

P²S: A Primary and Passer-by Scheduling Algorithm for On-demand Charging Architecture in Wireless Rechargeable Sensor Networks

Chi Lin, *Member, IEEE*, Ding Han, Jing Deng, *Fellow, IEEE*, and Guowei Wu,

Abstract—As the interdisciplinary of wireless communication and control engineering, the cooperative charging issue in Wireless Rechargeable Sensor Networks (WRSNs) is a popular researching problem. With the help of wireless power transfer technology, electrical energy can be transferred from wireless charging vehicles to sensors, providing a new paradigm to prolong the network lifetime. However, existing techniques on cooperative charging usually take the periodical and deterministic approach, but neglect the influences of the non-deterministic factors such as topological changes and node failures, making them unsuitable for large-scale WRSNs. In this paper, we develop a Primary and Passer-by Scheduling (P²S) algorithm for on-demand charging architecture for large-scale WRSNs. In P²S, task interdependency is utilized to enhance charging efficiency. We exploit a local searching algorithm, in which nearby nodes on the way to primary nodes, the targets of Wireless Charging Vehicle's (WCV's) current movement, will be charged as passer-by nodes. Such a strategy not only makes full use of the available remaining time of a charging deadline, but also solves the complex scheduling problem with spatial and temporal task interdependency. Analysis and simulations are conducted to show the superiority of our scheme, revealing that P²S has a higher survival rate, throughput, as well as other performance metrics.

Index Terms—Wireless Rechargeable Sensor Networks, Charging Scheduling, Wireless Charging Vehicle, On-demand Architecture.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are composed of abundant cheap micro sensor nodes to be deployed in different areas for monitoring a variety of ambient conditions such as temperature, humidity, pressure, soil makeup, noise levels, and so on [1]. With wireless communications, the sensors in a WSN can self-organize into a multi-hop system to monitor covered areas and collect information. Potential applications include monitoring control in industrial process, environmental protection, and many other security-critical systems [2].

However, most of these devices run on batteries and their overall sizes limit battery capacity and lifetime. In recent

years, with the help of promising *wireless power transfer* technique, researchers have proposed a new concept of Wireless Rechargeable Sensor Network (WRSN) to solve the problem of limited power in WSNs [3]–[5].

There are several main wireless power techniques pursued in the field of wireless charging, such as inductive coupling, Electromagnetic radiation (EM radiation), and magnetic resonance coupling [6]. Inductive coupling is driven by magnetic field induction. It is simple with high power transfer efficiency in centimeter range. But this technique can only be applied when charging distance is short and the charging direction needs to be quite accurately assigned. EM radiation, including omnidirectional and unidirectional versions, has advantages of tiny receiver size and high power transfer efficiency over kilometer-range distance respectively. However, same as inductive coupling, in omnidirectional radiation, the power wasted on transmission will rapidly increase with longer charging distance. And unidirectional radiation requires LOS (Line-Of-Sight) and complex tracking mechanisms, leading to large scale of devices. For magnetic resonance coupling, it has been demonstrated to deliver power more efficiently and at longer ranges than the far-field approaches and inductively coupled schemes [7]. It is most promising to address the energy provision problem and it becomes the mainstream of wireless power transfer for most wireless charging schemes.

In WRSNs, the small-size sensor nodes [8] made up of a sensing unit, a processing unit, a transceiver unit, and a power unit are randomly deployed inside or fairly close to the monitoring area. They must consume extremely low power, operate in high volumetric densities autonomously without manual supervision, and be adaptive to the environment [9]. Node density should be planned carefully, within tens of feet of each other [10] and as high as 20 *nodes/m*³ [11]. Sensor batteries can sometimes be recharged by a so-called Wireless Charging Vehicle (WCV) [6], [12]–[14]. WCV [14] is equipped with high density battery packs and charging coils. During network initialization, the sensor locations are collected by the WCV. With the help of powerful antennas, the communication capability is enhanced and nodes' status information can be queried wherever it locates. There is also a GPS positioning system and its location can be obtained by a so-called Base Station (BS) all the time. BS [14] is used for collecting data, managing the network, remotely commanding WCV, calculating recharging sequence, and dispatching charging vehicles. When WCV runs low on its own energy, it returns to BS for a quick battery replacement. Different

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

Ding Han is with the Department of Computer Science, Huazhong University of Science and Technology. Email: handing@hust.edu.cn

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

This research is sponsored by the National Natural Science Foundation of China (No.61402078 and No.61672129) and Fundamental Research Funds for the Central Universities (No.DUT16RC(4)61).

Manuscript received XXX, XX, 2016; revised XXX, XX, 2016.

perspectives of WRSNs have been investigated, including path planning [12], [15], collaborative charging [6], system performance optimizing [13], [16], and so on.

In WRSNs, nodes running out of battery energy usually send out charging requests to WCV, which will decide when and in what sequence to charge such dying sensors. Current approaches [6], [17] suffer the following issues: First, most algorithms use off-line approaches with deterministic charging cycles [18]. With such deterministic approaches, network dynamics such as abrupt changes in traffic and energy consumption rate are simply overlooked. Second, variations in local networks are usually ignored, wasting opportunities of promptly responding to local charging requests [19].

In this work, we focus on methods to balance the needs of globally urgent and locally not-so-urgent charging requests and propose an algorithm to derive charging cycles such that all requests are served efficiently. In our method, termed Primary and Passer-by Scheduling (P²S), we use the solution of Traveling Salesman Problem (TSP) to formulate the charging path of some primary nodes. Then auxiliary virtual circles will help to identify “passer-by” nodes to be included, which are close to the primary path. Therefore, both charging urgency and proximity are considered and balanced. With such a unique two-step selection process, the P²S scheme is able to support the task of charging more sensors.

Specifically, our contributions in this paper include:

- We address the charging scheduling problem from both temporal deadline and spatial closeness. While urgent charging requests should always be served first in a short path (i.e. Hamiltonian cycle), those nodes close to the route should be considered for the benefit of overall efficiency.
- We develop an analytical model to compare such temporal deadline and spatial closeness. A quantitative comparison is then implemented so that WCV can choose the best passer-by node to charge.
- We investigate schedulability of charging missions without any undetermined charging cases [20], avoiding such behaviors altogether.
- We implement comprehensive simulations to compare the performance of P²S, a state-of-the-art scheme Nearest-Job Next with Preemption (NJNP) [19], and a traditional effective scheme Earliest Deadline First (EDF). Then salient features of P²S are demonstrated in comparison.

The remainder of paper is organized as follows. Section II gives a brief overview on prior arts on WRSNs and their differences from our approach. In Section III, we detail system model, problem statement, as well as the design of key functions of P²S. The number of surviving nodes is estimated in Section IV. Evaluations and comparisons are given in Section V and we conclude this paper in Section VI.

II. LITERATURE REVIEW

In 2010, Peng et al. [12] presented the concept of WRSNs, laying the foundation for further extensive research. In recent years, researchers around the world have investigated different fields with respect to WRSNs, from periodical charging

methods, collaborative charging methods, to evaluations on different networks.

Periodical charging solutions [18], [21] integrate node distribution model with energy consumption model. They transform charging problems into solvable TSPs so that the key issue can be simplified into calculating Hamiltonian cycle as the traveling path of WCV. Two types of different charging techniques are possible: single-node charging, in which efficiency is quite low [21]; and multiple-node charging, in which multiple neighboring nodes around the mobile charger can be served at the same time with higher efficiency [21]. Xie et al. approached the problem of path planning [18] with a Smallest Enclosing Space (SES) solution [22]. SES contains all of sensor nodes when WCV serves as mobile base station. Then they set up concentric circles with position of nodes as the centers and charging attrition rate as the radius. The overlapped regions are then chosen as stop locations for WCV. Similarly, Fu et al. [23] proposed discretization planning theory for wireless charging, in which concentric circles are drawn in SES to identify the proper stop location for WCV from the overlap area. However, the amount of calculation based on SES is usually so large that it is unsuitable for large-scale WSNs and charging methods based simply on sensor locations are impractical for large-scale WRSNs. Complex topology changes caused by network dynamics require large re-computation costs, so collaborative charging mechanisms considering both sensor location and remaining energy should be used.

