

mTS: Temporal- and Spatial-Collaborative Charging for Wireless Rechargeable Sensor Networks with Multiple Vehicles

Abstract—Benefited from recent breakthrough in wireless power transfer technology, the lifetime of wireless sensor networks (WSNs) can be prolonged significantly, generating the concept of wireless rechargeable sensor networks (WRSNs). While most recent works have been focusing on WRSNs with a single wireless charging vehicle (WCV), we investigate the issue of multiple WCVs’ on-line collaborative charging schedules in this work. In our design, termed mTS, the network area is divided into subdomains for designated WCVs. Each WCV schedules its charging scheduling path by responding to the interdependency of temporal and spatial correlations from different charging requests. Higher priorities are given to sensor requests with a mixture of closer charging deadlines and closer distances. We further analyze the system performance with an M/M/n/mTS queueing model. Our further study through simulations revealed that our scheme excels in successful charging rate, sensor survival rate, and other related performance metrics. Our field experiments further confirmed these results and showed some further interesting findings on different charging hardware and methods.

I. INTRODUCTION

Benefited from recent breakthrough in wireless power transfer, the bottleneck of energy limitation that hinders the wide deployment of wireless sensor networks (WSNs) can be addressed. Thus, the concept of Wireless Rechargeable Sensor Networks (WRSNs) has gradually become reality. In a WRSN, energy can be delivered from a wireless charging vehicle (WCV) to a sensor node, making it theoretically perpetual [1].

In many recent works, much effort has been devoted to enhancing the performance of WRSNs through real-time charging scheduling. In general, charging scheduling approaches fall into two categories: off-line scheduling [2] and on-line scheduling [3]. In off-line scheduling [2], information such as the location and energy status over the network is maintained and updated by WCV or the base station, making such methods unsuitable to network changes. In on-line scheduling [3], charging is usually on-demand with the help from collaborations between sensor nodes and WCVs through messaging so as to fulfill the charging tasks. Once the remaining energy of a sensor is lower than a threshold, a charging request will be initiated and delivered to the WCV for energy provisioning. Then WCV will respond to these emergency nodes.

Many of the prior works focused on systems with a single WCV. While system complexity can be relatively low with single WCV, multiple WCVs will definitely improve successful charging rate and node survival rate. More importantly, charging requests usually carry two pieces of information with

them: the charging deadline (i.e. a hard deadline for real-time charging scheduling), beyond which the requesting node will run out of energy; and the distance from the sensor, usually through the means of sensor GPS locationing. The state-of-the-art techniques have failed to take into the consideration of the questions of making a joint decision based on such spatial and temporal requirements for the charging requests.

Motivated by these issues, we design a new real-time charging scheduling scheme that takes advantage of the availability of multiple WCVs and allows them to make optimal decisions based on a joint metric of spatial and temporal requirements from charging requests. The main contributions of this work include:

- The proposed mTS scheme combines two critical metrics, the temporal requirement and the spatial feature of charging requests, into a joint metric and uses it to make decisions on charging sequences. The optimal weights of combining these two metrics are investigated and are incorporated into the design.
- To promote the overall performance of WRSNs, the charging scheduling problem is modeled as a multiple-objective joint optimization problem, which focuses on maximizing energy usage efficiency and survival rate simultaneously. Then mTS is developed for finding optimal charging solution, aiming at achieving our objectives above.
- Extensive simulations and field-test experiments are performed to compare the proposed scheme with different state-of-the-art techniques and the results show that the new scheme outperforms others significantly.

The rest of this paper is organized as follow: Section II surveys technical literature. Section III demonstrates the mTS algorithm in detail. Section IV gives theoretical analysis for mTS towards queueing theory. Section V and VI present the results of simulations and experiments and we conclude the paper and point out the future work in Section VII.

II. LITERATURE REVIEW

There have been many research works on WRSNs [4]. Typically, the charging methods fall into two types: off-line scheduling methods [5], [6] and on-line scheduling methods [7]–[11].

The majority of off-line scheduling methods model the charging scheduling problem as some traditional problems. For instance, Madhja *et al.* [6] solved an optimization problem by

distributed solution. They proposed Distributed Coordination (DC) and Distributed Coordination Local Knowledge (DCLK) protocols to coordinate mobile chargers and finally obtain charging trajectories.

On-line charging methods focus on the collaboration between mobile charger and nodes, usually with some types of on-demand features. For instance, He *et al.* [12] and Rout *et al.* [13] focused on the energy replenishment of tree-based WRSNs and proposed tree-structure charging scheduling methods. While these state-of-the-art works function quite well, they fail to take into the consideration of joint requirements of temporal urgency and spatial correlation.

Besides on-line and off-line models, there are also different charging models depending on how many nodes can be charged simultaneously: single-node charging model [1] and multiple-node charging model [5]. Obviously, multiple-node charging can be more efficient, but it poses new requirements on distances between charger and the nodes.

Liang *et al.* [14] focused on the minimum number of mobile charging vehicles that are required by WRSNs. Zhang *et al.* [5] proposed the Pushwait algorithm in WRSNs. However, neither of these two schemes combine temporal and spatial requirements in their charging decision-making process. Deng *et al.* [15] did consider spatiotemporal constraints in their Decouple Spatiotemporally Coupled Constraint (DSCC) algorithm, but the network is for static-routing. Lin *et al.* [1], [3] combined both temporal and spatial requirements in the TADP (Temporal and Distantial Priority) and P2S (Primary and Passerby Scheduling) schemes, however they were designed for a single WCV and lacked considerations for multiple WCVs.

