Study of Joint Routing and Wireless Charging Strategies in Sensor Networks*

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Abstract. In recent years, wireless charging (a.k.a. wireless energy transferring) [3] has been recognized as a promising alternative to address the energy constraint challenge in wireless sensor networks. Comparing to the conventional energy conservation or harvesting approaches, wireless charging can replenish energy in a more controllable manner and does not require accurate location of or physical alignment to sensor nodes. In spite of these advantages, there has been little research on how much potential performance improvement may be achieved by applying the wireless charging approach to sensor networks and how to fully leverage its potential. In this paper, as one of the first efforts to study these issues, we (1) formulate the problem of maximizing the sensor network lifetime via co-determining routing and charging (ML-JRC), (2) prove the NP-hardness nature of the problem and derive an upper bound of the maximum sensor network lifetime that is achievable with ML-JRC, and (3) present a set of heuristics to determine the wireless charging strategies under various routing schemes, and demonstrate their effectiveness via in-depth simulation.

1 Introduction

The limited energy supply has constrained the lifetime of a sensor network, and this has been a long-lasting and fundamental challenge in sensor networks that are designed for long-term operation. Over the years, various schemes have been proposed to address this challenge, such as energy conservation [4], environmental energy harvesting [2, 7], incremental sensor deployment, and battery replacement [10, 11]. Unfortunately, all these schemes have their limitations. Energy conservation schemes can only slow down energy consumption but cannot compensate energy depletion. Harvesting the environmental energy is subject to their availability which often is uncontrollable by people. Incremental sensor deployment may not be environmentally friendly because deserted sensor nodes can pollute the environment.

As the wireless charging technology is being commercialized [9], it has become a promising alternative to address the energy constraint challenge in wireless sensor networks. Different from energy harvesting technologies, the wireless charging technology, together with more and more mature and inexpensive mobile robots, will make the controllable energy replenishment possible, with which energy can be replenished proactively to meet application requirements rather than passively from the energy resources available in the environment. Comparing with sensor node or battery replacement approaches, the wireless charging technology allows a mobile charger (MC) to

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transfer energy to sensor nodes wirelessly when they are apart by up to a few feet, and therefore does not require accurate localization of sensor nodes or strict physical alignment between the MC and sensor nodes.

In spite of the potential advantages of the wireless charging technology, little research has been conducted on how much sensor network lifetime may be prolonged with the technology and how to fully leverage its potential. Since communication is a major source of energy consumption in sensor networks and routing strategy has a significant impact on the communication efficiency, we are particularly interested in the problem of co-determining wireless charging and routing strategies to maximize the network lifetime. In general, this is a complicated problem due mainly to the mutual dependency between wireless charging and routing strategies. For example, depending on the routing schemes, such as the routing metric to be used and whether data is aggregated along the route, the MC may vary the sequence of the sensor nodes to be charged and the amount of energy allocated to each sensor. On the other hand, the location and moving speed of the MC may affect sensor nodes' routing decisions as it could be more beneficial in terms of energy efficiency by routing data through longer paths but closer to the MC. In this paper, as the starting point to study this complicated problem, we investigate a basic version of the problem by making a few simplifying assumptions. Particularly, we assume no aggregation during data forwarding and zero delay or energy cost for MC movement. We refer to this version of the problem as the ML-JRC (Maximizing Lifetime via Joint Routing and Charging) problem.

The rest of the paper is organized as follows. In Section 2, we formulate the ML-JRC problem, prove its NP-hardness nature and derive an upper bound of the maximum sensor network lifetime achievable with ML-JRC. In Section 3, we present a set of heuristics to determine the wireless charging strategy under various routing schemes. Section 4 evaluates the proposed heuristics against the theoretical upper bound via simulation and Section 5 concludes the paper.

2 Problem Formulation and Analysis

2.1 System Models

Network Model. We consider a wireless sensor network deployed for long-term, continuous monitoring of a certain field [6, 12]. A subset of sensors (denoted as src) in the network monitor the environment continuously and generate sensory data at the same constant rate (r). All sensors collaborate in forwarding sensory data to the base station hop by hop. There is only one base station in the network. We assume that data is not aggregated along the forwarding path. Each sensor is initially provisioned with a battery with full energy (E_s) and equipped with two antennas, one for wireless communication and the other for wireless charging.

