GTCCS: A Game Theoretical Collaborative Charging Scheduling for On-demand Charging Architecture

Chi Lin, *Member, IEEE,* Shuang Wei, Jing Deng, *Fellow, IEEE,* Mohammad S. Obaidat, *Fellow, IEEE,* Houbing Song, *Senior Member, IEEE,* Lei Wang, *Member, IEEE,* and Guowei Wu

***Abstract*—Battery energy is always limited in most wireless networked nodes, but wireless power transfer has the potential to address the problem for good. In this work, we study the problem of collaborative charging decisions in Wireless Rechargeable Sensor Networks (WRSNs). In these networks, multiple Wireless Charging Vehicles (WCVs) need to decide which of the requesting sensors to charge and in what order. Our approach is to convert the decision makers, i.e., WCVs, into game players for higher profit. With the use of Nash Equilibrium, our newly designed scheme, named Game Theoretical Collaborative Charging Scheduling (GTCCS), enables WCVs to make optimal charging decisions. Besides, the result of the game is Pareto-optimal by carefully designing the rules of this game. We introduce the game theory model in this work and explain how it is played by WCVs, with the goal of increasing overall energy usage efficiency. Extensive simulations and lab/field experiments show that GTCCS is able to achieve a much higher energy usage efficiency, lower the number of dead nodes. The dynamic characteristics of the GTCCS scheme also allow us to introduce two unique features to further improve system performance, including dynamic warning threshold for WCVs and sacrifice-charge.**

***Index Terms*—Wireless Rechargeable Sensor Networks, Game Theory, Wireless Charging Vehicle, Charging Scheduling, Pareto-optimal.**

I. Introduction

As networked devices proliferate in our world, stable energy remains elusive. Such elusiveness is not only in the perspective of global energy resources, but also the current level of battery energy that can keep the networked devices running. Battery capacity has not significantly increased for a very long time, even though wireless communication capability and computational power have both seen huge improvement.

A good example can be seen in wireless sensor networks (WSNs), where tiny sensors are expected to be deployed with even smaller batteries. Major research contributions have been made to increase network lifetime with the use of advanced networking strategies or redundant sensors, yet the problem of even theoretically immortal sensors cannot be addressed until a recent breakthrough in wireless power transfer (WPT). With WPT, batteries can be wirelessly replenished by a wireless charging vehicle (WCV) or robot (WCR), leading to the concept of wireless rechargeable sensor network (WRSN) [1].

Obviously, charging schedule is the most critical issue in WRSNs and there exist many prior related works reported in technical literature. Some techniques use off-line approaches [2]–[6], in which node locations and topology are converted to classical traveling salesman problem and fixed charging path for the WCVs to periodically travel are then computed. Usually, these approaches assume that deterministic information such as network topology and energy consumption rate are fixed and known in advance. However, in the real application of WSNs, it is infeasible to model such information as deterministic due to the dynamics and uncertainty of the networks. In order to overcome these restrictions, others use on-line approaches [7], requiring dying sensors to submit their charging requests to WCVs or the base station (BS), which will decide the charging sequence based on some predefined algorithms. Some employ a single WCV [8] or multiple WCVs [9], [10] with limited energy capacity that each of them works independently in the system. However, in a large-scale network, such schemes may lead to serious problems. For example, the sensors at the edge of the network will never get charged and run out of the energy because the WCV with limited energy can hardly reach them.

To solve this problem, others introduced collaborative mobile charging [11] allowing energy to transfer between WCVs and theoretically extending the network coverage infinitely. While collaborative charging scheme indeed has obvious superiority in network coverage, it still suffers from severe problems that influence the energy usage efficiency. Frequent and unnecessary patrolling back and forth between BS and charging region lead to extra travelling cost. In order to reduce the travelling cost, hierarchical charging solution [12] is designed, in which two types of WCVs are employed. One type is only responsible for charging nodes while the other one is only for charging WCVs. However, the behaviors of WCVs are predetermined, leading to low survival rate. Although Lin et al. [13] had solved the problem of deterministic charging mission with inflexibility by utilizing the game theory, they did

Chi Lin, Shuang Wei, Lei Wang and Guowei Wu are with the School of Software, Dalian University of Technology, Key Laboratory for Ubiquitous Network and Service Software of Liaoning Province. Email: {c.lin, wgw-dut}@dlut.edu.cn.

Jing Deng is with Department of Computer Science, University of North Carolina at Greensboro NC 27412, U.S.A. Email: jing.deng@uncg.edu

Houbing Song is with Department of Electrical, Computer, Software, and Systems Engineering, Embry-Riddle Aeronautical University, Daytona Beach, FL 32114 USA.

Mohammad S. Obaidat is with ECE Department, Nazarbayev University, Astana, Kazakhstan and King Abdullah II School of Information Technology, University of Jordan, Amman, Jordan.

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not consider the charging conflicts (i.e. where two WCVs tend to charge the same entity) yielding to low energy efficiency.

In this work, we use a unique approach to address the collaborative charging schedule issues in the large-scale WRSNs with multiple WCVs. We propose a game theoretical collaborative charging scheduling (GTCCS) algorithm to improve energy usage efficiency, lower the number of dead nodes in the network and solve the charging conflicts among WCVs by rationally designing payoff function. In our approach, WCVs are treated as game players with the same goal of increasing profits. The dynamic characteristics of the GTCCS scheme also allows us to introduce two unique features to further improve system performance, including dynamic warning threshold for WCVs and sacrifice-charge. In general, the main contributions of this paper are as follows:

- We study the charging schedule issue in WRSNs with multiple WCVs taking the charging conflicts into consideration. The use of Nash Equilibrium allows WCVs to identify the best charging targets collaboratively;
- By stipulating the rules of game, each WCV selects the same action tuple and the outcome of the game at each time is proved to be Pareto-optimal;
- Extensive simulations and lab/field experiments have been performed to evaluate GTCCS and compare it with other schemes. The GTCCS is shown to outperform all of them in terms of energy usage efficiency and number of supporting nodes;
- In order to further improve system performance, two unique design features of the GTCCS are designed, including dynamic warning threshold and sacrifice-charge.

The rest of this paper is organized as follows. Section II reviews the related works. In Section III, we present a brief overview of game theory, which will be used in our design and the problem statement. The GTCCS scheme is introduced in detail in Section IV. Simulation results are presented and discussed in Section V. We further investigate GTCCS through lab/field experiments in Section VI, followed by the conclusion in Section VII.

II. Background and Related Work

While there have been many works focusing on charging scheduling in WRSNs, these can be generally classified into two categories: 1) off-line scheduling and 2) on-line scheduling.

A. Off-line Scheduling

Off-line scheduling usually tries to calculate a Hamiltonian cycle to serve as the charging sequence based on the network topology and the energy consumption model. Some works focused on the network performance while employing a single charger. Chen et al. [14] designed a quasi-polynomial time algorithm to find the optimal charging path, maximizing the number of nodes charged within a fixed time horizon. Shu et al. [15] studied the problem of maximizing the charged energy in sensor nodes to further improve the network lifetime. In order to optimize path planning, a Markov Decision Process (MDP) [16] is utilized to solve the path selection problem. However, these methods are not suitable for large-scale networks due to inherent energy constraints. Recent works solved this problem by deploying multiple chargers [17] to charge sensors. Jiang et al. [18] proposed a novel periodic mobile charging method for large-scale networks by jointly considering charging tour planning and depot positioning. Usually, these off-line scheduling schemes are based on fixed energy consumption rates and fixed network topology. Thus, they may become impractical as WRSNs grow in size. Complex topology changes caused by network dynamics require costly repeatedly re-compute the charging paths for WCVs in order to adapt the new network topology.

B. On-line Scheduling

Compared to off-line scheduling, on-line scheduling schemes do not always require fixed network topology, predictable residual energy, and/or fixed energy consumption rates. Such information are usually hard to obtain with high accuracy in practice. In on-line scheduling schemes, a sensor node will send a charging request to the WCV when its remaining energy is lower than a certain threshold [7]. After receiving the request, the WCV will schedule its trip to include the node's location and visit each sensor to charge it. In order to improve charging request throughput and charging efficiency, Lin et al. [8] studied the charging scheduling problem by taking temporal and spatial priority into consideration. Similar approaches include utility coverage maximization [19], charging reward maximization [20], and evaluating the schedulability of charging mission [21]. However, they investigated the single charger charging problem, which is not suitable for large-scale network. To solve this problem, Liang et al. [22] studied the multiple chargers charging problem and tried to find the minimum charger to charge the sensors. Wang et al. [23] considered more general setting that the chargers can charge multiple sensors at the same time and proposed a two-step approximation algorithm to reduce the system cost. Nonetheless, they can only promise limited network coverage.

Some schemes focus on the cooperation between the WCVs for better network coverage and system optimality [11], [13], [24]. In order to reduce the time and extra energy for WCV returning back to the BS, Madhja et al. [12] proposed a hierarchical charging structure. Tang et al. [24] contributed to finding the minimum number of WCVs to maintain the network operation such that the cost for building and operating the network is the lowest.

However, these schemes still suffer from the problems of low energy usage efficiency and large number of dead nodes. The main issue is that they lack systematic collaborations of charging schedules among different WCVs throughout the entire network and some sensor nodes are simply left to running out of energy. In this work, we focus on the use of game theory to allow WCVs to make optimal charging decisions.

