GTCharge: A Game Theoretical Collaborative Charging Scheme for Wireless Rechargeable Sensor Networks

Chi Lin[a,b], Youkun Wu[a,b], Zhicheng Liu[a,b], Mohammad S. Obaidat,Fellow of IEEE and Fellow of SCS[c], Chang Wu Yu[d], Guowei Wu[a,b]

[a] *School of Software Technology, Dalian University of Technology, Road No. 8, Development Zone, Dalian 116620, China*
[b] *Key Laboratory for Ubiquitous Network and Service Software of Liaoning Province, Dalian, 116621, China*
[c] *Chair and Professor, Computer and Information Science, Fordham University,NY,USA E-mail: msobaidat@gmail.com*
[d] *Department of Computer Science and Information Engineering, Chung Hua University, Taiwan*

Abstract

Collaborative charging schemes are indeed helpful for energy replenishment. However, classic and traditional collaborative charging schemes are still suffering from a series of severe problems, which are almost neglected. The lacking of homogeneity and dynamical charging decisions on collaborative charging schemes in Wireless Rechargeable Sensor Networks (WRSN) deteriorate the charging efficiency. To enhance charging performance, especially in terms of charging efficiency, in this paper, a game theoretical collaborative charging scheme, namely GTCharge is devised. The charging process is converted into a collaborative game taken between wireless charging vehicles (WCVs). We investigate the functionalities of contribution degree, charging priority and profits. Then GTCharge is demonstrated in detail, in which each WCV seeks for the maximum profit when fulfilling charging tasks. The conditions including all WCVs charging strategies are proven to reach a Nash Equilibrium point. Finally, extensive simulations are conducted to show the advantages of the proposed scheme. Simulation results demonstrate the merits of the proposed scheme in terms of charging efficiency.

Keywords: Wireless rechargeable sensor networks;game theory;collaborative

Email addresses: `c.lin@dlut.edu.cn Tel.: +86-411-62274417; Fax: +86-411-62274417` (Chi Lin), `E-mail: msobaidat@gmail.com` (Mohammad S. Obaidat,Fellow of IEEE and Fellow of SCS)

charging

---

1. Introduction

As the interdisciplinary of wireless communication and sensing technologies, wireless sensor networks, which are composed of thousands of tiny sensing devices, are playing an essential part in data sensing, collecting and monitoring. In practical applications, batteries are commonly used and implemented as the sole source for energy supplement. As sensors are usually working in rigid or hostile environment, it is difficult or impossible to change batteries for maintaining a sensor working everlastingly. Therefore, the network lifetime of a WSN is limited. Although energy efficiency techniques, such as data fusion, data aggregation or even energy effectively MAC protocols have been developed. The bottleneck of the constraint energy capacity problem is hindering the large deployment of the wireless sensor networks, which should be paid much attention.

Recent breakthrough in wireless power transfer (WPT) technique [13] provides a new alternative for solving the limited power capacity problem, making it promising to charge energy for prolonging network lifetime. Different from energy harvesting, WPT together with more and more mature and inexpensive mobile robots, such as mobile wireless charging vehicles (WCVs), creates a controllable and perpetual energy source, with which power can be replenished proactively to meet application requirements rather than being passively adapted to the environmental resources. Nowadays, the WPT technique has been used for charging mobile devices, electric vehicles, implantable devices and WSNs [24]. Based on these applications, Xie et al. [28] has proposed the definition of the Wireless Rechargeable Sensor Networks (WSRNs) [30].

In recent year, great efforts have been devoted for enhancing the performance of charging efficiency in WRSNs. In literature, approaches fall into three categories: periodical charging, on-demand charging and collaborative charging schemes. Periodical charging schemes [28, 26, 24] converted the energy charging problem into a TSP problem and the shortest Hamiltonian cycle is regarded as the best solution. However, all information such as nodes' locations, energy status is assumed to be known by WCVs.

On the other hand, the on-demand charging is a non-deterministic charging scheme, in which a WCV is not required to maintain any information about sensor nodes. When the residual energy fall below a certain threshold, a sensor will initiate a charging request, and immediately send it to WCVs. As a promising charging scheme, the collaborative charging schemes [32, 31, 23] emphasize the cooperation between WCVs and nodes to achieving real-time wireless replenishment.

Collaborative charging schemes are indeed helpful for energy replenishment, however, classic and traditional collaborative charging schemes are still suffering from a series of severe problems which are almost neglected.

1. In pushWait, Zhang et al. [32, 31, 23] assumed that all WCVs are required to go back to the base station for energy replenishment. Although this method is prove to be optimal under the assumption, *returning to the base station is regarded as a compulsory task for any WCV*. Moreover, the charging behavior and charging locations of WCVs are fixed, which are not suitable for WRSNs especially from the perspectives of dynamical and non-deterministic features.
2. In hierarchical charging method [17, 18], two kinds of WCVs are designed. *Each WCV is required to execute "fixed" tasks, such as only charging nodes or charging WCVs, which lacks scalability and flexibility*.
3. The lack of adaptive mechanisms and homogenous functionality in WCVs leads to a low energy efficiency.

Suppose a WCV with nearly full energy moves to an area, where the nodes are almost exhausted, it will never charge for any node, leaving these nodes dead. According to references [17, 18], it cannot change its status from a WCV-charger into a Node-charger. Our initiative is developed based on this point. We tend to develop an adaptive charging scheme, each time, a WCV is able to determine whether to charge a node or a WCV. It can simultaneously act as a WCV-charger or a Node charger. The performance of the WRSN directly relates to the efficiency of the charging scheduling algorithm. If abovementioned problems are left unnoticed, the energy efficiency will be low, threatening the connectivity and functionality of the WRSNs.

Our motivation is to overcome these drawbacks and improve the flexibility and scalability of the charging scheme. In this paper, we developed a game theoretical collaborative charging scheme, GTCharge. The collaborative charging process is converted into a collaborative game taken between WCVs. We respectively investigate the functionalities of contribution degree, charging priority and profits. Then GTCharge is demonstrated in detail, in which each WCV seeks for the maximum profit when fulfilling charging tasks. Moreover, the conditions including all WCVs' charging strategies are clarified to reach a Nash Equilibrium point. The contributions of this paper can be summarized as follows.

1. To the best knowledge of the authors, we are the first to use game theory for solving the collaborative charging problem in WRSNs. We proposed the definitions contribution degrees, charging priorities and profits respectively for further guiding a WCV to choose the best choice.
2. The existence of Nash Equilibrium point is proved, which regulates the behaviors of WCVs in collaboratively fulfilling the charging tasks.
3. Extensive simulations are conducted to demonstrate the advantages of the proposed scheme. Simulation results show that our scheme is able to enhance the charging efficiency, which is the most prominent feature on researching charging schemes in WRSNs.

The remainder of this paper is organized as follows. Section 2 gives a brief overview about charging scheduling schemes in WRSNs. Section 3 introduces related background. In Section 4, a game theoretical charging algorithm GTCharge is proposed. Analysis and discussions on the characteristics of the proposed scheme are given in Section 5. Experimental simulations are conducted to show the advantages in Section 6. At last, we conclude this paper in Section 7.

2. Literature Review

Recent breakthrough on wireless power transfer technology envisioned flourish achievements in WRSNs. In recent years, much effort has been devoted to studying related issues in WRSNs, in general, approaches of scheduling charging tasks for

WRSN fall into four types: periodical charging scheme, collaborate charging schemes and on-demand charging schemes and performance analysis schemes.

2.1. Periodical charging scheme

Periodical charging schemes [28, 26, 24] converted the energy charging problem into a TSP problem [16] based on the energy distribution model and the energy consumption model, where the Hamiltonian cycle is calculated as the solution. Periodical charging schemes can be divided into two categories: single-node charging scheme [28] and multi-node charging scheme [26, 25]. In single-node charging scheme, at one time, a WCV is responsible for replenishing for one sensor, therefore, the charging efficiency is relatively low. A straight-forward method is to simultaneously charge several neighboring nodes, which is called multiple-node charging scheme [27, 20]. In the multiple-node charging scheme [27, 20], a WCV is able to charge multiple neighboring nodes within its charging range simultaneously, which greatly improves the charging efficiency [27, 20]. Based on the multiple-node charging solution, Xie et al. explored the path planning problem when WCVs are regarded as the mobile base stations [26, 25] by establishing the Smallest Enclosing Dist (SED) [6, 22]. Then they set up a number of concentric structures where nodes locate at the center of the circle. Then, overlapped concentric circles are regarded as stopping locations for WCVs. Similarly, Fu et. al. [6] proposed the discretization planning theory for wireless charging, in which concentric structure is formed in SED to work out the proper stopping locations for WCV from the overlapped area. However, in [5], Dai et al. pointed out that the calculation overhead based on SES is so large that it is not suitable for large-scale WRSNs, and charging methods simply based on sensor locations are impractical for large-scale WRSNs. Instead, complex topology changes caused by network dynamics require large re-computation costs and collaborative charging mechanisms, which concerns both sensor location and remaining energy.

