# Spatio-Temporal Mobile Cooperative Charging for Low-Power Wireless Rechargeable Devices

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***Abstract*—By deploying or scheduling wireless chargers, *Wireless Rechargeable Sensor Networks* (*WRSNs*) can provide continuous energy supply for the rechargeable devices. Recently, a novel *cooperative charging service model* was proposed for *WRSNs*, which provides a business framework of on-demand wireless charging service. Based on such model, the existing work mainly considered the spatially cooperative charging scheduling problem but ignored the cooperation in temporal dimension. In practice, we can find that the QoS requirement of applications often requires an upper bound constraint on the out-of-service time for each device, which implies the charging service cost can benefit from the temporal cooperation of the devices. In this paper, we focus on the device-initiated mobile cooperative charging problem in both spatial and temporal dimensions. Our objective is to find a spatio-temporal *cooperative charging scheduling strategy* to minimize the total charging service cost, subject to the constraints that the out-of-service time of each device does not exceed a given upper bound. We first prove the NP-hardness of our target problem, and then devise a greedy-based *Charging Service Cost Optimization Algorithm*, which can achieve an approximation ratio of $\ln n+1$ in most of real situations. The extensive simulation results reveal that our solution always outperforms the other solutions in terms of charging service cost.**

***Index Terms*—wireless rechargeable sensor networks, cooperative charging service model, charging service cost, spatio-temporal, approximation algorithm**

## I. INTRODUCTION

In the past decade, *Wireless Sensor Networks* (*WSNs*) has made a great progress in many fields, such as ecological environment monitoring [1], natural disaster early warning [2] and industrial production. For sensor devices, the limitation on battery capacity and the demand for long-term operation will require frequent battery replacement in real applications, which will bring technical difficulties and high cost, especially for harsh environments. Fortunately, the breakthrough of *Wireless Power Transmission* (*WPT*) technology well solves the energy supplement problem in *WSNs* and makes *Wireless Rechargeable Sensor Networks* (*WRSNs*) be possible. By deploying or scheduling wireless chargers, *WRSNs* can provide the sensor devices with uninterrupted electric power.

Most of the existing works on *WRSNs* consider either *charging utility maximization problem* [3]–[8] or *charging cost minimization problem* [9]–[13] under the *traditional charging network model*, where all the chargers are affiliated to the user and the charging cost manily consists of device fee, installation fee and maintenance fee. Recently, Xu *et al.* [14] came up with a novel device-initiated *cooperative charging service model*, where all the chargers are deployed and maintained by a *Charging Service Provider* (*CSP*). Specifically, the base station will periodically initiate a charging command to all the devices in the network, and each device will report its current residual energy to the base station immediately after receiving the charging command. Based on the received residual energy information and the given parameters, the user will promptly make a *cooperative charging scheduling strategy* (including *sensor-oriented scheduling strategy* and *charger-oriented scheduling strategy*) at the base station according to a specific optimization objective, and then provide *CSP* with the *charger-oriented scheduling strategy* to request the charging service. Upon receiving the charging service request from the user, *CSP* will immediately forward the *charger-oriented scheduling strategy* to all the chargers to schedule their charging service time. Meanwhile, the *sensor-oriented scheduling strategy* will be distributed from the base station to the network. By performing the *sensor-oriented scheduling strategy*, each device will move to the assigned target charger for charging. After completion of charging, each device will return to the original deployment position to proceed with the task monitoring. Finally, the user will pay *CSP* for the provided charging service in accordance with the requested charging service time.

Different from the *traditional charging network model*, the above-mentioned *cooperative charging service model* emphasizes the concept that *Charging as Service*. By deploying wireless chargers as the infrastructure, the *cooperative charging service model* provides a business framework of on-demand wireless charging service. Based on such model, [14] studied the spatially cooperative charging scheduling problem that how to assign the movable devices to the appropriate chargers to reduce the total cost. However, it ignores the cooperation in temporal dimension and does not restrict the out-of-service time of the device, which is defined as the duration that the device is not in the original deployment position. In practice, long out-of-service time of the device could affect the quality of service for task monitoring. For example, to the applications of event detection, such as fire detection, long out-of-service time could result in high false negative rate or long event detection delay, especially for the devices deployed in the areas where the event happens frequently. To guarantee a certain quality of service for the applications, each device is necessary to set an upper bound constraint on the out-of-service time.

In this paper, we adopt the *cooperative charging service model* and focus on the *Time-sensitive and Economical Mobile Cooperative Charging* (*TEMCC*) problem. Specifically, our objective is to find a spatio-temporal *cooperative charging scheduling strategy* to minimize the total charging service cost, subject to the constraints that the out-of-service time of each device does not exceed a given upper bound. The main contributions of this paper are outlined as follows:

- To the best of our knowledge, this is the first work to consider the device-initiated mobile cooperative charging problem in both spatial dimension and temporal dimension.
- Based on *cooperative charging service model*, we formulate the *Time-sensitive and Economical Mobile Cooperative Charging* (*TEMCC*) problem and prove its NP-hardness.
- For the case with single charging station, we consider both total charging service cost optimization and average marginal cost optimization, and propose the corresponding optimal solutions in polynomial time, respectively.
- To solve *TEMCC* problem, we devise a greedy-based *Charging Service Cost Optimization Algorithm*, which can achieve an approximation ratio of $\ln n + 1$ in most of real situations, where $n$ denotes the number of the devices in the network.
- The extensive simulation results reveal that compared with the other solutions, our proposed solution always has a better performance.

The rest of the paper is organized as follows: Section II illustrates the system model and formulates the problem. Section III presents the detailed description and performance analysis of our proposed approximation solution. Followed by the performance evaluation results in Section IV. Finally, our findings are concluded in Section V.

## II. System Model and Problem Formulation

### A. Network Model and Assumptions

In this paper, we let $U = \{u_1, \dots, u_n\}$ denote the set of $n$ rechargeable and movable low-power wireless sensor devices that are uniformly deployed in a 2-D monitoring field, and let $S = \{s_1, \dots, s_m\}$ denote the set of $m$ fixed charging stations in the monitoring field, where each charging station is equipped with an omnidirectional wireless charger to provide the arrived devices with short-distance omnidirectional wireless charging service. In order to guarantee charging efficiency, we only allow each device to be charged by moving from the original deployment position to the charging station, and also assume that the fixed charging power at different charging stations could be different. Specifically, each device can enjoy the charging service with the fixed received charging power $P_r(s_j)$ when arriving at any charging station $s_j$, and each charging station can provide the energy supply to multiple arrived devices simultaneously due to the omnidirectional charging technology [15]. After completion of charging, each device will return to the original deployment position to proceed with the task monitoring.

