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GTCharge: A game theoretical collaborative charging scheme for wireless rechargeable sensor networks

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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 lack of homogeneity and dynamic 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.

1. Introduction

As the interdisciplinary of wireless communication and sensing technologies, wireless sensor networks (WSNs), which are composed of thousands of tiny sensing devices, are playing an essential part in data sensing, collection 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 even impossible to change batteries for maintaining a sensor working everlastingly. Therefore, the network lifetime of a WSN is limited, although energy preservation techniques, such as data fusion, data aggregation or even energy effective 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 to.

Recent breakthrough in wireless power transfer (WPT) techniques Kurs et al. (2007) 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, termed 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 (Xie et al., 2013a). Based on these applications, Xie et al. (2012b) has proposed the definition of the wireless rechargeable sensor networks (WRSNs) (Yang and Wang, 2015).

In recent year, great efforts have been devoted to enhancing the charging efficiency in WRSNs. In literature, the existing approaches fall into three categories: periodical charging, on-demand charging and collaborative charging schemes. Periodical charging schemes Xie et al. (2012b); 2013c); 2013a) convert the energy charging problem into a Traveler Salesman Problem (TSP) and the shortest Hamiltonian cycle is regarded as the best solution. However, all information such as exact nodes' locations, timely energy status

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are assumed to be known by WCVs in a prior. On the other hand, the on-demand charging (He et al., 2013; 2015) is a non-deterministic charging scheme, in which a WCV is not required to maintain any information about sensor nodes. When the residual energy of a specific sensor falls below a certain threshold, it will initiate a charging request, and immediately send it to WCVs. As a promising charging scheme, the collaborative charging scheme (Zhang et al., 2015; 2012; Wu, 2014) emphasizes the cooperations between WCVs and sensor nodes to achieve 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. Some of these problems are discussed below. Previous works (Zhang et al., 2015; 2012; Wu, 2014) required that all WCVs are compulsory to go back to the base station for energy replenishment periodically. Moreover, the charging behaviors and charging locations of WCVs are fixed, which are not suitable for WRSNs especially from the perspectives of dynamical and non-deterministic features. In hierarchical charging method (Madhja et al., 2015; 2016), two kinds of WCVs, WCV-charger and Node-charger are designed. *Each WCV is required to execute "fixed" tasks, such as only charging nodes or charging WCVs, which lacks scalability and flexibility*. Moreover, the lack of adaptive mechanisms and homogenous functionality in WCVs leads to a low energy efficiency. Suppose a WCV carrying nearly full energy moves to an area, where nodes are almost exhausted, it will never charge for any node because of fixed charging tasks, leaving these nodes dead. In Madhja et al. (2015); 2016), their mechanisms cannot change the status from a WCV-charger into a Node-charger. Since 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.

To further improve the charging performance of WRSNs, we develop an adaptive charging scheme so that a WCV is able to determine whether to charge a node or a WCV dynamically. In this work, we use an one-to-one charging scheme to model the network and developed a game theoretical collaborative charging scheme, namely GTCharge, which converts collaborative charging process into a collaborative game taken between WCVs. In GTCharge, each WCV seeks for the maximum profit when fulfilling charging tasks. We investigate the functionalities of contribution degree, charging priority and profits. 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 of our knowledge, this is the first work to use game theory for solving the collaborative charging problem in WRSNs. The definitions of contribution degrees, charging priorities and profits are proposed 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 in WRSNs.

The rest 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. Extensive simulations are conducted to show the advantages in Section 6. Finally, Section 7 concludes this paper.

2. Literature review

Recent breakthrough in 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 three types: periodical charging scheme, collaborate charging schemes and on-demand charging schemes.

2.1. Periodical charging scheme

Periodical charging schemes (Xie et al., 2012b; 2013c; 2013a) convert the energy charging problem into a Traveler Salesman Problem (TSP) (Lin and Kernighan, 1973) based on the energy distribution model and the energy consumption model, where a Hamiltonian cycle is calculated as the solution. Periodical charging schemes can be divided into two categories: single-node charging scheme (Xie et al., 2012b) and multi-node charging scheme (Xie et al., 2013c; 2013b).

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 (Xie et al., 2012a; Shi et al., 2011).

In the multiple-node charging scheme (Xie et al., 2012a; Shi et al., 2011), a WCV is able to charge multiple neighboring nodes within its charging range simultaneously, which greatly improves the charging efficiency (Xie et al., 2012a; Shi et al., 2011). Based on the multiple-node charging solution, Xie et al. explored the path planning problem when WCVs are regarded as the mobile base stations (Xie et al., 2013c; 2013b) by establishing the Smallest Enclosing Dist (SED) (Fu et al., 2013; Welzl, 1991). Then they set up a number of concentric structures where nodes are located at the center of the circle. Overlapped concentric circles are regarded as stopping locations for WCVs. Similarly, Fu et al. (2013) 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. Then they analyzed the optimal movement strategy of WCVs (Fu et al., 2016). They proposed an optimal solution using the linear programming method. However, Dai et al. (2013c) 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 concern both sensor location and remaining energy.

2.2. On-demand charging scheme

The aforementioned schemes assumed that information, such as exact locations, energy status and energy consumption rate of nodes, is regarded as deterministic factors, which is 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, it is not practical to maintain or update such information.

In He et al. (2013); 2015), the on-demand charging architecture is designed. When the residual energy falls below a certain threshold, a sensor will initiate a charging request, and immediately sends it to WCV. By executing specific scheduling algorithm, a WCV will (a) select a charging candidate, (b) directly move forward to it and (c) replenish energy for it. In Yang and Wang (2015), 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. Xu et al. (2014), 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 Jiang et al. (2014a); 2014b), the problem of scheduling multiple WCVs in an on-demand way to maximize the covering utility is considered.

Besides that, some performance analysis and optimization methods are still deserved to be mentioned. They aimed at formalizing the charging process into a problem solving process, and set up particular criteria for guiding how to optimize the charging tasks. Zhang et al. (2016); Jiang et al. (2011) analyzed the optimal 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) (Cheng et al., 2013; Dai et al., 2013b; 2013a) in a given network. Thus, the performance of the system, including WCV behavior, data transfer protocol, coordination control and so on, is optimized. Angelopoulos et al. (2012) proposed the charging decision problem and proved its complexity. In order to optimize the performance of the system, they investigated how to weigh the paths, charging decisions and charging amount of WCVs. Wang et al. (2013) formulated the optimization problem into a Multiple Traveling Salesman Problem with Deadlines (m-TSP with Deadlines), which is NP-hard. Then a heuristic algorithm which chooses the node with the minimum weighted sum of traveling time and residual lifetime is proposed. Tong et al. (2010) investigated the impact of wireless charging technology on sensor network deployment and routing arrangement. It offers a new paradigm for guiding how to adapt sensor network design to leverage wireless charging technology. Wang et al. (2014) studied the recharging schedule that maximizes the recharging under specified constraints. Li et al. (2011) proposed a Joint Routing and Charging scheme (J-RoC). J-RoC not only replenishes energy but also improves the network energy utilization, thus prolonging the network lifetime.

2.3. Collaborative charging scheme

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 Zhang et al. (2015); 2012); Wu (2014); Madhja et al. (2015); 2016), researchers assumed that WCVs have limited energies, and will periodically return to the base station for energy provisioning. In their scheme, WCVs are regarded as the energy transferring medium, and their methods are named collaborative charging.

Collaborative charging methods emphasize the cooperations between WCVs and nodes to achieve real-time wireless replenishment. Wu (2014); Zhang et al. (2012); 2015) envisioned that multiple WCVs are able to charge for sensors and themselves. Madhja et al. (2015); 2016) argued that methods in Wu (2014); Zhang et al. (2012); 2015) still suffer from large traveling cost in WCVs' moving back and forth in the "PushWait" process. They designed a collaborative charging scheme with a hierarchical structure.[2] Two kinds of WCVs with specific functionalities are employed. One kind is only used for charging nodes and the other is for charging WCVs.

In our latest research (Lin et al., 2016b; 2015; 2016a), we proposed several charging algorithms for wireless rechargeable sensor networks. In Lin et al. (2016b), 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 missions. In Lin et al. (2016a), 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. In Lin et al. (2016a), a temporal and distantial priority charging scheduling algorithm TADP is proposed for WRSNs. TADP merges temporal priority and distantial priority into a mixed priority to achieve better scheduling performance.