Previous studies have shown that among all components of a sensor node, radio consumes the most significant amount of energy. Therefore, we only consider the communication energy cost and neglect others (i.e., sensing cost and computational cost). Based on [1], we model the energy consumption of transmitting one data packet between nodes i, j as $e_{ij} = L * \gamma * d_{ij}^n$, where L is the packet length (in bits), γ and n are the constants for a specific wireless system (usually $2 \leq n \leq 4$), and d_{ij} is the distance between nodes i, j. In this paper, we set $\gamma = 0.001$ and $n = 3$.

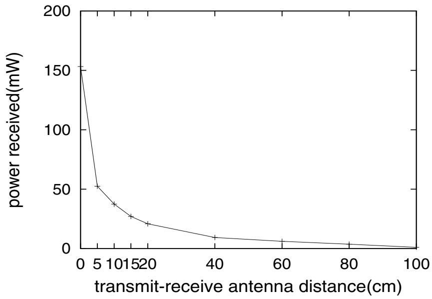


Fig. 1. Power charged to the receiver vs. transmit-receive antenna distance

Wireless Charging Model. The wireless charging-related assumptions are made based on the wireless charging devices provided by Powercast [9]. A mobile charger (MC) equipped with an energy transmitting antenna can move around in the field. Charging is conducted wirelessly without requiring that the MC and sensors touch each other or are aligned in position. The wireless band used for charging is different from that for communication; for example, the Powercast chargers transfer energy in the $903-927$MHz band while most sensor nodes use the 2.4GHz band for communication. When the MC operates, its power consumption is $3W$ (Λ_c). The effective amount of power that can be captured by a sensor (denoted as λ_c) varies with its distance to the MC. The relation is illustrated in Figure 1, which is obtained through our field test with the Powercast wireless energy transmitter and receiver. The antenna gain is 1.15 for both the transmitter and receiver. As shown in the figure, at the distance of $10cm$, the receiver can receive about $30mW$ power, meaning that the charging efficiency $\eta = \frac{\lambda_c}{\Lambda_c}$ is about 1%. As the distance increases, the charging efficiency decreases drastically. Initially, the MC is equipped with a battery with energy E_c for charging.

We assume that the MC has the full knowledge about the network, including the geographic locations of all sensor nodes and their current energy levels. Moreover, we assume zero delay or energy cost for the MC movement.

2.2 Problem Definition and NP-Hardness Nature

The problem to be studied in this paper is that, given the above system models, how to schedule the routing of sensory data packets from the source nodes to the base station and the charging activities of the MC so that the network lifetime may be maximized. Here, the network lifetime is defined as the time elapsed before the network fails to route a data packet from any source node to the base station (due to that either the source node has depleted its energy or all the routes from the source node to the base station have been broken). We refer to this problem as the ML-JRC (Maximizing Lifetime via Joint Routing and Charging) problem, which is NP-hard as to be proved below.

The decision version of the ML-JRC problem can be formally expressed as follows: *Given an ML-JRC instance $\langle G = (V \cup \{bs\}, E), src, e_{ij}, r, E_s, E_c, \Lambda_c, \eta\rangle$, can the network survive for N time slots (where the length of a slot is given)?* Our proof is motivated by [8] and based on the Disjoint Connection Path (DCP) problem which is well-known to be NP-complete. The DCP problem tries to determine that, given a graph $G' = (V', E')$ (either directed or undirected) and a set of k disjoint source and destination vertex pairs $(s_i, t_i), i = 1, 2, \ldots, k$, whether there are k vertex-disjoint paths each of which connects an (s_i, t_i) pair.

Theorem 1. *The decision version of the ML-JRC problem is NP-hard.*

Proof. (sketch) Given a DCP instance $\langle G', (s_i, t_i)\rangle$ where $i = 1, 2, \ldots, k$, we can construct an ML-JRC instance with the following procedure:

- Add one bs node, one source node src_0, and links (src_0, s_i) and (t_i, bs) (where $i = 1, 2, \ldots, k$) to G' to construct G;
- Set $e_{src_0,s_i} = 0$, and $e_{ij} = 1$ for all other links in G;
- r is set to one packet per time slot, E_s is set to 1, E_c, Λ_c and η are set to 0;
- N is set to k.

