MPF: Prolonging Network Lifetime of Wireless Rechargeable Sensor Networks by Mixing Partial Charge and Full Charge

***Abstract*—Recently, wireless power transfer is emerging as an enabling technology of wireless rechargeable sensor networks. Conventional methods that charge each sensor until its battery is full take unproportionally long time to finish, due to the limitation of charging efficiency and power transfer technologies. In this paper, we propose a mixed partial and full charge (MPF) scheme, including three specialized modules, *i.e.*, evaluation module, adjustment module, and selection module. MPF allows nodes to be replenished "partially" by a mobile charging vehicle (MCV). When executing adjustment module, a concept of power and path adjustment window is proposed for determining a proper power allocation scheme as well as charging path. Then a scheduling strategy termed return mechanism is designed to further utilize the energy of the MCV and improve effective energy utilization. Finally, we build a high-accuracy charging test-bed and evaluate the applicability as well as performance of the proposed scheme. For large-scale networks, we also perform simulations to demonstrate the effectiveness of MPF in promoting survival rate and reducing traveling distance of the MCV.**

I. Introduction

Wireless rechargeable sensor networks (WRSNs) [1], which benefit from recent breakthrough in wireless power transfer (WPT) technology, emerge as very promising solutions for network lifetime extension. This new charging technique makes the permanent operation of wireless sensor networks (WSNs) achievable via providing energy supply wirelessly, which is especially useful for sensor monitoring applications working in harsh environment and unreachable places. Therefore, in recent years, flourishing achievements have been made for exploring and enhancing the performance of such networks, for example, developing specialized routing protocols [2] and dedicated charging scheduling algorithms [3], [4].

Previous works have indeed made contributions for WRSNs' performance improvement. However, most of them assumed that an mobile charging vehicle (MCV) must replenish a sensor to its full energy capacity in fulfilling every charging mission [5], [6]. As full charge methods limit the maximum number of charges in a tour due to fixed energy capacity of both sensors and MCVs, the survival rate will significantly decline [7]. Besides, charging efficiency of Li-ion battery is not always a constant value (see Section V). When charging over 90% of capacity, the efficiency will dramatically reduce, extending the charging duration.

As an effective and flexible charging scheme, partial charge is regarded as the best alternative to avoid the aforementioned drawbacks. Through partial charge, more sensors can be served before their energy exhaustion and charging delay can be significantly shortened [7], avoiding exceeding their deadlines. Nevertheless, partial charge has an inherent drawback, which should be solved before taking into practical applications. It may lead to heavier charging burdens due to more frequent emerging of charging requests, which reduces survival rate of network and increases traveling distance in the future.

Our motivation here is to overcome drawbacks of both partial and full charge to further enhance the survival rate of network. We propose a mixed partial and full charge (MPF) scheme for WRSNs under the on-demand architecture with a return mechanism (RTM) for the MCV. There are two major challenges to tackle. The first challenge is that how to apply partial charge to survive more nodes and meanwhile relieve the heavy traveling cost burden. The second challenge is that the large-scale characteristic of network and limited energy resources will make inevitable death of sensor nodes, hence, a charging scheme that can fully utilize the energy is desired.

In MPF, partial charge together with full charge is jointly taken to exploit advantages of both charging methods. The corresponding path planing and energy allocation schemes are provided as well. Generally, the main contributions of this work are summarized as below.

- To the best of our knowledge, we are the first to formally propose a charging scheme which jointly combines full charge and partial charge in charging scheduling. We develop MPF to determine when and how to use partial charge to improve the network performance.
- To determine appropriate charging path as well as corresponding power allocation scheme, we propose the concept of power and path adjustment window (PPA). Moreover, to further utilize the limited energy, a scheduling strategy termed RTM is applied when the MCV heading toward BS.
- A high-accuracy charging test-bed is developed to show the applicability of MPF. Moreover, simulations are conducted for large-scale WRSNs to demonstrate the advantages by comparing with different state-of-the-art techniques (*i.e.*, Heuristic [7], EDF [8], and NJNP [9]). For example, the survival rate of sensor nodes when applying MPF outperforms the other algorithms by more than about 10%.

The rest of this paper is organized as follows. Section II surveys the state-of-the-art literature on WRSNs. Section III illustrates the network architecture and problem definitions.

Section IV presents MPF scheme in detail. Section V presents the results of test-bed experiments as well as simulations. Finally, Section VI concludes our work and points out the future work.

II. Literature Review

Many studies are committed to investigate wireless charging scheduling problems in WRSNs, which can be divided into two general categories: full charge and partial charge.

A. Full Charge

Full charge refers to replenishing nodes to their full capacity. Specifically, according to the number of MCVs serving throughout the network, charging scheduling approaches via full charge can be further classified into two categories: single-MCV charging mode [5], [10] and multiple-MCV charging mode [6], [11], [12].

Single-MCV Charging Mode. The single-MCV charging mode, which only employs one MCV to replenish energy for sensor nodes, has two types: off-line scheduling based [2], [5], [10], [13] and on-line scheduling based [3], [9]. For the former, traveling paths of the MCV are usually pre-calculated according to different optimization goals or geographic features. For instance, Fu *et al.* [5] calculated traveling path by identifying the optimal reader (*i.e.*, the MCV) stop locations and corresponding stop duration to minimize the total delay. Sangrae *et al.* [13] derived an optimal policy for the MCV to sequentially decide the optimal path and the subset of sensors to charge by using Markov decision process. For the latter, the MCV only tends to transfer energy for those taking the initiatives to require energy, acting like an on-demand scheme. He *et al.* [9] firstly studied the on-demand charging problem by using Nearest-Job-Next with Preemption (NJNP) discipline for the MCV, and theoretically analyzed the performance of NJNP. Lin *et al.* [3] designed a temporal-spatial charging scheduling algorithm (TSCA) for the on-demand charging architecture, which aims to save more dying nodes.

