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Optimal Recharging With Practical Considerations in Wireless Rechargeable Sensor Network

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ABSTRACT Wireless energy transfer technologies have attracted increasing attention on empowering the wireless sensor nodes in recent years. In this paper, we consider a typical wireless rechargeable network, where a mobile charging vehicle is scheduled to charge a wireless sensor network with practical nodes' deployment restrictions that may result in low charging efficiency for sensor nodes by charging vehicle. In our model, we take the effects of charging distance and angle on charging efficiency into consideration. Intuitively, there is an inevitable tradeoff between the charging distance and the angle. First of all, the scheduling traveling path of charging vehicle in previous studies has been proved to be NP-hard. Even worse, the nonlinear property between the charging distance and angle makes the problem even harder. For these concerns, we aim at minimizing the recharging cycle time, which contains the traveling time and recharging time. To this end, we prove that the charging vehicle would travel along the shortest Hamiltonian cycle. And we show the optimal charging location for each wireless charging incident. Experimental results demonstrate that our proposed solution could improve the charging efficiency around two times compared with the baseline scheme without optimization for angle and distance.

INDEX TERMS Wireless energy transfer, wireless sensor network, charging distance and angle.

I. INTRODUCTION

A. BACKGROUNDS AND MOTIVATION

Wireless energy transfer technologies, empowered by magnetic resonant coupling [1] or electromagnetic effects [2], have provided a promising solution to extend the life time of Wireless Sensor Networks (WSNs). Many previous studies in [3] and [4] have proposed solutions about scheduling mobile charger for rechargeable nodes and deployment of charging infrastructures. Moreover, [5] has investigated how to improve the energy transfer efficiency with longer range. Unfortunately, marginal works are focusing on energy harvesting efficiency with reasonable consideration of the physical constraints during wireless energy transfer. Inspired by [1], we focus on the fact that, the charging distance between charger and receiver is the main factor that needed to be fully considered for charging efficiency. Charging distance between charging infrastructure and rechargeable node should be taken into consideration. The effect of distance on WSNs have been considered in [6]. As described in [7], the efficiency of wireless energy transfer would be affected by angle between energy charger and receiver. To this end, the angle between charger and receiver should be incorporated for improving energy harvesting efficiency. There should be an improved charging schedule for mobile charger, when the efficiency of wireless energy transfer is affected by charging distance and angle simultaneously. Motivated by this basic fact, we make an attempt to optimize the charging efficiency incorporating the distance and angle between mobile charger and receiver. To the best of our knowledge, ours is the first work focusing on optimizing charging efficiency while considering the impacts of distance and angle during one charging schedule.

Typically, we consider a working scenario where a mobile wireless charging vehicle (WCV) travels across the network and charges all the rechargeable sensor nodes. In that, the WCV starts from the service station and charges the sensor nodes one by one. After visiting all the nodes, it would back to service station. Then the traveling path of the WCV forms a cycle path. Each node would be charged only once by WCV in one charging cycle. Due to practical deployment restrictions of sensor nodes, the charging efficiency for nodes would be affected by the charging distance and angle. In our work, we consider a simple case of recharging model. A tradeoff between charging distance and angle is full considered and formally addressed. We use a ladder function obtained by experiments in [7] and quadratic function in [6] to describe the charging efficiency of angle and distance, respectively. For above, we focus on optimizing the charging cycle time with the effects of charging distance and angle. With the objective, we prove that the cycle path of WCV is the shortest Hamiltonian cycle, which has been proved to be an NP-hard problem in previous work [3]. The non-linear property between the charging distance and angle should be carefully explored which makes the traditional shortest Hamiltonian cycle problem more complicated.

B. CONTRIBUTIONS

In summary, our contributions could be summarized as follows:

- We take the charging distance and angle between the charging infrastructure and the rechargeable nodes into consideration, and build an optimal recharging model. And we find the optimal point for WCV between charging distance and angle.
- We formulate our optimization problem with the objective of minimizing the cycle time. And we address it by CPLEX [8].
- We make extensive evaluations to validate the proposed optimal model. The experimental results demonstrate that, our proposed solution could decrease more than 50% charging time comparing with the baseline scheme without practical considerations.

C. PAPER ORGANIZATION

The remainder of this paper is organized as follows. In Sec. II, we review the wireless energy transfer technologies. In Sec. III, we introduce the system model which is the description of the scope of our problem for a rechargeable sensor network. In Sec. IV, we formulate the problem and propose the solution. In Sec. V, we conduct experiments and show our results and analyses. We conclude our work in Sec. VI.

II. RELATED WORK

It is well-known that wireless sensor network has many applications, such as environment and habitat monitoring. For different applications, there are many technical issues to be resolved for real deployment. However, traditional energy replenishing methods such as solar panel could not fully addressed the real deployment challenges for WSNs, since weather conditions or deployment restrictions would make these energy replenishing methods invalid.

