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Periodic Charging for Wireless Sensor Networks With Multiple Portable Chargers

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ABSTRACT Finite battery capacity limits the network lifetime of wireless sensor networks, and thus severely impedes the deployment of large scale sensor networks. To prolong the lifetime, researchers utilize mobile chargers to recharge sensors with external power sources. In this paper, we study both periodic charging time scheduling and charging path planning with multiple chargers. First, we present an efficient slot-based periodic charging time scheduling algorithm with both a fine-grained node classification scheme to prevent unnecessary visits of energy-sufficient nodes, and a balanced charging task assignment scheme to avoid charging starvation. To further enhance charging efficiency, we also propose a charging path planning algorithm, which enables parallel power replenishment with multiple chargers. The simulation results show that our algorithms are effective and competitive when compared with existing algorithms.

INDEX TERMS Wireless sensor networks, power replenishment, path planning, scheduling.

I. INTRODUCTION

Energy is a critical factor that influences the performance of wireless sensor networks (WSN). Since typical sensor networks are mainly powered by batteries, they can only work for limited time depending on battery capacities. Hence, finite network lifetime becomes a fundamental performance bottleneck that severely constrains the application of sensor networks.

To prolong the network lifetime, extensive research efforts have been made in recent years [6], [8], [24]. Typical strategies employed fall into two categories. One category aims to reduce energy consumption via conventional methods such as duty cycling, data compression, and dynamic routing [9], [28]. Such solutions are effective to some degree, but network lifetime is still determined by limited battery capacity. Another category utilizes the energy harvesting technique to relieve the energy limitation by replenishing sensors via thermal, mechanical, or electromagnetic energy captured from ambient environments [8], [29]. Nevertheless, their success for sensor networks remains limited in practice. This is because the proper operation of any energy-harvesting technique heavily depends on the environment. Further, the size of an energy-harvesting device may pose a concern in deployment, particularly when the size of such a device is of much larger scale than the sensor that it is attempting to power.

Recently, researchers started to adopt mobile chargers to recharge sensors with external power sources. Different from energy harvesting techniques that acquire dynamic and unreliable power supplies, the mobile chargers are capable of offering stable and reliable power sources for sensor networks, and thus enable sustainable system operations. With recent breakthroughs in wireless power transfer technology, mobility-assisted charging becomes more convenient and thus received much attention in academia. A handful of papers [21], [23], [25] have demonstrated the possibility of offering perpetual and stable power supplies to sensor networks via replenishing sensors with mobile wireless rechargers.

Due to the limited mobility of the charger, the scheduling of charging tasks for sensor nodes in the network plays a critical role in achieving a high charging efficiency. The Traveling Salesman Problem (TSP)-based charging protocols are common solutions to the mobile charging problem [7], [12], [13]. In TSP-based approaches, the mobile charger periodically executes a pre-optimized charging tour to replenish the energy of sensor nodes in the networks. However, the drawback of TSP-based solutions is that when nodes energy

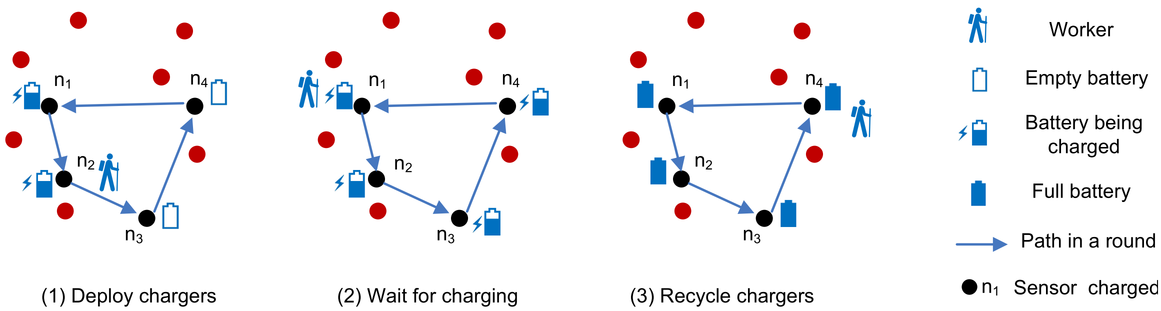

FIGURE 1. Example: simultaneous power replenishment with multiple chargers.

consumptions are diverse, it may lead to the unnecessary visits of energy-sufficient nodes. This not only increases the charger travel distance when performing the charging tasks of sensor nodes, but also prolongs the waiting time before the energy-hungry nodes can be charged.

To cope with this deficiency, a recent work Esync [20] synchronizes the power replenishment of sensor nodes based on a series of periodic TSP tours. In each tour only the energy-hungry nodes are charged, which prevent unnecessary visits of energy-sufficient nodes. In Esync, energy-hungry nodes are identified via a classification approach which clusters nodes according to their various energy consumption rates. Nevertheless, the classification method is coarse-grained and may still lead to the unnecessary visits of energy-sufficient nodes. Another problem is that in Esync the charging loads, i.e., the number of nodes to be charged in each tour, are not balanced among all tours. Specifically, in the last tour all nodes are charged at one time. The unbalanced charging schedule may lead to starvation of some nodes once some tours cannot be started on time. Since the duration of every tour is determined by the nodes with the fasted energy consumption, probably Esync cannot manage to finish charging all nodes in a single tour.

To this end, this paper contributes a *Periodic Scheduling algorithm with Balanced Load Assignment* (PSBLA). The proposed algorithm balances charging task assignments and periodically assigns charging tasks in multiple tours based on planned time slots. The balanced load assignment approach effectively prevents starvation caused by late power replenishment. To boost charging efficiency, we also design a fine-grained node classification policy, which avoids unnecessary visits of energy-sufficient nodes. When nodes are charged, their energy levels are guaranteed to be at a strictly low level.

Moreover, previous studies [7], [16], [20] customarily considered a scenario that one mobile charger serves the whole network. However, such methods are inefficient in the sense that the charger has to waste much time in waiting for the power replenishment to finish. Nowadays chargers off the shelf normally charge batteries in few hours. In this case, even if we neglect the time spent in traveling among sensors, it still requires hundreds of hours to recharge hundreds of sensors. Consequently, some sensors may use up their energy before the charger visit them. As a result, one mobile charger can only maintain small scale sensor networks. Moreover, the time expenses (and corresponding manpower expenses) for maintaining sensor networks with one mobile charger are also unaffordable. Observing the limitation of power replenishment with one mobile charger, our fourth contribution is a novel charging path planning strategy which replenishes sensors with a mobile worker carrying multiple portable chargers, as shown in Fig. 1. This strategy implements parallelism and thus greatly enhance the charging efficiency, finally reducing charging time when the charging duration is non-negligible.