Collaborative charging methods try to adopt to heterogeneous needs and node dynamics. He et al. proposed a dynamic path planning method for WCV based on Nearest Job Next with Preemption (NJNP) for better throughput and shorter latency [17]. As for charging schedule and choice of traveling path, they [17] proposed a charging scheduling method based on a tree structure, which decreases both of the charging attrition and charging latency. Li et al. [24] proposed J-Roc method by combining routing protocol and charging strategy, in which WCV can update the information of global energy state at any time and then schedule charging. Meanwhile, sensor nodes choose a path with low energy consumption to transfer data by using charging-aware routing protocol. In this way, energy consumption of network can be balanced with lifetime prolonged as well. Although collaborative charging method [19], [24] can effectively deal with the influence caused by uncertainties in WRSN, demand of reliability and instantaneity of charging request is neglected. Loss or latency of charging request information can lead to unsatisfactory scenario that WCV arrives at the charging position after power is exhausted, lowering network reliability. Thus the real-time reliable transmission of demand information and hybrid scheduling problem [25] on demand information and acquisition information should be considered at the same time.

The main evaluation on system performance of WRSN includes analysis and optimization. Jiang and Cheng et al. [26] analyzed the optimal scheduling problem of WRSN with random events. They optimized system performance from the application view of WCV's behavior, data transmission protocol, and cooperative control by establishing the performance

evaluation criteria based on Quality of Monitoring (QoM) [27]. Ye et al. [28] formulated a novel sensor recharging problem with an objective of maximizing the charging utility of sensors. Angelopoulos et al. [29] proposed charging decision problem and demonstrated its complexity, focusing on the approach to measure traveling path, charging strategy, and charging quantity of WCV to improve system performance. Tong et al. [30] demonstrated that the charging efficiency is decreased with an increasing distance for single-node charging and proposed a multiple-node charging scheme, in which WCV can charge nodes in a certain area simultaneously. Some recent works further investigated systems with multiple WCVs and different charging orders among these in WRSNs [31]–[34].

In [35], two charging algorithms HCCA (i.e. Hierarchical Clustering Charging Algorithm) and HCCA-TS (i.e. Hierarchical Clustering Charging Algorithm based on Task Splitting) aim at shortening charging time and distance via merging and splitting charging tasks. In [36], Lin et al. proposed a Double Warning Thresholds with Double Preemption (DWDP) charging scheme, in which double warning thresholds are used. In [37], a temporal and spatial priority charging scheduling algorithm TADP is proposed for WRSNs. TADP merges temporal priority and spatial priority into a mixed priority to achieve better scheduling performance.

Compared to the above prior arts, our approach is to develop a scheduling algorithm based on on-demand charging to meet the dynamic requirement in system. The advantages of our approach include enhancement of system stability as well as charging efficiency. Note that, although multiple-node charging can reduce the massive energy wasted when propagated in the air [30], in this paper we mainly focus on the design of WCV's charging behavior to achieve the optimal system performance in large-scale WRSNs with single-node charging. Multiple-node charging will be investigated in our future work.

III. THE PRIMARY AND PASSER-BY SCHEDULING ALGORITHM

A. System Model and Problem Statement

We consider a WRSN where sensor nodes are randomly deployed in a rectangle area (see Figure 1). There is only one WCV with limited energy capacity responsible for replenishing energy for all the sensors. When the residual energy level of a sensor falls below a threshold, it will send a charging request to WCV. The requests will be stored in the waiting queue Ω ordered by the sender's residual lifetime. Compared with WCV's traveling time and charging latency, the delay and extra energy cost of delivering requests at MAC and routing layers are much smaller [38], [39]. To the best of our knowledge, in a typical WRSN, it is unlikely that charging requests collide at the routing layer. We hereby simply take S-MAC (Sensor-MAC) [40], a contention-based medium access control protocol, which is particularly designed for saving power in wireless sensor networks. In order to focus on charging scheduling and our schemes overall performance, we simplify our model into assuming that such charging requests can be forwarded to WCV in a reasonably short time. Interestingly, as long as Ω has enough requests and the new

request is not desperately urgent, a short delay in its delivery toward WCV does not affect the overall performance of our scheme. Furthermore, our proposed approach does not rely on specific underlying technologies such as directional antenna, multiple device charging concurrently, etc.

All sensors are equipped with localization techniques such that charging requests are accompanied by such locations. We note that such location information does not post additional cost to the normal operation of WSNs, as many of such networks need these location information for sensing result reporting, data fusion, and other tasks [41]. We assume that each sensor's charging request can reach WCV anytime and anywhere through a real time transmission protocol [17]. The base station (BS), which serves as the data sink and energy source for the WCV, is located at the center of the rectangle region.

After receiving charging requests, WCV picks one or several as the destinations, using algorithms explained below, and travels toward them for charging. When all requests are served or WCV's residual energy is too low, it travels back to BS and its battery is recharged/replaced with a negligible delay.

We assume that WCV travels at a constant speed of v , consuming q_m joules per meter (J/m). Battery in each sensor node N_i discharges at a constant rate p_i , which might be different at different nodes. One node can only be charged when WCV arrives at its location. We assume that WCV charges sensor batteries at the rate q_c J/s. τ_i^k is used to depict the charging latency of N_i in charging sequence Π_k , equivalently to the sojourn time that WCV stays at N_i in Π_k . At any charge, the battery of the sensor node will be charged fully before WCV moves on. When a node's remaining power drops to zero before WCV arrives, it becomes dead. It is therefore important to design algorithms to ensure that as fewer nodes become dead as possible:

Problem Statement

In a WRSN with one WCV, charging requests are sent to the WCV from different locations. How does the WCV combine both charging deadlines and charging locations in its selection process in order to support the largest number of surviving nodes in the network system as runtime increases?

In our approach, we first use charging deadlines to develop a Hamiltonian cycle. Then a combination of charging deadline and charging distance is used to choose a few passer-by nodes (at most one between two consecutive charging targets) to improve the efficiency of such charging cycles.

B. Algorithms Structure of P²S

In this section, we detail the process of charging with P²S, which is composed of two stages: 1) choosing primary charging nodes and identifying the shortest Hamiltonian cycle; 2) choosing optimal "passer-by" nodes. Schedulability decision is considered in both of the two stages.

The first step of P²S is to choose the primary charging nodes from Ω and formulate a shortest path among themselves and BS. Obviously, deadlines should be considered first. We first choose $n = 10$ nodes from the head of Ω (reasons of the specific value will be depicted in Section IV). Then we will

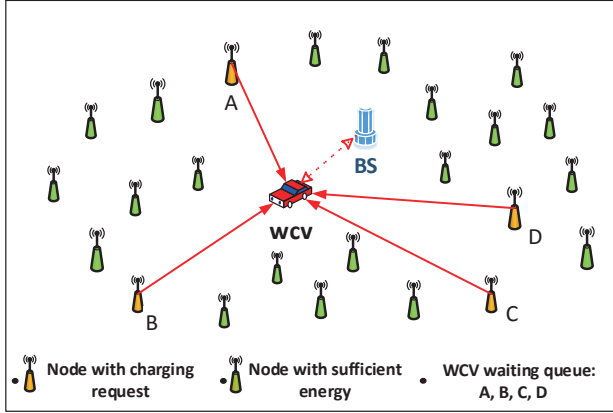


Fig. 1. Overview of an on-demand charging architecture

 TABLE I
 SYMBOLS AND DEFINITIONS

Symbol	Definition
\mathcal{N}	Sensor nodes deployed in a WRSN, $\mathcal{N} = \{N_1, N_2, \dots\}$.
$ \mathcal{N} $	The size of \mathcal{N} , i.e. sensor nodes' number.
WCV	The wireless charging vehicle in a WRSN.
BS	The base station in a WRSN.
Π_k	The k th charging schedule.
$d_{i,j}$	Distance between N_i and N_j .
e_i^k	Remaining power of N_i at the beginning of the k th charging round Π_k .
E_M	Battery capacity of the WCV.
E_S	Battery capacity of the sensor node.
t_i^k	Arrival time of the WCV at N_i in Π_k .
τ_i^k	Sojourn time of the WCV at N_i in Π_k , i.e. the charging latency of N_i in Π_k .
T^k	Duration of the k th charging round Π_k .
v	Traveling speed of the WCV.
q_c	Energy consumption rate of the WCV when charging.
q_m	Energy consumption rate of the WCV when moving.
p_i	Energy consumption rate of N_i .
η	Charging efficiency of the WCV.
ϕ	Warning threshold.
Ω	The waiting queue ordered by the residual lifetime of emergency nodes in WCV.
$P(i)$	Scheduling priority of the passer-by node i .
$T_l(i)$	Remaining lifetime of passer-by node i .

identify a shortest Hamiltonian cycle for the selected n nodes and BS. We check whether these n nodes are schedulable. If not, we will decrease n .