In this work, we focus on a decision-making process that is based on a joint metric of temporal and spatial requirements from urgent nodes in WRSNs. In addition, our work naturally support multiple charging vehicles and can scale well to large networks.

III. THE PROPOSED SCHEME

In this section, we firstly introduce our architecture and give the statement of objective problem. Then, we detail proposed scheme in this paper.

A. Network Architecture and Problem Statement

As shown in Figure 1, we consider a WRSN configured by an on-demand real-time charging architecture. It is composed of plenty of stationary sensor nodes, multiple WCVs, and a base station (BS). Both WCVs and sensors are equipped with GPS modules (or locationing algorithms [16]) and batteries with limited capacity. And nodes communicate under the default protocol or mechanism (i.e. directed diffusion [17]). WCVs are able to locate the positions of sensors accurately enough so as to conduct replenishing tasks. The primary task of sensor nodes is to monitor, collect, deliver information from the environment. BS is responsible for data aggregation and fusion to predict events for the entire monitored area. BS is assumed to have infinite energy reserves.

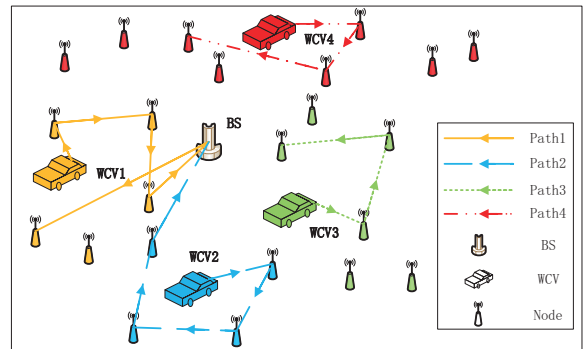


Fig. 1. System architecture of a WRSN with four WCVs

As the network operates, nodes consume battery energy by different rates. When the residual energy of a node falls below a threshold, it will broadcast a charging request, which will be forwarded to neighbor WCVs. The request carries node ID, its location, as well as its residual energy level and current energy consumption rate. Once the request is received, it will be inserted into the service queues to be served later. If the requesting node is not charged in time, its energy will eventually be used up. These nodes will stop providing any service in the network. Since in WRSNs with hard real-time requirement, unpredictable events may happen anywhere and anytime throughout the network, exhaustion of any node may lead to event detection failure that should be avoided. Therefore, in this work, we pay close attention to such real-time scheduling issues.

All real-time charging requests (within the designated region, see Section III-B2) are inserted in the service queue and sorted. WCV picks the head of the queue to service by traveling toward the requesting sensor's location. Once it is there, charging will begin. The next stop will be chosen again from the head of the queue once the charging is completed. When WCV detects that its own energy level falls below a warning threshold, it will travel to BS for a recharge of its own battery. WCV will fully charge the nodes every time and the charging time for each node is decided by energy receiving rate, q_r .

Charging efficiency is the ratio of energy that is eventually obtained by sensors from the WCVs (we list important variables in Table I):

$$\varepsilon = \frac{q_r}{q_c}, \quad (1)$$

where q_c refers to rate of energy inserted into the network by BS (through WCVs) and q_r denotes the rate of actual energy received by sensor nodes. However, we are more interested in the energy usage efficiency and ratio of surviving nodes.

Problem Statement: In a WRSN containing a BS, several WCVs and a series of sensor nodes, how do the WCVs simultaneously consider the influences of temporal and spatial interdependencies of charging tasks and choose nodes to replenish according to the order of charging requests so as

TABLE I
SYMBOLS AND DEFINITIONS

Symbols	Definitions
X	The width of the area of WRSN
Y	The length of the area of WRSN
N	The set of sensor nodes
$ N $	The number of sensor nodes
$ N _a$	The number of alive working nodes
N_i	The sensor node whose id is i
W	The set of WCVs
$ W $	The number of WCVs
W_j	The WCV whose id is j
η	Energy usage efficiency
δ	Survival rate of nodes
ε	Charging efficiency
q_i	Energy consumption rate of node N_i
q_r	Energy receiving rate of nodes
q_c	Energy consumption rate of WCVs' charging
q_m	Energy consumption rate of WCVs' moving
$C^{(n)}$	Battery capacity of nodes
$C^{(w)}$	Battery capacity of WCVs
e_i	Residual energy of N_i
E_j	Residual energy of W_j
Θ	Energy warning threshold of nodes
v	Traveling speed of WCVs
Ψ_j	Task queue containing received charging requests in W_j
$ \Psi_j $	Number of requests in W_j
t_i	Remaining lifetime of N_i
d_i^j	Distance between N_i and W_j
$d_{m,n}$	Distance between N_m and N_n
$\lambda_j^{(t)}(i)$	Temporal priority of N_i in $\Psi_j^{(t)}$
$\lambda_j^{(d)}(i)$	Spatial priority of N_i in $\Psi_j^{(d)}$
$\lambda_j^{(m)}(i)$	Mixed priority of N_i in $\Psi_j^{(m)}$
α	Weight of time
β	Weight of distance
Ω_k	The k^{th} area
r	Selecting radius of neighboring WCVs

to maximize the energy usage efficiency η and support the maximum number of surviving sensor nodes?