Let $T_m(u_i, s_j)$ denote the device $u_i$'s movement time from its original deployment position to $s_j$, and it is assumed that the movement time is symmetric, *i.e.*, the movement time that device $u_i$ returns to the original deployment position from $s_j$ is also equal to $T_m(u_i, s_j)$. For simplicity and without loss of generality, we ignore the energy consumption of movement for any device, since it is relatively small and negligible compared with that of long-term task monitoring. This implies if any device $u_i$ decides to be fully charged at charging station $s_j$, the required charging time $T_c(u_i, s_j)$ should be

$$T_c(u_i, s_j) = \frac{\mathcal{C}(u_i) - E(u_i)}{P_r(s_j)} \tag{1}$$

where $\mathcal{C}(u_i)$ and $E(u_i)$ denote the battery capacity and the current residual energy of device $u_i$, respectively.

Here, we adopt the *cooperative charging service model* that stated in Section I, and consider that the charging service pricing for the charging stations $\{s_1, \dots, s_m\}$ could be different, since the environmental difference between geographical locations of these charging stations could result in different difficulties and expenses for charger installation and maintenance, and we denote by $\bar{c}(s_j)$ the required payment per unit charging service time for any charging station $s_j$ where $j \in \{1, \dots, m\}$. For the base station, when to initiate a charging command mainly depends on the historical traffic information in the network. By utilizing in-network historical traffic data to dynamically predict the residual energy of each device, the base station will periodically decide to initiate a charging command at the time when the devices have already depleted most of their energy but each of them still has sufficient residual energy to move to any charging station.

In our model, we consider the *instant-moving policy*, where each device will suspend task monitoring and move to the assigned target charging station immediately after receiving the *sensor-oriented scheduling strategy*. Also, we assume the Low Power Wide Area Network (LPWAN) based single-hop communication technology is adopted in the network. This can naturally make the time to start performing the *sensor-oriented scheduling strategy* be synchronized for all the devices, since the single-hop broadcasting from the base station can provide the inherent receiving-time synchronization property. Fig. 1 illustrates a simple example of the network model with $m = 3$ and $n = 10$.

### B. Problem Formulation and Hardness Analysis

In our model, the user can benefit from the simultaneous charging of multiple devices at the same charging station, since the charging cost mainly depends on the charging service time and multiple devices in the common charging hours can economically share the charging cost. This implies the devices that arrive at the charging station earlier could appropriately

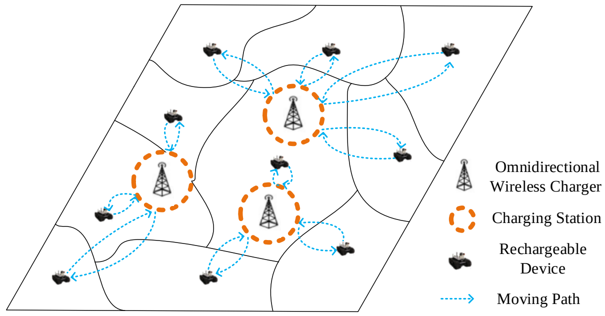
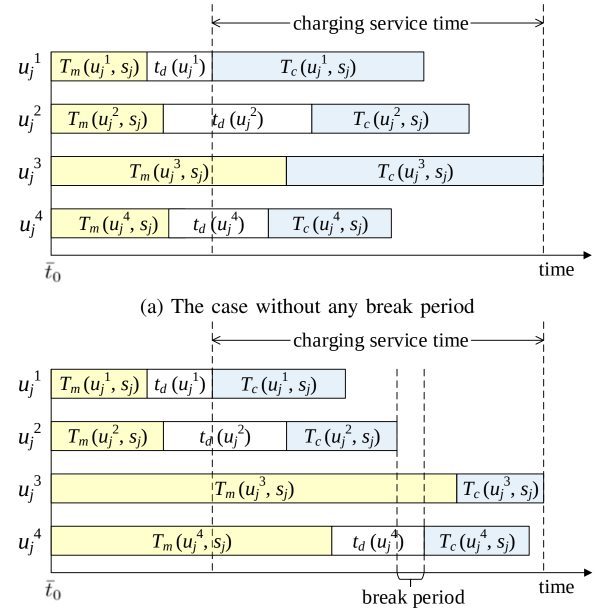



Fig. 1: Illustration of Network Model.




(a) The case without any break period

(b) The case with one break period

Fig. 2: Illustration of Charging Service Time.

defer their starting time points of charging, to increase the overlapping rate with the charging time of the devices that arrive relatively late at the same charging station. We let the nonnegative variable $t_d(u_i)$ denote the deferring time of any device $u_i$ at the charging station, *i.e.*, the time that the device $u_i$ waits for charging when arriving at the charging station.

Here, we require that each device should be fully charged at each round of charging scheduling. The *sensor-oriented scheduling strategy* is to decide each device's assigned target charging station and the corresponding sojourn time, where the sojourn time of any device at the charging station consists of the deferring time and the charging time. For any device $u_i$, we can employ the function $f_{st}(u_i, s_j, t_d(u_i))$ to denote the sojourn time of $u_i$ at the charging station $s_j$ with a given deferring time $t_d(u_i)$, which can be represented by

$$f_{st}(u_i, s_j, t_d(u_i)) = t_d(u_i) + T_c(u_i, s_j) \tag{2}$$

where $t_d(u_i) \geq 0$. Note that any device will return to the original deployment position from the charging station immediately after the sojourn time. According to Equation 1, the charging time of any device at any charging station is fixed, which implies the *sensor-oriented scheduling strategy* is essentially to decide each device's assigned target charging station and the corresponding deferring time.

For any charging station $s_j$, we denote by $S_j$ the set of the devices that are assigned to $s_j$ for charging, and let $t_d(S_j) = \{t_d(u) | u \in S_j\}$ denote the set of deferring time scheduling for all the devices in $S_j$. Suppose that the charging station assignment $S_j$ and the deferring time scheduling $t_d(S_j)$ are given, we let $T_c(s_j, S_j, t_d(S_j))$ and $C(s_j, S_j, t_d(S_j))$ respectively denote $s_j$'s charging service time and the corresponding charging service cost, where $T_c(s_j, S_j, t_d(S_j)) = \max_{u \in S_j}\{T_m(u, s_j) + f_{st}(u, s_j, t_d(u))\} - \min_{u \in S_j}\{T_m(u, s_j) + t_d(u)\}$ and $C(s_j, S_j, t_d(S_j)) = \bar{c}(s_j) \times T_c(s_j, S_j, t_d(S_j))$. Specially, $C(s_j, S_j, t_d(S_j)) = T_c(s_j, S_j, t_d(S_j)) = 0$ if $S_j = \emptyset$. Accordingly, we find that the *charger-oriented scheduling strategy*, which is to decide each charging station's charging service time, can be implicitly determined by the *sensor-oriented scheduling strategy*.

