Journal of Systems Architecture 000 (2016) 1–13

Contents lists available at ScienceDirect

Journal of Systems Architecture

journal homepage: www.elsevier.com/locate/sysarc

# TADP: Enabling temporal and distantial priority scheduling for on-demand charging architecture in wireless rechargeable sensor Networks

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ARTICLE INFO

*Article history:*
Received 10 September 2015
Revised 9 March 2016
Accepted 14 April 2016
Available online xxx

*Keywords:*
Wireless rechargeable sensor networks
Charging scheduling
Temporal & distantial priority charging scheduling
Preemption
On-demand charging architecture

ABSTRACT

Recently, adopting mobile energy chargers to replenish the energy supply of sensor nodes in wireless sensor networks has gained increasing attentions from the research community. The utilization of the mobile energy chargers provides a more reliable energy supply than systems harvesting dynamic energy from the surrounding environment. Wireless power transfer technique provides a new alternative for solving the limited power capacity problem for so many popular mobile wireless devices, and makes wireless rechargeable sensor networks (WRSNs) promising. However, mainly due to the underestimate of the unbalanced influences of spatial and temporal constraints posed by charging requests, traditional scheduling strategies for on-demand WRSNs architecture achieve rather low charging request throughput or successful rate, posing as a major bottleneck for further improvements. In this paper, we propose a TemporAl & Distantial Priority charging scheduling algorithm (TADP), which takes both the distance between nodes and the mobile charger and the arrival time of charging requests into consideration, and quantizes these two factors step by step. TADP forms a mixed priority queue which directs mobile charger to replenish the energy for nodes. At last extensive simulations are conducted to demonstrate the advantages of TADP. Simulation results reveal that TADP can achieve better scheduling performance in guaranteeing the scheduling success of the high-priority tasks and improving stability of the system.



## 1. Introduction

Wireless Sensor Networks (WSNs) are composed of a large amount of cheap micro sensors, which are deployed in a specific area for event monitoring. The functionalities of WSNs include sensors cooperative awareness, information collection and target monitoring. Potential applications cover military, aviation, disaster relief, environment, medical treatment, industry and other domains.

Usually, sensors in WSNs are powered with batteries, which have constrained energy capacity, leading to limited network lifetime. This has been a long lasting, fundamental problem faced by sensor networks. To resolve this problem, in recent years, more and more researchers have devoted their efforts to developing energy preservation schemes, for example, energy harvesting protocols [15,28,36], data aggregation protocols [20,23,33], energy preserving MAC protocols [27,34], etc. Although lifetime has been prolonged to some extent, the problem of limited energy constraints, especially the limited battery capacity has not been resolved yet. The network lifetime is still acting as a bottleneck, which is regarded as the core reason that hinders the widespread deployment and long life cycles of WSNs.

Recent breakthrough in wireless power transfer (WPT) technique [17] provides a new alternative for solving the limited power capacity problem, and it is regarded as a promising way to prolong the network lifetime. Different from energy harvesting, WPT together with 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 passively adapted to the environmental resources. Nowadays, the WPT technique has been used for charging mobile devices, electric vehicles, implant devices and WSNs [39]. Based on these applications, Xie et al. [43] coined the term of the wireless rechargeable sensor networks (WRSNs).

A WRSN is made up of three components: a base station, wireless charging vehicles and rechargeable sensors. The base station collects and aggregates data from sensor nodes. In the meanwhile,

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http://dx.doi.org/10.1016/j.sysarc.2016.04.005
1383-7621/

to avoid sensor energy exhaustion, a WCV is responsible for providing the energy supply for the rechargeable sensors. The network lifetime of WRSNs directly depends on the charging efficiency, especially for the large scale WRSNs. Because of the large number of sensors, only a slight deterioration in performance will yield to considerable extra resource expenditure.

One of the most common ways to solve the charging path planning problem is to convert the wireless charging problem into the Traveling Salesman Problem (TSP) [41–43]. These algorithms are deterministic methods, in which information such as location coordinates, energy status of nodes are assumed to be known by WCVs. To solve TSP, the shortest Hamiltonian cycle is constructed, which is regarded as a feasible solution as well as a practical charging path for a WCV. Although Hamiltonian cycles are feasible for both single-node charging schemes [43] and multi-node charging schemes [40,41], a series of prominent problems still exist, which make deterministic charging impractical.

1. Large computational & storage overhead. Previous methods assumed that a WCV records all information of nodes, such as location coordinates, energy consumption rate and residual energy status [5,41–43]. Given a large scaled WRSNs, thousands of nodes are deployed, recording the information of these nodes poses a large challenge for WCVs with respect to computational and storage overhead.
2. Stationary network topology. Traditional methods [6,38,41–43] assumed that nodes in WRSNs are stationary, and the network topology is fixed. However, in practice, topological structure frequently changes due to joining of new nodes or leaving of old nodes. Obviously, this assumption contradicts the characteristics of WSNs, such as dynamicity, self-organization and non-deterministic, which is not feasible for WRSNs.
3. Complicated network structures [45] have nodes taking different roles in energy charging, such as proxy nodes, head nodes and so on. Then, a hierarchical structure of the network is constructed for realizing charging scheduling. This technique is not practical, because heterogeneity of nodes in functionalities are required.

On the contrary, non-deterministic methods employ on-demand charging [9,10,13,14]. Sensors send their energy charging requests to WCVs when their energy levels run below a threshold in a real-time manner. Upon the reception of a request, WCVs will immediately rearrange the order of recorded charging tasks, select a candidate sensor, and proceed. One of the most typical non-deterministic methods for the on-demand mobile charging problem [9,10] is Nearest-Job-Next with Preemption (NJNP), which schedules the charging of individual nodes based on spatial attributes. NJNP allows the mobile charger to switch to a closer target node if the new requesting node is closer to the mobile charger. Regardless of the fact that the non-deterministic schemes are more feasible, there are still some prominent drawbacks, such as low efficiency in preemption and charging scheduling that cannot be overlooked.

Motivated to overcome the existing problems and enhance the charging efficiency, we proposed a temporal and distantial priority charging scheduling algorithm TADP for solving energy replenishment problem for WRSNs. TADP forms a priority queue which directs mobile charger to replenish the energy for nodes.

The contributions of this work can be summarized as follows:

1. To quantify the priority of a charging task, we merged temporal priority and distantial priority into a mixed priority. A table for quantifying the mixed priority into a real number is given.
2. To achieve real-time scheduling, we proposed TADP, which deals with preemption for scheduling. Each time, the charging request with the highest mixed priority will be served.
3. We implemented sophisticated simulations to compare the performance of TADP with a state-of-the-art scheme NJNP, which is designed for on-demand charging. Then salient features of TADP are demonstrated in comparison.

The remainder of this paper is organized as follows. In Section 2, we give a brief overview on current research on WRSNs. In Section 3, the charging algorithm TADP is described in detail. Extensive simulations are conducted to show the outperformed performance of TADP in Section 4. At last, Section 5 concludes this paper and outlines the future work.

## 2. Literature review

In literature, energy charging schemes for WRSNs fall into three categories: periodical charging, collaborative charging and optimizations for charging performance.

Periodical charging schemes [39,41,43] converted the energy charging problem into a Traveler Salesman Problem (TSP) [22] based on the energy distribution model and the energy consumption model, in which shortest Hamiltonian cycle is calculated as the solution. Periodical charging schemes can be divided into two types: single-node charging scheme [43] and multi-node charging scheme [19]. In single-node charging scheme, each time, a WCV is responsible for replenishing energy for one sensor, and the charging efficiency is relatively low. A straight-forward method is to simultaneously charge several neighboring nodes, which is called multi-node charging scheme. In multi-node charging solution, a WCV can simultaneously charge multiple neighboring nodes within its charging range, which improves the efficiency greatly [29,42]. Based on the multi-node charging solution, Xie et al. considered path planning problem when WCVs are regarded as the mobile base station [40,41] by establishing Smallest Enclosing Dist (SED) [6,38]. They set up concentric circle structures and regard the overlapping part of concentric circles as the resting spot of a WCV. Similarly, Fu et al. [6] proposed the discretization of wireless charging planning theory which also set up the concentric circles structure in the SED and searched of the resting spot of a WCV from the overlapping area. However, Dai et al. pointed out [5] that the amount of calculation based on SED is large and it is not suitable for large-scale wireless sensor networks.