Multiple-MCV Charging Mode. Different from the single-MCV mode, multiple-MCV charging mode concentrates on collaborations and energy delivering among MCVs. Zhang *et al.* [6] proposed a scheduling algorithm named PushWait, which maximizes energy usage effectiveness of WRSNs. Madhja *et al.* [14] explored the collaborative feature by forming a hierarchical charging architecture.

B. Partial Charge

Full charge has a potential drawback in reducing the survival rate. To solve this problem, Xu *et al.* [7] proposed partial energy charging (*i.e.*, partial charge) to increase sensor survival opportunities. However, in their work, sensors are always replenished by a fixed unit power each time and the traveling time is regarded as a fixed value, which are not very practical. Moreover, they only tried to reduce the extra traveling expenditure caused by partial charge and the issue of path planning is not mentioned.

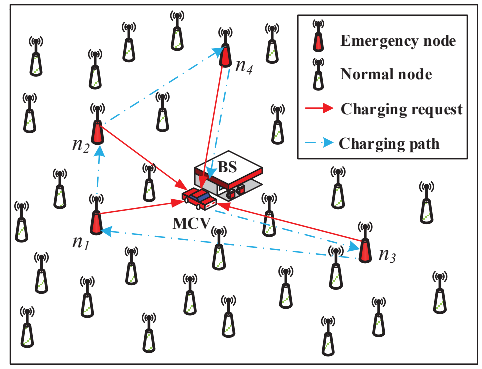


Fig. 1. Overview of an on-demand charging architecture.

In this work, we propose a novel charging scheme named MPF to tackle the aforementioned challenges, which simultaneously considers partial charge and full charge for the on-demand charging architecture.

III. Preliminaries

A. Network Architecture

Figure 1 shows the overview of an on-demand charging architecture. A WRSN is composed of a base station (BS), an MCV, and a set of rechargeable sensor nodes. BS locates at the center of a $d \times d$ region, which timely collects data from sensors. Moreover, it can provide a quick battery replacing service for the MCV. The MCV is employed for replenishing energy for sensor nodes via WPT technology, and can decide whether to conduct the full or partial charge after confirming the charging target. The sensor nodes, implemented with the classic MAC [15] and the routing protocol DD [16], are randomly deployed for monitoring events.

In our scenario, the on-demand charging architecture [7] is applied for constructing a flexible and scalable network topology. Nodes can join and leave the network at any time due to the dynamic nature of this architecture. Once the residual energy of a node n_i falls below a threshold ϕ, it will immediately initiate a charging request containing information such as average energy consumption rate p_i, residual lifetime $T_k(i)$ and location to the MCV. Upon the reception of such a request, the MCV will store it in a waiting queue W sorted by senders' residual lifetime in a descending order. Compared with the charging and traveling latency, time for transmitting requests is short enough to be omitted [17]. Afterwards, the MCV selects several requests to form a charging mission and computes a charging plan containing a charging path and corresponding power allocation scheme. When the MCV completes a charging mission, it will travel back to BS and take a quick battery replacing service with a negligible delay.

As the charging efficiency of WPT dramatically degrades with the distance between the MCV and the node [13], we hereby assume that a node n_i will not be charged until the MCV arrives at its location. Once a node n_i fails to be recharged before energy depletion, it will fall into a temporary death mode and stop working until revived by provisioning later. Such time interval is called dead duration.

B. Problem Formulation

First, a quick reference for main notations is provided in Table I.

TABLE I
MAIN NOTATIONS FOR QUICK REFERENCE

Symbols	Definitions
$\|*\|$	Size or length of a set, a queue or a window.
N	Number of charging missions.
η	Charging efficiency of MCV.
ρ_c	Average charging consumption rate of MCV.
ρ_m	Traveling consumption rate of MCV.
E_m	Battery capacity of MCV.
E_s	Battery capacity of sensor nodes.
T	Running time of WRSN.
n_0	Base station in a WRSN.
n_i	A sensor node, i=1,2,...,$\|N\|$.
$d_{i,j}$	Distance between n_i and n_j.
r_i^k	Residual energy of n_i in the kth charging mission M_k.
ϕ	Warning threshold of nodes.
τ_i^k	Charging duration for n_i.
$A_k(i)$	Arrival time of MCV at n_i in the kth charging mission M_k.
$T_k(i)$	Remaining lifetime of n_i at the beginning of the kth charging mission M_k.
D_k	Total traveling distance of MCV in the kth charging mission M_k.

As unpredictable events may happen anywhere and anytime throughout the network, exhaustion of any node may lead to event missing, which should be avoided in safety-critical applications. Thus, the primary concern is the lifetime of sensors. We first define the survival rate ξ as

$$\xi = 1 - \frac{1}{T}\sum_{k=1}^{N}\sum_{i=1}^{|M_k|} t_d^k(i) \ , \tag{1}$$

to quantify the lifetime of sensors. In Equation (1), $t_d^k(i)$ refers to the dead duration of node n_i in the kth charging mission M_k, which is calculated as

$$t_d^k(i) = max\ \{0, A_k(i) - T_k(i)\} \ . \tag{2}$$

Assume the maximum survival rate ξ^* has been guaranteed, the other concern is to minimize the traveling cost since the mechanical movement of MCV consumes numerous energy [18]. Moreover, partial energy charging has an inherent drawback of casting extra charging and traveling burdens due to generating more charging requests. Taking both concerns into consideration, we formulate our problem as: *minimizing the traveling cost χ (see Equation (3)) with the maximum survival rate ξ^*.*

$$min\ \chi = \sum_{k=1}^{N} D_k \cdot \rho_m. \tag{3}$$

Subject to

$$P_k(i) - E_s\phi > 0,\ 1 > \phi > 0,\ \forall i, k = 1, 2...N \tag{4}$$

$$\xi = \xi^* \tag{5}$$

In Equation (3), $D_k \cdot \rho_m$ refers to the total traveling cost in M_k. Constraint (4) guarantees that the replenishing power is larger than the energy threshold.

