On-Demand Energy Replenishment for Sensor Networks via Wireless Energy Transfer

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***Abstract*—In this paper, we study the use of a wireless charging vehicle (WCV) to replenish energy to sensors in a wireless sensor network so that none of the sensors will run out of its energy, where sensor batteries can be recharged. Specifically, we first propose a flexible on-demand sensor energy charging paradigm that decouples sensor energy replenishment and data collection into separate activities. We then formulate an optimization problem of wireless charging with an aim to maximize the ratio of the amount of energy consumed for charging sensors to the amount of energy consumed on traveling of the WCV as the WCV consumes its energy on both traveling and sensor charging. We also devise a novel algorithm for scheduling the tours of the WCV by jointly considering the residual lifetimes of sensors and the charging ratio of charging tours. We finally evaluate the performance of the proposed algorithm by conducting simulation. Experimental results show that the proposed algorithm is promising, and can improve the energy charging ratio of the WCV significantly.**

I. Introduction

Wireless sensor networks (WSNs) have played a key role in structural health monitoring, environmental sensing, target tracking, etc [13]. As sensors in conventional WSNs are powered by batteries, their limited battery energy has hampered the large scale deployment of WSNs for long-term monitoring purposes. There have been a flourish of energy conservation techniques developed in the past decade to elongate the lifetime of WSNs by minimizing the energy consumption of sensors or balancing energy expenditures among sensors [1]. Despite lots of efforts, the lifetime of WSNs still remains a main performance bottleneck in the real deployment of WSNs as energy conservation cannot prevent sensors from depleting their energy. To ensure that a sensor network can operate for long periods, energy replenishment to its sensors is necessitated. Extensive efforts on replenishing energy to sensors have been taken in the past decade. In general, existing energy replenishment approaches can be classified into sensor replacement, energy harvesting, and wireless energy charging. However, sensor replacement and energy harvesting methods are very limited in practice, since deploying new sensors is not only costly but also environmentally unfriendly [8], while the amount of energy harvested and the harvesting rate of each sensor is hard to predict due to the time-varying nature of renewable energy resources [5].

The recent breakthrough of a wireless energy transfer technique based on strongly coupled magnetic resonances has attracted scientists' attention [3]. Kurs *et al.*[3] showed that it is feasible to efficiently transfer electric energy from one storage device to another without any plugs or wire lines. Wireless energy charging becomes a very promising approach to prolong the lifetime of WSNs since it can provide steady and high charging rates to sensors.

In this paper we study the use of a wireless charging vehicle (WCV) to replenish energy to sensors in a large-scale wireless sensor network so that none of the sensors in the network will fail due to its energy expiration. We propose a flexible on-demand sensor energy charging paradigm that only is there a need for charging some sensors that will run out of energy soon, the WCV then travels to the vicinities of the sensors and replenishes them wirelessly. Unlike existing studies that ignore the energy consumption of the WCV [7], [9], [10], [14], we consider an optimization problem that maximizes the ratio of the amount of energy consumed by the WCV for charging sensors to its energy consumption on traveling for a given monitoring period. The challenges to tackle this problem are: when should the WCV start a new charging tour? which sensors are to be included in each tour? and what is the charging order of the sensors in each tour?

The main contributions of this paper can be summarized as follows. We first propose a flexible sensor energy charging model that decouples energy replenishment from data collection, in which energy consumption rates of sensors are allowed to vary over time and the WCV can adaptively replenish sensor energy. Under the proposed energy replenishment model, we then formulate an optimization problem with the objective of maximizing the charging ratio of the WCV, while ensuring that none of sensors will run out of energy. We thirdly devise a novel heuristic algorithm for the optimization problem. We finally conduct extensive experiments by simulations to evaluate the performance of the proposed algorithm. Experimental results show that the proposed algorithm can significantly improve the charging ratio of the WCV.

The rest of the paper is organized as follows. Section II reviews related work. Section III introduces the system model and problem definition. Section IV devises a heuristic algorithm for the problem. Section V evaluates the performance of the proposed algorithm, and Section VI concludes the paper.