Wireless energy transfer offers a promising opportunity for wireless sensor nodes, since the it is empowered by wireless charging technology with mobile chargers in network. Generally, wireless energy transfer technologies can be classified into three categories, *i.e.*, inductive coupling [9], electromagnetic radiation [10], and magnetic resonant coupling [1]. Inductive coupling works by magnetic field induction. The transmitter generates a varying magnetic field and induces a voltage at the receiver. The weaknesses herein are short charging distance (*e.g.*, centimeter-range) and requiring accurate alignment in charging direction. Electromagnetic radiation is working by emitting energy from the transmitter antenna to the receiver antenna via radiative electromagnetic waves. This technology suffers from a serious problem of its electromagnetic radiation waves decay quickly over distance and ultra low-power reception at receiver [11]. The third category of wireless energy transfer technology is magnetic resonant coupling. Energy can be transferred efficiently from a source coil to a receiver coil by having magnetic resonant coils operate at the same resonance frequency. The technology is working with high efficiency over several meters, and insensitive to weather conditions. Magnetic resonant coupling is a promising way to serve mobile devices, electric vehicles, and WSNs [12]. The latest researches find that resonant repeaters can realize multi-hop wireless charging thereby extending the charging range [13], [14].

The foundation of our work in this paper is based on magnetic resonant coupling because of its higher efficiency as compared to others. And we also recognize the weakness of magnetic resonant coupling is highly efficiency only within several-meter range. For the limited charging range, the highly efficiency suffers from some factors such as distance and angle between energy transmitter and receiver. Our objective is how to ensure the highly efficiency under the practical conditions within several-meter range.

III. SYSTEM MODEL

A. NETWORK MODEL

We consider that there are N sensor nodes distributed over a limited square area. The three-dimensional coordinate of node i is (x_i, y_i, z_i). Each node is equipped with a battery of maximum capacity E_{max}. And the minimum energy level for regular operation is E_{min}. The initial energy level is E_i at node i. Denote $e_i(t)$ the node i residual energy at time t (*e.g.*, $e_i(0) = E_i$). The nodes would stop working (we call it death status) if residue energy is lower than E_{min}. To recharge the sensor nodes, a mobile WCV is employed. The WCV can charge nodes if nodes fall in its charging range. In our work, we consider the simple case that nodes are charged sequentially. For the sensor network, there is a fix Base Station (BS) which is a sink node for collecting sensing data. We assume that the energy of BS is unlimited comparing to nodes.

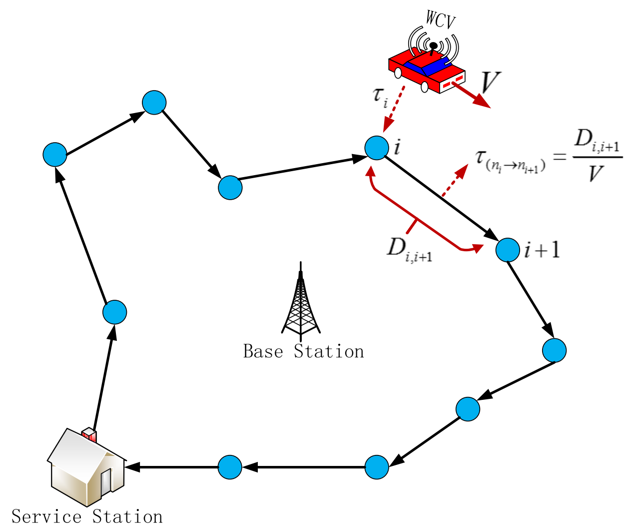


FIGURE 1. **The scenario of wireless recharging sensor network with wireless mobile charger.**

As shown in Fig. 1, the WCV starts from the service station and travels through all nodes at speed of V. By carrying the battery and wireless energy transmitter, WCV can charge nodes in wireless mode. The energy transmitted to nodes derives from the battery carried by WCV, and it is huge comparing to nodes. When finishing charging node i, the WCV travels to the next one. After visiting and charging all nodes, it will return to service station and be serviced (*e.g.*, replacing or recharging itself) [15], and then continue to travel for the next round. The trace of WCV forms a cycle which starts from and ends at the service station. We ignore the time spent on service station. The time for a trip cycle of WCV is denoted by T. Denote $P = \{n_0, n_1, \ldots, n_N, n_0\}$ the physical path traveled by the WCV over a cycle, and the i^{th} node experienced by WCV is denoted as n_i, $1 \leq i \leq N$. As aforementioned, the physical path P is a cycle path (*i.e.*, n_0 is the service station). And the length of physical path P is denoted by D_P. The horizontal length between node i and node $i+1$ is defined by Euclidean distance, such as

$$D_{i,i+1} = \|(x_i - x_{i+1}, y_i - y_{i+1})\|_2 .$$

Example, $D_{0,1}$ is the distance between service station and the first node, and $D_{N,N+1}$ is the distance between the last node and service station. Denote τ_{path} the time spent on path over a cycle which can be expressed as

$$\tau_{path} = \sum_{i=0}^{n} \frac{D_{i,i+1}}{V}. \tag{1}$$

We assume that data routing topology is invariable and the energy consumption rate is a constant value for each node. Denote p_i the energy consumption rate of node i, and the residual energy of node i at time t can be expressed as $e_i(t) = E_i - t \cdot p_i$ before charging. Denote τ_i the charging time at node i. The WCV executes wireless charging behavior, when it stops a location where close to nodes. To support a renewable sensor network, we assume that all nodes would not switch to death status over a cycle. Then the residue energy at nodes need be greater than E_{min} anytime (*i.e.*, $e_i(t) \geq E_{min}, 0 < t < \infty$). Denote r_i the time of reaching at node i for WCV. Then we have

