You Can Charge over the Road: Optimizing Charging Tour in Urban Area

Xunpeng Rao[1], Panlong Yang[1,2(✉)], and YuboYan[1,2]

[1] PLA University of Science and Technology, Nanjing, China
raoxunpeng@gmail.com, panlongyang@gmail.com, yanyub@gmail.com
[2] University of Science and Technology of China, Hefei, China

Abstract. Wireless energy transfer has provided a promising technology to extend the lifetime of wireless rechargeable sensor network. Most of previous studies focus on scheduling chargers or deploying stationary charging stations to replenish energy for rechargeable sensors. These methods could not be applicable when real deployment is concerned, because the roadway needs to be fully respected for mobile chargers in typical urban area. In dealing with this difficulty, we investigate the problem of scheduling mobile chargers with mobility constraints in the scenario of a city graph. First of all, we aim at optimizing the traveling path for chargers to minimize the traveling cost. Consequently, we convert our scheduling problem into edge coverage problem, which is quite different from the point coverage problem. Then classical problem CARP (Capacitated Arc Routing Problem), which has been proved NP-hard, is applied to solve aforementioned problem. To this end, a simple but efficient genetic algorithm cooperated with decoding algorithm Split is proposed. Finally, we evaluate the impacts of different parameters on our algorithm and get the near optimal solution.

Keywords: Wireless rechargeable sensor network · Capacitated Arc Routing Problem · Genetic algorithm

1 Introduction

1.1 Backgrounds and Motivation

With the extensive development of wireless sensor network, it had been applied in urban road monitor system [2,4]. The wireless public transportation monitoring network, which can efficiently promote improved transportation efficiency, has been studied in [1]. Considering the characteristics of traffic monitoring and the urban traffic architectures, numerous routing protocols have been proposed to optimize the energy conservation and extend the network life [6]. Specially, the concerns in energy efficiency had attracted more attentions. Many solutions, *e.g.*, [7,8] focus on the optimal energy-efficient route by taking routing cost and remaining energy of nodes into consideration simultaneously. Considering the balance between energy consumption and time delay, [5] proposed an optimal

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energy-efficient routing scheme. In summary, most of existing work in urban traffic-monitoring network usually aim to pursue the minimum energy consumption or the maximum network lifetime. Due to the sensors limited power, innovative techniques that prolong the network lifetime are highly required.

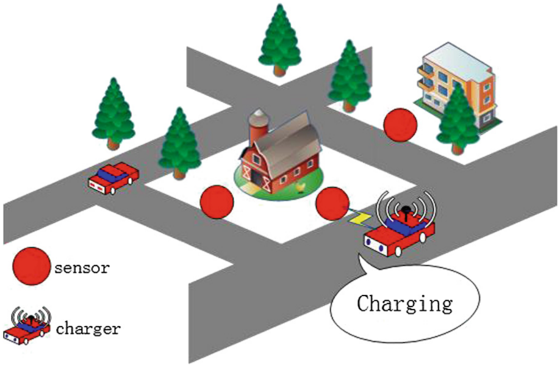


Fig. 1. The scenario of roadside wireless rechargeable traffic sensing network.

