

Constrained energy supply limits the lifetime of a sensor network, which has persisted as a big challenge in sensor network design especially when the network is deployed for long-term monitoring. Existing energy conservation schemes [1]–[5] can slow down energy consumption rate, but cannot compensate energy depletion. Therefore, the effectiveness of these schemes is inherently restrained by the amount of energy preloaded to sensor nodes. New technologies are demanded to fundamentally solve the energy constraint problem.

Researchers have proposed to harvest various types of environmental energy such as sunlight and acoustic vibrations [6]–[9]. However, the energy that a solar cell can harvest is proportional to its surface area, and it is infeasible to equip a tiny sensor node with a large solar cell; the low harvesting efficiency of small solar cells, together with uncontrollable environmental conditions (e.g., sensor nodes deployed in shadow areas, cloudy skies), make it possible that the harvested energy is limited and cannot satisfy the needs. Incrementally deploying new sensor nodes [10], [11] seems to be a convenient solution. However, the approach is not environmental friendly or practical in many scenarios. For example, in the applications of natural environmental monitoring [12], continuously deploying sensor nodes without reclaiming the deserted ones may pollute the environment; in the applications of structure health monitoring and factory monitoring [13], [14], sensor nodes are often embedded in or tightly attached to walls, surfaces of bridge, containers of hazard materials, etc. In these situations, human intervention or robotic reclaiming/remounting of sensors [15] may be too dangerous, costly or technically infeasible.

A. Feasibility of Wireless Rechargeable Sensor Networks

The emergency of wireless power charging technology [16] has shed a light on the power constraint problem in sensor networks. With this new technology, power can be transferred from the transmitting antenna of a power charger to the receiving antenna of sensor nodes via radio. The power is then transformed to DC voltage which can either be utilized by the sensors directly or stored in the rechargeable batteries.

We have conducted field experiments with equipments from Powercast [16], where a charger continuously sends out RF radio in frequency 903-927 MHz to rechargeable sensor nodes. The preliminary experiments, as detailed in Section II, demonstrate the feasibility of applying the wireless charging technology in sensor networks. The charger and sensor nodes could be several feet apart without alignment. It can be anticipated that robots, vehicles or even human operators carrying wireless chargers can move around and recharge sensor nodes deployed on the ground, and that climbing robots [17] can recharge sensor nodes deployed to the walls or tops of high buildings.

B. New Challenges in Rechargeable Sensor Network Design

As sensor networks become rechargeable, some basic principles in network design change fundamentally. In designing non-rechargeable sensor networks especially those needing to operate for a long time, a common challenge is to balance energy consumption among all sensors to prolong the life time with constrained amount of preloaded energy. In rechargeable sensor networks, however, the challenges faced by the design change. Among the new challenges, how to minimize the cost for power recharging is obviously an important one.

The cost of long-term power recharging is fundamentally determined by two factors, namely, long-term energy consumption rate in the sensor network, and long-term recharging efficiency to the network (i.e., power recharged to the network vs. power consumed by the recharger). To minimize the power recharging cost, the energy consumption rate of the network should be reduced and the recharging efficiency should be improved. As discussed below, these two goals are difficult to accomplish simultaneously.

To improve recharging efficiency, we propose a new deployment strategy motivated by our field experiment result. As detailed in Section II, our experiments show that when there is single sensor receiver $20cm$ away from a charger, the typical charging efficiency is less than 1% and more than

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99% energy is wasted in the air. However, as the number of sensors being charged simultaneously increases, the total obtained energy by all the sensors increases approximately linearly. The experimental results motivate us to propose a new deployment strategy, which deploys multiple nodes together in each post and let them work in a rotation manner. Considering the low cost of sensor nodes and generally employed redundant deployment methodology, deploying multiple nodes in one post can increase the recharging efficiency and fault tolerance while decrease long-time recharging maintenance cost (i.e., recharging cost). Thus it is a choice of high performance/cost ratio. How many nodes should be deployed in each post is affected by the energy consumption rate in the post. The higher the rate, the more nodes should be deployed, such that the recharger does not need to come frequently to the post to recharge nodes and meanwhile the recharging efficiency is high. On the other hand, if a post has multiple nodes and thus has a high recharging efficiency, more workload should be allocated to these nodes, such that nodes with low recharging efficiency (in other posts) can be allocated with low workload to reduce their energy consumption rate.

To increase energy efficiency, i.e., reduce the energy consumption rate of the network, an optimal communication topology and routing arrangement should be found such that the overall data reporting activities can follow the most energy efficient routes from sensors to the sink. This is especially important considering communication is usually the biggest source of energy consumption. By adjusting energy level, nodes can have different communication range, and thus there exists a large number of possible topologies and routes to choose from. The optimal one depends on the locations of posts and the workload at each post.

The energy efficiency-targeted routing arrangement and the recharging efficiency-targeted node deployment cannot be determined independently and simply merged together to achieve the minimum power recharging cost. Instead, they are entangled together. On one hand, the routing strategy affects the power consumption rate at every post; specifically, a post passed through by more packets has higher power consumption rate than that passed through by less packets. This in turn affects node deployment decision because more nodes should be deployed in posts where power consumption rates are high. On the other hand, node deployment also affects the routing decision. If a post has more nodes deployed and hence a higher charging efficiency, it should be assigned more forwarding tasks. Due to the above reasons, *the optimal decisions on routing and node deployment should be made at the same time* to minimize the total recharging cost of the system, which is the problem studied in this paper.

C. Our Contributions

This paper makes the following contributions: Firstly, we conduct field experiments to demonstrate the feasibility of applying wireless charging technology in sensor networks and show the approximately linear relationship between the efficiency of recharging power to a network and the number of nodes being recharged simultaneously, which can be used as a guideline in designing rechargeable sensor networks. Secondly, the problem of determining network deployment and routing arrangement simultaneously to minimize power recharging cost for a rechargeable sensor network has been defined, and the problem is proved to be NP-complete. Thirdly, heuristic algorithms have been proposed to address the problem efficiently and effectively. We have also conducted simulations to evaluate and compare the performance of the heuristic algorithms, as well as compare it with that of the exact solution in small-scale networks. To the best of our knowledge, this is the first effort on studying how to re-design sensor networks to fully leverage the emerging wireless power charging technology.