Approaches proposed in Madhja et al. (2015); 2016) are proved to be feasible for managing a large scale network. However, some drawbacks still exist which cannot be overlooked.

1. Big energy consumptions are spent in traveling between nodes and the base station back and forth. No need to require all WCVs to return to the base station.
2. Functionality or charging location of any WCV is fixed, lacking of flexibility and scalability. Once the network topology is constructed, charging behaviors of WCVs are fixedly determined, not suitable for the dynamicity of WRSNs.
3. Lacking of adaptive mechanisms and homogenous functionality in WCVs leads to low energy efficiency.

In this work, 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 here.

3.1. Notations in game theory

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

- **Player set** V: The set of all WCVs in the network. $V = \{1, 2, \ldots, n\}$.
- **Strategic set** S_i: Each WCV $v_i \in V$ owns a strategy set S_i with size m. Here S_i can be expressed as $S_i = \{s_i\} = \{s_i{}^1, s_i{}^2, \ldots, s_i{}^m\}$, where s_i denotes the strategy set of v_i, and $s_i{}^j$ represents the jth strategy of v_i. Similarly, s_{-i} denotes the strategy set of other WCVs except v_i. After each WCV $v_i \in V$ determines its strategy $s_i{}'$, we define $\{s_1{}', s_2{}', \ldots, s_n{}'\}$ as the **situation** which contains every WCV's strategy.
- **Profit function** $\mathbb{P}(s_1{}', s_2{}', \ldots, s_n{}')$: The profit function stands for the benefit of WCV v_i in **situation** $\{s_1{}', s_2{}', \ldots, s_n{}'\}$ which can be simplified as $\mathbb{P}(s_i', s_{-i}')$.

Each WCV is rational to be able to choose its strategy based on the profit it rewards. Therefore, every WCV wishes to seek for the maximum profit in the given game.

3.2. Nash equilibrium

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

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

3.3. Charging model

In this work, we adopt an omnidirectional wireless charging model, in which one-to-one charging is employed. 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 (Shu et al., 2016). 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. Here 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 the 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 He et al. (2013).

3.4. Problem statement

We consider a problem that in a WRSN, sensor nodes are randomly deployed in an open environment. They are homogeneously equipped with identical energy capacity and energy consumption rates. A number of WCVs are responsible for replenishing energy for all the sensors. When the remaining energy of a node decreases to a threshold, it will immediately send a charging request to the base station. Then the base station will inform WCVs about the request. After that, a WCV will be designated to reply the request later by scheduling, in which an one-to-one charging technique is employed. In our scenario, WCVs have limited energy capacities, when the remaining energy of a WCV is lower than a threshold, it also needs returning to the base station for energy replenishment such as quick battery replacement.

Each WCV is rational, it can dynamically select an appropriate strategy such as charging a node or a WCV. Hence, the charging scheduling problem for fulfilling energy provisioning tasks can be converted into a repeated game taken between WCVs. Each round, when choosing an operation, every WCV focuses on acquiring profit as much as possible. Here, our problem is *how to develop rules or specifications for the game to regulate the behaviors of WCVs so that the overall profit is maximized, which can be formalized as Eq. (2).*

$$\mathbf{max} \quad \mathbb{P}(s_i, s_{-i}) \tag{2}$$

Here, s_i refers to the latest strategy that the WCV chooses, s_{-i} indicates the strategies which are chosen by other WCVs. The obtained profit $\mathbb{P}()$ is demonstrated in Section 4.4.4 in detail, which contains the temporal, spatial and energy interdependency of a charging task.

4. Our scheme

In this section, the proposed scheme is described 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 tth time slot
$s_t(v_i)$	The moving speed of WCV v_i at the tth time slot
$\mathbb{P}_t(v_i)$	The profit of WCV v_i at tth time slot

4.2. Design principles

To overcome existing problems mentioned in previous sections, we use game theory to develop a charging scheme for WRSNs in this work. 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 that strategy to control its behavior.

Since the computation, storage and communication capability of a WCV is much higher than a sensor node, in this work, it is feasible to envision that, in a WRSN, each WCV is "rational" 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 selfish node refers to a node that refuses to do anything, such as delivering packets so as to preserve its own energy. Although the profits of selfish nodes are maximized, other nodes, especially the neighboring nodes, will suffer from more heavy burden. The selfish behaviors of nodes may accelerate energy consumption of normal nodes and even worse, shorten the 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 schemes and selfish behavior issue into consideration. The 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 (WCV to WCV) charging technology to replenish for some WCVs outside.
2. WCVs should own homogenous architecture and functionality, which enhance the scalability and flexibility characteristics. Although WCVs designed in Madhja et al. (2015); 2016) are able to execute V-V and V-N (WCV to nodes) energy replenishment. They are implemented and configured with heterogeneous architecture especially in energy capacity. In fact, they may belong to two different kinds.
3. Lazy or selfish behaviors of WCVs should be avoided. Regulations or rules should be proposed in the game theory process so as to restrict and guide the behaviors of WCVs. Whenever 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. Thus 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 work, the proposed game theoretical charging scheme, termed GTCharge, is able to meet these three principles and requirements. Detailed implementations of GTCharge are given as follows.

4.3. Network model

In this work, we assume that a WRSN is composed of n homogenous rechargeable sensor nodes and a base station which

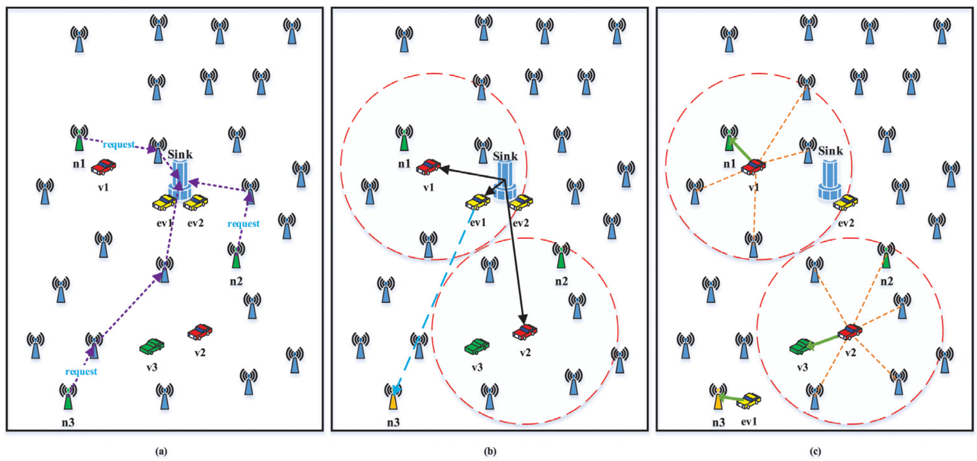

Fig. 1. An example of the system architecture.

acts as an energy source and data sink. A number of homogenous WCVs are employed, which are responsible for replenishing energy for 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 to 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 base station. Then the base station will designate a WCV v_i to charge n_i. An example of the system architecture is shown in Fig. 1.

As shown in Fig. 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 (v_1, v_2 and v_3) 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 base station. The charging requests are delivered to the base station in a hop by hop manner. In Fig. 1(b), the base station informs v_1 and v_2 about their charging regions.

Since n_3 does not locate in any charging region, it will be recognized as a panic node. In the meanwhile, the base station initiates an emergent charging command to ev_1 which contains the location of n_3. In Fig. 1(c), ev_1 arrives at the location of n_3 and then replenishes it. In the meanwhile, v_1 and v_2 select the best charging strategy within their charging regions based on profits. Finally, v_1 decides to charge n_1 and v_2 chooses v_3. Our aim is to maximize the charging efficiency of the network, which is defined as the ratio of energy that is finally received by sensors (Wu, 2014; Zhang et al., 2012; 2015).

In our scheme, WCVs are equipped with GPS for acquiring locations anytime and anywhere. To reduce the storage overhead of WCVs, a WCV only records information such as its remaining energy, the current and next charging objective's locations and residual energy amounts. To guarantee every WCV can come back to the base station for energy replenishment, the location of the base station is also required to be stored by WCVs. With regard to the rechargeable sensors, they only need to maintain their remaining energy and the threshold for initiating a request. The base station collects the locations and energy information of nodes and WCVs. It also detects whether panic nodes exist in the network.

We define actions of 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. $len \leq s_t(v_i) \times \tau$, here, $s_t(v_i)$ is the traveling speed of the WCV and τ 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 one 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 stands for returning back to the base station, it is composed of one or more walk actions.