For any $s_j$ with any given $S_j$ and $t_d(S_j)$, note that there could exist some *break periods* during the charging service time $T_c(s_j, S_j, t_d(S_j))$, where a *break period* is a duration in which no device is being charged at $s_j$. In our model, however, we let $s_j$ provide a continuous charging service during the time $T_c(s_j, S_j, t_d(S_j))$ without considering the *break periods*, this is because the total length of the *break periods* in practice is usually very short compared with the length of charging service time and frequently turning on/off the charger in a short duration could also degrade the energy effciency. Fig. 2 shows two examples to illustrate the relationship between the devices' charging scheduling and the charging stations' scheduled charging service time, where $\bar{t}_0$ denotes the time point that any device starts moving from the original deployment position, $S_j = \{u_j^1, u_j^2, u_j^3, u_j^4\}$ for the charging station $s_j$ and the scheduled deferring time $t_d(u_j^2) > t_d(u_j^4) > t_d(u_j^1) > t_d(u_j^3) = 0$.

Further, we let the function $f_{ost}(u_i, s_j, t_d(u_i))$ denote the device $u_i$'s out-of-service time when it is assigned to the charging station $s_j$ for charging with the deferring time $t_d(u_i)$, namely

$$f_{ost}(u_i, s_j, t_d(u_i)) = 2T_m(u_i, s_j) + f_{st}(u_i, s_j, t_d(u_i)) \tag{3}$$

As mentioned above, allowing the devices to schedule the deferring time before the charging time could increase the overlapping rate on charging time of the devices at the same charging station, thus reducing the total charging service cost. However, it will explictly increase the out-of-service time of the devices. Let $B_{ost}(u)$ denote the constrained upper bound of the out-of-service time for any device $u \in U$. Note that the upper bound constraints on the out-of-service time could be different for all the devices, this is because different geographical locations could have different requirements on quality of service in real applications.

Accordingly, our objective is to address the following *Time-sensitive and Economical Mobile Cooperative Charging* (*TEMCC*) problem.

**Problem 1** (TEMCC). *Given a wireless rechargeable sensor network that includes a set of $n$ devices $U = \{u_1, \ldots, u_n\}$ and a set of $m$ charging stations $S = \{s_1, \ldots, s_m\}$, how to find a sensor-oriented scheduling strategy to minimize the total charging service cost that the user should pay to CSP, subject to the constraints that the out-of-service time of each device $u \in U$ does not exceed a given upper bound $B_{ost}(u)$.*

Due to the constraints on out-of-service time, the mobility of each device will be constrained, that is, each device can only move to a limited range of the candidate charging stations for charging. We denote by $R_j^c$ the set of the devices that are able to reach the charging station $s_j$ for charging under the out-of-service time constraints, specifically,

$$R_j^c = \{u | u \in U \ \& \ f_{ost}(u, s_j, 0) \leq B_{ost}(u)\} \tag{4}$$

Based on the *instant-moving policy*, the objective of *TEMCC* problem is essentially to find the optimal partition $S_1, \ldots, S_m$ from the device set $U$ and the optimal scheduled deferring time $t_d(u_1), \ldots, t_d(u_n)$, where $S_j \subseteq R_j^c$ for any $j \in \{1, \ldots, m\}$, and any device $u \in S_j$ if and only if the device $u$ is assigned to the charging station $s_j$ for charging. Thus, the *TEMCC* problem can be formulated by follows.

$$\begin{aligned} & \min \sum_{j=1}^{m} C(s_j, S_j, t_d(S_j)) \\ & s.t. \begin{cases} \bigcup_{j=1}^{m} S_j = U \\ S_i \bigcap S_j = \emptyset, \quad \forall i, j \in M \ and \ i \neq j \\ f_{ost}(u, s_j, t_d(u)) \leq B_{ost}(u), \ \forall j \in M, \ \forall u \in S_j \\ S_j \subseteq R_j^c, \ t_d(u) \geq 0, \quad \forall j \in M, \ \forall u \in U \end{cases} \end{aligned} \tag{5}$$

where $M = \{1, \ldots, m\}$.

According to the optimal solution to the *TEMCC* problem, *i.e.*, $S_1^*, \ldots, S_m^*$ and $t_d^*(u_1), \ldots, t_d^*(u_n)$, we can naturally get the optimal *charger-oriented scheduling strategy*. Besides, we assume that the given upper bound parameters on out-of-service time will make each device belong to at least one set $R_j^c$ where $j \in \{1, \ldots, m\}$, this implies there must exist a feasible solution space for the *TEMCC* problem.

Further, we can show the NP-hardness of the *TEMCC* problem by a polynominal-time reduction from the *Weighted Set Cover Problem*, which is a well-known NP-hard problem.

**Theorem 1.** *The TEMCC problem is NP-hard.*

*Proof.* Given any instance $\mathcal{I}$ of the *Weighted Set Cover Problem*, *i.e.*, a family of subsets $C$=$\{C_1, \ldots, C_q\}$ of a given universe $E$=$\{e_1, \ldots, e_p\}$ and the associated positive weights $w(C_1), \ldots, w(C_q)$, we can construct an instance $\mathcal{I}'$ of the *TEMCC* problem in polynomial-time by follows: (1) Defining $q$ charging stations $S = \{s_1, \ldots, s_q\}$ and $p$ rechargeable devices $U = \{u_1, \ldots, u_p\}$; (2) For each $i \in \{1, \ldots, p\}$ and $j \in \{1, \ldots, q\}$, to set $\mathcal{C}(u_i)$, $E(u_i)$ and $P_r(s_j)$ such that $\mathcal{C}(u_1) = \ldots = \mathcal{C}(u_p)$, $E(u_1) = \ldots = E(u_p)$ and $P_r(s_1) = \ldots = P_r(s_q)$, which implies $T_c(u_1, s_1) = \ldots = T_c(u_p, s_q)$ according to Equation 1; (3) For each $i \in \{1, \ldots, p\}$ and $j \in \{1, \ldots, q\}$, to set $B_{ost}(u_i)$ and $T_m(u_i, s_j)$ such that 1) $B_{ost}(u_1) = \ldots = B_{ost}(u_p)$, and 2) $u_i \in R_j^c$ if and only if $e_i \in C_j$; (4) For each $j \in \{1, \ldots, q\}$, to set $\bar{c}(s_j) = w(C_j)/T_c$, where $T_c = T_c(u_1, s_1) = \ldots = T_c(u_p, s_q)$.

By such instance construction, we can easily show that the minimum-weight set cover solution on $\mathcal{I}$ can be found in polynomial-time if and only if the minimum-cost cooperative charging scheduling solution on $\mathcal{I}'$ can be found in polynomial-time, the detailed proof process is omitted here due to the space limitation. Thus, the *Weighted Set Cover Problem*, which is a well-known NP-hard problem, is polynomial-time reducible to the *TEMCC* problem. The proof is completed. □

## III. Solution

### A. Charging Service Cost Optimization for Single Station

Before solving our target problem, we first investigate the *TEMCC* problem for the case with single charging station, which is called the *Single Charging Station based Time-sensitive and Economical Mobile Cooperative Charging* (*SCS-TEMCC*) problem.