Optimal Objective: To solve the problem, we formalize it as a multiple-objective joint optimization problem, which owns two goals: maximizing the energy usage efficiency η and maximizing the survival rate δ simultaneously:

$$\begin{aligned} \max \eta &= \frac{E_{node}}{E_{charge} + E_{move} + E_{WCV}} \\ &= \frac{t \sum_{i=1}^{|N|} q_i + \sum_{i=1}^{|N|} e_i}{\frac{(t \sum_{i=1}^{|N|} q_i + \sum_{i=1}^{|N|} e_i) q_c}{q_r} + q_m \left(t - \frac{t \sum_{i=1}^{|N|} q_i + \sum_{i=1}^{|N|} e_i}{q_c} \right) + \sum_{i=1}^{|N|} E_j}, \end{aligned} \quad (2)$$

subject to:

$$\begin{aligned} 0 &< q_i, q_c, q_r, q_m, \\ 0 &< e_n^i \leq C^{(n)}, \\ 0 &< e_w^j \leq C^{(w)}. \end{aligned}$$

Here, E_{node} and E_{WCV} are total energy of nodes and WCVs, E_{charge} and E_{move} are defined as total energy used

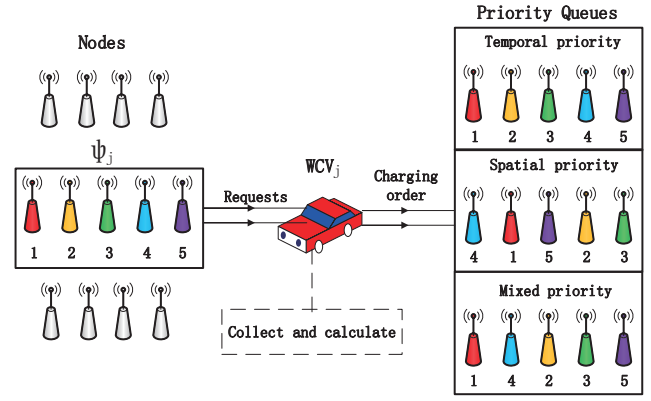


Fig. 2. An example of queuing process in mTS

for charging and traveling.

The survival rate δ can be calculated as:

$$\max \delta = \frac{|N|_a}{|N|}, \quad (3)$$

subject to:

$$0 < |N|_a \leq |N|.$$

Here, $|N|$ is the total number of nodes and $|N|_a$ is the number of alive nodes which are working normally.

B. mTS: Temporal- and Spatial-Collaborative Charging for Multiple WCVs

As shown in Figure 2, in mTS, every WCV, W_j , maintains a service queue Ψ_j sorted by a metric based on distance and charging deadline.

Charging deadline is computed based on residual energy and energy consumption rate:

$$t_i = \frac{e_i}{q_i}, \quad (4)$$

where e_i and q_i are the residual energy and energy consumption rate of N_i . In current task queue, we mark the arrival time of the earliest task as t_- and the latest one as t_+ . A temporal priority is then defined as:¹

$$\lambda_j^{(t)}(i) = \left\lceil \frac{t_i - t_-}{t_+ - t_-} \right\rceil = \left\lceil \frac{(t_i - t_-)|N|}{t_+ - t_-} \right\rceil. \quad (5)$$

Similarly, we define d_i^j as the distance between node N_i and WCV W_j . We mark the distance of the nearest node as d_-^j and the furthest one as d_+^j . Therefore, spatial priority $\lambda_j^{(d)}(i)$ can be calculated:

$$\lambda_j^{(d)}(i) = \left\lceil \frac{d_i^j - d_-^j}{d_+^j - d_-^j} \right\rceil = \left\lceil \frac{(d_i^j - d_-^j)|N|}{d_+^j - d_-^j} \right\rceil. \quad (6)$$

¹Other assignments are possible, e.g., a function t_i , $f(t_i)$, but we leave the investigation of these to our future work.

A joint priority $\lambda_j^{(m)}(i)$ is obtained by combining spatial and temporal priorities:

$$\lambda_j^{(m)}(i) = \alpha \lambda_j^{(t)}(i) + \beta \lambda_j^{(d)}(i) + \lg(\lambda_j^{(t)}(i) \lambda_j^{(d)}(i) + 1), \quad (7)$$

where α and β stand for the weights of temporal and spatial priorities and the logarithm term is inserted to avoid excessive duplicate priority values. We discuss the actual assigned values of α and β in Section VI.

Generally, nodes with smaller values of mixed priorities, $\lambda_j^{(m)}(i)$, are given higher priorities to be served first.

1) *Algorithm Overview*: Algorithm 1 and Algorithm 2 detail the process of the mTS scheme, which respectively focus on subdomain clustering and charging scheduling. The network is firstly divided into several subdomains by an enhanced K -means algorithm through Algorithm 1. In Algorithm 1, it details the initialization of cluster centers (line 4-13) and the process of refreshing node lists and cluster centers (line 15-31). Then in Algorithm 2, nodes transmit charging requests to their designated WCVs when they ask for energy replenishment (line 8-19). If a request cannot be served, the designated WCV will send it to a neighboring WCV for help (line 20-26).

An illustration is shown in Figure 3. First, mTS initializes the network (see Figure 3(a)). Then, it selects domain centers and divides clusters (see Figure 3(b), (c), and (d)) by Algorithm 1. Last, nodes send requests and WCVs charge nodes collaboratively (see Figure 3(e), (f), (g), and (h)) by Algorithm 2.

To group the network into subdomains, K -means clustering algorithm is adopted to divide the network into subareas $\{\Omega_k\}$, $k \in [1, |W|]$. Every Ω_k has a designated WCV, mainly responsible for energy replenishment for sensors located inside.

In order to ensure the shortest collaboration paths and reduce the time of traveling, we construct a shortest Hamiltonian cycle for cluster centers created by K -means clustering algorithm using Equation (8):

$$\min V = \sum_{i=1}^k \sum_{N_j \in S_i} \sqrt{(x_j - \bar{x}_i)^2 + (y_j - \bar{y}_i)^2}, \quad (8)$$

where V is the sum of distances from nodes to cluster center in clusters, S_i means the set of nodes in the i^{th} cluster and k means the number of clusters. (x_j, y_j) is the position of N_j and (\bar{x}_i, \bar{y}_i) denotes the center of cluster i .