IV. MPF: MIXED PARTIAL AND FULL CHARGE SCHEME

To solve the above problem, we propose a mixed partial and full charge scheme, named MPF, for generating a charging plan to guarantee the maximum ξ^* and minimize χ in each M_k. Besides, a scheduling strategy called return mechanism (RTM) is designed for network to further promote effective energy utilization $Q = \frac{E_r}{E_r+\chi}$, where E_r refers to the total received energy of sensors.

A. Design of MPF

MPF aims to generate a charging plan $B_k(\Omega_k^j, P_k)$, which is composed of two parts: a charging path Ω_k^j and the corresponding power allocation scheme P_k.

Originally, after collecting a number of requests, an initial charging mission will be set up. We choose u requests from the waiting queue W to form a mission M_k (*i.e.*, the kth mission) and u satisfies

$$u = min\ \{\beta, |W|\} \ , \tag{6}$$

where β is the maximum size of M_k. The value of β and u will be discussed in Section V-B.

Comparing with partial charge, full charge ensures more stable emergence of charging requests, which further reduces the traveling cost. Therefore, MPF prefers to adopt full charge if it can minimize the traveling cost with all nodes alive (*i.e.*, $\xi = \xi^*$). Otherwise, if full charge cannot achieve ξ^*, MPF will adopt partial charge to maximize ξ. Hence, MPF first initializes a charging plan B_k for mission M_k by adopting full charge for each node. Accordingly, the allocated power for each node is $P_k(i) = E_s$. Then, a charging path set $\Omega_k = \{\Omega_k^0, \Omega_k^1, \cdots, \Omega_k^j, \cdots\}$ ordered by path length will be generated (*i.e.*, $\Omega_k^i < \Omega_k^j, 0 \leq i < j$). To minimize the traveling cost, we utilize the shortest Hamiltonian path (*i.e.*, Ω_k^0) to initialize the charging path. Consequently, an initial charging plan $B_k(\Omega_k^0, P_k)$ is set to guide MCV's further charging behavior.

Sometimes, such a plan may not be schedulable because some nodes cannot be timely replenished before depletion (*i.e.*, full charge is not schedulable with Ω_k^0). To address this issue, we propose three modules: evaluation module (***EM***), adjustment module (***AM***), and selection module (***SM***) to testify, adjust, and select charging plan, respectively. The general process of the three modules is shown in Figure 2.

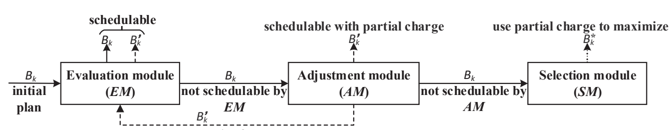


Fig. 2. General process of EM, AM and SM.

At first, an initial charging plan B_k is input, then ***EM*** is used to check the schedulability of full charge based on path Ω_k^j. If schedulable, B_k will be chosen to guide the MCV's behavior. Otherwise, ***AM*** will be executed to adjust the charging path or power allocation scheme to find a schedulable charging plan B'_k with full charge or partial charge. If no schedulable B'_k exists, MPF will generate a charging plan B^*_k with maximum ξ by applying ***SM*** and in that case, we have to use partial charge to serve selected nodes to maximize ξ.

Next, we demonstrate these three modules and the process of MPF in detail.

Evaluation Module (EM). ***EM*** is used to testify the schedulability of a charging plan with full charge which contains the following three constraints:

(1) Energy constraint of MCV: The MCV should always hold enough residual energy before returning back to the BS, which is formulated as

$$\sum_{i=1}^{|M_k|} \tau_i^k \rho_c + D_k \rho_m \leq E_m, \ \forall k = 1, 2, \cdots, N \ . \tag{7}$$

(2) Energy constraint of nodes: all nodes in M_k should keep alive before the MCV's arrival. First, we calculate charging duration of each node τ_i^k:

$$\tau_i^k = \begin{cases} \frac{E_s - (r_i^k - A_k(i) p_i)}{q_c \eta}, & A_k(i) \leq T_k(i) \\ \frac{E_s}{q_c \eta}, & A_k(i) > T_k(i) \ , \end{cases} \tag{8}$$

where the arrival time $A_k(i)$ of the MCV is calculated by a iterative method:

$$A_k(1) = \frac{d_{01}}{v} \ , \tag{9}$$

$$A_k(i) = \frac{d_{i-1,i}}{v} + A_k(i-1) + \tau_{i-1}^k, \ i > 1 \ . \tag{10}$$

Then, the energy constraint of nodes can be formulated as

$$T_k(i) - A_k(i) \geq 0 \ . \tag{11}$$

(3) Energy constraint of the next charging mission: when the size of waiting queue exceeds its maximum length (*i.e.*, $|W| > \beta$), indicating that the MCV still has new requests to serve after completing the current mission. In this case, M_k should not only satisfy the above two constraints, but also guarantee the survival of all nodes belonging to the next charging mission M_{k+1}. Hence, we propose a constraint to ensure the first node in the next charging round (*i.e.*, the earliest dead node) n_{u+1} is alive when the MCV fulfills M_k. The completion time of M_k can be calculated as

$$T_{M_k} = A_k(u) + \tau_u^k + \frac{d_{u,0}}{v} \ . \tag{12}$$

Therefore, this constraint can be deduced as

$$T_{M_k} + \frac{d_{0,u+1}}{v} < T_k(u+1) \ . \tag{13}$$

A charging plan B_k simultaneously meeting the above three constraints is regarded as a schedulable one. To quantify the schedulability of the charging plan, we define a function $\Psi(B_k(\Omega_k^j, P_k))$ for computing the total dead duration as follows:

$$\Psi(B_k(\Omega_k^j, P_k)) = \sum_{k=1}^{|M_k|} t_d^k(i) + t_d^{k+1}(u+1) \ , \tag{14}$$

where $t_d^{k+1}(u+1)$ is the dead duration of the earliest dead node in M_{k+1}. This function can distinguish the gap for deciding whether to take a full charge or partial charge.