As for collaborative charging method, He et al. [8,9,25,26] indicated that many constraints in periodical charging that cannot be overlooked, such as certainty and periodicity. Uncertain factors may cause immeasurable effects for both energy demand and energy supply. Hence, it is necessary to adopt collaborative charging mechanism [8,9] to meet the non-homogeneous demands for uncertain factors, dynamic topology and node properties. They proposed a dynamic programming method for the path of one WCV based on NJNP. Moreover, they evaluated the system from aspects of system throughput and charging delay. In WCVs' charging schedule and route choice, Guo et al. [7] proposed a charging scheduling method based on a tree structure to reduce charging consumption rate and charging delay. Li et al. [18] proposed a method named J-Roc that combines routing protocol with charging policy. WCVs update global energy status information and then schedule to charge. At the same time, nodes use a rechargeable awareness routing protocol to select a path of low energy consumption for transmission. In this way, network energy consumption is balanced and network lifetime is prolonged.

Although collaborative charging method can effectively solve the impact of uncertainty factors in WRSNs, it still neglects the reliability of charging demand information and real-time transmission requirements. Loss or delay of charging demand information may lead to disability for WCVs to arrive at the charging place before exhaustion of nodes. It will also influence the reliability of the network. Hence, the real-time and reliability for demanding information transmissions are needed to be focused on, along with hybrid scheduling problem of demand information and gathering information.

As for performance analysis and optimization of WRSN, Jiang and Cheng et al. [12,48] 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] in network. They optimized the performance of the system in terms of WCVs' behaviors, data transfer protocol, coordination control and so on. Angelopoulos et al. [1] posed the charging decision problem and proved its complexity. In order to optimize the performance of the system, they deeply studied how to quantize path of WCVs, charging decision of WCVs and charging the amount of WCVs.

All of the optimization methods above can indeed improve the network performance. However, charging for a large-scale WRSN is a long process. Therefore, continuous optimizations for system parameters are needed. Moreover, there exists uncertainty in system performance due to the influence of uncertain factors. Hence, heuristic algorithms are not suitable here [24]. Besides, in recent years, researchers are also aiming at multiple WCVs coordinated charging mechanism. Zhang [46,47] has designed multiple cooperating WCVs charging mechanism, in which WCVs can transfer energy to each other. In their scheme, charging orders are scheduled and system charging efficiency is also optimized.

In our latest works [19,21], we proposed several charging algorithms for wireless rechargeable sensor networks. In [19], two charging algorithms HCCA (i.e. Hierarchical Clustering Charging Algorithm) and HCCA-TS (i.e. Hierarchical Clustering Charging Algorithm based on Task Splitting), which aim at shortening charging time and distance via merging and splitting charging tasks, are proposed. In [21], 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.

Now, designing scheduling algorithms of WRSNs still faces some problems. With respect to deterministic method, charging for each node is periodically taken. It is impractical to obtain detailed system descriptions, such as, nodes' positions and channel condition and so on. On the other hand, non-deterministic methods envision an on-demand charging process. When the node's energy is less than a threshold, it will immediately send a charging request to WCVs. After receiving this request, WCVs will reschedule the order of charging tasks and choose a node as the objective. NJNP is one of classical non-deterministic methods which realize on-demand charging [9,10]. It makes decisions on which node to be charged based on the spatial attributes of nodes. A charging request that belongs to the node which locates nearest to the WCV will be responded first.

Although the non-deterministic methods are more realistic, there are still some disadvantages that cannot be overlooked.

(1) In NJNP, time is divided into slices. Preemption can only occur once in each slice. Suppose the preemption occurs frequently, a large amount of energy will be wasted in movement due to frequently changing the charging target nodes.
(2) Since preemptions occur randomly at any time, if they occur at the last few time slices, NJNP can only satisfy the last charging request, and the scheduling will become useless. In that case, the charging throughput is low.
(3) Many methods tend to increase the proportions of spatial correlations, which will cause remote nodes cannot timely get charged and starve to death (i.e. run out of power).

**Table 1**
Symbols and definitions.

| Symbol | Definition |
|---|---|
| $D(A)$ | Distance between WCV and node $A$ |
| $T(A)$ | Remaining lifetime of node $A$ |
| $Pd(A)$ | Distantial priority of node $A$ |
| $Pt(A)$ | Temporal priority of node $A$ |
| $P(A)$ | Mixed priority of node $A$ |
| $De(A)$ | Distantial density of node $A$ |
| $\phi$ | A warning threshold for initiating a charging request |
| $t_w(A)$ | Waiting time of node $A$ |
| $t_0$ | A warning threshold for increasing the temporal priority |
| $V_m$ | Running speed of the WCV |
| $V_d$ | Energy consumption rate of nodes |
| $V$ | Ratio between $D(A)$ and $T(A)$ |
| $N$ | Number of nodes |

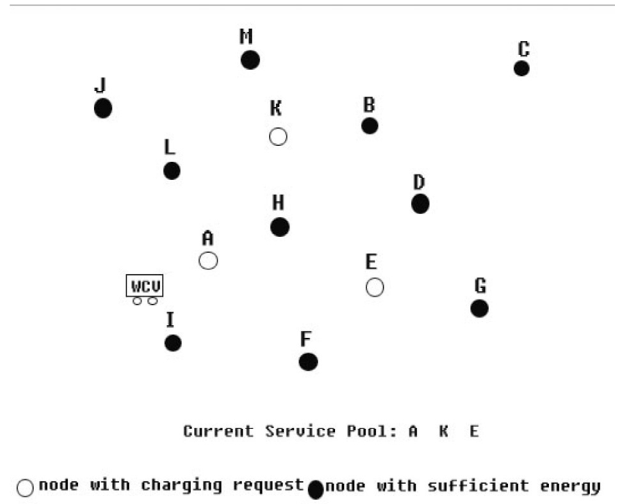


**Fig. 1.** On-demand charging architecture.

In the following, we will propose a temporal & distantial priority charging scheduling algorithm to improve the performance under the on-demand charging framework.

## 3. Proposed scheme

### 3.1. Problem statement

Before starting, we firstly list the variables used throughout the paper in Table 1.

Fig. 1 depicts the framework of the on-demand charging architecture. A set of nodes, which have the same battery capacity and energy consumption rate $V_d$ are distributed over a square area with the side length $L$. After deploying nodes, the location of each node can be determined by using some localization methods, such as [30]. When a node's power is lower than a certain threshold $\phi$, it will immediately send a real-time charging request to the WCV by adopting these state-of-the-art protocols [16], used for tracking and communicating with the mobile charger. For easy comparison, the request delivery time is assumed to be negligible [44] in this work, when compared with WCV's traveling time. Similar to the assumptions in [9], sensor nodes are able to locate the position of the WCV timely.

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 [31]. Specially, we adopt the following equation as the wireless charging model:

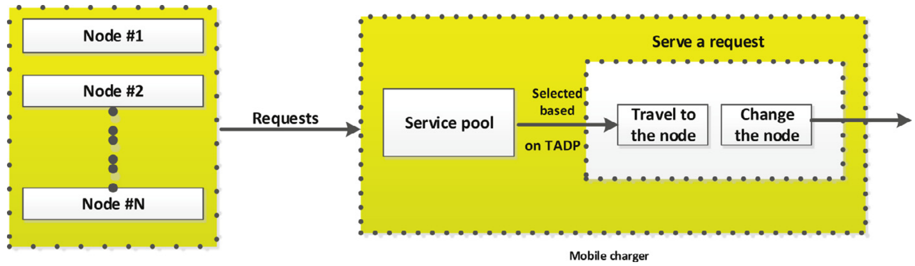


**Fig. 2.** Formalized queuing model.

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

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. $\lambda_0$ is referred to wavelength. $L_p$ indicates the polarization loss. $\eta$ is used to represent the rectifier efficiency. $d$ is the distance between WCV and the sensor node on charging. The parameter $\xi$ is assigned to 0.2316 according to [11].

We also assume that only one WCV is available in a WRSN. The WCV collects all the charging requests and saves them in the service pool. As shown in Fig. 1, the service pool records the information of positions of node A, node K and node E. Since charging requests are limited by time, charging scheduling problem can be regarded as a real-time task scheduling problem. And it needs to sort the charging requests in a queue by urgency and priority. Once a request is selected as the immediate responsive task, WCV will charge the node at once. Therefore, the order in the task queue directly relates to the travel path from WCV to the node. In the framework of on-demand charging, the WCV is traveling at a constant speed. Similar to [11], we ignore the influence of charging time.

Under the on-demand charging architecture, when the residual energy of a node falls below a certain threshold $\phi$, it will immediately originate a charging request to the WCV in a real-time manner. In the scheduling process under on-demand architecture, we define a Poisson distribution of the charging requests, which means their inter-arrival time is exponentially distributed [9]. The service time for each request follows negative exponential distribution.