D. Organization

In the rest of the paper, Section II presents our field experiments and results. Section III presents the system model. Section IV proves the optimization problem is NP-complete. Section V presents the heuristic algorithms. Section VI reports the simulation results, and Section VII concludes the paper.

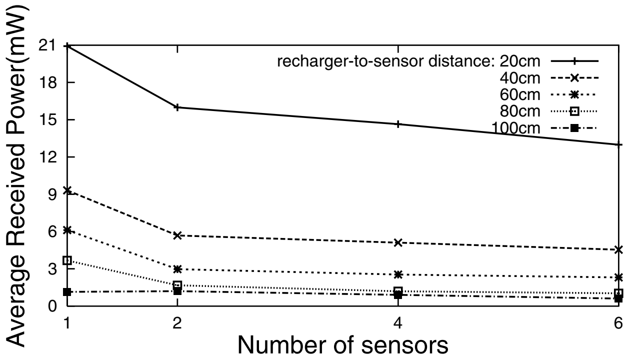
II. Preliminary: Field Experiments and Observations

We have conducted field experiments to study the feasibility of recharging sensor nodes in a wireless fashion with equipments provided by Powercast [16], and collected associated data. The results show that the efficiency to recharge a single node is low and most of the energy is wasted when propagated in the air. Particularly, when a sensor is $20cm$ away from the charger, on average the node can obtain less than 1% of the energy consumed by the charger. As the distance increases, the efficiency decreases exponentially.

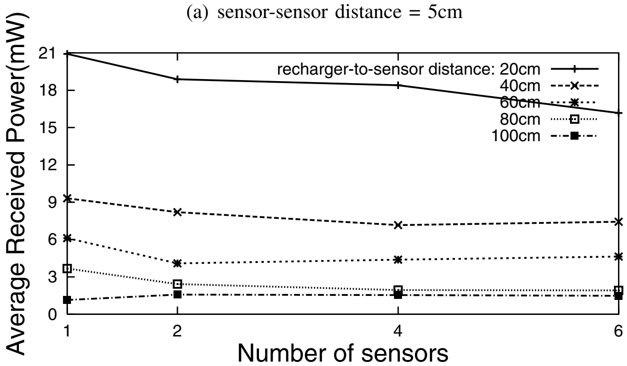
Parameter	Value
Number of sensors	1, 2, 4, 6
Charger-to-sensor distance	20cm, 40cm, 60cm, 80cm, 100cm
Sensor-to-sensor distance	5cm, 10cm

To study how recharging efficiency can be improved, we conduct experiments on recharging multiple sensor nodes simultaneously. We vary three parameters, the number of nodes being recharged simultaneously, the distance between nodes, and the distance between the nodes and the charger. Table II summarizes the values used in the experiment. For each value of the three parameters, we conduct 40 experiments and plot the average of the received power rate in Fig. 1.

Both figures show that, when the number of sensor nodes charged simultaneously increases from 2 to 6, the average power received at each node remains approximately the same, i.e., the efficiency for charging power to the network (note: not the charging efficiency for a single node) has a linear relationship with the number of sensors being charged. When the number of nodes changes from 1 to 2, a noticeable decrease in the average power received by each node is observed when sensor-sensor distance is 5cm, the difference decreases when the sensor-sensor distance increases to 10cm.



(a) sensor-sensor distance = 5cm



(b) sensor-sensor distance = 10cm

Fig. 1. Field experiment result

In addition, comparing Fig. 1(a) and (b), we can see that when inter-sensor distance becomes larger, the charging efficiency increases more when multiple sensors are charged together. This is because when sensors are more spread out, they can better capture the energy in the air without interfering with each other. Considering $10cm$ is a relatively short distance, the linear relationship between charging efficiency and the number of sensors can be more obvious when inter-sensor distance increases.

III. System Model

Focusing on how wireless charging technology affects network deployment and routing arrangement, we consider the following simplified system model.

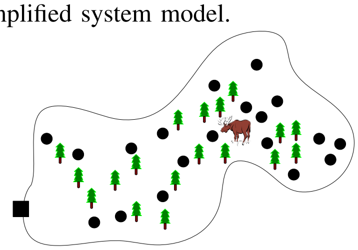


Fig. 2. Example of post configuration in an island. The solid square represents the base station, and the solid circles represent post.

As shown in Fig. 2, a sensor network is deployed in a field for long-term, continuous monitoring. The field has N posts of interest and each post must have at least one sensor node deployed. The locations of the posts are determined by applications based on the shape of the terrain, the required sensing quality, etc., and are given. The network has M sensor nodes ($N \leq M$). Sensor nodes monitor their nearby environment and every certain time interval, one node at each post generates a report. The report will be forwarded hop by hop to the base station, which is located at a corner of the deployment field. If a post has multiple nodes deployed, these nodes rotate in performing the sensing/reporting tasks such that they maintain nearly the same level of residual energy.

Each node is assumed to have k transmission levels (denoted as $l_1, \cdots, l_k$), which enables it to transmit a message to the distances of $d_1(d_{min})$, d_2, $\cdots$, d_{k-1} and $d_k(d_{max})$, respectively. Assume the energy consumed for transmitting one bit to distance d_t is denoted as e_t, and the energy consumed for receiving one bit is denoted as e_r. e_t and e_r can be calculated as follows:

$$\begin{cases} e_t &= \alpha + \beta d^{\gamma}, \\ e_r &= \alpha \end{cases} \tag{1}$$

where α is the energy needed to run the transceiver circuitry, β is the energy consumed in the amplifier circuitry to transmit the data, and γ is the loss factor, which varies from 2 to 4, depending on the quality of channel. Based on Eq. (1), the amount of energy for transmitting one bit when using each of the k power levels can be computed, and the value is denoted as e_i ($i = 1, \cdots, k$). Note that, in this paper, we only consider the energy consumption for packet transmission and reception, the biggest source of energy consumption. However, the results can be extended to other sources of energy consumption such as sensing and computation.

We assume sensor nodes can always be recharged in time before they run out of energy. How to schedule the wireless charger to guarantee this is not the focus of this paper. We denote the charging efficiency when a charger recharges a single sensor node to be η ($0 < \eta < 1$). If the recharger disseminate y units of energy and the sensor receives x, $\eta = \frac{x}{y}$. The charging efficiency increases if the charger simultaneously recharges multiple sensors. When charging m sensor nodes simultaneously, the charging efficiency becomes a function of m: $\eta(m) = k(m) * \eta$. Our field experiment shows that $k(m)$ is a linear or sub-linear function of m. To get a quantitative result of sensor deployment, we assume $k(m) = m$ in this paper. Since simultaneous charging increases charging efficiency, it is beneficial to deploy multiple sensor nodes together to a post whenever possible.