$$r_i = \sum_{j=1}^{i} \frac{D_{j-1,j}}{V} + \sum_{j=1}^{i-1} \tau_j, \tag{2}$$

where $\sum_{j=1}^{i} \frac{D_{j-1,j}}{V}$ is the time from service station to node i, and $\sum_{j=1}^{i-1} \tau_j$ is the total charging time from first node to $(i-1)^{th}$ node. Also we can get $e_i(r_i) = E_i - r_i \cdot p_i$, and its necessary constrain

$$e_i(r_i) \geq E_{min}. \tag{3}$$

The time spent in traveling is $\tau_{path} + \sum_{i=1}^{N} \tau_i$. Then a cycle time can be expressed as

$$T = \tau_{path} + \sum_{i=1}^{N} \tau_i. \tag{4}$$

B. RECHARGING MODEL

To meet some requirements of applications in complex physical environment, some sensor nodes would be deployed at some location where WCV can not reach, such as on the wall or tree. Thus the power reception rate at nodes would be suffered by charging efficiency factors. On the basis of work in [6] and [7], we consider two charging efficiency factors, *distance* between node and charger, and *angle* of antenna orientation between node and charger.

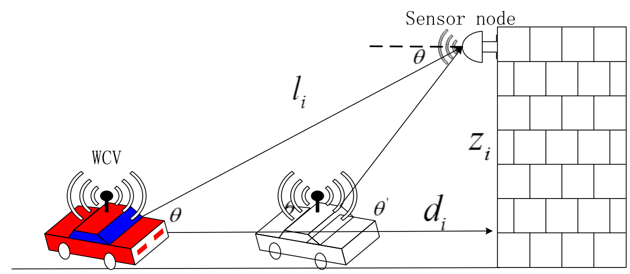


FIGURE 2. **The scenario of wireless mobile charger for sensor node.**

As shown in Fig. 2, we consider a simple case. We consider the antenna orientation at node is fixed. Because large energy consumption in the mechanization operation of changing the antenna orientation, is not suitable for sensor nodes, but variable orientation for WCV with huge energy. We assume that the charging power at nodes is maximum when the charger and nodes are toward each other. Denote d_i the horizontal distance from node i to WCV and l_i the charging distance from node to WCV. Let θ_i denote the charging angle between horizon and power transfer orientation. Then charging power at node i is

$$U_i = \delta(l_i) \cdot \delta(\theta_i) \cdot U_{full}, \tag{5}$$

where U_{full} is full output charging power from WCV, and $\delta(l_i)$ is the charging efficiency about distance l_i, $\delta(\theta_i)$ is the efficiency about angle θ_i. Note that both $\delta(l_i)$ and $\delta(\theta_i)$ are decreasing functions and $0 \le \delta(l_i) \le 1$, $0 \le \delta(\theta_i) \le 1$. As depicted in Fig. 2, we can see that power reception rate is affected by distance and angle. By the WCV moving toward the node, the angle and distance is changing and effects of these factors is changing. When the WCV moving towards the node, horizontal distance d_i and l_i is decreasing but increasing for angle θ_i. Then the challenge comes from the tradeoff between distance and angle. For describing the tradeoff, we get that the relationship formula is $\sin\theta_i = z_i/l_i$. For above, the angle θ_i is determined by l_i and z_i. Then equation Equ. (5) can be replaced by

$$U_i = \delta(l_i, z_i) \cdot U_{full}. \tag{6}$$

In order to obtain the maximal charging efficiency, the WCV need to find an optimal location to execute power transfer. For optimal location, we have considered the Pythagorean theorem can be used in this optimal problem. By this theorem, the charging distance l_i can be formulated as $l_i = \sqrt{d_i^2 + z_i^2}$ and the charging efficient of distance can be got by $\delta(l_i) = \delta(\sqrt{d_i^2 + z_i^2})$, which we would show it in Sec. V. Otherwise the charging efficiency of angle $\delta(\theta_i)$ can be got by ladder function which is inspired by [7]. The charging efficiency for angle can be described as follows. The initial orientation is denoted as Zero degree rotation (*i.e.*, $\theta_i = 0^0$) and the efficiency of energy transfer is maximum, so that we define the angle efficiency factor as $\delta(\theta_i) = 1$ when $\theta_i = 0^0$. As shown in Fig. 3, we consider that the charging efficiency is the same within the range of 30 degrees. Then we have $\delta(\theta_i) = 1$ when $\theta_i \in [-15^0, 15^0]$. When the orientation increases 30 degrees, the angle efficiency factor $\delta(\theta_i)$ would decrease by 0.2, thus $\delta(\theta_i) = 0.8$ when $\theta_i = 30^0$. Similarly, $\delta(\theta_i) = 0.8$ when $\theta_i \in [15^0, 45^0]$. In our problem, we only need to take zero degree to 90 degree into consideration. The rest can be done in the same manner, then we have

$$\delta(\theta_i) = \begin{cases} 1 & \theta_i \in (0, \frac{\pi}{12}] \\ 0.8 & \theta_i \in (\frac{\pi}{12}, \frac{\pi}{4}] \\ 0.6 & \theta_i \in (\frac{\pi}{4}, \frac{5\pi}{12}] \\ 0.4 & \theta_i \in (\frac{5\pi}{12}, \frac{\pi}{2}) \end{cases}$$

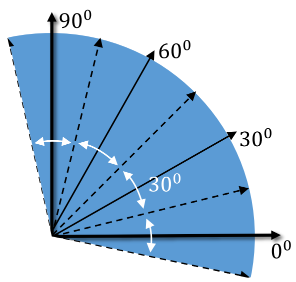


FIGURE 3. Hint of ladder function of charging efficiency for angle.