By and large, the contribution of this paper is multi-fold. We study both periodic charging time scheduling and charging path planning with multiple chargers. We first present an efficient slot-based periodic charging time scheduling algorithm with a fine-grained node classification scheme to prevent unnecessary visits of energy-sufficient nodes and a balanced charging task assignment scheme to avoid charging starvation. To further enhance charging efficiency, we also propose a charging path planning algorithm which enables parallel power replenishment with multiple chargers. The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 formulates the problem and introduces preliminaries. Section 4 describes the periodic charging scheduling algorithm with balanced load assignment. Section 5 proposes the multi-charger path planning strategy. Section 6 presents simulation results, with conclusion following in Section 7.

II. RELATED WORK

A number of studies on the power replenishment of sensor networks have been reported in literature [1]–[25]. Peng *et al.* [18] proposed a wireless charging system for WSN and built a proof-of-concept prototype in small-scale networks. Tong *et al.* [27] designed heuristics for a joint network deployment and routing problem for wireless rechargeable sensor networks. Peng *et al.* [22] studied an optimal scheduling problem in rechargeable sensor networks for stochastic event capture, i.e., how to jointly mobilize the charger for energy distribution and schedule sensors for optimal quality of monitoring. Liang *et al.* [1] proposed approximation algorithms with constant approximation ratios so that the sum of charging rewards collected from all charged sensors by the mobile charger per tour is maximized. Shu *et al.* [10] proposed a localization technique for rechargeable wireless sensor networks. Han *et. al.* [2] designed a joint energy replenishment and data collection algorithm based on semi-Markov energy prediction model. Their algorithm divides the target region into multiple clusters and each cluster is handles by two mobile chargers. Li *et al.* [15] presented a joint routing and charging approach, which not only charge sensor networks but also effectively improves network energy utilization via guiding routing paths and recharge energy on demand. This solution recharge sensor nodes on demand, and thus cannot offer performance guarantees from a global perspective. He *et al.* [26] deployed RFID readers to supply energy to RFID tags for continuous operation while the tags can collect and transfer environmental data with energy harvested from RF signals.

A handful of studies assumed network energy consumptions are rather stable and thus formulated the problem as periodic power replenishment. Xie *et al.* [7] considered a scenario wherein a mobile charger periodically visits and charges all nodes in sensor networks to enable sustainable network operations. They studied an optimization problem maximizing the ratio of the charging vehicle's vacation time over the cycle time. They proposed pre-optimized TSP-based charging protocols to solve the problem. Actually, the pre-optimized TSP based charging approaches are a kind of classic solutions to the periodic mobile charging problem [7], [12], [13]. In such approaches, the mobile charger periodically carries out a pre-optimized tour to charge a set of sensors in the network. However, in the TSP-based solutions, when nodes energy consumptions are diverse, it may lead to the unnecessary visits of energy-sufficient nodes. This not only increases the charger travel distance when performing the charging tasks of sensor nodes, but also prolongs the waiting time before the energy-hungry nodes can be charged.

To handle this limitation, [20] proposed Esync, which constructed a set of nested TSP tours based on the energy consumption rates of different sensors, and only the nodes with low remaining energy are involved in each charging tour. Since in every tour only the energy-hungry nodes are charged, the strategy effectively prevents unnecessary visits of energy-sufficient nodes. However, in Esync, the charging loads, i.e., the number of nodes to be charged in each tour, are not balanced among all tours, while we propose balanced solutions which offer guaranteed and sustainable power supplies via periodic charging schedules.

Data collection with a mobile base station has significant benefits on load balancing. Therefore, some previous works utilized a mobile base station to simultaneously support mobile data collection and power replenishment. Guo *et al.* [16] proposed a joint approach of energy replenishment and anchor-point based mobile data gathering by considering both diverse energy consumptions and the time-varying nature of energy replenishment. Xie *et al.* [12] studied optimization problems for co-locating the mobile base station on the wireless charging vehicle and minimized energy consumption of the entire system while ensuring none of the sensors runs out of energy. In another work [13], Xie *et al.* proposed to jointly optimize traveling path, stopping points, charging schedule, and flow routing. Zhao *et al.* [17] also studied the joint optimization of effective energy charging and high-performance data collections. Their proposed algorithm searches for a maximum number of anchor points where sensors hold the least battery energy under limited tour length and maximizes data gathering performance with a distributed algorithm. By and large, these prior works employed a multi-functional vehicle carrying a mobile base station and a charger to serve a sensor network with joint data collection and power replenishment. All the aforementioned papers assumed that the whole network is served by only one mobile charger. Such a design may incur considerable charging time which deteriorates charging efficiency. In contrast, we propose to enhance charging efficient at a low cost via employing one mobile worker carrying multiple portable chargers.

Only a few previous studies attempted to charge multiple sensors simultaneously for scalable network power supplies. Xie *et al.* [14] showed that multiple sensors can be concurrently recharged by one wireless charger. Reference [14] utilized this multi-node wireless energy transfer technology to address charging problems in sensor networks. Nevertheless, wireless chargers off the shelf can only charge devices within one meter while normally multiple sensors are deployed at locations 50 to 100 meters from each other for economic considerations. Consequently, their solution is too ahead of its time as current charging technologies cannot support such a large charging coverage. In contrast, our multi-charger design is more realistic for multi-node charging as each portable charger can be placed at one node even if the nodes are sparsely deployed. Another work [21] studied the deployment of the minimum number of mobile charging vehicles to charge a large-scale WSN such that no sensor will run out of energy. In the paper Liang et al. proposed an approximation algorithm and a heuristic algorithm to address the deployment problem. Wang *et al.* [19] also exploited multiple mobile chargers to charge a sensor network. They solved a multi-charger problem with heuristics based on concepts borrowed from Named Data Networking. Different from [21] and [19], we employ only one mobile charger to carry multiple portable chargers. Since the cost of a portable charger is probably much lower than the mobile carrier (either an robotic vehicle or a human being), we claim that our novel design can achieve a high charging efficiency at a much lower cost.

III. PROBLEM FORMULATION

A. MODELS

We consider a wireless sensor network consisting of many stationary energy rechargeable sensors. The sensors can be recharged by a mobile worker who carries a number of K portable chargers. The worker can be a human worker, a vehicle driven by a human, or an unmanned robot. A charger is a power transmitter equipped with a high capacity rechargeable battery to store sufficient energy. The worker can carry multiple chargers and use them to simultaneously recharge multiple sensors. When reaching a region where the sensors need to be charged, the worker visits K nearby sensors and places K chargers on the sensors, respectively. The chargers can charge the sensors simultaneously. Let B be the battery capacity. It takes a period of time T^C to fully recharge a sensor from zero capacity. The worker then waits a while until the chargers finish charging. Afterwards, the worker re-visits the K sensors again to recycle the chargers, which completes a charging round. Then the worker can leave for the next target region and start another round. Fig. 1 shows the 3 steps of a charging round wherein 4 sensors are replenished by an mobile worker.