The above construction procedure can be completed in polynomial time. Next, we need to prove that a given DCP instance and its corresponding ML-JRC instance are equivalent. Suppose there exist k vertex-disjoint paths P_i where each P_i connects the pair $(s_i, t_i), i = 1, 2, \ldots, k$ in the DCP problem. Then, in the ML-JRC problem, we have k disjoint paths from src_0 to bs. As a result, the system can survive $N = k$ time slots since in each time slot, the src_0 could use one of the k disjoint paths to deliver a data packet to bs. Conversely, if in the ML-JRC problem, the system has a lifetime of N time slots, there must exist N disjoint paths (denoted as P_i') from src_0 to bs. This is because each node in the network only has the energy to transmit one data packet. Therefore, no node can be part of multiple paths to deliver multiple packets. Let P_i be the path obtained from P_i' by removing the nodes src_0, bs and the links (src_0, s_i), (t_i, bs) $i = 1, 2, \ldots, N$. Then, all P_i paths are vertex disjoint, meaning that there exist k vertex-disjoint paths in the corresponding DCP instance. Since DCP is known to be NP-complete, we have proved that ML-JRC is NP-hard.

2.3 Upper Bound of Lifetime Achievable with ML-JRC

In this section, we utilize the linear programming (LP) technique to derive an upper bound of the maximum network lifetime that can be achieved in the ML-JRC problem. Formally, it is formulated as follows:

$$\max \quad p/r$$

subject to:

$$p + \sum_{j \in N_i} f_{ji} = \sum_{j \in N_i} f_{ij}, \quad \forall i \in src \tag{1}$$

$$\sum_{j \in N_i} f_{ji} = \sum_{j \in N_i} f_{ij}, \quad \forall i \in (V - src) \tag{2}$$

$$|src| * p = \sum_{j \in N_{bs}} f_{j,bs} \tag{3}$$

$$\sum_{j \in N_i} f_{ij} * e_{ij} \leq E_s + \Delta E_i * \eta, \quad \forall i \in V \tag{4}$$

$$\sum_{i=1}^{n} \Delta E_i \leq E_c \tag{5}$$

$$f_{ij}, \Delta E_i \geq 0 \tag{6}$$

Here, p stands for the total number of data packets generated by each source node during the network lifetime. Since the data generation rate r is the same over all source nodes, they should produce the same number of packets during the network lifetime. Therefore, p/r defines the lifetime. ΔE_i is the total amount of energy used by the MC to charge node i. f_{ij} is the total number of packets transmitted from node i to node j.

Constraints (1), (2) and (3) reflect the flow conservation requirements. Constraint (4) reflects that the energy used for transmission should be smaller than E_s – the initial battery energy at a sensor node – plus the energy charged from the MC. Constraint (5) states that the total energy used for charging cannot exceed E_c – the initial battery capacity of the MC. The output $\langle f_{ij}, \Delta E_i \rangle$ is the joint routing and charging decision. More specifically, it specifies the number of data packets transmitted over link (i, j) and the amount of energy distributed to node i by the MC so that the network lifetime can be maximized.

3 Heuristic Solutions

As the ML-JRC problem is NP-hard, finding an optimal solution may have high computational complexity as the network scale increases. Hence, we propose low-complexity heuristic solutions. Instead of solving the complicated joint problem directly, the proposed heuristic solutions adopt the following philosophy: each node in the network runs a routing algorithm which requires only little, locally available information, and the MC runs a charging scheduling algorithm based on the global network knowledge.

The general framework of the proposed heuristic solutions is as follows. Time is divided into slots and the length of each time slot is δ_t. At the beginning of each time slot, each sensor node exchanges the latest routing cost to the base station with its neighbor nodes and, based on the received information, selects the least-cost route to deliver its data towards the base station. Meanwhile, based on its knowledge about the routes selected by all source nodes, the MC plans its activity to spend $\delta_t \Lambda_c$ amount of energy to charge sensor nodes during the slot. As Λ_c is the power consumed by the MC for charging operation, $\delta_t \Lambda_c$ gives the maximum energy available for charging in a slot. In the following, we describe the routing metrics used by sensor nodes to define least-cost routes and the heuristic algorithms for the MC to decide its charging activity.