As we mentioned above, each node's information, including position, remaining power, and energy consumption rate, etc. can be obtained by WCV anywhere and anytime. Then WCV can predict the arrival time and sojourn time at each node and the total consumed power after the charging cycle. Denote e_i^k as the residual power of N_i at the beginning of Π_k , t_i^k and τ_i^k as the arrival time and the sojourn time of N_i in Π_k , respectively. Suppose that WCV comes and stays at one node for a while just for charging, τ_i^k is namely the charging latency of N_i . T^k is the duration of Π_k , and R_M^k represents the residual power of WCV when it comes back to BS. All of these are characterized in Figure 2. To simplify the presentation, BS

is denoted by N_0 . The other primary nodes are numbered by N_1, N_2, \dots, N_n according to their position in Ω . Therefore, we divide the schedulable decision into three individual parts.

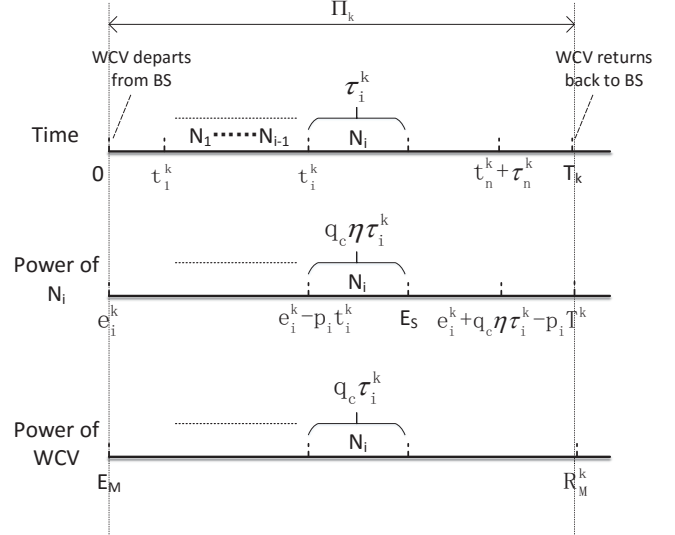


Fig. 2. Illustration of timeline and power level

1) *Nodes' power constraint*: This constraint requires that the n primary nodes must stay alive (i.e. residual power is more than zero) before WCV comes to charge them. First of all, we need to calculate the projected arrival time and sojourn time of each node and the duration of Π_k by iterative method.

$$t_1^k = \frac{d_{0,1}}{v} \quad (1)$$

$$\tau_i^k = \frac{E_S - (e_i^k - p_i t_i^k)}{q_c \eta} \quad \text{where } 1 \leq i \leq n \quad (2)$$

$$t_i^k = t_{i-1}^k + \tau_{i-1}^k + \frac{d_{i-1,i}}{v} \quad \text{where } 2 \leq i \leq n \quad (3)$$

$$T^k = t_n^k + \tau_n^k + \frac{d_{n,0}}{v} \quad (4)$$

So the nodes' power constraint can be depicted as:

$$e_i^k - p_i t_i^k \geq 0 \quad \forall i \in \{1, 2, \dots, n\}. \quad (5)$$

2) *WCV's power constraint*: There should be enough remaining power of WCV to return to BS after all of charging missions in Π_k are finished. Equivalently, WCV's power constraint is met if and only if the remaining power of WCV R_M^k is more than zero when it returns to BS, which is

$$R_M^k = E_M - q_m D_0 - \sum_{i=1}^n q_c \tau_i^k \geq 0, \quad (6)$$

where D_0 is the length of the determined Hamiltonian cycle.

3) *Next round constraint*: The above two constraints mainly focus on the schedulability in the current charging round (i.e. Π_k). However, if there are additional nodes waiting to be charged, they should be charged before their deadlines as well. Therefore, from system long-term behavior perspective, we need to ensure the schedulability of the next charging round (i.e. Π_{k+1}).

We use the concept of *Latest Starting Time (LS)* and *Latest Finishing Time (LF)* to check whether Π_{k+1} is schedulable after accomplishing all tasks in Π_k . Equivalently, Π_{k+1} is schedulable if the latest finishing time of Π_k (i.e. T^k in (4)) can not exceed the worst latest starting time of Π_{k+1} , which is

$$T^k \leq \max T_{LS}^{k+1}. \quad (7)$$

As a matter of fact, the key node in Π_{k+1} is the one with the least residual lifetime (i.e. N_{n+1}). The schedulability of Π_{k+1} mainly depends on the schedulability of N_{n+1} . As for this node, the worst condition is that WCV has to charge it first in Π_{k+1} to avoid its death, even if it is not the first one in Hamiltonian cycle. With satisfaction of this pessimistic condition, N_{n+1} must be schedulable. Accordingly, the worst latest starting time of Π_{k+1} is regarded as the remaining lifetime of N_{n+1} when WCV directly moves to it. Then the schedulability of Π_{k+1} will be met if

$$T^k \leq \max T_{LS}^{k+1} = \frac{e_{n+1}^k}{p_{n+1}} - \frac{d_{0,n+1}}{v}. \quad (8)$$

After executing the three schedulability decisions, in majority of cases, we can select the optimal n primary nodes from Ω and identify the Hamiltonian cycle for WCV accordingly.

Sometimes, no possible schedules can be obtained even if n is decreased to 1. There are three possible reasons: 1) WCV simply cannot charge one node (being too far away, battery too small, or ϕ too small); 2) one of the current more urgent nodes cannot be charged in a timely manner; or 3) the next round cannot charge another node in time. In the latter two cases, the first node in Ω (with the earliest deadline) will be dropped from the queue and left dead.

In Algorithm 1, we use the flag “isSchedulable” to record whether nodes’ power constraint is met (line 1). Line 3 is the preliminary part for the initial value of iteration t_1^k . Lines 4–12 calculate the arrival time and sojourn time at each node. If ensuring all of nodes’ liveness (line 13–14), then estimate the other two constraints (line 19–24). After traversing the conditions from $n = 10$ to 1, if no valid schedules occur, N_1 will be removed and Algorithm 1 will be repeated.

With comprehensive considerations, we obtain the optimal primary nodes and their Hamiltonian cycle. The basic mission for WCV in this charging round is to replenish n primary nodes in accordance with the Hamiltonian cycle. Nevertheless, looking ahead, WCV should also choose some additional nodes in Ω to charge. These are called passer-by nodes, the selection of which is discussed in detail in Section III-C.

Algorithm 1 Choose schedulable primary charging nodes

Input: the waiting queue Ω
Output: Π_k

- 1: boolean isSchedulable=true;
- 2: **for** $n = 10$ (or $\Omega.length$) to 1 **do**
- 3: $\Pi_k = \Omega.get(0, n)$;
- 4: Generate a shortest Hamiltonian cycle for Π_k and BS (Make sure that $N_0=BS$);
- 5: Renumber nodes in Π_k based on the visit order in Hamiltonian cycle.
- 6: $t_1^k = \frac{d_{0,1}}{v}$;
- 7: **for** $i = 1$ to n **do**
- 8: $\tau_i^k = \frac{E_S - (e_i^k - p_i t_i^k)}{q_c \eta}$;
- 9: **if** $e_i^k - p_i t_i^k < 0$ **then**
- 10: isSchedulable=false;
- 11: **end if**
- 12: **if** $i + 1 \leq n$ **then**
- 13: $t_i^k = t_{i-1}^k + \tau_{i-1}^k + \frac{d_{i-1,i}}{v}$
- 14: **end if**
- 15: **end for**
- 16: **if** isSchedulable==false **then**
- 17: **continue**;
- 18: **end if**
- 19: $T^k = t_n^k + \tau_n^k + \frac{d_{n,0}}{v}$;
- 20: $\max T_{LS}^{k+1} = \frac{e_{n+1}^k}{p_{n+1}} - \frac{d_{0,n+1}}{v}$;
- 21: $R_M^k = E_M - q_m D_0 - \sum_{i=1}^n q_c \tau_i^k$;
- 22: **if** $R_M^k \geq 0$ and $T^k \leq \max T_{LS}^{k+1}$ **then**
- 23: isSchedulable=true;
- 24: **break**;
- 25: **end if**
- 26: **end for**
- 27: **if** $n == 0$ **then**
- 28: $\Omega.remove(0)$;
- 29: **repeat**
- 30: Executing this algorithm;
- 31: **until** $n > 0$
- 32: **else**
- 33: **return** Π_k
- 34: **end if**

C. “PASSER-BY” Selection

Once the primary nodes are chosen, passer-by node selection is simple. It balances between the temporal requirement (charging deadline) and spatial requirement of the requests. In essence, we want to choose several passer-by nodes that will not lead to any primary node running out of energy before they are charged and they should not exhaust the energy on WCV either.