As shown in Fig. 1, three nodes (i.e. A, K and E) have sent charging requests to WCV, then WCV stores them in the waiting queue according to their arrival time. By executing specific scheduling algorithms, WCV selects one request, sets the sender of the request message as the objective node, and moves towards the objective node. Therefore, the problem of task scheduling under on-demand architecture by using TADP scheduling algorithm can be formalized as an M/M/1/∞/N/TADP queuing model (see Section 3.2), which is depicted in Fig. 2.

### 3.2. M/M/1/∞/N/TADP queuing model

In this section, we analyze the characteristic of the proposed M/M/1/∞/N/TADP model ($N = 100$), which provides fundamental guidance for designing the charging algorithm and simulations.

In the M/M/1/∞/N/TADP queuing model, the packet arrival follows a Poisson distribution with a parameter $\lambda$. The service time follows a negative exponential distribution with the mean value $\frac{1}{\mu}$. The process of packet arrival and the service time are mutually independent. In the WRSN, one WCV is available, which means the number of servers is 1. While system capacity can be infinite, that is ∞. Since the network is deployed by 100 nodes ($N = 100$), the number of customer sources is 100. Next, the adopted service rule in this work is TADP. We use $\{N(t) = j, t \geq 0\}$ to indicate the number of packets in the system at any time $t$, the state space is $\psi = \{0, 1, 2, \ldots, j, \ldots\}$.

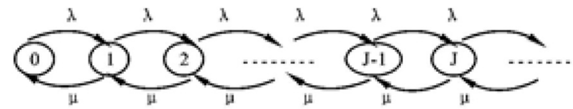


**Fig. 3.** State transition model.

The state transition probability of $N_j = N(t = j\sigma)$ is:

(1) The probability of one charging request arriving is $\lambda\sigma + o(\sigma)$. The probability of 0 request arriving is $1 - \lambda\sigma + o(\sigma)$. Here, $o(\sigma)$ means the higher order infinitesimal of $\sigma$.
(2) When a WCV is responding to a request, the probability that one data request is fully served is $\mu\sigma + o(\sigma)$, otherwise, the probability is $1 - \mu\sigma + o(\sigma)$.
(3) The probability of more than one data request arriving or leaving is $o(\sigma)$.

The state transition relation model is shown in Fig. 3.

Based on the above analysis, we can calculate the average number of packets within the system as:

$$L_s = \sum_{k=0}^{\infty} k p_k = \rho(1-\rho)\sum_{k=0}^{\infty} k\rho^{k-1} = \frac{\rho}{1-\rho} = \frac{\lambda}{\mu-\lambda} \tag{2}$$

where $\rho$ is the service intensity of system, which can be computed as $\rho = \frac{\lambda}{\mu}$. When $\rho < 1$ satisfies, the system will remain stable. $p_k$ refers to the probability of arrivals of k packets.

**Theorem 1.** *Assume that arrivals of charging requests follow a Poisson flow, with the average intensity $\lambda$, while the service time of the WCV follows negative exponential distribution, whose average service rate is $\mu$. Then:*

$$L_s = \lambda W_s \tag{3}$$

$$L_q = \lambda W_q \tag{4}$$

*Here, $L_s$ and $L_q$ indicate the average number of sojourning requests and average number of waiting groups in the queuing system.*

**Proof.** We express the sojourning time for the requests within the time $T$ as $t_1, t_2, \ldots$. The mean number of arriving requests is $\lambda T$. Then the average number of sojourning requests within the system can be calculated as:

$$L_s = \frac{\sum_i t_i}{T} \tag{5}$$

The average time for a request that sojourns in the service pool is:

$$W_s = \frac{\sum_i t_i}{\lambda T} \tag{6}$$

Hence, we have the Eq. (3), (4). □

According to Theorem 1, the average delay for a charging request to be responded can be computed as:

$$W_s = \frac{L_s}{\lambda} = \frac{1}{\mu - \lambda} \quad (7)$$

The average number of waiting groups in the queuing system is:

$$L_q = L_s - \rho = \frac{\lambda^2}{\mu(\mu - \lambda)} \quad (8)$$

At last, we express the average waiting time for the requests to be responded as:

$$W_q = \frac{L_q}{\lambda} = \frac{\lambda}{\mu(\mu - \lambda)} \quad (9)$$

In WRSNs, due to the temporal and spatial characteristics of charging tasks, the scheduling algorithm should cover both aspects. In the proposed scheme, we merge both temporal priority and spatial priority of a task into a mixed priority. Thus, the mixed priority is utilized to guide the charging behavior of the WCV.

We define $\phi$ as the warning threshold value of minimum residual energy. In other words, when the residual energy of a node is lower than $\phi$, it will immediately send a charging request including coordinates and energy status to the WCV. We define $t_w(A)$ as the time of waiting before WCV arrives.

On-demand task scheduling should meet various requirements, such as, mutual independence of time and space, preemption, priority adjustment and so on. Therefore, we will present the approach to meet the above requirements next.

### 3.3. Determination of warning threshold

A critical value in request ordering is the warning threshold $\phi$, in the followings, we will explain how to calculate the warning threshold $\phi$. We define $L$ as the side length of the region and $V_m$ as the running speed of WCV. $T$ is denoted as the maximum time consumption for WCV to move from one location to another in the square area. We can get Eq. (10):

$$T = \frac{\sqrt{2} * L}{V_m} \quad (10)$$

In order to keep all nodes alive, when a charging request is delivered to the WCV, the remaining time for the corresponding node to live should be equivalent to $T$, which ensures that node could get charged before exhausted. At the same time, since not all charging requests would be eventually responded, we have to consider the length of charging queue $L_q$. We define $\mathrm{V_d}$ as the energy consumption rate of nodes. Therefore, we can get the remaining power threshold $\phi$ by Eq. (11):

$$\phi = T * V_d * L_q \quad (11)$$

### 3.4. Adjustment of temporal priority

In this section, we demonstrate how to adjust the priorities of charging requests in the queue.

In practice, in a WRSN, there exists a fraction of nodes that eventually run out of power due to a long period of starvation (i.e. waiting for get charged). Hence, it is not enough to determine requests' priorities only by warning critical value. A promising approach is to increase the temporal priorities of nodes when the waiting time $t_w$ arrives at a threshold value $t_0$. Hence, a major problem is how to determine the value of $t_0$. We use $P_{\mathrm{cur}}$ to indicate the residual energy of the current node:

$$P_{\mathrm{cur}} = \phi - V_d * t_w \quad (12)$$

When the energy of node arrives at the critical value, we denote $T_{cur}$ as the remaining life time of node, which is calculated as below:

$$T_{\mathrm{cur}} = \frac{P_{\mathrm{cur}}}{V_d} \quad (13)$$

Therefore, we can determine the value of $t_0$ as:

$$t_0 = T - T_{\mathrm{ma}} \quad (14)$$

where $T_{ma}$ is the average maximum service time of all the charging requests in the service pool.

### 3.5. Preemption

Since the residual energy of nodes and waiting time of charging requests are changing and new charging requests may join in the service pool at any time, we need to design a preemptive mechanism to rearrange the charging behavior of WCV and improve the charging throughput.

As we mentioned earlier, when $t_w$ increases to $t_0$, the temporal priority of a charging request will be increased.

Although, nodes' energy arriving at critical value or $t_w$ increasing to $t_0$ may happen at a different time, we only need to make sure that every charging request's $t_w$ value is smaller than $t_0$. No need to care about when it happens. This method can change the temporal priority and guarantee that there will always be a node whose $t_w$ value increases to $t_0$. Therefore, preemption interval should be $t_0$.

### 3.6. TADP scheduling algorithm

In this subsection, we demonstrate how to compare the priorities of two charging requests in detail. In our work, there are two main factors that determine the priority of a charging request: the first one is a *temporal factor*, which is so called the charging deadline of a charging request. It can also reflect the time when a charging request is sent. Shorter the charging deadline is, higher the *temporal priority* is. The second factor is a *distantial factor*, which refers to the distance from the node that is needed to get charged to the WCV. Nearer they are, higher the *distantial priority* is.

When a number of requests are received by the WCV, it needs to order the requests based on priorities. First of all, we compare the temporal priorities of two charging requests, which are presented in Algorithm 1:

According to Algorithm 1, we can obtain a charging request with a higher temporal priority between two requests $A$ and $B$ by comparing deadlines. Then we sort requests into a queue based on the temporal priority. A request with the highest priority will be put in the front of the queue. Then, a request's temporal priority is quantified into an integer, indicating the position it locates in the temporal priority queue.

Similarly, we compare the distantial priorities of two charging requests, which is shown in Algorithm 2:

According to Algorithm 2, we compare the distantial priority of two requests. Similarly, the distantial priority is also converted into an integer.