3.1 Routing Metric

As there have been lots of research on designing routing algorithms to prolong the network lifetime, we adopt a representative one and focus on designing charging algorithms with this particular routing algorithm. Specifically, the routing metric we adopt is $C_{ij,t} = e_{ij} * u^{1-\frac{w_{i,t}}{E_s}}$ [5], where u is a system parameter and $w_{i,t}$ is the residual energy of node i at the beginning of time slot t. This metric is a combination of the minimum energy (e_{ij}) and max-min residual energy ($u^{1-\frac{w_{i,t}}{E_s}}$) metrics. When $u = 1$, it is reduced to the minimum energy metric; when $u > 1$, the route is selected by trading off the communication cost and nodal residual energy. The larger is u, the more balanced is the energy distribution among sensor nodes after the route is used.

3.2 Heuristic Charging Algorithms

An effective charging algorithm should charge first the nodes whose lifetime constrains the network lifetime the most, and should utilize the network routing information to adjust the charging decisions adaptively. With these considerations, we propose three heuristics to prolong the network lifetime.

Least Residual Energy First (LRE). Balancing energy consumption among all nodes is a well-known technique to prolong the network lifetime. We propose a simple LRE heuristic that applies this technique. Specifically, at the beginning of time slot t, the MC sorts all nodes into a list denoted as $l = (l_0, \ldots, l_n)$ in the ascending order of nodal residual energy, and performs the following max-min calculation:

$$\sum_{i=l_0}^{l_m} \Delta e_{i,t} \leq \delta_t \Lambda_c,\ m \leq n \tag{7}$$

$$w_{l_0,t} + \Delta e_{l_0,t} * \eta = w_{l_1,t} + \Delta e_{l_1,t} * \eta = \cdots = w_{l_m,t} + \Delta e_{l_m,t} * \eta,\ m \leq n \tag{8}$$

$$w_{l_k,t} + \Delta e_{l_k,t} * \eta \leq E_s,\ k \in [0, m] \tag{9}$$

In the above, $\Delta e_{i,t}$ is the energy to be charged to node i in time slot t. (7) restricts the total energy allocated in a time slot, (8) specifies the m nodes selected to be charged to the same energy level, and (9) constrains the maximum energy level of each node to be below the battery capacity. All of the $\delta_t \Lambda_c$ amount of energy shall be used up in the slot unless all nodes already have their batteries fully charged to the capacity.

Least Estimated Lifetime First assuming Fixed Routes (LEL). Similar to LRE, the intuition behind LEL is also to charge first the nodes whose lifetime has been the bottleneck of the network lifetime. However, different from LRE, LEL considers not only nodes' current residual energy but also their future energy consumption rates. To estimate nodes' future energy consumption rates, routes adopted by nodes should be predicted. In LEL, it is simply assumed that the routes used currently are the same as those to be used in the future. Therefore, the lifetime of each node is estimated as follows:

$$\begin{gathered} \mathit{lifetime}_{i,t} = w_{i,t}/\mathit{workload}_{i,t}, \\ \mathit{workload}_{i,t} = \alpha * \mathit{workload}_{i,t-1} + (1-\alpha) * (w_{i,t} - w_{i,t-1}). \end{gathered}$$

The list l used in LRE is sorted by the estimated lifetime and (8) is modified to

$$\frac{w_{l_0,t} + \Delta e_{l_0,t} * \eta}{\mathit{workload}_{l_0,t}} = \frac{w_{l_1,t} + \Delta e_{l_1,t} * \eta}{\mathit{workload}_{l_1,t}} = \cdots = \frac{w_{l_m,t} + \Delta e_{l_m,t} * \eta}{\mathit{workload}_{l_m,t}}.$$

In the above, $\mathit{workload}_{i,t}$ estimates the energy consumption of node i in time slot t, and $\mathit{lifetime}_{i,t}$ estimates the number of time slots node i could survive if it operates continuously at the estimated workload by assuming that routing paths do not change in the future. α is a system parameter used to tune the impact of the historical workload. The larger is α, the more important is the historical average workload.