The above four operations of WCV are preemptive. When a WCV is 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 puts 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 the panic node. It will perform an o_chargenode operation, which is composed of multiple walk actions and a final n_charge action. In the meanwhile, we demand that such an urgent operation cannot be preempted.

4.4. Game theoretical charging scheme GTCharge

The profit of a WCV plays an important role for guiding its behavior, in this section, we introduce our charging scheme based on game theory, namely GTCharge.

4.4.1. Contribution degree of a WCV

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

In the proposed scheme, the contribution degree $c_t(v_i)$ of a WCV depends on its serving frequency to the WRSN, which can be calculated as Eq. (3).

$$c_t(v_i) = (1-\alpha)\cdot c_{t-1}(v_i) + \alpha \cdot (-\mathbb{P}_t(v_i)) \tag{3}$$

Here, $c_i(v_i)$ refers to the contribution degree of WCV v_i on time slot t. Initially, contributions of all WCVs are set to 0 (i.e. $c_0(v_i) = 0, i = 1, 2, \dots w$). $\mathbb{P}_t(v_i)$ denotes 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 lazy or selfish behaviors of WCVs. A larger value of α stands for a bigger proportion 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 its energy consumption rate, residual energy overhead and charging efficiency of WCVs, which is defined as Eq. (4):

$$c_t(n_i) = \frac{2-X}{2}\cdot[(1-\alpha)\cdot(1-E_t(n_i)+v_t(n_i))+\alpha\cdot(\mathbb{P}_t(n_i))] \tag{4}$$

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. $E_t(n_i) = E_0$. Here $v_t(n_i)$ refers to the energy consumption rate of node n_i. Moreover, X indicates whether a node is fully charged in time slot t, which is given in Eq. (5):

$$X = \begin{cases} 0 & \text{charged} \\ 1 & \text{uncharged} \end{cases} \tag{5}$$

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) with 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 GTCharge, 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 consists of multiple actions. As time goes on, the components of an operation may change. Here 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 by Eq. (6).

$$p_t(n_i) = \begin{cases} \frac{c(n_i)^{\beta_1}}{1+c(n_i)^{\beta_1}} & E(n_i) < \delta_1 \\ 0 & E(n_i) \geq \delta_1 \end{cases} \tag{6}$$

Similarly, with respect to charging a WCV, we have Eq. (7).

$$p_t(v_j) = \begin{cases} \frac{c(v_j)^{\beta_1}}{1+c(v_j)^{\beta_1}} & E(v_j) < \delta_2 \\ 0 & E(v_j) \geq \delta_2 \end{cases} \tag{7}$$

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. Charging profit

Given a WCV, in the charging process, its profit can be calculated as Eq. (8).

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

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. Notation m_α denotes the number of WCVs in the service regions 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 the following three conditions.

Condition (1): the profit of a node n_i that gets charged can be calculated as:

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

Condition (2): the profit of a WCV v_i that gets charged is:

$$\mathbb{P}_t(v_i) = -\left(\Delta B + \Delta U\cdot\frac{p_t(v_i)}{\sum_{k=1}^{m_\alpha} p_t(v_k) + \sum_{k=1}^{m_\beta} p_t(n_k)}\right) \tag{10}$$

Condition (3): without calculating profits, a WCV immediately makes a decision.

$$action = \begin{cases} \text{Return} & \sum_{k=1}^{m_\alpha} p_t(v_k) + \sum_{k=1}^{m_\beta} p_t(n_k) = 0 \,\&\&\, E(v_i) < \delta_3 \\ \text{Wait} & \text{Otherwise} \end{cases} \tag{11}$$

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 in Zhang et al. (2015); 2012); Wu (2014); He et al. (2013); 2015), 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 yields 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 proportion of priority is bigger. Therefore, charging for a node or a WCV with a high contribution value will lead to higher profit. Eq. (11) points out the threshold δ_3 for determining whether a WCV needs to return to the base station.

4.4.5. GTCharge algorithm

In the proposed 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 computes the priorities $p_t(n_i)$ and $p_t(v_j)$ and sends it 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 simplicity, we illustrate the process for one round only. According

Table 2
Profit matrix.

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

Algorithm 1 GTCharge algorithm.

Input: Network parameters
Output: The best charging strategy for each WCV $s*$
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 degree of x_i on time slot t, (i.e. $c_t(x_i)$) according to Equation (3) and Equation (4)
  Calculate the priority of x_i on time slot t (i.e. $p_t(x_i)$) according to Equation (6) and Equation (7)
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 (9) and Equation (10)
  end for
end for
Each WCV selects the best strategy $s*$ which maximizes the profit and follows it

to Algorithm 1, GTCharge proceeds as follows. First of all, parameters such as locations of WCVs, remaining energy of nodes are initialized. Then each WCV sends the query message to the base station for 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 WCVs, which locate in the service regions of the WCVs are obtained. After that, the charging priority is computed based on Eqs. (6) and (7). 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 characteristic of GTCharge in detail.

5.1. Existence of nash equilibrium

In this subsection, the existence of Nash Equilibrium of the proposed GTCharge is shown in the following theorem.

Theorem 1. *The situation that all WCVs choose their charging strategies according to GTCharge achieves 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. Thus the strategy space of the game can be formalized as $S = S_{v_1} \times S_{v_2} \times \ldots \times S_{v_n}$.

For simplicity, we assume 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:

$$p_t(v_j) > p_t(n_k), j \in [1, n], k \in [1, n] \tag{12}$$

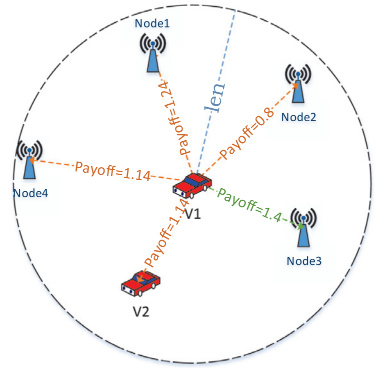

Fig. 2. A case study.

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

Obviously, the following equation is satisfied.

$$\frac{p_t(v_j)}{\sum_{t=1}^{m_\alpha} p_t(v_t) + \sum_{s=1}^{m_\beta} p_t(n_s)} > \frac{p_t(n_k)}{\sum_{t=1}^{m_\alpha} p_t(v_t) + \sum_{s=1}^{m_\beta} p_t(n_s)} \tag{13}$$

Since charging for a node or a WCV will reduce the residual energy of a WCV, we have $\Delta R < 0$. Moreover, we can obtain the following equation:

$$-\left(\Delta L + \Delta R \cdot \frac{p_t(v_j)}{\sum_{t=1}^{m_\alpha} p_t(v_t) + \sum_{s=1}^{m_\beta} p_t(n_s)}\right) > -\left(\Delta L + \Delta R \cdot \frac{p_t(n_k)}{\sum_{t=1}^{m_\alpha} p_t(v_t) + \sum_{s=1}^{m_\beta} p_t(n_s)}\right) \tag{14}$$

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, changing the current strategy 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 achieves a Nash Equilibrium, and the solution obtained by GTCharge is a Nash Equilibrium point. □

5.2. Case study

To intuitively demonstrate the charging behavior of a WCV in GTCharge, the following example is given.

As shown in Fig. 2, four rechargeable sensors (n_1, n_2, n_3, n_4) and two WCVs (v_1 and v_2) are deployed. The service region of v_1 is constructed based on a circle with radius *len*.

Similar to Table 5, we have $L = 1$ and $R = 5$. After executing GTCharge, the corresponding priority table and profit table of v_1 can be obtained (see Table 3 and 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 obtain a higher profit, which increases its

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

own contribution value to the greatest extent. Hence, WCV should charge a node (1) with a high contribution degree or (2) which makes itself a high contribution WCV. As the contribution degree of a node mainly 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 to: (a) minimize the charging times, and (b) charge for nodes which have the minimum remaining energy.

6. Performance evaluations

In this section, extensive simulations are conducted to show the advantages of the proposed scheme. Since our model requires that a WCV can get replenished from another, we compare our scheme with the state-of-the-art collaborative charging algorithms PushWait (Zhang et al., 2012; Wu, 2014) and Hierarchical (Madhja et al., 2015; 2016) in which delivering energy between WCVs are adopted.

6.1. Simulation setup

First of all, parameters used in the simulations are listed in Table 5 unless specified.