For the relationship $\sin\theta_i = \frac{z_i}{l_i}$, we can replace $\delta(\theta_i)$ with $\delta(\arcsin\frac{z_i}{l_i})$. That is

$$\delta(\arcsin\frac{z_i}{l_i}) = \begin{cases} 1 & \frac{z_i}{l_i} \in (0, \sin\frac{\pi}{12}] \\ 0.8 & \frac{z_i}{l_i} \in (\sin\frac{\pi}{12}, \sin\frac{\pi}{4}] \\ 0.6 & \frac{z_i}{l_i} \in (\sin\frac{\pi}{4}, \sin\frac{5\pi}{12}] \\ 0.4 & \frac{z_i}{l_i} \in (\sin\frac{5\pi}{12}, \infty) \end{cases}$$

Then we can conclude that the Equ. (6) be reformulated as

$$U_i = \delta(l_i, z_i) \cdot U_{full} = \delta(l_i) \cdot \delta(\arcsin\frac{z_i}{l_i}) \cdot U_{full}. \tag{7}$$

To ensure the charging result, we consider that it is necessary for all nodes to be charged to E_{max}.

C. RENEWABLE ENERGY CYCLE MODEL

We formally define a renewable energy cycle as follows like the work in [15].

Definition 1 (Renewable Energy Cycle): In order to meet a renewable energy cycle, the residual energy $e_i(t)$ of node i ($1 \le i \le N$) must meet two requirements. Firstly, it starts and ends with the same residual energy over a cycle T; Secondly, it never falls below E_{min}.

According to *Definition* 1, during a renewable cycle, the amount of energy charged must be equal to the amount of energy consumed at each node in the cycle. That is, at node i,

$$T \cdot p_i = \tau_i \cdot U_i. \tag{8}$$

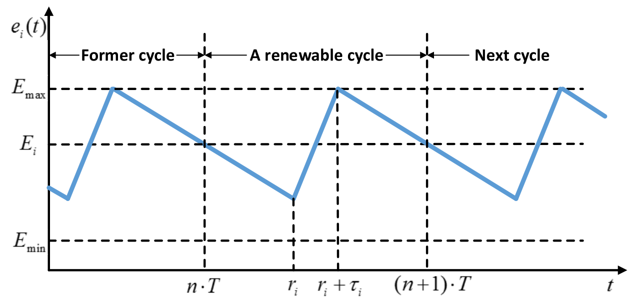


FIGURE 4. The changing curve of node energy for renewable cycle.

When the WCV visits a node i at time r_i over a cycle, the node is recharged to E_{max}. And the residual energy of sensor nodes should be greater than E_{min} when WCV visits nodes. The variation tendency of one node's energy level is illustrated in Fig. 4. And firstly we focus on the energy variation tendency in interval $[nT, (n+1)T]$. Based on the *Definition* 1 and Fig. 4, we can get that the minimum energy level at node i is at time r_i. To ensure that the second requirement in *Definition* 1, we have

$$e_i(r_i) = E_i - r_i \cdot p_i \ge E_{\min}. \tag{9}$$

For nodes starting and ending with the same energy level over a cycle time T, and the maximum energy level at time $r_i + \tau_i$, we can get

$$E_i = e_i(r_i + \tau_i) - (T - r_i - \tau_i) \cdot p_i = E_{\max} - (T - r_i - \tau_i) \cdot p_i \quad (10)$$

Combining Equ. (9) and Equ. (10), we can have

$$E_{\max} - (T - \tau_i) \cdot p_i \geq E_{\min}. \quad (11)$$

Then the renewable energy cycle can be maintained if constraints Equ. (4), Equ. (8), Equ. (11) are met for each node.

IV. PROBLEM FORMULATION AND SOLUTION

A. PROBLEM ANALYSIS

With the constraints that we have discussed in section III, we focus on the effects of charging factors on wireless charging efficiency. Thus we consider the objective of optimizing charging performance. In order to enhance the efficiency of wireless charging at different limits of distances or angles, we aim to minimize cycle time, *i.e.*, T.

With the objective of minimizing the cycle time, the cycle traveling time τ_{path} and U_i, charging time τ_i are optimization variables. So far, there are not any non-linear terms except the efficiency functions of charging distance and angle. U_i can be optimized according the charging distance and angle, and τ_i also can be determined after determining r_i. Before computing r_i, we need know the charging sequence by WCV, *i.e.*, traveling path. The point is that the traveling path is unknown so far. There are many traveling paths that would result in different traveling distance. Then the time spent on traveling paths would be different. Even the path planning has been researched in previous work [15], but the charging power suffered by distances and angles results in big changes in charging time for each node. In order to meet that there are not any nodes that would change into death status, the previous path scheduling scheme may be unsuitable for our problem. Now we need to know that which path the WCV would travel along. For our optimal objective, an optimal traveling path would be suit for our objective. We would discuss this in next subsection.