The sensor nodes periodically gather data from ambient environment and deliver it to a base station in a multi-hop manner. All nodes are identical and they are initially fully charged. We assume the network topology is comparable stable and the routing paths (or routing table) of all nodes rarely change. We also assume communications are the dominant source of the nodes' energy consumptions. In this case, the power consumptions of sensor nodes are stable and diverse. Sensor nodes near the base station deplete their batteries much faster than other sensor nodes. Consequently, nodes near the base station require more frequent power replenishment than other nodes. Since the power consumption rates of the nodes are stable, such information is known to the scheduler. It is thus possible to periodically charge the sensor nodes such that the energy consumptions and supplies can achieve a balance.

B. PRELIMINARIES

Since TSP-based approaches is inefficient to handle diverse node energy consumption rates, [20] proposed to cluster nodes as nested TSP tours based on their various energy consumption rates. For the convenience of constructing nested TSP tours, the authors in Esync use a *power-α* classification approach to categorize nodes according to their energy consumptions. Let r_{max} and r_{min} as the maximal and minimal energy consumption rates of the sensors, respectively. Esync classifies a number of m intervals and

$$m = \lceil log_{\alpha}(\frac{r_{max}}{r_{min}})\rceil \tag{1}$$

where $\lceil x \rceil$ is the first integer that is greater than x; α is an integer parameter that is greater than 1. We write the m intervals in the non-decreasing order of energy consumption rates as: $[r_{min}, \frac{r_{max}}{\alpha^{m-1}}]$, $(\frac{r_{max}}{\alpha^{m-1}}, \frac{r_{max}}{\alpha^{m-2}}]$, ..., $(\frac{r_{max}}{\alpha^{2}}, \frac{r_{max}}{\alpha^{1}}]$, $(\frac{r_{max}}{\alpha^{1}}, r_{max}]$. The energy consumption rates of all sensor nodes fall into the m intervals, i.e., m classes.

With this classifying algorithm, the ratio between the maximal and the minimal energy consumption rates of the sensor nodes in the same class (interval) is upper bounded by α. Suppose all nodes are synchronized in the sense that all nodes are initially full of energy and they start operation at the same time. In i-th ($i = 1, \ldots, \alpha^{m-1}$) tour, the first N_i^{cnt} classes of nodes are involved in power replenishment, where the number N_i^{cnt} can be derived by algorithm 1.

Algorithm 1 Get C_i

1: $temp \leftarrow \alpha$
2: $N_i^{cnt} \leftarrow 1$
3: **while** $temp \leq \alpha^{m-1}$ or $i \mod \beta = 0$ **do**
4: $\quad temp \leftarrow temp * \alpha$
5: $\quad N_i^{cnt} \leftarrow N_i^{cnt} + 1$
6: **end while**

In i-th tour, when the first C_i classes are charged, the nodes in these classes remain at most $\frac{\alpha-1}{\alpha}$ of their total energy. Such nodes are so-called energy hungry nodes. If not charged in this tour, they will run out of energy. Since in each tour only the energy-hungry nodes are charged, the strategy effectively prevents unnecessary visits of energy-sufficient nodes.

Clearly, α plays a critical role in determining the charging performance. The charging efficiency is related to the remaining energy of the nodes when they are being charged. In the worst case, a node would have $\frac{\alpha-1}{\alpha}$ of remaining energy. This means, a smaller α value leads to better worst case charging efficiency. Therefore, in this paper, we fix α as 2. Accordingly, in the worst case a node would have half of remaining energy when it is charged.

However, in Esync, the charging loads, i.e., the number of nodes to be charged in each tour, are not balanced among all tours. Specifically, in the last tour all nodes are charged at one time. The unbalanced charging schedule may lead to starvation of some nodes once some tours cannot be started on time. Since the duration of every tour is determined by the nodes with the fasted energy consumption, probably Esync cannot manage to finish charging all nodes in a single tour.

IV. PERIODIC SCHEDULING WITH BALANCED LOAD ASSIGNMENT

This paper studies power replenishment problem of a sensor network wherein each sensor node incurs a stable energy consumption rate. We synchronize the power supply of sensor nodes via a set of periodic charging tours. In the following, Section IV-A first clusters nodes into fine-grain classes, in preparation for node scheduling. Section IV-B presents a slot-based scheduling algorithm, which determines the time schedules for periodic sensor power replenishment, i.e., sensors are charged in which slots. Section IV-C further optimizes the scheduling algorithm on load balancing.

A. FINE-GRAINED NODE CLASSIFICATION

Since sensors consume power in different rates, for the convenience of constructing nested TSP tours, the authors in Esync use a power-α classifying algorithm to group nodes according to their energy consumptions. As illustrated above, α plays a key role in determining the charging performance. When the nodes are charged, they remain at most $\frac{\alpha-1}{\alpha}$ of their total energy. Classification algorithm groups nodes in relatively

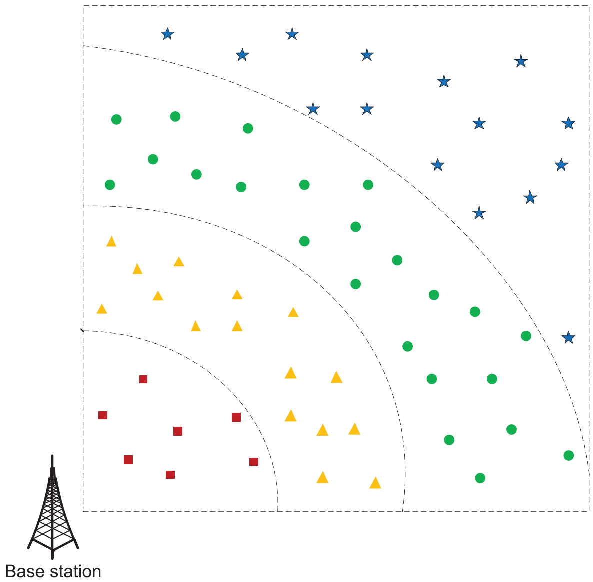

FIGURE 2. Example of node classification. Four different colors/shapes denote four classes.

coarse-grain as α can only be selected as integers. This limits the flexibility of node classification and may also restricts the efficiency of power replenishment since the nodes may still remain abundant energy when they are charged.

In this case, we propose a fine-grain α-β classifying algorithm based on the power-α algorithm [19]. In this algorithm, both α and β are integer design parameters, where $\alpha \geq 2$ and $\beta \geq 1$. This algorithm group nodes in two steps. In step 1, we construct m intervals of required charging period. Let $T_{min} = \frac{B}{r_{max}}$, which is the shortest required charging period among all nodes. The charging periods of the sensors fall into the m intervals: $[T_{min}, \alpha T_{min})$, $[\alpha T_{min}, \alpha^2\ T_{min})$, $\ldots$, $[\alpha^{M-2} T_{min}, \alpha^{M-1} T_{min})$, $[\alpha^{M-1} T_{min}, \frac{B}{r_{min}}]$.