2.2. On-demand charging

Aforementioned schemes assumed that information, such as exact locations, energy status and energy consumption rate of nodes are regarded as deterministic factors, which are known to WCVs in advance. Moreover, WCVs are aware of timely changes within the network, such as changes in network topology, network connection and energy level of nodes. Obviously, this notion is not feasible in practice, because deterministic factors are not easy to acquire.

In [7, 8], the on-demand charging architecture is designed. When the residual energy fall below a certain threshold, a sensor will initiate a charging request, and immediately send it to WCV. By executing specific scheduling algorithm, a WCV will 1) select a charging candidate, 2) directly move forward to it and 3) replenish energy for it. In [30], another on-demand charging architecture is designed, in which a complicated architecture is constructed which categorized rechargeable sensors into normal nodes, head nodes and proxy nodes. In [29], Xu et al. devised an algorithm for scheduling the tours of the WCV by jointly considering the residual lifetime of sensors and the charging ratio of charging tours. In [11, 12], considered the problem of scheduling multiple WCVs in an on-demand way to maximize the covering utility. In our previous method [15], we proposed a Double Warning Thresholds with Double Preemption (DWDP) charging scheme, in which double warning thresholds are used when residual energy levels of sensor nodes fall below certain thresholds. We introduced specific comparison rules, then warning thresholds are used to adjust charging priorities of different sensors, warn the upcoming recharge deadlines, as well as support preemptive scheduling. However, it still lacks a theoretical approach to model and solve the wireless charging scheduling problem.

Besides that, some performance analysis and optimizations methods are still deserved to be mentioned. They aimed at formalizing the charging process into problem solving process, they set up particular criteria for guiding how to optimize the charging work. Jiang and Cheng et al. [33, 10] analyzed optimization scheduling problem of WRSNs in detail under the condition of random events. They established the performance evaluation criteria on the basis of Quality of Monitoring (QoM) [2, 4, 3] in a given network. They optimized the performance of the system from WCV behavior, data transfer protocol, coordination control and so on. Angelopoulos et al. [1] posed the charging decision problem and prove its complexity. In order to optimize the performance of the system, they investigated how to weigh the path of WCV, charging decision of WCV and charging amount of WCV.

2.3. Collaborative charging

Methods mentioned in previous two sections (i.e. Section 2.1 and Section 2.2) assume that the energy capacity of WCVs are infinite, which are not suitable for applications in practice. In [32, 31, 23, 17, 18], researchers assumed that WCVs have limited energies, and will periodically return to the base station for getting charged. The WCVs are regarded as the energy transferring medium, and their methods are named collaborative charging.

Collaborative charging methods emphasize the cooperation between WCVs and nodes to achieve real-time wireless replenishment. In [32, 31, 23], Zhang and Wu et al. envisioned that multiple WCVs are able to charge for sensors and themselves. In [19], Madhja et al. [17, 18] argued that methods in [32, 31, 23] still suffer from large traveling energy consumption in WCVs moving back and forward in the "PushWait" process. They designed a collaborative charging scheme with a hierarchical structure [1]. Two kinds of WCVs are designed based on different functionalities. One kind is only used for charging nodes and the other is for charging WCVs.

In our latest research [14, 15], we proposed several charging algorithms for wireless rechargeable sensor networks. In [14], two charging algorithms HCCA (i.e. Hierarchical Clustering Charging Algorithm) and HCCA-TS (i.e. Hierarchical Clustering Charging Algorithm based on Task Splitting) are proposed which aim at shortening charging time and distance via merging and splitting charging tasks. In [15], we proposed a Double Warning Thresholds with Double Preemption (DWDP) charging scheme, in which double warning thresholds are used when residual energy levels of sensor nodes fall below certain thresholds.

Although collaborative charging schemes are more realistic, because it is difficult or even impossible for a single WCV to manage a whole network. Approaches proposed in [17, 18] are prove to be feasible for managing a large scale network. However, some drawbacks still exist which cannot be overlooked.

1. Big energy consumption spent in traveling between nodes and base stations back

[1]For ease of referring, we name these two methods PushWait and Hierarchical in the rest of this paper.

and forth. No need to require all WCVs to return to the base station.

2. Functionality or charging locations of any WCV are fixed, lacking flexibility and scalability. Once the network topology is constructed, charging behaviors of WCVs are fixed determined, not suitable for dynamicity of WRSNs.
3. Lacking adaptive mechanisms and homogenous functionality in WCVs, which leads to low energy efficiency.

In this paper, our aim is to design an adaptive charging scheme for WRSNs to overcome the aforementioned problems.

3. Preliminaries

In this section, related preliminaries are given in detail for deeply comprehending our scheme.

3.1. Game theory

Game theory involves three basic components, which are defined as follows:

- **Player set** V: The set of all vehicles in the network. $V = \{1, 2, ..., n\}$.
- **Strategic set** S_i: Each WCV $v_i \in V$ owns a strategy set S_i with size m. S_i can be expressed as $S_i = \{s_i\} = \{{s_i}^1, {s_i}^2, ..., {s_i}^m\}$, where s_i denotes the strategy of v_i, ${s_i}^j$ represents the jth strategy of v_i. s_{-i} is the strategy set of other WCVs except v_i. After each WCV $i \in V$ determines its strategy $s_i{}'$, we define $\{s_1{}', s_2{}', ..., s_n{}'\}$ as the **situation** which contains every node's strategy.
- **Profit function** $\mathbb{P}(s_1{}', s_2{}', ..., s_n{}')$: stands for the benefit of WCV i in **situation** $\{s_1{}', s_2{}', ..., s_n{}'\}$ which can be simplified as $\mathbb{P}(s'_i, s'_{-i})$. Since each WCV is intelligent, any WCV is able to choose its strategy based on the profit it rewards.

Therefore, every WCV wishes to seek for the maximum profit:

$$\max \mathbb{P}(s_i, s_{-i})$$

3.2. Nash Equilibrium

Nash Equilibrium is a solution concept of a game involving two or more nodes, in which each node is assumed to know the equilibrium strategies of the other nodes, and no node has anything to gain by changing only its own strategy unilaterally. If each node has chosen a strategy and no node can benefit by changing its strategy while the other nodes keep unchanged, then the current set of strategy choices and the corresponding payoffs constitute Nash Equilibrium. If a strategy set $s^* = \{s_1{}^*, s_2{}^*, ..., s_n{}^*\} = \{s_i{}^*, s_{-i}{}^*\}$, for any strategy $s_i \in S_i$, there holds $u_i(s_i{}^*, s_{-i}{}^*) \geq u_i(s_i, s_{-i})$. Therefore, the $s^* = \{s_1{}^*, s_2{}^*, ..., s_n{}^*\} = \{s_i{}^*, s_{-i}{}^*\}$ is called a Nash Equilibrium point and the result of the strategy is considered as Nash Equilibrium.

3.3. Charging Model

In this work, we adopt an omnidirectional wireless charging model. We assume that the wireless charging power at different nodes is determined by the distance between nodes and the charger, and the transmission power of the charger [21]. Specially, we adopt the following equation as the wireless charging model:

$$P_{rx}(d) = \frac{\tau}{(d + \xi)^2} \tag{1}$$

where $\tau = \frac{G_{tx}G_{rx}\eta}{L_p}(\frac{\lambda_0}{4\pi})^2 P_{tx}$ is a constant dictated by WCV and sensor nodes. P_{tx} is the source power from WCV. G_{tx} and G_{rx} denote source antenna gain and receiver antenna gain, respectively. λ_0 is referred to wavelength. L_p indicates the polarization loss. η represents the rectifier efficiency. d is the distance between WCV and the sensor node on charging. The parameter ξ is assigned to 0.2316 according to [9].

4. Our Scheme

In this section, proposed scheme is demonstrated in detail.

4.1. Definitions and notations

We summarize the notations used in this paper in Table 1.