In Algorithm 1, everytime a node $N_i'(x'_i, y'_i)$ (N_i' is the index number in its belonging domain, which is different from the value of N_i) is added to a domain Ω_k . The cluster center $P_k(\bar{x}_k, \bar{y}_k)$ will be updated by Equation (9) and Equation (10):

$$\begin{aligned} \bar{x}'_k &= \frac{\sum_{i=1}^{|\Psi_k|} x_i}{|\Psi_k|} \\ &= \frac{\bar{x}_k(|\Psi_k| - 1) + x'_i}{|\Psi_k|}; \end{aligned} \quad (9)$$

Algorithm 1 Enhanced K -means Algorithm

Input: Node set N , WCV set W

Output: All subdomains Ω_k

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1:  $K \leftarrow |W|$ ;
2: Define  $P_k(\bar{x}_k, \bar{y}_k)$  as the clusters center of  $\Omega_k$ ;
3: Initialize  $P_k$ ;
4: for  $i \leftarrow 1$  to  $K$  do
5:   Randomly select a node  $N_j(x_j, y_j)$  as  $N'_i(x_i, y_i)$ ;
6:   if  $N'_i \neq N'_{i-1}$  to  $N'_1$  then
7:      $\bar{x}_i \leftarrow x_i$ ;
8:      $\bar{y}_i \leftarrow y_i$ ;
9:   else
10:    Re-select a node as  $N'_i$ ;
11:     $i \leftarrow i - 1$ ;
12:   end if
13: end for
14: ChangeFlag  $\leftarrow 1$ ;
15: while ChangeFlag = 1 do
16:   ChangeFlag  $\leftarrow 0$ ;
17:   for  $i \leftarrow 1$  to  $K$  do
18:      $P'_i \leftarrow P_i$ ;
19:   end for
20:   for  $i \leftarrow 1$  to  $|N|$  do
21:     Calculate distances between  $N_i$  to all  $P_k$ ;
22:     Choose the nearest one as  $P_j$ ;
23:     Add  $N_i$  to  $\Omega_j$ ;
24:     Refresh  $P_j$  by Equation (9) and Equation (10);
25:   end for
26:   for  $i \leftarrow 1$  to  $K$  do
27:     if  $P'_i \neq P_i$  then
28:       ChangeFlag  $\leftarrow 1$ ;
29:     end if
30:   end for
31: end while
32: return All  $\Omega_k$ ;

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$$\begin{aligned} \bar{y}'_k &= \frac{\sum_{i=1}^{|\Psi_k|} y_i}{|\Psi_k|} \\ &= \frac{\bar{y}_k(|\Psi_k| - 1) + y'_i}{|\Psi_k|}. \end{aligned} \quad (10)$$

Additionally, we set the number of the clusters as $|W|$ when dividing the clusters.

In some extreme cases, when a WCV is unable to tackle with charging a number of nodes, some of them will be forwarded to neighboring WCVs through specific forwarding rules. And we define the neighboring WCVs as: if the distance between two cluster centers is less than a specific radius r , we denote that the designated WCVs are neighboring WCV mutually and r can be calculated by Equation (11):