Adaptive Energy Allocation with Dynamic Routes (AEA). LEL assumes that routes remain unchanged in the future, which may not be realistic. Thus, we further propose an AEA heuristic to take dynamic routes into account.

In Section 2.3, the solution to the LP formulation, $\langle f_{i,j}, \Delta E_i \rangle$, contains both flow information and energy allocated to each node during the network lifetime. Yet, the exact amount of energy replenished to each node at each time slot was not given. This formulation, however, inspires us to design the AEA heuristic which tells the MC the exact amount of energy replenished to each node in each time slot. Specifically, at the beginning of time slot t, the MC solves a modified LP formulation (i.e., replacing E_c with $\delta_t \Lambda_c$ to limit the maximal charging energy in a slot, and replacing E_s with $w_{i,t}$ to use the latest energy information), and charges the nodes according to the solution to this modified LP formulation.

The AEA heuristic aims to maximize the network lifetime through dynamically updating the charging decisions with the assumption that future routes would change accordingly. Essentially, if the actual network flows yielded by the routing algorithm are similar to the flow solution to the LP formulation, charging according to the energy solution to the LP formulation would approximate the upper bound of the maximum network lifetime well. However, if the actual flows differ much from the flow solution to the LP formulation, the performance of AEA would degrade inevitably.

4 Performance Evaluation

4.1 Simulation Settings

In the simulation, the node battery capacity E_s is set to $15000J$, the MC battery E_c is set to $2000000J$, the charging efficiency η is 0.01, Λ_c is $3W$, and all nodes are randomly placed in a $400m*400m$ area. We study the performance of different charging schemes as the workload, the time slot length and the density of source nodes vary. The performance metric is the network lifetime. The evaluated charging schemes include LRE, LEL-0 (i.e., LEL with $\alpha = 0$), LEL-0.8 (i.e., LEL with $\alpha = 0.8$) and AEA. The performance of these schemes is also compared with that of NoC (i.e., no charging), and the lifetime upper bound computed with the LP formulation presented in Section 2.3.

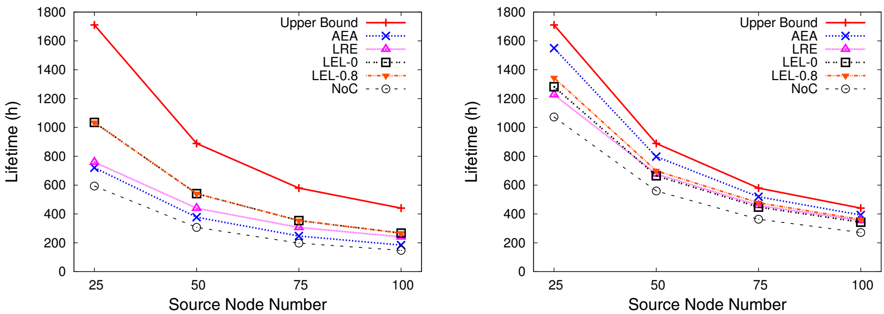
4.2 Simulation Results

Lifetime with Varying Workload. As the workload changes, the network-wide energy distribution may be different, which may impact the performance of the charging heuristics. To evaluate the impact, we fix the number of nodes in the network (i.e., 100) but vary the number of source nodes from 25 to 75. Results are plotted in Figure 2.

As shown in the figure, all the proposed charging heuristics yield longer network lifetime than NoC. In addition, though the lifetime achieved with the charging heuristics declines as the workload increases, the ratio of the achieved lifetime to the theoretic upper bound keeps almost the same. For example, LRE, LEL-0 and LEL-0.8 achieve around 80% and AEA achieves 90% of the upper bound, when $u = 100$. Moreover, as the routing parameter u increases from 1 to 100, the achieved lifetime also increases because, as discussed in Section 3.1, the route selection tends to balance energy consumption among all nodes as u increases.

Figure 2(a) shows the results when $u = 1$. It can be seen that the LEL schemes (i.e., LEL-0 and LEL-0.8) outperform other charging heuristics, while the AEA scheme yields the worst performance among all heuristics. This is due to the following reasons.