**Algorithm 1** Temporal Priority Comparison

**Require:** $T(A), T(B)$
**Ensure:** Comparison of $Pt(A)$ and $Pt(B)$

```
if T(A) < T(B) then
    Pt(A) > Pt(B)
else
    Pt(A) ≤ Pt(B)
end if
```

**Algorithm 2** Distantial Priority Comparison

**Require:** $D(A), D(B)$
**Ensure:** Comparison of $Pd(A)$ and $Pd(B)$
**if** $D(A) < D(B)$ **then**
  $Pd(A) > Pd(B)$
**else**
  $Pd(A) \leq Pd(B)$
**end if**

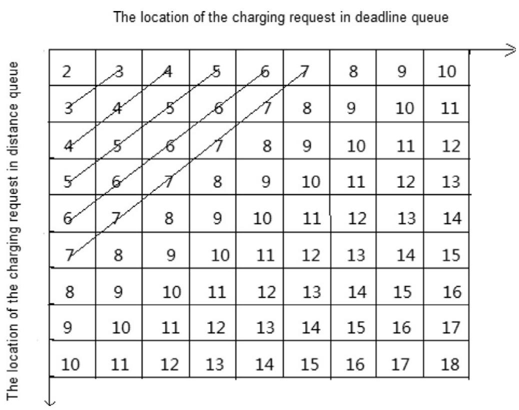


**Fig. 4.** Temporal and distantial priority table.

According to Algorithm 1 and Algorithm 2, we get two priority queues in the service pool. As what we have mentioned, temporal priority and distantial priority are represented by two integers.

Then, we combine temporal and distantial priority together into a mixed priority. Similar to [37], the mixed priority of a request can be acquired by looking up the table shown in Fig. 4. Every charging request has a mixed priority $P(A)$. It determines the preliminary charging order for the WCV. Here, $Pt(A)$ and $Pd(A)$ indicate the temporal and distantial priority of a request $A$ respectively. We can get $P(A)$ by calling Eq. (15).

$$P(A) = \alpha Pt(A) + \beta Pd(A) \tag{15}$$

Here, $\alpha$ and $\beta$ are defined as the proportions of temporal priority and space priority. Define $\vartheta = \frac{\alpha}{\beta}$ as the ratio of $\alpha$ and $\beta$. If $\vartheta \to +\infty$, then our algorithm can be converted into the EDF scheduling algorithm [32,35]. On the other hand, if $\vartheta \to 0$, it can be transformed as the NJNP scheduling algorithm [9,10]. In our scenario, we let $\vartheta = 1$. Then we devise Algorithm 3 to compare mixed priorities of between charging request $A$ and $B$.

Algorithm 3 can be referred to compare the mixed priorities between two nodes. Another situation we cannot ignore is that, it is possible that two different charging requests have the same mixed priority after executing Algorithm 3. For example, two nodes' mixed priorities belong to the same diagonal line, which is depicted in Fig. 4. It is impossible that the WCV charges the two nodes at the same time. Then, we develop further comparison to solve the priority equivalent problem.

**Algorithm 3** Mixed Priority Comparison Algorithm

**Require:** $Pt(A), Pt(B), Pd(A), Pd(B)$
**Ensure:** Comparison of $P(A)$ and $P(B)$
**if** $\alpha Pt(A) + \beta Pd(A) < \alpha Pt(B) + \beta Pd(B)$ **then**
  $P(A) < P(B)$
**else if** $\alpha Pt(A) + \beta Pd(A) = \alpha Pt(B) + \beta Pd(B)$ **then**
  $P(A) = P(B)$
**else**
  $P(A) > P(B)$
**end if**

**Algorithm 4** Further priority comparison based on distantial density

**Require:** $D(A), T(A), D(B), T(B)$
**Ensure:** Comparison of $De(A)$ and $De(B)$
**if** $D(A) * T(A) < D(B) * T(B)$ **then**
  $De(A) < De(B)$
**else**
  $De(A) > De(B)$
**end if**

**Table 2**
Distances among nodes and WCV in the beginning.

| Distances(m) | WCV | Node E | Node D | Node C | Node B | Node A |
|---|---|---|---|---|---|---|
| Node A | 40 | 20 | 32 | 30 | 15 | – |
| Node B | 50 | 34 | 35 | 35 | – | – |
| Node C | 20 | 45 | 20 | – | – | – |
| Node D | 30 | 50 | – | – | – | – |
| Node E | 45 | – | – | – | – | – |
| WCV | – | – | – | – | – | – |

We introduced the concept of distantial density, which is denoted by $De(A)$. A smaller distantial density yields to a higher mixed priority. By referring to [37], distantial density can be calculated as Eq. (16).

$$De(A) = D(A) * T(A) \tag{16}$$

Then, we introduce Algorithm 4 for further comparing according to distantial density.

According to Algorithm 4, we sort the order of the charging requests in the service pool by their distantial density, which can be used for guiding the charging movements for the WCV.

Before performing the charging actions, we still need to ensure whether a charging action can be successfully accomplished. We compute the value of $V$ as Eq. (17).

$$V = \frac{D(A)}{T(A)} \tag{17}$$

If $V < V_m$ or $V = V_m$ satisfies, it means that the WCV can charge the node before it runs out of power. Then the WCV will charge for the node immediately. Otherwise, it means that the node cannot get charged before exhaustion. Hence, WCV deletes the charging request from the service pool.

Therefore, an extreme case, that a WCV determines to charge for a node which is impossible to survive, will no longer happen (i.e. a node whose request cannot be responded due to temporal or distantial constraints). Besides, it will not delay the entire scheduling process.

### 3.7. Case study

To intuitively show the merits of the proposed scheme, a simple example is given below. We respectively execute TADP and NJNP to show the charging behavior of the WCV so as to demonstrate the strengths of TADP.

As depicted in Fig. 5, five nodes (i.e. A, B, C, D and E) are randomly deployed in the WRSN. Distances among nodes and WCV are shown in Table 2. Notice that data in the lower part are the same with that in the upper part, hence, we ignore these cells to avoid redundancy. The five nodes send their charging requirements to WCV respectively at 12:00:00, 12:01:00, 12:01:30, 12:01:45 and 12:02:30. For simplicity, we set $\phi = 30\%$, the energy consumption rate is 0.1%/s and the energy capacities of nodes are all 30J. The distances between WCV and A, B, C, D and E are 40 m, 50 m, 20 m,

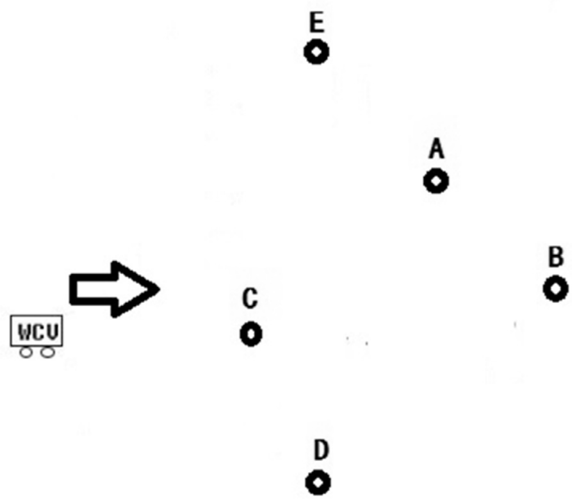


**Fig. 5.** Deployment of rechargeable sensor nodes.

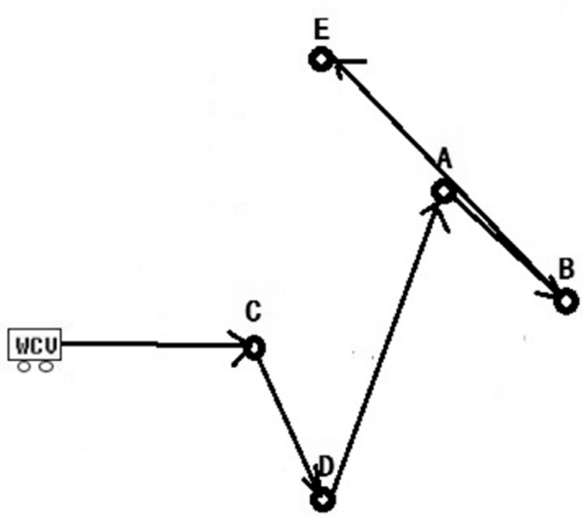


**Fig. 6.** Charging Path of NJNP.

30 m and 45 m respectively. At time 12:04:00, the WCV finishes other charging requests and prepares to make a decision on how to plan the charging path based on these five requests.

When NJNP is applied, a node that is nearer to WCV will have a higher priority to be charged. Every time when WCV finishes a charging task, it will recalculate its distance with other unserved nodes and find the next target. Therefore, the charging priority relations should be $C > D > A > B > E$. The charging sequence obtained by executing NJNP should be $C \to D \to A \to B \to E$, which is shown in Figure 6.

