Speed Control of Mobile Chargers Serving Wireless Rechargeable Networks

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Abstract

Wireless rechargeable networks have attracted increasing research attention in recent years. For charging service, a mobile charger is often employed to move across the network and charge all network nodes. To reduce the charging completion time, most existing works have used the "move-then-charge" model where the charger first moves to specific spots and then starts charging nodes nearby. As a result, these works often aim to reduce the moving delay or charging delay at the spots. However, the charging opportunity *on the move* is largely overlooked because the charger can charge network nodes *while* moving, which as we analyze in this paper, has the potential to greatly reduce the charging completion time. The major challenge to exploit the charging opportunity is the setting of the moving speed of the charger. When the charger moves slow, the charging delay will be reduced (more energy will be charged during the movement) but the moving delay will increase. To deal with this challenge, we formulate the problem of delay minimization as a Traveling Salesman Problem with Speed Variations (TSP-SV) which jointly considers both charging and moving delay. We further solve the problem using linear programming to generate 1) the moving path of the charger, 2) the moving speed variations on the path and 3) the stay time at each charging spot. We also discuss possible ways to reduce the calculation complexity. Extensive simulation experiments are conducted to study the delay performance under various scenarios. The results demonstrate that our proposed method achieves much less completion time compared to the state-of-the-art work.

Keywords: wireless rechargeable networks, speed control, scheduling, delay optimization

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1. Introduction

Energy has always been a major obstacle for practical deployment of wireless sensor networks [1, 2, 3]. The network lifetime is strictly limited by the battery capacity [4, 5]. While many works focus on the duty cycling to reduce the energy consumption [6, 7], another trend is energy provisioning [8, 9, 10, 11]. The recent advances in wireless energy transfer technology [8] have enabled the development of Wireless Rechargeable Sensor Networks (WRSNs), where sensor nodes can be recharged via magnetically resonant objects before energy drain happens. Different from traditional energy harvesting sensor networks, WRSN is more reliable and can provide stable and sufficient energy supply services for the sensing tasks.

Since the charging range of a charger is limited, a mobile wireless charger is often required to move and charge the network nodes. A typical rechargeable sensor node has to be charged above a threshold before it can perform sensing, communication and computation tasks [12]. Due to the limited wireless charging speed, the charging is often time consuming. For example, it requires about 155 seconds to fully charge a WISP node [12] in a 10m distance. This will greatly affect the network performance especially in large scale networks.

As a result, the charging completion time plays a critical role for overall performance of WRSNs and has attracted increasing research attention in recent years [9, 13, 10]. Most existing works follow the "move-then-charge" model: a mobile charger moves to each charging spot and then charges the nodes nearby the spot. The process goes until all networks nodes are fully charged. However, the charging opportunity on the movement is overlooked in the "move-then-charge" model, bacause a charger can charge considerable amount of energy to the network nodes on its movement, which could be used for better charging scheduling to further reduce the charging completion time. To exploit the charging opportunity on the movement, the speed control of the charger is of great significance. The paradox of speed control is as follows. For charging the network nodes, the speed is required to be low such that more energy can be charged and the charging time is expected to be reduced. On the other hand, the speed is required to be high to reduce the moving delay. We will analyze the impact of the charging opportunity and moving speed in Section 2.

In this paper, we investigate the problem of speed control of the mobile charger in WRSNs. Aiming to minimize the completion time, we propose a speed optimization scheme for the mobile charger which jointly considers both the moving and charging delay. We first cluster the network nodes into a certain number of spots and then calculate the route and speed variations of the charger on visiting the charging spots. The problem is formulated as a Traveling Salesman Problem with Speed Variations (TSP-SV), which is NP-hard. We propose a heuristic solution which finds a good tradeoff between the moving delay and charging delay, and the charger is expected to achieve the minimum charging completion time. Our scheme has two distinct features compared to the existing works: 1) Instead of minimizing the moving distance or the charging time at specific spots, the optimization goal is the end-to-end metric, completion time; 2) The speed can vary during the charging process, which allows the charger to fully exploit the charging opportunity during the movement.

We implement the approach and conduct extensive simulation experiments. The evaluation results show that by exploiting the charging opportunity on the movement of the charger and allowing speed variations for the charger, the proposed approach outperforms the state-of-the-art work in terms of charging completion time (23.8%). The major contributions of this paper are listed as follows.