**Problem 2** (SCS-TEMCC). *Given a wireless rechargeable sensor network that includes a set of $n$ devices $U = \{u_1, \ldots, u_n\}$ and single charging station $s$, how to find a sensor-oriented scheduling strategy to minimize the total charging service cost that the user should pay to CSP, subject to the constraints that the out-of-service time of each device $u \in U$ does not exceed a given upper bound $B_{ost}(u)$.*

As there is only one charging station $s$ in the monitoring field, it is obvious that $U$ must be the set of the devices that are assigned to $s$ for charging. Accordingly, the objective of *SCS-TEMCC* problem is essentially to find an optimal deferring time scheduling $t_d(U) = \{t_d(u) | u \in U\}$ to minimize $C(s, U, t_d(U))$, on the condition that the out-of-service time constraints for all the devices are satisfied. The *SCS-TEMCC* problem can thus be formulated by follows.

$$\begin{aligned} & \min C(s, U, t_d(U)) \\ & s.t. \begin{cases} f_{ost}(u, s, t_d(u)) \leq B_{ost}(u), \quad \forall u \in U \\ t_d(u) \geq 0, \quad \forall u \in U \end{cases} \end{aligned} \tag{6}$$

where each device $u \in U$ is assumed to satisfy that $f_{ost}(u, s, 0) \leq B_{ost}(u)$, it implies there must exist a feasible solution space for the *SCS-TEMCC* problem.

For each device $u \in U$, let $t_d^{max}(u)$ denote its allowable maximum deferring time at the charging station $s$ under the out-of-service time constraint, obviously,

$$t_d^{max}(u) = B_{ost}(u) - f_{ost}(u, s, 0) \tag{7}$$

Thus, Equation 6 can be simplified as follows:

$$\begin{aligned} & \min C(s, U, t_d(U)) \\ & s.t. \quad 0 \leq t_d(u) \leq t_d^{max}(u), \quad \forall u \in U \end{aligned} \tag{8}$$

Further, we denote by $U_{LF}^{(s,U)}$ the set of the devices with the latest finish time of charging under the case where $t_d(u) = 0$ for all $u \in U$, namely,

$$U_{LF}^{(s,U)} = \arg\max_{u \in U} \{T_m(u, s) + T_c(u, s)\} \tag{9}$$

For *SCS-TEMCC* problem, we can find that the total charging service time mainly depends on the relative distance between the charging time at $s$ of all the devices, our objective is essentially to try the best to shorten their relative distance in charging time, *i.e.*, to increase the overlapping rate of their charging time, by appropriately deferring the charging time of some earlier-arrived devices to try to catch up with the charging time of the devices in $U_{LF}^{(s,U)}$, and we can easily find the following observation conclusion.

**Observation 1.** *For* SCS-TEMCC *problem, the total charging service cost will not benefit from letting $t_d(u) > 0$ for any $u \in U_{LF}^{(s,U)}$, in other words, it should have $t_d(u) = 0$ for all $u \in U_{LF}^{(s,U)}$ from the perspective of optimal solution.*

It is obvious that Observation 1 must hold, this is because compared with the decision to let $t_d(u) = 0$ for all $u \in U_{LF}^{(s,U)}$, the decision to let $t_d(u) > 0$ for any $u \in U_{LF}^{(s,U)}$ will increase the ralative distance between the charging time of device $u$ and the other devices, which implies each of the other devices should take more deferring time to catch up with the device $u$'s charging time, and the fixed and limited allowable maximum deferring time constraints will make the total charging service time of optimal solution under such decision absolutely not be shorter than that under the decision to let $t_d(u) = 0$ for all $u \in U_{LF}^{(s,U)}$.

According to Observation 1, we will set $t_d(u) = 0$ for all $u \in U_{LF}^{(s,U)}$. For any device $u \in U \backslash U_{LF}^{(s,U)}$, we will try our best to defer its charging time under the constraints that its deferring time is bounded by $t_d^{max}(u)$ and its finish time of charging is not later than that of any device in $U_{LF}^{(s,U)}$. Specifically, we will set

$$t_d(u) = \min\{t_d^{max}(u), \Delta t_u\} \tag{10}$$

where $u \in U \backslash U_{LF}^{(s,U)}$ and $\Delta t_u = \max_{u' \in U}\{T_m(u', s) + T_c(u', s)\} - (T_m(u, s) + T_c(u, s))$. Note that $\Delta t_u = 0$ for each $u \in U_{LF}^{(s,U)}$, thus, we can generally set $t_d(u) = \min\{t_d^{max}(u), \Delta t_u\}$ for all $u \in U$.

Let $OPT_{SCS}(s, U)$ denote the optimal total charging service cost at charging station $s$ in *SCS-TEMCC* problem. We propose an *Optimal Deferring Time Scheduling (ODTS) Algorithm* for SCS-TEMCC problem, as shown in Algorithm 1, to get $OPT_{SCS}(s, U)$ and the corresponding optimal deferring time scheduling $t_d^*(U) = \{t_d^*(u) | u \in U\}$. Specially, $OPT_{SCS}(s, U) = 0$ and $t_d^*(U) = \emptyset$ if $U = \emptyset$.

**Algorithm 1** $ODTS(s, U)$

**Input:** the charging station $s$ with unit time price $\bar{c}(s)$; the device set $U = \{u_1, \ldots, u_n\}$ with the given $T_m(u_i, s)$, $T_c(u_i, s)$ and $B_{ost}(u_i)$ where $i \in \{1, \ldots, n\}$

**Output:** $OPT_{SCS}(s, U)$ and the corresponding optimal deferring time scheduling $t_d^*(U) = \{t_d^*(u) | u \in U\}$

1: $T_{max} \leftarrow \max_{u \in U}\{T_m(u, s) + T_c(u, s)\}$;
2: **for** each $u \in U$ **do**
3: $\quad t_d^{max}(u) \leftarrow B_{ost}(u) - f_{ost}(u, s, 0)$;
4: $\quad \Delta t_u \leftarrow T_{max} - (T_m(u, s) + T_c(u, s))$;
5: $\quad t_d^*(u) \leftarrow \min\{t_d^{max}(u), \Delta t_u\}$;
6: **end for**
7: $T_{min} \leftarrow \min_{u \in U}\{T_m(u, s) + t_d^*(u)\}$;
8: $OPT_{SCS}(s, U) \leftarrow \bar{c}(s) \cdot (T_{max} - T_{min})$;
9: **return** $OPT_{SCS}(s, U)$, $t_d^*(U)$;

**Theorem 2.** *For SCS-TEMCC problem, Algorithm 1 must be an optimal solution with the time complexity of $O(n)$.*

*Proof.* For each $u \in U_{LF}^{(s,U)}$, we can get $\Delta t_u = 0$ and set $t_d^*(u) = \min\{t_d^{max}(u), \Delta t_u\} = \min\{t_d^{max}(u), 0\} = 0$ in Algorithm 1, this is because Observation 1 implies that there must exist an optimal solution where $t_d^*(u) = 0$ for all $u \in U_{LF}^{(s,U)}$. Once the deferring time scheduling of all the devices in $U_{LF}^{(s,U)}$ are fixed, the optimal deferring time scheduling of all the devices in $U \backslash U_{LF}^{(s,U)}$ must be independent of each other. Specifically, for each $u \in U \backslash U_{LF}^{(s,U)}$,