Then, every interval is evenly divided into β sub-intervals. The i-th ($i = 1, 2, \ldots, m$) interval $[\alpha^{i-1} T_{min}, \alpha^{i} T_{min})$ is divided into the following intervals: $[\alpha^{i-1} T_{min}, \frac{\alpha^{i-1} T_{min}(\beta+\alpha-1)}{\beta})$, $[\frac{\alpha^{i-1} T_{min}(\beta+\alpha-1)}{\beta}, \frac{\alpha^{i-1} T_{min}(\beta+2(\alpha-1))}{\beta})$, $\ldots$, $[\frac{\alpha^{i-1} T_{min}(\beta+(\beta-2)(\alpha-1))}{\beta}, \frac{\alpha^{i-1} T_{min}(\beta+(\beta-1)(\alpha-1))}{\beta})$, $[\frac{\alpha^{i-1} T_{min}(\beta+(\beta-1)(\alpha-1))}{\beta}, \frac{\alpha^{i} B}{r_{max}}]$. The required charging periods of all nodes fall into the sub-intervals. Every sub-interval corresponds to a class and thus finally we have βm classes. The required charging period of a class is the lower bound of its corresponding sub-interval. Hence, for the i-th interval, the required charging period of its corresponding β classes are: $\alpha^{i-1} T_{min}$, $\frac{\alpha^{i-1} T_{min}(\beta+\alpha-1)}{\beta}$, $\ldots$, $\frac{\alpha^{i-1} T_{min}(\beta+(\beta-2)(\alpha-1))}{\beta}$, $\frac{\alpha^{i-1} T_{min}(\beta+(\beta-1)(\alpha-1))}{\beta}$. There are totally at most βm sub-intervals (i.e., classes).

With the fine-grained node classification, charging efficiency can be improved. When a node is being charged, its remaining energy is at most $\frac{\alpha-1}{\beta+\alpha-1}$. Obviously, a smaller α and a greater β lead to a smaller upper bound of remaining energy. In other words, reducing α and increasing β can increase charging efficiency. Since α and β are integer design parameters satisfying $\alpha \geq 2$ and $\beta \geq 1$, one may wish to choose a small α and a large β to enhance charging efficiency. However, it is not wise to choose a large β for two reasons. Firstly, the slot length (discussed in the next subsection) is reciprocal to β. If β is too large, the slot length may become insufficient for one charging tour. Secondly, if β is too large, the number of nodes in one class may be too few, which may deteriorate the charging efficiency. According to our experiments, we recommend setting $\alpha = 2$ and $\beta = 2$. Fig. 3 shows an example of the two-step classification method. Descriptions on the example can be found in the next subsection.

B. SLOT-BASED PERIODIC SCHEDULING

The proposed scheduling algorithm derives a charging schedule which periodically works over cycles. The scheduling of every cycle is identical and thus all charging activities repeat in every cycle. Due to the time-varying nature of the energy replenishment demand, to facilitate our study, we divide the time into fixed time intervals of length T, namely "time slots". A cycle contains multiple slots.In each time slot the worker runs a tour to selectively recharge sensors at low energy levels. A slot is the smallest time unit wherein one charging tour can execute. As sensors consume power in different rates, in each slot different classes may be charged. Notice that each tour should be finished before the current slot ends, to assure that the next tour can timely start in the next period. This issue is addressed via load balancing discussed in the next section.

The length of a slot is $T = \frac{(\alpha-1)T_{min}}{\beta}$, which is the duration of the first (smallest) sub-interval. The required charging periods of all classes are multiples of slot length. The cycle length L is the least common multiple of the required charging periods of all classes. In this case, both the duration of the cycle and required charging periods of the classes can be counted in the terms of slots. All the classes can be charged periodically in terms of slots. Suppose the nodes are categorized into a number of J ($J = \beta m$) classes ($C_1, C_2, \ldots, C_J$). The required charging period of class C_j ($j = 1, 2, , J$) is p_j. Class C_j is charged in slots $\frac{np_j}{T}$ ($n = 1, 2, \ldots, \frac{L}{T}$). With the node classification and slot based design, we can periodically schedule the power replenishment into slots based on node classes. Also, we are able to schedule multiple classes into one slot. According to the schedules, in each period the worker selectively charges a part of sensors such that for each sensor, the interval between every two consecutive charges is no greater than its required minimal charging interval.

Fig. 3 shows an example of slot-based periodic scheduling. In this example, our two-step classification method is applied. Let $\alpha = 2$, we first obtain 3 classes with periods equaling to $2T$, $4T$, and $8T$. Then, let $\beta = 2$, the nodes finally fall into 6 classes, namely $C_1, C_2, \ldots, C_6$. The charging periods of the 6 classes are: $p_1 = 2T$, $p_2 = 3T$, $p_3 = 4T$, $p_4 = 6T$, $p_5 = 8T$, $p_6 = 12T$. The cycle length is $24T$, which means

slot	1	2	3	4	5	6	7	8
class	N/A	C_1	C_2	C_1, C_3	N/A	C_1, C_2, C_4	N/A	C_1, C_3, C_5
slot	9	10	11	12	13	14	15	16
class	C_2	C_1	N/A	C_1, C_2, C_3, C_4, C_6	N/A	C_1	C_2	C_1, C_3, C_5
slot	17	18	19	20	21	22	23	24
class	N/A	C_1, C_2, C_4	N/A	C_1, C_3	C_2	C_1	N/A	$C_1, C_2, C_3, C_4, C_5, C_6$

FIGURE 3. Example of slot-based periodic scheduling: 6 classes scheduled in 24 slots.

slot	1	2	3	4
class	$C_{11}, C_{21}, C_{31}, C_{41}$	$C_{12}, C_{22}, C_{32}, C_{42}$	$C_{11}, C_{23}, C_{33}, C_{43}$	$C_{12}, C_{21}, C_{34}, C_{44}$
slot	5	6	7	8
class	$C_{11}, C_{22}, C_{31}, C_{45}$	$C_{12}, C_{23}, C_{32}, C_{46}$	$C_{11}, C_{21}, C_{33}, C_{41}$	$C_{12}, C_{22}, C_{34}, C_{42}$
slot	9	10	11	12
class	$C_{11}, C_{23}, C_{31}, C_{43}$	$C_{12}, C_{21}, C_{32}, C_{44}$	$C_{11}, C_{22}, C_{33}, C_{45}$	$C_{12}, C_{23}, C_{34}, C_{46}$

FIGURE 4. Example of balanced assignment: 15 subclasses from 4 classes scheduled in 12 slots.

a cycle consists of 24 slots. Fig. 3 shows the classes charged in every slot in a cycle. The charging tasks are issued in parts of slots in a cycle. A slot is called a working slot once there are charging tasks issued in the slot. Notice that not all slots are working slots. The algorithm obtains all working slots in a cycle.