A charging plan B_k successfully passing ***EM*** with $\Psi = 0$ indicates that M_k is schedulable by only taking full charge. If not, an original non-schedulable charging plan (*i.e.*, $\Psi \neq 0$) might be converted into a schedulable one by adjusting the value of Ψ to zero. We hereby use module ***AM***.

Adjustment Module (AM). The aim of ***AM*** is to minimize the value of Ψ through adjusting charging plan B_k. It has two alternatives:

- A_1: Update the power allocation scheme for the charging path Ω_k^j in B_k.
- A_2: Change node sequence of charging path Ω_k^j based on the power allocation scheme P_k in B_k.

As the charging path is initialized by the shortest path (*i.e.*, Ω_k^0), through which traveling cost has already been minimized. Therefore, we try to minimize Ψ via A_1 first. We aim to select and charge a fraction of nodes partially to recover the schedulability of the mission. Moreover, the value of Ψ can be minimized through adjusting allocated power of these nodes. To find such nodes, we define a dead node set S_d and propose a concept of path and power adjustment window (PPA). A PPA window, denoted as ω_p^i, records a set of nodes, positioned in front of the dead node n_i in the charging plan, whose allocated power need adjusting. When constructing a PPA, the size should satisfy:

$$|\omega_p^i| = i - 1 - |\omega_p^{i-1}|, i > 1, |\omega_p^1| = 0 \ . \tag{15}$$

To revive n_i, the only way is to reduce the charging duration for nodes in the window. The dead duration $t_d^k(i)$ of dead node n_i is calculated as the total charging duration that needs to be diminished for nodes in ω_p^i.

Accordingly, the total allocated power that needs to be reduced can be calculated as $\Delta P_k = \eta \rho_c t_d^k(i)$. Next, we need to decide how many nodes need partial charge and how to allocate the charging power for them.

In MPF, we allocate power by averaging ΔP_k for nodes that need partial charge. Next, we need to determine the quantity of nodes that will be charged partially. An unnegligible problem when determining the quantity and corresponding allocating power is as follows: although nodes' allocated power can be reduced, replenishing too little energy in partial charge may cause heavy traveling burdens in the future for serving more frequent charging requests. Thus, we set a constraint:

$$\tau_i^k \rho_c - \varepsilon E_s = P_k(i) - (r_i^k - A_k(i) p_i) - \varepsilon E_s \geq 0 \ . \tag{16}$$

It guarantees that the allocated power for n_i cannot be less than the borderline ε. As proved in [7], to ensure well network functionality, $\varepsilon = 0.5$ should be guaranteed. Hence, to determine the number of nodes γ applying partial charge, γ should satisfy:

$$\frac{E_s - \frac{\Delta P_k}{\gamma} - (r_i^k - A_k(i) p_i)}{E_s} \geq \varepsilon, \gamma < |\omega_p^i|, \ i = 1, 2, \cdots, \gamma \ . \tag{17}$$

Equation (17) indicates that the dead duration $t_d^k(i)$ can be reduced to 0 by decreasing charging duration of γ nodes in

ω_p^i. In other words, these nodes can be partially charged and the new allocated power of each node can be determined as $P'_k(i) = E_s - \frac{\Delta P_k}{\gamma}$.

After determining γ, we need to choose γ nodes to charge partially in the corresponding PPA (*i.e.*, $\gamma \le |\omega_p^i|$). Since we intend to provide full charge for important nodes to keep them always alive, ***AM*** will choose γ nodes with lower importance from the PPA. Here, we use energy consumption rate as criterion of importance: a node with higher importance owns heavier workload, and accordingly will have higher average energy consumption rate p_i [19].

Algorithm 1 Updating power allocation

Input: The current charging mission M_k, a dead node queue S_d and a charging plan B_k with full charge
Output: A new charging plan B'_k or null

for $i \leftarrow 1$ to $|S_d|$ **do**
  Calculate the size of PPA window ω_p^i;
  Add nodes located in front of n_i into ω_p^i;
  Calculate the power needs to be reduced $\Delta P_k \leftarrow \eta \rho_c t_d^k(i)$;
  for $\gamma \leftarrow 1$ to $|\omega_p^i|$ **do**
    if $\frac{E_s - (r_m^k - A_k(m)p_m) - \frac{\Delta P_k}{\gamma}}{E_s} \ge \varepsilon$ is satisfied for all γ nodes **then**
      Sort nodes in ω_p^i by energy consumption rate p_i;
      for $m \leftarrow 1$ to γ **do**
        $P'_k(m) \leftarrow E_s - \frac{\Delta P_k}{\gamma}$;
      end for
      for $j \leftarrow i+1$ to $|S_d|$ **do**
        Update $t_d^k(j)$ and S_d;
      end for
      break;
    end if
  end for
  if $\gamma > |\omega_p^i|$ **then**
    return $null$;
  end if
end for
return B'_k;

The above process is described in Algorithm 1. First, we construct a PPA window ω_p^i and determine its size for dead node n_i recorded in the temporary dead node set S_d. Then, MPF updates values of allocated power for nodes in ω_p^i to reduce the value of Ψ. This process repeats until $\Psi = 0$ is obtained, and a new charging plan $B'_k(\Omega_k^j, P'_k(i))$ will be selected for M_k.

Once no schedulable B'_k can be found by A_1, which means that only altering power allocation cannot maximize ξ. In that case, we intend to adjust charging sequence to reduce value of Ψ by means of alternative A_2.