The selecting rule includes two aspects: (i) *feasibility*. i.e. no influence to the schedulability of primary nodes. (ii) *optimality*. i.e. smallest effect to Π_k . Here we innovatively propose the method of “drawing circles” to select feasible “passer-by” nodes from Ω . We draw circles centered at each edge with diameter of its length. Then emergency nodes in these circles are regarded as the alternative “passer-by” ones. And for smallest effect on latter primary nodes, only one

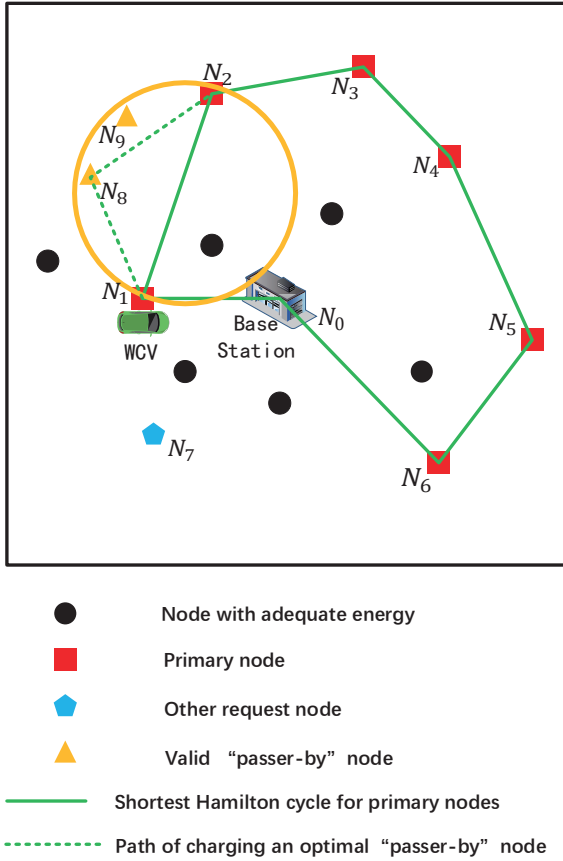


Fig. 3. Example of primary nodes and a passer-by node

optimal “passer-by” node can be charged in each circle.

Algorithm 2 shows the detailed calculation process of selecting feasible “passer-by” nodes. Line 3 sets a flag to decide the schedulability for nodes. Lines 4 – 7 initialize some values to update the arrival time and sojourn time at lines 12 – 14. Lines 23 – 25 update the residual power when WCV reaches BS and the duration of Π_k . Since schedulability for nodes, WCV, and next round are all met (lines 20 – 22, 26), N_j will be added to $\Pi_k^{i,i+1}$ (line 27). If $\Pi_k^{i,i+1}$ is not empty, meaning that there exist schedulable “passer-by” nodes between N_i and N_{i+1} , then the optimal selection is necessary. Otherwise, WCV moves directly to the next primary node instead of executing the next step.

Then it is essential to find the optimal “passer-by” node from the valid ones. Here, we mainly consider the key factors influencing temporal and spatial priority. The temporal priority of a node is determined by its deadline, namely the remaining lifetime. According to the selecting principles of primary nodes and ordering rules of Ω , N_{n+1} has the least deadline of all non-primary nodes. Whereas its deadline may be close to the primary nodes’ (especially N_n ’s), we except N_{n+1} to be selected as the optimal “passer-by” node if it is in $\Pi_k^{i,i+1}$ (i.e. it is schedulable). As for the other non-primary nodes, closer the deadline is with that of N_{n+1} , higher the temporal priority is. Denote $T_l(j)$ as the residual lifetime of N_j . So we

Algorithm 2 Choose valid passer-by nodes from N_i to N_{i+1}

Input: N_i, N_{i+1}

Output: The set of valid passer-by nodes $\Pi_k^{i,i+1}$

- 1: Identify a circle $C_{i,i+1}$ that centered at the middle of N_i and N_{i+1} with the diameter of $d_{i,i+1}$;
- 2: **for all** $N_j \in \Omega$ in $C_{i,i+1}$ **do**
- 3: boolean isSchedulable=true;
- 4: $\Delta s_j = d_{i,j} + d_{j,i+1} - d_{i,i+1}$;
- 5: $\Delta e_j = E_S - (e_j^k - (t_i^k + \tau_i^k + \frac{d_{i,j}}{v}) * p_j)$;
- 6: $\Delta \tau = \frac{\Delta s_j}{v} + \frac{\Delta e_j}{q_c \eta}$;
- 7: $t_{i+1}^{k'} = t_{i+1}^k + \Delta \tau$;
- 8: **if** $\Delta e_j > E_S$ **then**
- 9: **continue**;
- 10: **end if**
- 11: **for** $r = i + 1$ **to** n **do**
- 12: $\tau_r^{k'} = \frac{E_S - (e_r^k - p_r t_r^k)}{q_c \eta}$;
- 13: **if** $r + 1 \leq n$ **then**
- 14: $t_{r+1}^{k'} = t_r^{k'} + \tau_r^{k'} + \frac{d_{r,r+1}}{v}$;
- 15: **end if**
- 16: **if** $e_r^k - p_r t_r^{k'} < 0$ **then**
- 17: isSchedulable=false;
- 18: **end if**
- 19: **end for**
- 20: **if** isSchedulable == false **then**
- 21: **continue**;
- 22: **end if**
- 23: $\Delta E_M = \frac{\Delta e_j}{\eta} + q_m \Delta s_j + \sum_{l=i+1}^n q_c (\tau_l^{k'} - \tau_l^k)$;
- 24: $R_M^{k'} = R_M^k - \Delta E_M$;
- 25: $T^{k'} = T^k + \Delta \tau + \sum_{l=i+1}^n (\tau_l^{k'} - \tau_l^k)$;
- 26: **if** $R_M^{k'} \geq 0$ and $T^{k'} \leq \max T_{LS}^{k+1}$ **then**
- 27: $\Pi_k^{i,i+1}.$ add(N_j);
- 28: **end if**
- 29: **end for**
- 30: **return** $\Pi_k^{i,i+1}$

have $T_l(j) = \frac{e_j^k - p_j t_j^k}{p_j}$. The temporal priority of N_j (denoted as $P_t(j)$) is positively related to $\frac{T_l(n+1)}{T_l(j)}$. On the other hand, spatial priority is decided by the moving distance difference of WCV (i.e. Δs_j). The one will get a higher spatial priority if Δs_j is smaller. Therefore the spatial priority of N_j (denoted as $P_d(j)$) is negatively correlated to Δs_j .

In P²S, the stability of system is always stressed. Therefore, nodes with earlier deadline should be considered first, which indicates that temporal property should weigh more than spatial factor. Denote $P_t(j) = \lim_{\delta \rightarrow 0} (\frac{n}{\log_n \frac{T_l(j)}{T_l(n+1)} + \delta})$, $P_d(j) = -\omega \Delta s_j$ and $P(j) = P_t(j) + P_d(j)$. When a node’s deadline is approaching to that of N_{n+1} , its mixed priority will exponentially grow, ensuring the nodes with earlier deadlines are more likely to be selected as optimal “passer-by” nodes. Hence we have:

$$P(j) = \lim_{\delta \rightarrow 0} (\frac{n}{\log_n \frac{T_l(j)}{T_l(n+1)} + \delta}) - \omega \Delta s_j. \quad (9)$$

Denote the circle with diameter of the line between N_i and

N_{i+1} as $C_{i,i+1}$. We define $\Pi_k^{i,i+1}$ as the set of nodes with requests within $C_{i,i+1}$. Essentially, the selection process can be explained by the following:

$$N_{op} = \operatorname{argmax}_{N_j \in C_{i,i+1}} \left\{ \lim_{\delta \rightarrow 0} \left(\frac{n}{\log_n \frac{T_i(j)}{T_i(n+1)} + \delta} \right) - \omega \Delta s_j \right\}, \quad (10)$$

such that

$$\Delta e_j \leq E_S \quad (11)$$

$$e_r^k - p_r t_r^k \geq 0, \quad r = i+1, \dots, n \quad (12)$$

$$R_M^k \geq 0 \quad (13)$$

$$T^k \leq \max T_{LS}^{k+1} \quad (14)$$

where $\Delta s_j = d_{i,j} + d_{j,i+1} - d_{i,i+1}$. Δe_j is the charged power of N_j . As for each alternative node N_j in $C_{i,i+1}$, we need to recalculate the related information in Section III-B for the latter primary nodes beginning from N_{i+1} and evaluate whether the schedulability is still met. Then all of the valid N_j will be added to $\Pi_k^{i,i+1}$ and N_{op} can be finally found by executing (11).