Table 1: Symbols and Definitions

Symbol	Definition
n	The number of rechargeable sensor nodes
w	The number of WCVs
k	The number of emergent WCVs
$E(n_i)$	The remaining energy of node n_i
$v(n_i)$	The energy consumption speed of node n_i
τ	The period of time slot
$c_t(v_i)$	The contribution degree of WCV v_i at t-th time slot
$p_t(v_i)$	The priority of WCV v_i at t-th time slot
$s_t(v_i)$	The moving speed of WCV v_i at the t-th time slot
$\mathbb{P}_t(v_i)$	The profit of WCV v_i at t-th time slot

4.2. Design Principles

To overcome existing problems mentioned in previous sections, in this paper, we tend to use game theory to develop a charging scheme for WRSNs. Previous research on WSNs lay sufficient fundamentals for applying game theory. In their paradigms, due to the fast development of artificial intelligence, a smart sensor node is capable of controlling its behavior. Each time, a node can dynamically select the best strategy for maximizing its profit. Then it will follow the strategy to control its behavior.

Since the computation, storage and communication capability of a WCV is much higher than a sensor node, in this paper, it is feasible to envision that, in a WRSN, each WCV is smart enough to control its behavior. It can proactively select a strategy based on profits, which directly relate to the charging action. However, a negligible underlying problem when using the game theory is the selfish behavior issue. In WSNs, a fraction of nodes refuse to do anything, such as drop all packets, stop monitoring and etc, so as to preserve energy to prolong the lifetime. Although the profits of selfish nodes are maximized, other nodes, especially the surroundings, will suffer from more heavy burden. The selfish behavior of nodes may accelerate energy consumption of normal node and even worse, shorten the network lifetime of the whole network.

Therefore, it is necessary to develop a scheme that avoids the lazy or selfish behavior for WCVs in fulfilling charging tasks. Hence, when designing a charging scheduling algorithm using game theory, we take both drawbacks existing in previous charging scheme and selfish behavior issue into consideration. Following principles and requirements are summarized for guiding us how to design feasible charging strategies for smart WCVs.

1. Avoid frequent moving back and forth to base stations for all WCVs. To reduce such energy cost, some nodes should act as “mobile” base stations. They should apply V-V charging technology to replenish for some WCVs outside.
2. WCVs should own homogenous architecture and functionality. Although WCVs designed in [17, 18] are able to execute V-V (WCV to WCV) and V-N (WCV to nodes) energy replenishment. They are implemented and configured with heterogenous architecture especially in energy capacity. In fact, they may belong to two kinds.
3. Lazy or selfish behaviors of intelligent WCVs should be avoided. Regulations or rules should be proposed in the game theory process so as to restrict and guide the behaviors of smart WCVs. Each time, a WCV seeks for the best choice (i.e. a strategy to achieve the maximum profit). It periodically determines whether to perform a V-V or V-N charging strategy. The charging mission of a WCV is no longer deterministic. A WCV is able to charge for any node or any other WCV at any place.

In this paper, our GTCharge is able to meet these three principles and requirements are satisfied. Detailed implementations are given in the followings.

4.3. Network Model

We envision a scenario that in a WRSN is composed of n massive homogenous rechargeable sensor nodes and a base station which acts as a energy source and data sink. A number of homogenous WCVs are responsible for replenishing energy for

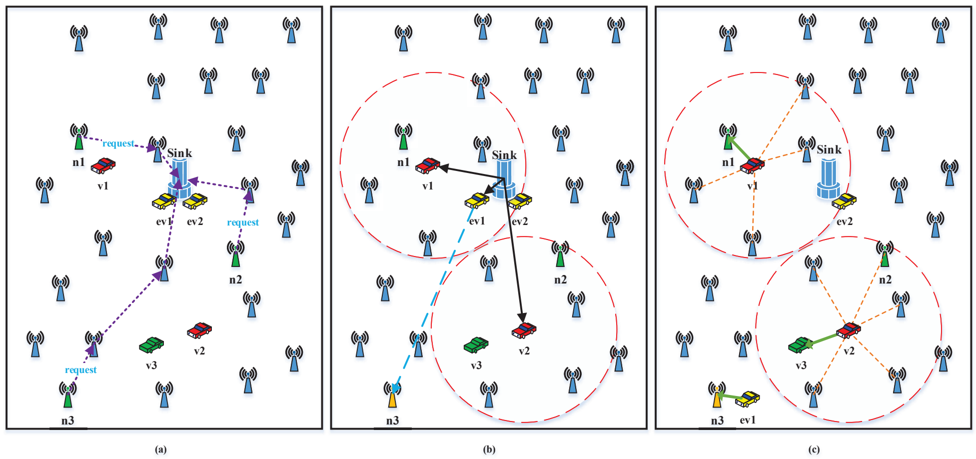

Figure 1: An example of the system architecture

nodes. Each node has the same amount of energy capacity $E(n_i)$. Specific routing protocols are implemented to set up transmission paths or routes from the source nodes and destination nodes. Due to different surrounding environments, such as distances between neighboring nodes, sampling frequencies, and so on, nodes have different energy consumption rate $v(n_i)$. To preserve massive exhaustion of nodes, we reserve k *emergency WCVs* located at the base station for dealing with urgent charging actions. When the remaining energy of a node, say n_i, falls below a threshold, it will immediately send a charging request to inform the sink node. Then the sink node will designate a WCV v_i to charge n_i. An example of the system architecture is shown in Figure 1.

As shown in Figure 1(a), five WCVs (i.e. v_1, v_2, v_3, ev_1 and ev_2) are deployed in a WRSN, which are responsible for replenishing energy for nodes. Three WCVs (in red) are charging for nodes or other WCVs, besides that two WCVs are urgent WCVs (in yellow) which are set out when panic nodes appear. At one time, n_1, n_2 and n_3's energy fall below a threshold and they send out charging requests to the sink node. The charging requests are delivered to the sink node in a hop by hop manner. In Figure 1(b), the sink node informs v_1 and v_2 about their charging regions. Since node nearby WCV locations neighboring to n_3, it is recognized as a panic node. Therefore, the sink node initiates an charging order to uv_1 about the location of n_3. In Figure 1(c), uv_1 arrives at the location of n_3 and replenishes it. In the meanwhile, v_1 and v_2 select the best charging strategy within their charging regions based on profits. v_1 decides to charge n_1 and v_2 chooses to charge v_3.

We define actions of all units (i.e. nodes and WCVs) as *operations*. One operation is composed of one or more *actions*. Each action should be completed within a *time slot*, which is defined as the period of game theory. All actions of nodes or WCVs should be completed in one time slot. Actions fall into four kinds.

- *wait*: A WCV does not do anything but wait.
- *walk*: A WCV moves forward to a node within distance *len* (i.e. $len \leq s_t(v_i) \times \mathrm{T}$, here, $s_t(v_i)$ is the traveling speed of the WCV and T refers to the interval of time slot.)
- *n_charge*: A WCV charges for a node within distance of *len*.
- *v_charge*: A WCV charges for another WCV within distance of *len*.

An operation refers to all actions performed in fulfilling a charging task, which is made up of a series of actions. In general, operations have four kinds.

- *o_wait*: A o_wait operation is composed of one or more *wait* actions.
- *o_chargenode*: An o_chargenode operation is made up of one or more walk actions and an eventual n_charge action.
- *o_chargeWCV*: A o_chargeWCV operation is made up of one or more walk actions and a last v_charge operation.
- *o_return*: A o_return action refers returning back to the base station, it is composed of one or more walk actions.

Four operations of WCV are preemptive. When a WCV is executing fulfilling an operation, it can be preempted by other operations at any time. After an operation is finished, the WCV stays still and selects the best strategy operation for the next time slot.

Due to preemptive characteristics of the proposed scheme, an urgent operation may be interrupted, causing exhaustion of nodes. To solve this prominent problem, we define an urgent condition in which an operation cannot be interrupted. When a node, say i, is panic, it will send its dying alert to the base station. The base station records its information and put it into a death queue Q_{death}. When the number of emergency WCVs is bigger than 0, i.e. $k > 0$, one WCV will be designated to charge for the panic node. It will perform a o_chargenode operation, which is composed as multiple walk actions and a final n_charge action. In the meanwhile, we demand that such an urgent operation cannot be preempted.

4.4. Contribution degree

To quantify the profit of each charging operation, we firstly introduce the definition of contribution degree for nodes and WCVs respectively.