IV. Problem Definition and Its Nature

A. Problem Definition

The problem of determining the optimal node deployment and routing arrangement can be formulated as follows. Given:

- M sensor nodes are in the network and a base station is connected to some of the nodes.
- Each node has k levels of transmission power ($l_1, \cdots, l_k$). At level l_i ($i \in \{1, \cdots, k\}$), the transmission range is d_i and the energy to transmit one bit is e_i.

- There are N deployment posts $(p_1, \cdots, p_N)$. Each post needs at least one node deployed.
- If post p_i $(i \in \{1, \cdots, N\})$ has been deployed with m_i $(m_i \geq 1)$ nodes, the charging efficiency at p_i is $m_i * \eta$. That is, for every unit of energy consumed by the charger, each of the m_i nodes in p_i can receive η units of energy.

The problem is to

(a) determine how to deploy M sensor nodes to N posts;
(b) for each post p_i $(i \in \{1, \cdots, N\})$, determine the transmission power level that should be used and which post should be chosen as its parent,

such that:

- based on the chosen transmission power level and parent for each post, data generated by each sensor node can be transmitted to the base station;
- the total amount of energy consumed by the charger to compensate the energy consumption of each post for sending one bit to the base station is minimized.

B. Nature of the Problem

Next, we prove that the afore-defined problem is NP-complete. To ease the proof, we restrict the problem a bit, and show that even the restricted problem is NP-complete. The original, more general problem is therefore also NP-complete. Our restrictions are as follows:

- Each node has 2 transmission power levels l_1 and l_2 and $4e_1 = e_2$. The amount of energy for each node to receive one bit is denoted as $e_0 (e_0 < e_1)$.
- Each post can have at most two sensor nodes. Note that, posts with two sensor nodes have twice charging efficiency than posts with one sensor node.

The proof is as follows.

Proof: First of all, we show that the problem is in NP. Clearly, if how M sensor nodes are deployed in N posts is given, and the transmission levels and the parent choices of N posts are also given, the total power recharging cost at the charger can be calculated. It is determinable if the cost is no greater than a given value W. Thus, the problem is in NP.

Next, we prove the problem is NP-hard by reducing the 3-CNF SAT problem to this problem.

Suppose there is an instance of the 3-CNF SAT problem which consists of n Boolean variables $x_1, x_2, \cdots, x_n$, and m conjunctive normal forms (CNFs) $C_1, C_2, \cdots, C_m$, where for each $j \in \{1, \cdots, m\}$, $C_j = y_{j,1} \vee y_{j,2} \vee y_{j,3}$ and the three literals $y_{j,1}, y_{j,2}, y_{j,3} \in \{x_1, \bar{x}_1, x_2, \bar{x}_2, \cdots, x_n, \bar{x}_n\}$. We can construct an instance of our problem as follows.

- Let a network have $M = 3n + 3m$ sensor nodes and $N = 2n + 2m$ posts. That is, $n + m$ posts should have two sensor nodes each, and the rest $n + m$ posts should have only one sensor node each.
- The posts are constructed as follows: (a) for each CNF clause, there are two corresponding posts U_j and V_j, $1 \leq j \leq m$; (b) for each Boolean variable x_i, $1 \leq i \leq n$, there are two corresponding posts $S_{i,1}$ and $S_{i,2}$.

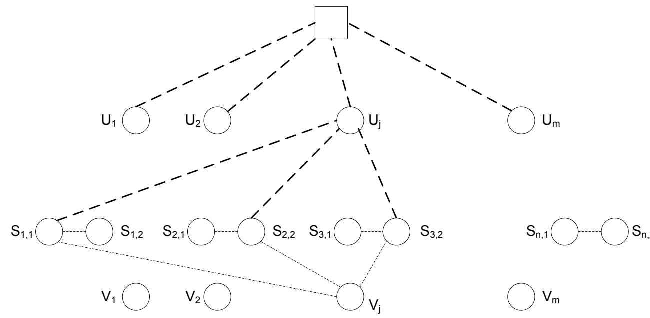


Fig. 3. NP-Completeness proof. The square represents the base station, and the circles represent posts. Thick dotted lines indicate two end posts can reach each other using transmission power l_2, and thin dotted lines means two end posts can reach each other using transmission power l_1. This example assumes $C_j = x_1 \vee \bar{x}_2 \vee \bar{x}_3$.

- The base station can be directly reached by any post U_j, $1 \leq j \leq m$, only if they set their transmission power to l_2, but it cannot be reached directly by other posts.
- Assuming the three literals of CNF clause C_j $(1 \leq j \leq m)$ are $y_{j,1}$, $y_{j,2}$ and $y_{j,3}$, if x_i is one of these literals, post $S_{i,1}$ can reach U_j only when using transmission power l_2; if $\bar{x}_i$ is one of these literals, post $S_{i,2}$ can reach U_j only when using transmission power l_2.
- Each pair of posts $S_{i,1}$ and $S_{i,2}$ $(1 \leq i \leq n)$ can reach each other when using transmission power l_1.
- Each V_j $(1 \leq j \leq m)$ can reach the same set of posts as U_i does except the base station, when using transmission power l_1.

Fig. 3 shows an example of the constructed instance. Let $W = 7m\frac{e_1}{\eta} + 9n\frac{e_1}{\eta} + m\frac{e_0}{\eta} + n\frac{3e_0}{2\eta}$. We claim that

(i) if there exists an assignment of Boolean values to $x_1, x_2, \cdots, x_n$ such that the instance of 3-CNF SAT is evaluated to be true, then there is a solution to the afore-constructed instance of our problem in which the total power recharging cost of the afore-constructed network is no greater than W; and
(ii) the reverse of Claim (i).