The optimal “passer-by” nodes selecting process can be described in Algorithm 3. Variable *max* is used to record the maximum value of $P(j)$. Lines 3 – 9 traverse the alternative “passer-by” nodes and record the temporary optimal one N_{op} whose mixed priority is higher than *max*. Therefore, after the computation, N_{op} is the optimal “passer-by” node between N_i and N_{i+1} . Every time when WCV finishes a primary charging mission, it will do the “passer-by” selection process until reaching BS. As is mentioned above, only one “passer-by” node can be selected in each circle. So if there are $n+1$ nodes (n sensor nodes and BS) in the Hamiltonian cycle, then there will at most be $n+1$ “passer-by” nodes in total.

Algorithm 3 Choose the optimal passer-by from N_i to N_{i+1}

Input: $\Pi_k^{i,i+1}$

Output: The optimal passer-by N_{op}

```

1: if ! $\Pi_k^{i,i+1}$ .isEmpty() then
2:    $max = 0$ ;
3:   for all  $N_j \in \Pi_k^{i,i+1}$  do
4:      $P(j) = \lim_{\delta \rightarrow 0} \left( \frac{n}{\log_n \frac{T_i(j)}{T_i(n+1)} + \delta} \right) - \omega \Delta s_j$ ;
5:     if  $P(j) > max$  then
6:        $max = P(j)$ ;
7:        $N_{op} = N_j$ ;
8:     end if
9:   end for
10:  return  $N_{op}$ 
11: else
12:  No valid “passer-by” nodes;
13:  return null
14: end if
```

Figure 3 shows an illustration. At a certain time, there are 9 emergency nodes in Ω , which are numbered from N_1 to

N_9 according to the queueing order. After the schedulability decision, 6 nodes (from N_1 to N_6) will be the primary nodes in this charging cycle. Then WCV travels along the Hamiltonian path, constructing circles at each edge. When finishing replenishing N_1 , it detects non-primary nodes N_8 and N_9 in the yellow circle. Hence WCV will make another schedulability decision and find the optimal “passer-by” node and charge it. This process is repeated until WCV comes back to BS, namely N_0 . All of primary nodes, along with some other emergency nodes, are served in this charging cycle.

In summary, the whole charging process can be concluded as follows. Before WCV departs from BS, it will make schedulability decision to find optimal primary nodes and formulate the shortest Hamiltonian charging cycle for them. When WCV leaves BS or finishes replenishing a primary node, it will identify circles based on the edges in Hamiltonian cycle, find optimal “passer-by” nodes in these areas. If no valid “passer-by” nodes exist, go ahead to the next primary node. Otherwise charge the “passer-by” node and turn back to Hamiltonian cycle. When all of primary missions are completed, WCV moves to BS with a full battery replaced for next charging cycle. During the process, primary nodes schedulability is executed once in every charging cycle, while the “passer-by” nodes schedulability is done once at every primary node (including BS). The advantage of increased calculation is the accurate schedulability decision, ensuring a long-term stability for WRSN, which will be proved in the simulation part.

IV. PERFORMANCE ANALYSIS

In analysis, we focus on estimating the number of surviving nodes in the network as it reaches a stable state. Our approach is based on WCV’s work schedule, which should be able to serve all surviving nodes based on WCV’s speed and battery capacity.

Assume that each charging trip for the WCV covers a distance of D and it charges L sensors, on an average. Suppose, on an average, the total amount of time of each charging trip is T_1 . Overall, the service rate ζ_s is

$$\zeta_s = L/T_1, \quad (15)$$

i.e., such a number of sensors will be charged in each unit time. Also, on an average, these sensors will wait for $T_1/2$ unit times before they are charged. That means, each of the L sensors will be charged for the following amount of energy

$$(1 - \phi)E_S + \frac{T_1}{2} \cdot \bar{p}, \quad (16)$$

where $(1 - \phi)E_S$ represents the energy needed when the sensor sent out its charging request, \bar{p} is the average energy consumption rate of the sensors, and $\frac{T_1}{2} \cdot \bar{p}$ represents the amount of energy consumed while it waits to be charged.

T_1 is basically the sum of travel time and charging time for WCV,

$$T_1 = D/v + L \frac{(1 - \phi)E_S + \frac{T_1}{2} \cdot \bar{p}}{\eta qc}, \quad (17)$$

where D/v represents WCV’s travel time and the second part in (17) is the total charging time for all of these L sensors.

The overall energy consumption of each trip for WCV must be smaller than its battery capacity:

$$E_M \geq q_m D + L \frac{(1-\phi)E_S + \frac{T_1}{2} \cdot \bar{p}}{\eta}, \quad (18)$$

where $q_m D$ is the overall energy consumed in transit, the second part in (18) represents the energy consumed in charging all L nodes, and T_1 must satisfy (17).

Assume that there are N_a surviving nodes as the network goes into an equilibrium state and node i 's energy consumption rate is p_i . Starting from a full charge, node i will send out a charging request after $(1-\phi)E_S/p_i$ unit times. In equilibrium, such charging requests will arrive at a rate of ζ_a

$$\zeta_a = \sum_{i=1}^{N_a} \frac{1}{(1-\phi)E_S/p_i} = \frac{\sum_{i=1}^{N_a} p_i}{(1-\phi)E_S} = \frac{N_a \bar{p}}{(1-\phi)E_S}. \quad (19)$$

In a system with equilibrium, the request arrival rate, ζ_a , should equal to the service rate, ζ_s ,

$$\frac{N_a \bar{p}}{(1-\phi)E_S} = L/T_1. \quad (20)$$

Therefore, N_a can be computed as

$$N_a = \frac{L(1-\phi)E_S}{T_1 \bar{p}}. \quad (21)$$

We still need to find the relationship between D and L , which depends on the location distribution of all sensors. A rigorous analysis is considered out of the scope of this work, so we take an approximate approach. We assume that these L sensors fall within different hexagon-shaped sectors in the rectangle region and the Hamiltonian cycle needs to cover all of these sectors exactly once. We further assume that each of these L sensors located at the center of a sector. The problem is then transformed into finding the average distance between two neighboring sectors.

But first, we need to estimate how much area such N randomly-placed nodes will cover. This is the area from which the final $N_a \leq N$ nodes will be chosen to support (with WCV's charging). We approximate it by assuming the $X_{max} \cdot Y_{max}$ area to be circular and the radius being R_{max} ,

$$\pi R_{max}^2 = X_{max} \cdot Y_{max} \quad (22)$$

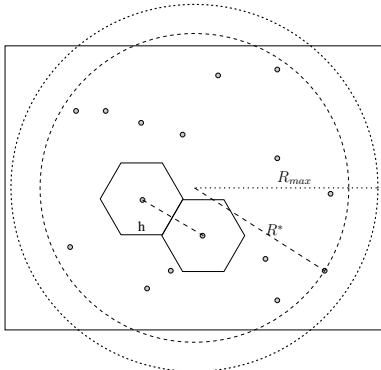


Fig. 4. Illustration for analysis

Denote a node's radius to the center of the circle as r . Randomly placing N nodes into the circle (see Figure 4), the probability density function of r can be expressed as

$$f(r) = kr, \quad (23)$$

where k should allow

$$\int_0^{R_{max}} f(r)dr = \int_0^{R_{max}} krdr = k \frac{R_{max}^2}{2} = 1. \quad (24)$$

Therefore, we have

$$k = \frac{2}{R_{max}^2}. \quad (25)$$

Assuming that the placement of all N nodes is i.i.d., the probability that all N nodes are within a radius of R from the center of the circle is

$$P(r \leq R) = \left[\int_0^R krdr \right]^N = \frac{R^{2N}}{R_{max}^{2N}}, \quad (26)$$

where $0 \leq R \leq R_{max}$.