As mentioned in [9], wireless energy transfer technologies [10] have become a promising method to extend the lifetime of wireless rechargeable sensor network. Most of existing studies [11,12,16] focus on how to schedule mobile chargers to replenish energy for rechargeable sensors, such as maximizing network lifetime, minimizing charging delay or traveling path. For example in [15], the chargers travel along their predefined paths to charge sensors. As depicted in Figs. 1 and 2, which are similar to [15], the vehicles have to move along the streets belong to topological graph. In that, the recharging with practical considerations of deployment constraints of sensor nodes in urban area should be concerned. We notice that the charging distance between charger and receiver is the main factor that needed to be fully considered for charging efficiency, which has been shown in [10]. Therefore, it is essential for mobile chargers to optimize the charging distance between node and charger carefully. Meanwhile, the mobility constraint caused by roadway should be respected. However, most of existing studies [13,26] regard the recharging for a sensor node as visiting or covering a point. Therefore, the points coverage problems, that all points are required to be covered by chargers over a cycle path, are usually been converted into Traveling Sales Problem. The common feature of above studies is ignoring the mobility constraints caused by geography. These methods are impractical when the mobility constraints cannot be ignored, *e.g.*, city graph. Also, the paths selection problem in the [15] is converted into set cover problem which is unsuitable for scheduling chargers. To the best of our knowledge, there are not any studies focus on handling this kind of scheduling problem with mobility constraints. Motivated by this kind of insufficient in scheduling with mobility constraints, we investigate the problem of scheduling mobile chargers to service nodes with mobility constraints caused by city topological graph. In Fig. 1, some of streets are installed with sensor nodes which could monitor the traffic situation. The mobile chargers start from a service station to replenish energy for sensor nodes with wireless energy transfer technologies. After visiting the arranged sensor nodes, it would return to the service station. In the streets, the mobile charger is regarded as a car which should obey the traffic rules. In our problem, we consider how to schedule the mobile charger for sensor nodes deployed on the street. In our concern, the recharging sensors are deployed along the street. For efficient and effective coverage, the mobile charger should go along the entire street segmentation. To this end, the streets equipped with sensors should be regarded as edges in graph perspective. Then the edge coverage problem is incorporated for further study. A preliminary study [3] has been presented, while for this version, we convert our scheduling problem into Capacitated Arc Routing Problem, which has been proved NP-hard. The classical genetic algorithm cooperated with a decoding algorithm is proposed to handle out the problem. Finally, we conduct extensive evaluations, and the results show the improved performance of the genetic algorithm.

1.2 Contributions

In summary, our contributions could be summarized as follows:

– We investigate the scheduling problem for mobile chargers with mobility constraints which has not been studied before. It can be a supplement contribution for scheduling in wireless rechargeable sensor network.

Table 1. Annotations for frequently used symbols

Symbol	Definition
$G = (V, E)$	The city graph
$V = \{v_1, v_2..., v_n\}$	The set of crossroads
E	The set of edges
d_{ij}	The distance between crossroad i and j
$S = \{s_1, s_2, ..., s_m\}$	The set of sensor nodes
$E^0 = \{e_1, e_2, ..., e_m\}$	The set of nodes' initial energy
D	The maximum charging distance
p_k^c	Charging power of node k
r_k	The charging distance for node k
$\mathbb{T} = \{t_1, t_2, ..., t_m\}$	The set of recharging time for all nodes
$Q = \{q_k \mid 1 \leq k \leq m\}$	The set of recharging cost for all nodes
RC	The total recharging cost
$\mathcal{R} = \{R_1, R_2, ..., R_{\vert\mathcal{R}\vert}\}$	The set of traveling path
MC	The moving cost
x_i	The symbol indicates node i is visited or not

– We formulate our problem and convert it into Capacitated Arc Routing Problem. We handle this problem by classical genetic algorithm cooperated with a decoding algorithm Split.
– We made extensive experiments to evaluate the impacts of different parameters on algorithm, and get the near-optimal solution.

1.3 Paper Organization

The remainder of this paper is organized as follows. In Sect. 2, we introduce our proposed network model and recharging model, cost model. In Sect. 3, we formulate our problem and convert it into Capacitated Arc Routing Problem. A genetic algorithm is proposed to solve it. We conduct extensive simulations and show our results with comprehensive analyses in Sect. 4. Finally, we conclude our work in Sect. 5 (Table 1).

2 System Model

2.1 Network Model

We start our scenario with a city graph $G = (V, E)$, where V is the set of vertexes (*i.e.*, crossroads), $V = \{v_1, v_2..., v_n\}$, and E is the set of edges (*i.e.*, streets). Practically, we assume that all of streets are two-way streets. The length d_{ij} between neighbouring crossroad i and j is Euclidean distance, which is given by

$$d_{ij} = ||(v_i, v_j)||_2.$$

As shown in Fig. 1, for sensing the streets traffic, the sensor nodes are deployed at roadsides. The set of sensor nodes is denoted by $S = \{s_1, s_2, ..., s_m\}$. In our model, we assume that each street can only be installed with one sensor node. That is to say, we have $m \leqslant |E|$. All the sensor nodes construct a wireless sensor network that can sensing the traffic for each street in this city.