Firstly, we prove Claim (i). Suppose there is an assignment of Boolean values to $x_1, x_2, \cdots, x_n$, which satisfies the instance of 3-CNF SAT, we construct a solution to our problem as follows. For each post U_j, $1 \leq j \leq m$, we deploy two sensor nodes, and they use transmission power l_2 to send data to the base station. For a 3-CNF clause $C_j = y_{j,1} \vee y_{j,2} \vee y_{j,3}$, without losing arbitrariness, let us assume literal $y_{j,k}$ $(1 \leq k \leq 3)$ is true. So there will be two cases: $y_{j,k} = x_i$ or $y_{j,k} = \bar{x}_i$. If $y_{j,k} = x_i$, we do the following:

- Two sensor nodes are deployed in post $S_{i,1}$, and one sensor node is deployed in post $S_{i,2}$.
- $S_{i,1}$ uses transmission power l_2 to send data to U_j, and $S_{i,2}$ uses transmission power l_1 to send data to $S_{i,1}$.
- One sensor node is deployed in each V_j, $1 \leq j \leq m$, which uses transmission power l_1 to send data to $S_{i,1}$.

On the other hand, if $y_{j,k} = \bar{x}_i$, we do the following:

- Two sensor nodes are deployed in post $S_{i,2}$, and one sensor node is deployed in post $S_{i,1}$.
- $S_{i,2}$ uses power level l_2 to send data to U_j, and $S_{i,1}$ uses transmission power l_1 to send data to $S_{i,2}$.
- One sensor node is deployed in each V_j, $1 \leq j \leq m$, which uses transmission power l_1 to send data to $S_{i,2}$.

In this way, we have distributed all $3m + 3n$ sensor nodes to the $2m + 2n$ posts, and have chosen transmission power levels and parents for all posts. Next we show the total power recharging cost of this network is no greater than W.

- To compensate the energy consumed for reporting one-bit information at each post U_j $(1 \leq j \leq m)$, the amount of energy consumed at the charger is $\frac{4e_1}{2\eta}$. Therefore, the total for all the m posts is $2m\frac{e_1}{\eta}$.
- For each pair of posts $S_{i,1}$ and $S_{i,2}$ $(1 \leq i \leq n)$, one of them (with two sensor nodes deployed) incurs a recharging cost of $\frac{4e_1}{2\eta} + \frac{4e_1}{2\eta} + \frac{e_0}{2\eta}$ for every bit information it has reported to the base station ($\frac{4e_1}{2\eta}$ incurred at itself, another $\frac{4e_1}{2\eta}$ and $\frac{e_0}{2\eta}$ incurred at post U_j for forwarding and receiving this data, respectively), and the other (with one sensor node deployed) incurs a recharging cost of $\frac{4e_1}{2\eta} + \frac{4e_1}{2\eta} + \frac{e_1}{\eta} + 2\frac{e_0}{2\eta}$. Therefore, the total for all the $2n$ posts is $n\frac{e_1}{\eta} * (2 + 2 + 2 + 2 + 1) + n\frac{e_0}{2\eta}(1 + 2) = 9n\frac{e_1}{\eta} + 3n\frac{e_0}{2\eta}$.
- For each post V_j $(1 \leq j \leq m)$, the recharging cost is $\frac{4e_1}{2\eta} + \frac{4e_1}{2\eta} + \frac{e_1}{\eta} + 2\frac{e_0}{2\eta}$ for every bit information it has reported. Therefore, the total recharging cost for all the m posts is $m\frac{e_1}{\eta} * (2 + 2 + 1) = 5m\frac{e_1}{\eta} + m\frac{e_0}{2\eta}$.

Summing up the above amounts of different types of posts, we obtain the total recharging cost of the network for the one-bit data that every post has reported, which is $7m\frac{e_1}{\eta} + 9n\frac{e_1}{\eta} + m\frac{e_0}{\eta} + n\frac{3e_0}{2\eta} = W$.

Secondly, we prove Claim (ii). To prove this claim, we first show that if there is a solution to the afore-constructed instance of our problem, the network must satisfy the following two properties:

(ii-A) Each post U_j $(1 \leq j \leq m)$ has two sensor nodes; Each post V_j $(1 \leq j \leq m)$ has one sensor node; and for each pair of posts $S_{i,1}$ and $S_{i,2}$ $(1 \leq i \leq n)$, exactly one of them has two sensor nodes, and the other has only one sensor node.

(ii-B) Given the distribution method of sensor nodes stated in Property (ii-A), there is only one way to choose the transmission power level and the parent for each post, such that the total recharging cost of the network is no greater than W. The way to choose the transmission power level and the parent post for each post is as follows: (a) each post U_j $(1 \leq j \leq m)$ uses transmission power level l_2 to send data to the base station; (b) for each pair of posts $S_{i,1}$ and $S_{i,2}$, the post with two sensor nodes uses transmission power level l_2 to send data to a post U_j $(1 \leq j \leq m)$, and the other uses transmission power level l_1 to send data to the former, and (c) each post V_j $(1 \leq j \leq m)$ uses transmission power level l_1 to send data to a post $S_{i,k}$ $(1 \leq i \leq n, 1 \leq k \leq 2)$ which has two sensor nodes.

We now prove Property (ii-B). Firstly, it is clear that the afore-described way for choosing the transmission power level and the parent post of each post results in a total recharging cost of W. Secondly, we want to prove that, if there is another way for choosing the transmission power and the parent post, there exists a sequence of transformations which results in another set of choices of the transmission power level and the parent post with less amount of total recharging cost. In other words, any way for choosing the transmission power and the parent post that is different from the one described in (ii-B) will incur a total recharging cost that is greater than W. The transformations are as follows:

- For pairs of posts $S_{i,1}$ and $S_{i,2}$ $(1 \leq i \leq n)$: Without the loss of generality, assume $S_{i,1}$ $(1 \leq i \leq n)$ has only one sensor node, and it uses power level l_2 to send data to a post U_j $(1 \leq j \leq m)$. We can reset $S_{i,1}$'s power level to l_1, and let it send data to $S_{i,2}$, which has two sensor nodes. Clearly, the recharging cost of $S_{i,1}$ and $S_{i,2}$ is reduced without affecting other posts.
- For posts V_j $(1 \leq j \leq m)$: Without the loss of generality, assume V_j uses transmission power l_1 to send data to post $S_{i,1}$ $(1 \leq i \leq n)$ which has only one sensor node. We can let V_j to send data to $S_{i,2}$, which has two sensor nodes, with a reduced recharging cost of $S_{i,1}$ and $S_{i,2}$ without affecting other posts.