When applying A_2, we only preserve paths that can reduce the value of Ψ by removing paths with longer dead duration. Here, the size of PPA window for dead node n_i is: $|\omega_p^i| = i, i \ge 1$. Once the location of n_i in Ω_k^j is not included in the locations of nodes contained in ω_p^i, meaning that Ω_k^j will cause longer dead duration, then we remove Ω_k^j from Ω_k. Next, we choose the shortest path Ω_k^j in Ω_k and use ***EM*** to test the schedulability of charging plan $B'_k(\Omega_k^j, P_k(i) = E_s)$. Once B'_k is schedulable, full charge will be used to serve all nodes sequentially. Otherwise, MPF will repeat the process of A_1 for continuously reducing value of Ψ, and partial charge will be taken to serve several nodes.

Finally, if ***AM*** still cannot generate a schedulable B'_k until $\Omega_k = \emptyset$, the selection module (***SM***) will be executed.

Selection Module (SM). After executing ***AM***, if no schedulable plan is obtained, (*i.e.*, using full charge will inevitably cause node exhaustion), partial charge will be applied to shorten the dead duration. MPF will use *SM* to generate a charging plan B_k^* with minimum dead duration based on the charging plans generated in ***EM*** and ***AM*** to calculate ξ^*. We formally express B_k^* as

$$B_k^* = arg\,min\, \Psi(B_k(\Omega_k^j, P_k)) \ . \tag{18}$$

To generate the charging plan B_k^*, we use identical approaches as ***AM***. The only difference is that when $\gamma > |\omega_p^i|$, nodes will be powered by borderline ε of partial charged, *i.e.*, $P'_k(i) = \varepsilon E_s + T_k(i) p_i$.

Finally, we prove MPF can always guarantee Equation (5).

Theorem I. MPF can always guarantee the maximum value of ξ^*.

Proof. For each charging mission M_k, MPF will generate a charging plan for it through ***EM***, ***AM***, or ***SM***. When a charging plan is determined by ***EM*** or ***AM***, $\Psi = 0$ can be guaranteed, which means $\sum_{i=1}^{|M_k|} t_d^k(i) + t_d^{k+1}(u+1) = 0$ (*i.e.*, ξ^* is achieved, $\xi^* = 1$) by applying above process. Otherwise, a B_k^* is generated by ***SM*** with minimum Ψ which implies that ξ is maximized (see Equation (18)). Hence, MPF can always guarantee ξ is maximized. $\square$

In the following, a scheduling strategy termed RTM will be introduced to further optimize the performance of network.

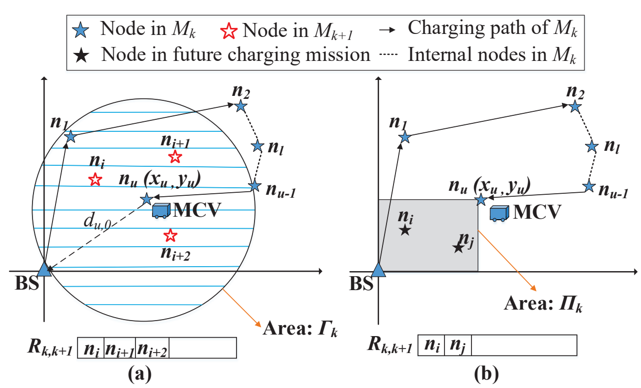


Fig. 3. Illustration of RTM.

B. Design of RTM

After determining charging plan via the above three modules, the MCV will start to work. When completing charging the last node n_u in M_k, it will return to BS. During this process, we observe an interesting phenomenon: *when heading towards BS, the residual energy of MCV r_v may still be sufficient to serve more nodes*. Moreover, due to the dynamic nature of the on-demand charging architecture, nodes can join and leave the network at any time which may cause extra charging requests.

Therefore, we design RTM to fully utilize such energy (*i.e.*, promote effective energy utilization) and adapt it to the dynamic nature simultaneously. We first exemplify such a case in Figure 3, in which an MCV is undertaking a charging mission M_k with u nodes. According to the energy constraint of the MCV (*i.e.*, Equation (7)), the residual energy will at least support the MCV to travel $d_{u,0}$. Hence, we define the circular region with a radius $d_{u,0}$ to represent the MCV's neighboring region Γ_k. If a node n_i belonging to the next charging mission M_{k+1} satisfies

$$n_i(x, y) \in \{\Gamma_k | (x - x_u)^2 + (y - y_u)^2 \leq d_{u,0}^2\} \ , \qquad (19)$$

where (x_u, y_u) is denoted as the location of n_u, it will be regarded as a nearby node. Afterward, n_i will be added into a set $R_{k,k+1}$, which represents the temporary charging mission between M_k and M_{k+1} ordered by residual lifetime (see Figure 3(a)).

In RTM, the MCV only charges nodes in M_{k+1} which will not cause the exhaustion of other emergency nodes. Algorithm 2 shows how to generate a charging plan $B_{k,k+1}$ based on Γ_k.

Algorithm 2 RTM for nodes in Γ_k

Input: Waiting queue W
Output: A charging plan $B_{k,k+1}$ or $\emptyset$
Add nodes in Γ_k to $R_{k,k+1}$;
if $R_{k,k+1} \neq \emptyset$ **then**
  for $i \leftarrow 1$ to $|R_{k,k+1}|$ **do**
    if n_i passed *EM* or $\Psi = 0$ by using AM **then**
      $\Omega_{k,k+1} \leftarrow \Omega_{k,k+1} \cup \{n_i\}$;
      Update r_v;
    end if
  end for
end if
if $\Omega_{k,k+1} \neq \emptyset$ **then**
  return $B_{k,k+1}$;
else
  return $\emptyset$;
end if

Algorithm 2 proceeds as follows. We first add nodes that located in Γ_k into $R_{k,k+1}$. Then, we sequentially testify whether nodes in $R_{k,k+1}$ can be charged by applying ***EM*** and ***AM***, and qualified nodes will be added into the charging path set $\Omega_{k,k+1}$. Finally a charging plan $B_{k,k+1}$ is generated.