The probability density function of the largest radius from the center of the circle is

$$\frac{\partial}{\partial R} P(r \leq R) = \frac{2NR^{2N-1}}{R_{max}^{2N}}. \quad (27)$$

The expected value of the largest radius is then

$$R^* = \int_0^{R_{max}} R \frac{2NR^{2N-1}}{R_{max}^{2N}} dR = \frac{2NR_{max}}{2N+1}, \quad (28)$$

and the area covered by all such N nodes is

$$\pi(R^*)^2 = \pi \left(\frac{2NR_{max}}{2N+1} \right)^2. \quad (29)$$

With such an area covered by N nodes divided into L sectors, each sector has a size of $\pi(R^*)^2/L$. Assume that each side of the hexagon-shaped sector is h . The size of the hexagon is

$$6 \cdot \frac{h}{2} \cdot \frac{\sqrt{3}h}{2} = \frac{\pi \left(\frac{2NR_{max}}{2N+1} \right)^2}{L}. \quad (30)$$

The distance of each pair of neighboring sensors to be charged on one charging cycle can then be estimated as $\sqrt{3}h$ and the overall distance of the charging cycle is then

$$D = \epsilon(L+1) \cdot \sqrt{3}h = \epsilon \sqrt{\frac{2\pi}{\sqrt{3}}} \cdot \frac{2NR_{max}}{2N+1} \cdot \frac{L+1}{\sqrt{L}}, \quad (31)$$

where $\epsilon = 0.9$ is a constant adjusting the difference between practical charging cycles with the theoretical cycles resulted from the above approximations.

Solving T_1 in (17), applying it into (18) by assuming equality, then applying D from (31) into (18), we should be able to find L (at least numerically). $L = 9.16$ when $N \rightarrow \infty$ so we initially set $n = 10$ in Section III-B. Finally we apply L into (21) before N_a can be calculated.

V. SIMULATIONS

In this section, we evaluate P²S through extensive simulations first. Complexity analysis of P²S is conducted next to see the efficiency of this algorithm.

A. Performance Comparisons

Performance comparisons are mainly made with the state-of-the-art charging scheduling schemes NJNP [19] and EDF, which were designed for on-demand charging. But first, we present our simulation setup. All parameters are as follows in Table II unless specified otherwise. Here, we simulate realistic charging processes by programming a Java project on Eclipse (version: eclipse-java-kepler-SR2-win32-x86_64) on Windows 10. Besides the simulation parameters in Table II, all configurations of Eclipse are the default values.

TABLE II
SIMULATION PARAMETERS

Parameters	Values
Network Size (m^2)	1000×1000
Number of Nodes	80
Energy Consumption Rate of Node (J/s)	0.06-0.11
Energy Consumption Rate of WCV's Moving (J/m)	8
Energy Consumption Rate of WCV's Charging (J/s)	11
Charging Efficiency	0.5
Emergency Level	40%
Initial Energy of Node (J)	13669
Initial Energy of WCV (KJ)	190
WCV Speed (m/s)	1

We randomly placed $N = 80$ sensors in a square area of size $1000m \times 1000m$. The base station is located at the center of the area. The energy consumption rate of each sensor node is randomly chosen between $0.06J/s$ to $0.11J/s$, but fixed throughout its lifetime. Every time when a node's remaining energy falls below 40% of its full charge, a charging request is sent to WCV. WCV moves at a speed of $1m/s$ with $8J$ consumed per meter. It consumes $11J/s$ energy to charge a sensor node, but due to charging efficiency (of 0.5), sensor battery only gets charged at a rate of $5.5J/s$. These number have been chosen mostly based on [20]. All results presented below are average of 30 runs with random seeds.

First, we justify our selection of ω . In Figure 5, we compare the survival rate of P²S with different mixed priority coefficient, ω . A large ω means that nodes with closer deadlines have a higher priority. When $\omega \rightarrow +\infty$, the optimal passer-by selection process acts in a fashion similar to the NJNP scheme. On the other hand, a small ω means that nodes with shorter distance from the current location have a higher priority. When $\omega \rightarrow 0$, our scheme behaves similar to the EDF charging scheme. Therefore, the ω parameter in our scheme works as a useful knob to tune our schemes behavior. From Figure 5, it can be observed that, even though the overall survival rates do not fluctuate significantly, $\omega = 3$ is the best choice to sustain the best performance. Hence, $\omega = 3$ will be chosen in the rest of our simulations.

Then, we compare P²S, EDF, and NJNP with respect to different performance metrics. Note that all performance metrics are computed as the average of an entire month, if possible.

Figure 6 compares charging throughput, which is defined as the number of successful charges in each unit time (hour), and is an assurance for system stability, keeping nodes operational and prolonging network lifetime. As demonstrated in Figure

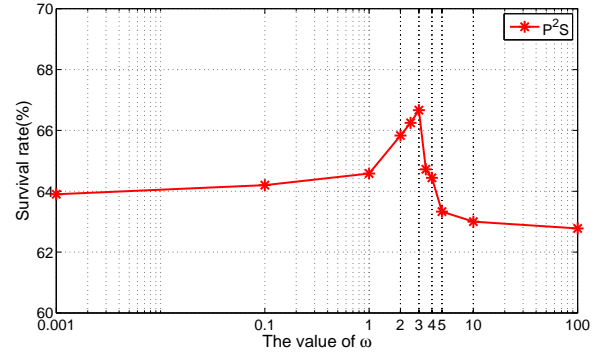


Fig. 5. Survival rate varying ω

6, the charging throughput of P²S is always higher than that of NJNP, underlying that P²S helps WCV serve more nodes than the other two schemes. This is because we use TSP solutions to formulate the charging path, which reduces WCV's overall travel time to serve charging requests. The slight increase of P²S' throughput over time is due to the increasingly more optimal sets of nodes being charged. On the contrary, EDF selects the most urgent request without any optimization, which is also absent in NJNP.

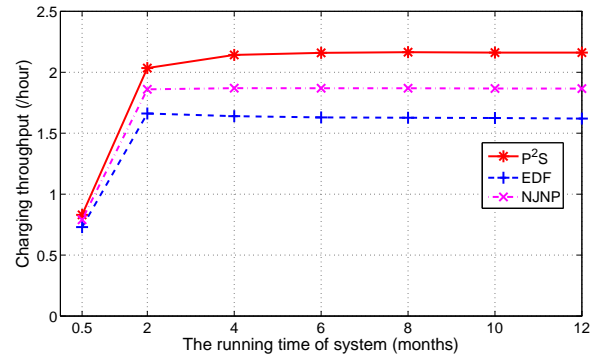


Fig. 6. Charging throughput for P²S, EDF, and NJNP.

Next, we compare survival rates of the nodes for the three schemes. If a node's residual energy drains completely before it is charged, it is considered dead. At any time, survival rate is measured as the ratio between the number of alive nodes and the original number of sensor nodes. System with higher survival rate is more reliable and stable. As shown in Figure 7, in the first 8 months, nodes die out slowly in all three schemes because WCV cannot serve such a large number of nodes. From then on, P²S supports the surviving nodes normally for a long time. While in NJNP and EDF, more and more nodes are left dead. P²S is thus demonstrated to be able to support more nodes.

The unresponded charging request rate is studied over running time to evaluate system stability. It is computed as the ratio between number of remaining emergency nodes in Ω after one charging cycle and number of total requests. In the first two months, the unresponded charging request rate of

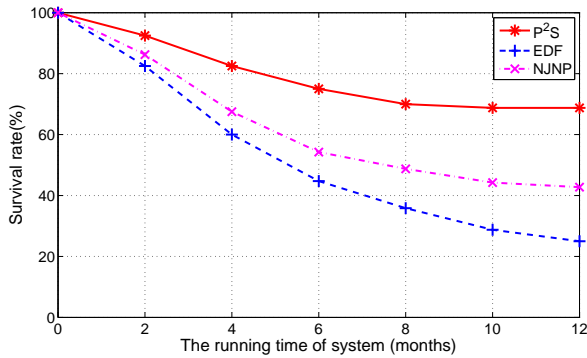


Fig. 7. Survival rate for P²S, EDF, and NJNP

EDF is mostly higher than those of P²S and NJNP, leaving more nodes to run out of battery energy. As runtime increases, rates of the three schemes drop and eventually stabilize less than 1%, entering stable system operation regions.