Then we use TADP to schedule the charging path. Firstly, charging requests are sorted based on the time that they are initiated to construct a temporal priority queue. Then Algorithm 2 is utilized to generate spatial priority for five nodes. After obtaining two priority queues, Algorithm 3 is executed to quantify mixed priority for each charging request. According to the arriving time and distance between nodes and the WCV, we get $T(A) < T(B) < T(C) < T(D) < T(E)$ and $D(C) < D(D) < D(A) < D(E) < D(B)$. So $Pt(A) = 1, Pt(B) = 2, Pt(C) = 3, Pt(D) = 4, Pt(E) = 5$ and $Pd(A) = 3, Pd(B) = 5, Pd(C) = 1, Pd(D) = 2, Pd(E) = 4$. Then by Eq. (15), we get $P(A) = 4,\ P(B) = 7,\ P(C) = 4,\ P(D) = 6$ and $P(E) = 9$. Afterwards, the charging sequence will be ordered as $A = C > D > B > E$. As node $A$ and node $C$ have the same mixed priority, we apply Algorithm 4 for further comparing mixed priorities. In accordance with warning threshold $\phi = 30\%$ and energy consumption rate $0.1\%/s$, the emergency node can survive 300s after sending its charging request. At 12:04:00, we get the remaining lifetime of node A and C: $T(A) = 300 - 240 = 60$ and $T(C) = 300 - 150 = 150$. And $D(A) = 40$ and $D(C) = 20$. Therefore, the distantial density values are $De(A) = D(A) * T(A) = 2400$ and $De(C) = D(C) * T(C) = 3000$. Hence, the priority of $A$ is higher than that of $C$, and the scheduling sequence in service pool of WCV will be ordered as $A, C, D, B, E$. Then WCV will firstly charge node $A$. After finishing charging node $A$, the selection of the next node will be recalculated based on the current location of the WCV (i.e. location of node $A$). These calculations repeatedly proceed four times and we finally get the charging path of the WCV as $A \to B \to D \to C \to E$, which is shown in Fig. 7.

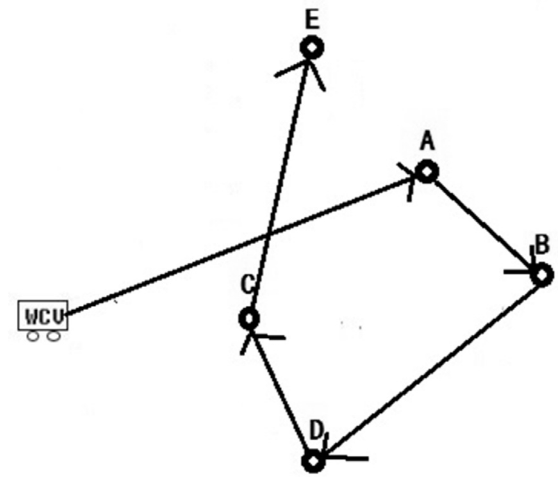


**Fig. 7.** Charging Path of TADP.

**Table 3**
Simulation parameters.

| Parameters | Values |
|---|---|
| Charging algorithm | TADP, NJNP, EDF |
| Network size($m^2$) | 100 × 100 |
| Number of nodes | 100 |
| Energy consumption rate(kJ/s) | 0.002 |
| Warning threshold | 30% |
| Initial energy (kJ) | 100 |
| WCV speed(m/s) | 4 |

By comparing the path length and charging delay between NJNP and TADP, we note that TADP has shorter charging path and charging delay. Next, we will conduct extensive simulations to deeply analyze the advantages of TADP.

## 4. Simulations

In this section, we conduct extensive simulation experiments to evaluate the performance of the TADP charging scheduling algorithm. We mainly compare with NJNP [9,10], which is the latest scheduling algorithm. Moreover, earliest deadline first algorithm (i.e. EDF) is also implemented for comparison.

### 4.1. Simulation setup

As shown in Table 3, in our simulations, we randomly deploy 100 nodes into a 100m × 100m square area. Without loss of generality, we set the energy consumption rate of wireless sensor nodes

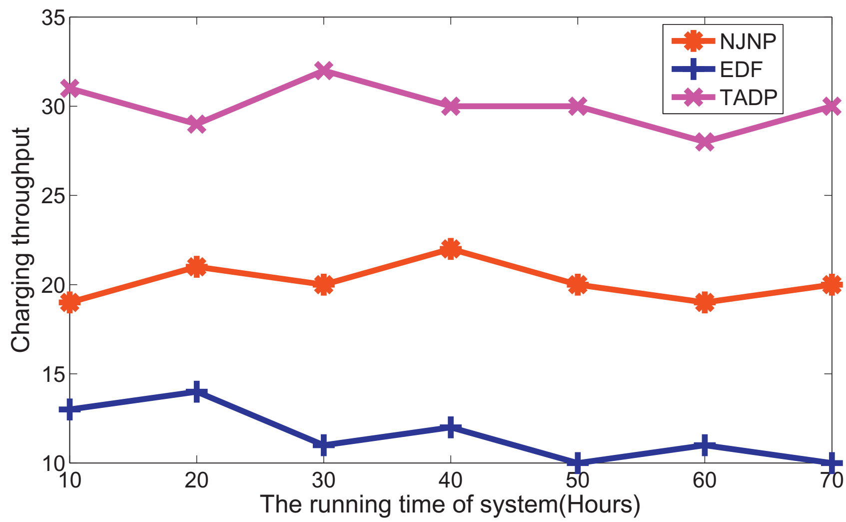


**Fig. 8.** Charging throughput comparison.

as $V_d = 0.002$ kJ/s and the running speed of a WCV is 4 m/s. We set $\phi = 30$ as the warning threshold for sensor nodes sending a charging request to the WCV. WCV will order all the charging requests in the service pool by a mixed priority and make a decision on which node to charge.

### *4.2. Throughput of charging requests*

In the on-demand charging framework, the throughput capacity of charging requests is an important evaluation metric of charging scheduling algorithm. From the perspective of the mobile charger, throughput capacity of the charging process is defined as the number of charging requests which are successfully responded in a time unit. Higher throughput capacity means shorter moving time for WCV and lower charging consumption.

As shown in Fig. 8, we observe that, the throughput capacity of TADP scheduling algorithm increases with the time going on. However, the throughput capacity of NJNP scheduling algorithm is not stable. Moreover, the throughput capacity of TADP scheduling algorithm is much higher than those of NJNP and EDF scheduling algorithm. Statistically, the throughput capacity of NJNP is only half of that of TADP. It is obvious that TADP has a significant progress on improving charging throughput. More starving nodes can get charged before exhaustion.

### *4.3. Survival node number*

In this simulation, we compare the number of survival nodes among TADP, NJNP and EDF. As shown in Fig. 9, it is obvious that, with the simulation running on, the number of nodes in TADP, NJNP and EDF gradually reduce. That's because, limited by charging capability (i.e. suppose two remote nodes simultaneously initiate charging requests, only one gets charged due to temporal and distantial constraints ), there must be some nodes that cannot timely get charged.

We also observe that the number of survival nodes in TADP is bigger than those of NJNP and EDF, which indicates that TADP has a higher successful charging rate.

### *4.4. Average response time*

In this simulation, we evaluate the comparison on the average response time. Average response time of a request, which is also regarded as the charging delay, is defined as the time interval that begins from a node sending the charging request and ends at successfully getting charged. It also reflects the reaction speed of the WCV. It is an important metric to verify the efficiency of a charging algorithm as well.

As shown in Fig. 10, we note that the average response time in TADP declines slowly. On the contrary, a fast decrement appears in NJNP. The reason is that, in NJNP, due to low charging throughput, a couple of nodes cannot be timely charged. The average response time in NJNP is five minutes longer than that in TADP. A shorter average response time leads to a higher successful charging rate. We also note that, the average response time of EDF gradually increases. As a result, we can conclude the charging efficiency of TADP is higher than those of NJNP and EDF.

### *4.5. Average length of waiting queue*

The average length of the waiting queue refers to the number of charging requests in the service pool. It is an important factor that reflects the working condition of a WCV. Shorter length of the waiting queue indicates fewer charging requests, implying higher successful charging rate and higher charging efficiency.

According to Fig. 11, we note that the average length of the waiting queue of TADP is stable at four. However, the average length of the waiting queue in NJNP and EDF are much longer. Since shorter average length means faster accomplishment of charging tasks, we can conclude that TADP have higher charging efficiency.