Once the MCV cannot serve nodes in $R_{k,k+1}$ or no node locates in Γ_k, it will query whether there exist nodes in the rectangle area Π_k (see Figure 3(b)). If such nodes are found, they will be added into $R_{k,k+1}$ and the charging plan $B_{k,k+1}$ can be obtained by Algorithm 3. This time, the MCV tends to serve the nodes that will request for replenishment in the future on the way back to BS. As the residual energy of nodes in $R_{k,k+1}$ is still higher than the threshold ϕ, the charging path $\Omega_{k,k+1}$ for $R_{k,k+1}$ is established according to the spatial distance. The allocated power for nodes in $R_{k,k+1}$ depends on the MCV's residual energy r_v. When satisfying $r_v - (d_{i,0} + d_{u,i})\rho_m > 0$, the MCV has extra energy for charging. Detailed design is shown in Algorithm 3.

Algorithm 3 RTM for nodes in Π_k

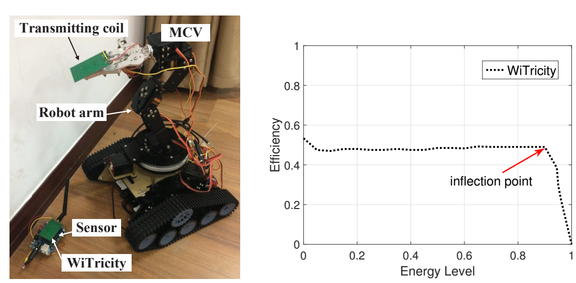
Input: Nodes set $R_{k,k+1}$
Output: A charging plan $B_{k,k+1}$
1: **while** $R_{k,k+1} \neq \emptyset$ **do**
2:   Choose the nearest n_i;
3:   **if** $r_v - (d_{i,0} + d_{u,i})\rho_m < 0$ **then**
4:     break;
5:   **else if** $(r_v - d_{i,0}\rho_m - d_{u,i}\rho_m)\eta + (T_{k,k+1}(i) - A_{k,k+1})p_i \geq E_s$ **then**
6:     $P_{k,k+1}(i) \leftarrow E_s$;
7:   **else**
8:     $P_{k,k+1}(i) \leftarrow (r_v - d_{i,0}\rho_m - d_{u,i}\rho_m)\eta + p_i(T_{k,k+1}(i) - A_{k,k+1}(i))$;
9:   **end if**
10:   **if** $B_{k,k+1}$ satisfies Equation (13) **then**
11:     $R_{k,k+1} \leftarrow R_{k,k+1} \setminus \{n_i\}$;
12:     $\Omega_{k,k+1} \leftarrow \Omega_{k,k+1} \cup \{n_i\}$;
13:     Update r_v;
14:   **end if**
15: **end while**
16: return $B_{k,k+1}$;

Algorithm 3 proceeds as follows. First, the nearest node n_i in $R_{k,k+1}$ will be chosen. Then, we calculate its allocated power based on the MCV's residual energy r_v (line 5-9). If the current charging plan $B_{k,k+1}$ can satisfy the constraint of next charging mission (*i.e.*, Equation (13)), n_i will be added into $\Omega_{k,k+1}$. Once the MCV still has residual energy for charging, the above process will be repeated. Finally, a charging plan $B_{k,k+1}$ can be generated for nodes in Π_k.

V. Experiments and Simulations

A. Test-bed Experiments

To clarify the applicability of MPF, test-bed experiments are conducted in our lab.

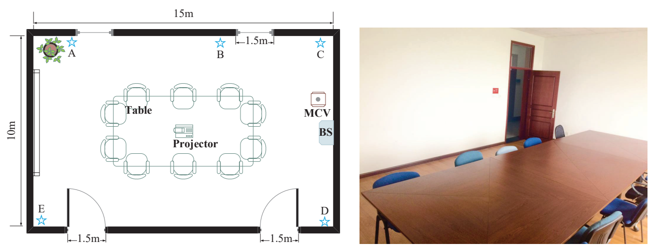


(a) (b)

Fig. 4. Test-bed: (a) a mobile robot arm and a rechargeable sensor and (b) charging efficiency of WiTricity

As shown in Figure 4(a), rechargeable sensor nodes, each equipped with a $12KJ$, $3.7V$ Li-ion battery and a $31mm \times 47.5mm$ receiving coil, are deployed. A robot armed with a transmitting coil is employed as the MCV to replenish energy wirelessly. It is also equipped with GPS and camera to target the receiving coil accurately. In our experiment, we use the classic WPT standard WiTricity [20] to implement rechargeable nodes.

We firstly measured the charging efficiency η of WiTricity for better exploring the charging characteristic of Li-ion battery. When the MCV is charging a sensor, it consumes μ energy per time unit, and the sensor receives λ energy in the meanwhile. Thus, we have $\eta = \frac{\lambda}{\mu}$. As shown in Figure 4(b), we observe that after a dramatic inflection point, η sharply reduces. The reason is that, at that charge level, the amount of residual energy approaches to full capacity of the battery (*i.e.*, over 90% approximately). Therefore, partial charge will be more promising and applicable to alleviate such low efficiency problem for practical applications. Note that, the charging efficiency of WiTricity is near $\eta = 0.48$.



(a) (b)

Fig. 5. Test-bed experiment in a meeting room: (a) the floor plan and (b) actual room

To show the applicability of MPF, a test-bed experiment is taken in a $10m \times 15m$ room for five months in which five rechargeable sensors (*i.e.*, A, B, C, D, and E) are used for monitoring temperature and humidity (see Figure 5). The coordinates of five sensors are A(0.2,10), B(10,10), C(15,10), D(15,0), and E(0,0), respectively. Due to the limited space and number of sensors, sensors will directly send packets to BS. The traveling speed of the MCV is $v = 1m/s$. The traveling consumption rate is $\rho_m = 8J/m$ and average charging consumption rate is $\rho_c = 4J/s$.