III. Preliminary and Problem Statement

In this section, a brief introduction on game theory [25] is given and then we introduce the problem statement.

A. Basic Elements of Game Theory

Game theory is composed of three basic elements: players, strategy set, and payoff functions.

In this paper, we build a game theory model for formalizing the charging decision making process. Each WCV is regarded as a player involving in the game process. We use $\mathcal{V} = \{v_1, v_2, ..., v_M\}$ to denote the set of all WCVs in the network. For each WCV v_j, it owns a strategy set S_j which contains all possible actions for it to choose and guide its future movement. The strategy chosen by WCV v_j is denoted by s_j, and the strategy chosen by all WCVs are denoted by an action tuple $s = \{s_1, s_2, ..., s_M\}$. For each WCV v_j, its payoff is determined by these action tuples and we use $P_{v_j}(s_j, s_{-j})$ to denote the payoff where $s_{-j} = \{s_1, ..., s_{j-1}, s_{j+1}, ...s_M\}$ indicates all other WCVs' strategies except v_j.

In game theory, Nash Equilibrium is often used to analyze the situation of all strategies made by WCVs. In Nash Equilibrium, each player has no motivation to change its strategy. Formally, the strategy set $s^* = \left\{s_1^*, s_2^*, ..., s_M^*\right\}$ is a Nash Equilibrium if $P_{v_j}(s_j^*, s_{-j}^*) \geq P_{v_j}(s_j, s_{-j}^*)$ for $\forall s_j \in S_j$ and $\forall v_j \in \mathcal{V}$, where S_j denotes the strategy set of WCV v_j. A Nash Equilibrium is a balanced state, in which individuals select their best strategies and they cannot benefit from unilateral deviation. It is a promising method for restricting the behaviors of WCVs. Therefore, we will convert the charging scheduling problem into a game process and develop appropriate payoff functions to achieve Nash Equilibrium so that the behaviors of WCVs can be optimized.

B. Problem Statement

Before we move on, we present variables that are used throughout the paper in Table I.

TABLE I
SYMBOLS AND DEFINITIONS

Symbols	Definitions
$\mathcal{N}$	A set of sensor nodes
$\mathcal{V}$	A set of WCVs
$\|\mathcal{N}\|$	Number of sensor nodes
M	Number of WCVs
E	Energy capacity of sensor nodes
E^v	Energy capacity of WCVs
$E_i(t)$	Current energy level of sensor nodes
$E_j^v(t)$	Current energy level of WCVs
E_u	Total energy that eventually obtained by sensor nodes
E_t	Total energy of WCVs
η	Energy usage efficiency
β	Warning threshold of sensor nodes
R_{max}	Maximum energy consumption rate of node n_i
R_{min}	Minimum energy consumption rate of node n_i
t_i	Charging time of node n_i
ρ_1	Energy transfer efficiency between a WCV and a node
ρ_2	Energy transfer efficiency between two WCVs
v	Traveling speed of WCVs
c	Traveling cost rate of WCVs
ε	Charging power of WCVs
$d_{i,j}$	Distance between node n_i and WCV v_j
s_j	Strategy of WCV v_j
$P_{v_j}(s_j, s_{-j})$	Payoff value of WCV v_j with situation (s_j, s_{-j})
δ	Threshold of waiting time for WCV
α	Transmission energy ratio for charging another WCV
r	The service region radius of a WCV

We envision a scenario that a set of rechargeable nodes are randomly deployed in a two-dimensional area. The sensor nodes send charging requests when their energy fall below a certain threshold. Multiple WCVs with limited energy are employed to charge the nodes. First, we ensure the nodes at the edge of the network can be charged. Inspired by collaborative charging [11], we let each WCV can not only replenish the sensor nodes, but also replenish a WCV within its service region such that the network coverage is not limited. A WCV will send a charging request when its residual energy satisfies specific conditions (see Section IV-D). Usually, the charging requests consist of the unique identity, location and other information.

The energy consumption of a WCV constitutes charging consumption and moving consumption. We use E_u to indicate the total energy eventually obtained by sensor nodes, which can be calculated as follows:

$$E_u = \sum_i E - E_i(t) + t_i \cdot r_i \qquad n_i \in \mathcal{N}. \tag{1}$$

The total energy carried by all WCVs E_t is:

$$E_t = M \cdot E^v. \tag{2}$$

Energy usage efficiency (EUE), η, is defined as the ratio of the total energy obtained by sensor nodes and WCVs' total energy. This paper aims at maximizing the energy usage efficiency to enhance the performance:

$$\begin{aligned} \text{maximize} \quad & \eta = \frac{E_u}{E_t} = \frac{\sum\limits_i E - E_i(t) + t_i \cdot r_i}{M \cdot E^v}, \\ \text{subject to} \quad & 0 < E_i(t) < \beta E \qquad n_i \in \mathcal{N}\ . \end{aligned} \tag{3}$$

Here, β indicates the warning threshold of sensor nodes. E and E^v represent the battery capacity of sensor nodes and WCVs, respectively. $E_i(t)$ indicates the current energy level of node n_i and its average energy consumption rate in the charging process is r_i. t_i indicates the charging time of node n_i. M stands for the number of WCVs.

In order to maximize η, we need to maximize the energy obtained by the sensors. Taking deep insight of the energy flow, energy transfer between two WCVs leads to less energy obtained by the sensors since the wireless charging efficiency can not reach 100%. Hence, maximizing η is contradictory with maximizing the network coverage. In this paper, we first ensure the network coverage is maximized, and then try to maximize η. The key of maximizing η is to carefully select charging strategy for each WCV among some charging requests. Therefore, in this paper, we convert the multiple WCVs charging problem into a game among WCVs. Hence, instead of maximizing the EUE, we aim at maximizing the payoff for WCVs, which can be formalized as follows:

$$\text{maximize} \qquad P_{v_j}(s_j, s_{-j}) \qquad v_j \in \mathcal{V}\ , \tag{4}$$

where payoff function $P_{v_j}(s_j, s_{-j})$ will be defined in Section IV.

IV. The Proposed Scheme

A. System Architecture

In this paper, we consider a two-dimensional network composed of some sensor nodes. $\mathcal{N}$ indicates the set of the sensor nodes and it changes over time as new sensors may join in the network or some old ones run out of the energy. The number of the sensors is $|\mathcal{N}|$. The location of a node n_i can be expressed as (x_i, y_i). Each sensor node is equipped with the same rechargeable Lithium battery E. Its maximum energy consumption rate is R_{max} and R_{min} is the minimum energy consumption rate. $R_{i,t}$ indicates the energy consumption rate of sensor n_i at time t and $R_{i,t} \in [R_{min}, R_{max}]$. We divide the network time T into same time slots τ and $T = \{\tau_1, \tau_2, ..., \tau_K\}$. Then, we denote the average energy consumption in time slot τ_k as $r_{i,k}$. In this paper, we assume that the sensors can monitor their current energy and $E_i(t)$ indicates the current energy of the node n_i at time t. When the remaining energy of a node falls below a threshold β, it will initiate a charging request to the sink nodes. Then WCV will respond to the request later by scheduling for energy provisioning. For sensor n_i, we permit only one WCV to charge it in the energy replenishment process in order to improve the efficiency and its charging time is t_i, which is determined by the residual energy level of the sensor. Besides, the average energy consumption rate of sensor n_i in the charging process is r_i and $r_i = r_{i,\lceil t/\tau \rceil}$.

M homogeneous WCVs with the same energy capacity E^v are responsible for energy replenishment. Each time, a WCV v_j selects a charging target and moves toward it at a speed of v. The traveling cost rate of a WCV is denoted as c and ε is the charging power. Due to the existing limitation of the WPT, the energy source cannot ensure that all energy is eventually received by the receiver. Therefore, similar to [11], we use ρ_1 to represent the energy transfer rate between WCVs and nodes. ρ_2 indicates the charging rate between two WCVs. BS is responsible for replenishing WCVs such as energy provisioning or battery replacement. Once the residual energy of a WCV satisfies specific conditions (see Section IV-E), it will come back

B. Game Theory Process

We use the non-cooperative game theory to solve the charging scheduling problem. In our scheme, we divide the WCVs in the network into two categories: 1) normal WCVs and 2) panic WCVs. A WCV is called normal WCV when its energy level is enough to complete a charging mission. Otherwise, it is called a panic WCV. Only the normal WCVs are regarded as the players in the game and each of them is rational enough to select a strategy, which gains the maximum payoff. For each normal WCVs, they need to make charging decisions after completing one charging task. In the game process, the strategy set of a WCV includes charging the sensor nodes and charging WCVs, which have sent charging requests and within its service region r. Therefore, a WCV's strategies can be classified into two categories: charging a node (CN) and charging a WCV (CW). In this paper, the unique identification of the sensor nodes and the WCVs are numbered together. s_j^k indicates the charging strategy of WCV v_j, which is defined as Equation (5).

$$s_j^k = \begin{cases} CN & k \in [1, |\mathcal{N}|] \\ CW & k \in [|\mathcal{N}|+1, |\mathcal{N}|+M] \end{cases} \tag{5}$$

Here, k indicates the unique identification of WCV or node which is selected to be the charging target for WCV v_j.