- We identify the key limitations of the existing works caused by overlooking the charging opportunity on the movement of the charger.
- We formalize the problem as Traveling Salesman Problem with Speed Variations, which jointly considers path planning and speed control.
- We propose a heuristic algorithm to the problem and conduct simulation experiments to investigate its performance. The results show that the charging delay is greatly reduced compared to the state-of-the-art works.

The remainder of this paper is organized as follows. Section 2 presents the network model and preliminaries. Section 3 presents the proposed model for delay optimization and the heuristic algorithm. Section 4 evaluates the algorithm using simulation experiments. Section 5 presents the related works. Finally, Section 6 concludes this paper and points future directions.

2. Preliminaries and motivation

In this section, we present the preliminaries and the motivation of this work.

2.1. Preliminaries

Wireless rechargeable nodes Wireless rechargeable nodes are capable of sensing, computing and energy harvesting with wireless chargers. For example, Wireless Identification and Sensing Platform (WISP) [12] is a typical wireless rechargeable low power node developed by Intel Research. Compared to the traditional RFID tags, A WISP node can be charged by the nearby RFID readers (denoted as chargers in this paper).

Energy charging model: In this paper, we use the charging model proposed in [11] as follows:

$$P_r = \frac{G_s G_r \eta}{L_p}\left(\frac{\lambda}{4\pi(d+\beta)}\right)^2 P_0 \tag{1}$$

where d denotes the distance between the node and the charger, P_0 denotes the charging power of the charger, G_s denotes the source antenna gain, G_r denotes the receive antenna gain, L_p denotes the polarization loss, λ denotes the wavelength, η denotes the rectifier efficiency and β denotes the parameter to adjust the $Friis'$ free space equation for short distance transmission. d is the only variable in the equation. The above model is based on the $Friis'$ free space equation and has been tested empirically by [14, 11].

The network charging model: In the existing works, some specific charging spots are selected for charging the nearby network nodes. The spots can be obtained by clustering algorithms [14]. The mobile charger moves to charging spots and then charges the nodes nearby the spots. When all nodes near one charging spot are fully charged, the charger moves to the next spot for charging. This process continues until all network nodes are fully charged.

Charging completion time: In this paper, we focus on optimizing the charging completion time, which is the time period elapsed from the time when the charger starts charging to the time when it returns back to the starting spot. Apparently the completion time consists of two parts: the moving time and the charging time at each charging spot.

1. **Moving time.** The moving time denotes the time duration of the charger's movement, which equals the sum of the moving delay on each edge in the path.
2. **Charging time** The charging time denotes the sum of the stay time at each charging spot.

It is worth noting that, as we will analyze in this paper, there exists an overlap between the moving time and the charging time considering the charging opportunity during the movement of the charger.

In this work, we focus on the speed control of the case of a single charger and jointly consider the moving time and the charging time optimization.

2.2. Motivation

In this subsection, we use two typical examples to illustrate the motivation of our work.

Charging opportunity on the movement: In the aforementioned works, the charging opportunity during the movement of the charger is widely overlooked, which may greatly reduce the completion time. Figure 1 shows an example where one charger

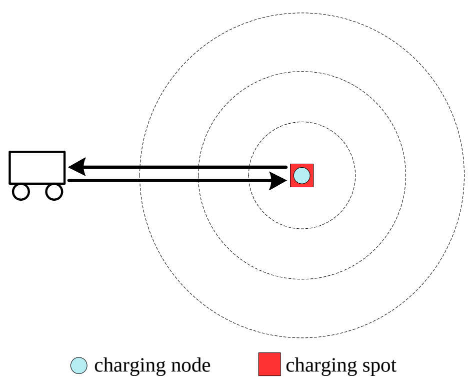

Figure 1: Motivating example for charging on the movement.

is used to charge a network with one node. The charger spot is exactly the same as the node's position. With the existing works, the charger first moves to the charging spot and then starts charging the node. The distance between the charger and the node is 50m. The moving speed of the charger is 18km/h and the charging model is as described in Section 1. Then the completion time is calculated as the sum of the moving time and charging time: $T = 10 + 42.6 = 52.6s$.