To validate the correctness of our test-bed experiments, we compare theoretical results with experimental results and corresponding simulation results in survival rate (note that simulations are conducted in the next section, we put it here to validate its correctness). As shown in Figure 6, we observe that experimental/simulation results approximately coincide with theoretical results. We additionally implement our equipments with three classic charging schemes, namely, a partial energy charging algorithm called Heuristic [7] and two full energy charging schemes: one always serves the node with earliest deadline (*i.e.*, EDF for short) [8], another always serves the nearest node called NJNP [9] to demonstrate the advantages of MPF. The comparison results of the experiments are listed in Table II.

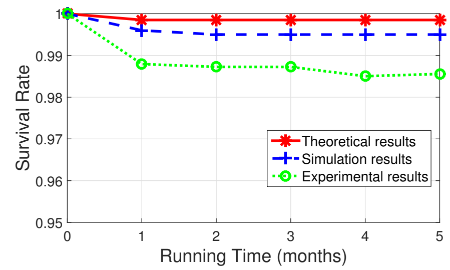


Fig. 6. Comparison between simulation results, experimental results and theoretical results in terms of survival rate.

TABLE II
CHARGING PERFORMANCE COMPARISONS IN TEST-BED EXPERIMENTS

	Successful charging rate	**Dead duration (h)**	**Number of partial charges**	**Traveling cost (J)**
EDF	0.8	0.8	0	456
NJNP	0.8	0.8	0	400
Heuristic	1	0	1	662
MPF	**1**	**0**	**1**	**440**

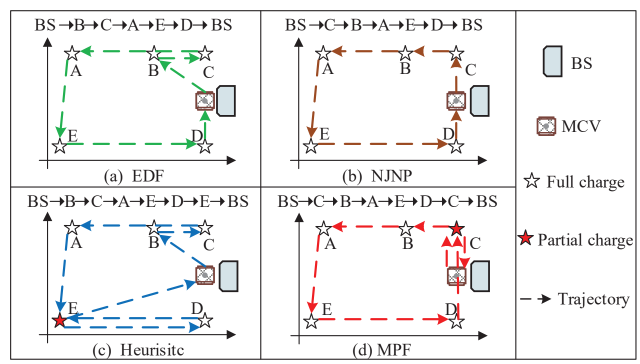


Fig. 7. Traveling trajectories of (a) EDF, (b) NJNP, (c) Heuristic, and (d) MPF

According to the first three columns in Table II, the successful charging rate of EDF and NJNP is 0.8, which indicates that full charge causes exhaustion of one node, leading to a dead duration of about 0.8 hours, respectively. Whereas in partial charge, such node can be saved by MPF and Heuristics, indicating their advantages in preserving nodes.

According to traveling trajectories and corresponding traveling cost given in Figure 7 and Table II, the cost of Heuristic and MPF is obviously higher than NJNP and EDF. Moreover, the cost of Heuristic is still higher than MPF. The reason is that, Heuristic only reduces the extra traveling expenditure caused by partial charge without a path planning method; however, in MPF, path planning is considered and PPA is used to adjust the charging path, which substantially reduces the traveling cost.

B. Simulations

In this section, we evaluate MPF by comparing it with the state-of-the-art charging scheduling algorithms: Heuristic [7], EDF [8], and NJNP [9] in a large-scale network.

Simulation Configurations: Related simulation parameters are listed in Table III.

TABLE III
PARAMETERS OF SIMULATION

Parameters	Values
Network size (m^2)	1000×1000
Number of nodes	60
Consumption rate of node (mJ/s)	$4.5 - 9.5$
Traveling consumption rate of MCV (J/m)	8
Charging consumption rate of MCV (J/s)	4
Charging efficiency	0.48
Initial energy of node (KJ)	12
Initial energy of MCV (KJ)	190
Speed of MCVs (m/s)	1.0
Charging scheme	MPF, Heuristic, EDF, NJNP

Sensor nodes are randomly deployed in a 1000×1000 m^2 area with different energy consumption rates. The WiTricity charging standard is adopted with the charging efficiency $\eta = 48\%$ as test-bed experiment.

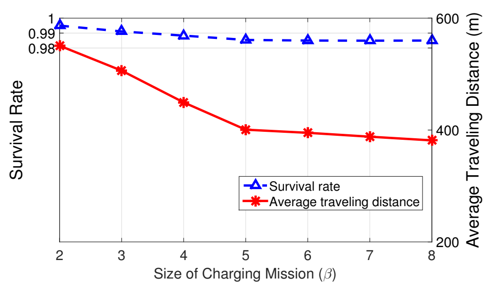


Fig. 8. Impact of value β on survival rate and average traveling distance.

Determination of Value β and ϕ: First, we determine the best size of the charging mission M_k (*i.e.*, the value of β). We mainly analyze the influence of β on survival rate and traveling distance respectively. As shown in Figure 8, the left coordinate reflects the survival rate and the right one represents average traveling distance. The horizontal ordinate denotes the value of β. We observe that, survival rate varies a little and the traveling distance reduces gradually. Moreover, the average traveling distance slightly decreases when $\beta \geq 5$. To reduce the computational complexity of calculating the charging path, we let $\beta = 5$. Therefore, according to Equation (6), $u \leq 5$.

Next, as the warning threshold ϕ impacts the charging performance significantly, we investigate the selection of a feasible value of ϕ. A small threshold will lead to a long dead duration since the MCV cannot replenish nodes in time. Nevertheless, a big threshold will cause more frequent emergence of charging requests. As shown in Figure 9, when $\phi = 0.4$, the survival rate is the highest, hence, we let $\phi = 0.4$. When the energy of nodes falls below 40%, they will send charging requests to the MCV.