### *4.6. Successful charging rate*

Then we compare the success rates among three algorithms. In Fig. 12, we notice that, with the simulation running on, the success rates of NJNP and EDF increase. The successful charging rate of TADP stables at 100%. The reason is that, due to limitations posed by charging capacity of the WCV, it cannot maintain all the nodes alive by energy replenishment. Therefore, the alive nodes in the network gradually decrease, and the number of requests received by the WCV will be fewer and fewer, which thus potentially increases the successful charging rate. We also observe that the successful charging rate of TADP is obviously higher than those of NJNP and EDF. It indicates that WCV can satisfy more requests and complete the charging tasks effectively.

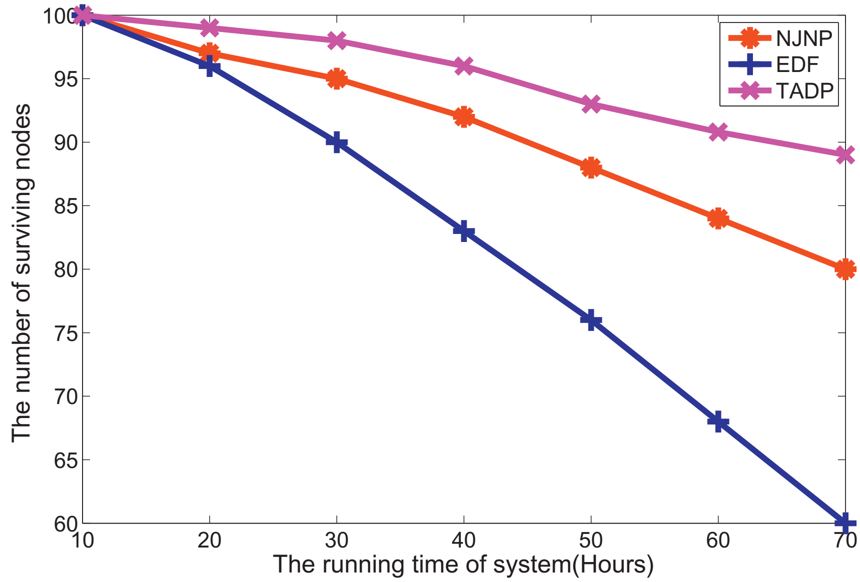


**Fig. 9.** Survival nodes number comparison.

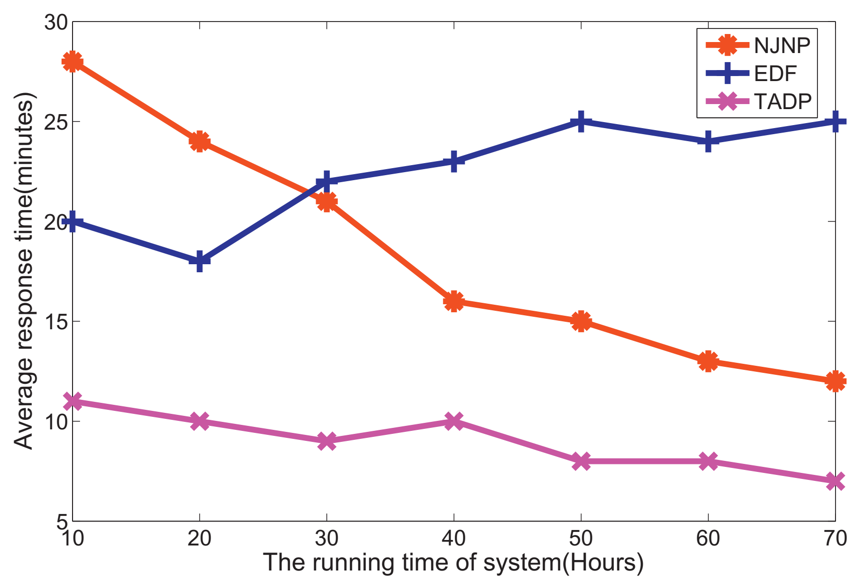


**Fig. 10.** Average response time Comparison.

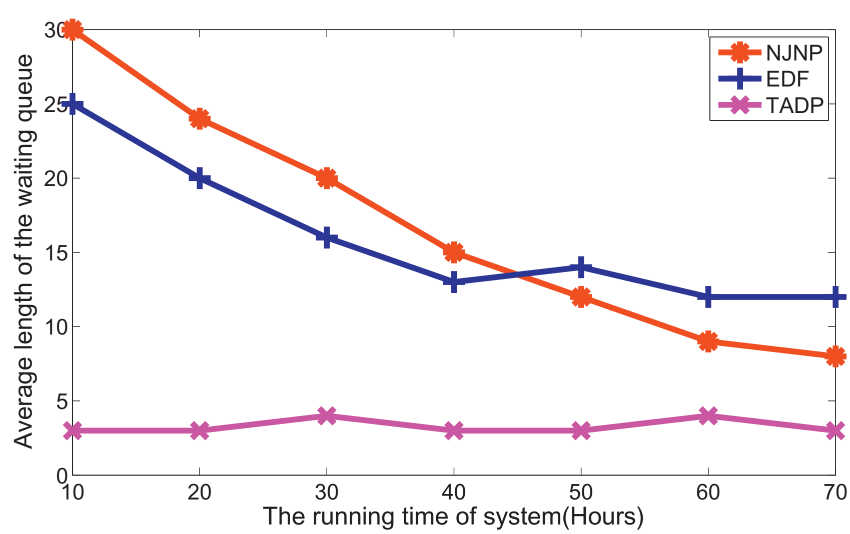


**Fig. 11.** Average length of waiting queue comparison.

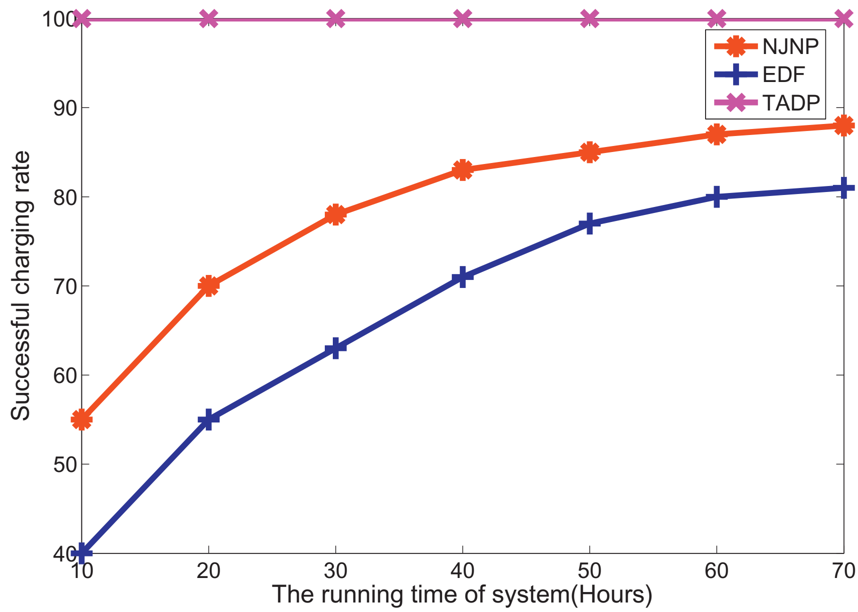


**Fig. 12.** Successful charging rate comparison.

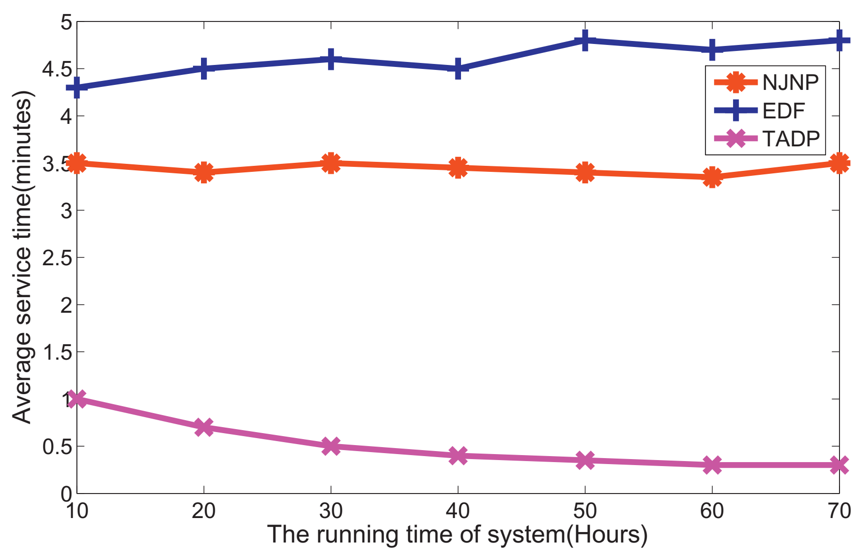


**Fig. 13.** Average service time comparison.

### 4.7. Average service time

At last, we compare the average service time between three algorithms. Average service time is defined as the average moving time of the WCV for completing a charging request. In some degree, average service time can reflect the charging efficiency of a charging algorithm.