In the game process, the payoff function is used for restricting the behaviors of players. We use payoff $P_{v_j}(s_j^k, s_{-j}^m)$ to represent the profit of WCV v_j. Here variable s_j^k refers to the charging strategy chosen by WCV v_j and variable s_{-j}^m is the charging strategy tuple chosen by another WCVs in the game.

The payoff of a WCV is a value that indicates the profit it gains or loses, which can be increased or reduced. When traveling, the energy cost is regarded as the payoff loss whereas the gain is considered as the amount of energy that the sensor node eventually obtains. It is related to the distance $d_{v_j,k}$ between WCV v_j and the target k which can be calculated according to Equation (6).

$$d_{v_j,k} = \sqrt{(x_{v_j} - x_k)^2 + (y_{v_j} - y_k)^2} \tag{6}$$

In our method, a successful charging happens when their distance is 0. Moreover, as the battery capacity of the mobile WCV is much larger than the sensor node, after charging, a node will be fully charged to its energy capacity. When conducting a WCV charging, we aim at enabling WCV to complete a charging mission. Hence, a WCV will share α percentages of the residual energy and reserve sufficient energy for traveling to the target and returning to BS.

To compute the value of the payoff function $P_{v_j}(s_j^k, s_{-j}^m)$, we define the corresponding profit as Equation (7).

$$P_{v_j}(s_j^k, s_{-j}^m) = \begin{cases} 0 & k = m \\ \Delta B_1 - c \cdot d_{v_j,k} & k \neq m,\ k \in [1, |\mathcal{N}|] \\ \Delta B_2 - c \cdot d_{v_j,k} & k \neq m,\ k \in [|\mathcal{N}|+1, |\mathcal{N}|+M] \end{cases} \tag{7}$$

Here ΔB_1 and ΔB_2 stand for the energy eventually obtained by a WCV and a node. $d_{v_j,k}$ indicates the distance between the WCV v_j and its charging target k. c is the energy consumption rate for traveling.

According to Equation (7), we note that the payoff function contains the profit of a WCV in three different circumstances.

(1) When two WCVs simultaneously choose the same node or WCV (i.e. a conflict happens, $k = m$), we define the corresponding profit as 0 for avoiding such a conflict.

(2) When v_j plans to charge a node, it will gain a profit of $\Delta B_1 - c \cdot d_{v_j,k}$.

(3) When v_j tends to charge another WCV, it will be awarded $\Delta B_2 - c \cdot d_{v_j,k}$ profit.

Moreover, we discuss the detail of the last two circumstances to clearly calculate the payoff value for WCVs.

Case I: Charging a node, $k \neq m$, $k \in [1, |\mathcal{N}|]$. In this case, the profit ΔB_1 eventually obtained by a node n_k can be formalized as follows:

$$\Delta B_1 = E - E_k(t) + t_k \cdot r_k. \tag{8}$$

Here, E and $E_k(t)$ indicates the energy capacity and current energy level of sensor nodes, respectively. t_k is the charging time of sensor node n_k and r_k stands for the average energy consumption rate during the charging process. Combine Equation (7) and Equation (8), we have the payoff value for charging a sensor node as:

$$P_{v_j}(s_j^k, s_{-j}^m) = E - E_k(t) + t_k \cdot r_k - c \cdot d_{v_j,k}. \tag{9}$$

Case II: Charging a WCV, $k \neq m$, $j \in [|\mathcal{N}|+1, |\mathcal{N}|+M]$. In this case, the profit ΔB_2, which is eventually obtained by the charging target k can be calculated as follows:

$$\Delta B_2 = \alpha \cdot \rho_1 \cdot \rho_2 \cdot E_j^v(t) - c \cdot d_{v_j,k} - c \cdot d_{k,BS}. \tag{10}$$

Here, $E_j^v(t)$ indicates the current energy when the WCV is making a decision. α is the transmission energy ratio. By combining Equation (7) and Equation (10), we obtain the payoff value for charging a WCV v_k as:

$$P_{v_j}(s_j^k, s_{-j}^m) = \alpha \cdot \rho_1 \cdot \rho_2 (E_j^v(t) - 2c \cdot d_{v_j,k} - c \cdot d_{k,BS}). \tag{11}$$

According to Equation (9) and Equation (11), we can see that if the residual energy level of the charging target is lower, the corresponding payoff value will be larger. Similarly, the payoff value will be greater when the distance between the WCV and charging target is shorter. Therefore, we can easily reduce that the WCV is likely to charge the object with least residual energy and shortest distance to maximize the payoff.

C. GTCCS Algorithm

In this section, we take two players (v_1 and v_2) as an example to discuss the game process. Their profits can be expressed as the payoff matrix $P_{(v_1,v_2)}$ as:

$$P_{(v_1,v_2)} = \begin{bmatrix} \mathbf{(0,0)} & (P^1_{n_1},P^2_{n_2}) & \cdots & (P^1_{n_1},P^2_{v_3}) & (P^1_{n_1},P^2_{v_4}) & \cdots \\ (P^1_{n_2},P^2_{n_1}) & \mathbf{(0,0)} & \cdots & (P^1_{n_2},P^2_{v_3}) & (P^1_{n_1},P^2_{v_4}) & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ (P^1_{v_3},P^2_{n_1}) & (P^1_{v_3},P^2_{n_2}) & \cdots & \mathbf{(0,0)} & (P^1_{v_3},P^2_{v_4}) & \cdots \\ (P^1_{v_4},P^2_{n_1}) & (P^1_{v_4},P^2_{n_2}) & \cdots & (P^1_{v_4},P^2_{v_3}) & \mathbf{(0,0)} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}. \tag{12}$$

In Equation (12), value $P^j_{n_i}$ and $P^j_{v_k}$ indicate the profit of WCV v_j when charging node n_i and WCV v_k respectively.

In this paper, charging scheduling problem is regarded as a game where all WCVs are players. They are rational and tend to choose the best strategy to obtain maximum payoff value. Specially, a conflict may happen, indicating that two WCVs tend to charge the same entity. An example of a conflict is shown in Figure 1(a). In this case, v_1 and v_2 will move to v_3. In practice, it is unfeasible for two WCVs to charge the same object since the sensor or panic WCV can only be charged by one WCV at a time. Hence, v_3 will get charged from the WCV, which is closer to it, while another WCV will move to v_3 without conducting charging, resulting in energy waste. We solve this conflict through appropriately designing payoff function and the rules of this game. Then the conflict will be avoided as shown in Figure 1(b).

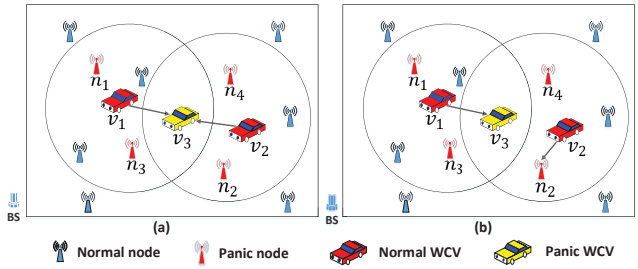


Fig. 1. An example of conflict.

Our analysis is taken from two aspects: 1) a conflict exists and 2) a conflict does not exist.

Theorem I: The condition that all WCVs follow the rules of GTCCS when a conflict exists constitutes two Nash Equilibrium points.

Proof: For ease of simplicity, we prove Theorem I based on the payoff matrix which is mentioned before. When a conflict exists, we can easily learn that the two gaming WCVs, v_1 and v_2 both tend to charge the same node n_i or WCV v_j. Furthermore, When WCV v_1 and v_2 tend to charge node n_i, $P^1_{n_i} > P^1_{n_k}$, $P^1_{n_i} > P^1_{v_k}$, $P^2_{n_i} > P^2_{n_k}$, and $P^2_{n_i} > P^2_{v_k}$ are satisfied for $\forall k \in [1, |\mathcal{N}|+M]$. Then, we can underline row i for the profit of v_1 and column i for the profit of v_2 to indicate that strategy s_i is superior to other strategies in the payoff matrix (see the Equation (13) in which we assume both WCVs tend to charge node n_1). However, in the column 1 for the profit of v_1, we underline the $P^1_{v_3}$ because the best strategy for v_1 is s_3 rather than s_1 when v_2 selects the strategy s_1. Similarly, given a fixed strategy for v_1, we underline the best strategy for v_2. By using this method, we can acquire two Nash Equilibrium points, $(P^1_{n_1}, P^2_{n_2})$ and $(P^1_{v_3}, P^2_{n_1})$. Similarly, two Nash Equilibrium points exist when the WCVs tend to charge WCV v_j. □

$$P_{(v_1,v_2)} = \begin{bmatrix} \mathbf{(0,0)} & \boxed{(\underline{P^1_{n_1}}, \underline{P^2_{n_2}})} & \cdots & (\underline{P^1_{n_1}},P^2_{v_3}) & (\underline{P^1_{n_1}},P^2_{v_4}) & \cdots \\ (P^1_{n_2},\underline{P^2_{n_1}}) & \mathbf{(0,0)} & \cdots & (P^1_{n_2},P^2_{v_3}) & (P^1_{n_1},P^2_{v_4}) & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \boxed{(\underline{P^1_{v_3}},\underline{P^2_{n_1}})} & (P^1_{v_3},P^2_{n_2}) & \cdots & \mathbf{(0,0)} & (P^1_{v_3},P^2_{v_4}) & \cdots \\ (P^1_{v_4},\underline{P^2_{n_1}}) & (P^1_{v_4},P^2_{n_2}) & \cdots & (P^1_{v_4},P^2_{v_3}) & \mathbf{(0,0)} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix} \tag{13}$$

Since our scheme is based on complete information game theory, the conflict can be avoided by gathering other WCVs' information such as location, payoff function. In the situation that multiple Nash Equilibrium points exist, we stipulate each WCV selects its charging target by following the principle of Pareto-optimal. For example, in the Figure 1(a), v_1 and v_2 both tend to charge v_3. According to Theorem I, we note that two Nash Equilibrium points exist in the payoff matrix. In this case, each WCV calculates the total payoff of two players involved in the game in the same situation. Then they will select the charging target according to the action tuple which gains the maximum total payoff.