4.4.1. Contribution Degree of A WCV

In our scheme, the contribution degree $c_t(v_i)$ of a WCV depends on its serving frequency to the WRSN, which can be calculated as Equation (2).

$$c_t(v_i) = (1-\alpha)\cdot c_{t-1}(v_i) + \alpha \cdot (-\mathbb{P}_t(v_i)) \tag{2}$$

Here, $c_i(v_i)$ refers to the contribution of WCV v_i on time slot t. Initially, contributions of all WCVs are set 0 ($c_0(v_i) = 0, i = 1, 2, ...w$). $\mathbb{P}_t(v_i)$ is denoted as the profit obtained by WCV v_i in the t-th time slot, which will be defined in later sections. Parameter α is a constant, which indicates the proportions of historical contributions. It is a vital parameter because it combines previous and current performance together, which is useful to avoid the lazy or selfish behavior of WCVs. A larger value of α stands for a bigger proportions of historical performance in former $t-1$ time slots.

4.4.2. Contribution Degree of A Node

The contribution degree of a node largely depends on the energy consumption rate of nodes, residual energy overhead and charging efficiency of WCVs, which is defined as Equation (3)

$$c_t(n_i) = \frac{2-X}{2}\cdot[(1-\alpha)\cdot(1-E_t(n_i)+v_t(n_i)) + \alpha\cdot(\mathbb{P}_t(n_i))] \tag{3}$$

Here, $E_t(n_i)$ refers to the residual energy of node n_i in time slot t. Initially, when a node is deployed in the network, its initial energy amount equals the energy capacity, i.e. $E_t(n_i) = E_0$. $v_t(n_i)$ refers to the energy consumption rate of node n_i. X indicates whether a node is charged in time slot t, which is given in Equation (4)

$$X = \begin{cases} 0 & \text{charged} \\ 1 & \text{uncharged} \end{cases} \tag{4}$$

4.4.3. Charging Priority Determination

Each time, a WCV needs to determine an operation for guiding its movement. In each time slot, a WCV v_i initiates a message that contains its location to the base station. Then the base station scans a circle region (i.e. service region) of a *len* radius around the location of WCV, where $len = s_t(v_i) \times time\_slot$. Here, $s_t(v_i)$ refers to the traveling speed of a WCV. Usually, a response message that contains a number of nodes and WCVs which are needed to be replenished, will be delivered to v_i. Then v_i should evaluate the priority of them and decide which is the best choice.

In our scheme, for a WCV, responding to a panic node is different from a panic WCV. Obviously, we should take the contribution degree of them into consideration. Moreover, as defined in Section 4.3, an operation is constitute of multiple actions, as time goes on, components of an operation may change. We introduce two probabilistic functions $p_t(n_i)$ and $p_t(v_j)$ to indicate the charging priority respectively.

With respect to charging a node, the priority can be obtained as Equation (5).

$$p_t(n_i) = \begin{cases} \frac{c(n_i)^{\beta_1}}{1+c(n_i)^{\beta_1}} & E(n_i) < \delta_1 \\ 0 & E(n_i) \geq \delta_1 \end{cases} \tag{5}$$

Similarly, with respect to charging a WCV, we have Equation (6).

$$p_t(v_j) = \begin{cases} \frac{c(v_j)^{\beta_1}}{1+c(v_j)^{\beta_1}} & E(v_j) < \delta_2 \\ 0 & E(v_j) \geq \delta_2 \end{cases} \tag{6}$$

Here, $c(n_i)$ and $c(v_j)$ indicate the contribution degree of node n_i and WCV v_j respectively. Besides that, we define two thresholds δ_1 and δ_2 for comparing the remaining energy for nodes and WCVs. When the remaining energy of a node (or a WCV) is bigger than threshold δ_1 (or δ_2), it is regarded to own sufficient energy, and hence, the corresponding priority will be small.

4.4.4. Profit

For a given WCV, in the charging process, its profit can be calculated as Equation (7).

$$\mathbb{P}_t(v_i) = -\left(\Delta L + \Delta R \cdot \frac{p_t(v_i)}{\sum_{k=1}^{m_\alpha} p_t(v_k) + \sum_{k=1}^{m_\beta} p_t(n_k)}\right) \tag{7}$$

where ΔL indicates the energy cost of a WCV in listening to other WCVs or nodes. ΔR refers energy consumption in charging for nodes or WCVs. m_α denotes the number of WCVs in the service region which need charging during time slot t. Similarly, m_β indicates the number of nodes which are listened.

Intuitively, in the charging process, a node (or a WCV) to be charged will receive energy from WCVs. After getting charged, the residual energy will increase. Obliviously, the charged node (or WCV) will get profits. To calculate how much profit will be obtained by a node or a WCV, we propose two following equations.

Condition one: the profit of a node n_i that get charged can be calculated as:

$$\mathbb{P}_t(n_i) = -\left(\Delta B + \Delta U \cdot \frac{p_t(v_i)}{\sum_{k=1}^{m_\alpha} p_t(v_k) + \sum_{k=1}^{m_\beta} p_t(n_k)}\right) \tag{8}$$

Condition two: the profit of a WCV v_i that get charged is:

$$\mathbb{P}_t(v_i) = -\left(\Delta B + \Delta U \cdot \frac{p_t(v_i)}{\sum_{k=1}^{m_\alpha} p_t(v_k) + \sum_{k=1}^{m_\beta} p_t(n_k)}\right) \tag{9}$$

Condition three: without calculating profits, a WCV immediately makes a decision.

$$action = \begin{cases} \text{Return} & \sum_{k=1}^{m_\alpha} p_t(v_k) + \sum_{k=1}^{m_\beta} p_t(n_k) = 0 \&\& E(v_i) < \delta_3 \\ \text{Wait} & \text{Otherwise} \end{cases} \tag{10}$$

Here ΔB refers to the energy cost in broadcasting its own charging request. ΔU means the amount of energy received in charging process. In the meanwhile, as stated

Table 2: Profit matrix

WCV v_b / WCV v_a	*wait*	*v_charge*	*n_charge*
wait	(0,0)	(0,$\mathbb{P}_t(v_i)$)	(0,$\mathbb{P}_t(n_i)$)
v_charge	($\mathbb{P}_t(v_i)$, 0)	($\mathbb{P}_t(v_i)$,$\mathbb{P}_t(v_i)$)	($\mathbb{P}_t(v_i)$,$\mathbb{P}_t(n_i)$)
v_charge	($\mathbb{P}_t(n_i)$, 0)	($\mathbb{P}_t(n_i)$,$\mathbb{P}_t(v_i)$)	($\mathbb{P}_t(n_i)$,$\mathbb{P}_t(n_i)$)

in [32, 31, 23, 7, 8], the charging efficiency for wireless charging technology is still low. The amount of energy sent out is larger than those eventually acquired by a receiver. Therefore, $\Delta B + \Delta U < \Delta L + \Delta R$. Since a bigger value of contribution degree $c_t(n_i)$ will lead to a larger $p_t(n_i)$, which yield to a higher value of $\frac{p_t(v_i)}{\sum_{k=1}^{m_\alpha} p_t(v_k)+\sum_{k=1}^{m_\beta} p_t(n_k)}$. Hence, the proportions of priority is bigger. Therefore, charging for a node or a WCV with a high contribution value will lead to higher profit.

4.4.5. GTCharge Algorithm

In our scheme, game theory is used for regulating the WCVs' charging decisions. To maximize the profit, each WCV seeks to increase its own contribution value. In each time slot, every WCV will initiate a query signal to the base station. The base station compute the priorities $p_t(n_i)$ and $p_t(v_j)$ and send back to the corresponding WCV. Then we can obtain the profit for each WCV and node.

The game is taken between two WCVs. Related profit matrix is given in Table 2.

Since the condition of all strategies of WCVs reach a Nash Equilibrium (see proofs in Section 5.1), we further develop a charging algorithm *GTCharge* for WRSNs.

The game theory process is repeatedly taken in rounds, for ease of simplicity, we illustrate the process of one round. As demonstrated in Algorithm 1, GTCharge proceeds as follows. First of all, information such as locations of WCVs, remaining energy of nodes are initialized. Then each WCVs will send the query message to the base station aiming at obtaining information about its service region (i.e. a circle locates in WCV's coordinates with *len* as its radius). Then the contribution degrees for each node and

Algorithm 1 GTCharge Algorithm

Input:

Output:

Network initializations

Construct service regions for each WCV with radius $len = v_t(v_i) \times \tau$

for all x_i in service region (i.e. x_i refers to a node or a WCV) **do**

  Calculate the contribution of x_i on time slot t, (i.e. $c_t(x_i)$) according to Equation (3) and Equation (2)

  Calculate the priority of x_i on time slot t (i.e. $p_t(x_i)$) according to Equation (5) and Equation (6)

end for

for all $v_i \in V$ **do**

  for all $x_i \in \{V' \bigcup N'\}$ **do**

    Calculate profit $\mathbb{P}_t(x_i)$ according to Equation (8) and Equation (6)

  end for

end for

Each WCV selects the best strategy $s*$ which maximizes the profit and follows it.