C. BALANCED LOAD ASSIGNMENT

The above section proposes a scheduling algorithm for periodic power replenishment. However, the charging loads, i.e., the number of nodes to be charged in each tour, are not balanced among all tours (slots). For example, in Fig. 3, all classes are scheduled in slot 24 while no class is scheduled in slot 23. If the slot duration is comparatively short, the schedule may become infeasible as the worker cannot finish the job in slot 24 in time.

To tackle this problem due to unbalanced charging policies, we improve load balancing via a balanced load assignment approach. This approach proposes to balance the charging tasks through all slots. That is, we evenly charge nodes on every slot such that the number of nodes charged in every slot is roughly identical. We evenly divide class C_j into $n_j^{sub} = \frac{p_j}{T}$ subclasses. Then, the n_j^{sub} subclasses are charged in turn through every n_j^{sub} slots. In every slot, we charge a set of nodes, which contains J subclasses selected from J classes, one subclass from one class. Figs. 2, 5 and 4 depict an example of balanced assignment. In this example, nodes are clustered into 4 classes, C_1, C_2, C_3, and C_4, as shown in Fig. 2. Their required charging periods are $p_1 = 2T$, $p_2 = 3T$, $p_3 = 4T$, $p_4 = 6T$, respectively. The cycle length is thus $12T$. Fig. 5 shows the 15 subclasses of the example. Fig. 4 shows the assignment of slots and subclasses. As shown in the figure, C_1 is divided into 2 subclasses C_{11} and C_{12} since the period of C_1 is 2 spans 2 slots. Hence, in every slot, one subclass from C_1 is scheduled. In this case, in every slot totally 4 subclasses from 4 classes are scheduled. In Fig. 5,

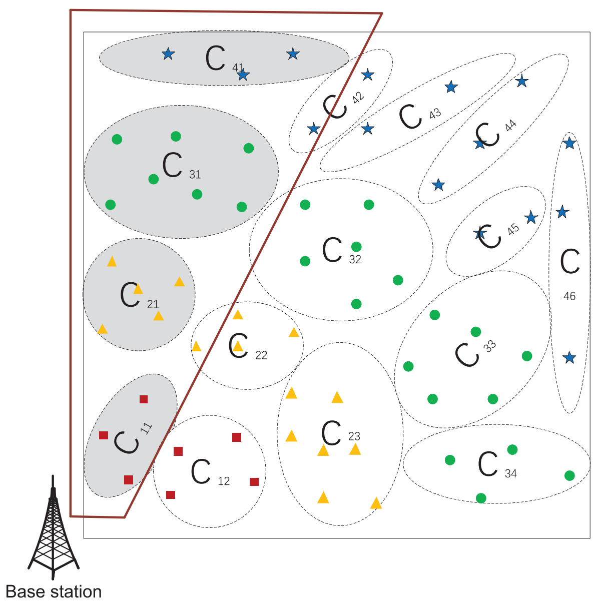

FIGURE 5. Example of balanced assignment: 15 subclasses in the field. The four subclasses C_{11}, C_{21}, $C31$, and C_{41} are scheduled in the same slot, which is slot 1 in Fig. 4.

the 4 subclasses in gray color (C_{11}, C_{21},C_{31}, and C_{41}) are scheduled in the same slot, which is slot 1 in Fig. 4.

Having outlined the basic idea of the algorithm, we now present a two-step approach, as described in the following 2 subsections. In step 1 we divide every class into multiple subclasses and in step 2 we assign the subclasses into slots. In both steps, we aim to optimize charging efficiency via minimizing travel distance for each charging tour.

1) NODE SUB-CLASSIFICATION

We apply clustering algorithms to partition the classes into subclasses. In the above subsections we have categorized

Algorithm 2 Node Sub-Classification of Class C_j

input: class C_j
output: n_j^{sub} subclasses
for 1 to n_j^{sub} **do**
  select a cluster for partitioning.
  for 1 to N^{iter} **do**
    Bisect the selected cluster with basic K-Means
  end for
  take the split that produces the clustering with the highest overall similarity.
end for

Algorithm 3 Balanced Sub-Class Assignment

for each class j, get n_j^{sub} subclasses via Node Sub-Classification
$\forall k \ \psi_k \leftarrow \emptyset$
for $j = 1$ to J **do**
  for $i = 1$ to n_j^{sub} **do**
    select schedule ψ_k and C_{ij} that minimizes $\delta(C_{ij}, \psi_k)$ $(k \leq n_j^{sub})$
    for $k' = 0$ to $\frac{L}{n_j^{sub}T} - 1$ **do**
      $\psi_{k+k'n_j^{sub}} \leftarrow \psi_{k+k'n_j^{sub}} \cap C_{ij}$
    end for
  end for
end for

sensor nodes according to their energy consumptions. Now in this subsection, to balanced load assignment, we partition each node class C_j into n_j^{sub} subclasses. We propose to use a bisecting K-means algorithm, which is a simple and efficient implementation of the basic K-means algorithm. The bisecting K-means algorithm incrementally updates centroids through N^{iter} iterations, which produces results with better overall similarity and avoid inefficient choice of initial centroids. In every iteration the algorithm picks a cluster and splits it into two smaller clusters. There are a number of different ways to choose which cluster is split. We choose the largest cluster at each step to balance the subclass sizes, i.e., balance the number of nodes charged in every period.

2) BALANCED SUB-CLASS ASSIGNMENT

Given subclasses partitioned, the algorithm then determines the schedules in every slot, i.e., which subclasses are scheduled in every slot. We shall guarantee 2 periodicity conditions for scheduling: firstly, each subclass in class C_j is charged in every $\frac{p_j}{T}$ slots; secondly, only one subclass from class C_j is charged in every slot. Also, to enhance charging efficiency, we aim to minimize the travelling distance to charge all subclasses in every slot.

The balanced assignment approach is shown in Algorithm 3. The algorithm starts with a number of $\frac{L}{T}$ empty partial schedules, $\psi_1, \psi_2, \ldots, \psi_{\frac{L}{T}}$. The algorithm executes J iterations to generate schedules. In every iteration, the algorithm updates the partial schedules by assigning subclasses to them.