$$r = \frac{\sum_{k=1}^{|W|} L_k}{|W|}. \quad (11)$$

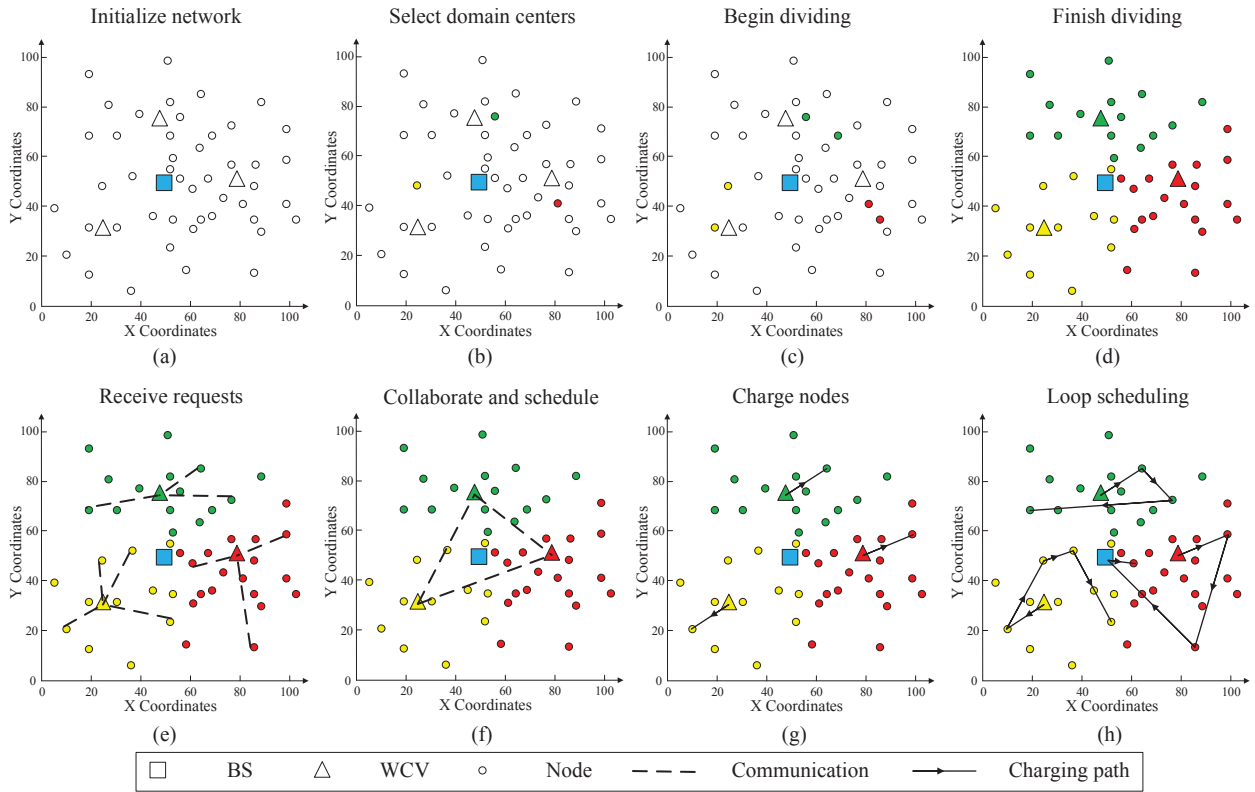


Fig. 3. The working process of a network with mTS algorithm (a) Initialize network, (b) Select domain centers, (c) Begin dividing, (d) Finish dividing, (e) Receive requests, (f) Collaborate and schedule, (g) Charge nodes, and (h) Loop scheduling

Here, L_k represents the length of k^{th} part of Hamiltonian path constructed based on cluster centers. Another case appealing for neighboring WCVs is that once a WCV returns to BS for energy provisioning, a neighboring WCV will probably be requested for help instead.

We use H_i to represent the length of i^{th} part of Hamiltonian path created based on nodes in Ψ_j including the location of W_j . We denote the distance between N_m and N_n as $d_{m,n}$, and H_i can be calculated by Equation (12):

$$H_i = \begin{cases} d_{s_2}^j, & i = 1 \\ d_{s_i, v_i}, & 1 < i \leq |\Psi_j|, \end{cases} \quad (12)$$

where, s_i is the first node of i^{th} path and v_i is the last node.

2) *Scheme Analysis*: In the on-demand charging architecture, WCVs receive charging requests from sensor nodes and determine a charging sequence. A subtle issue is that, no matter how hard the WCV works, there might exist charging requests that will never be served. Such requests should be either removed from the queue or delivered to a neighboring region's WCV for help. A similar but more unique situation is that the current WCV runs out of energy and needs to be recharged at BS. Most, if not all, of the charging requests need to be supported somehow by neighboring WCVs.

Reachable-in-Time Test: When a charging request is received, WCV should compute the earliest time to reach the

node and compare it with the charging deadline. If WCV cannot reach the sensor before its charging deadline, the charging request should be simply dismissed or forwarded to neighboring WCVs for help.

This decision can be calculated by Equation (13) as well:

$$\text{Reachable-In-Time Test} = \begin{cases} \text{serve,} & t_i \geq \frac{\sum_{k=1}^i H_k}{v} \\ \text{remove,} & t_i < \frac{\sum_{k=1}^i H_k}{v}. \end{cases} \quad (13)$$

Residual Energy Test: After selecting a target node N_i , a WCV will pre-calculate whether its residual energy is enough for returning to the BS after finishing the replenishment. If so, it will move forward to node N_i ; otherwise, it will directly head towards BS after forwarding all the requests to neighboring WCV:

$$\text{Residual Energy Test} = \begin{cases} \text{BS,} & \frac{E_j - \frac{C^{(n)} - e_i}{\epsilon}}{q_m} < \frac{d_i^j + d_i^{BS}}{v} \\ N_i, & \frac{E_j - \frac{C^{(n)} - e_i}{\epsilon}}{q_m} \geq \frac{d_i^j + d_i^{BS}}{v}, \end{cases} \quad (14)$$

where E_j is the remaining energy of W_j and q_m is energy consumption rate of WCVs.

IV. ANALYSIS

In this section, we use queuing theory to investigate mTS. In the network, sensor nodes and WCVs are deployed ran-

Algorithm 2 mTS Scheduling Algorithm

Input: Domains Ω_k , WCV set W
Output: Target charging nodes N_i

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1: Initialize parameters:  $\alpha, \beta$ ;
2: Initialize WCVs;
3:  $K \leftarrow |W|$ ;
4: for  $i \leftarrow 1$  to  $K$  do
5:   Add  $W_i$  to  $\Omega_i$ ;
6: end for
7: for  $j \leftarrow 1$  to  $K$  do
8:   Get current task queue  $\Psi_j$ ;
9:   for  $i \leftarrow 1$  to  $|\Psi_j|$  do
10:    Sort  $\Psi_j^{(t)}$  by  $t_i$  according to Equation (4);
11:    Sort  $\Psi_j^{(d)}$  by  $d_{i,j}$ ;
12:    Get  $\lambda_j^{(t)}(i)$  and  $\lambda_j^{(d)}(i)$  according to Equation (5) and
    Equation (6);
13:   end for
14:   for  $i \leftarrow 1$  to  $|\Psi_j|$  do
15:    Calculate  $\lambda_j^{(m)}(i)$  according to Equation (7);
16:   end for
17:   Sort  $\Psi_j^{(m)}$  by  $\lambda_j^{(m)}(i)$ ;
18:   Get top of the sorted queue:  $N_i$ ;
19:   Test whether  $N_i$  is reachable by Equation (13);
20:   if Reachable then
21:     return Target  $N_i$ ;
22:   else
23:     Send request of  $N_i$  to neighbor  $WCV_k$  ( $k \neq j$ );
24:      $WCV_k$  adds the request to its priority queue;
25:     Re-select node  $N_i$  by priority in  $\Psi_j^{(m)}$ ;
26:   end if
27: end for