WCV that are in the service region are obtained. After that, the charging priority is computed based on Equation (5) and Equation (6). Then each WCV calculates profits for every unit in the service region to select the best choice. The WCV applies the best choice to guide its future movement so as to achieve the maximum profits.

5. Characteristic Analysis

In this section, we analyze the insight characteristic of GTCharge.

5.1. Existence of Nash Equilibrium

In this subsection,

Theorem: The situation that all WCVs choose their charging strategies according to GTCharge is a Nash Equilibrium

Proof: In our scheme, each WCV makes a decision repeatedly based on GTCharge. We define the player set $A = v_i, i \in [1, n]$, which is composed of n WCVs in WRSNs. Each WCV has three strategies, $S_{v_i} = \{s_1, s_2, s_3\}$. Here, s_1, s_2 and s_3 indicate the action *wait*, *v_charge* and *n_charge* respectively. The strategy space of the game can be formalized as $S = S_{v_1} \times S_{v_2} \times ... \times S_{v_n}$

For ease of simplicity, we envision a scenario that a WCV, say v_i determines to charge another WCV v_j rather than charging a node n_k, both of which locate in the charging region of v_i. In that case, we have:

$$p_t(v_j) > p_t(n_k), j \in [1, n], k \in [1, n] \tag{11}$$

Obviously, the following equation is satisfied.

$$\frac{p_t(v_j)}{\sum\limits_{t=1}^{m_\alpha} p_t(v_t) + \sum\limits_{s=1}^{m_\beta} p_t(n_s)} > \frac{p_t(n_k)}{\sum\limits_{t=1}^{m_\alpha} p_t(v_t) + \sum\limits_{s=1}^{m_\beta} p_t(n_s)} \tag{12}$$

Since charging for a node or a WCV will reduce the residual energy of a WCV. Hence, $\Delta R < 0$. We can further obtain that:

$$-(\Delta L + \Delta R \cdot \frac{p_t(v_j)}{\sum\limits_{t=1}^{m_\alpha} p_t(v_t) + \sum\limits_{s=1}^{m_\beta} p_t(n_s)}) > -(\Delta L + \Delta R \cdot \frac{p_t(n_k)}{\sum\limits_{t=1}^{m_\alpha} p_t(v_t) + \sum\limits_{s=1}^{m_\beta} p_t(n_s)}) \tag{13}$$

Therefore, $\mathbb{P}_t(v_j) > \mathbb{P}_t(n_k)$ can be obtained, which means the profit for charging a WCV v_j is larger than charging a node n_k. At this time, charging v_j can obtain the maximum profit and changing the current strategy s_2 cannot gain more profit. Similarly, when other WCVs have determined their choices according to GTCharge, changing a strategy cannot ensure increasing their profits. Therefore, the situation that all WCVs choosing their charging strategies according to GTCharge is a Nash Equilibrium, the solution obtained by GTCharge is the Nash Equilibrium $s* = GTCharge(A, S_{v_i}, S)$.

5.2. A Case Study

To intuitively demonstrate the charging behavior of a WCV. The following example is given for comprehension.

As shown in Figure 2, four rechargeable sensors (n_1 n_4) and two WCVs (v_1 and v_2) are deployed. The service region of v_1 is constructed based on *len*.

Table 3: Priority table of v_1

Symbol	**Value**
$p_t(n_1)$	0.7
$p_t(n_2)$	0.2
$p_t(n_3)$	0.4
$p_t(n_4)$	0.9
$p_t(v_2)$	0.5

Similar to Table 5, we have $L = -1$ and $R = -5$. After v_1 executing GTCharge, the corresponding profit table can be obtained (see Table 4).

As shown in Table 4, charging for node n_4 will have the maximum profit. Therefore, the best choice for v_1 is to charge n_4. This case indicates an insightful phenomenon, by applying GTCharge, WCVs tend to cooperate with each other for fulfilling energy replenishment. In GTCharge, charging a node with a higher contribution degree will lead to a higher obtained profit, which increases its own contribution value at the greatest extent. Hence, WCV should charge for a node with high contribution degree or to make itself a high contribution WCV. As the contribution degree of a node mainly

Table 4: Profit table of v_1

Symbol	Value
$\mathbb{P}_t(n_1)$	1.24
$\mathbb{P}_t(n_2)$	0.8
$\mathbb{P}_t(n_3)$	1.14
$\mathbb{P}_t(n_4)$	**1.4**
$\mathbb{P}_t(v_2)$	1

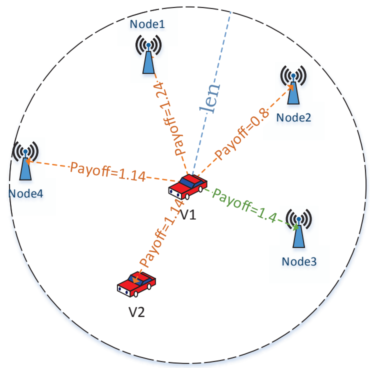

Figure 2: A Case Study

depends on the capacity of residual energy and energy consumption rate, after a charging action is completed, it will be halved. Therefore, to maximize its own profit, each WCV intends 1) to minimize the charging times, and 2) to charging for nodes which has the minimum remaining energy.

6. Simulations

In this section, experimental simulations are conducted to show the advantages of the proposed scheme. We compare our scheme with the state-of-the-art collaborative charging algorithms: PushWait [32, 31, 23] and Hierarchical [17, 18].

6.1. Simulation setup

In this section, parameters used in the simulations are listed in Table 1.

Table 5: Simulation parameters

Parameters	**Values**
Network region	10000m $\times$ 10000m
Node number	2000
Region Size	$100m \times 100m$
Sensing Range	$2m$
Energy consumption rate	0.01
Traveling speed of WCVs	$1m/s$
Maximum energy capacity of nodes	$10.8KJ$[7, 8]
Maximum energy capacity of WCVs	$2000KJ$
Energy threshold for a node to initiate a charging request	$5J$
Charging efficiency for V-V	30% [32, 31, 23]
Charging efficiency for V-N	1.5% [32, 31, 23]
Time slot period	$60s$
Sampling times	500

As listed in Table 5, in our simulation experiment, 2000 nodes are randomly deployed over a $10000m \times 10000m$ area. The energy consumption rate for sensors is 0.02. The energy capacity of a WCV is 2000KJ. When the remaining energy of a sensor falls below the threshold, a charging request will be sent to the base station. 10 WCVs are responsible for supplying energy for nodes and WCVs, their moving speed are $1m/s$. Each WCV will follow GTCharge to deal with the charging issue.

6.2. Influence of Node Number

Firstly of all, we compare the energy efficiency among three charging algorithms. It is the most essential factor for demonstrating how much energy is eventually transmitted from the energy source (i.e. the base station) to the network (i.e. sensor nodes) through WCVs.

As shown in Figure 3, with the increment of node numbers, the charging efficiencies of three algorithms gradually increase. The energy efficiency of GTCharge is higher than those of PushWait [32, 31, 23] and Hierarchical [17, 18].

Comparing with the PushWait algorithm, GTCharge does not require all WCVs move between nodes and the base station back and forth, therefore, traveling energy consumption will be reduced, which enhances the charging efficiency. With respect to Hierarchical, a couple of nodes are only specified for charging other WCVs. The traveling cost of such WCVs is high, which reduces the amount of energy used for charging nodes, leading to lower energy efficiency.

In Figure 3, we note that the energy efficiency of GTCharge finally stabilizes at 0.825%. The reason is that, the increment of sensor nodes will lead to a higher density of nodes. Hence, the energy cost for traveling will be saved and the energy efficiency will increase. In GTCharge, each round, every WCV selects the best decision, a node will low residual energy will be charged first with a high probability. Therefore, GTCharge has the highest charging efficiency.