We define the distance between a subclass C_{ij} and a partial schedule ψ_k $(k = 1, 2, \ldots, \frac{L}{T})$ as the distance between two nearest nodes from the subclass and the schedule. We denote the distance as $\delta(C_{ij}, \psi_k)$. A small distance value implies that the mergence is favorable and the total travelling distance to charge all subclasses in the partial schedule is rather short. The algorithm tends to select a pair of partial schedule and subclass with the smallest distance value to combine as a new partial schedule. In iteration j, the algorithm considers the first n_j^{sub} partial schedules. It iterates to assign n_j^{sub} subclasses to update the first n_j^{sub} partial schedules. Once a subclass C_{ij} is assigned to a schedule ψ_k $(k \leq n_j^{sub})$, it will also be assigned to schedules $\psi_{k+k'n_j^{sub}}$ $(k' = 1, 2, \ldots, \frac{L}{n_j^{sub}T} - 1)$. Finally, every schedule ψ_k contains J subclasses from J classes, as shown in an example Fig. 4.

V. MULTI-CHARGER TOUR PATH PLANNING

The above sections determines in which slot the nodes are recharged. In this section, we will address how to recharge the nodes in one slot, i.e., the path planning of each tour.

A. MULTI-ROUND TOUR DESIGN

Since the mobile worker carries a number of K chargers, in every charging tour it charges sensors with multiple rounds. In each round the worker can simultaneously charge up to K sensors in its proximity, one charger for each sensor. The worker first visits the sensors that are to be charged and deploys a charger at each sensor. It then waits for the chargers to finish charging and returns to recycle the chargers. Afterwards it travels to the next target region and starts another round to distribute and recycle chargers. Accordingly, in each tour the worker can execute multiple rounds to charge many sensors. Fig. 1 shows the 3 steps of a round which charges 4 sensors.

We claim that the multi-charger strategy is much more efficient than traditional single-charger strategies widely absorbed in the previous studies. Firstly, simultaneously charging multiple nearby sensors with multiple chargers can significantly reduce waiting time (i.e., charging time) incurred per sensor. Secondly, the charging time can be overlapped with travelling time to some degree, which further reduce the worker's working time. That is, in each round when some sensors are being charged, the worker can visit other sensors to deploy or recycle sensors. Since the cost of employing a mobile worker (e.g., paying salaries to human workers) is probably much higher than that of purchasing chargers, the proposed simultaneous charging strategy achieves much higher charging efficiency than the single-charger strategy at the cost of only minor budget increases.

In each round, the sequence to visit nodes and place chargers is a travelling salesman problem [30], which can be

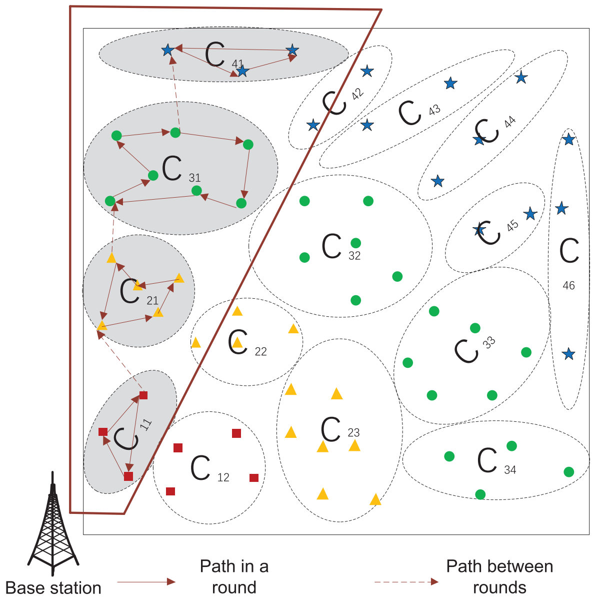

FIGURE 6. Path planning in a multi-round charging tour.

addressed by a TSP solver (e.g., Concorde TSP Solver [31]). The example in Fig. 6 depicts a tour containing 4 rounds, while the path in each round is shown as a node-level TSP. As shown in Fig. 6, a complete charging tour consists of paths within the rounds and paths between the rounds. The path within each round is a circuit obtained by the TSP solver, while the paths between the rounds link all rounds (i.e., circuits) together. We seek the paths between the rounds via a TSP with neighborhoods problem (TSPN) [32]. In TSPN, we are given a collection of disjoint subsets of vertexes in the plane, called neighborhoods, and we seek the shortest tour that visits each neighborhood (i.e., visits any vertex in each specified subset). In our charging problem, each round specifies a circuit path, which is indeed a neighborhood in TSPN. We assume that the worker can arrive at any node in each round and regard the node as the origin node of the round where the worker starts to distribute chargers. After power replenishment finishes, the worker returns to the origin node and leaves for the next round. In this case, seeking the shortest tour between the rounds (i.e., the shortest tour that visits all neighborhoods) is a TPSN. Such a problem has been proved to be NP-complete, and a handful of algorithms have been proposed to address it [30].

B. NODE CLUSTERING IN A TOUR

In the following, we focus on how to organize nodes in every tour into multiple rounds while the TSP problems are left to TSP solvers. The critical challenge of the round organization problem is how to organize sensors into rounds in every tour for efficient power replenishment. We formulate the problem as a clustering problem: a number of n nodes involved in a tour are classified as multiple clusters. Each cluster consists of up to K sensors in proximity. In this case, all sensors in one cluster can be simultaneously charged in one round. Once the nodes in one tour are efficiently clustered such that each round only involves nearby nodes, the time incurred in every round can be minimized and the time of a tour can be reduced.

The proposed node clustering algorithm is shown in Algorithm 4. The algorithm executes 3 stages. Stage 1 partitions the nodes into clusters via a bisecting K-means approach while Stages 2 and 3 refine the results. The time complexity of the algorithm is $O(n * K * N^{iter})$ where n is the number of nodes in the tour, K is the number of chargers, and N^{iter} is the number of iterations executed.

Algorithm 4 Node Clustering Algorithm

```
1:  while there exists any cluster whose size is greater than K do
2:    select a cluster whose size is greater than K for partitioning.
3:    for 1 to N^iter do
4:      Bisect the selected cluster with basic K-Means
5:    end for
6:    take the split that produces the clustering with the highest similarity.
7:  end while
8:  put all clusters in S
9:  while S ≠ Ø do
10:   pick a cluster c with the largest size from S
11:   if bisecting c reduces working time then
12:     bisect c
13:   end if
14:   S ← S \ c
15: end while
16: put all clusters in S
17: while S ≠ Ø do
18:   pick a cluster c with the smallest size from S
19:   if dismissing c reduces working time then
20:     dismiss c and migrate its nodes to nearby clusters
21:   end if
22:   S ← S \ c
23: end while
```

Stage 1 (lines 1 - 7 of Algorithm 4) executes N^{iter} iterations to partition all nodes into small clusters whose sizes are no greater than K. Each cluster corresponds to a cluster of neighboring nodes which are to be charged in parallel with up to K chargers. In each iteration, the algorithm picks a cluster whose size is greater than K for bisecting. This stage terminates once the size of every cluster is no greater than K.