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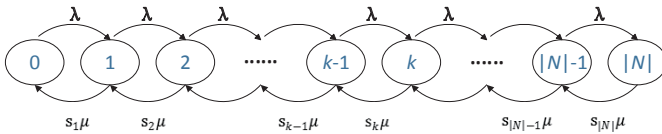


Fig. 4. State flow-chart

domly. Each WCV is regarded as a service window and they are cooperative. Request arrivals follow Poisson distribution with the parameter λ and the service time follows negative exponential distribution with service rate μ . Therefore, it can be regarded as an $M/M/n/mTS$ queueing model. When $\frac{\lambda}{n\mu} < 1$ satisfies, the system has a stable state, which is depicted in Figure 4. Here, s_k means the number of working WCVs at state k and can be calculated by Equation (15):

$$s_k = \begin{cases} \sum_{i=1}^k \frac{C_{k-1}^{i-1}}{2^{k-1}} i, & 0 < k < |W| \\ \sum_{i=1}^{|W|} \frac{C_{|W|-1}^{i-1}}{2^{|W|-1}} i, & |W| \leq k \leq |N|. \end{cases} \quad (15)$$

We define the value of the current state as the number of all charging requests (i.e. k), and the corresponding probability

as p_k , which can be calculated as Equation (16):

$$p_k = \frac{\rho_1^k}{\prod_{i=1}^k s_i} p_0. \quad (16)$$

Here, $\rho_1 = \frac{\lambda}{\mu}$ and $\rho = \frac{\lambda}{n\mu}$. Since we have:

$$\sum_{k=0}^{|N|} p_k = 1, \quad (17)$$

we can get:

$$p_0 = \left(\sum_{k=0}^{|N|} \frac{\rho_1^k}{\prod_{i=1}^k s_i} \right)^{-1}. \quad (18)$$

Then some features of the system can be deduced. The average length of the waiting queue L_q can be computed as Equation (19):

$$L_q = \sum_{k=0}^{|N|} k p_k. \quad (19)$$

Then the service time T_s^k of a single WCV can be formalized as:

$$T_s^k = \begin{cases} \frac{d_1^j}{v} + \frac{C^{(n)} - e_1}{q_r}, & k = 0 \\ \frac{d_{k-1,k}}{v} + \frac{C^{(n)} - e_1}{q_r}, & k > 0. \end{cases} \quad (20)$$

Here, $d_{k-1,k}$ is the distance between N_{k-1} and N_k .

The average service time of all WCVs is:

$$\overline{T_s} = \sum_{k=0}^{|N|} T_s^k p_k. \quad (21)$$

The response time of a charging request T_w^k can be computed as:

$$T_w^k = \sum_{l=1}^k T_s^l. \quad (22)$$

The corresponding average response time $\overline{T_w}$ can be obtained as Equation (23):

$$\overline{T_w} = \sum_{k=0}^{|N|} T_w^k p_k. \quad (23)$$

We will compare average response time computed numerically with those obtained in our field tests in Section VI-B.

TABLE II
PARAMETERS OF SIMULATION

Parameters	Values
Network size (m^2)	1000×1000
Number of nodes	50
Number of WCVs	5
Consumption rate of node (mAh/s)	0.02 – 0.03
WCVs' traveling consumption rate (mAh/s)	10
WCVs' charging consumption rate (mAh/s)	500
Charging efficiency	0.90
Emergency level	0.30
Initial energy of node (mAh)	900
Initial energy of WCV (mAh)	50000
Speed of WCVs (m/s)	5.0
Weight of time α	1.0
Weight of distance β	1.0

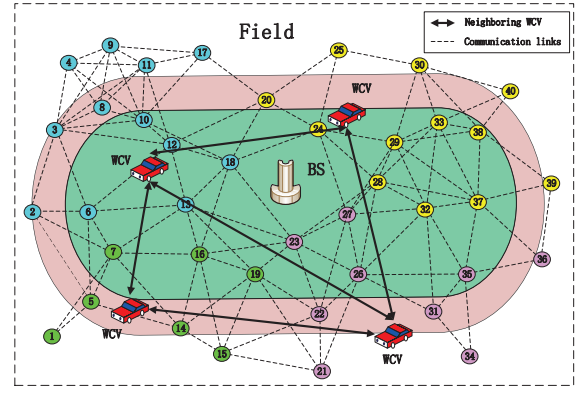


Fig. 6. Soccer field experiment

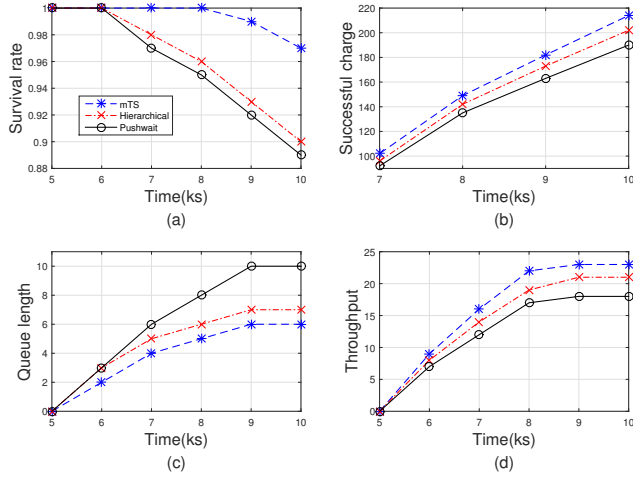


Fig. 5. Comparison between mTS, Pushwait and Hierarchical in terms of (a) survival rate, (b) successful charge, (c) queue length, and (d) throughput

V. SIMULATION EVALUATIONS

We evaluate the mTS algorithm by comparing with two state-of-the-art collaborative charging scheduling algorithms Pushwait [5] and Hierarchical [18] to demonstrate its advantages. Related simulation parameters are detailed in Table II.