B. FORMULATION AND SOLUTION

In this subsection, firstly, we will give a lemma for finding the traveling path by WCV. We can get the proof of this lemma by contradiction.

Lemma 1: With the optimal objective of minimizing T, the WCV must travel along the shortest Hamiltonian cycle that connects the nodes and service station.

Proof: Assumption: Given an optimal solution $\varphi^* = (\tau_i^*, \tau_{path}^*, T^*)$, where the WCV does not travel along the shortest Hamiltonian cycle path.

Then we could construct a new solution of our problem $\hat{\varphi} = (\hat{\tau}_i, \hat{\tau_{path}}, \hat{T})$ where the WCV travels along the shortest Hamiltonian cycle. With the assumption, τ_{path}^* in φ^* is the traveling time that the WCV does not travel along the shortest Hamiltonian cycle. Then the new solution $\hat{\varphi}$ could be constructed as follows. Let $\hat{\tau}_{TSP}$ denote the traveling time that the WCV travels along the shortest Hamiltonian cycle and $\tau_i^* = \hat{\tau}_i$. Obviously, we can get $\hat{\tau}_{TSP} \leq \tau_{path}^*$ for the shortest Hamiltonian cycle path generating the shortest traveling time. On the other hand, due to the cycle time T consists of total charging time at nodes and traveling time, we can get $\hat{T} \leq T^*$. Then the solution $\hat{\varphi}$ could provide an improved objective.

Next, we show that the solution $\hat{\varphi}$ is feasible for our optimal linear programming problem. To verify feasibility, we need to show that $\hat{\varphi}$ satisfies Equ. (8) and Equ. (11). Since the φ^* is a feasible solution for our problem, it should satisfy the constraints Equ. (8) and Equ. (11). For $\tau_i^* = \hat{\tau}_i$, we can get $\hat{T} \cdot p_i \leq \hat{\tau}_i \cdot U_i$ which could maintain the first requirement in *Definition* 1 and satisfy Equ. (8). For the feasible solution $\hat{T} \leq T^*$, it is straightforwardly that $E_{\max} - (\hat{T} - \hat{\tau}_i) \cdot p_i \geq E_{\max} - (T^* - \tau_i^*) \cdot p_i \geq E_{\min}$. Then we can get $E_{\max} - (\hat{T} - \hat{\tau}_i) \cdot p_i \geq E_{\min}$, which satisfies the Equ. (11). Thus, the solution $\hat{\varphi} = (\hat{\tau}_i, \hat{\tau_{path}}, \hat{T})$ is a feasible solution, which could provide an improved objective comparing to the optimal solution φ^*.

For above, we could conclude that the WCV would travel along the shortest Hamiltonian cycle path with the objective of minimizing the cycle time by leveraging contradiction. ■

Lemma 1 shows that the WCV should travel along the shortest Hamiltonian cycle, which is the well known Traveling Salesman Problem (TSP) [16]. More analogous details of proof process could be found in [15]. Denote D_{TSP} as the path distance in the shortest Hamiltonian cycle and $\tau_{TSP} = \frac{D_{TSP}}{V}$ as time for traveling along the shortest Hamiltonian cycle. By the shortest Hamiltonian traveling path, the Equ. (4) can be rewritten as

$$T = \tau_{TSP} + \sum_{i=1}^{N} \tau_i. \quad (12)$$

Based on the reformulation and discussion, our optimization problem could be formulated as follows:

$$\begin{aligned} &\min \ T \\ &\text{s.t. } T = \tau_{TSP} + \sum_{i=1}^{N} \tau_i && (12) \\ &\quad T \cdot p_i = \tau_i \cdot U_i && (8) \\ &\quad E_{\max} - (T - \tau_i) \cdot p_i \geq E_{\min} && (11) \\ &\quad U_i, \tau_i > 0, \quad (1 \leq i \leq N) \end{aligned}$$

In this problem, Equ. (12) can ensure that the cycle time is consist of traveling time and charging time. Equ. (11) can ensure the nodes would not switch to death status over a cycle. And Equ. (8) can ensure that the amount of charged energy at each node is equal to the amount of energy consumed in the cycle. Then the renewable energy cycle can be maintained. We also can get that there are not nonlinear terms or objectives. Then our problem is a linear programming problem.

We note that, the power reception rate U_i is determined by Equ. (7). In order to meet the objective, the power reception rate U_i should attain the maximum value by adjusting the horizontal distance d_i under the fixed height z_i at node i (we ignore the time spent on adjusting the horizontal distance because it is much less than the total cycle time T). For accurate computation, we use a tool Concorde to compute the shortest Hamilton cycle instead of approximation algorithms. For Equ. (7), we can acquire the maximum value of U_i by derivation. For the linear programming problem, we consider that our problem could be solved by a solver named by CPLEX [8]. The solution which is consist of four steps, is shown in Algorithm. 1.