However, we can notice that the charger can actually start charging after it enters the charging range of the node. Considering the charged energy in the movement in the charging range, the energy required at the charging spot can be reduced. Considering this, the completion time can be re-calculated as: $T = 10 + 42.6 - 13.3 = 39.3$s, where 13.3s is the reduced charging time at the charging spot calculated as $\delta t = \frac{\delta e}{s_c}$, where δe denotes the charged energy on the movement and s_c denotes the charging speed. We can see that the completion time is reduced by 25.3%.

Therefore, considering the charging opportunity on the movement of the charger has the potential to greatly reduce the completion time and should be considered for minimizing the completion time.

Speed control on the movement To exploit the charging opportunity on the movement, the speed is an important factor since it essentially determines the charging time on the movement given the charging range.

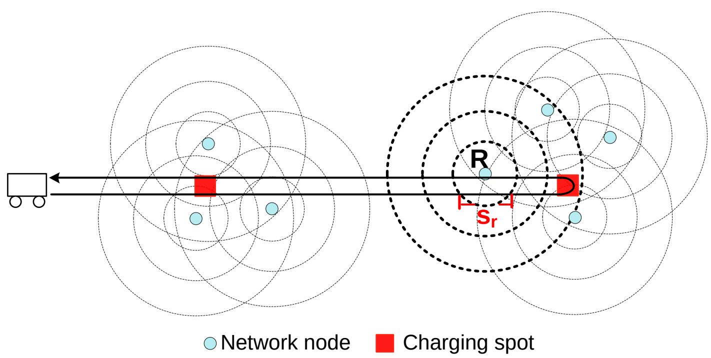

Figure 2: Motivating example for speed control of the charger.

In the above example, the charger moves to the charging spot with the maximum speed. The reason is that the charging speed becomes higher when the charger moves closer to the spot. However, when the charging spots and the node positions are not the same, the charging speed and the distance between the charger and the charging spot may not be linearly related. As a result, the maximum speed may not achieve the minimum delay.

For example, two charging spots in Figure 2 are clustered according to the network topology. We consider the charged energy during the movement in determining the completion time. When the charger moves with the maximum speed, the completion time is 258.33s. During the above charging process, we notice that the charging time at spot 2 is determined by the charging time of node R since charging spot 2 is far from node R and the charging speed is the lowest among all nodes. At the same time, we can see that when the charger moves in segment s_r, the charging speed for node R is in the highest level. Intuitively, if we slow down the charger in segment s_r and charge more energy to node R, the completion time can be further optimized. Then we set the speed in s_r so as to fully charge node R at the moment when the charger leaves the charging range of node R on its way back from spot 2 to spot 1. The completion time is $T = 210.84s$, which is reduced by 18.4% compared to that with the maximum speed.

The essential problem beneath the speed control is the tradeoff between the moving delay and charging delay on the charger routes.

3. Minimizing the completion time by speed control

Motivated by the above observations, we investigate the problem of speed control for minimizing the charging completion time. By generating the speed variations during the route visiting all charging spots of the charger, we aim to minimize the total time for charging all network nodes.

3.1. Overview

The network consists of N wireless rechargeable nodes. Each node i has a unique location denoted by $(x_i,\ y_i)$. The wireless charger moves in the network area with a *self-driving car* [15, 16] or a Unmanned Aerial Vehicle (UAV) [17, 18, 19], where the maximum speed is limited to s_t. To minimize the charging completion time, we need to 1) identify the charging spots where the charger stops for charging, 2) the path visiting all charging spots, and 3) the corresponding speed on the path.

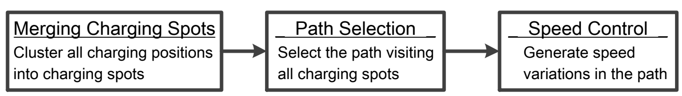

Figure 3: The working flow of the proposed speed control scheme.

Our approach works in the framework as shown in Figure 3. Firstly, all charging positions are clustered into k charging spots. These spots are for the charger to stop by and charge the network nodes. Secondly, we select the best path that visits all charging spots. Thirdly, we calculate the speed variations during the movement of the charger on the selected path. It is worth noting that, since the speed is not constant along the path, the best path cannot be determined if speed is not taken into consideration. On the other hand, the speed variations cannot be determined if the path is not given. Therefore, we jointly consider path selection and speed control to minimize the completion time.