The average service time is made up of two parts: 1) the time for a WCV to run from the current position to the node's position and 2) the time for a WCV to charge a node. As stated in [49], the former time is much longer than the latter. Therefore, the charging time can be ignored.

As shown in Fig. 13, it is obvious that the average service time of NJNP is four to five times of that of TADP. In other words, for completing the same charging request, on average, after TADP finishes the task, NJNP and EDF may need three more minutes. Therefore, the charging path of WCV is reduced a lot in TADP. More charging requests can be responded which promotes the charging efficiency.

### 4.8. Other characteristics analysis

In this part, we discuss the influences of $\alpha$ and $\beta$ to the charging performance. In Section 3.6, $\alpha$ and $\beta$ are defined as the weight of temporal and distantial priority, respectively. And $\vartheta$ is regarded as the ratio of $\alpha$ and $\beta$. According to Eq. 17, when $\vartheta > 1$, it means that the temporal priority has a bigger impact than the distantial priority. Here are two examples of $\alpha = 2$ and $\beta = 1$, namely $\vartheta = 2$. Assume that temporal and distantial priority of node A and B are (1, 2) and (2, 1) respectively. When $\vartheta = 1$, $P(A) = 3$ and $P(B) = 3$, we have $P(A) = P(B)$. The precedence order of A and B cannot be determined and Algorithm 4 will be executed, which wastes computation time. However, when $\vartheta = 2$, $P(A) = 4$, $P(B) = 5$, a node with a higher temporal priority will be charged first.

Then we come to analyze the charging sequence of node C and D, whose temporal and distantial priority are (4, 2) and (3, 4) respectively. When $\vartheta = 1$, $P(A) < P(B)$, meaning that a node with a lower temporal priority will get higher mixed priority. But when $\vartheta = 2$, $P(A) = 10$, $P(B) = 10$, we have $P(A) = P(B)$. Then

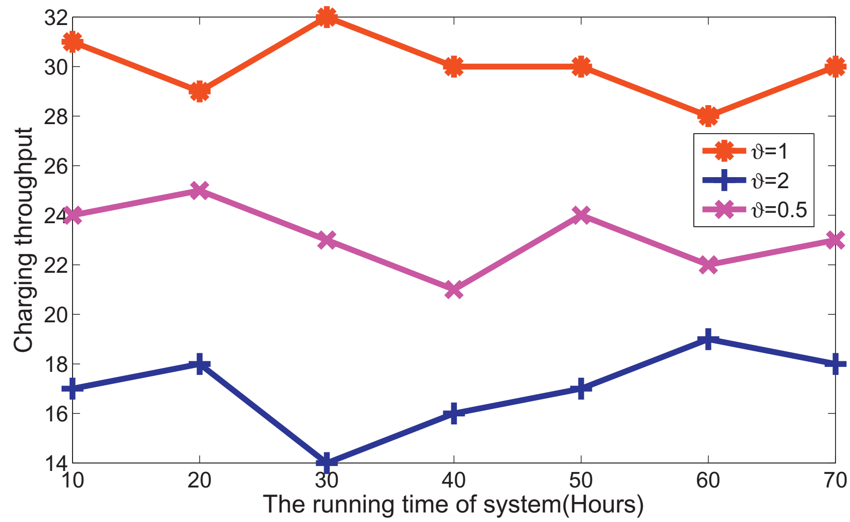


**Fig. 14.** Influence of $\vartheta$ on charging throughput.

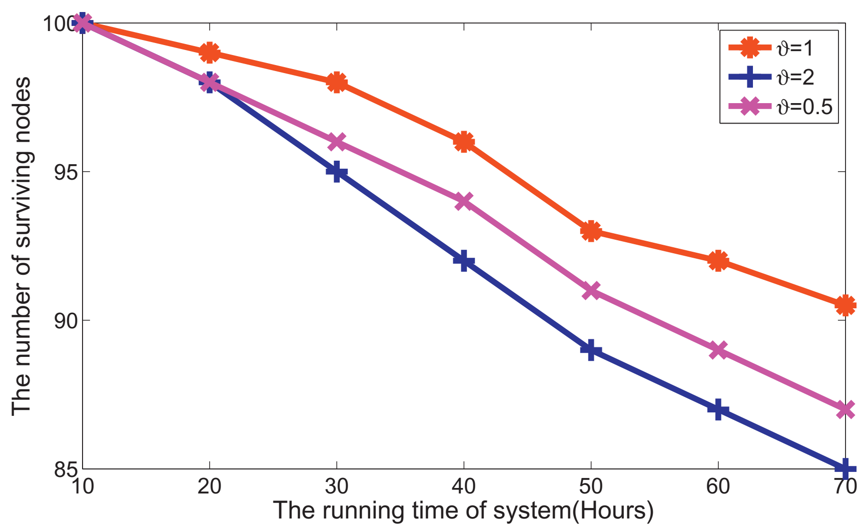


**Fig. 15.** Influence of $\vartheta$ on surviving nodes.

Algorithm 4 will be used to deeply compare two nodes' distantial density. In that case, it becomes possible that a node with a higher temporal priority can be charged first.

To more precisely demonstrate the influences of $\vartheta$, we conduct the following experiments. Fig. 14 and Fig. 15 show the comparison result of different $\vartheta$. We firstly utilize charging throughput as the measurement. When $\vartheta = 2$, TADP is nearly the same with EDF but with a better performance. When $\vartheta = 0.5$, TADP seems like the advanced version of NJNP, with more effective charging behavior. However, neither of the two cases can transcend the performance of $\vartheta = 1$. Therefore, temporal and distantial priority should be balanced in TADP algorithm.

As for the number of surviving nodes, there is not so much difference between different $\vartheta$. As shown in Fig. 15, during the first 20 hours, almost 98 nodes can survive in these three cases. However, when the simulation is taken for over 70 hours, the decreasing rates in the cases of $\vartheta = 2$ and $\vartheta = 0.5$ are higher than that in $\vartheta = 1$. It can be predicted that when $\vartheta = 1$, more survival nodes exist and the system lifetime can be prolonged.

## 5. Conclusion and future work

In this work, we have proposed a new non-deterministic scheduling method for WRSNs under the on-demand charging architecture, namely TADP. We convert and formalize the scheduling problem into a M/M/1/∞/N/TADP queuing model. In TADP, temporal priority and distantial priority of a request are quantified and merged into a mixed priority. Then, techniques such as determination of warning threshold and preemption are demonstrated in detail. After that, TADP which takes advantages of spatial and distantial priority scheduling is given. At last, several simulations are conducted to show the outperformed advantages of our scheme. Simulation results show that TADP improves charging performance in terms of bigger throughput, shorter response time, higher successful charging rate and so on.

As parts of our future work, some possible extensions will be taken from two perspectives:

1. Collaborative charging of multiple WCVs using TADP. We will take deep insight on how to apply TADP into collaborative charging model.
2. 3D Charging with obstacles. We will use TADP into the real environment, in which obstacles exist in the real application. We also consider to UAV (Unmanned Aerial Vehicle) to act as the mobile charger.

Please cite this article as: C. Lin et al., TADP: Enabling temporal and distantial priority scheduling for on-demand charging architecture in wireless rechargeable sensor Networks, Journal of Systems Architecture (2016), http://dx.doi.org/10.1016/j.sysarc.2016.04.005