The initial residue energy of nodes is denoted by $E^0 = \{e_1, e_2, ..., e_m\}$. For long-time continuing energy replenishment, a mobile charger with a battery of capacity E_c (we call charging ability) is scheduled to service sensor nodes by wireless power transfer technologies. The mobile charger starts to service the nodes from a service station. The charger have to travel along the traffic routes and observe traffic regulation. After visiting all sensor nodes, it will return to the service station for recharging or refueling. Similar to [13], we also assume that the nodes' residue energy level is invariable over a charging cycle.

2.2 Recharging Model

Inspired by [14], we know that the charging efficiency would be affected by charging distance between charger and rechargeable device. As depicted in Fig. 2, we take the charging distance into consideration in the recharging model. Denote D the threshold of charging distance, which is the maximum charging distance for nodes. Charger can service nodes if charger is within the charging range determined by a threshold. To minimize energy lost, the mobile charger transmits power to a node at the location which is the closest point to that node. The minimum charging distance is denoted by r_k for node k $(1 \leqslant k \leqslant m)$. Inspired by the experiments in [23], the charing power p_k^c of node k by charger can be quantified by an empirical model as follows:

$$p_k = (-0.0958r_k^2 - 0.0377r_k + 1) \cdot P_o$$

where the P_o is output power from charger. The charging power for all nodes can be denoted by $P = \{p_k | 1 \leq k \leq m\}$. We assume that the all nodes require being charged to full energy E_{max}. Then the charging time at node k can be given by:

$$t_k = \frac{E_{\max} - e_k}{p_k}.$$

Denote $\mathbb{T} = \{t_1, t_2, ..., t_m\}$ the recharging time for all sensor nodes.

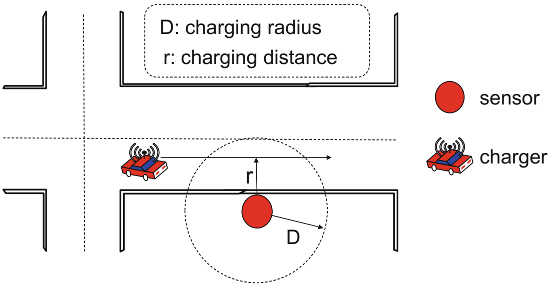


Fig. 2. The recharging model

2.3 Cost Model

In this subsection, we would introduce the recharging cost and moving cost. As mentioned in Sect. 2.2, the charging power received on nodes would be affected by charging distance, which means that the recharging cost for each node is different. For node k, the recharging cost of charger can be given by $q_k = p_k \cdot t_k$. Therefore, the required recharging cost for all nodes can be denoted by $Q = \{q_k | 1 \leq k \leq m\}$, and RC is the sum of each node's required recharging cost, which is

$$RC = \sum_{k=1}^{m} q_k.$$

Another cost is moving cost with respect to the moving distance. We assume that the mobile charger moves with a constant moving speed. The traveling path of mobile charger is assumed with $\mathcal{R} = \{R_1, R_2, ..., R_{|\mathcal{R}|}\}$ which consists of edges in graph G, *i.e.*, $\mathcal{R} \subseteq E$. Also, the symbol R_i could be used to denote the traveling cost in R_i. Then the total moving cost denoted by MC can be given by:

$$MC = D(\pi, R_1) + \sum_{i=1}^{|\mathcal{R}|-1} [R_i + D(R_i, R_{i+1})] + R_{|\mathcal{R}|} + D(R_{|\mathcal{R}|}, \pi)$$

where the $D(R_i, R_{i+1})$ is the moving distance from R_i to R_{i+1} and π is the service station.