Lemma 1: In the multiple WCVs game, each WCV has no incentive to deviate from the principle of Pareto-optimal when there exist multiple Nash Equilibrium points.

Proof: Assume that the result of the game is an action tuple $s = \{s_j, s_{-j}\}$, which is obtained by following the principle of Pareto-optimal. When multiple Nash Equilibrium points exist in the payoff matrix, the game is similar to the game of battle of sex [25] in which one player gains the maximum payoff value while the other player gains the suboptimal payoff in any Nash Equilibrium points. Hence, from WCV v_j's point of view, we analyze two cases that v_j may encounter obeying the action tuple s.

Case I: v_j gains the maximum payoff following the action tuple s. There is no doubt that v_j has no incentive to deviate from the principle of Pareto-optimal.

Case II: v_j gains the suboptimal payoff following the action tuple s. That means the opponent WCV gains the maximum payoff in the action tuple s. In our game, each WCV is rational to gain maximum payoff. By following this rule, it seems that WCV v_j tends to deviate from the principle of Pareto-optimal and select other strategy. However, this situation will never occur. As the reward of v_j is determined by both its action and the opponent player's action, we first consider the action of the opponent WCV v_k. Obviously, WCV v_k selects the strategy s_{-j} ($s_{-j} \in s$), because it gains the maximum payoff in the action tuple s. Besides, the action tuple s is also a Nash Equilibrium point. Then we have $P_{v_j}(s_j, s_{-j}) > P_{v_j}(s_j^{'}, s_{-j})$ for $\forall s_j^{'} \in S_j \setminus \{s_j\}$ and S_j includes all possible strategies of WCV v_j. Therefore, v_j will select the strategy s_j ($s_j \in s$).

In summary, each WCV has no incentive to deviate from the principle of Pareto-optimal when multiple Nash Equilibrium points exist in the payoff matrix. □

Next, we discuss the situation that a conflict does not exist in the charging process. The property of GTCCS in this case is formally given in the following theorem.

Theorem II: The condition that all WCVs obey the rules of GTCCS when a conflict does not exist constitutes one Nash Equilibrium point.

Proof: We assume that $P^1_{n_i}$ and $P^2_{n_j}$ ($i \neq j$) are superior to other strategies for WCV v_1 and v_2. Hence, $P^1_{n_i} > P^1_{n_k}$, $P^1_{n_i} > P^1_{v_k}$, $P^2_{n_j} > P^2_{n_k}$ and $P^2_{n_j} > P^2_{v_k}$ are satisfied for $\forall k \in [1, |\mathcal{N}|+M]$. Then we underline row i for the profit of V_1 to indicate that strategy s_i is superior to other strategies in the payoff matrix (see the Equation (14)). Similarly, column j for the profit of v_2 is underlined. Therefore, we can acquire one Nash Equilibrium point: $(P^1_{n_i}, P^2_{n_j})$ ($i \neq j$). □

$$P_{(v_1,v_2)} = \begin{bmatrix} \mathbf{(0,0)} & \boxed{(\underline{P^1_{n_1}}, \underline{P^2_{n_2}})} & \cdots & (\underline{P^1_{n_1}}, P^2_{v_3}) & (\underline{P^1_{n_1}}, P^2_{v_4}) & \cdots \\ (P^1_{n_2}, P^2_{n_1}) & \mathbf{(0,0)} & \cdots & (P^1_{n_2}, P^2_{v_3}) & (P^1_{n_2}, P^2_{v_4}) & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ (P^1_{v_3}, P^2_{n_1}) & (P^1_{v_3}, \underline{P^2_{n_2}}) & \cdots & \mathbf{(0,0)} & (P^1_{v_3}, P^2_{v_4}) & \cdots \\ (P^1_{v_4}, P^2_{n_1}) & (P^1_{v_4}, \underline{P^2_{n_2}}) & \cdots & (P^1_{v_4}, P^2_{v_3}) & \mathbf{(0,0)} & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix} \tag{14}$$

As mentioned before, our method is based on complete information game theory. It is necessary for the WCVs to communicate with each other to exchange information. Assume that the maximum communication distance of two WCVs is R. Then we can define the radius of service region belonging to a WCV as r. Usually, the largest r can be set as $r = E_j^{(v)}(t)/2c$. However, it will bring extra communication cost and failure communication. In order to guarantee successful communication between two WCVs, we set r as $r = R/2$. For two WCVs v_i and v_j, we have $d_{v_i,v_j} \leq 2r$ if $S_i \bigcap S_j \neq \emptyset$. In this case, a conflict may occur between v_i and v_j. According to Theorem I and the principle of Pareto-optimal, each WCV has to communicate with each other to exchange information. Hence, we have $2r \leq R$. We take its upper bound and $r = R/2$.

In this paper, game theory is utilized to guide WCVs' behaviors. To maximize the payoff, each WCV is rational enough to choose the best strategy. Since the charging schedule problem is converted into repetitive games among WCVs, we illustrate the game process for one round only. Algorithm 1 is proposed to help WCV to select the best charging target. According to Algorithm 1, GTCCS proceeds as follows. First of all, the WCV checks if there are new charging requests and then adds them to the charging queue Q (Line 4-8). For each request in Q, the WCV will calculate its corresponding payoff value. When the charging target is a sensor node and its residual lifetime is larger than the time for WCV to move towards it, WCV will calculate the payoff according to Equation (9). The payoff can be computed according to Equation (11) when the charging target is another WCV. When the residual lifetime of a sensor node is not sufficient for the WCV to reach it, the payoff will be set as 0. Then the WCV will communicate with other WCVs which are within the communication range to get their information. Next, we construct the payoff matrix and find the Nash Equilibrium points from the payoff matrix (Line 22-23). Finally, the WCV will select the best strategy which gains the maximum payoff by following the principle of Pareto-optimal. Moreover, the WCV will move towards the best target to charge it and make charging decision after completing the charging mission.

D. Dynamic Warning Threshold for WCVs

Due to the limited energy capacity, a WCV with low residual energy will force itself to return back to the BS for energy provisioning. Previous articles [13] required the energy threshold of all WCVs to be identical. However, a dynamic threshold would outperform than a fixed threshold in enhancing the energy efficiency.

For example, configured with the fixed threshold, WCVs locating nearby the BS will hold extra energy when arriving at the BS. Indeed, such threshold ensures the survivance of WCVs, however, extra residual energy is not fully utilized. Moreover, occasionally, a WCV with an energy ratio slightly lower than the fixed threshold may still help in replenishing nodes nearby the BS rather than leaving it exhausted. Once the dynamic threshold is employed, such an case will never happen, the original panic WCV will immediately save the dying node and move back, rendering a higher energy usage.

Thus, when dynamic threshold is applied, the energy of a WCV should be greater than the value, which is defined as the total energy cost in charging and the traveling cost from current place to the target and finally moving to BS. We have Equation (15) and Equation (16):

$$E_j^v(t) > \Delta E + c(d_{v_j,i} + d_{i,BS}), \tag{15}$$

Algorithm 1 GTCCS Algorithm

Input: Normal WCV v_j.
Output: The best strategy set for WCV s_j^*.
$Q \leftarrow \emptyset$;
for Node n_i or WCV v_k within the service region **do**
  if $E_i(t) < \beta E$ or WCV v_k send a charging request **then**
    $Q \leftarrow Q \cup \{n_i\}$;
    $Q \leftarrow Q \cup \{v_k\}$;
  end if
end for
for all $s_k \in Q$ **do**
  if $d_{(v_j,k)}/v < E_i(t)/r_i$ && $k \in [1, |\mathcal{N}|]$ **then**
    Calculate the payoff value $P_{v_j}(s_k, s_{-k})$ according to Equation (9);
  else if $k \in [|\mathcal{N}|+1, |\mathcal{N}|+M]$ **then**
    Calculate the payoff value $P_{v_j}(s_k, s_{-k})$ according to Equation (11);
  else
    $P_{v_j}(s_k, s_{-k}) \leftarrow 0$;
  end if
end for
for Each WCV within communication region **do**
  Exchange information with each other;
end for
Construct the payoff matrix;
Find Nash Equilibrium points and put them in the S_{NE};
if $|S_{NE}| == 1$ **then**
  WCV selects the best strategy s_j^*;
  return s_j^*.
end if
for all $s \in S_{NE}$ **do**
  Calculate the total payoff;
  Find the maximum total payoff;
end for
WCV selects the best strategy s_j^*;
return s_j^*.

$$\Delta E = (E - E_i(t) + t_i \cdot r_i)/\rho_1. \tag{16}$$

Here, $E_j^v(t)$ indicates the remaining energy of the WCV v_j at time t, $c(d_{v_j,i} + d_{i,BS})$ refers the total energy consumption for the WCV to move to the charging target n_i and return back to BS. ΔE is the energy consumption for a WCV in charging the object, which can be calculated as Equation (16).