Stage 2 (lines 8 - 15 of Algorithm 4) attempts to further divide the clusters into smaller ones. The algorithm examines all clusters according to the non-increasing order of the cluster size. For each cluster examined, the algorithm attempts to bisect it and checks whether the bisection can result in shorter working time during the tour. If the bisection leads to shorter working time, it is bisected. This stage prevents the case that the nodes within a round are far from each other, such that the travelling time within a round compromises the time saved via parallel charging with multiple chargers.

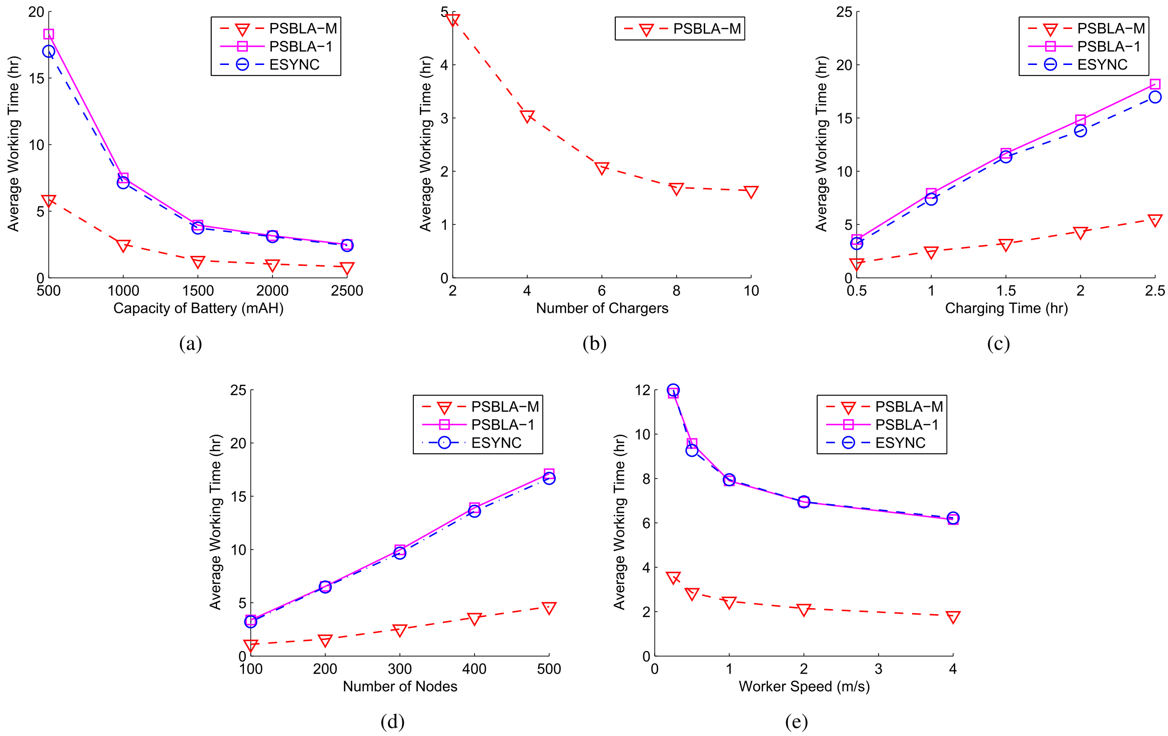

FIGURE 7. Average working time. (a) Average working time versus battery capacity. (b) Average working time versus number of chargers. (c) Average working time versus charging time delay. (d) Average working time versus number of sensors. (e) Average working time versus worker speed.

Finally, in stage 3 (lines 16 - 23 of Algorithm 4), the algorithm attempts to dismiss the excessive clusters and assign the nodes of the dismissed clusters to nearby clusters. The algorithm examines all clusters according to the non-decreasing order of the cluster size. For each cluster examined, if the following conditions are simultaneously met, it will be dismissed and all its nodes are migrated to nearby clusters: Firstly, the sizes of the nearby clusters are no greater than K after they receive nodes from the cluster. Secondly, the total time costs after the node migration can be reduced, i.e., the dismissal and migration are beneficial.

VI. PERFORMANCE EVALUATION

In order to assess the effectiveness of the proposed scheduling policies, we will now present a performance evaluation study, carried out by means of a discrete-event simulator. To understand the merits of the proposed algorithms, we compare them with Esync. The proposed algorithms are denoted as PSBLA-1 (with single charger) and PSBLA-M (with multiple chargers), respectively. We can evaluate the effect of PSBLA via comparing the performance between Esync and PSBLA-1, and evaluate the effect of the multi-charger path planning component via comparing the performance between PSBLA-1 and PSBLA-M, respectively.

We are interested in two performance metrics: The first one is average working time, i.e., the average time in a cycle that the worker is out in the field. This metric reflects the overall charging efficiency of an algorithm. The second one is maximum working time, i.e., the maximum time that the worker is out in the field in one tour among all tours in a cycle. This metric indicates how an algorithm balances the charging jobs among all tours.

The default system configurations are set as follows: The target sensor network has 300 nodes, which are uniformly randomly deployed in a 1 km × 1 km sensing field. The service station is located at one corner of the sensing field. The worker carries 5 portable chargers and travels at a speed of 1 m/s (3.6 km/h). The charging time required for serve one sensor is set as 1 hour. The nodes' battery capacity is set as 1,000 mAH. The energy consumption rate for the sensing tasks is 1.5 mW. The communication energy costs of sensor nodes are set based on the data sheet of the MICA2 node: the transmitting and receiving energy consumption rates are 50 mW and 16 mW, respectively. After nodes deployed, a routing structure is constructed based on the TinyOS standard CTP [11]. Then the environment information, after captured by individual nodes, is transmitted to the sink through multi-hop communications.