3.2. Identifying the charging spots

We follow the work [14] to determine the charging spots. The charging power is firstly discretized into several charging levels, and the charging positions are merged into k clusters using k-means. Inspired by [20, 21], we set the value of k as follows. The k starts from a small value (e.g., 2) and increases by 1 for each round of re-calculation until the average intra-group distance is smaller than a threshold or k exceeds N. Each node is assigned to the nearest cluster head and the corresponding charging levels are marked on the figure.

3.3. Path generation

The path selection problem can be formulated as a Traveling Salesman Problem with Speed Variations(TSP-SV) which is NP-hard. We propose a greedy heuristic as shown in Algorithm 1. First, we add all nodes in the smallest enclosing nodes set into the path, P. After that, we start adding nodes out of P one by one.

In each round of spot selection, we choose the spot v_i that achieves the smallest charging delay visiting all nodes in $v_i + P$. For each spot v_i, we calculate its expected delay on every insertion position p_i. By listing all possible nodes and insertions, we can choose the spot and the corresponding insertion position that achieves the minimum completion time. This process goes until all network nodes are added in P. The initial position of the charger can be any charging spot and the total charging delay is unchanged.

Apparently the calculation of completion time involves the speed variations. We introduce the derivation of speed variations in the next subsection.

Algorithm 1 Path generation algorithm

Input: The energy state of the network nodes, $E = \{e_i\}$;
The set of all charging spots, $V = \{v_i\}$;
The charging threshold for each node, c_t;
The speed limit of the charger, s_t;
Output: The path (i.e., the visiting sequence of the charging spots) $P = \{v_i\}$ and speed value set $S = \{s_i\}$, with which the completion time is minimized.
H_c = cch(); //Generating a convex closed hull H_c that covers all charging spots
$\forall v_i \in H_c$, push v_i, P;
while $\exists v_i \in V, v_i \notin P$ **do**
  for *each* $v_i \in V - P$ **do**
    for *each insert point* p_i **do**
      push cTime($\{v_i\}$+P, p_i), T;
      // save the completion time with insert position p_i *into the time set* T.
    end
  end
  (v_m,p_i) = arc min $cTime_i \in T$;
  insert (v_m, p_i), P;
  //insert charging sport v_m *in position* p_i
end
return P;

3.4. Generation of the speed variations

A key challenge for speed control is to determine how many speed variations are needed for an edge connecting two charging spots.

Theorem 1. *For different strategies of speed variations on a segment, if the moving time on each sub-segment with a given charging level is the same, the charging completion time is also the same.*

The reason goes as follows. According to the charging model [11], the amount of the charged energy is determined by the charging time and the charging speed only. Since the charging speed is discretized into charging levels, the time within a charging level is the only impacting factor for the amount of charged energy. Therefore, as long as the charging time remains unchanged, the speed variations within the segment do not have impact on the completion time and can be treated as constant.□

With the above observation, we can discretize each edge into several segments according to the charging levels. Each segment i is assigned with a different value of moving speed s_i and corresponds to a different charging level. We assume that the maximum and minimum charging speed is *Cmax* and *Cmin* respectively and set a threshold ε. The charging speed ratio of two adjacent levels is $1+\varepsilon$. We are able to obtain the value of ε through 2. According to MCD [14], the charging delay after discretization has a $1/(1-\varepsilon)$ approximated ratio to the theoretically optimal charging delay.

$$Cmin = Cmax(1+\varepsilon)^{-(L-1)} \tag{2}$$

L denotes the number of charging levels. Next, our job is to calculate the moving speed on each segment and the stay time on each charging spot. The problem can be mathematically formulated as follows. The goal is to minimize the completion time, which is the sum of all the time spent on the segments and the charging spots. All possible solutions should be subject to the following requirements.

1. all nodes n_i should be fully charged (with the charged energy above the charging threshold c_T).
2. the speed values and stay time should be in the corresponding value domain.

Then the formulation is given as:

$$\min T = \sum \frac{p_i}{s_i} + \sum t_i \tag{3}$$

$$\begin{aligned} s.t. \quad & \forall n_i \in N, \sum\left(\frac{p_i}{s_i} \cdot e_i + t_j \cdot e_j\right) \geq c_T \\ & \forall i, 0 \leq s_i \leq s_T \\ & \forall i, t_i \geq 0 \\ & e_{ij} = \frac{\alpha}{(d_{ij}+\beta)^2}, i \in N, j \in (1,2,...,\infty) \\ & d_{ij} = \sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \end{aligned} \tag{4}$$

where t_i denotes the stay time at charging spot i, p_i denotes the length of segment i, e_{ij} denotes the charging speed, and d_{ij} denotes the distance between position i and j for the charger and the rechargeable node, respectively. The problem is solved as follows.