In Section VI-G, the impact of dynamic threshold is evaluated through experiments.

E. Sacrifice-charge

Usually, when the remaining energy of a WCV is not sufficient to fulfill one charging task, it will immediately send a charging request. Furthermore, it will come back to the BS holding extra energy, leading to a waste of energy when the waiting time is larger than a certain threshold δ. Obviously, the energy efficiency will be further improved by appropriately making full use of such energy. In our scenario, we introduce the concept of sacrifice-charge. A WCV performing a sacrifice-charge will contribute most of remaining energy to sensor nodes; only reserving the energy for returning back to the BS. Usually, it donates to a nearby sensor node with the most remaining energy. The sacrifice-charge ensures that a WCV returning to BS will not have much energy left, maximizing the energy injected into the network and further improving energy usage efficiency. We formalize such process as:

$$\begin{aligned} &\underset{n_i \in N}{\text{maximize}} \quad E_j^v(t) - c(d_{v_j,n_i} + d_{n_i,BS}) \\ &\text{subject to} \quad E_j^v(t) < (E - E_i(t) + r_i t_i)/\rho_1 + c(d_{v_j,n_i} + d_{n_i,BS}). \end{aligned} \tag{17}$$

Once a WCV determines to return to BS, it will find the optimal charging target to preform a sacrifice-charge. We illustrate this process in Algorithm 2. First, the WCV calculates the energy consumption for moving to the sensor node n_i and returning to BS (Line 4-5). Then it will compute the available energy after moving to n_i and returning to BS. Next, the total amount of energy that n_i can obtain is calculated (Line 7). Finally, we find the optimal charging target by minimizing the energy consumption for moving. If the optimal charging target has sent charging request, the WCV will notify other normal WCVs to recall the charging request of the target. Otherwise, WCV will directly move to the target and charge it.

Algorithm 2 Find the optimal charging target in sacrifice-charge

1: **Input:** The current energy of WCV v_j, $E_j^v(t)$ and location (x_j, y_j).
2: **Output:** The optimal charging target for v_j.
3: **for all** n_i **do**
4: Calculate the distance d_{v_j,n_i} and $d_{n_i,BS}$;
5: $E_c \leftarrow c(d_{v_j,n_i} + d_{n_i,BS})$;
6: $E_u \leftarrow E_j^v(t) - E_c$;
7: $E_n \leftarrow (E - E_i(t) + r_i t_i)/\rho_1$;
8: **if** $E_u > E_n$ **then**
9: Continue;
10: **end if**
11: Find the minimum E_c and remark the n_i;
12: **end for**
13: **return** The optimal charging target n_i.

The impact of the sacrifice-charge will be clarified in Section VI-F.

F. Analysis

In this section, we analyze the property of GTCCS algorithm and elaborate how it gains the maximum energy usage efficiency (η) by utilizing this property. Before discussing the property of GTCCS algorithm, we first give the definition of Pareto-optimal, which is useful in later analysis.

Definition: An outcome of a game is Pareto-optimal if there are no other outcomes, which would give all players higher profits or would give partial players higher profits but the other players the same profits. Formally, an action tuple (s_j^*, s_{-j}^*) is said to be Pareto-optimal, if and only if $\sum_{v_j \in \mathcal{V}} P_{v_j}(s_j^*, s_{-j}^*) > \sum_{v_j \in \mathcal{V}} P_{v_j}(s_j, s_{-j})$ for $\forall (s_j, s_{-j}) \in S$ and $S = S_1 \times S_2 \times ... \times S_M$.

Theorem III: The outcome of GTCCS algorithm is Pareto-optimal.

Proof: We prove it by analyzing two cases, which may occur in the gaming process.

Case I: A conflict exists. According to Theorem I, there exist multiple Nash Equilibrium points in the payoff matrix. We define the result of this game as an action tuple $s^* = \{s_1, s_2, .., s_M\}$. Suppose that the result of the game is not Pareto-optimal, and the Pareto-optimal action tuple is $s^{'}$ and $s^{'} \in S$. This means $\sum_{v_j \in \mathcal{V}} P_{v_j}(s^{'}) > \sum_{v_j \in \mathcal{V}} P_{v_j}(s^*)$. According to Lemma 1, all WCVs will gain the action tuple s^* by following the principle of Pareto optimality. Then we have $\sum_{v_j \in \mathcal{V}} P_{v_j}(s^*) > \sum_{v_j \in \mathcal{V}} P_{v_j}(s)$ for $\forall s \in S$. This is contradictory to the assumption. Therefore, the outcome of game in the Case I is Pareto-optimal.

Case II: A conflict does not exist. According to Theorem II, there exists only one Nash Equilibrium point in the payoff matrix and each WCV selects its best strategy, which gains the maximum payoff. Therefore, we have $\sum_{v_j \in \mathcal{V}} P_{v_j}(s^*) > \sum_{v_j \in \mathcal{V}} P_{v_j}(s)$ for $\forall s \in S$. Hence, the outcome of game in the Case II is Pareto-optimal.

In summary, the outcome of GTCCS algorithm is Pareto-optimal. □

In order to present that our scheme gains the maximum η, we first further calculate the total energy of WCVs as:

$$E_t = ME_{(v)} = \sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} \frac{E - E_i(t) + t_i r_i}{\rho_1} + c d_{n_i, v_j}. \tag{18}$$

Hence, η can be further formalized as follows:

$$\eta = \frac{\sum_{i \in [1,|\mathcal{N}|]} E - E_i(t) + t_i r_i}{\sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} (E - E_i(t) + t_i r_i)/\rho_1 + c d_{n_i, v_j}}. \tag{19}$$

As mentioned before, our objective is to maximize η which is equivalent to minimize $\frac{1}{\eta}$:

$$\begin{aligned} \frac{1}{\eta} &= \frac{\sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} (E - E_i(t) + t_i r_i)/\rho_1 + c d_{n_i, v_j}}{\sum_{i \in [1,|\mathcal{N}|]} E - E_i(t) + t_i r_i} \\ &= \frac{1}{\rho_1} + \frac{\sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} c d_{n_i, v_j}}{\sum_{i \in [1,|\mathcal{N}|]} E - E_i(t) + t_i r_i}. \end{aligned} \tag{20}$$

In this work, charging scheduling problem is converted to repetitive games among WCVs. According to Theorem III, we can conclude that $\sum_{v_j \in \mathcal{V}} P_{v_j,t}$ is maximized at each gaming process. Here, $P_{v_j,t}$ indicates the payoff of WCV v_j at tth gaming process. Hence, after multiple rounds of game, $\sum_{t=1}^{\infty} \sum_{v_j \in \mathcal{V}} P_{v_j,t}$ is maximized. Then the value of $\sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} E - E_i(t) + t_i r_i - c d_{n_i, v_j}$ is also maximized. Since the energy capacity of WCV is fixed, then $\sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} E - E_i(t) + t_i r_i + c d_{n_i, v_j}$ is a constant. Therefore, we note that $\frac{\sum_{i \in [1,|\mathcal{N}|], v_j \in \mathcal{V}} c d_{n_i, v_j}}{\sum_{i \in [1,|\mathcal{N}|]} E - E_i(t) + t_i r_i}$ is minimized and accordingly $\frac{1}{\eta}$ is minimized. Hence, energy usage efficiency is maximized by using GTCCS.

V. Simulations

In this section, the performance of the GTCCS is evaluated through extensive simulations with different network settings.

A. Simulation Setup

First of all, parameters used in the simulations are listed in Table II.

TABLE II
Simulation parameters

Parameters	Values
The network region	$10Km \times 10Km$
The number of sensor nodes	200
Energy capacity of sensor nodes	$10.8KJ$
The number of WCVs	18
Moving speed of WCVs	$1m/s$
Energy capacity of WCVs	$2000KJ$
Moving cost of WCVs per unit distance	$50J/m$
Energy transfer efficiency between WCVs	30%
Energy transfer efficiency between WCV and sensor	1.5%
Warning threshold of sensor nodes	30%
Transmission energy ratio for charging another WCV	1/2
Threshold of waiting time for WCV	$500s$
The service region radius of a WCV	$1000m$

Unless stated otherwise, the following parameters are used in the simulated network. 200 stationary sensor nodes are deployed in a two-dimensional square area. The BS is located at $(0, 0)$. Following similar settings in [11], [12], the battery capacities of sensors and WCVs are $10.8KJ$ and $2000KJ$, respectively. The WCV moves at a speed of $1m/s$ with the traveling cost rate $50J/m$. The energy transfer efficiency between two WCVs is 30% and 1.5% between a WCV and a node.