1) if $t_d^{max}(u) \leq \Delta t_u$, we can easily find that $t_d^*(u) = \min\{t_d^{max}(u), \Delta t_u\} = t_d^{max}(u)$ must be $u$'s optimal deferring time scheduling, since it has tried its best to defer its starting time point of charging and such scheduling does not change the latest finish time of the entire charging service;

2) if $t_d^{max}(u) > \Delta t_u$, Algorithm 1 will set $t_d^*(u) = \min\{t_d^{max}(u), \Delta t_u\} = \Delta t_u$, which will still be $u$'s optimal deferring time scheduling, this is because compared with the decision to let $t_d^*(u) = \Delta t_u$, letting $t_d^*(u) < \Delta t_u$ will absolutely not change the latest finish time of the entire charging service and not make the earliest start time of the entire charging service be later, and also letting $\Delta t_u < t_d^*(u) \leq t_d^{max}(u)$ will absolutely not make the increment on the latest finish time of the entire charging service be smaller than that on the earliest start time of the entire charging service.

Accordingly, Algorithm 1 must be an optimal solution to *SCS-TEMCC* problem. Obviously, Line 1 takes $O(n)$ time, Line 2 to Line 6 take $O(n)$ time, Line 7 takes $O(n)$ time and Line 8 takes $O(1)$ time, the total time complexity is thus $O(n)$+$O(n)$+$O(n)$+$O(1)$=$O(n)$. The proof is completed. □

### *B. Average Marginal Cost Optimization for Single Station*

For any charging station, we can define *assigned device set*, *candidate device set* and *average marginal cost* as follows.

**Definition 1** (Assigned Device Set)**.** *For the charging station $s$, its assigned device set is defined as the set of the devices that have already been assigned to $s$ for charging.*

**Definition 2** (Candidate Device Set)**.** *For the charging station $s$, its candidate device set is defined as the set of the candidate devices that have not yet been assigned to any charging station for charging.*

**Definition 3** (Average Marginal Cost)**.** *Given the charging station $s$ with the assigned device set $U_a$ and the candidate device set $U_c$ in the network, the average marginal cost of any nonempty candidate device subset $U'_c \subseteq U_c$ is defined as*

$$\widehat{C}_\Delta(s, U_a, U'_c) = \frac{OPT_{SCS}(s, U_a \cup U'_c) - OPT_{SCS}(s, U_a)}{|U'_c|}$$

*which denotes the average increment of total charging service cost at $s$ per unit candidate device in $U_c'$, if all the candidate devices in $U_c'$ are assigned to $s$ for charging. Here, $OPT_{SCS}(s,\cdot)$ can be figured out by Algorithm 1.*

For better description of the solution to *TEMCC* problem, in this subsection, we will first propose and solve the following subproblem of the *TEMCC* problem, *i.e.*, the *Single Charging Station based Minimum Average Marginal Cost Charging* (*SCS-MAMCC*) problem.

**Problem 3** (SCS-MAMCC)**.** *Given a wireless rechargeable sensor network that includes single charging station $s$ with the assigned device set $U_a$, how to find a nonempty subset $U_c'$ from the candidate device set $U_c$ ($U_a \cap U_c = \emptyset$) and assign all the devices in $U_c'$ to $s$ for charging, such that the average marginal cost $\widehat{C}_\Delta(s, U_a, U_c')$ is minimized.*

In other words, the *SCS-MAMCC* problem can be represented by the following formulation.

$$\begin{aligned} &\min \widehat{C}_\Delta(s, U_a, U_c') \\ &s.t. \;\; U_c' \subseteq U_c \;\; and \;\; U_c' \neq \emptyset \end{aligned} \tag{11}$$

Note that based on the optimal solution $U_c^*$ to *SCS-MAMCC* problem, we can naturally get all the assigned devices' optimal deferring time scheduling $t_d^*(U_a \cup U_c^*)$ according to Algorithm 1. To address the *SCS-MAMCC* problem, a naive approach is to exhaustively enumerate all the feasible solutions (*i.e.* all the subsets of $U_c$) and then compare their average marginal costs, however, it will take $O(2^{|U_c|})$ time in the worst case. Here, we will devise an efficient polynominal-time solution to the *SCS-MAMCC* problem by pruning the exponential feasible solution space back to the polynominal one.

For any feasible solution $U_c' \subseteq U_c$, we can employ a *start-end time pair* $< t_s^{U_c' \cup U_a}, t_e^{U_c' \cup U_a} >$ to implictly characterize it, specifically, the *start time* $t_s^{U'}$ and the *end time* $t_e^{U'}$ can be represented as follows:

$$t_s^{U'} = \min_{u \in U'} \{T_m(u,s) + t_d^*(u)\} \tag{12}$$

$$t_e^{U'} = \max_{u \in U'} \{T_m(u,s) + T_c(u,s)\} \tag{13}$$

where $t_d^*(u)$ ($u \in U'$) can be figured out by calling $ODTS(s, U')$ (Algorithm 1). For any possible *start-end time pair* $< t_s, t_e >$, we denote by $S^{<t_s,t_e>}$ the set of the feasible solutions with *start-end time pair* $< t_s, t_e >$, *i.e.*, $S^{<t_s,t_e>} = \{U_c' | U_c' \subseteq U_c \;\&\; t_s^{U_c' \cup U_a} = t_s \;\&\; t_e^{U_c' \cup U_a} = t_e\}$. Letting $U_{max}^{<t_s,t_e>} = \arg\max_{U_c' \in S^{<t_s,t_e>}} |U_c'|$, we can obviously find that the feasible solution $U_{max}^{<t_s,t_e>}$ must have the minimum average marginal cost for all the feasible solutions in $S^{<t_s,t_e>}$, this is because all the feasible solutions in $S^{<t_s,t_e>}$ must have the identical optimal charging service time $t_e - t_s$ and it must have $|U_{max}^{<t_s,t_e>}| > |U_c''|$ for all $U_c'' \in S^{<t_s,t_e>} \backslash \{U_{max}^{<t_s,t_e>}\}$. This indicates that all the feasible solutions in $S^{<t_s,t_e>} \backslash \{U_{max}^{<t_s,t_e>}\}$ must not be the optimal solution, here, they are called the *invalid feasible solutions* since we can definitely find a feasible solution $U_{max}^{<t_s,t_e>}$ that is better than them, and $U_{max}^{<t_s,t_e>}$ is thus called the *valid feasible solution* for such *start-end time pair* $< t_s, t_e >$ and will be added into the *valid feasible solution set* $F_v$. Accordingly, our basic idea is to enumerate all the possible *start-end time pairs* by finding out all the possible corresponding *start time* for each possible *end time*, and to find the corresponding *valid feasible solution* for each possible *start-end time pair*.