When $u = 1$, the routing algorithm is reduced to that with the minimum energy metric. In this case, the routes are stable and not adjusted frequently to changes in the energy distribution among nodes. As this situation resembles the assumption of the LEL schemes well but is much different from that of the AEA scheme, the LEL schemes outperform the AEA scheme. On the other hand, due to the stability in route selection, factoring the historical workload more (as in LEL-0.8) or less (as in LEL-0) into estimating the future workload of sensor nodes do not make significant difference, which contributes to the performance similarity between LEL-0 and LEL-0.8.



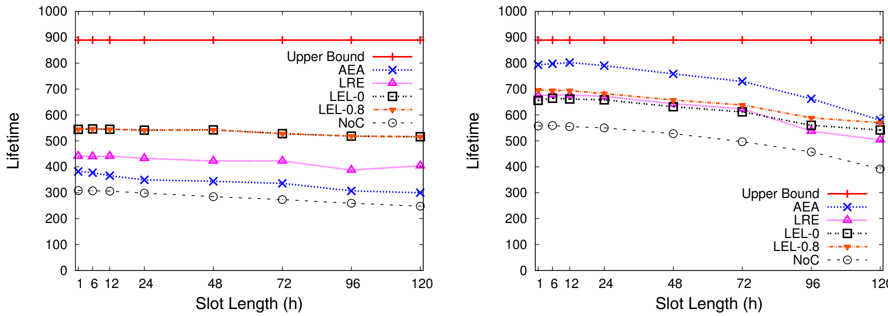
(a) $u = 1$ (b) $u = 100$

Fig. 2. Lifetime with varying workload. X-axis represents the number of source nodes and Y-axis represents the network lifetime in units of hours. The time slot length is $6h$, packet rate is $30pkt/h$ per source node, and the total number of nodes is 100.

Figure 2(b) shows the results when $u = 100$. In this case, AEA yields the best performance among all, followed by LEL-0.8, LEL-0 and LRE in order. In contrary to the case of $u = 1$, with $u = 100$, the routing algorithm tends to actively adjust routes to balance the energy consumption among all nodes. This situation resembles the assumption of the AEA scheme well but is much different from that of the LEL schemes; therefore, the AEA scheme outperforms the LEL schemes. For the LEL schemes, LEL-0.8 uses more historical information in estimating future workload, which results in more accurate estimation and hence better performance than LEL-0. Regardless of the parameter u, the LEL schemes always outperform the LRE scheme because route selection is considered in LEL but not in LRE.

Lifetime with Varying Time Slot Length. In the proposed heuristics, updating routes and charging planning happen only at the beginning of a time slot. Therefore, the frequency of route updating and charging planning decreases as the slot length increases. To investigate how this frequency impacts the network lifetime, we have conducted simulations with the slot length varying from $1h$ to $120h$.

Figure 3(a) shows the results when $u = 1$. We can see that all charging heuristics are insensitive to changes in slot length. This is because, in this case, minimum energy routes are always selected and remain unchanged regardless of the slot length. In comparison, when $u = 100$, as shown in Figure 3(b), the performance of all heuristics drop as the slot length increases, since the impact of lifetime extension resulted from balanced route selection has been reduced. Among all the heuristics, the performance of



(a) $u = 1$ (b) $u = 100$

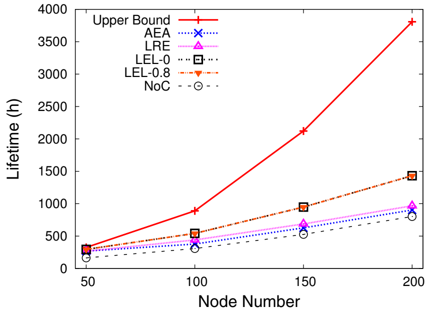
Fig. 3. Lifetime with varying time slot length. X-axis represents the time slot length and Y-axis represents the network lifetime in units of hours. The total number of nodes is 100, the number of source nodes is 50, and the packet rate is $30pkt/h$ per source node.

AEA drops the most rapidly. This is because AEA assumes frequent route updates in the future. However, as the slot length increases, such update happens less frequently. As a result, the performance of AEA degrades significantly. On the contrary, other heuristics either assume fixed routes or do not consider route selection, hence are less sensitive to changes in the slot length. Figure 3(b) also reveals that, when the slot length is in the range of $[1, 24]$, the performance of all charging heuristics remains at a high level. Therefore, it is not necessary to choose too short a time slot, which may incur more computational and movement overhead for the MC.