Algorithm 1 Procedure of Solution for Our Problem

Input:
The three-dimensional coordinate $[x_i, y_i, z_i]$ and the energy consumption power p_i of sensor nodes, the upper and lower limit value of battery in sensor node, E_{max}, E_{min}, the speed of WCV, V.

Output:
The optimal charging location d_i, charging power U_i, charging time τ_i and cycle time T;

1: Find the optimal location of WCV for charging each node by seeking extreme value, such as derivation;
2: Compute the corresponding maximum charging power for each node based on the optimal location in step 1;
3: Find the Hamiltonian cycle and compute the length of Hamiltonian cycle path by Concorde solver, and the time spent on cycle by the speed of WCV;
4: Solve the linear programming problem by CPLEX, and obtain our solution;

V. EXPERIMENTAL EVALUATION

In this section, we conduct extensive simulations and show the results to analyse the effects of different parameters on charging efficiency.

A. SIMULATION SETTINGS

In our simulation, we consider $N = 30, 50, 70$ sensor nodes which are randomly distributed over a square area of $1km \times 1km$. For each sensor node, the energy consumption rate is a value $p_i \in [10, 15]mw$ at node i. The table 1 lists the three-dimensional coordinate of each node and its energy consumption rate for 50-node network. Due to the limited wireless energy transfer distance, we consider that the nodes' height $z_i \in [0.5, 2.5]cm$ can keep charging power is efficient at node i. For the other cases, we will discuss about them in future work. The service station's coordinate is assumed to be the origin $(0, 0)$. The WCV keeps moving at the speed of $V = 5m/s$. About the battery capacity, we choose a regular NiMH battery with $10.8KJ$ [17]. It means $E_{max} = 10.8KJ$, and we let $E_{min} = 0.05 \cdot E_{max} = 540J$. The maximum energy transfer rate is $U_{full} = 5w$.

For the two charging efficiency factors, we have discussed in Sec. III that we use ladder function to express the angle factor. About the distance efficiency factor, we use the formulation $\delta(l_i) = -0.0958l_i^2 - 0.0377l_i + 1.0$, which is obtained through curve fitting to experiment results in [18].

TABLE 1. Coordinate and power of 50 nodes.

Node	Location(m)	p_i(mw)	Node	Location(m)	p_i(mw)
1	(280,815,0.82)	10.34	26	(350,100,2.24)	12.70
2	(680,906,2.09)	11.49	27	(200,750,0.67)	14.86
3	(655,127,1.12)	10.64	28	(250,390,1.30)	14.82
4	(163,913,1.56)	10.66	29	(616,655,1.02)	12.17
5	(120,632,0.83)	13.27	30	(473,170,2.10)	13.61
6	(500,98,1.7)	10.72	31	(352,706,1.36)	14.51
7	(960,278,1.03)	11.76	32	(830,30,2.32)	11.50
8	(340,547,1.81)	14.78	33	(585,277,0.86)	12.33
9	(580,958,1.88)	11.80	34	(550,146,1.03)	11.75
10	(224,150,2)	14.15	35	(917,95,0.79)	12.08
11	(750,158,1.40)	13.62	36	(286,610,0.77)	10.40
12	(255,120,0.67)	12.30	37	(757,695,2.24)	12.14
13	(506,957,0.96)	14.30	38	(754,317,1.66)	12.49
14	(700,485,2.33)	14.48	39	(380,950,1.60)	10.46
15	(890,800,0.80)	10.04	40	(568,34,0.79)	10.48
16	(950,400,2.15)	11.38	41	(76,440,2.21)	11.81
17	(545,422,1.58)	13.95	42	(54,382,1.74)	10.84
18	(140,916,2.49)	11.90	43	(530,766,1.20)	14.10
19	(150,792,0.66)	14.59	44	(780,795,1.53)	12.07
20	(258,960,1.39)	14.26	45	(934,380,1.30)	12.82
21	(840,656,0.71)	12.44	46	(130,490,0.65)	14.59
22	(254,36,2.42)	13.19	47	(570,446,0.98)	13.72
23	(815,850,0.51)	10.57	48	(470,646,0.75)	14.22
24	(244,934,2.05)	12.06	49	(15,710,0.87)	14.29
25	(910,680,2.13)	13.75	50	(337,755,0.98)	11.78

B. RESULTS AND ANALYSIS

Before investigating the effects of charging efficiency on charging time of total sensor network, we are going to analyze the impacts of angle and distance efficiency factors on charging efficiency.

Comparing with the angle efficiency function $\delta(\theta_i)$ we have discussed in system model, we consider another angle efficiency function $\delta'(\theta_i)$ to describe the impact of charging angle on charging efficiency. That is $\delta'(\theta_i) = 1 - 0.55 \times \sin(\theta_i)$. The difference between $\delta(\theta_i)$ and $\delta'(\theta_i)$ would be shown in our simulation. As depicted in Fig. 5, it shows that how the charging distance and angle affect the charging efficiency, when considering the WCV charges a node deployed at $z_i = 1m$ by increasing the horizontal distance d_i. In Fig. 5a, it shows the variation tendency of charging efficiency with the angle and distance effects by increasing the horizontal distance d_i. The charging angle θ_i decreases and distance l_i increases when increasing the horizontal distance d_i. We can see that, by increasing the horizontal distance d_i, the charging efficiency of angle increases, and the charging efficiency of distance decreases. The reason is that $\delta(d_i)$ and $\delta(\theta_i)$ are decreasing functions. Fig. 5b and Fig. 5c show the impacts of distance and angle on charging efficiency when considering two kinds of angle utility functions, which are ladder function and continuous function. These two figures show that the curves of charging efficiency affected by angle and distance increase firstly and then decrease by increasing the horizontal distance d_i. That is to say there are peak values in these two curves. In Fig. 5b, when the horizontal distance $d_i \leq 1m$, the peak value of charging efficiency is around 0.5, when the horizontal distance $d_i \leq 2.5m$, the peak value of charging efficiency is around 0.6. Comparing with Fig. 5, the effects of charging distance and angle on charging efficiency,