We randomly placed $N = 50$ rechargeable sensor nodes in a $1000 \times 1000 m^2$ field. $M = 5$ WCVs are employed to charge these sensors, with a charging efficiency of 0.9 (see iNPOFi [19]). The warning threshold of the on-demand charging architecture is 30%.

Then, we compare the performance of mTS with Pushwait and Hierarchical in terms of queue length, successful charge, survival rate and throughput in Figure 5. In Figure 5(a), the survival rate of nodes in mTS is the highest. With respect to successful charges, mTS always maintains 5% and 10% higher than others (see Figure 5(b)). Figure 5(c) demonstrates the comparison of queue length. mTS is on average 29% less than others. Moreover, Figure 5(d) indicates that mTS has the highest throughput when comparing with the other two schemes.

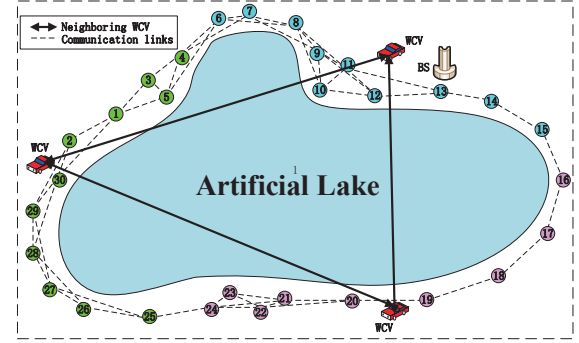


Fig. 7. Artificial lake experiment

VI. EXPERIMENTS AND RESULT ANALYSIS

A. Experiment Configurations

To demonstrate the applicability of the proposed scheme, experiments are conducted. Two experimental scenes, a field and an artificial lake are selected as shown in Figure 6 and Figure 7. Detailed configurations of the experiments are listed in Table III.

TABLE III
PARAMETERS OF EXPERIMENTS

Parameter	Field	Lake
Network size (m^2)	300×150	100×100
Number of nodes	40	30
Number of WCVs	4	3
Consumption of nodes (mAh/s)	0.02 – 0.03	0.02 – 0.03
WCVs' moving consumption (mAh/s)	10	10
WCVs' charging consumption (mAh/s)	500	500
Charging efficiency	0.90	0.90
Emergency level	0.30	0.30
Initial energy of nodes (mAh)	900	900
Initial energy of WCVs (mAh)	50000	50000
Speed of WCVs (m/s)	5.0	5.0
Weight of time	1.0	1.0
Weight of distance	1.0	1.0

The size of the rechargeable sensor nodes is $50mm \times 70mm$. Each node is equipped with a receiving coil for acquiring energy. We use different hardware with three charging standards:

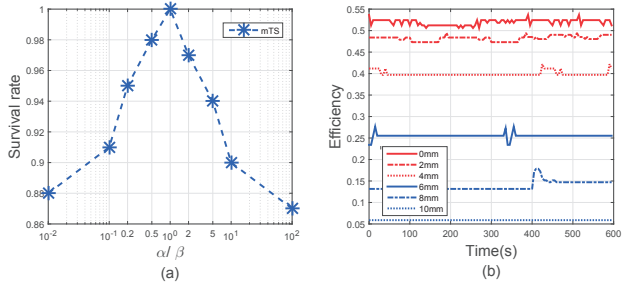


Fig. 8. Determining the values of (a) $\frac{\alpha}{\beta}$ and (b) ε

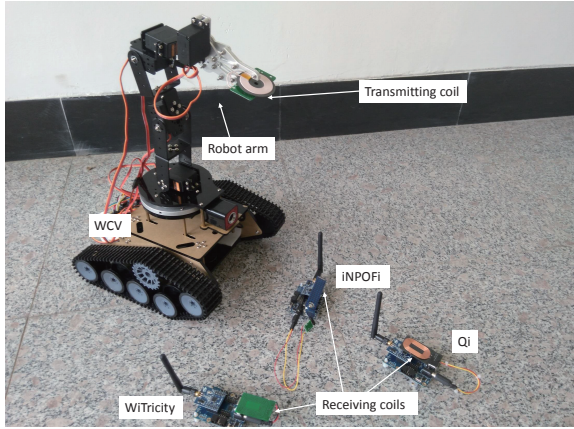


Fig. 9. Test-bed: mobile robot arm and three types of rechargeable sensors

iNPOFi [19], WiTricity [20] and Qi [21] to implement our rechargeable sensors as shown in Figure 9.

Our experiment firstly decides the best ratio to combine temporal and spatial priorities (i.e. α and β). In Figure 8(a), a sharp change in node survival rate can be observed around $\frac{\alpha}{\beta} = 1$. Such a change could be due to the inappropriate combination of these two priorities. On one hand, if temporal priority is weighted too heavy, nodes that are too far away will be left alone to run out of energy. On the other hand, a heavy-weighted spatial priority may skip those nodes requiring immediate charging with lower spatial priority. Therefore, to maximize the charging efficiency, in the following experiments, we set $\frac{\alpha}{\beta} = 1$.

Then we measure the impact of coil distance on energy efficiency, we observe that, as shown in Figure 8(b), the charging efficiency decreases as distance increases. Hence, the maximum efficiency can be obtained when two coils touch each other. Different from using mobile vehicles in prior arts [3], [9], in our experiment, robot arms implemented with GPS and camera modules are employed, which ensure the locating and touching charging accurately. Moreover, robot arms can suit both non-contact (WiTricity and Qi) and contact charging standards (iNPOFi). And the results verify the applicability of our scheme.