6.3. Influence of WCVs' Energy Capacities

In this simulation, we focus on the impact of WCVs' energy capacities to the energy efficiency. As shown in Figure 4, the increment of WCVs' energy capacity will lead

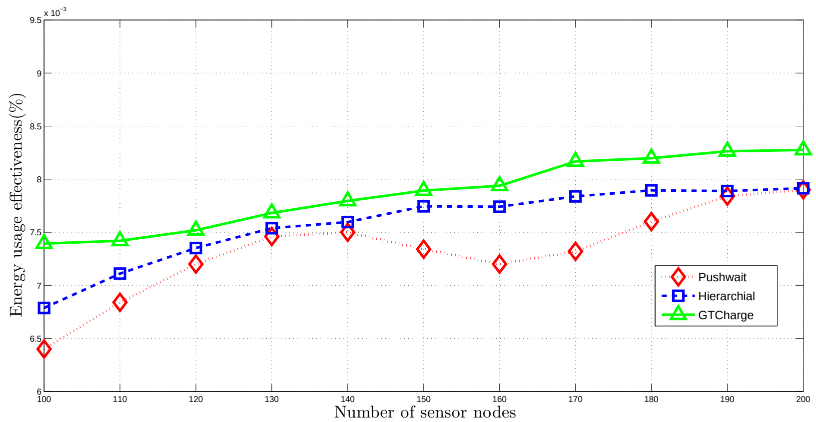

Figure 3: Influence of Node Number

to a slow increasing tendencies of three algorithm in the perspective of energy efficiency. The energy efficiency of GTCharge is slightly higher than those of PushWait and Hierarchical. However, when the energy capacity of a WCV is bigger than 2800KJ, an obvious difference appears among these three algorithms. The reason is that, in that case, the frequency of one WCV returning to the base station is reduced in GTCharge. Therefore, more energy will be used for satisfying the charging requests for sensor nodes. It also indicates that the proposed scheme is able to satisfy more sensor nodes, which also increases the charging efficiency.

6.4. Influence of Nodes' Energy Capacities

In this simulation, we concentrate on the influence of nodes' energy capacities to the charging efficiency. A larger capacity of node indicates a longer working time. As shown in Figure 5, when the energy capacity of a node is enlarged, its corresponding lifetime is prolonged, which enhances the energy efficiency. Because when the energy capacity is increased, it will have a longer lifetime and the charging times will be reduced. We also observe that the energy efficiency is approximately proportional to nodes' energy capacity and the charging efficiency of GTCharge is always higher than PushWait [32, 31, 23] and Hierarchical [17, 18].

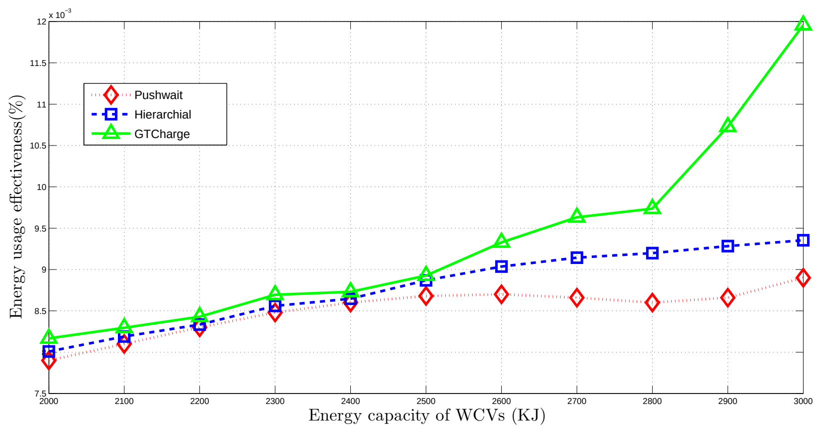

Figure 4: Influence of WCVs' Energy Capacity

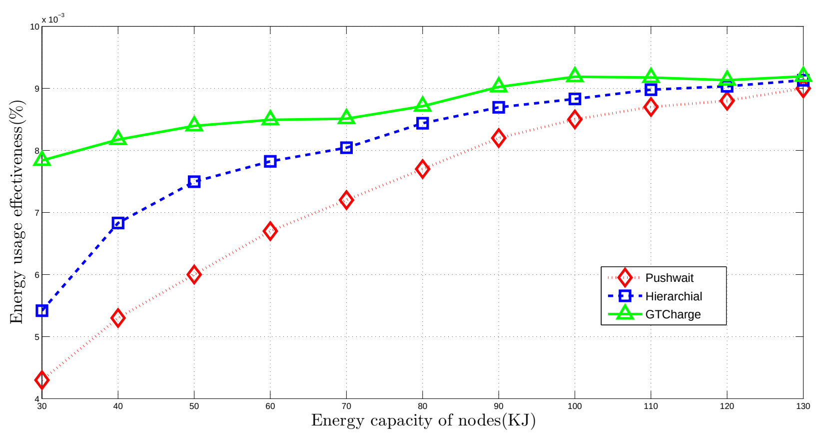

Figure 5: Influence of nodes' energy capacity

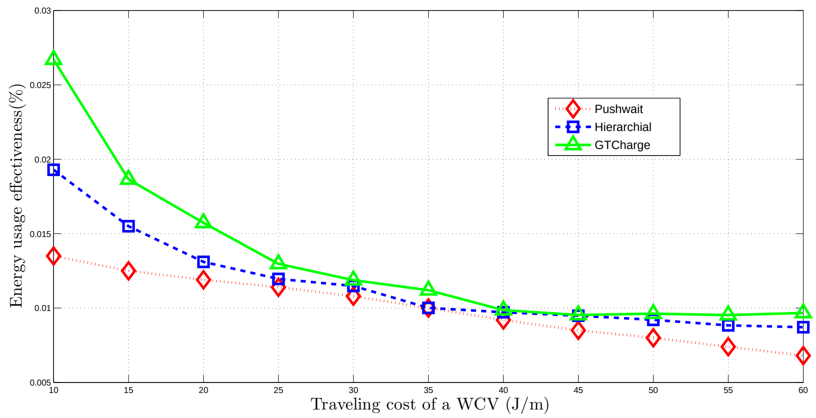

Figure 6: Traveling cost comparison

6.5. Influence of Traveling Cost

In this simulation, we mainly compare energy consumption in traveling of three algorithms. As shown in Figure 6, with the increment of traveling cost, the energy efficiencies of three algorithms gradually reduce and finally stabilize at 1%. We note the energy efficiency of GTCharge is higher than those of PushWait and Hierarchical. The reason is that, when the energy cost in traveling increases, the fraction of energy which is used for charging will be reduced, which thus decreases the energy utility.

6.6. Characteristics of GTCharge

Besides comparing energy efficiency with two latest and classic charging algorithms, we also conduct simulations for analyzing the insight characteristic of GTCharge.

6.6.1. Influence of WCV Number

We firstly evaluate the performance of GTCharge when the network is implemented with 10 and 12 WCVs. As shown in Figure 7, with the simulation running on, the energy efficiency dramatically increases. Then it grows slowly and finally stabilizes at 1.05%. In the former stages of the simulations, the energy efficiency of the network is relatively low. Because at that time, the number of nodes which need charging is small and the majority of WCVs are waiting. Therefore, the situation of strategies

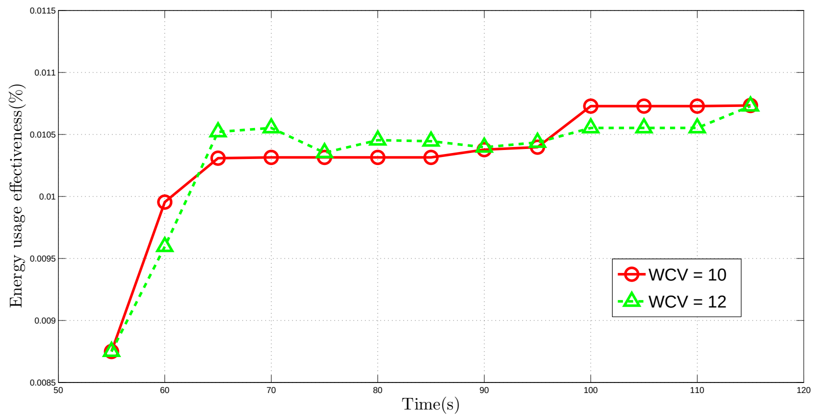

Figure 7: Energy efficiency under different number of WCVs

of all WCVs do not reach Nash Equilibrium. With the time going on, when more and more nodes are requesting for replenishment, situation reaches Nash Equilibrium, which will improve energy efficiency because of regulating WCVs to choose the best choices. Afterwards, when a panic node exists, the urgent WCV comes out from the base station, which ensure panic nodes to work again. In that case, the energy efficiency of the network is further improved and finally stabilizes.