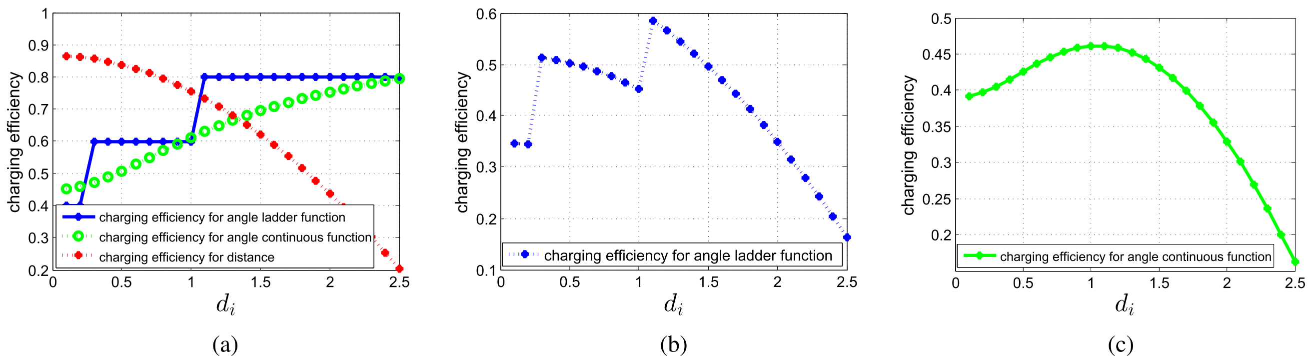


FIGURE 5. Impacts of charging distance and angle on charging efficiency when considering charging a node deployed at $z_i = 1m$. (a) Charging efficiency for angle and distance. (b) Charging efficiency for angle ladder function. (c) Charging efficiency for angle continuous function.

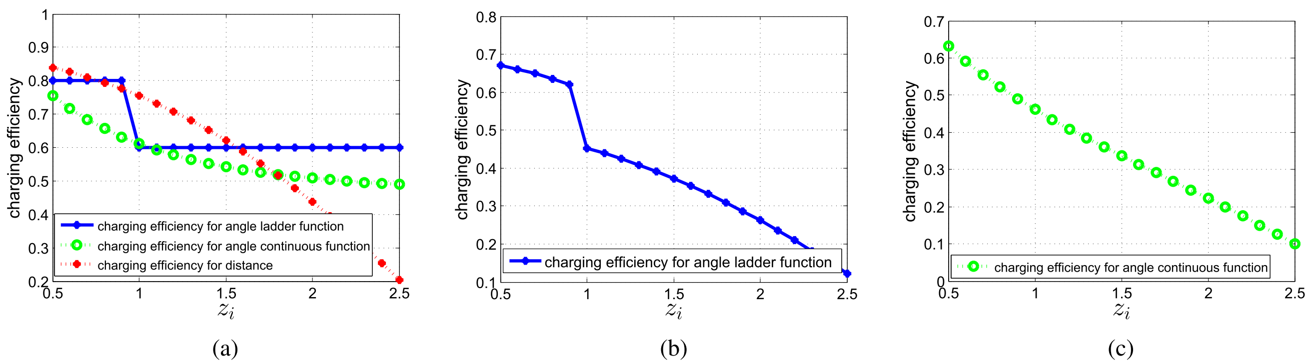


FIGURE 6. Impacts of charging distance and angle on charging efficiency when considering the WCV stopping at $d_i = 1m$. (a) Charging efficiency for angle and distance fix horizontal. (b) Charging efficiency for angle ladder function. (c) Charging efficiency for angle continuous function.