We next prove Property (ii-A). Suppose there is a way to distribute $3m + 3n$ sensor nodes into $2m + 2n$ posts which is different from the way described in (ii-A), there exists a series of transformations to re-distribute sensor nodes such that with the resulting deployment, less amount of total recharging cost can be obtained. The transformations are as follows:

- For each post U_j that has only one sensor node, there must be either a post V_j having two sensor nodes, or a pair of posts $S_{i,1}$ and $S_{i,2}$ both having two sensors. If we move a sensor node from V_j or either of $S_{i,1}$ and $S_{i,2}$ to U_j, it is clear that the total recharging cost is reduced.
- For each pair of posts $S_{i,1}$ and $S_{i,2}$ that both have only one sensor node, there must be either a post V_j having two sensor nodes, or another pair of posts $S_{i',1}$ and $S_{i',2}$ both having two sensor nodes. If we move a sensor node from V_j or either of $S_{i',1}$ and $S_{i',2}$ to one of $S_{i,1}$ and $S_{i,2}$, it is clear that the total recharging cost is also reduced.

Therefore, both Properties (ii-A) and (ii-B) hold when there is a solution to an instance of our problem.

Based on Properties (ii-A) and (ii-B), we can assign Boolean values to the corresponding instance of the 3-CNF problem as follows: For each pair of post $S_{i,1}$ and $S_{i,2}$, if $S_{i,1}$ has two sensor nodes, then we let $x_i = true$; on the other hand, if $S_{i,2}$ has two sensor nodes, then we let $\bar{x}_i = true$. Due to the way we construct the network, each post U_j $(1 \leq j \leq m)$ must have at least one post $S_{i,k}$ $(1 \leq i \leq n, 1 \leq k \leq 2)$ as its child. Furthermore, if $k = 1$, then x_i is a literal in 3-CNF clause C_j; and if $k = 2$, then $\bar{x}_i$ is a literal in 3-CNF clause C_j. Due to Property (ii-B), $S_{i,k}$ must have two sensor nodes, and thus $x_i = true$ if $k = 1$, or $\bar{x}_i = true$ if $k = 2$. In either case, C_j is true.

So far, our problem is proven to be NP-hard. Since the problem is also in NP, it is NP-complete. ■

V. Proposed Heuristic Algorithms

A. Routing-First Heuristic (RFH) Algorithms

1) Basic Ideas: The objective for co-designing the network deployment and the routing strategies is to minimize the total recharging cost of the network for infinite network lifetime. As discussed in Section I, the total recharging cost is affected by two factors: the amount of energy consumed by sensor nodes and the efficiency for recharging sensor nodes. The routing-first heuristic algorithms attempt to first minimize the amount of energy consumed by sensor nodes, which is achieved through finding the most-energy-efficient routing paths for every post. Then, based on the found paths, a routing tree is constructed to facilitate every sensor node to send/forward their data to the base station. The routing tree should satisfy the dual conditions: Firstly, the tree contains only the most-energy-efficient routing paths, which ensure the minimum of energy consumption in sensor nodes. Secondly, the routing workload is concentrated to as few posts as possible, which is motivated by the idea that, letting these posts consume the most energy and meanwhile deploying a large number of nodes to these posts to improve the efficiency for charging energy to these posts may collectively minimize the total recharging cost. After the tree is constructed, the routing workload at each post is computed, and then sensor nodes are deployed to all posts in the way that the number of nodes deployed to each post is proportional to the workload of the post. In the following, we first describe the basic version of the algorithm, which is followed by an advanced version which iteratively adjusts the routing arrangement and the deployment to reduce the total recharging cost as much as possible.

2) The Basic Routing-First Heuristic Algorithm: The basic Routing-First algorithm runs in the following four phases.

Phase I: Finding the minimum-energy paths from every post to the base station

This phase is conducted as follows:

- A graph $G = (V, E, w)$ is constructed, where V is the set of posts plus the base station. For any pair of nodes v_i and v_j in V, if the distance between them is less than the maximum transmission range (i.e., $dist(v_i, v_j) < d_{max}$), then there is an edge between v_i and v_j (i.e., $(v_i, v_j) \in E$). $w : E \longmapsto \mathbb{R}$ is the weight function for edges. For each edge (v_i, v_j), $w(v_i, v_j)$ is the amount of energy consumed for sending one bit between v_i and v_j, and as described in Section II, $w(v_i, v_j)$ can be computed as $w(v_i, v_j) = \alpha + \beta \cdot d_x^{\gamma}$, where $x \in \{1, 2, \cdots, k\}$, and d_x is the smallest transmission range which is larger than the distance between v_i and v_j.
- For each post in V, the Dijkstra algorithm can be run to find the shortest path to the base station. Note that, with the above definition of edge weight, the found shortest path is actually the minimum energy path to the base station. The traditional Dijkstra algorithm returns only one shortest path. If multiple shortest paths exist, we need to find them out to enable the optimization in the next steps. Several methods can be applied to find all the shortest paths. For example, the Dijkstra algorithm can be modified such that it can record multiple shortest paths.

Phase II: Building the minimum-energy and workload-concentrated routing tree

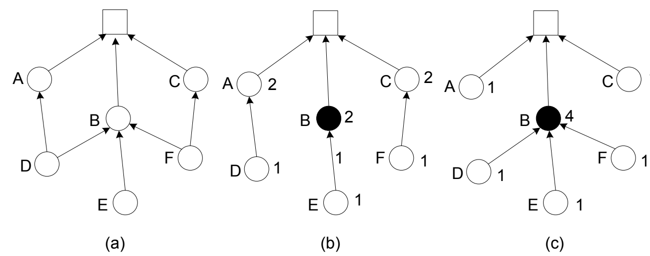


Fig. 4. The benefit of concentrating routing workload. The square represents the base station, and the circles represent posts. The number to the right of each post is its routing workload. Each post uses e units of energy to send one bit to its next hop post. The total number of sensor nodes is 7.