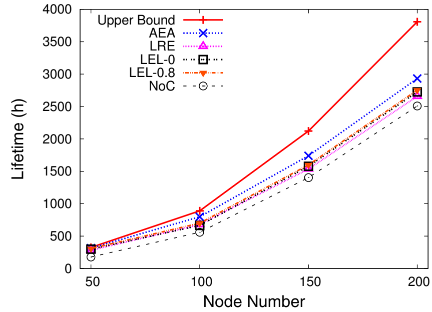
Lifetime with Varying Network Density. Given fixed number of source nodes, increasing the network density (i.e., increasing the number of nodes in the network) provides more options for selecting routes and distributing workload. It is interesting to evaluate whether the proposed heuristics may exploit the more options presented in a larger scale network and how well they may do so. For this purpose, we have conducted simulations with fixed number of source nodes but varying total number of nodes.

As shown in Figure 4, as the total number of nodes increases, the network lifetime increases with all heuristics and the performance gain of heuristics over NoC becomes more significant. This demonstrates that the heuristics have the capability of exploiting the more options brought in by the higher network density. Furthermore, comparing Figures 4(a) and 4(b), we can see that, when the parameter u gets larger, the lifetime achieved by the heuristics increases with the network density more rapidly. This is because a larger u implies that the balance of residual energy among all nodes is favored more in path selection. Hence, workload is distributed more proactively among nodes; this way, the advantages brought in by the increased network density can be better exploited.

Among all the heuristics, AEA performs the best, followed by LEL-0.8, LEL-0 and LRE when $u = 100$. The difference is due mainly to the following reasons. As the network density increases, routes are updated more frequently as there are more available routes with dynamically changing costs. This situation resembles the assumption of AEA better than that of the LEL schemes; hence, AEA outperforms the LEL. LEL-0.8 estimates the future workload more accurately than LEL-0 when the routes are updated more frequently; hence, LEL-0.8 outperforms LEL-0. LRE does not consider the effect



(a) $u = 1$



(b) $u = 100$

Fig. 4. Lifetime with varying network density. X-axis represents the total number of nodes in the network and Y-axis represents the network lifetime in units of hours. The number of source nodes is 50, the packet rate is $30pkt/h$ per source node, and the time slot length is $6h$.

of path selection and therefore performs worse than other heuristics. Figure 4 also shows that, the lifetime upper bound ascends faster than all heuristics as the network density increases. This is because the routing and charging strategies are scheduled jointly in the LP formulation, while the routing in all heuristics is planned without considering the charging activity of the MC.

Summary: We obtain the following insights and preliminary conclusions from the simulation results: (1) With the proposed charging heuristics, the achieved network lifetime can reach a decent fraction of the upper bound, which indicates that the application of wireless charging may prolong the network lifetime even with simple charging strategies. Nevertheless, the performance gap between the proposed charging heuristics and the upper bound is still noticeable in some scenarios, which motivates us to design more delicate joint routing and wireless charging algorithms to further approach the upper bound. This is part of our future work. (2) As the routing algorithm favors more balanced energy distribution among nodes, the AEA heuristic is the preferred choice. On the other hand, the LEL heuristic is more desired when the route selection is mainly affected by the link cost rather than the balance among nodal residual energy. (3) Simulation results also indicate that effective joint routing and charging schemes should be adaptive to the changes in network density.

5 Conclusions

In the paper, we study a new type of sensor networks which consists of sensor nodes with replenishable energy supplies and a mobile charger that is able to charge the batteries of sensor nodes wirelessly. We formulate the problem of maximizing the sensor network lifetime via joint routing and charging (ML-JRC), prove its NP-hardness nature, and derive the upper bound of the maximum network lifetime that is achievable with ML-JRC. We also present a set of heuristics to determine the energy charging strategies for the mobile charger under different routing schemes. Simulation results demonstrate the effectiveness of applying the wireless charging technology to prolong the sensor network lifetime, even with simple charging heuristics.

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