II. Related work

With the advance on efficient wireless energy transfer technology based on strongly magnetic resonances, wireless energy replenishment has been adopted for the lifetime prolongation of WSNs in literature [7], [9], [10], [14], [11], [12], [4], [6]. Most of these studies considered sensor energy replenishment and data flow routing jointly. For example, Shi *et al.* [7], [9], [10] employed a WCV periodically to travel in a monitoring area to charge each sensor per tour. They studied an optimization problem of maximizing the ratio of the vacation time of the WCV over the renewable energy cycle time, assuming that the data generation rate of each sensor does not change over time. Zhao *et al.* [14] proposed a joint design framework of energy replenishment and data gathering by exploiting sink mobility, in which they employed a multi-functional vehicle to periodically patrol a sensor network to charge sensors and collect sensing data. These mentioned joint consideration of energy replenishment and data flow routing may have limited applications in practice due to the flow conservation assumption at each sensor. The flow conservation assumption ignores an important fact of data aggregation at intermediate nodes, which is one of the most efficient operations in WSNs to reduce data traffic volume since sensing data from different sensors are usually temporal-spatially correlated [2]. In contrast, we here decouple the sensor energy replenishment from data routing. The WCV only passively charges sensors that will run out of their energy soon.

There are also recent studies that considered passive energy replenishment to sensors. Xu *et al.* [11] proposed constant approximation algorithms for scheduling k mobile chargers to replenish a set of to-be-charged sensors, such that the maximum time spent among the k chargers is minimized. Xu *et al.* [12] devised an approximation algorithm for scheduling multiple mobile chargers to maintain the perpetual operation of a sensor network, so that the total traveling distance of the mobile vehicles is minimized. Liang *et al.* [4] proposed an approximation algorithm for minimizing the number of mobile vehicles needed for charging a set of to-be-charged sensors, under the energy capacity constraint on each mobile vehicle. Ren *et al.* [6] employed a mobile charger to charge on-demand sensors under the travel distance constraint. Orthogonal to these works, we devise an efficient charging scheduling algorithm to maintain the sensor network operating perpetually, such that the ratio of the amount of energy consumed by the WCV for charging sensors to its energy consumption on traveling for a certain given period is maximized. This ratio is critical to reduce the WSN maintenance cost.

III. Preliminaries

A. Network model

We consider a WSN deployed for a monitoring purpose in a two-dimensional space. We represent the network by an undirected graph $G = (V \cup \{b\} \cup \{d\}, E; w)$, where V is a set of static sensors with $n = |V|$, b is a stationary base station, and d is a depot at which a wireless charging vehicle (WCV) is located. For any two nodes in $V \cup \{b\} \cup \{d\}$, there is an edge (or a link) e in E between them with their Euclidean distance $w(e)$. For any simple cycle C in G, denote by $w(C)$ the weighted sum of the edges in C, i.e., $w(C) = \sum_{e \in C} w(e)$.

B. Energy consumption model of sensors

We assume that each sensor $v_i \in V$ is powered by a chargeable battery with energy capacity B_i, and it consumes its energy when performing various operations including sensing, processing data, data transmission, etc. Assume that the energy consumption rate of sensor v_i at time t is $\rho_i(t)$. Each sensor is able to monitor its own energy status such as its residual energy and energy consumption rate periodically (e.g., every a few hours). Each sensor adopts a lightweight prediction technique to estimate its energy consumption rate in the near future. Specifically, each sensor v_i can calculate its predicted energy consumption rate $\hat{\rho}_i(t+1)$ at time $t+1$ as $\hat{\rho}_i(t+1) = \alpha \cdot \rho_i(t) + (1-\alpha) \cdot \hat{\rho}_i(t)$, where $0 < \alpha < 1$ is a weighted factor, $\rho_i(t)$ and $\hat{\rho}_i(t)$ are the sampled and predicted energy consumption rates of sensor v_i at time t, respectively. Given the predicted energy consumption rate $\hat{\rho}_i(t+1)$ and the amount of residual energy $re_i(t)$ of sensor v_i at time t, it can estimate its residual lifetime $l_i(t)$ as $l_i(t) = re_i(t)/\hat{\rho}_i(t+1)$.

C. Sensor energy replenishment paradigm

We propose a flexible sensor energy replenishment paradigm for the network as follows. When the residual lifetime of each sensor falls below a given threshold ΔT, it sends a charging request to the base station. Once receiving a charging request from a sensor, the base station then commands the WCV located at the depot to replenish energy to the sensor sending the request and some other sensors by applying a scheduling algorithm. The WCV will perform the charging task specified by a command sent from the base station, which includes the sensors to-be-charged and the charging order of the sensors. Assume that the WCV travels at a constant speed s, and it consumes an amount of energy ζ on traveling per unit distance. We here consider a point-to-point charging, i.e., to charge a sensor efficiently, the WCV must be within the vicinity of the sensor. When the WCV replenishes energy to a sensor node, it will charge the sensor to its full energy capacity. Furthermore, assume that U is the output power of the WCV, and η is its wireless transferring efficiency which is a constant with $0 < \eta < 1$. Then, it takes $(B_i - re_i(t))/(\eta U)$ time for the WCV to fully charge sensor v_i, where t is the time point that the WCV begins charging sensor v_i. When the WCV completes its current charging tour, it returns the depot for recharging itself and waiting for its next charging tour. A sensor usually consumes its energy slowly as we consider a monitoring application scenario. We thus assume that the energy draining of a sensor during a charging tour is negligible when comparing with the energy capacity of the sensor.