3 Problem Formulation and Solution

3.1 Problem Formulation

With the models we have discussed in Sect. 2, we need to find an optimal traveling path for mobile charger to minimize the moving cost. Denote x_i at the state that the node i is visited by charger or not, which is given by:

$$x_i = \begin{cases} 1 & visited \\ 0 & not\, visited \end{cases}$$

Then our problem can be formulated as follows:

$$\begin{aligned} \min \quad & MC \\ s.t. \quad & \sum_{i=1}^{m} x_i = m; \\ & RC < K \cdot E_c; \end{aligned}$$

where the K is the number of mobile chargers. Then our problem is how to schedule the mobile chargers with the objective of minimizing moving cost. In this paper, our problem could be formulated into a famous Arc Routing Problem (ARP) with two cases:

(1) $m = |E|$. It means all streets are installed with one node. That is to say, all edge in graph G should be visited, which we call Chinese Postman Problem (CPP) [18];
(2) $0 < m < |E|$. It means only some of edges in G should be visited. And we call it Rural Postman Problem (RPP) [19], which has been proved NP-hard.

3.2 Problem Analysis

Given a graph $G = (V, E)$, in the first case, CPP is an edge coverage problem in a graph with minimum distance. For ease of conversion, the postman is regarded as the mobile charger and visiting an edge is considered as recharging a that the node in the edge should be charged by charger. This problem can be reduced into Eulerian Tour problem [20] if the graph is Eulerian graph. It has been proved that typical CPP could be solved in polynomial time. An algorithm with computation complexity $O(|V|^3)$ proposed by Edmonds and Johnson [21] can be used.

In the second case, RPP need constrained combinatorial computation, where the selected visiting edges are the subset of all edges in the graph. Taking the charging ability into consideration, it is also known as CARP (Capacitated Arc Routing Problem) [24] which has been proved NP-hard. That is to say, only the edges in subset $E' \subseteq E$ are allowed to visit. This case is more practical than the first one. For this problem, an efficient heuristic algorithm called GA (Genetic Algorithm) can be used to handle. Considering the limited charging ability, the case of multi-chargers should be concerned. Then a decoding algorithm called Split [22] could be used for a partitioning method of dividing the service edges into several parts. Each part can be serviced with one mobile charger.

3.3 Algorithm and Solution

Inspired by heuristic algorithm in Traveling Sales Problem, we use the Genetic Algorithm to handle it. As shown in Algorithm 1, it consists of two functions which represent two kinds of algorithms. The first function indicates the genetic algorithm iteration procedures. The below function is an algorithm named Split, which can be used to decode the iteration results. *Select* is the operation of natural selection, and $CrMu$ is the operation of crossover and variation in genetic algorithm. In the crossover operation procedure, we used the general operation of interstitial chiasma. About the variation operation, we select two genes to exchange randomly. From line 15 to 38, the Split can divide all arcs into the several traveling cycle paths with minimum number of chargers. In this function, it output two arrays which are traveling cost array V and the array $Pred$ that can be used to recover the all traveling paths. Given a feasible solution, Split can acquire the minimum traveling cycle paths and chargers with the time complexity $O(n^2)$.

4 Simulation

4.1 Experimental Setups

Given a city graph $G = (V, E)$ in an area of $45\,\text{km} \times 30\,\text{km}$, we use MATLAB to generate $n = |V| = 90$ locations of intersections V and the streets E between some intersections randomly. The city graph is shown in Fig. 3. Similar to existing works [11], the charging output power P_o is set by $5w$. The battery capacity of sensor is $10.8\,\text{kJ}$ [25].

4.2 Evaluation Results and Analyses

The simulation results are shown in Figs. 4, 5 and 6. These figures show the relationship between the number of sensor nodes and traveling cost or charging ability E_c of charger.