We introduce two state-of-the-art competing algorithms for comparison, in which the energy can be transferred from a WCV to a sensor and between two WCVs.

PushWait [11]: It first divides the sensors into several groups according to their energy consumption rate. For each group, the shortest Hamiltonian cycle is calculated. Then, the cycle is treated as a line and the charging trajectory is computed.

Hierarchical [12]: It employs special WCVs and mobile WCVs. Firstly, the network is divided into areas of equal size and each mobile WCV is responsible for an area. Special WCVs determine which mobile WCV will be the next charging target based on minimum energy and minimum distance.

We compare our algorithms with the two algorithms and all results are the average of 100 runs of simulations.

B. Determining Warning Threshold β

First, we demonstrate how a warning threshold of 30% is chosen, by investigating the impact of warning threshold β on η. As shown in Figure 2, we note that the energy usage efficiency peaks around a warning threshold of 30%. The main reason is the lower frequency for sending charging requests and the higher energy that sensors can obtain. If β is too small (closer to 0), there is little time for the WCV to respond to dying sensors. On the other hand, a larger β (closer to 1) runs the risk of requesting frequent, but unnecessary charging and costing too much for WCV's travel.

Based on the results shown in Figure 2, we chose $\beta = 30\%$.

C. Energy Usage Efficiency η

Our scheme aims at improving the energy usage efficiency, defined as the ratio between the energy obtained by sensor

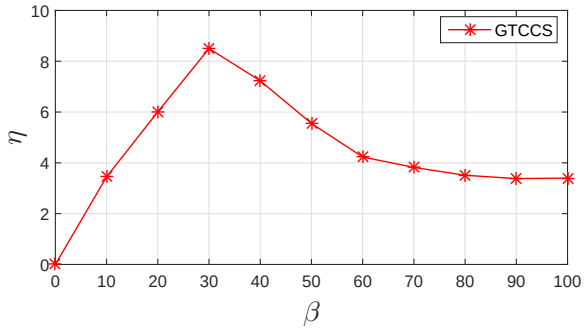


Fig. 2. The impact of warning threshold.

nodes and the overall energy transferred from the BS to WCVs. As shown in Figure 3(a), η of these three algorithms mostly increases with node numbers. GTCCS is always higher than the other two schemes and achieves 0.01 when the number of sensor nodes is 200. On an average, the energy usage efficiency of GTCCS is 20% and 15% higher than PushWait and Hierarchical. First, the GTCCS can avoid the charging conflicts, which leads to lower η. Then, the outcome of GTCCS algorithm is Pareto-optimal, which means the overall profit is maximized. In other words, the result of GTCCS algorithm gains the highest payload energy (i.e. E_p) and lowest traveling cost.

D. Impact of Energy Capacity of WCV

Then we study the impact of WCV's energy capacity. As depicted in Figure 3(b), a larger WCV battery capacity leads to an increase in the energy usage efficiency. Such an increase is due to the extra time for WCVs to charge sensors before they are forced to return to BS. Overall, GTCCS has the highest efficiency.

E. Impact of Nodes' Energy Capacity

The impact of the sensor nodes' energy capacity is demonstrated in Figure 3(c). A larger energy capacity leads to a longer recharging cycle, resulting in a longer survival time. In addition, a WCV will deliver more energy to a sensor node in one charge while the traveling cost is a constant. Thus, η of three algorithms increases with the sensor nodes' energy capacity. In GTCCS algorithm, the WCVs always select the best strategy that improves energy usage efficiency. As shown in Figure 3(c), η of GTCCS is the highest among the three schemes that we simulated.

VI. Test-bed Experiments

In this section, we conduct the test-bed experiment to verify the GTCCS algorithm and results are represented.

A. Experiment Setup

We conduct experiments on a track and soccer field and at our lab. Detailed experimental deployments are shown in Figure 4 and Figure 5.

In Figure 4, 50 nodes and 3 WCVs are deployed in a $100m \times 80m$ track and soccer field. The nodes are powered by a $3.7V$ $900mAh$ rechargeable battery (with a capacity of

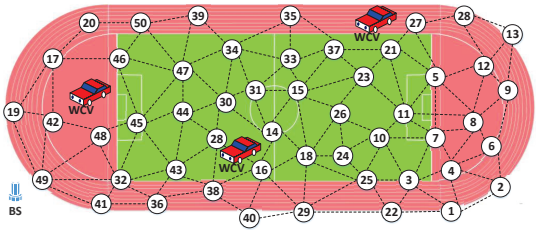


Fig. 4. Experiment layout on a track and soccer field.

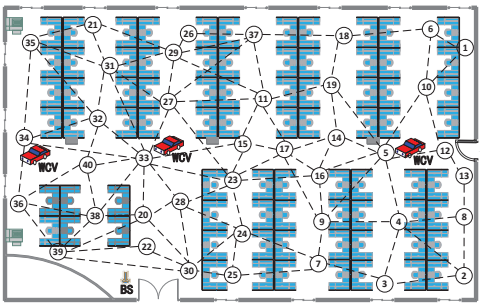


Fig. 5. Experiment layout in an office space around our lab.

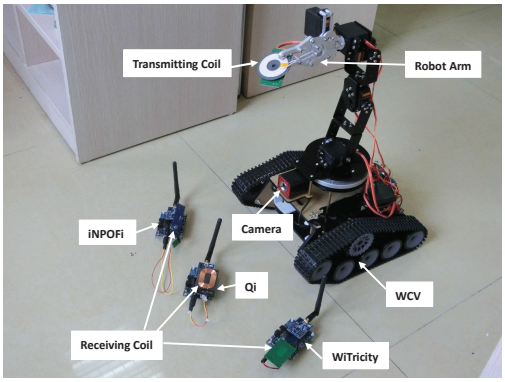


Fig. 6. WCV and sensors with different receiving charging coils.

$3.7V \times 0.9A \times 3600sec \approx 12KJ$) and its warning threshold is 30%. The traveling speed of WCV is $0.84m/s$ and traveling cost is $18.64J/m$. WCV's energy capacity is $413.35KJ$ and the service region radius of a WCV is $30m$. In Figure 5, we employ 40 nodes in an $35m \times 15m$ office space. In this experiment, the distance between two nodes is defined as the shortest distance over the obstacle.

In general, WPT techniques mainly fall into two categories: non-radiative [26] (near-field) and radiative [16] (far-field). Radiative wireless charging method transfers the energy based on electromagnetic radiation and works at low power. However, it may cause health impairments and safety problem [27]. Since one of the experiments is conducted in the office lab where the safety should be considered, we adopt non-radiative wireless charging method which is based on the coupling of the magnetic-field between two coils. Figure 6 shows the device used in these experiments. Each sensor is implemented with a $70mm \times 50mm$ main board. We explore the performance of three charging methods: WiTricity [26], Qi [28] and iNPOFi [29]. Due to the limited size of the sensor, small receiving coils are used. In our experiments, three different coil sizes: $31mm \times 7.5mm$ for WiTricity, $34mm \times 45.5mm$ for Qi and $17.5mm \times 74mm$ for iNPOFi, are employed (see Figure 6).

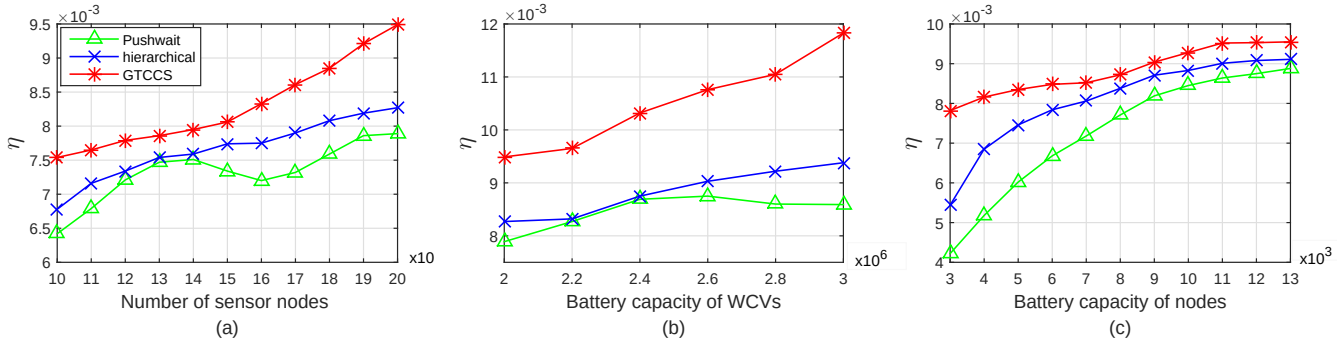


Fig. 3. Performance comparison among GTCCS, PushWait and Hierarchical in terms of η, (a) the impact of nodes' number, (b) different battery capacity of WCV, (c) different battery capacity of nodes.