As listed in Table 5, 2000 nodes are randomly deployed over a 10,000 m × 10,000 m area. The energy consumption rate for sensors is 0.01. The energy capacity of a WCV is 2000 KJ. When the remaining energy of a sensor falls below 5 J (the threshold), a charging request will be sent to the base station. Ten WCVs are responsible for supplying energy for nodes and WCVs, their moving speeds are all equal to 1 m/s. Each WCV will follow GTCharge to deal with the charging issue.

6.2. Influence of node number

First, 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 Fig. 3, with the increase in number of nodes, the charging efficiencies of three algorithms gradually increase. The energy efficiency of GTCharge is higher than those of PushWait (Zhang et al., 2015; 2012; Wu, 2014) and Hierarchical (Madhja et al., 2015; 2016).

Comparing with the PushWait algorithm, GTCharge does not require all WCVs to move between nodes and the base station back and forth, therefore, traveling cost will be reduced, which enhances the charging efficiency. With respect to the Hierarchical algorithm, 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 Fig. 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 node density. Hence, the traveling cost will be saved and the energy efficiency will increase. In GTCharge, in each round, every WCV selects the best decision, and a node with 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 Fig. 4, the increment of WCVs' energy capacities will lead to slow increasing tendencies of the three algorithms 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 2800 KJ, a significant 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 nodes indicates a longer working time. As shown in Fig. 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 those of PushWait (Zhang et al., 2015; 2012; Wu, 2014) and Hierarchical (Madhja et al., 2015; 2016).

Table 5
Simulation parameters.

Parameters	Values
Network region	10,000 m × 10,000 m
Node number	2000
Region Size	100 m × 100 m
Sensing Range	2 m
Energy consumption rate	0.01
Traveling speed of WCVs	1 m/s
Maximum energy capacity of nodes	10.8 KJ (He et al., 2013; 2015)
Maximum energy capacity of WCVs	2000 KJ
Energy threshold for a node to initiate a charging request	5 J
Charging efficiency for V-V	30% (Zhang et al., 2015; 2012; Wu, 2014)
Charging efficiency for V-N	1.5% (Zhang et al., 2015; 2012; Wu, 2014)
Time slot period	60 s
Sampling times	500

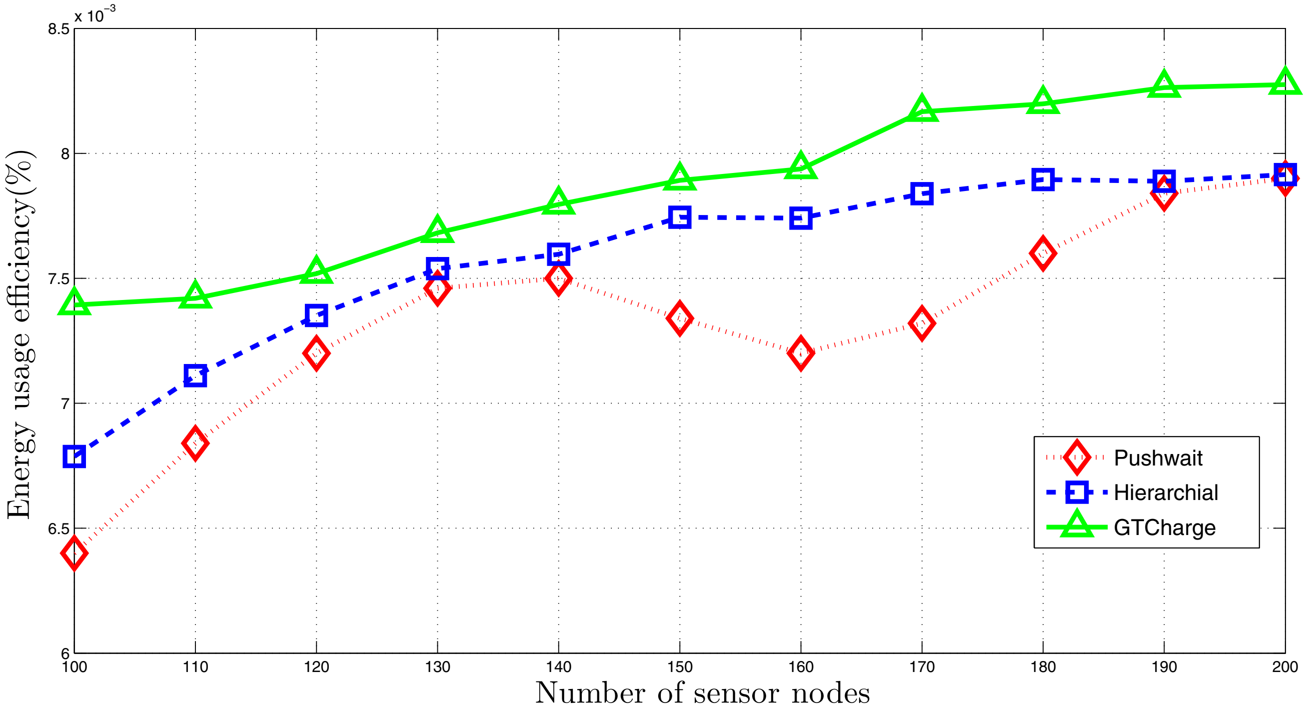

Fig. 3. Influence of node number.

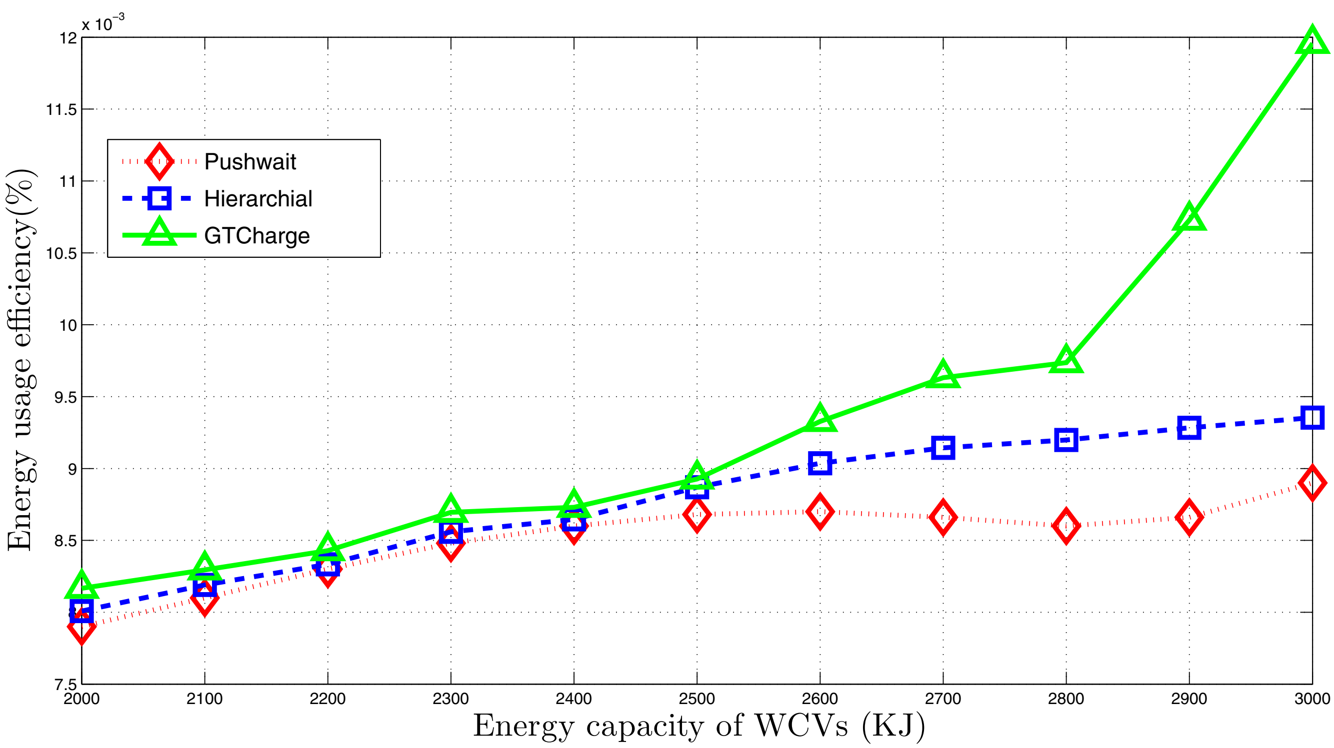

Fig. 4. Influence of WCVs' energy capacity.