---

**Algorithm 2** $AMCO(s, U_a, U_c)$

---

**Input:** the charging station $s$, the assigned device set $U_a$, the candidate device set $U_c$
**Output:** the optimal subset $U_c^* \subseteq U_c$

```
F_v ← ∅;  U_1 ← U_a ∪ U_c;
while U_a ∩ U_LF^(s,U_1) = ∅ & U_1 ≠ ∅ do
    U_2 ← U_1;
    while U_a ∩ U_ES^(s,U_2) = ∅ & U_2 ∩ U_LF^(s,U_1) ≠ ∅ do
        F_v ← F_v ∪ {U_2\U_a};  U_2 ← U_2\U_ES^(s,U_2);
    end while
    if U_a ∩ U_ES^(s,U_2) ≠ ∅ & U_2 ∩ U_LF^(s,U_1) ≠ ∅ then
        F_v ← F_v ∪ {U_2\U_a};
    end if
    U_1 ← U_1\U_LF^(s,U_1);
end while
if U_a ∩ U_LF^(s,U_1) ≠ ∅ & U_1 ≠ ∅ then
    U_2 ← U_1;
    while U_a ∩ U_ES^(s,U_2) = ∅ do
        F_v ← F_v ∪ {U_2\U_a};  U_2 ← U_2\U_ES^(s,U_2);
    end while
    F_v ← F_v ∪ {U_2\U_a};
end if
for each U_c' ∈ F_v do
    Ĉ_Δ(s, U_a, U_c') ← (OPT_SCS(s, U_a ∪ U_c') − OPT_SCS(s, U_a)) / |U_c'|;
end for
select any U_c* ∈ arg min_{U_c' ∈ F_v} Ĉ_Δ(s, U_a, U_c');
return U_c*;
```

---

Let $U_{ES}^{(s,U)}$ denote the set of the devices with the earliest start time of charging under the optimal solution $t_d^*(U)$ to *SCS-TEMCC* problem, namely,

$$U_{ES}^{(s,U)} = \arg\min_{u \in U} \{T_m(u,s) + t_d^*(u)\} \tag{14}$$

where $t_d^*(U) = \{t_d^*(u) | u \in U\}$ can be figured out by calling Algorithm 1. Here, we come up with an *Average Marginal Cost Optimization (AMCO) Algorithm* to solve the *SCS-MAMCC* problem, which is shown in Algorithm 2. In our solution, it is obvious that $U_2$ in each round of the iterations must be the *valid feasible solution* for the *start-end time pair* $< t_s^{U_2}, t_e^{U_2} >$. By iteratively updating $U_1$ and $U_2$, essentially, we can definitely traverse all the possible *start-end time pairs*.

If $|U_a| > 0$, we can easily find that for any $U_c' \subseteq U_c$, it must have $t_e^{U_c' \cup U_a} \geq t_e^{U_a}$ since all the devices in $U_a$ are surely assigned to $s$ for charging. As shown in Algorithm 2, we traverse every possible *end time* $t_e^{U_1}$ by iteration of $U_1$, and the iteration termination condition of $U_1$ is $U_1 = \emptyset$ or $U_a \cap U_{LF}^{(s,U_1)} \neq \emptyset$, this is because $U_a \cap U_{LF}^{(s,U_1)} \neq \emptyset$ implies $t_e^{U_1} = t_e^{U_a}$ and the subsequent iteration of $U_1$ will make at least one assigned device in $U_a$ be removed. By iteration of $U_2$, Algorithm 2 will further traverse every possible *start time* $t_s^{U_2}$ for each fixed *end time* $t_e^{U_1}$, and the iteration termination condition of $U_2$ is $U_a \cap U_{ES}^{(s,U_2)} \neq \emptyset$ or $U_2 \cap U_{LF}^{(s,U_1)} = \emptyset$. Here, note that 1) $U_a \cap U_{ES}^{(s,U_2)} \neq \emptyset$ implies $t_s^{U_2} = \min_{u \in U_a}\{T_m(u,s)+t_d^*(u)\}$, and the subsequent iteration of $U_2$ will not proceed any more due to the fact that $t_s^{U_2}$ must not be larger than $\min_{u \in U_a}\{T_m(u,s)+t_d^*(u)\}$, where $t_d^*(u)$ ($u \in U_a$) can be figured out by calling $ODTS(s, U_1)$ (Algorithm 1), and 2) $U_2 \cap U_{LF}^{(s,U_1)} = \emptyset$ implies the fixed *end time* $t_e^{U_1}$ has been changed by the current iteration of $U_2$ (*i.e.*, $t_e^{U_1} \neq t_e^{U_2}$), and thus the subsequent iteration of $U_2$ will not proceed any more.

**Observation 2.** *For any $U_c' \subsetneq U_c$, there must exist a $U_c'' \in F_v$ such that $\widehat{C}_\Delta(s, U_a, U_c'') \leq \widehat{C}_\Delta(s, U_a, U_c')$.*

**Theorem 3.** *For SCS-MAMCC problem, Algorithm 2 must be an optimal solution with the time complexity of $O(n^3)$..*

*Proof.* The objective of *SCS-MAMCC* problem is to find a nonempty subset $U_c' \subseteq U_c$ such that $\widehat{C}_\Delta(s, U_a, U_c')$ is minimized. According to Observation 2 and the fact that each solution in $F_v$ must be a feasible solution to *SCS-MAMCC* problem, we can find that the optimal solution to *SCS-MAMCC* problem must exist in $F_v$, which indicates that the objective of *SCS-MAMCC* problem is essentially to find a $U_c' \in F_v$ such that $\widehat{C}_\Delta(s, U_a, U_c')$ is minimized. In Algorithm 2, $U_c^*$ is obtained by comparing the average marginal costs of all the feasible solutions in $F_v$ (Line 22), and thus it must be the optimal solution to *SCS-MAMCC* problem. Obviously, the time complexity of Algorithm 2 is dominated by Line 2-11 and Line 19-21, which takes $O(n^3) + O(n^3) = O(n^3)$ time. The proof is completed. □

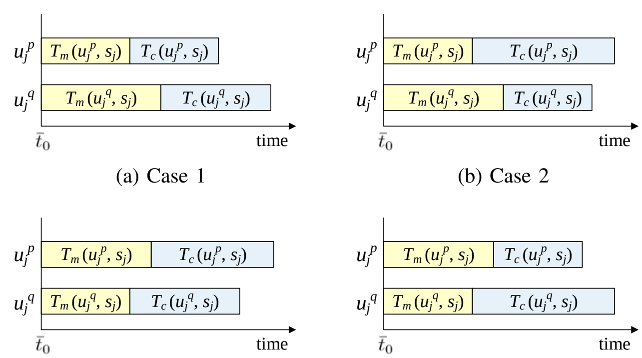
### *C. Approximation Algorithm to* TEMCC *Problem*