D. Problem definition

We note that it is unnecessary to charge each sensor per charging tour as the energy consumption rates of different sensors may vary significantly. For example, since sensors near the base station have to relay data for other remote sensors, their energy consumption rates are much faster than that of the others, from this observation it can be seen that a naive strategy of charging all sensors per tour will significantly increase the traveling distance of the WCV. It thus is critical to schedule the WCV by jointly taking the energy consumption rate of the WCV and geographical locations of sensors into consideration.

Given the WSN, the energy consumption model of sensors, the energy charging paradigm, and a monitoring period T (T typically is quite long), *the charging ratio maximization problem* is to find a series of the WCV's charging tours that can maintain the sensors operating during T, such that the ratio of the amount of energy consumed by the WCV for charging the sensors to its energy consumption on traveling is maximized. Specifically, assume that there are k charging tours $C_1(t_1), C_2(t_2), \cdots, C_k(t_k)$ for the WCV charging the sensors during the period T, such that none of the sensors runs out of its energy, where tour $C_j(t_j)$ contains the depot d and at least one sensor to be charged, the WCV starts charging sensors in tour $C_j(t_j)$ at time t_j, and $0 < t_j < T$. Denote by $E_T^{payload}$ and $E_T^{overhead}$ the amounts of energy consumed by the WCV for charging sensors and traveling during T, respectively, i.e., $E_T^{payload} = \sum_{j=1}^{k} \sum_{v_i \in C_j(t_j)} (B_i - re_i(t_j))/\eta$ and $E_T^{overhead} = \sum_{j=1}^{k} \zeta \cdot w(C_j(t_j))$, where $re_i(t_j)$ is the amount of residual energy of sensor v_i at time t_j, and $w(C_j(t_j))$ is the length of tour $C_j(t_j)$. We aim to maximize the ratio $ratio_T$ of $E_T^{payload}$ to $E_T^{overhead}$, i.e., $ratio_T = E_T^{payload}/E_T^{overhead}$. The ratio $ratio_T$ characterizes the efficiency of the charging tours for maintaining the WSN operating for period T.

IV. Heuristic Algorithm for the Charging Ratio Maximization Problem

In this section, we devise a novel heuristic algorithm for the charging ratio maximization problem. Given a period T, the algorithm delivers a series of charging tours $C_1(t_1), C_2(t_2), \cdots, C_k(t_k)$ at different time points $t_1, t_2, \cdots, t_k$, where $0 < t_1 < \cdots < t_k < T$ and the WCV replenishes the sensors in the tour $C_j(t_j)$ one by one.

Assume that the first $j-1$ tours so far have been scheduled at time points $t_1, t_2, \cdots, t_{j-1}$, respectively. Initially, we can assume that $j = 1$. We now determine the next time point t_j and next charging tour $C_j(t_j)$. As the problem is an NP-hard optimization problem, we decouple it into three subproblems and deal with each subproblem separately. In other words, we will address the following three questions. (1) When does the WCV begin its next charging tour? (2) Which sensors should be included in the charging tour? (3) What is the charging order of sensors in the charging tour? In the following, we first provide the basic idea of the proposed algorithm, followed by elaborating the detailed algorithm.

A. Basic idea

The basic idea of the algorithm is as follows. The WCV will start its next charging tour as late as possible, as long as each sensor is charged before it depletes its energy. Thus, more energy can be charged into sensors and the charging ratio can be significantly improved. To this end, we compute a critical residual lifetime $l_{critical}$ for each sensor sending its charging request to the base station. When the base station receives a charging request from a sensor, it activates the next charging tour of the WCV, by applying the proposed algorithm to find a set of sensors to-be-charged in the forthcoming tour. The algorithm selects the set of to-be-charged sensors by jointly considering their residual lifetimes and the charging ratio of the tour of selected sensors. In other words, the algorithm may include sensors whose residual lifetimes are far more than $l_{critical}$ and have not yet sent their charging requests. The algorithm finally determines the charging order of the selected sensors through finding a shortest closed tour consisting of all selected sensors and the depot.