## Acknowledgement

This research is sponsored in part by the National Natural Science Foundation of China (No.61202441 and No.61402078), Nuclear high base of major projects (2012ZX01039-004-21) and Program for New Century Excellent Talents in University (NCET-13-0083). 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: Proceedings of the 15th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, ACM, 2012, 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 Trans. Wireless Commun. 12 (6) (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), IEEE, 2013a, 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), IEEE, 2013b, 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), IEEE, 2013c, pp. 1–7.
[6] L. Fu, P. Cheng, Y. Gu, J. Chen, T. He, Minimizing charging delay in wireless rechargeable sensor networks, in: 32th IEEE International Conference on Computer Communications (INFOCOM 2013), IEEE, 2013, pp. 2922–2930.
[7] S. Guo, C. Wang, Y. Yang, Mobile data gathering with wireless energy replenishment in rechargeable sensor networks, in: 32th IEEE International Conference on Computer Communications (INFOCOM 2013), IEEE, 2013, pp. 1932–1940.
[8] L. He, P. Cheng, Y. Gu, J. Pan, T. Zhu, C. Liu, Mobile-to-mobile energy replenishment in mission-critical robotic sensor networks, in: The 33th IEEE International Conference on Computer Communications (INFOCOM 2014), IEEE, 2014, pp. 1195–1203.
[9] 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), IEEE, 2013a, pp. 28–36.
[10] L. He, L. Kong, Y. Gu, J. Pan, T. Zhu, Evaluating the on-demand mobile charging in wireless sensor networks, IEEE Trans. Mobile Comput. 14 (9) (2015) 1861–1875, doi:10.1109/TMC.2014.2368557.
[11] S. He, J. Chen, F. Jiang, D.K. Yau, G. Xing, Y. Sun, Energy provisioning in wireless rechargeable sensor networks, IEEE Trans. Mobile Comput. 12 (10) (2013b) 1931–1942.
[12] 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), IEEE, 2011, pp. 69–74.
[13] 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, 2014a, pp. 732–736.
[14] L. Jiang, X. Wu, G. Chen, Y. Li, Effective on-demand mobile charger scheduling for maximizing coverage in wireless rechargeable sensor networks, Mobile Netw. Appl. 19 (4) (2014b) 543–551.
[15] A. Kansal, J. Hsu, S. Zahedi, M.B. Srivastava, Power management in energy harvesting sensor networks, ACM Trans. Embedded Comput. Syst. 6 (4) (2007) 32.
[16] V. Kulathumani, A. Arora, M. Sridharan, M. Demirbas, Trail: A distance-sensitive sensor network service for distributed object tracking, ACM Trans. Sensor Netw. (TOSN) 5 (2) (2009) 1–40.
[17] A. Kurs, A. Karalis, R. Moffatt, J.D. Joannopoulos, P. Fisher, M. Soljačić, Wireless power transfer via strongly coupled magnetic resonances, Science 317 (5834) (2007) 83–86.
[18] Z. Li, Y. Peng, W. Zhang, D. Qiao, J-roc: a joint routing and charging scheme to prolong sensor network lifetime, in: 19th IEEE International Conference on Network Protocols (ICNP), IEEE, 2011, pp. 373–382.
[19] C. Lin, G. Wu, M.S. Obaidat, C.W. Yu, Clustering and splitting charging algorithms for large scaled wireless rechargeable sensor networks, J. Syst. Softw. 113 (2016) 381–394.
[20] C. Lin, G. Wu, F. Xia, M. Li, L. Yao, Z. Pei, Energy efficient ant colony algorithms for data aggregation in wireless sensor networks, J. Comput. Syst. Sci. 78 (6) (2012) 1686–1702.
[21] C. Lin, B. Xue, Z. Wang, D. Han, J. Deng, G. Wu, 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), 2015.
[22] S. Lin, B.W. Kernighan, An effective heuristic algorithm for the traveling-salesman problem, Oper. Res. 21 (2) (1973) 498–516.
[23] H. Luo, H. Tao, H. Ma, S.K. Das, Data fusion with desired reliability in wireless sensor networks, IEEE Trans. Parallel Distributed Syst. 22 (3) (2011) 501–513.
[24] A. Madhja, S. Nikoletseas, T.P. Raptis, Efficient, distributed coordination of multiple mobile chargers in sensor networks, in: Proceedings of the 16th ACM International Conference on Modeling, Analysis & Simulation of Wireless and Mobile Systems, ACM, 2013, pp. 101–108.
[25] A. Madhja, S. Nikoletseas, T.P. Raptis, Distributed wireless power transfer in sensor networks with multiple mobile chargers, Comput. Netwo. 80 (2015) 89–108.
[26] A. Madhja, S. Nikoletseas, T.P. Raptis, Hierarchical, collaborative wireless energy transfer in sensor networks with multiple mobile chargers, Comput. Netw. 97 (2016) 98–112. http://dx.doi.org/10.1016/j.comnet.2016.01.007.
[27] P. Ren, Y. Wang, Q. Du, Cad-mac: A channel-aggregation diversity based mac protocol for spectrum and energy efficient cognitive ad hoc networks, IEEE J. Selected Areas Commun. 32 (2) (2014) 237–250.
[28] V. Sharma, U. Mukherji, V. Joseph, S. Gupta, Optimal energy management policies for energy harvesting sensor nodes, IEEE Trans. Wireless Commun. 9 (4) (2010) 1326–1336.
[29] Y. Shi, L. Xie, Y.T. Hou, H.D. Sherali, On renewable sensor networks with wireless energy transfer, in: 30th IEEE International Conference on Computer Communications (INFOCOM 2011), IEEE, 2011, pp. 1350–1358.
[30] Y. Shu, P. Cheng, Y. Gu, J. Chen, T. He, Toc: Localizing wireless rechargeable sensors with time of charge, ACM Trans. Sen. Netw. 11 (3) (2015) 1–22, doi:10.1145/2700257.
[31] 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 Trans. Mobile Comput. (2016).To appear
[32] M. Spuri, G.C. Buttazzo, Efficient aperiodic service under earliest deadline scheduling, in: Real-Time Systems Symposium, 1994., Proceedings., IEEE, 1994, pp. 2–11.
[33] R. Tan, G. Xing, B. Liu, J. Wang, X. Jia, Exploiting data fusion to improve the coverage of wireless sensor networks, IEEE/ACM Transactions on Networking 20 (2) (2012) 450–462.
[34] L. Tang, Y. Sun, O. Gurewitz, D.B. Johnson, Pw-mac: An energy-efficient predictive-wakeup mac protocol for wireless sensor networks, in: 30th IEEE International Conference on Computer Communications (INFOCOM 2011), IEEE, 2011, pp. 1305–1313.
[35] A. Thekkilakattil, S. Baruah, R. Dobrin, S. Punnekkat, The global limited preemptive earliest deadline first feasibility of sporadic real-time tasks, in: 2014 26th Euromicro Conference on Real-Time Systems (ECRTS), IEEE, 2014, pp. 301–310.
[36] C.M. Vigorito, D. Ganesan, A.G. Barto, Adaptive control of duty cycling in energy-harvesting wireless sensor networks, in: 4th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON'07), IEEE, 2007, pp. 21–30.
[37] Y.-y. Wang, Q. Wang, H.-a. Wang, H. JIN, G.-Z. DAI, A real-time scheduling algorithm based on priority table and its implementation, J. Softw. 3 (2004) 005.
[38] E. Welzl, Smallest enclosing disks (balls and ellipsoids), New Results and New Trends in Computer Science, Springer, Graz, Austria, 1991.
[39] L. Xie, Y. Shi, Y.T. Hou, A. Lou, Wireless power transfer and applications to sensor networks, IEEE Wireless Commun. 20 (4) (2013a) 140–145.
[40] 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: 32th IEEE International Conference on Computer Communications (INFOCOM 2013), IEEE, 2013b, pp. 1636–1644.
[41] 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, 2013c, pp. 109–118.
[42] 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, 2012a, pp. 10–18.
[43] L. Xie, Y. Shi, Y.T. Hou, H.D. Sherali, Making sensor networks immortal: An energy-renewal approach with wireless power transfer, IEEE/ACM Trans. Netw. 20 (6) (2012b) 1748–1761.
[44] G. Xing, T. Wang, W. Jia, M. Li, Rendezvous design algorithms for wireless sensor networks with a mobile base station, in: Proceedings of the 9th ACM International Symposium on Mobile ad hoc Networking and Computing, ACM, 2008, pp. 231–240.
[45] Y. Yang, C. Wang, Wireless Rechargeable Sensor Networks, Springer, London, 2015.
[46] S. Zhang, J. Wu, S. Lu, Collaborative mobile charging for sensor networks, in: IEEE 9th International Conference on Mobile Adhoc and Sensor Systems (MASS), IEEE, 2012, pp. 84–92.
[47] S. Zhang, J. Wu, S. Lu, Collaborative mobile charging, IEEE Trans. Comput. 64 (3) (2015) 654–667.
[48] 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), IEEE, 2013, pp. 273–281.
[49] M. Zhao, J. Li, Y. Yang, A framework of joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks, IEEE Trans. Mobile Comput. 13 (12) (2014) 2689–2705, doi:10.1109/TMC.2014.2307335.

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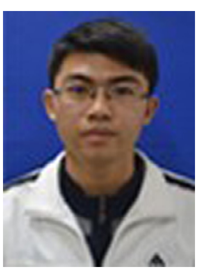

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Please cite this article as: C. Lin et al., TADP: Enabling temporal and distantial priority scheduling for on-demand charging architecture in wireless rechargeable sensor Networks, Journal of Systems Architecture (2016), http://dx.doi.org/10.1016/j.sysarc.2016.04.005