Based on the above-mentioned solution to *SCS-MAMCC* problem, we further consider the case with multiple charging stations and propose a greedy-based *Charging Service Cost Optimization (CSCO) Algorithm* to solve the *TEMCC* problem. Algorithm 3 shows the detailed description of our proposed *CSCO* algorithm, the basic idea is to iteratively find a device assignment according to the greedy criterion of *average marginal cost* minimization. In each iteration, specifically, we will first get each charging station $s_j$'s optimal assignment $U_c^*[j]$ by calling $AMCO(s_j, S_j^*, U' \cap R_j^c)$ (Algorithm 2) and select the winner $s_{j^*}$ where $U'$ is the current *candidate device set*, $S_j^*$ is the current *assigned device set* of $s_j$ and $j^* \in \arg\min_{j \in J} \widehat{C}_\Delta(s_j, S_j^*, U_c^*[j])$ (Line 6 to Line 13), then add all the devices in $U_c^*[j^*]$ into $S_{j^*}^*$ and update $U' = U' \backslash U_c^*[j^*]$ (Line 14). Obviously, the time complexity of Algorithm 3 is dominated by Line 5-15, which takes $O(n) \times O(m) \times O(n^3) = O(mn^4)$ time.

**Algorithm 3** $CSCO(S, U)$

**Input:** the set of charging stations $S = \{s_1, \ldots, s_m\}$, the set of devices $U = \{u_1, \ldots, u_n\}$
**Output:** the optimal partition $S_1^*, \ldots, S_m^*$, the optimal scheduled deferring time $t_d^*(u_1), \ldots, t_d^*(u_n)$ and the optimal total charging service cost $OPT$.

1: $U' \leftarrow U$; $OPT \leftarrow 0$;
2: **for** $j$=1 to $m$ **do**
3: $S_j^* \leftarrow \emptyset$; $U_c^*[j] \leftarrow \emptyset$;
4: **end for**
5: **while** $U' \neq \emptyset$ **do**
6: $J \leftarrow \emptyset$;
7: **for** $j$=1 to $m$ **do**
8: **if** $U' \cap R_j^c \neq \emptyset$ **then**
9: $U_c^*[j] \leftarrow AMCO(s_j, S_j^*, U' \cap R_j^c)$;
10: $J \leftarrow J \cup \{j\}$;
11: **end if**
12: **end for**
13: select any $j^* \in \arg\min_{j \in J} \widehat{C}_\Delta(s_j, S_j^*, U_c^*[j])$;
14: $S_{j^*}^* \leftarrow S_{j^*}^* \cup U_c^*[j^*]$; $U' \leftarrow U' \backslash U_c^*[j^*]$;
15: **end while**
16: **for** $j$=1 to $m$ **do**
17: $OPT \leftarrow OPT + OPT_{SCS}(s_j, S_j^*)$;
18: **end for**
19: **return** $S_1^*, \ldots, S_m^*$, $t_d^*(u_1), \ldots, t_d^*(u_n)$ and $OPT$;




(a) Case 1 (b) Case 2

(c) Case 3 (d) Case 4

Fig. 3: Illustration of Pairwise Charging Overlapping.

**Observation 3.** *Given any nonempty set $J' \subseteq \{1, \ldots, m\}$ and any nonempty set $S_j' \subseteq R_j^c \backslash S_j^*$ for each $j \in J'$, it must have*

$$\min_{j \in J'} \widehat{C}_\Delta(s_j, S_j^*, S_j') \leq \frac{\sum_{j \in J'} OPT^\Delta(s_j)}{\sum_{j \in J'} |S_j'|} \tag{15}$$

*where $OPT^\Delta(s_j) = OPT_{SCS}(s_j, S_j^* \cup S_j') - OPT_{SCS}(s_j, S_j^*)$ and $S_j^* \subset R_j^c$ denotes the assigned device set of $s_j$.*

**Definition 4** (Charging Overlapped)**.** *Any charging station $s_j$ is called charging overlapped if and only if any two different devices $u_j^p$ and $u_j^q$ in $R_j^c$ satisfy the following condition:*

$$(T_{mc}^{u_j^p} - T_m(u_j^q, s_j)) \times (T_m(u_j^p, s_j) - T_{mc}^{u_j^q}) < 0 \tag{16}$$

*where $T^u_{mc} = T_m(u, s_j) + T_c(u, s_j)$, and Fig. 3 explicitly shows all the possible cases that the above-mentioned condition holds.*

**Theorem 4.** *For TEMCC problem, if the charging stations $s_1, \ldots, s_m$ are all charging overlapped, Algorithm 3 can achieve an approximation ratio of* $\ln n + 1$.

*Proof.* Before adopting Algorithm 3, we can't predict the number of iterations in Line 5-15. Without losing generality, we assume it has a total of $k$ iterations. At the beginning of iteration $p$ ($p \leq k$), we record $U'$ as residual set $RS^p$ and record $U_c^*[j^*]$ as $SOL^p$. For any $RS^p$, there is a feasible solution space $FSS^p$, we record $OPT^p$ ($OPT^p \in FSS^p$) as the optimal solution for $RS^p$, $OPT^p$ may not be obtained in polynomial time, but it must exist. Obviously, $OPT^1$ is the optimal solution to the whole problem. With the increase of $p$, both $|RS^p|$ and $cost(OPT^p)$ will get smaller, where $cost(OPT^p)$ represents the cost for charging by $OPT^p$.

In iteration $p$, our task is to find $SOL^p$ to minimize $\widehat{C}_\Delta(s, U_a, SOL^p)$, note that $SOL^p \subseteq e \in FSS^p$, where $e$ is a feasible solution satisfying conditions. For any $SUBOPT^p \subseteq OPT^p$, we have $\widehat{C}_\Delta(s, U_a, SOL^p) \leq \widehat{C}_\Delta(s, U_a, SUBOPT^p)$. Due to the drawer principle, there exists $\widehat{C}_\Delta(s, U_a, SUBOPT^p) \leq cost(OPT^p)/|RS^p|$.

According to Observation 3, we can find the charging service cost of Algorithm 3 satisfies $\sum_{p=1}^{k} \widehat{C}_\Delta(s, U_a, SOL^p)|SOL^p| \leq \sum_{p=1}^{k} \frac{cost(OPT^1)}{|RS^p|}|SOL^p| \leq \sum_{i=1}^{n} \frac{cost(OPT^1)}{n-i+1} \leq cost(OPT^1)(ln\ n + 1)$. The proof is thus completed. ☐

In real applications, it is usually true that each charging station is *charging overlapped*, since the omnidirectional charging technology will usually make each device experience a relatively long charging duration. This indicates that in most of real situations, Algorithm 3 can achieve an approximation ratio of $\ln n + 1$ according to Theorem 4.