Firstly, in Fig. 4, we explore the impacts of the increased number of nodes and charging ability E_c on number of chargers and traveling cost. In Fig. 4(a), we can

Algorithm 1. Genetic Algorithm for Capacitated Arc Routing Problem

Require: $AdjMat$, $MAXGEN$, $Sink$, E_c
Ensure:

function GA($AdjMat, Chrom, MAXGEN, Sink$)
    while $num < MAXGEN$ **do**
        $FitnV \leftarrow \textsc{Split}(Chrom, Sink, E_c, AdjMat)$
        $SelCh \leftarrow Select(Chrom, FitnV)$
        $Selch \leftarrow CrMu(Selch, P_{cro}, P_{mut})$
        $SelFitnV \leftarrow \textsc{Split}(Selch, Sink, E_c, AdjMat)$
        if $SelFitnV < min(FitnV)$ **then**
            $Chrom \leftarrow Chrom + Selch$;
        end if
        $num \leftarrow num + 1$
    end while
    return $SelCh$
end function

function SPLIT($Chrom, Sink, E_c, AdjMat$)
    for $i = 1 \rightarrow n$ **do**
        $load \leftarrow 0$
        $cost \leftarrow 0$
        $j \leftarrow i$
        while $j <= n$ **and** $load <= E_c$ **do**
            $load \leftarrow load + q[j]$
            if $i == j]$ **then**
                $cost \leftarrow AdjMat[Sink, Chrom[j]] + \omega(Chrom[j]) + AdjMat[Chrom[j], Sink]$
            else
                $cost \leftarrow cost - AdjMat[Chrom[j-1], Sink] + djMat[Chrom[j-1], Chrom[j]] + \omega(Chrom[j]) + AdjMat[Chrom[j], Sink]$
            end if
            if $load <= E_c$ **then**
                $VNew \leftarrow V[i-1] + cost$;
                if $VNew < V[j]$ **then**
                    $V[j] \leftarrow VNew$;
                    $Pred[j] \leftarrow i - 1$;
                end if
                $j \leftarrow j + 1$;
            end if
        end while
    end for
    return $result$
end function

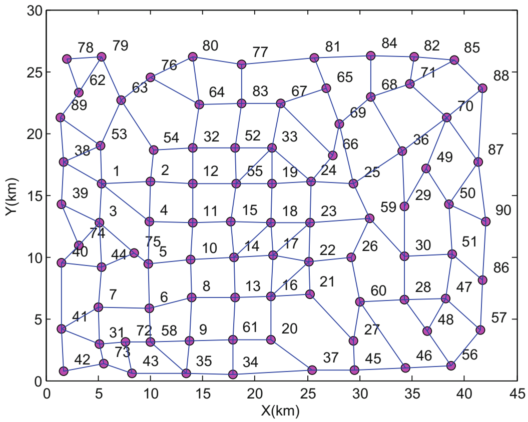
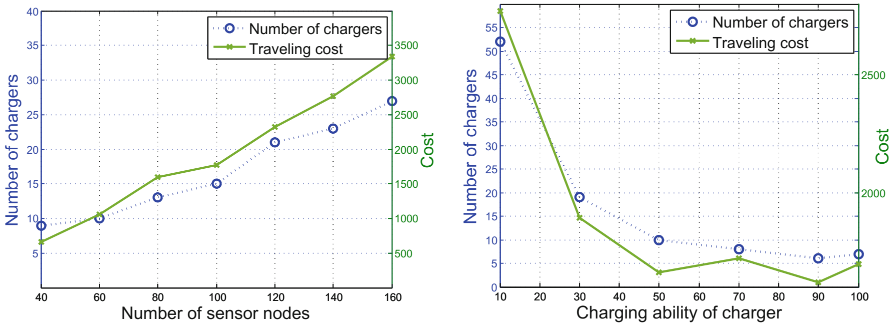


Fig. 3. City roadmap for simulation

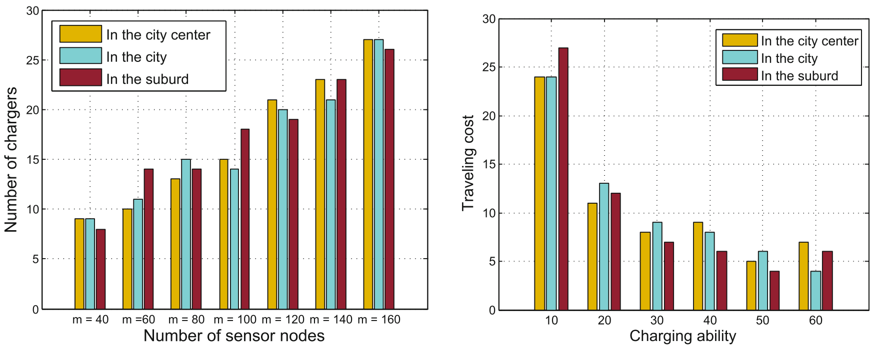


(a) Change in terms of number of nodes (b) Change in terms of E_c

Fig. 4. The changes of number of chargers and traveling cost.