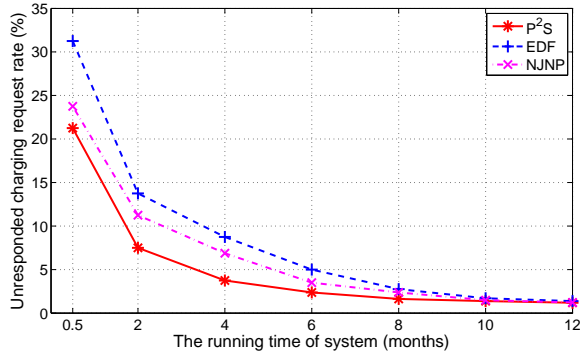


Fig. 8. Unresponded charging request rate for P²S, NJNP, and EDF

Then, we compare average service distance, defined as WCV’s moving distance for each charged node on average. A shorter service distance means a more efficient charging, which can save substantial time and energy for WCV on the way, serving more nodes. In Table III, we show the average service distance in the 12 months for P²S, EDF, and NJNP. The average service distance in P²S is about 340m, shorter than those in EDF and NJNP. EDF always selects nodes with earliest deadlines to charge, resulting in long travel distance for WCV. Meanwhile, NJNP is a local greedy algorithm for nearest distance. Although the moving distance can be shortened, the charging sequence might not be globally optimal. While P²S formulates shortest Hamiltonian cycle in each charging round from a global perspective, minimizing the service distance.

TABLE III
COMPARISON OF AVERAGE SERVICE DISTANCE FOR P²S, EDF, AND NJNP

Schemes	P ² S	EDF	NJNP
Average service distance(m)	340	560	375

As WCV’s speed increases, it should be able to serve more

nodes. In Figure 9, we compare the survival rate of P²S, EDF, and NJNP under different WCV speeds. Naturally, survival rate increases with speed and P²S performs better than both EDF and NJNP for all WCV speeds.

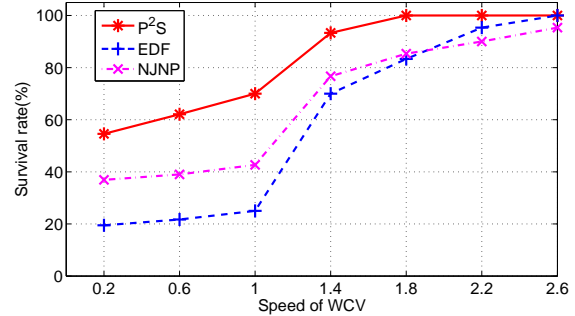


Fig. 9. Survival rate comparison varying WCV’s speed

The impact of node density and WCV’s speed is demonstrated in Figure 10, which also shows numerical results of our analysis in Section IV. As the number of nodes in the network increases, the number of surviving nodes increases until reaching a saturation point. Then it decreases slightly because of the wider spread of sensors in the entire network, allowing WCV to support slightly fewer nodes. When WCV’s speed increases from 1 m/s to 5 m/s, the number of surviving nodes increases about 20% in dense networks. Comparing simulation results and numerical results, we can see that they match each other quite well considering the different approximations we made in our analysis.

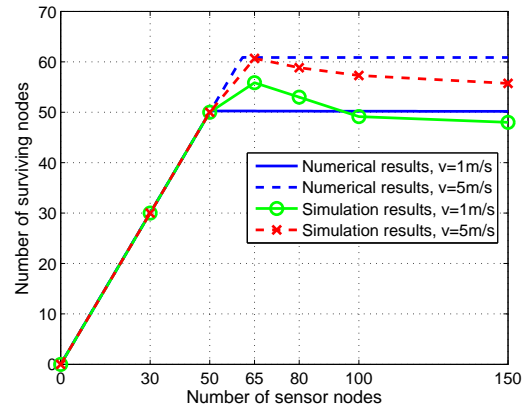


Fig. 10. Number of surviving nodes with different WCV speeds and network density

B. Algorithm Complexity

As discussed above, our charging algorithm P²S is made up of three individual components, i.e. choosing schedulable primary charging nodes (Algorithm 1) at the beginning of a charging round, choosing valid passer-by nodes (Algorithm 2) between adjacent primary nodes, and choosing optimal passer-by node (Algorithm 3) if there exist feasible ones after running Algorithm 2. So we investigate the complexity analysis of each:

Complexity analysis of Algorithm 1: WCV will execute Algorithm 1 after it receives several charging requests from nodes. For n request nodes, we start at the maximum possible value of n (no more than 10). We select the first n nodes in the waiting queue, generate the shortest Hamiltonian cycle and sort them based on their visit order. Then the expected arrival time and sojourn time will be calculated and these are used to decide the schedulability of the n nodes. If not schedulable, n will be decreased until all of the constraints are met. The core structure in this algorithm is a two-layer loop, in which the external one decreases n while the internal one calculates detailed information of the n conditions. In line 4, we need to construct Hamiltonian cycle for selected n nodes and BS. To the best of our knowledge, TSP is a NP-hard problem so we use the greedy algorithm to formulate the Hamiltonian cycle approximatively. This process finishes in $O(n^2)$ time. In line 5, the ordering process is done based on the determined Hamiltonian cycle in a constant time $O(1)$. The rest of the processes have constant complexity. Therefore, the time complexity of Algorithm 1 is $O(n^3)$. Note that n is required to be less than 10, thus the time complexity will not grow beyond control.

Complexity analysis of Algorithm 2: After having the primary charging missions, WCV will go through these nodes and find all valid non-primary nodes at each edge of the determined Hamiltonian path. Based on the schedulability decision, WCV needs to traverse all of the non-primary nodes in the circle with diameter of the line between N_i and N_{i+1} and find how they affect the primary nodes. In Algorithm 2, there are also two loops that construct the majority of this algorithm. Lines 4-10, lines 12-17, and lines 23-25 calculating new properties of latter primary nodes can be finished in constant time $O(1)$. Hence, the time complexity is $O(n^2)$, which is related to the number of non-primary nodes in $C_{i,i+1}$.

Complexity analysis of Algorithm 3: Algorithm 3 is an alternative depending on the passer-by selection result of Algorithm 2. If there are several valid passer-by nodes, our algorithm just calculates their priorities via (9) in linear time complexity $O(n)$ (lines 3-9). Accordingly, the time complexity is $O(n)$.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a new charging scheduling algorithm, termed P²S, for wireless rechargeable sensor networks. The P²S scheme combines primary charging and passer-by charging by considering both temporal and spatial relationships among different requests. The on-demand technique is highly efficient while it takes advantage of the wireless charging vehicle's (WCV) proximity to charge some of the not-so-urgent nodes. Such a combined method reduces the number of urgent charging requests in the future and thus improves WCV's efficiency, charging throughput, and successful charging rate. It also lowers death rate, and charging latency, as having been verified by our performance evaluation.

Our future work will focus on multiple WCVs and their potential distributions on the impact of charging efficiency. Implementation of our technique in practical WRSNs will be performed and investigated as well.