1. Obtain the feasible region defined by the constraints.
2. Obtain the level sets of the objective function.
3. Identify the level set corresponding to the least objective function value that intersects the feasible region.

4. The point (S,T) intersecting the least level set is the solution to the linear programming problem, where S denotes the speed variations set, $S = \{s_i | i = 1,2,3,...\}$ and T denotes the stay time set for all charging spots, $T = \{t_i | i = 1,2,3,...\}$.

After solving the above linear program problem, we can obtain the speed variations for each segment and the stay time for each charging spot.

Tradeoff between optimality and complexity: An edge between two charging spots in dense networks may go across multiple different charging levels. If all segments crossing different charging levels are differentiated and assigned with different speed values, the complexity would be considerably large. To deal with the problem, we propose a merging scheme for the segments, which merges the segments into a constant number of new segments. The charging speed of a new merged segment s_{np} to a network node n is approximated as follows:

$$s_{np} = \sum E(d_{n,c_{pi}}), i = 1,2,3,... \tag{5}$$

where $E(d_{n,c_{pi}})$ denotes the charging speed from the center of segment pi to node n, and can be calculated using Eq. (1).

We set a threshold for the number of segments in each edge, and start the above merging process when the number of segments exceeds the threshold.

3.5. Incorporation of the above components

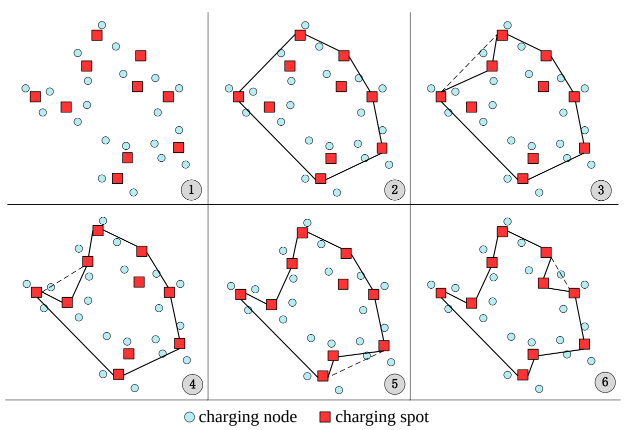

Figure 4: The working process of the proposed work

In this section, we use an illustrative example (as shown in Figure 4) to demonstrate the generation of the path and the corresponding speed. The red rectangles denote the charging spots and the green dots denote the network rechargeable nodes. The first step is to identify the smallest enclosing set that covers all charging spots, as shown in Step 1. All charging spots are pushed into the spot set of the path. Then all other nodes become candidate nodes to be selected for insertion. For each node, we calculate the possible insertions to the current node set and select the insertion position that adds minimum extra delay to the path. After that, the node that achieves the minimum delay with the corresponding position is added to the path set. The above procedure continues until all nodes are added to the path, as shown in Step 2-6. The speed variations are calculated at the same time with the path delay using Eqs.(3) and (4). When the path sequence is selected, the corresponding speed variations and the stay time at each charging spot are as well selected. The charger can then start charging at the nearest spot and follows the path and corresponding speed.

4. Performance Evaluation

We conduct simulation experiments to evaluate the performance of the proposed scheme in terms of completion time and the variance of the charged energy. We compare our scheme with the one proposed in [14] in terms of the completion time. We further compare the two works in different network topologies with various parameter settings to further explore in which scenarios our scheme works better.

4.1. Methods

Metrics: We use the following two metrics to evaluate our scheme.

1. Completion time. The completion time denotes the duration from the time the charger starts moving to the time the charger moves back to the starting spot.
2. Variance of the charged energy. Ideally, the minimum completion time can be achieved when all nodes are fully charged but not over charged [1]. Besides, no energy is wasted in this case. When variance is large, it means that more energy and charging time are wasted.