6.5. Influence of traveling cost

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

6.6. Characteristics of GTCharge

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

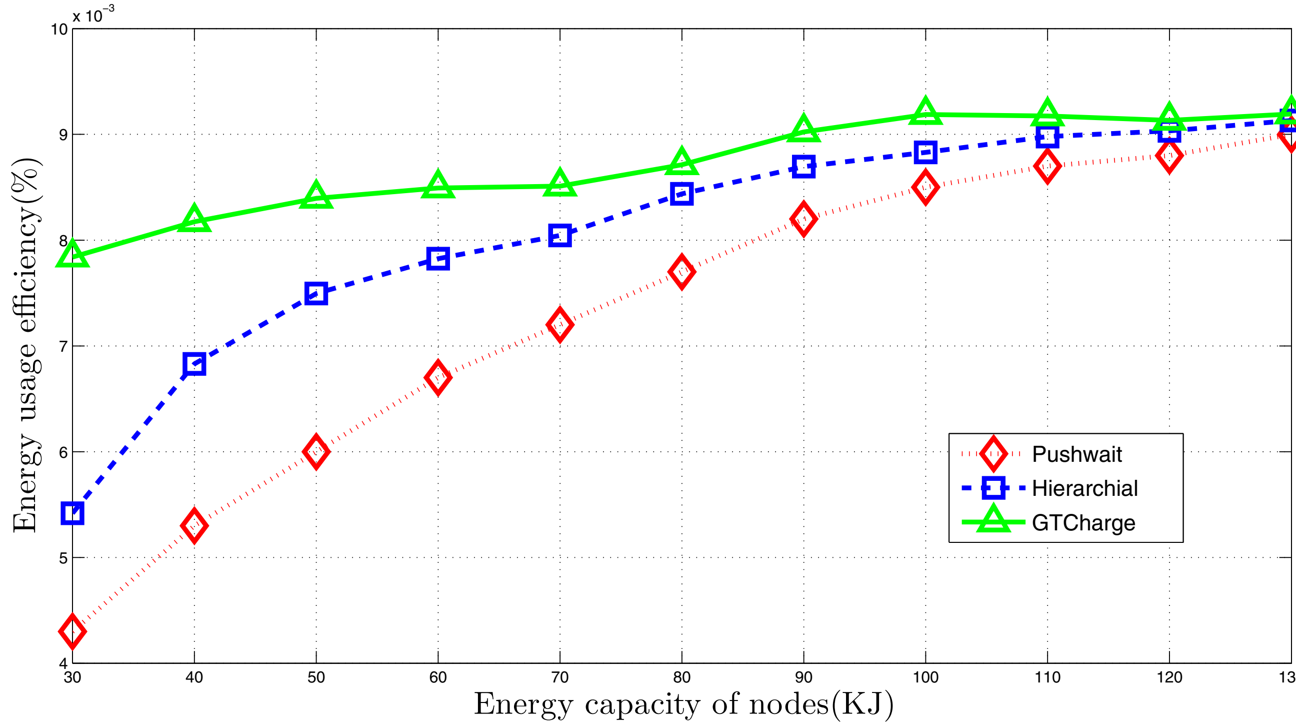

Fig. 5. Influence of nodes' energy capacity.

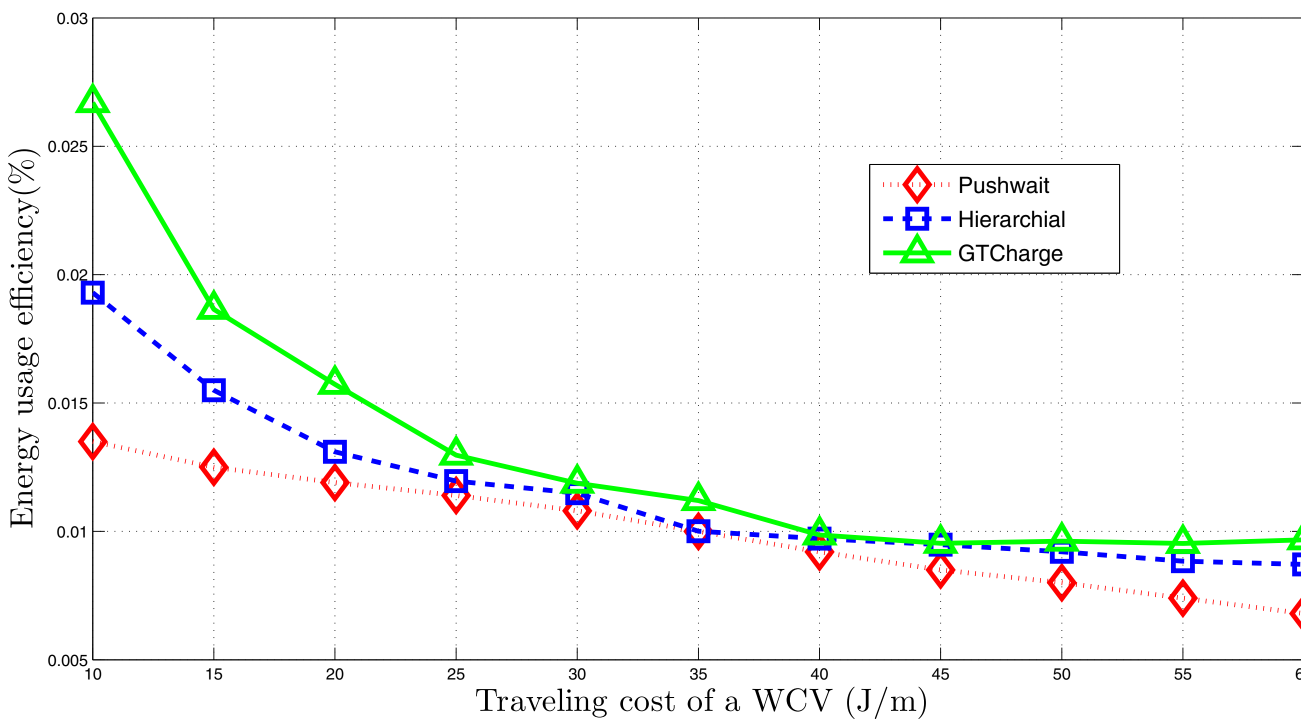

Fig. 6. Traveling cost comparison.

6.6.1. Influence of WCV number

First of all, we evaluate the energy usage efficiency when different numbers of WCVs are employed. As described in Fig. 7, a rapid increment of energy usage efficiency of GTCharge appears, and then stabilizes. The reason is that, in the early stage, the amount of residual energy of all nodes are high, nearly no nodes need energy provisioning, leading to low efficiency of energy replenishment. Then the number of panic nodes gradually increases, and the corresponding energy efficiency arises. In the charging process, each WCV makes the best charging strategy so as to achieve the highest profit, the selecting condition is proved to reach a Nash Equilibrium, which thus causes the stabilizations of the charging efficiency. Afterwards, when a panic node exists, the urgent WCV comes out from the base station, which ensures panic nodes to work again. In that case, the energy efficiency of the network is further improved and finally stabilizes. The results also