Phase I returns a number of minimum-energy paths for each post. We can form a shortest path "fat tree" by combining these paths of all the posts. Note that the final structure is not a tree but a "fat tree", since a post may have multiple parents. We need to trim this fat tree into a tree. As discussed in the subsection of *Basic Ideas*, we adopt the heuristic of concentrating routing workload to a few number of posts when trimming the tree. The example in Fig. 4 further explains why we adopt the heuristic. Here, Fig. 4 (a) shows a fat tree composed of shortest paths from every post to the base station. Fig. 4 (b) and (c) show two different routing tree structures that can be derived from the fat tree in (a): In Fig. 4 (b), routing workload is evenly distributed to three intermediate posts, while in Fig. 4 (c), the workload is concentrated to post B. Suppose we have 7 sensor nodes to deploy to 6 posts. Obviously the extra one nodes should be deployed to one of posts A, B and C in Fig. 4 (b) and post B in Fig. 4 (c), since leaf posts have less routing workload. In Fig. 4 (b), the total recharging cost of this network (for every bit information reported by every post) is $3e + 2 \cdot 2e + 2e/2 = 8e$, while the total recharging cost is reduced to $5e + 4e/2 = 7e$ in Fig. 4 (c). We find that, in a larger scale network with limited number of sensor nodes to deploy, the benefit of routing workload concentration is even more significant. Specifically, the fat tree is trimmed as follows:

- *Step 1.* The routing workload at each post on the fat tree is computed. In RFH, the routing workload of a post on the fat tree is defined as *the number of descendants* of the post.

- *Step 2*. Posts are sorted based on the decreasing order of their routing workload. Then, the sorted posts are stored into a queue L based on the order; specifically, the post with the largest workload is at the head of the queue.
- *Step 3*. Let the current head element of queue L be post p. The following operations are conducted: For each descendant of p, denoted as d_p, its edge to any parent p' (where p' is not p's descendant or p) is deleted. This triggers p' and some of its upstream nodes to update their routing workload because reports from d_p may not pass through them. Consequently, their positions in the queue may have to be changed to maintain that all posts in L are stored in the decreasing order of their routing workload. After the operations are finished, post q is removed from the queue, and this step is repeated on the new head element if the queue is not empty.

After the above steps, a minimum-energy workload-concentrated routing tree is formed. Fig. 5 demonstrates a complete example to further illustrate the execution of Phase II.

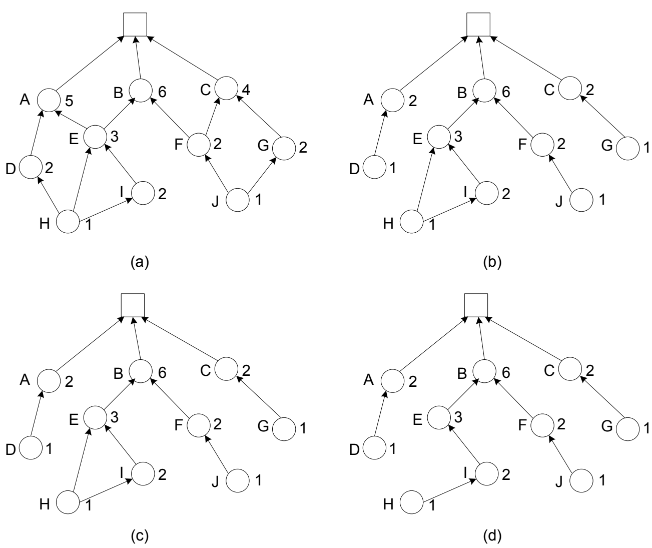


Fig. 5. Trimming a fat tree into a minimum-energy workload-concentrated routing tree. The square represents the base station. The circles represent posts. The number to the right of a post is its routing workload (the number of its descendants) (a) is a fat tree of all shortest paths. In (b), the post with the highest routing workload (post B) is examined, and all the edges from its sub-tree to the other part of the tree, including (E, A),(F, C),(H, D),(J, G), are deleted, and the workload on affected posts is adjusted. In (c), post E is examined, and no edge is deleted. In (d), post I is examined, and edge (H, E) is deleted.

<u>*Phase III:*</u> Opportunistic merging of sibling posts

In the routing tree constructed so far, there may be multiple sibling posts that are close to each other and can reach each other using low transmission power but need to use high transmission power to reach their common parent. If this is the case, we can ask these sibling posts to send their data to one of them, and the latter is responsible for forwarding the data to their common parent post. This way, routing workload can be further concentrated. Concretely, this phase can be conducted as follows: for each post p in the tree, it is checked whether there are some of its children that can reach each other with smaller transmission range than what they need to reach itself. If there exists such children, they are organized into groups in which each member post can send its data to a designated post (the *head* of the group), and then the head forwards the all the data to p.

<u>*Phase IV:*</u> Workload-based deployment of sensor nodes

According to the routing tree constructed so far, sensor nodes can be deployed. The basic idea for deployment is, the number of nodes deployed in each post is proportional to the routing workload of that post. Assuming the workload is α_i for post i ($1 \leq i \leq N$), the problem for distributing M sensor nodes to N posts can be formulated as the following minimization problem:

$$\text{Minimize}: \quad \sum_{i=1}^{N} \alpha_i/m_i$$

$$\text{Subject to}: \quad \sum_{i=1}^{N} m_i = M$$

Where m_i is the number of sensor nodes to be deployed in post i.

Although the classical Lagrange multipliers method [18] can be run to find out m_i ($i = 1 \leq i \leq N$), the resulting m_i may not be integers. Hence, we address the problem in the following way:

- The Lagrange multipliers method is used to obtain first round of the values for m_i ($1 \leq i \leq N$). For the smallest m_j among $m_1, \cdots, m_N$, we round it to the nearest integer, which is the number of sensor nodes to be deployed in post j. Note that if the resulting number is 0, we set the number to 1 since every post should have at least one sensor node.
- Excluding post j and the number of sensor nodes that have been deployed in post j, the Lagrange multipliers method is reused to obtain another round of values for m_i ($i \in \{1, \cdots, N\}/\{j\}$). Similar to the previous step, the smallest m_k among all m_i is rounded to the nearest integer to get the actual number of sensor nodes deployed to post k. Then, this step is repeated until the deployments to all posts have been determined.

When heap data structure is utilized to maintain the list in Phase II, the time complexity of RFH is $O(N^2 \log N)$ which equals that of the most time-consuming part, Phase II.

3) The Iterative Routing-First Heuristic Algorithm: The basic version of the routing-tree first heuristic algorithm is composed of two macro-steps: a minimum-energy and workload-concentrated routing tree is first constructed, and then sensor nodes are distributed based on this tree. The routing tree obtained from the first macro-step is of critical importance to the quality of final deployment and routing decisions. The tree is regarded as a *minimum-energy* tree based on the implicit assumption that every post has only one sensor node deployed, which however is not right. The iterative RFH algorithm is aimed to address this problem.