6.6.2. Average Queue Length

Then we come to analyze the performance of the proposed scheme from the perspective of average queue length. It refers to the number of nodes that are waiting to be charged. This property reflects the charging ability of the WCV. A longer charging queue indicates a lower charging capability of the WCV, which is not helpful to maintain the energy replenishment. As shown in Figure 8, the average queue length is 8, which indicates that, the WCV only needs to maintain a short queue when working. We can also observe that, in the former 65 time slots, the queue length moves up and down. With the simulation running on, when the time approaches 80th time slot, the queue length stays steady, which also reflects that the proposed scheme can limit the queue length at a low level. We can conclude that more WCVs will lead to shorter queue length and higher energy efficiency.

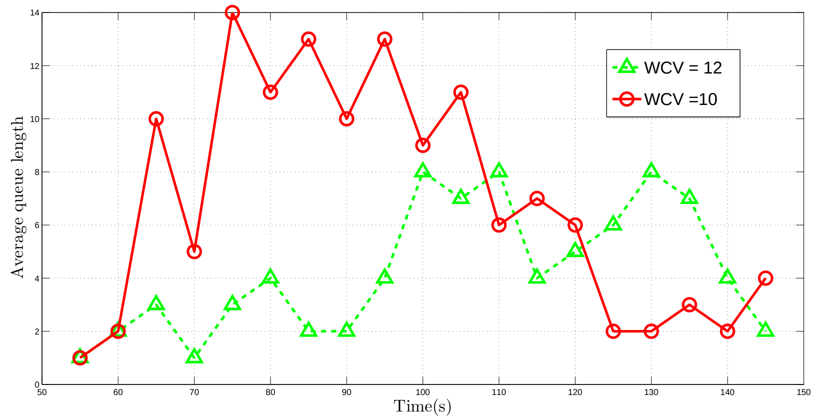

Figure 8: Energy efficiency under different average queue length

6.6.3. Number of Panic Nodes

In this simulation, we mainly concentrate on the number of the panic nodes. It indicates the ability of the WCV in maintaining the network. A larger number of panic nodes demonstrates that the capability of a WCV in maintaining the network is low. Otherwise, fewer nodes are suffering from exhaustion, guaranteeing the network connectivity.

As depicted in Figure 9, with the simulation running on, the number of panic nodes in the beginning is nearly 0. Then only a couple of panic nodes appear (i.e. no more than 5), in that case, the urgent WCV will be set out. We also observe that after 65-th time slot, when Nash Equilibrium is reached, the number of panic nodes dramatically increases due to massive booming of panic nodes. After 80-th time slot, the number gradually reduces and maintains in a low level. This phenomenon is caused by energy replenishment by urgent WCVs. From then on, the number of panic nodes stays low, and according to the conclusion posed in Section 6.2, the energy efficiency of the network can be maintained at a high level. We can conclude that more WCVs can yield to fewer panic nodes and higher energy efficiency.

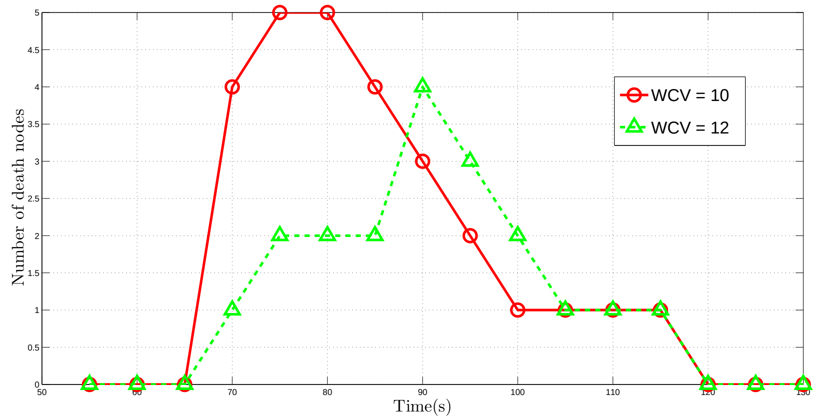

Figure 9: Energy efficiency under different number of panic nodes

6.6.4. Average Response Time

The average response time is defined as the time interval beginning when an operation is determined and ending when a node is completely charged. It reflects the ability of a WCV in satisfying the requirements of panic nodes. As shown in Figure 10, with the increment of the charging request number, the average response time gradually increases. That's because, in that case, the urgent WCVs will be called for providing energy supplement. As a WCV cannot simultaneously charge for two nodes, therefore, sometimes, a panic node has to wait for charging. Accordingly, its response time is long. We mainly compare the performance when 10 and 12 WCVs are used for maintaining the network. We observe that more WCVs will lead to a shorter response time and a higher energy efficiency.

6.6.5. Average Waiting Time

Finally, we measure the average waiting time of the sensor nodes. It refers to the time interval that begins when a node seeks for charging and ends when it is getting fully charged. It indicates the urgency for charging requests. When the number of nodes is big, the corresponding average waiting time will be long, which expresses that a large number of charging requirements needs satisfying. As shown in Figure 11, the average waiting time grows up and down in the beginning. After 85-th time slot, the

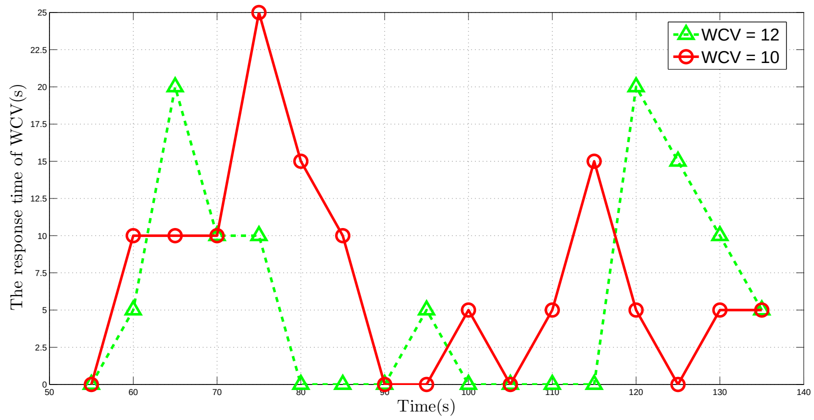

Figure 10: Energy efficiency under different average responding time

urgent WCVs are set out, leading to a reduction in waiting time. Finally, when Nash Equilibrium is reached, the waiting time gradually converges in a small region. We also note that the energy efficiency of 12 WCVs is higher than that of 10 WCVs under different average waiting time. We can conclude that more WCVs can also improve the energy efficiency.

7. Conclusions and Future Work

In this paper, we have proposed a game theoretical collaborative charging scheme GTCharge for WRSNs. In GTCharge, each WCV is able to intelligently control its behavior. The collaborative charging process is converted into a collaborative game taken among WCVs. We respectively investigate the functionalities of contribution degree, charging priority and profits. Then GTCharge is demonstrated in detail, in which each WCV seeks for the maximum profit when fulfilling charging tasks. The conditions including all WCVs' charging strategies are prove to reach a Nash Equilibrium point. At last, extensive simulation experiments are conducted to demonstrate the outperformed characteristic of the proposed scheme. Simulation results show that, comparing with the state-of-the-art collaborative charging algorithms, GTCharge can enhance the energy efficiency. Moreover, salient features of the proposed are also investigated in detail.

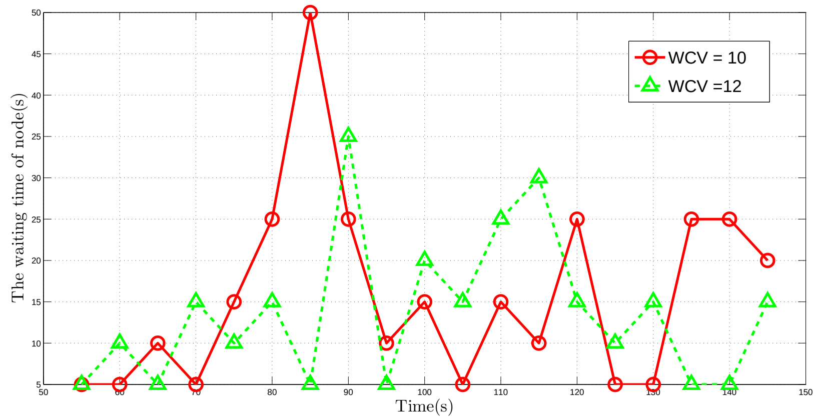

Figure 11: Energy efficiency under different average waiting time

The impact of WCV number is discussed from perspectives of average queue length, number of panic nodes, average responding time and so on.