In the following experiments, we only vary one parameter at a time while keeping the other settings. The corresponding results on average working time and maximum working time are shown in Fig. 7 and Fig. 8, respectively. Specifically, we first vary battery capacity from 500 mAH to 2500 mAH, and the corresponding results are shown in Fig. 7(a) and Fig. 8(a), respectively. We then vary the number of chargers from 2 to 10, and the corresponding results are shown

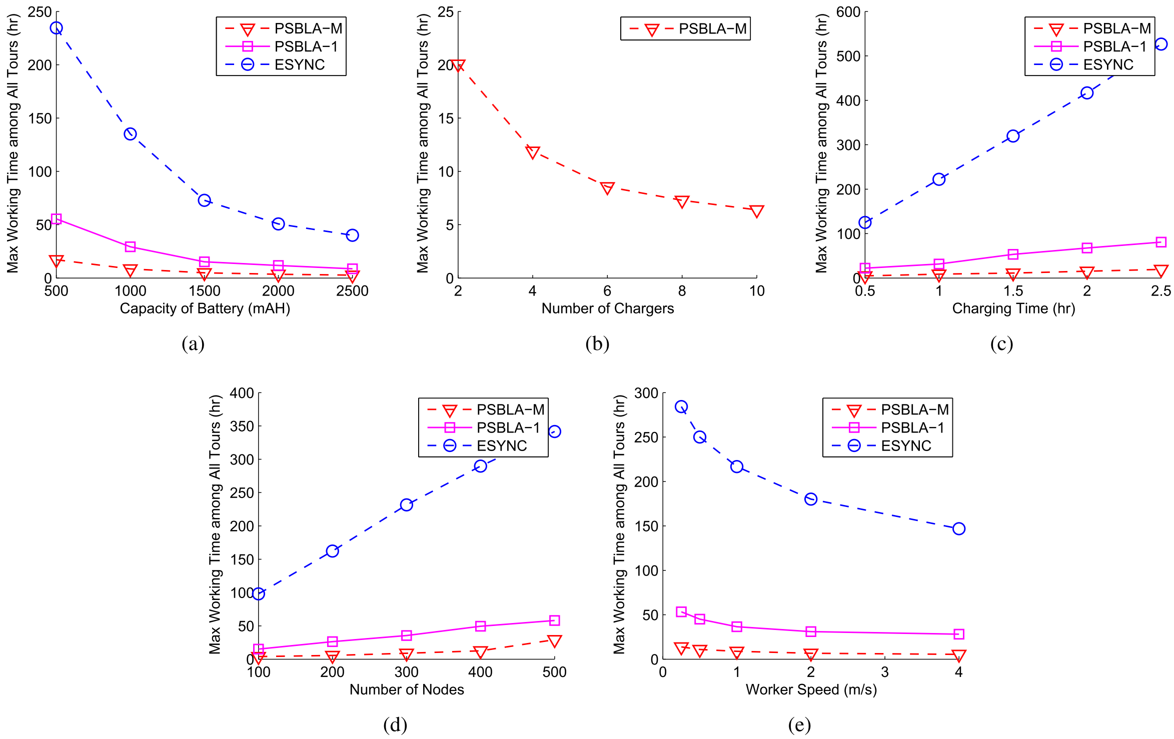

FIGURE 8. Maximum working time. (a) Maximum working time versus battery capacity. (b) Maximum working time versus number of chargers. (c) Maximum working time versus charging time delay. (d) Maximum working time versus number of sensors. (e) Maximum working time versus worker speed.

in Fig. 7(b) and Fig. 8(b). Notice that these 2 figures only present the results for PSBLA-M since only this algorithm utilizes multiple chargers. We also vary the charging time for serving one sensor from 0.5 to 2.5 hours, and the corresponding results are shown in Fig. 7(c) and Fig. 8(c). Further, to evaluate the scalability of our algorithm we vary the number of sensors in the network from 100 to 500, and the corresponding results are shown in Fig. 7(d) and Fig. 8(d). Finally, we vary worker speed from 0.25 m/s to 4 m/s, and the corresponding results are shown in Fig. 7(e) and Fig. 8(e).

The results in Fig. 7 show that the proposed algorithm outperforms the baseline algorithms by a clear margin under various scenarios. Specifically, we can observe two facts. Firstly, the PSBLA-1 and Esync delivers close performance in terms of average working percentage. This implies that our balanced tour scheduling scheme cannot help to lower overall working time. Secondly, compared to PSBLA-1 and Esync, PSBLA-M only requires about 1/3 to 1/5 working time on average. This means that in our simulations, the multi-charger tour design can reduce 2/3 - 4/5 of the overall working time than the single-charger TSP solution.

Fig. 8 shows that for maximum working percentage, PSBLA-1 and PSBLA-M significantly outperform Esync, which demonstrates that our balanced tour scheduling scheme can effectively balance charging jobs among all tours. Specifically, comparing Fig. 7 and Fig. 8, we can find that the maximum working time is 4 - 5 times of average working time for PSBLA-1 and PSBLA-M, while for Esync, the maximum working time is about 20-30 times of its average working time. This indicates that PSBLA achieves better load balancing than Esync. In many cases of Fig. 8, Esync requires hundreds of hours in the longest tours. Since the maximum working time is too long, Esync probably will fail to keep the network operational in some time intervals.

In Fig. 7(a) and Fig. 8(a), when large volume batteries are applied, all algorithms require less working time. This is because when battery capacity grows, the required charging frequency is lowered for every node and thus the worker less frequently works. Fig. 7(b) and Fig. 8(b) show that as the number of chargers grows, PSBLA-M requires much less working time, demonstrating the advantage of using multiple chargers in parallel. In addition, when the number of chargers is greater than 6, the working time gradually saturates. A plausible explanation is that the density of the sensors are limited, and excessive chargers cannot be effectively utilized for parallel charging. In Fig. 7(c) and Fig. 8(c) the performance of PSBLA is comparatively stable when charging time delay grows. This implies that the multi-charger tour design can effectively resist the increase of charging delay. Also, when the charging time is small, the time taken for the worker to move among the sensors dominates the total working time. Accordingly, the performance of our proposed algorithms becomes more stable when the charging time is small. In Figs. 7(d) and 8(d), the performance gap increases when the network scales. This means the proposed multi-charger approach is more efficient and scalable for large networks. Figs. 7(e) and 8(e) show that increasing worker speed helps to save total working time. But when the worker speed is greater than 1m/s, the total working time gradually saturates. This is because when the worker speed is sufficiently large, the total time is mostly related to charging time, which is unrelated to the worker speed, resulting in stable performance. In conclusion, the results show that PSBLA constantly achieves both lower average working percentage and lower maximum working percentage than all other algorithms.

VII. CONCLUSIONS

In this paper we have investigated the problem of periodic mobile power replenishment for wireless sensor networks with multiple portable chargers. We study both charging time scheduling and charging route path planning problems. Our contributions are multi-fold. Firstly, we have designed a periodic charging scheduling with balanced load assignment approach, which evenly assign charging tasks in multiple tours periodically. Secondly, we have also presented a fine-grained node classification policy, which avoids unnecessary visits of energy-sufficient nodes. Thirdly, prior studies customarily assumed that a mobile charger sequentially visits and charges sensors. However, this method is inefficient since it normally incurs considerable charging waiting time. To address the limitation, we have proposed a novel charging path planning strategy, which replenishes sensors with a mobile worker carrying multiple portable chargers. This strategy greatly enhance the charging efficiency and reduce charging time when the charging duration is non-negligible. Performance evaluation results are presented to demonstrate the effectiveness and competitiveness of our approaches when compared with existing algorithms.

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