see that the number of chargers and traveling cost increase with the increased number of sensor nodes. And Fig. 4(b) shows that the number of chargers and traveling cost decrease with the increased charging ability E_c. Considering the constraints of charging ability E_c, it is obvious that more sensor nodes need more chargers. Similarly, more sensor nodes mean more traveling cost. Meanwhile, the number of chargers and traveling cost can be reduced by increasing the charging ability E_c. It means that the way to reduce the number of chargers and traveling cost is to enhance the charging ability of charger.

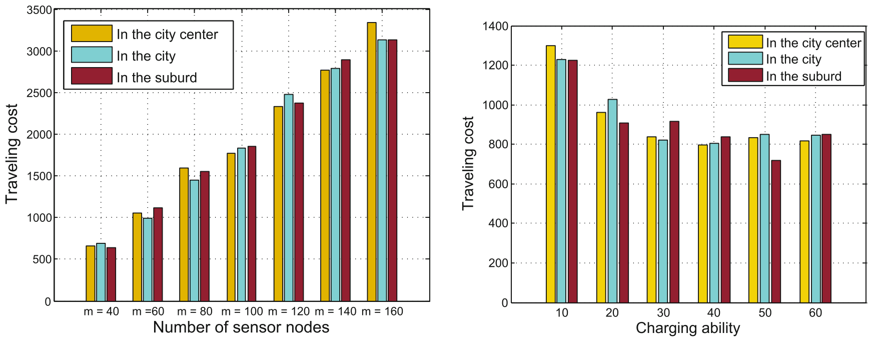
In addition, we consider that the location of service station may affect the number of chargers. Two experiments are conducted, that the results are shown in Fig. 5. Three cases of service station locations are taken into consideration, that are city center, city and suburb. In Fig. 5, it shows that the number of chargers would not be affected with different service stations in terms of the increased number of nodes or charging ability E_c. From these two figures, we



(a) Chargers' number in terms of number of nodes

(b) Chargers' number in terms of E_c

Fig. 5. The changes of number of chargers with different service stations.



(a) Traveling cost in terms of number of nodes

(b) Traveling cost in terms of E_c

Fig. 6. The changes of traveling cost with different service stations.

can get that the number of chargers wouldn't be affected by the location of service station.

Lastly, we investigate the impact of different locations of service station on traveling cost with the increased number of nodes or charging ability E_c. In Fig. 6, it can see that the traveling cost would not be affected by different service stations with the increased number of nodes or charging ability E_c. Otherwise, we can see that the traveling cost would decrease firstly and then maintain unchanged. Because, in the decreasing stage, the traveling cost is determined by the chargers's total traveling cost. In the maintaining stage, the traveling cost is determined by the locations of nodes and service station.

By combining the same phenomenon between Figs. 5 and 6, we can see that the number of chargers and traveling cost is insensitive to the location of service station.

5 Conclusion

In this paper, we investigate the problem of scheduling mobile chargers with mobility constraints. The chargers start from and end with the service station, which are scheduled to charged sensor nodes following the city topological graph. With the objective of minimizing the traveling cost, we aim at optimizing the traveling path for chargers. And we convert our scheduling problem into a class Capacitated Arc Routing Problem, which has been proved NP-hard. Then a simple but efficient genetic algorithm is proposed to handle it. Furthermore, a decoding algorithm named Split is cooperated to acquire the exact solution. Finally, we evaluate the impact of different parameters on our algorithm. And we can see that the number of chargers and traveling cost are insensitive to the location of service station.

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