B. Detailed algorithm

The proposed algorithm consists of calculating a critical residual lifetime $l_{critical}$ for each sensor and selecting sensors to be charged for the forthcoming tour in the following.

1) Setting a critical residual lifetime $l_{critical}$ for each sensor: Recall that when the residual lifetime of one sensor falls below a given threshold $l_{critical}$, the WCV will start to charge some sensors. To ensure that each sensor will be replenished before running out of its energy, we compute the longest duration of the WCV for charging all sensors in the network as follows. Let w_{TSP} be the length of the shortest tour visiting all sensors and the depot. Then, the maximum duration for the WCV finishing one charging tour is $\frac{w_{TSP}}{s} + \sum_{i=1}^{n} \frac{B_i}{\eta U}$, where s is the traveling speed of the WCV and $\sum_{i=1}^{n} \frac{B_i}{\eta U}$ is the maximum amount of time consumed for charging all sensors in the network. To ensure that no sensors will fail, we conservatively let $l_{critical} = \frac{w_{TSP}}{s} + \sum_{i=1}^{n} \frac{B_i}{\eta U}$.

2) Selecting sensors to be charged: Selecting sensors to be charged in the next tour consists of two phases. In the first phase, we choose sensors to be charged by their emergency of residual lifetimes. To this end, the algorithm selects the sensors with residual lifetime no more than the threshold of residual lifetimes ΔT, where $\Delta T \geq l_{critical}$. The rationale behind this is that the WCV can consume much less energy on traveling for charging those sensors that will deplete their energy soon (e.g. residual lifetime is no more than ΔT) in one charging tour rather than replenishing them separately in multiple charging tours. In the second phase, the algorithm selects some sensors from the residual sensors with an objective to maximize the charging ratio of the forthcoming charging tour. We do this by considering whether it is beneficial to charge some sensors that are geographically close some of the selected sensors, though their residual lifetime are not so short (more than ΔT). Denote by S_1 and S_2 the sets of sensors selected in Phase one and two, respectively. The WCV will charge all sensors in set $S = S_1 \cup S_2$ in its forthcoming tour.

The rest is to deal with the second phase. In this phase, the algorithm finds a charging tour C including all sensors from S_1 and a subset S_2 of $V - S_1$ such that the charging ratio is maximized, where the charging ratio of a charging tour C at time t is defined as: $ratio(C) = \sum_{v_i \in C}(B_i - re_i(t))/(\eta\zeta w(C))$. This metric characterizes the amount of energy consumed by the WCV charging sensors for each unit energy that is consumed on traveling. We aim to find a tour C with the maximum charging ratio $ratio(C)$ as follows.

Recall that S_1 is the set of sensors chosen in Phase one, we define $R = V - S_1$. We then select a subset S_2 of R and compute a tour C that contains all nodes in $S_1 \cup S_2 \cup \{d\}$ such that $ratio(C)$ is maximized. We construct the set S_2 greedily. Each time we pick such a sensor from R that can maximally increase the charging ratio. This procedure continues until either the charging ratio cannot be further improved or R becomes an empty set. Specifically, $S_2 = \emptyset$ initially. We pick one sensor from R and add it into S_2 iteratively. In each iteration, we first compute a shortest tour C including nodes in $S_1 \cup S_2 \cup \{d\}$ and the charging ratio $ratio(C)$ of tour C. Then, for each node v in R, we also compute a shortest tour C_v that includes nodes in $S_1 \cup S_2 \cup \{d, v\}$ and the charging ratio $ratio(C_v)$ of C_v. Denote by v_{max} the node with the maximum $ratio(C_v)$ among the nodes in R, i.e., $v_{max} = \arg\max_{v \in R}\{ratio(C_v)\}$. We pick node v_{max} from R and add it to S_2 if $ratio(C_{v_{max}}) > ratio(C)$, and this procedure continues until R becomes empty. We describe the detailed algorithm in **Algorithm** 1.