Our design of the iterative algorithm is motivated by the following observation. After one complete execution of the basic RFH algorithm, the deployment of sensor nodes to posts is decided. From the deployment decision, we can find out the efficiency for charging every post. Taking this into account, we can now compute a more accurate *minimum-energy* tree, and then based on the tree to refine the deployment decision. This way, better routing and deployment decisions can be found. Furthermore, if the above steps are performed for multiple times, decisions can be continuously improved. The above idea is confirmed by the simulation results to be reported in Section V: If we run our algorithm iteratively, the total recharging cost of the network decreases monotonically, and it converges at a certain value after a small number of iterations.

B. Incremental Deployment-Based (IDB) Heuristic Algorithm

The naive method to compute the exact optimal solution of the routing and deployment problem is as follows: For each of the possible ways to deploying M sensor nodes to N posts, a minimum-energy routing tree is computed, and the total recharging cost is recorded; then, the deployment strategy and the minimum-energy routing tree structure that result in the least total recharging cost is the solution. However, the method incurs a runtime complexity of $O(\left(\begin{array}{c} M-1 \\ N-1 \end{array}\right))$, which is not affordable when the system scale is large. To reduce the time complexity, we propose an incremental deployment heuristic as follows:

- Initially, each post is deployed with one sensor node.
- The rest $M-N$ sensor nodes are deployed in multiple rounds. In each round, we deploy δ number of sensors, and the total number of rounds is $\frac{M-N}{\delta}$ rounds, where δ is a system parameter.

In each round of the deployment, we examine each possible way to deploy the δ sensor nodes to posts. Thus, each round has a time complexity

$$O(\left(\begin{array}{c} N+\delta-1 \\ N-1 \end{array}\right)).$$

Then, for each of the deployment strategies, the corresponding minimum-energy tree and the associated total recharging cost are found. Note that, when computing the minimum-energy tree, all sensor nodes that have been deployed in previous rounds are assumed to exist in their deployment posts. After all possible ways have been examined, the one with the minimum-energy tree is chosen; i.e., δ sensor nodes are incrementally deployed to posts according to the chosen deployment strategy. After $\frac{M-N}{\delta}$ rounds of incremental deployment, we obtain the final strategy for deploying all M sensor nodes to N posts. The total time complexity for the algorithm is

$$O(\frac{M-N}{\delta}\left(\begin{array}{c} N+\delta-1 \\ N-1 \end{array}\right)).$$

VI. Performance Evaluation

Our performance evaluation has two objectives: (i) comparing the proposed heuristics with the optimal solution for small-scale networks; (ii) evaluating the proposed heuristic schemes in large scale networks under different system parameter settings to provide insights on choosing these parameters for network designers.

A. Simulation Setup

In the simulation, we assume the sensor network is deployed within a two-dimensional square field. The base station is located at its lower left corner. Posts are randomly selected within the field. The evaluation metric is the *total recharging cost*, which is defined as the total energy disseminated by the wireless charger to compensate the energy consumption of each post for sending one bit to the base station.

The following are the system parameters we used: In the equation regarding the energy consumption model (Eq. (1)), we set $\alpha = 50nJ/bit$, $\beta = 0.0013pJ/bit/m^4$, and $\gamma = 4$, as suggested in [19]. We choose three transmission ranges, i.e., $(d_1, d_2, d_3) = (25, 50, 75)$ meters in all the experiments except the one studying the effect of number of transmission ranges, in which we used six transmission ranges, i.e., $(d_1, d_2, d_3, d_4, d_5, d_6) = (25, 50, 75, 100, 125, 150)$ meters.

B. Performance of Iterative RFH Algorithm

We first study the performance of iterative RFH algorithm under different iteration steps to determine the best iteration number. The deployment field is a $500m * 500m$ square, the number of posts is 100, and the number of sensor nodes varies in $\{400, 600, 800, 1000\}$. The results are the average of 20 simulations on different post distributions.

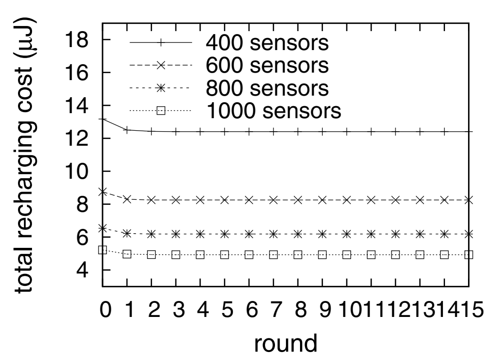


Fig. 6. The benefit of running RFH iteratively

As shown in Fig. 6, the total recharging cost decreases with more iterations, and it converges quickly after a small number of rounds. The figure shows that all the instances converage after 7 rounds either to a single value or to a very small narrow range. In some instances, the total recharging cost does not converage at a single value, but oscillates among two or more values that are very close to each other. For instance, when the number of nodes is 600, the total recharging cost for the RFH algorithm oscillates among $\{8.2592, 8.2581\}\mu J$ after the fifth round. We conjecture that the reason is, when we assign sensor nodes to posts, we round the values returned by the Lagrange multipliers method, and the rounding may have different effects in different rounds.

In the following sections, we always use the iterative RFH algorithm with seven iterations as a representative.

C. Comparing the Performance of Heuristic Algorithms with Optimal Solution

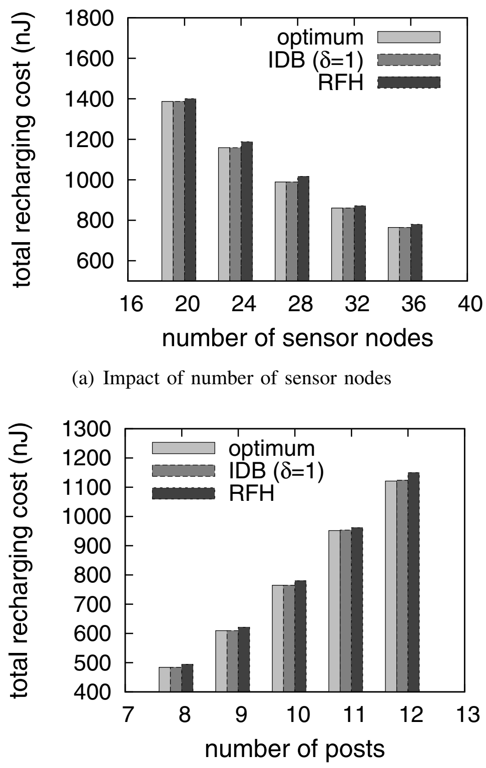
Due to the NP-hardness of the network deployment and routing problem, it is infeasible to compute the optimal solution for a large scale sensor network. Therefore, we only compute the optimal solution for a small-size network, and compare the optimal solution with the results obtained from our proposed heuristic schemes under the same network settings. The comparison is to find out the difference between the optimal solutions and the solutions obtained by the heuristic algorithms. The results are the average of five simulations on different post distributions.