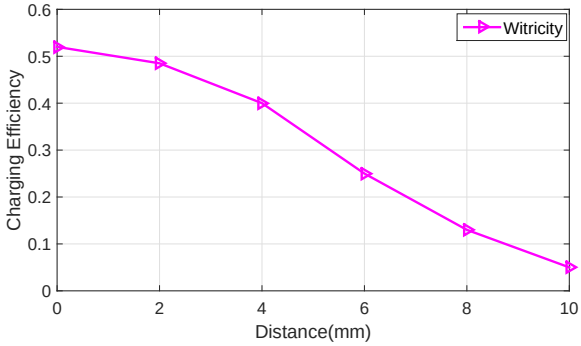


Fig. 7. The impact of coil distance on charging efficiency for WiTricity charging.

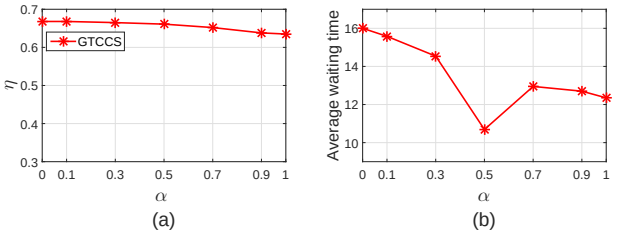


Fig. 8. Impact of α in terms of η and average waiting time for sensor nodes with Qi.

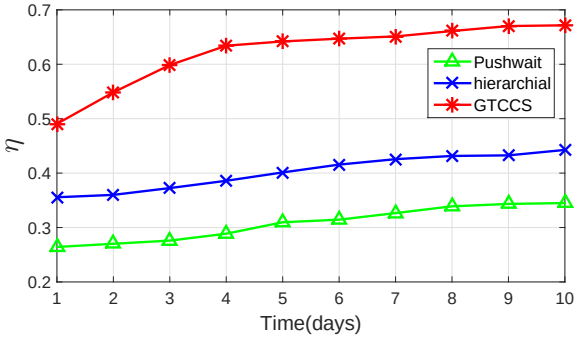


Fig. 9. Performance comparison among GTCCS, PushWait and Hierarchical in terms of η.

B. Impact of the Distance between Coils

First, we explore the influence of distances between charging and receiving coil on charging efficiency. Since the charging distance of Qi is required to be less than 8*mm* and iNPOFi is a touch-based charging scheme, here we only analyze the WiTricity charging method. From Figure 7, we see that the charging efficiency decreases with the increment of distance. The charging efficiency is the highest when the distance between charging coils touches each other (efficiency of 52% for 0*mm*). With a distance of 10*mm*, the efficiency drops to 5%. Our experiments thus confirm the reason to use the seemingly extremely-low charging efficiency of 1.5% for our simulations: it takes extra energy and time to move these two coils closer than 10*mm*. In order to ensure a high efficiency, we used a programmable mobile robot arm carrying GPS and camera (see Figure 6) to get these coils touching with each other. Besides, experiments are conducted to measure the charging efficiency for Qi and iNOPOFi with the different coil distance. We find that the largest charging efficiency of Qi and iNOPOFi is 70% and 89%, respectively when the coil distance is 0*mm*.

C. Impact of α

As mentioned in Equation (10), parameter α determines how much energy will be delivered to a "panic" WCV, when charging is taken between WCVs. Here, we mainly investigate the impact of α on network performance in terms of η and average waiting time. As shown in Figure 8(a), the value of η decreases slowly as α increases due to the inevitable energy loss in the charging process. The waiting time for sensor nodes reach the lowest value when $\alpha = 0.5$ in Figure 8(b), indicating that when α is small, the probability of charging a WCV will be low as it requires a large amount of energy held by the WCV. Besides that, a larger value of α will result in less remaining energy for a WCV after charging another WCV. In that situation, a WCV will serve fewer sensor nodes. Based on these findings, we finally choose the optimal value of $\alpha = 0.5$.

D. Energy Usage Efficiency

In this section, we conduct the experiment to evaluate the performance of GTCCS algorithm. As shown in Figure 9, η of three algorithms increase with the working time increasing. Besides, compared with Pushwait and Hierarchical algorithm, GTCCS algorithm achieves the highest energy usage efficiency. The reason is that each WCV in the GTCCS algorithm selects the best charging target and the result of game is Pareto-optimal.

We validate our simulation results with experimental results in Figure 10. Both set of results on energy usage efficiency slightly improve as the system settles down, stabilizing around

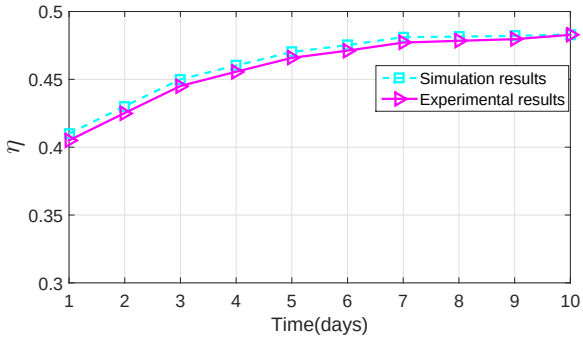


Fig. 10. Comparison of simulation and experiment in terms of η with WiTricity.

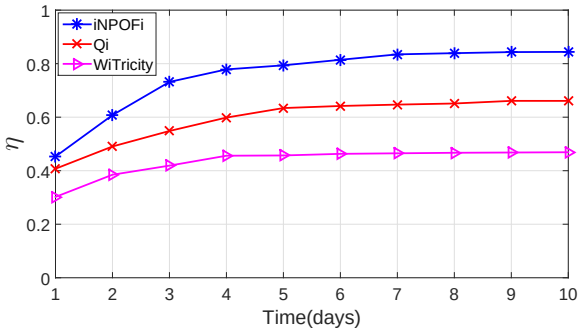


Fig. 11. Energy usage efficiency of the three charging methods experimented on the track and soccer field.

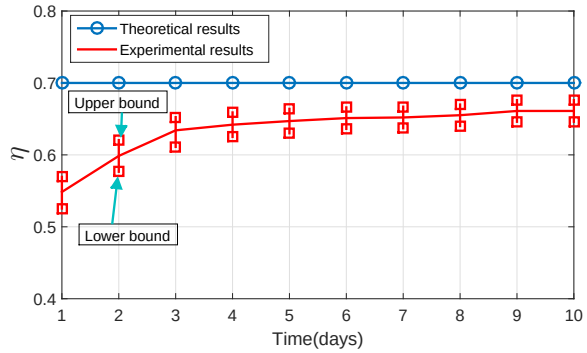


Fig. 12. Comparison of theoretical and experimental results in terms of η with Qi on the track and soccer field.

48%. The gap might have been caused by inaccuracy in experimental measurements.

Figure 11 shows η for the three different charging methods experimented on the track and soccer field. The highest η values belong to the iNPOFi charging method, corresponding well with the higher charging efficiency.

To validate the realization of our objective formalized in Equation (3), we depict Figure 12 to compare the differences between theoretical and experimental results of η. Specifically, we choose Qi as the charging standard and adopt variable energy consumption rates to conduct this experiment on the soccer field. From the Figure 12, we note that our experimental results (including the upper bound and the lower bound) approximate to the theoretical results, verifying the correctness of validity of our objective for maximizing the energy efficiency.

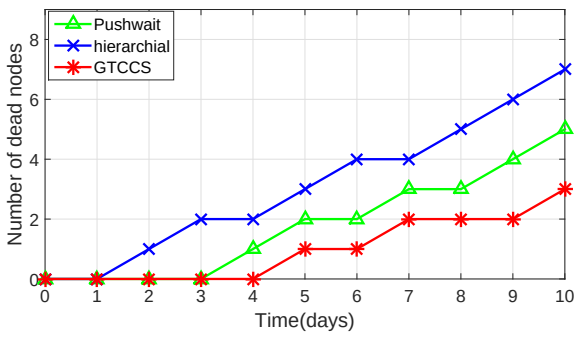


Fig. 13. Performance comparison among GTCCS, PushWait and Hierarchical algorithm in terms of number of dead nodes with lab.

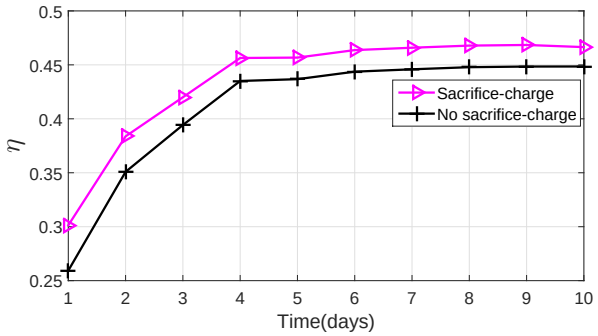


Fig. 14. Impact of sacrifice-charge scheme in terms of η with WiTricity in lab.

E. Dead Node Number

Figure 13 demonstrates the number of dead nodes of three algorithms. We note that the number of dead nodes increases as the simulation goes. Besides, the number of dead nodes of GTCCS algorithm is the lowest, while the number of dead nodes is the highest if we employ hierarchical algorithm. In GTCCS algorithm, we do not impose any restrictions on the behaviors of WCVs. Hence, the panic node can get energy from any WCVs with enough energy and will not run out of its energy.

F. Impact of Sacrifice-charge

As sacrifice-charge makes full usage of the remaining energy for WCVs before they arrive at BS, Figure 14 is depicted to demonstrate such impacts. On an average, employing sacrifice-charge will bring additional 4.5% energy usage efficiency, an improvement of about 10%.