Performance Comparison: We compare the performance among MPF, Heuristic, EDF, and NJNP from four aspects.

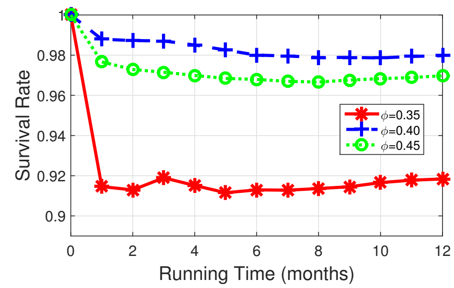


Fig. 9. Influence of warning threshold ϕ on survival rate.

In Figure 10(a), we observe that partial energy charging can effectively improve survival rate since it can save more dying nodes. Besides, MPF allocates power in a dynamic way according to the dead duration. Thus, it owns higher survival rate than Heuristic. MPF has an approximately 13%, 11%, and 7% higher survival rate than those of NJNP, EDF, and Heuristic, respectively. Next, we compare the effective energy utilization with different speeds of MCV in Figure 10(b). The faster the MCV moves, less traveling cost it invests. Hence, effective energy utilization increases with speed. Since EDF and Heuristic are lack of path planning, MPF performs better than them. When comparing with NJNP, MPF has a lower effective energy utilization because NJNP adopts full charge and has less traveling cost.

The comparison of traveling distance and throughput with different node densities are shown in Figure 10(c) and Figure 10(d), respectively. When the number of nodes increases, more charging requests will appear so that the throughput and traveling distance of four methods increase. In Figure 10(c), the total traveling distance of MPF is shorter than EDF and Heuristic but longer than NJNP. The reason is that MPF owns an adjustment module which always chooses the shortest schedulable path for MCV, ensuring its superiority to EDF and Heuristic. However, NJNP adopts full charge and always serves spatially closest nodes and thus it has the shortest traveling distance. Besides, we observe that the throughput of partial charge is higher than those of full charge in Figure 10(d), since partial charge is able to serve more nodes. Statistically, the throughput of EDF is approximately 18% and 15% lower than those of Heuristic and MPF, respectively.

Effectiveness of RTM: We also evaluate necessity of RTM (*i.e.*, Algorithm 2 and Algorithm 3). As shown in Figure 11, when MPF is implemented without RTM, the average traveling distance is 9% longer than with such a mechanism. Furthermore, the effective energy utilization is higher when RTM is used. This demonstrates that RTM is able to further enhance the effective energy utilization.

Objective Verification: Finally, we compare the theoretical results and simulation results in terms of traveling distance. As shown in Table IV, the simulation results of traveling distance match well with theoretical results.

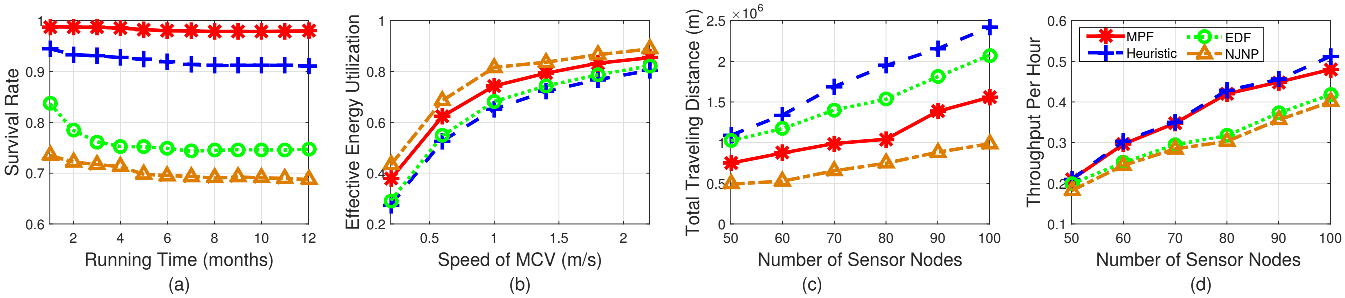


Fig. 10. Comparison between MPF, Heuristic, EDF, and NJNP in terms of (a) survival rate, (b) effective energy utilization, (c) total traveling distance, and (d) throughput per hour.

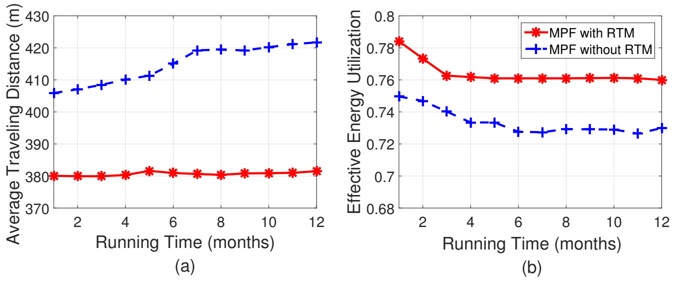


Fig. 11. Validation of RTM in terms of (a) average traveling distance and (b) effective energy utilization.

TABLE IV
COMPARISON BETWEEN THEORETICAL RESULTS AND SIMULATION RESULTS IN TOTAL TRAVELING DISTANCE

Time (months)	1	2	3	4	5	6
Theoretical results (km)	58.68	127.8	200.52	266.76	338.76	410.76
Simulation results (km)	58.93	130.56	204.34	269.50	343.37	415.74

VI. Conclusion

In this paper, we have proposed a mixed charging scheme MPF that computes the feasible charging plan through three specified modules to further reduce traveling cost with maximum survival rate. Then, RTM is designed to fully utilize the residual energy of the MCV and adapt the dynamic nature of network. Our experimental results show the feasibility of partial charging mechanism and disclose practicability of MPF. Our simulation results demonstrate the advantages of MPF in terms of survival rate, traveling cost, effective energy utilization, *etc*.

In our future work, we will focus on how to apply MPF into collaborative charging scenario for multiple MCVs.

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