In this study, the network field is a $200m*200m$ square. We conduct two experiments. Firstly, we fix the number of posts to 10, vary the number of nodes among $\{20, 24, 28, 32, 36\}$, and measure the total recharging cost. As can be seen from Fig. 7(a), the total recharging cost for all the algorithms decreases when there are more sensor nodes, since the energy recharging efficiency increases as more sensors are deployed to the same post. We can also see that, both the heuristic algorithms achieve a performance close to the optimal solutions under these network settings. Between them, the IDB scheme with $\delta = 1$ has better performance. Specifically, the IDB algorithm delivers the same solutions as the optimal one for all the numbers of the sensor nodes in $\{20, 24, 28, 32, 36\}$. Furthermore, the total recharging cost of the solutions found by RFH is up to 3% higher the optimal solutions.

Secondly, we fix the number of nodes to 36, vary the number of posts among $\{8, 9, 10, 11, 12\}$, and measure the total recharging cost of the solutions produced by different schemes. As shown in Fig. 7(b), the total recharging cost decreases as the number of posts increases. This is because more data should be sent to the base station as the number of posts increases. Similar to the previous comparison in Fig. 7(a), we can see that the performance of the heuristic algorithms is also close to that of the optimal solution. When the number of posts is 11 and 12, the total recharging cost given by IDB ($\delta = 1$) is slightly higher than that given by the optimum solution.

D. Performance of Heuristic Algorithms in Large-Scale Networks

In this section, we show the performance of our heuristic algorithms in large-scale networks. Assuming the sensor network is deployed to a $500m*500m$ square field, we evaluate the impact of the number of sensors, the number of posts, and the number of transmission ranges on the performance of the heuristics. The results are the average of 20 simulations on different post distributions.



(a) Impact of number of sensor nodes

(b) Impact of the number of posts

Fig. 7. Comparison between the heuristics and the optimal solution

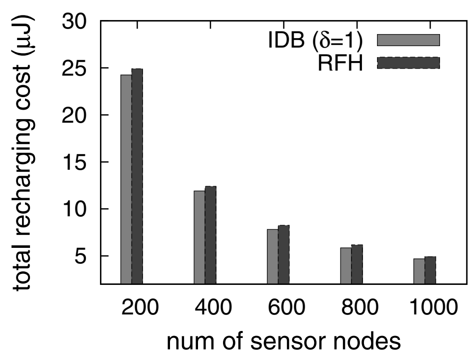


Fig. 8. Impact of the number of sensor nodes

Impact of number of sensor nodes. We fix the number of posts at 100, and vary the number of nodes among $\{200, 400, 600, 800, 1000\}$. Fig. 8 shows that IDB leads with a margin over RFH, which indicates IDB is a better heuristic in terms of performance. For instance, when the number of posts is 1000, IDB with $\delta = 1$ computes a solution with total recharging cost of $4.6914\ \mu J$, and RFH computes one with total recharging cost of $4.9283\ \mu J$, i.e., 5% higher than IDB with $\delta = 1$. On the other hand, our simulation also indicates

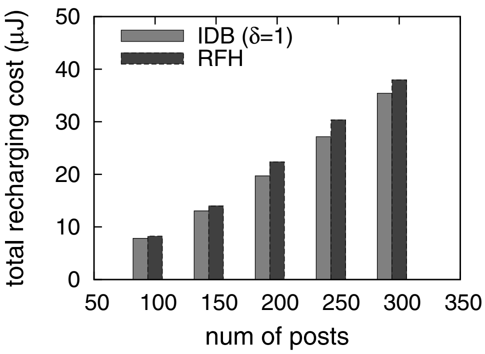


Fig. 9. Impact of the number of posts

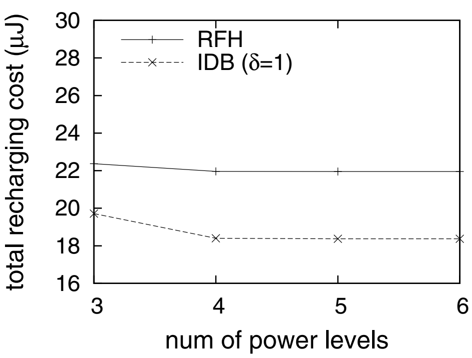


Fig. 10. Impact of the number of power levels

IDB runs much slower than RFH. Therefore, for large-scale networks, the RFH scheme may be a good choice considering its much shorter running time and a little worse performance.

Impact of number of posts: We fix the number of nodes at 600, and vary the number of posts among $\{100, 150, 200, 250, 300\}$. Fig. 9 shows a similar trend as Fig. 8.

Impact of number of transmission ranges: We fix the number of nodes at 600, the number of posts at 200, and vary the number of transmissions among $\{3, 4, 5, 6\}$. When the number of transmission ranges is i, the set of transmission ranges is $\{25, 50, \cdots, 25 * i\}$ accordingly. Fig. 10 shows that, when more transmission ranges are available, the total recharging cost almost keeps at the same value for IDB and RFH. The reason is that, under the constraint of keeping the network connected, shorter transmission ranges are preferable to larger ones since the power consumption increases much faster than transmission range does as shown by Eq. (1). As a result, larger transmission ranges do not have a significant impact on the heuristic algorithms.

VII. Conclusions

In this paper, we investigated the impact of newly emerging wireless charging technology on sensor network deployment and routing arrangement. Specifically, we formalized the deployment and routing problem as an optimization problem, proved the problem as NP-complete, and designed and evaluated various heuristic algorithms to solve the problem.

VIII. Acknowledgments

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