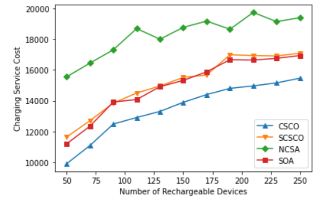
## IV. Performance Evaluation

### A. Simulation Setup

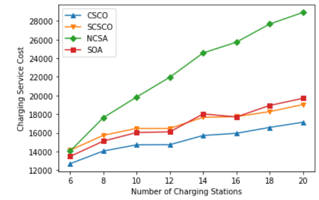
We consider a $1000m \times 1000m$ monitoring filed and assume all the rechargeable devices and charging stations are evenly distributed in the field. Each sensor device $u_i$ is powered by a rechargeable battery with the capacity $\mathcal{C}(u_i) = 1.5V \times 2A \times 3600sec = 10.8KJ$. Unless otherwise stated, we set $n = 150$, $m = 10$, and for each device $u_i$, the moving speed is set to 0.5*m/s*, the residual energy $E(u_i)$ is set to a random value between 500*J* and 2000*J*, the upper bound $B_{ost}(u_i)$ is set to a random value such that $u_i$ must belong to at least one set $R^c_j$ where $j \in \{1, \ldots, m\}$. For simplicity and without loss of generality, we assume that $P_r(s_j) = 5W$ and $\bar{c}(s_j) = 1$ for each charging station $s_j$. All the experiment results are generated by averaging over 50 times.

### B. Baselines

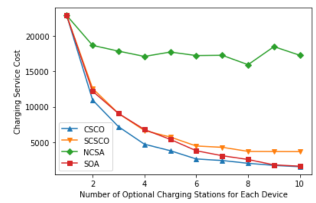
Next, we will take the following 3 typical heuristic solutions as the baselines to evaluate the performance of our proposed *CSCO* algorithm.



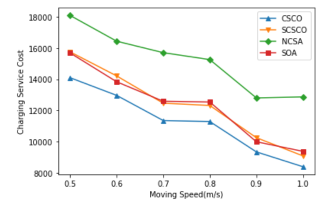

(a) number of rechargeable devices vs. charging service cost



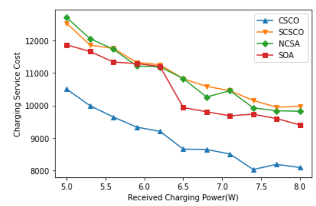

(b) number of charging stations vs. charging service cost



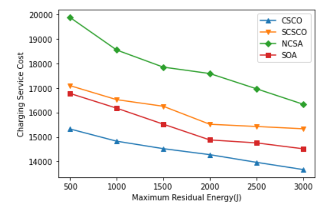

(c) number of optional charging stations vs. charging service cost




(d) moving speed vs. charging service cost




(e) received charging power vs. charging service cost




(f) maximum residual energy vs. charging service cost

Fig. 4: Performance Comparison

- *Simple-CSCO* (*SCSCO*): This algorithm is similar to *CSCO* algorithm. The only difference is that *SCSCO* algorithm does not consider the deferring time of rechargeable devices, that is, $t_d(u_i) = 0$ by default for any device $u_i$.
- *Nearest Charging Station Algorithm* (*NCSA*): Each device $u_i$ moves to the nearest charging station $s^*$ for charging, where $s^* \in \arg\min_{s \in S} T_m(u_i, s)$. After the charger-device assignment, each charging station will execute the *ODTS* algorithm to derive the deferring time scheduling for the assigned devices.
- *Single Optimal Algorithm* (*SOA*): In each iteration, to select the device with the lowest current total charging service cost and assign it to the corresponding charging station. After $n$ rounds of iterations, each charging station will execute the *ODTS* algorithm to derive the deferring time scheduling for the assigned devices.

### C. Simulation Results

We first verify the impact of the number of rechargeable devices on charging service cost. Fig. 4(a) shows that as the number of rechargeable devices increases, the total charging service cost increases and the growth rate gradually decreases for all the solutions. Specifically, by varing the number of rechargeable devices from 50 to 250, the total charging service cost increases about 40% but the average charging service cost of the devices decreases about 72% for our proposed *CSCO* algorithm. This is because more rechargeable devices in the common charging hours can share charging service cost more significantly. On average, *CSCO* algorithm can reduce the total charging service cost by at least 20% compared with the other solutions.

By varying the number of charging stations from 6 to 20, in Fig. 4(b), we can find that the total charging service cost of all the solutions increase. Also, we find that *CSCO* algorithm always outperforms the other solutions, and has a lower growth rate on total charging service cost compared with *NCSA*, which implies *CSCO* algorithm will have a significantly larger performance advantage over *NCSA* as the number of charging stations increases. In Fig. 4(c), we vary the number of optional (candidate) charging stations from 1 to 10 for each device, which can be realized by carefully adjusting $B_{ost}(u_i)$ of each device $u_i$. It can be seen that the number of optional charging stations is a key factor that affects performance, this is because cooperative charging will greatly reduce the charging service cost, and a greater number of optional charging stations will provide more cooperation opportunities for all the devices. With the number of optional charging stations increases, we can find the charging service cost of *CSCO* algorithm decreases with the highest rate, and always keeps the performance advantage over the other solutions.

Fig. 4(c) and Fig. 4(d) exhibit the impact of the device's moving speed and received charging power on total charging service cost, respectively. We can find that *CSCO* algorithm always exhibits the best performance over all the solutions no matter how moving speed or received charging power varies, and also find that with the increase of moving speed or received charging power, the total charging service cost of all the solutions decrease, this is because faster moving speed or larger received charging power will make each device save more time and have more number of optional charging stations, which provides more opportunities for cooperative charging.

In Fig. 4(f), we vary the maximum residual energy of each device from $500J$ to $3000J$, and define the residual energy as a random value between $500J$ and maximum residual energy. With the increase of maximum residual energy, we can find *CSCO* algorithm always has the best performance over all the solutions, and the charging service cost decreased slightly for all the solutions. This is because larger maximum residual energy usually implies less required charging time for each device, which will result in lower charging service cost.

## V. CONCLUSION

In this paper, we focus on the *Time-sensitive and Economical Mobile Cooperative Charging* (*TEMCC*) problem based on the *cooperative charging service model*, *i.e.*, how to find a spatio-temporal *cooperative charging scheduling strategy* to minimize the total charging service cost, subject to the constraints that the out-of-service time of each device does not exceed a given upper bound, which is NP-hard. By considering the spatio-temporal cooperation of the devices, we propose a greedy-based *Charging Service Cost Optimization Algorithm*, which can achieve an approximation ratio of $\ln n + 1$ in most of real situations. Through extensive simulations, we can conclude that the total charging service cost of our solution is always lower than that of the other solutions.

## ACKNOWLEDGMENT

This work is partly supported by the National Natural Science Foundation of China (Grant Nos. 62072254, 61872193, 61872178).

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