As part of our future work, we will concentrate on how to use evolutionary game theory to further enhance the performance especially in terms of self-adaptive optimizations for GTCharge.

Acknowledgement

We want to deliver our gratitude to the reviewers of this article.

We'd like to show our greatest respects to Adelina Madhja from Computer Technology Institute and Press "Diophantus" (CTI) & University of Patras, Greece for her significant contributions and guidance in our research.

This research is sponsored in part by the National Natural Science Foundation of China (No.61402078). This research is also sponsored in part supported by the Fundamental Research Funds for the Central Universities (No.DUT14RC(3)090).

References

[1] C.M. Angelopoulos, S. Nikoletseas, T.P. Raptis, C. Raptopoulos, F. Vasilakis, Efficient energy management in wireless rechargeable sensor networks, in: Pro-

ceedings of the 15th ACM international conference on Modeling, analysis and simulation of wireless and mobile systems, ACM, pp. 309–316.

[2] P. Cheng, S. He, F. Jiang, Y. Gu, J. Chen, Optimal scheduling for quality of monitoring in wireless rechargeable sensor networks, IEEE Transactions on Wireless Communications 12 (2013) 3072–3084.

[3] H. Dai, L. Jiang, X. Wu, D.K. Yau, G. Chen, S. Tang, Near optimal charging and scheduling scheme for stochastic event capture with rechargeable sensors, in: IEEE 10th International Conference on Mobile Ad-Hoc and Sensor Systems (MASS 2013), IEEE, pp. 10–18.

[4] H. Dai, X. Wu, L. Xu, G. Chen, Practical scheduling for stochastic event capture in wireless rechargeable sensor networks, in: 2013 IEEE Wireless Communications and Networking Conference (WCNC 2013), IEEE, pp. 986–991.

[5] H. Dai, X. Wu, L. Xu, G. Chen, S. Lin, Using minimum mobile chargers to keep large-scale wireless rechargeable sensor networks running forever, in: 2013 22nd International Conference on Computer Communications and Networks (ICCCN 2013), IEEE, pp. 1–7.

[6] L. Fu, P. Cheng, Y. Gu, J. Chen, T. He, Minimizing charging delay in wireless rechargeable sensor networks, in: The 32nd IEEE International Conference on Computer Communications (INFOCOM 2013), IEEE, pp. 2922–2930.

[7] L. He, Y. Gu, J. Pan, T. Zhu, On-demand charging in wireless sensor networks: Theories and applications, in: IEEE 10th International Conference on Mobile Ad-Hoc and Sensor Systems (MASS 2013), IEEE, pp. 28–36.

[8] L. He, L. Kong, Y. Gu, J. Pan, T. Zhu, Evaluating the on-demand mobile charging in wireless sensor networks, IEEE Transactions on Mobile Computing 14 (2015) 1861–1875.

[9] S. He, J. Chen, F. Jiang, D.K. Yau, G. Xing, Y. Sun, Energy provisioning in wireless rechargeable sensor networks, Mobile Computing, IEEE Transactions on 12 (2013) 1931–1942.

[10] F. Jiang, S. He, P. Cheng, J. Chen, On optimal scheduling in wireless rechargeable sensor networks for stochastic event capture, in: IEEE 8th International Conference on Mobile Adhoc and Sensor Systems (MASS 2011), IEEE, pp. 69–74.

[11] L. Jiang, H. Dai, X. Wu, G. Chen, On-demand mobile charger scheduling for effective coverage in wireless rechargeable sensor networks, in: Mobile and Ubiquitous Systems: Computing, Networking, and Services, Springer, 2014, pp. 732–736.

[12] L. Jiang, X. Wu, G. Chen, Y. Li, Effective on-demand mobile charger scheduling for maximizing coverage in wireless rechargeable sensor networks, Mobile Networks and Applications 19 (2014) 543–551.

[13] A. Kurs, A. Karalis, R. Moffatt, J.D. Joannopoulos, P. Fisher, M. Soljačić, Wireless power transfer via strongly coupled magnetic resonances, science 317 (2007) 83–86.

[14] C. Lin, G. Wu, M.S. Obaidat, C.W. Yu, Clustering and splitting charging algorithms for large scaled wireless rechargeable sensor networks, Journal of Systems and Software 113 (2016) 381–394.

[15] C. Lin, B. Xue, Z. Wang, D. Han, J. Deng, Dwdp£a double warning thresholds with double preemptive scheduling scheme for wireless rechargeable sensor networks, in: 17th IEEE International Conference on High Performance Computing and Communications (HPCC 2015), IEEE, pp. 803–805.

[16] S. Lin, B.W. Kernighan, An effective heuristic algorithm for the traveling-salesman problem, Operations research 21 (1973) 498–516.

[17] A. Madhja, S. Nikoletseas, T.P. Raptis, Distributed wireless power transfer in sensor networks with multiple mobile chargers, Computer Networks 80 (2015) 89–108.

[18] A. Madhja, S. Nikoletseas, T.P. Raptis, Hierarchical, collaborative wireless energy transfer in sensor networks with multiple mobile chargers, Computer Networks 97 (2016) 98 – 112.

[19] A. Madhja, S. Nikoletseas, T.P. Raptis, C.M. Angelopoulos, C. Raptopoulos, F. Vasilakis, M. Rapti, K. Veroutis, J. Rolim, A. Moschos, et al., Hierarchical, collaborative wireless charging in sensor networks, in: Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–8.

[20] Y. Shi, L. Xie, Y.T. Hou, H.D. Sherali, On renewable sensor networks with wireless energy transfer, in: The 30th IEEE International Conference on Computer Communications (INFOCOM 2011), IEEE, pp. 1350–1358.

[21] Y. Shu, H. Yousefi, P. Cheng, J. Chen, Y. Gu, T. He, K. Shin, Optimal velocity control for time-bounded mobile charging in wireless rechargeable sensor networks, IEEE Transactions on Mobile Computing (2016) To appear.

[22] E. Welzl, Smallest enclosing disks (balls and ellipsoids), Springer, 1991.

[23] J. Wu, Collaborative mobile charging and coverage, Journal of Computer Science and Technology 29 (2014) 550–561.

[24] L. Xie, Y. Shi, Y.T. Hou, A. Lou, Wireless power transfer and applications to sensor networks, Wireless Communications, IEEE 20 (2013) 140–145.

[25] L. Xie, Y. Shi, Y.T. Hou, W. Lou, H. Sherali, S.F. Midkiff, Bundling mobile base station and wireless energy transfer: Modeling and optimization, in: The 32th IEEE International Conference on Computer Communications (INFOCOM 2013), IEEE, pp. 1636–1644.

[26] L. Xie, Y. Shi, Y.T. Hou, W. Lou, H.D. Sherali, On traveling path and related problems for a mobile station in a rechargeable sensor network, in: 14th ACM international symposium on Mobile ad hoc networking and computing (Mobihoc 2013), ACM, 2013, pp. 109–118.

[27] L. Xie, Y. Shi, Y.T. Hou, W. Lou, H.D. Sherali, S.F. Midkiff, On renewable sensor networks with wireless energy transfer: The multi-node case, in: 9th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON 2012), IEEE, 2012, pp. 10–18.

[28] L. Xie, Y. Shi, Y.T. Hou, H.D. Sherali, Making sensor networks immortal: An energy-renewal approach with wireless power transfer, IEEE/ACM Transactions on Networking 20 (2012) 1748–1761.

[29] W. Xu, W. Liang, X. Ren, X. Lin, On-demand energy replenishment for sensor networks via wireless energy transfer, in: Personal, Indoor, and Mobile Radio Communication (PIMRC), 2014 IEEE 25th Annual International Symposium on, IEEE, pp. 1269–1273.

[30] Y. Yang, C. Wang, Wireless Rechargeable Sensor Networks, Springer, 2015.

[31] S. Zhang, J. Wu, S. Lu, Collaborative mobile charging for sensor networks, in: 2012 IEEE 9th International Conference on Mobile Adhoc and Sensor Systems (MASS 2012), IEEE, pp. 84–92.

[32] S. Zhang, J. Wu, S. Lu, Collaborative mobile charging, Computers, IEEE Transactions on 64 (2015) 654–667.

[33] Y. Zhang, S. He, J. Chen, Data gathering optimization by dynamic sensing and routing in rechargeable sensor networks, in: 10th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON 2013), IEEE, pp. 273–281.