REFERENCES

- [1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer networks*, vol. 38, no. 4, pp. 393–422, 2002.
- [2] A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, and J. Anderson, "Wireless sensor networks for habitat monitoring," in *Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*. ACM, 2002, pp. 88–97.
- [3] M. Erol-Kantarci and H. T. Mouftah, "Suresense: sustainable wireless rechargeable sensor networks for the smart grid," *IEEE Wireless Communications*, vol. 19, no. 3, pp. 30–36, 2012.
- [4] S. He, J. Chen, F. Jiang, D. K. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE Transactions on Mobile Computing*, vol. 12, no. 10, pp. 1931–1942, 2013.
- [5] T. He, K.-W. Chin, and S. Soh, "On using wireless power transfer to increase the max flow of rechargeable wireless sensor networks," in *2015 IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)*. IEEE, 2015, pp. 1–6.
- [6] L. Xie, Y. Shi, Y. T. Hou, and A. Lou, "Wireless power transfer and applications to sensor networks," *IEEE Wireless Communications*, vol. 20, no. 4, pp. 140–145, 2013.
- [7] A. P. Sample, D. T. Meyer, and J. R. Smith, "Analysis, experimental results, and range adaptation of magnetically coupled resonators for wireless power transfer," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 2, pp. 544–554, 2011.
- [8] G. J. Pottie and W. J. Kaiser, "Wireless integrated network sensors," *Communications of the ACM*, vol. 43, no. 5, pp. 51–58, 2000.
- [9] J. M. Kahn, R. H. Katz, and K. S. Pister, "Next century challenges: mobile networking for smart dust," in *Proceedings of the 5th annual ACM/IEEE international conference on Mobile computing and networking*. ACM, 1999, pp. 271–278.
- [10] C. Intanagonwiwat, R. Govindan, and D. Estrin, "Directed diffusion: a scalable and robust communication paradigm for sensor networks," in *Proceedings of the 6th annual international conference on Mobile computing and networking*. ACM, 2000, pp. 56–67.
- [11] E. Shih, S.-H. Cho, N. Ickes, R. Min, A. Sinha, A. Wang, and A. Chandrakasan, "Physical layer driven protocol and algorithm design for energy-efficient wireless sensor networks," in *Proceedings of the 7th annual international conference on Mobile computing and networking*. ACM, 2001, pp. 272–287.
- [12] Y. Peng, Z. Li, W. Zhang, and D. Qiao, "Prolonging sensor network lifetime through wireless charging," in *31st IEEE Real-Time Systems Symposium (RTSS)*. IEEE, 2010, pp. 129–139.
- [13] F. Zhang, X. Liu, S. A. Hackworth, R. J. Scabassi, and M. Sun, "In vitro and in vivo studies on wireless powering of medical sensors and implantable devices," in *2009 IEEE/NIH Life Science Systems and Applications Workshop*. IEEE, 2009, pp. 84–87.
- [14] Y. Yang and C. Wang, *Wireless Rechargeable Sensor Networks*. Springer, 2015.
- [15] S. K. Sudarshan and A. T. Becker, "Using gradient descent to optimize paths for sustaining wireless sensor networks," in *2015 Texas Symposium on Wireless and Microwave Circuits and Systems (WMCS)*. IEEE, 2015, pp. 1–6.
- [16] M. Zhao, J. Li, and Y. Yang, "A framework of joint mobile energy replenishment and data gathering in wireless rechargeable sensor networks," *IEEE Transactions on Mobile Computing*, vol. 13, no. 12, pp. 2689–2705, 2014.
- [17] L. He, P. Cheng, Y. Gu, J. Pan, T. Zhu, and C. Liu, "Mobile-to-mobile energy replenishment in mission-critical robotic sensor networks," in *2014 Proceedings of IEEE International Conference on Computer Communications*. IEEE, 2014, pp. 1195–1203.
- [18] L. Xie, Y. Shi, Y. T. Hou, W. Lou, H. D. Sherali, and S. F. Midkiff, "Bundling mobile base station and wireless energy transfer: Modeling and optimization," in *2013 Proceedings on IEEE International Conference on Computer Communications*. IEEE, 2013, pp. 1636–1644.
- [19] L. He, Y. Gu, J. Pan, and T. Zhu, "On-demand charging in wireless sensor networks: Theories and applications," in *10th IEEE International Conference on Mobile Ad-Hoc and Sensor Systems (MASS)*. IEEE, 2013, pp. 28–36.
- [20] C. Hu and Y. Wang, "Schedulability decision of charging missions in wireless rechargeable sensor networks," in *2014 Eleventh Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*. IEEE, 2014, pp. 450–458.

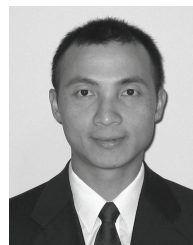
- [21] L. Xie, Y. Shi, Y. T. Hou, and H. D. Sherali, "Making sensor networks immortal: An energy-renewal approach with wireless power transfer," *IEEE/ACM Transactions on Networking (TON)*, vol. 20, no. 6, pp. 1748–1761, 2012.
- [22] E. Welzl, *Smallest enclosing disks (balls and ellipsoids)*. Springer, 1991.
- [23] L. Fu, P. Cheng, Y. Gu, J. Chen, and T. He, "Minimizing charging delay in wireless rechargeable sensor networks," in *2013 Proceedings of IEEE International Conference on Computer Communications*. IEEE, 2013, pp. 2922–2930.
- [24] Z. Li, Y. Peng, W. Zhang, and 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.
- [25] Y. Zhang, S. He, and 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.
- [26] P. Cheng, S. He, F. Jiang, Y. Gu, and J. Chen, "Optimal scheduling for quality of monitoring in wireless rechargeable sensor networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 6, pp. 3072–3084, 2013.
- [27] H. Dai, L. Jiang, X. Wu, D. K. Yau, G. Chen, and S. Tang, "Near optimal charging and scheduling scheme for stochastic event capture with rechargeable sensors," in *10th IEEE International Conference on Mobile Ad-Hoc and Sensor Systems (MASS)*. IEEE, 2013, pp. 10–18.
- [28] X. Ye and W. Liang, "Charging utility maximization in wireless rechargeable sensor networks," *Wireless Networks*, pp. 1–13, 2016.
- [29] C. M. Angelopoulos, S. Nikolettseas, T. P. Raptis, C. Raptopoulos, and 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.
- [30] B. Tong, Z. Li, G. Wang, and W. Zhang, "How wireless power charging technology affects sensor network deployment and routing," in *2010 IEEE 30th International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 2010, pp. 438–447.
- [31] A. Madhja, S. Nikolettseas, and T. P. Raptis, "Distributed wireless power transfer in sensor networks with multiple mobile chargers," *Computer Networks*, vol. 80, pp. 89–108, 2015.
- [32] Z. Sheng, W. Jie, and L. Sanglu, "Collaborative mobile charging for sensor networks," in *9th IEEE International Conference on Mobile Ad-Hoc and Sensor Systems (MASS)*. IEEE, 2012, pp. 84–92.
- [33] W. Liang, W. Xu, X. Ren, X. Jia, and X. Lin, "Maintaining large-scale rechargeable sensor networks perpetually via multiple mobile charging vehicles," *ACM Transactions on Sensor Networks (TOSN)*, vol. 12, no. 2, pp. 14:1–14:26, 2016.
- [34] C. Lin, Y. Wu, Z. Liu, M. S. Obaidat, C. W. Yu, and G. Wu, "Gtcharge: A game theoretical collaborative charging scheme for wireless rechargeable sensor networks," *Journal of Systems and Software*, vol. 121, pp. 88–104, 2016.
- [35] C. Lin, G. Wu, M. S. Obaidat, and C. W. Yu, "Clustering and splitting charging algorithms for large scaled wireless rechargeable sensor networks," *Journal of Systems and Software*, vol. 113, pp. 381–394, 2016.
- [36] C. Lin, B. Xue, Z. Wang, D. Han, and J. Deng, "DWDP: A double warning thresholds with double preemptive scheduling scheme for wireless rechargeable sensor networks," in *17th IEEE International Conference on High Performance Computing and Communications (HPCC 2015)*. IEEE, 2015, pp. 503–508.
- [37] C. Lin, Z. Wang, D. Han, Y. Wu, C. W. Yu, and G. Wu, "TADP: Enabling temporal and distantal priority scheduling for on-demand charging architecture in wireless rechargeable sensor networks," *Journal of Systems Architecture*, vol. 70, pp. 26–38, 2016.
- [38] V. Kulathumani, A. Arora, M. Sridharan, and M. Demirbas, "Trail: A distance-sensitive sensor network service for distributed object tracking," *ACM Transactions on Sensor Networks (TOSN)*, vol. 5, no. 2, pp. 15:1–15:40, 2009.
- [39] G. Xing, T. Wang, W. Jia, and 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.
- [40] J. H. Wei Ye and D. Estrin, "An energy-efficient mac protocol for wireless sensor networks," in *21st International Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM 2002)*. IEEE, 2002, pp. 1567–1576.
- [41] Y. Shu, P. Cheng, Y. Gu, J. Chen, and T. He, "TOC: Localizing wireless rechargeable sensors with time of charge," *ACM Transactions on Sensor Networks (TOSN)*, vol. 11, no. 3, pp. 44:1–44:22, 2015.



Chi Lin (M'15) received B.E. and Ph.D. from Dalian University of Technology, China, in 2008 and 2013, respectively. He has been an assistant professor in School of Software, Dalian University of Technology (DUT), China since 2014. Dr. Lin has authored over 50 scientific papers. In 2015, he was awarded ACM Academic Rising Star. His research interests include pervasive computing, cyber-physical systems (CPS), and wireless sensor networks.



Ding Han received the B.E. degree in software engineering from Dalian University of Technology (DUT), China, in 2016. He is now working towards the PhD degree of computer science in Huazhong University of Science and Technology (HUST), Wuhan, China. His research interests include real-time scheduling and real-time database.



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



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