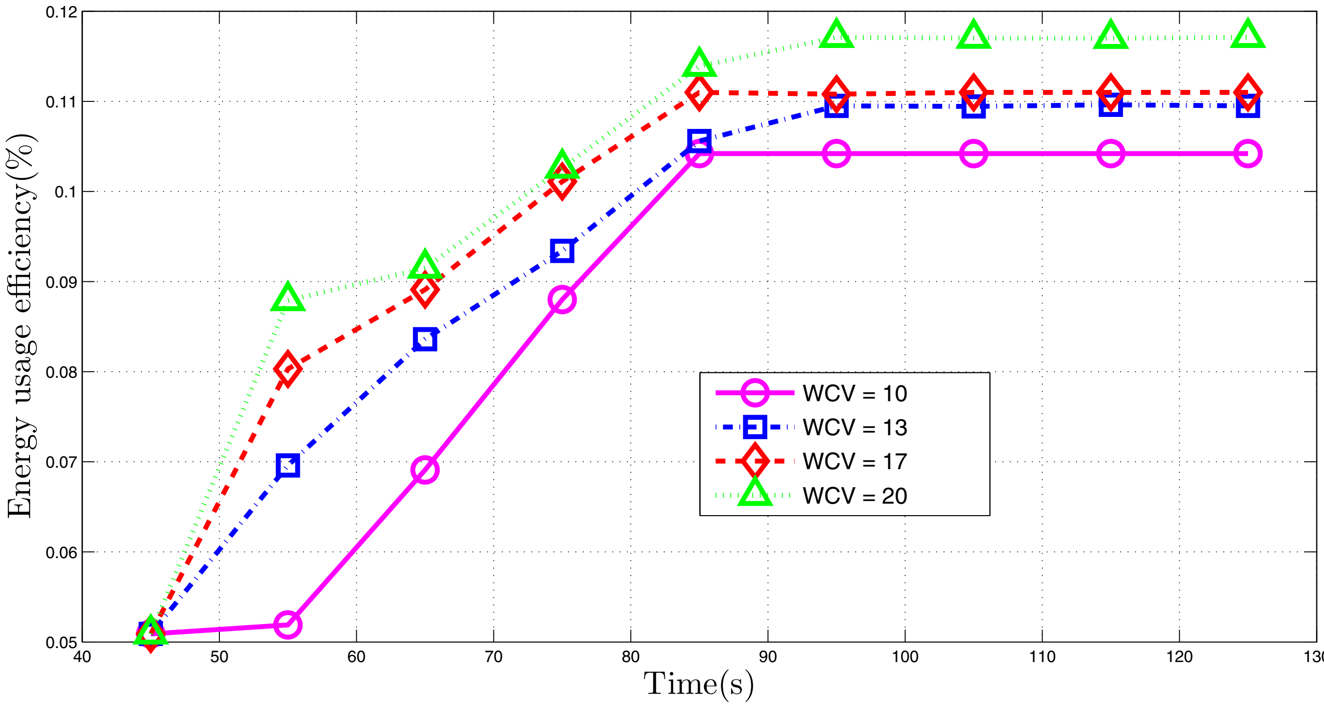

Fig. 7. Energy efficiency under different number of WCVs.

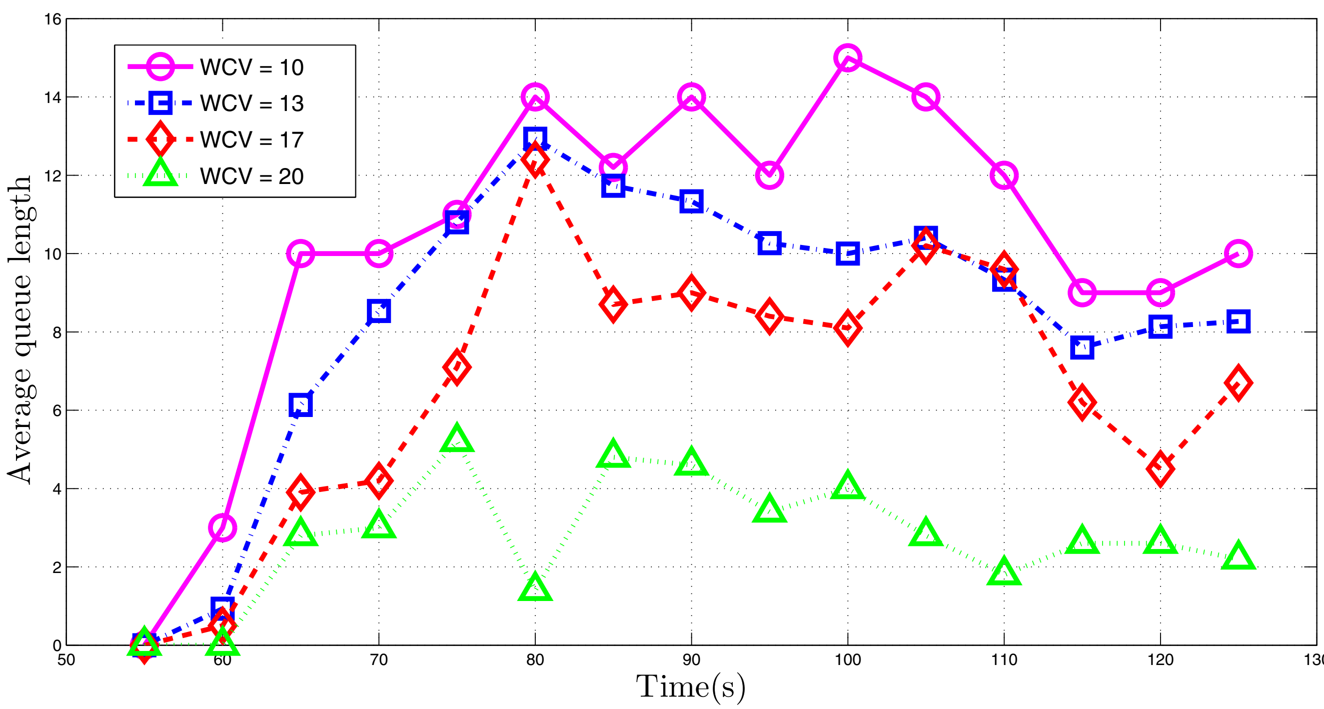

Fig. 8. Comparison of average queue length under different number of WCVs.

reveal that, a larger number of WCVs lead to a higher charging efficiency. As shown in Fig. 7, when WCV=20, the efficiency is the highest. Because more WCVs are available, the average number of nodes a WCV needs to serve is reduced, hence, the energy cost in traveling between nodes is also decreased, which finally enhances the energy usage efficiency.

6.6.2. Average queue length

Next we analyze the performance from the perspective of average queue length. It refers to the number of nodes recorded in WCVs 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 described in Fig. 8, the average queue length is at most 15, which indicates that, the WCV only needs to maintain a short queue when working. We also observe that more WCVs will lead to smaller queues.

6.6.3. Number of panic nodes

In this simulation, we count the number of the panic nodes. It indicates the ability of the WCV in maintaining the network. A larger number of panic nodes stand for a lower capability in

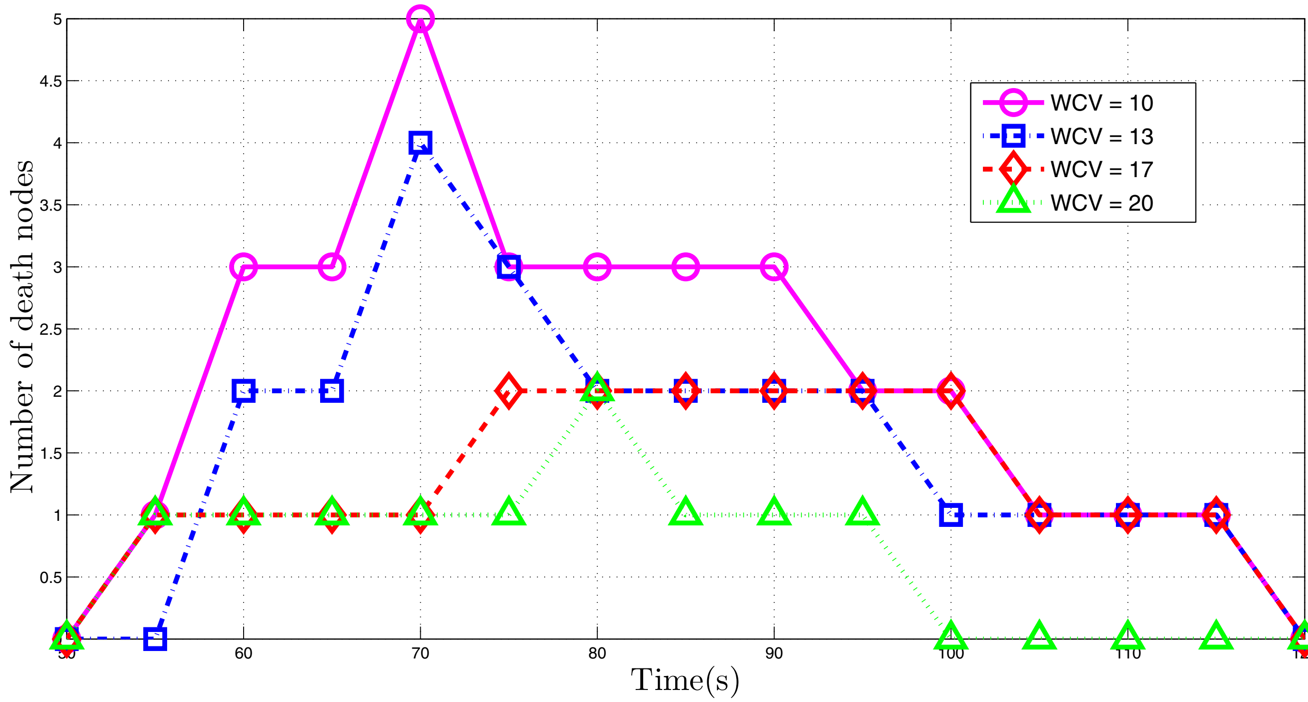

Fig. 9. Comparison of number of panic nodes under different number of WCVs.