Simulation settings: In the simulation, we set three charging levels for each node according to the charging model. The network topology is randomly generated, and our approach works in the same topology with MCD [14] for comparison. We deploy wireless sensor nodes over a 100m * 100m two-dimensional square area. The node energy threshold is 2J, which is essential to preform several sensing and computing tasks [14, 12]. Noting that the capacity could increase with the development of battery technologies, we also conduct simulations with varying battery capacity such as 10 Joule, 100 Joule, and 200 Joule.

4.2. Evaluation and Analysis of Performance Results

Figure 5 compares the completion time of the proposed approach and MCD [14] with different network densities. We can see that, 1) compared to MCD, our approach reduces the delay by 23.8%. The reason is that our approach can effectively exploit the charging opportunity during the movement. With the charged energy on the move, the stay time at the charging spots can be reduced. Moreover, the optimization on speed

[1] It can be proved as follows: when a node is over-charged, it must require extra time for the over-charging and the completion time is prolonged.

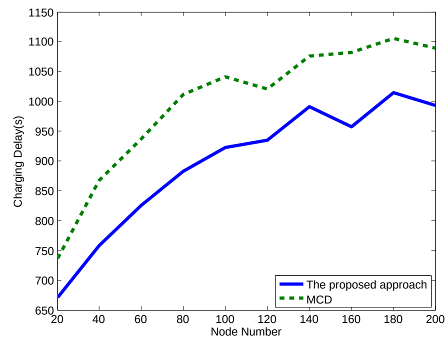

Figure 5: Delay vs. Node Number

control can also identify the segments on the charger's route which could be used to reduce the charging delay. 2) when network density increases, the improvement over MCD first increases and then decreases. The reason is that with very low density where the charging ranges of all nodes do not overlap, the energy accumulated on the movement is limited and thus the improvement is low. With very high density where the charging ranges of all nodes highly overlap, charging at the charging spots would be the best choice and the space for improvement is limited. As a result, the improvement over MCD first increases and then decreases.

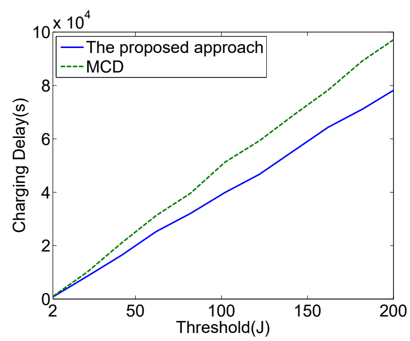

Figure 6: Delay performance with varying threshold.

Figure 6 compares the completion time with different charging threshold, which is determined by the capacity of the rechargeable nodes. It is worth noting that the typical bettery capacity is 1-2 Joule for current rechargeable sensor nodes []. However, considering the development of battery technologies, we vary the charging threshold to 200 Joule. The variation of the charging threshold can help us identify in which situations the proposed approach performs better or worse. We can see that as the capacity increases, the improvement over MCD increases. The reason is that with larger capacity, there are more charging opportunities that can be exploited on the move. As a result, the network with high-capacity nodes can benefit more from the proposed approach compared to the network with low-capacity nodes.

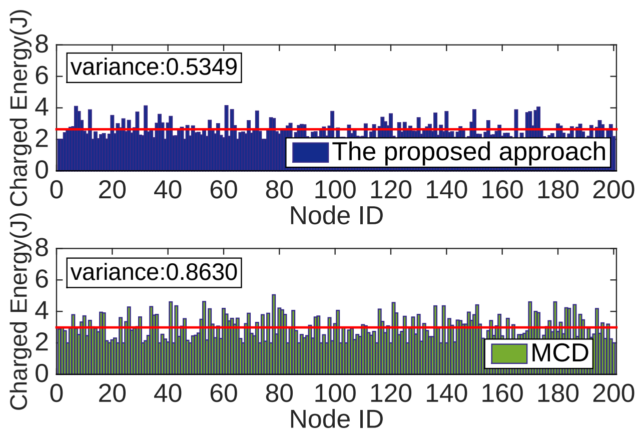

Figure 7: The distribution of the charged energy on all network nodes. The red line denotes the mean value.

Figure 7 shows the charged energy distribution of 200 nodes. The red line denotes the mean value of the charged energy. We can see that 1) the mean charged energy is reduced from 3.183J to 2.368J compared to MCD. 2) The variance is reduced from 0.863 to 0.5349. This implies that the proposed approach can also reduce the energy waste during the speed optimization. The reason is that with more fine-grained speed variation, the charging time to each node can be more accurately scheduled, which is expected to further reduce the energy waste on each node.