G. Impact of Dynamic Warning Threshold

Figure 15 shows the number of dead nodes for GTCCS with dynamic warning threshold and fixed dynamic warning threshold. We note that GTCCS with dynamic warning threshold gains less dead nodes. In the fixed warning threshold scheme, all WCVs' warning threshold are identical and large since they should satisfy the worst case. However, the WCV's warning threshold only depends on whether its current energy level can fulfill a charging mission in the dynamic warning threshold scheme. Therefore, the WCV can charge sensors even if its energy does not satisfy the worst case.

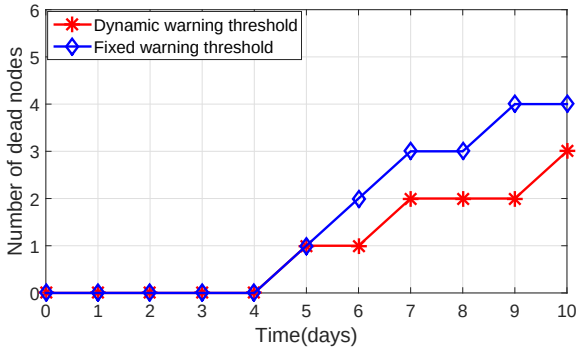


Fig. 15. Comparison of the dynamic warning threshold and fixed warning threshold scheme in terms of number of dead nodes with lab.

VII. Conclusions

In this paper, game theory has been applied to address the collaborative charging issues in WRSNs with multiple WCVs. The proposed scheme, termed GTCCS, allows multiple WCVs to collaboratively decide charging sequences based on node location, charging deadline, as well as subdomains. The dynamic characteristics of the GTCCS scheme also enable the exploitation of two unique features to further improve system performance, including dynamic warning threshold for WCVs and sacrifice-charge. Both of them have been thoroughly investigated and discussed. The GTCCS scheme has been demonstrated to outperform other previous competing schemes in terms of energy usage efficiency and number of dead nodes.

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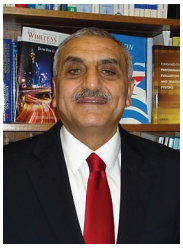
Chi Lin (M'15) received B.E. and Ph.D. from Dalian University of Technology, China, in 2008 and 2013, respectively. He has been an Assistant Professor in School of Software, Dalian University of Technology (DUT), China since 2014. He is currently an Associate Professor with the School of Software, Dalian University of Technology since 2017. Dr. Lin has authored over 50 scientific papers including INFOCOM, SECON, ICDCS, IEEE Trans. on Mobile Computing, ACM Trans on. Embedded Computing Systems. In 2015, he was awarded ACM Academic Rising Star. His research interests include pervasive computing, cyber-physical systems (CPS), and wireless sensor networks.



Shuang Wei received the B.E. degree in software engineering from Dalian University of Technology (DUT), China, in 2016. She is now working towards the M.E. degree of software engineering in Dalian University of Technology, Dalian, China. Her research interests include wireless rechargeable sensor network and game theory.



Jing Deng (S'98−M'02−SM'13−F'17) received the B.E. and M.E. degrees in electronics engineering from Tsinghua University, Beijing, China, in 1994 and 1997, respectively, and the Ph.D. degree from the School of Electrical and Computer Engineering, Cornell University, Ithaca, NY, USA, in 2002. He served as a Research Assistant Professor with the Department of Electrical Engineering and Computer Science, Syracuse University, from 2002 to 2004. He visited the Department of Electrical Engineering, Princeton University, and the Department of Electrical and Computer Engineering, WINLAB, Rutgers University, in Fall 2005. He was with the Department of Computer Science, University of New Orleans, from 2004 to 2008. He is an Associate Professor with the Department of Computer Science, The University of North Carolina at Greensboro, Greensboro, NC, USA. Dr. Deng is an Editor of the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. He was a co-recipient of the 2013 Test of Time Award by the ACM Special Interest Group on Security, Audit, and Control. His research interests include wireless network and security, information assurance, mobile ad hoc networks, and social networks.



Mohammad S. Obaidat (S'85-M'86-SM'91-F'05) is an internationally well-known academic/ researcher/ scientist. He received his Ph.D. and M. S. degrees in Computer Engineering with a minor in Computer Science from The Ohio State University, Columbus, Ohio, USA. Among his previous positions are Advisor to the President of Philadelphia University for Research, Development and Information Technology, President of the Society for Molding and Simulation International, SCS, Senior Vice President of SCS, Dean of the College of Engineering at Prince Sultan University, Chair and Professor at the Department of Computer and Information Science and Director of the MS Graduate Program in Data Analytics at Fordham university, Chair and Professor of the Department of Computer Science and Director of the Graduate Program at Monmouth University. He is now a Full Professor at the ECE Department, Nazarbayev University and KASIT of University of Jordan. He has received extensive research funding and has published to date over (60) books, over (60) Book Chapters and over Seven Hundred and Eighty (758) refereed technical articles in scholarly international journals and proceedings of international conferences- about half of them Journal Papers. Professor Obaidat has served as a consultant for several corporations and organizations worldwide. Dr. Obaidat is the Founding Editor-in-Chief of the Wiley Security and Privacy Journal. He is also the Editor-in-Chief of the Wiley International Journal of Communication Systems, the FTRA Journal of Convergence. He served as the Editor-in-Chief of the KSIP Journal of Information Processing.

He served also as editor or advisory editor of many other journals such as IEEE Wireless Communications, IEEE Systems Journal, Elsevier Commuter Communications, IET Wireless Sensor Systems, among others. He served as an IEEE Distinguished Speaker and and ACM Distinguished Lecturer. He has been serving as an SCS Distinguished Lecturer since 2004. He is the founder or co-founder of 4 international conferences. He has received numerous worldwide awards for his technical and service contributions, such as Nokia Research Fellowship, distinguished Fulbright Scholar Award, SCS Outstanding Service Award. the prestigious McLeod Founder's Award, IEEE ComSoc- GLOBECOM 2010 Outstanding Leadership Award for his outstanding leadership of Communication Software Services and Multimedia Applications Symposium, CSSMA 2010, SCS Presidential Service Award, SCS Modeling and Simulation Hall of Fame CLifetime Achievement Award, IEEE CITS Hall of Fame Distinguished and Eminent Award. He has been awarded with the Amity University Distinguished Honorary Professor Award and the University of Science and Technology Beijing Distinguished Visiting Professor Award. Prof. Obaidat is a Fellow of IEEE and SCS.



Houbing Song (M12CSM14) received the Ph.D. degree in electrical engineering from the University of Virginia, Charlottesville, VA, in August 2012.

In August 2017, he joined the Department of Electrical, Computer, Software, and Systems Engineering, Embry-Riddle Aeronautical University, Daytona Beach, FL, where he is currently an Assistant Professor and the Director of the Security and Optimization for Networked Globe Laboratory (SONG Lab, www.SONGLab.us). He served on the faculty of West Virginia University from August 2012 to August 2017. In 2007 he was an Engineering Research Associate with the Texas A&M Transportation Institute. He serves as an Associate Technical Editor for IEEE Communications Magazine. He is the editor of four books, including Smart Cities: Foundations, Principles and Applications, Hoboken, NJ: Wiley, 2017, Security and Privacy in Cyber-Physical Systems: Foundations, Principles and Applications, Chichester, UK: Wiley-IEEE Press, 2017, Cyber-Physical Systems: Foundations, Principles and Applications, Boston, MA: Academic Press, 2016, and Industrial Internet of Things: Cybermanufacturing Systems, Cham, Switzerland: Springer, 2016. He is the author of more than 100 articles. His research interests include cyber-physical systems, cybersecurity and privacy, internet of things, edge computing, big data analytics, unmanned aircraft systems, connected vehicle, smart and connected health, and wireless communications and networking.

Dr. Song is a senior member of ACM. Dr. Song was a recipient of the prestigious Air Force Research Laboratory's Information Directorate (AFRL/RI) Summer Faculty Research Fellowship in 2018, and the very first recipient of the Golden Bear Scholar Award, the highest campus-wide recognition for research excellence at West Virginia University Institute of Technology (WVU Tech), in 2016.



Lei Wang Dr. Lei Wang is currently a full professor of the School of Software, Dalian University of Technology, China. He received his B.S., M.S. and Ph.D. from Tianjin University, China, in 1995, 1998, and 2001, respectively. He was a Member of Technical Staff with Bell Labs Research China (2001-2004), a senior researcher with Samsung, South Korea (2004-2006), a research scientist with Seoul National University (2006-2007), and a research associate with Washington State University, Vancouver, WA, USA (2007-2008). His research interests involve wireless ad hoc network, sensor network, social network and network security. He has published 70+ papers and the papers have 1000+ citations. He is a member of the IEEE, ACM and a senior member of the China Computer Federation (CCF).



Guowei Wu received B.E. and Ph.D. degrees from Harbin Engineering University, China, in 1996 and 2003, respectively. He was a Research Fellow at INSA of Lyon, France, from September 2008 to March 2010. He has been a Professor in School of Software, Dalian University of Technology (DUT), China, since 2011. His research interests include embedded real-time system, cyber-physical systems (CPS), and wireless sensor networks.