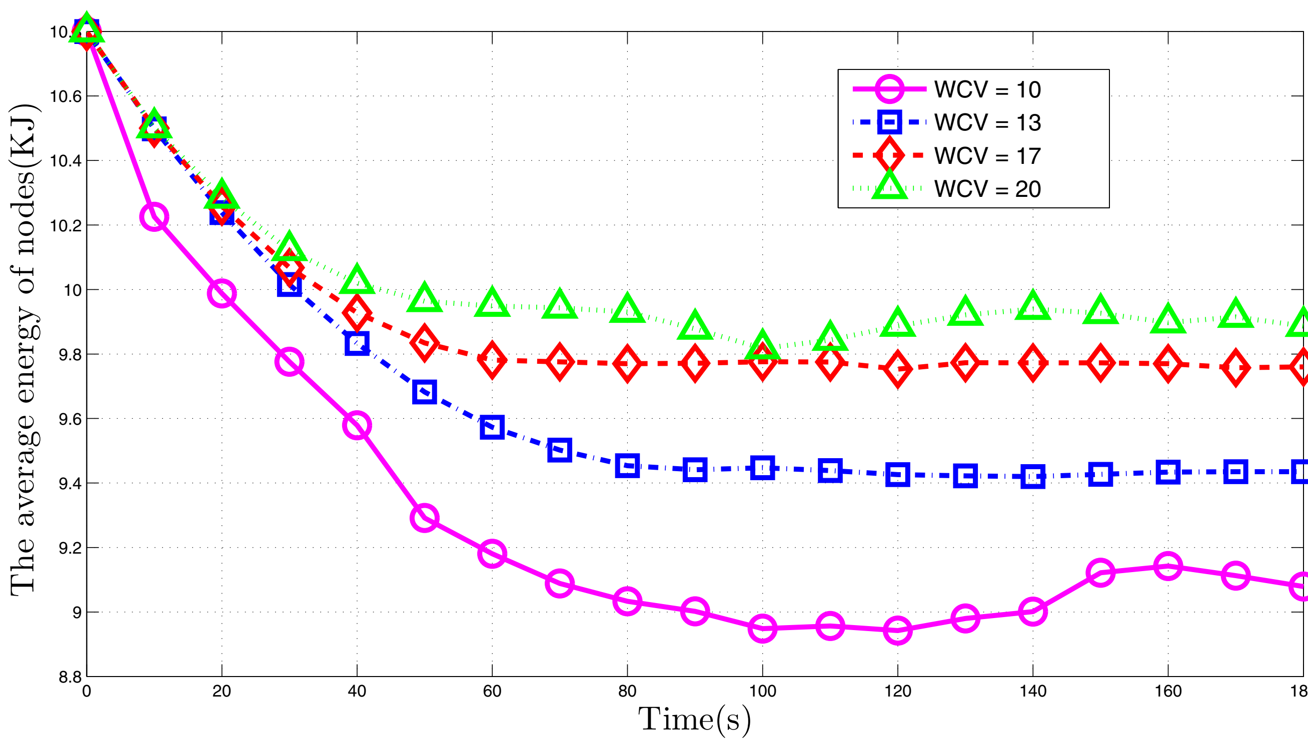

Fig. 10. Comparison of average energy of charging regions under different number of WCVs.

maintaining survivance and functionality of the network. On the contrary, fewer nodes are suffering from exhaustion, guaranteeing the network connectivity. In Fig. 9, with the simulation running on, the number of panic nodes in the beginning is nearly 0. We observe that after 65th time slot, when Nash Equilibrium is reached, the number of panic nodes dramatically increases due to massive booming of panic nodes. After 90th 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 presented 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.

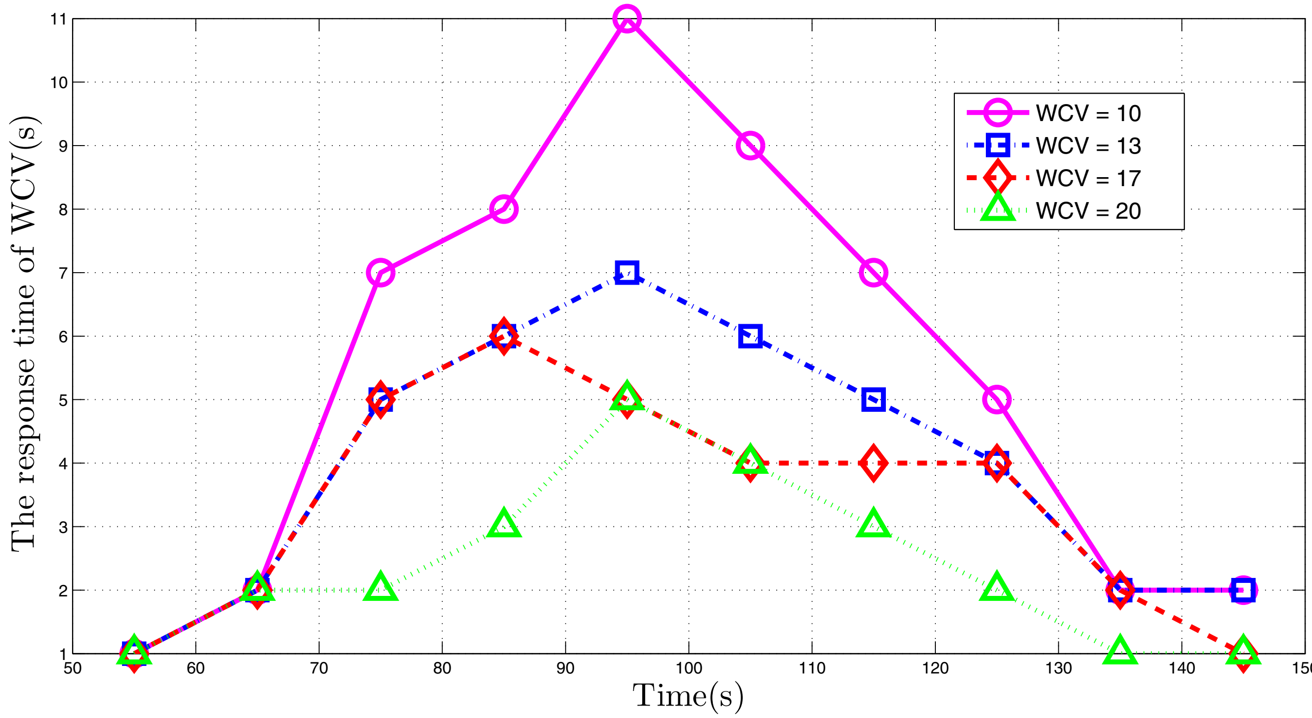

Fig. 11. Comparison of average response time under different number of WCVs.