By revisiting the network topology, we find that the over-charged nodes are located in very dense areas of the topology. The possible reason is that these nodes are near to the charging spots as well as the low-speed segments. As a result, these nodes are over-charged. Comparatively, the over-charged nodes in MCD are randomly distributed. The reason is that when considering the charged energy on the move, the nodes are likely to be over-charged and the nodes near to the charging spots are highly over-charged. We take a further step to compare the variance of the proposed approach and MCD.

Figure 8 shows the standard deviation of the charged energy of all network nodes. Compared to MCD, 1) the proposed work generally achieves lower variance of the charged energy than MCD. The reason is that our approach allows for speed variations during the movement. Besides, the energy provisioning on the move and on the charge spots are jointly considered in the optimization. Therefore, the energy variance and energy waste are largely reduced compared to MCD. 2) as the threshold increases, the variance of both MCD and the proposed approach increases. The reason is that when the energy threshold increases, the variance increases in proportion of the increase of the threshold. 3) we can also notice that for some specific thresholds, MCD can achieve variance similar to that of our approach. The reason is that in MCD, different starting points in the *k*-means may result in different charging positions and corresponding charging time. If the positions are clustered as the case where the best choice for the charger is to use maximum moving speed, the variance of MCD would be similar with

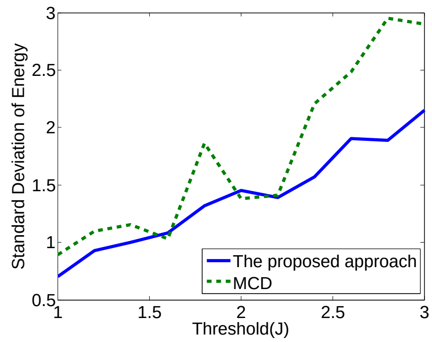

Figure 8: The standard deviation of the charged energy of all network nodes.

our scheme.

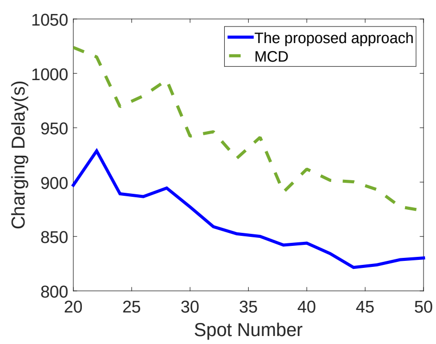

Figure 9: The delay comparison with different number of charging spots.

Figure 9 shows delay comparison of the proposed approach and MCD with different number of charging spots for the mobile charger. We can see that: (1) As the number of spots increases, both approaches approximately decrease in delay. The reason is that when the number of spots is larger, more nodes will be charged in a relatively long distance(either with charging spots or during the movement). In either case, the delay is expected to increase compared to the case of more charging spots. (2) The delay of the proposed approach is decreased compared to MCD. The reason is that by carefully scheduling the moving speed of the charger, our approach can effectively exploit the charging opportunity during the charger movement which is expected to reduce the charging time required on the charging spots. (3) There are some outliers that the delay with more spots is larger than the delay with fewer spots. The reason is that when the number of charging spots changes, the positions of the spots change as well. At the outliers, the fewer spots are merged in more appropriate positions, which achieves similar delay or less delay than that of the more spots.

Recall that we segment each edge into different segments according to the different charging levels. To reduce the calculation complexity, we can set a constant threshold

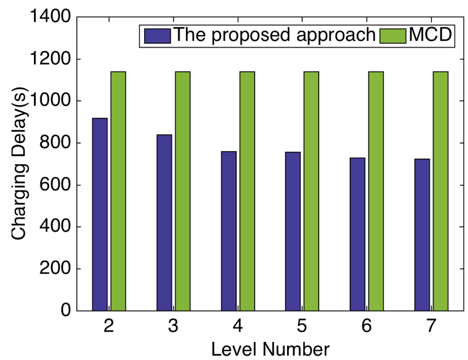

Figure 10: The delay comparison with different number of segments on the edges.

for the number of segments per edge. Figure 10 shows the delay comparison with different threshold for the number of segments per edge. When the threshold increases, there are more speed variations in each different edge between two charging spots. As shown in the figure, 1) as the number of levels increases, the reduction on charging delay also increases. The reason is that the speed can be more accurately scheduled to save more delay and energy. 2) The improvement becomes smaller. The reason is that when the number of levels becomes larger, the difference between different levels also smaller, which further results in smaller improvement on the end-to-end charging delay.