Algorithm 1 `MaxRatio`

Input: $G = (V \cup \{b\} \cup \{d\}, E)$, energy capacity $B : V \mapsto \mathbb{R}^+$, residual lifetime $l : V \mapsto \mathbb{R}^+$, and ΔT.
Output: A closed charging tour C

$S_1 \leftarrow \emptyset$; $S_2 \leftarrow \emptyset$;
Select sensors with residual lifetime less than ΔT into S_1;
$R \leftarrow V - S_1$; $tag \leftarrow' true'$;
Compute a shortest tour C visiting nodes in $S_1 \cup \{d\}$;
Compute $ratio(C)$ of tour C.
while $R \neq \emptyset$ and tag **do**
  Select a node v_{max} from R such that the shortest tour $C_{v_{max}}$ visiting nodes in $S_1 \cup S_2 \cup \{d, v_{max}\}$ has the maximum charging ratio $ratio(C_{v_{max}})$;
  if $ratio(C_{v_{max}}) > ratio(C)$ **then**
    $S_2 \leftarrow S_2 \cup \{v_{max}\}$; $R \leftarrow R - \{v_{max}\}$;
    $C \leftarrow C_{v_{max}}$; $ratio(C) \leftarrow ratio(C_{v_{max}})$;
  else
    $tag \leftarrow' false'$;
  end if
end while
return C.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed algorithm through experimental simulations.

A. Experimental environment setting

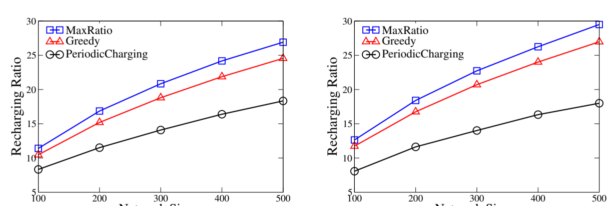
A WSN consisting of from 100 to 500 sensors are randomly deployed in a $500m \times 500m$ area. The base station is at the center of the area while the depot is located at one corner of the square. The battery capacity B_i of each sensor v_i is randomly drawn from the interval $[500, 1000]$. The energy transfer efficiency of the mobile vehicle is $\eta = 80\%$ and the vehicle consumes $\zeta = 1$ unit energy per unit traveling distance.

We consider two different distributions of sensor energy consumption rates: the *linear distribution* and the *random distribution*. In the linear distribution, the energy consumption rate ρ_i of sensor v_i is proportional to its distance to the base station. The nearest sensors to the base station have the maximum energy consumption rates ρ_{max} and the farthest sensors have the minimum energy consumption rates ρ_{min}. While in the random distribution, the energy consumption rate ρ_i of each sensor $v_i \in V_s$ is randomly chosen from an interval $[\rho_{min}, \rho_{max}]$, where $\rho_{min} = 1$ and $\rho_{max} = 10$.

To evaluate the performance of the proposed algorithm we also implement other two algorithms for the problems: `Greedy` and `PeriodicCharging`. In the `Greedy` algorithm, each time the WCV performs a charging task, it only charges sensors with lifetime less than ΔT in each charging tour. While in the `PeriodicCharging` algorithm, the WCV will replenish each sensor in the network to its full capacity when there is a charging need. The entire monitoring period is $T = 10,000$. We set ΔT as the minimum charging cycle τ_{min}, i.e., $\Delta T = \tau_{min} = \min_{i=1}^{n}\{\frac{B_i}{\rho_i}\}$. Each value in figures is the average of the results by applying each mentioned algorithm to 20 different network topologies of the same network size.

B. Performance evaluation of different algorithms

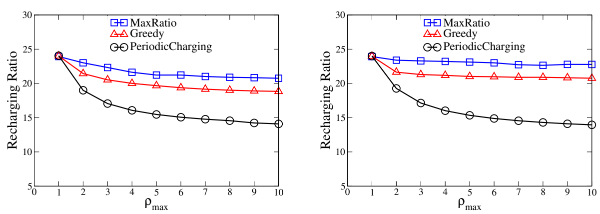
We first evaluate the performance of the three algorithms by varying network size n. Fig. 1 studies the performance of the proposed algorithm `MaxRatio` against that of algorithms `Greedy` and `PeriodicCharging`, by varying the network size from 100 to 500 under the random and the linear settings. Fig. 1(a) clearly shows that algorithm `MaxRatio` always outperforms the other two, and the performance gap among them grows bigger and bigger with the growth of network size. Specifically, the charging ratio of algorithm `MaxRatio` is about 8% and 10% higher than that of `Greedy` when network size is between 100 and 500, while the ratio can reach 35% and 45% higher when comparing with `PeriodicCharging`. Note that the charging ratios of these three algorithms go up when there are more sensors in the network since the WCV can replenish more sensors during each charging tour. Fig. 1(b) shows that the performance of the three algorithms in the linear setting behave similarly as them in the random setting.