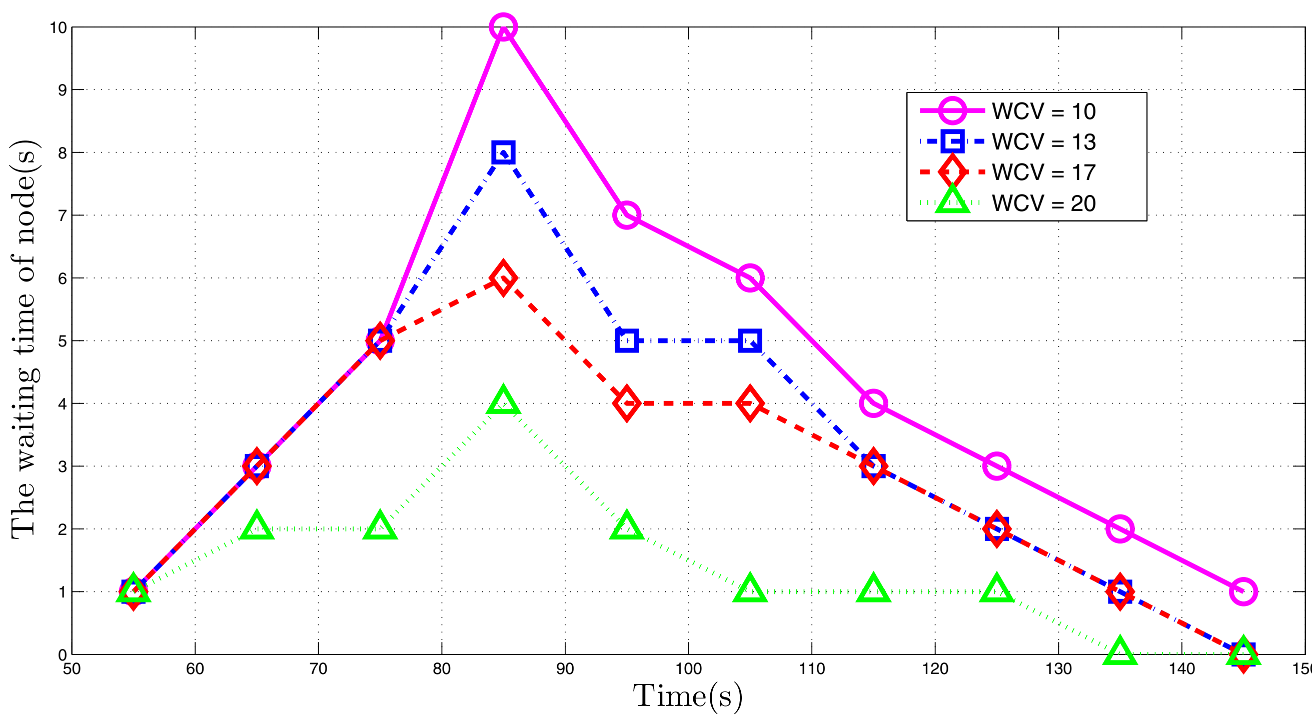

Fig. 12. Comparison of average waiting time under different number of WCVs.

6.6.4. Average energy of charging regions

The characteristic "average energy of charging regions" refers to the ratio of overall energy amount and the number of WCVs (i.e. one WCV corresponds to one charging region). A higher average energy indicates a lower intensity of charging demands. As shown in Fig. 10, in the former time slots, the Nash Equilibrium point has not been reached, which thus causes a sharp decrease in average energy. After 75-th time slot, the condition of charging strategies reaches Nash Equilibrium, the average energy of nodes gradually stabilizes. We also note that, a higher number of WCVs yields a higher energy amount. When WCV=20, the corresponding energy of regions is higher than the others.

6.6.5. Average response time

The average response time is defined as the time delay beginning when charging request is sent and ending when a node is

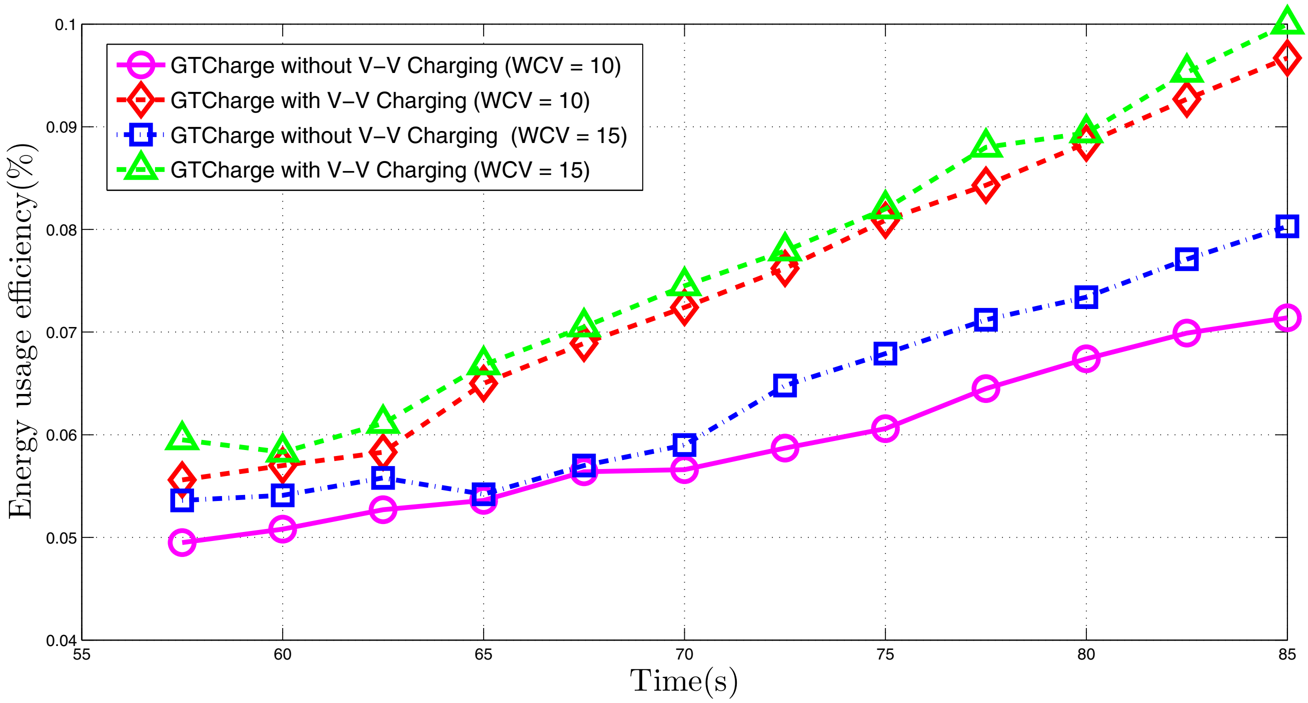

Fig. 13. Energy efficiency of V-V charging.

completely charged. It reflects the ability of a WCV in satisfying the requirements of panic nodes. As shown in Fig. 11, with the increment of the charging request number, the average response time gradually increases. That is because, in that case, the urgent WCVs will be called for providing energy supplement. Since a WCV cannot simultaneously charge for two nodes, sometimes, a panic node has to wait for charging. Accordingly, its response time is long. We also note that, a larger number of WCVs lead to a shorter response time. After that, then urgent WCVs are set out for energy provisioning and the corresponding time gradually reduces. Larger number of WCVs can decrease the response time, hence, when WCV=20, the charging delay is the shortest.

6.6.6. Average waiting time

At last, 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 fully charged. It indicates the urgency for serving 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 are needed to be satisfied. As shown in Fig. 12, the average waiting time grows up and down in the beginning. After 85th time slot, the urgent WCVs are set out, leading to a reduction in waiting time. Finally, when Nash Equilibrium is reached, the waiting time gradually converges into a small value. Fig. 12 also implies that a larger number of WCVs lead to shorter charging response. We conclude that more WCVs can improve the energy efficiency.

6.6.7. Feasibility of V-V charging

A prominent feature of GTCharge is that the charging between WCVs is employed (i.e. V-V charging technique). To demonstrate the advantage and feasibility of V-V charging technique, we compare the performance of GTCharge with and without V-V charging scheme. As shown in Fig. 13, the energy usage efficiency when WCV=15 no matter V-V charging technique is applied or not is higher than those of WCV=10. The energy efficiency of V-V charging is higher than GTCharge without V-V charging. The energy efficiency gap between V-V charging and without V-V charging gradually increases with time going on. This phenomenon indicates that the collaborative charging, especially when the V-V charging technique is implemented, is feasible for enhancing the charging efficiency, laying foundations for applying game theoretical scheme in collaborative charging applications. Therefore, it is feasible to apply V-V charging in WRSNs.

7. Conclusions and future work

In this paper, a game theoretical collaborative charging scheme GTCharge for WRSNs has been proposed. In GTCharge, each WCV is able to rationally control its behavior. The collaborative charging process is converted into a collaborative game taken between WCVs. We investigated 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 proved to reach a Nash Equilibrium point. At last, simulations are conducted to demonstrate the superiority of the proposed scheme. Simulation results also show that, comparing with the state-of-the-art collaborative charging algorithms, GTCharge can enhance the energy efficiency. Moreover, salient features of the proposed scheme are also investigated. The impact of WCV number is discussed from perspectives of average queue length, number of panic nodes, average response time and so on.

As part of our future work, we will concentrate on the following issues.

1. How to use evolutionary game theory to further enhance the performance especially in terms of self-adaptive optimizations for GTCharge.
2. How to merge path planning algorithm into GTCharge for reducing the extra traveling cost posed by preemptions in playing a game.

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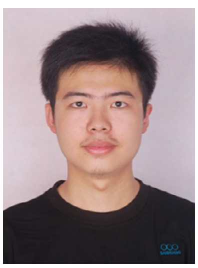

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