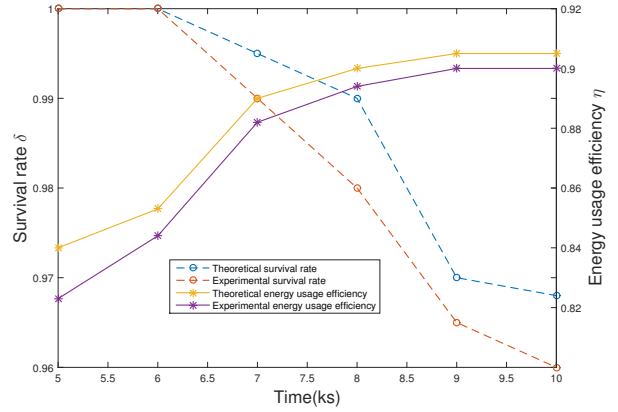


Fig. 11. Comparison between theoretical results and experiment results

B. Experimental Result Analysis

We analyze the performance of mTS when three kinds of rechargeable sensors are implemented.

mTS groups the sensor nodes into clusters based on the number of WCVs employed in two scenarios, the clustering results are shown in Figure 6 and Figure 7, then we discuss their performance in details. As illustrated in Figure 10, the comparisons of three standards on the soccer field and around the lake are demonstrated. When nodes are deployed in the field, the service time firstly increases fast and slows down later (see Figure 10(a)). Figure 10(b) depicts the comparison of survival rate of nodes, indicating the network maintaining capability. We observe that higher rate leads to the higher charging efficiency (i.e. iNPOFi). Then we measure throughput for three scenarios, from Figure 10(c), we observe that system tends to work steadily after a period of time. At last, we evaluate the average waiting time for three scenarios. Experimental results shown in Figure 10(d) indicate that the waiting time increases at the beginning and grows tending to a stable value.

The conclusion obtained around our artificial lake is similar to those in the field (see Figure 10(e), (f), (g), and (h)), we also conclude that a higher charging efficiency (i.e. iNPOFi) will lead to a higher survival rate as well as a shorter waiting time.

On the basis of above simulations and experiments, the objectives including energy usage efficiency and survival rate are demonstrated in Figure 11, which also shows theoretical results of our analysis in Section IV. The results of experiments approximately correspond with theory. Therefore, this result validates our theoretical analysis and proves its correctness.

VII. CONCLUSIONS

In this paper, we have proposed a real-time temporal- and spatial-collaborative charging scheme for WRSNs with multiple WCVs. Our scheme, termed mTS, combines the temporal requirement as well as spatial features into a single priority metric, which is then used to sort real-time charging requests for WCVs to serve. The network area is divided

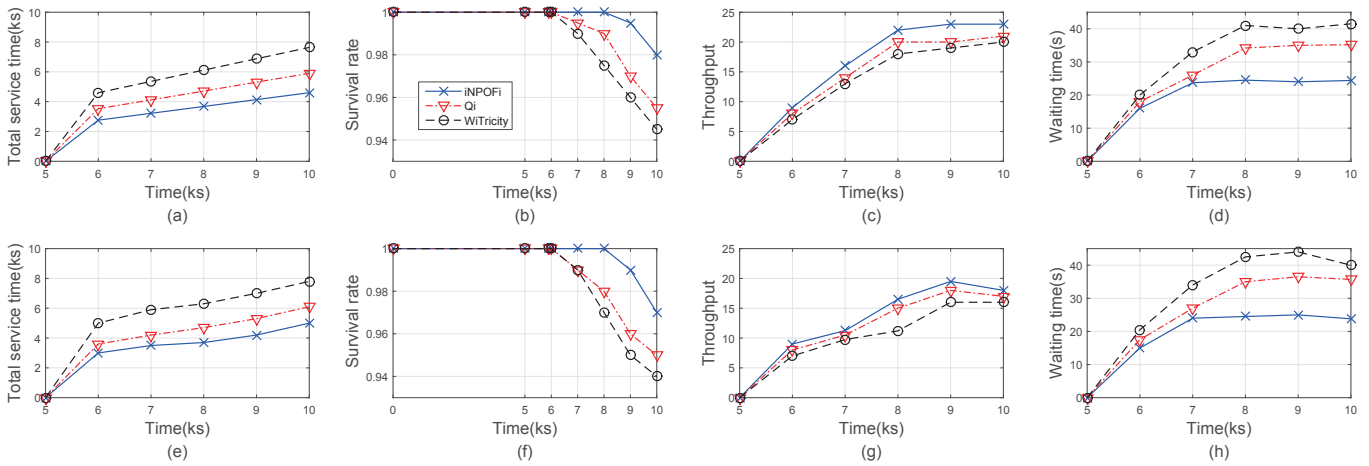


Fig. 10. Comparison between performances with iNPOFi, WiTricity and Qi in terms of (a), (e) service time, (b), (f) survival rate, (c), (g) throughput and (d), (h) average wait time, for field and lake, respectively.

into subdomains, each of which is designated to one of the several WCVs. The scheme achieves the objectives that maximize energy usage efficiency and survival rate. Extensive simulations as well as field experiments have been performed to evaluate the mTS scheme against different state-of-the-art schemes in various network conditions. Evaluations have shown that the mTS scheme achieves high successful charging rate and supports more sensor nodes.

In our future work, we will focus on the computational complexity as well as potential drawbacks of additional communication overhead caused by the mTS scheme.

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