(a) Random Setting (b) Linear Setting

Fig. 1. Performance of different algorithms by varying network size n when $\rho_{min} = 1$ and $\rho_{max} = 10$.

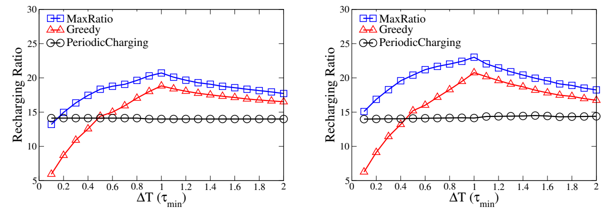
We then examine the impact of the variance of sensor energy consumption rates by varying ρ_{max} from 1 to 10 and fixing ρ_{min} at 1. Fig. 2 plots the performance of the three algorithms in a WSN with 300 sensors by varying the maximum energy consumption rate ρ_{max}. Both Fig. 2(a) and Fig. 2(b) show that the charging ratio of algorithm `MaxRatio` is higher than that of `Greedy` and `PeriodicCharging`. It can be noticed that the charging ratios of the three algorithms decrease with the increase of the maximum energy consumption rate ρ_{max}. The rationale behind the phenomenon is that the variance of energy consumption rates increases with a larger ρ_{max}. Then, the WCV scheduled by algorithm `MaxRatio` or `Greedy` will replenish less sensors during each charging tour, while the WCV scheduled by algorithm `PeriodicCharging` must charge all sensors in each charging tour, including those with plenty of residual lifetime. In spite of dropping in the performance, the charging ratios of algorithm `MaxRatio` and `Greedy` decline much slower than that of algorithm `PeriodicCharging` as the WCVs scheduled by these two algorithms do not often charge the sensors with low energy consumption rates.



(a) Random Setting (b) Linear Setting

Fig. 2. Performance of different algorithms by varying maximum energy consumption rate ρ_{max} when $n = 300$ and $\rho_{min} = 1$.

We finally investigate the impact of energy threshold ΔT of a sensor to be chosen on the performance of the algorithms by varying ΔT from $0.1\tau_{min}$ to $2\tau_{min}$, where $\tau_{min} = \min_{i=1}^{n}\{\frac{B_i}{\rho_i}\}$ is the minimum charging cycle among sensors. Fig. 3 shows that the charging ratio of algorithm `MaxRatio` is the best among the three algorithms. It is interesting to see that the charging ratios of algorithms `MaxRatio` and `Greedy` increase first and then go down, and they achieve the best performance when $\Delta T = \tau_{min}$, while the charging ratio of `PeriodicCharging` does not vary too much with the change of ΔT. The reason behind is that, in algorithms `MaxRatio` and `Greedy`, the WCV will replenish those sensors with residual lifetimes less than ΔT in each charging tour. Then, there will be no charging requests from sensors during the following $\min\{\Delta T, \tau_{min}\}$ time when the WCV completes its current charging tour, where τ_{min} is the minimum charging cycle among sensors. Therefore, when ΔT is less than τ_{min}, the WCV does not need to charge sensors in the following ΔT time and the WCV can consume less energy on traveling, thus the charging ratios of the two algorithms increase. However, when ΔT grows larger than τ_{min}, a bigger ΔT does not result in a less frequent charging of the WCV. On the other hand, with a larger ΔT, the WCV has to charge more sensors in each charging tour, which prolongs the length of the tour. The reason that the charging ratio of `PeriodicCharging` does not change with ΔT is that the WCV must visit and replenish all sensors regardless of their residual lifetimes.



(a) Random Setting (b) Linear Setting

Fig. 3. Performance of different algorithms by varying ΔT when $n = 300$, $\rho_{min} = 1$, and $\rho_{max} = 10$.

VI. Conclusions

In this paper, we employed a wireless charging vehicle (WCV) to wirelessly replenish sensor energy in a WSN to respond to charging requests from sensors, so that none of the sensors will run out of energy, thereby the WSN can operate perpetually, for which we first formulated a charging ratio maximization problem for maximizing the ratio of the amount of energy consumed by the WCV for charging sensors to its energy consumption on traveling, we then devised a heuristic solution. We finally conducted extensive experiments by simulations to evaluate the performance of the proposed algorithm. Experimental results demonstrated that the proposed algorithm is efficient, scalable, and insensitive to the variance of sensor energy consumption rates.

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