5. Related works

The delay minimization problem has attracted much research attention in recent years. Most existing works are based on the "move then charge" assumption, i.e., a charger moves to specific charging spots and then charges the network nodes nearby the spots. These works could be divided into three categories according to the optimization goal: 1) minimizing moving delay, 2) minimizing charging delay, and 3) minimizing both kinds of delay.

Works on minimizing moving delay: Works on minimizing moving delay mainly include [22, 23, 24, 25]. In this category, the charging delay at each charging spot is considered constant (i.e., the duration that all nearby nodes can be fully charged). These works often formulate the problem as TSP and try to minimize the traveling distance of the charger. NETWRAP [22] aims to minimize the traveling cost of the wireless chargers based on the energy monitoring and reporting protocols. In RSWSN [23], the charger capacity is also considered in addition to the traveling cost. SEHWC [24] jointly considers solar energy harvesting and the wireless charging with mobile chargers. The objective is to minimize the moving cost of the charger. MMER [26] aims to minimize the traveling cost of the charger without energy depletion of any node in robotic sensor networks. Our work differs from the above works by considering the fact that the charger can charge nearby nodes during its movement and the speed of the charger can vary. As a result, 1) the minimum moving delay cannot guarantee the minimum completion time; 2) the minimum traveling distance does not necessarily lead to the minimum moving delay.

Works on minimizing charging delay: Works on minimizing charging delay mainly include [27, 14]. In this category, the moving delay of the charger is not considered. These works often formulate the problem as an optimization problem, e.g., linear programming. R-MQCSP [27] jointly schedules the computational and communication tasks and the charging time at each node. The charger is required to visit the specific nodes. MCD [14] clusters all charging positions into charging spots (which are not the specific positions of the network nodes), and optimizes the charging time on each spot. These works assume a given path with a constant speed, and thus minimizing the charging time is equal to minimizing the completion time. However, once the charging opportunity on the movement is considered, the above assumption does not hold any more.

Works on minimizing both moving delay and charging delay: There are also works on minimizing both kinds of delay. However, the moving delay and the charging delay are separately considered. ESync [28] is a representative work that considers both delay. However, the charging delay and the moving delay are separately considered in the nested TSP tours.

Short summary Since the existing works employ the "move-then-charge" model, the moving delay and charging delay are separately considered and optimized. We argue that considering the charging opportunity on the move, there exists an overlap between the two kinds of delay, which may greatly degrade the charging performance. To effectively exploit the charging opportunity on the move, we devise a novel "charging while moving" model. Based on this model, the charging opportunity on the move can be effectively exploited and the speed of the charger is of great importance in minimizing the completion time. We further propose an approach to generate the path, corresponding speed variations and the stay time at each charging spots, which is expected to achieve the minimum completion time.

6. Conclusion and future directions

In this paper, we identify the problem of speed control for mobile chargers serving wireless rechargeable networks. Aiming to overcome the discrepancy between the charging delay and the moving delay of the charger, we propose to exploit the charging opportunity *on the move* and target to find a good trade-off between the charging delay and the moving delay. The problem is formulated as a TSP-SV (TSP with speed variations). The outcome of our scheme are the traveling path of the charger to visit all charging spots, corresponding speed variations on the path and the stay time at each charging spot, which can greatly reduce the charging completion time compared to the state-of-the-art work MCD.

However, some issues such as multiple chargers and charging with deadlines are not considered in this paper. The challenge to extend our work to support the above scenarios lies in the optimization modeling and the corresponding complexity. For example, the problem of multiple chargers can be modeled as multiple traveling salesman problem with speed variations. However the challenge is the explosion of the searching space for optimization: Each node can be charged multiple times by multiple chargers, the modeling needs to consider all possibilities to find the best paths and speed variations for each charger, which is of high complexity. We will conduct in-depth analysis on the speed control problem with multiple chargers and with charging deadlines.

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