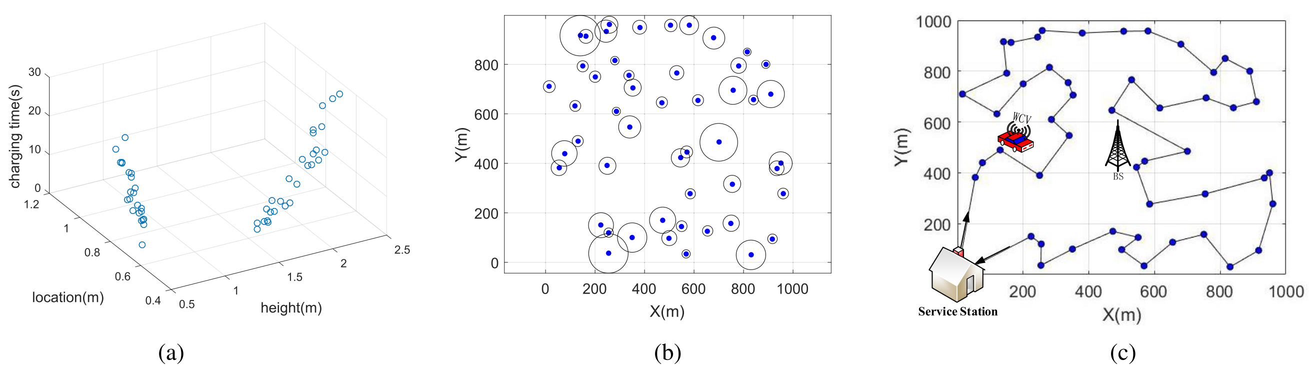
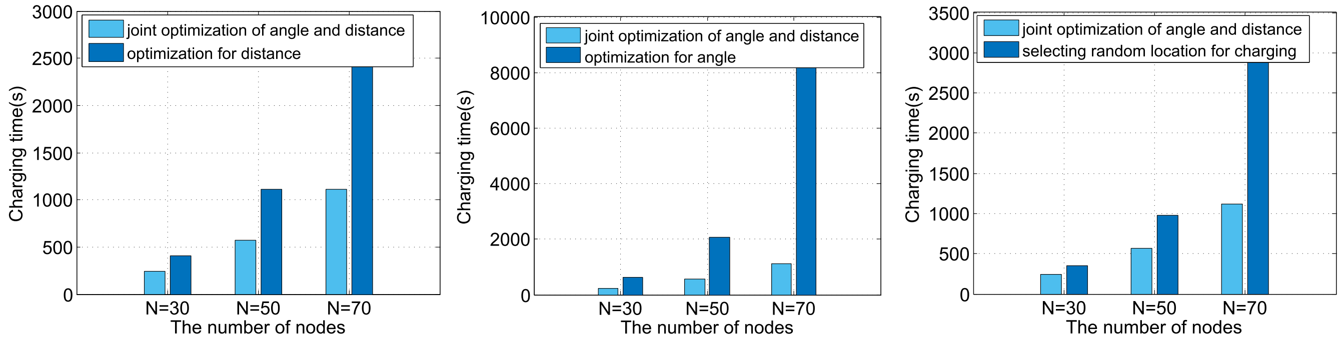


FIGURE 7. The optimal simulation results of 50-node sensor network. (a) The optimal charging location and time for each node in 50-node sensor network. (b) The distribution of charging time for each node in 50-node sensor network. (c) An optimal traveling path for 50-node sensor network.

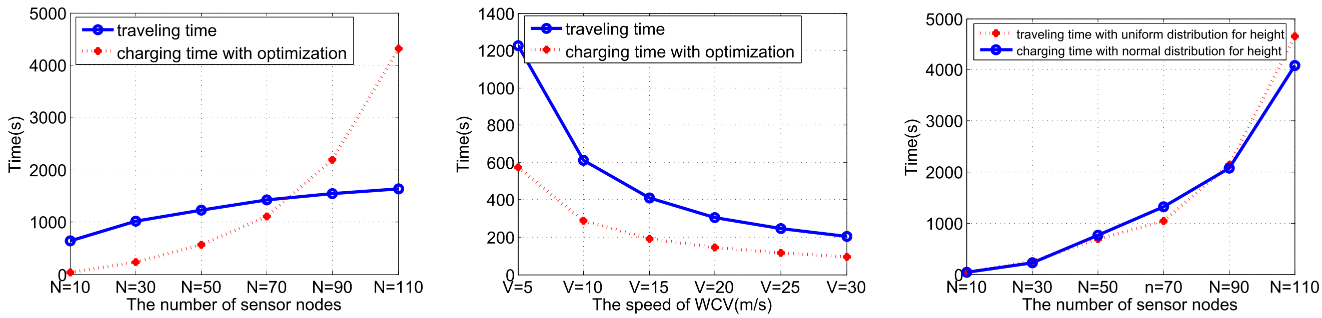
when considering the WCV stopping at $d_i = 1m$ charges a node by increasing the node's height z_i, is shown in Fig. 6. Similarity, in Fig. 5a, it shows the variation tendency of charging efficiency with the angle and distance impacts by increasing the node's height z_i. That is an obvious tendency because the charging angle and distance increase when increasing the node's height z_i. In order to compare the difference between The impacts of distance and angle are shown in Fig. 6b and Fig. 6c. These two figures are the impacts of considering two kinds of different angle utility functions respectively, which are ladder function and continuous function. And the variation tendency of these two figures can be explained easily by following the monotonous decreasing rule of $\delta(l_i)$ and $\delta(\theta_i)$.

Based on the simulation settings, we consider that the shortest hamiltonian cycle can be found by using Concorde [19], and the result is shown in Fig. 7c. And we can get that the shortest hamiltonian cycle distance is $D_{TSP} = 6123m$, the time $\tau_{TSP} = 1224.6s$. Then the linear programming problem is solved by CPLEX solver [8]. For the



(a) (b) (c)

FIGURE 8. **The impacts of different optimal objective. (a) The optimization for distance comparing with joint optimization of angle and distance. (b) The optimization for angle comparing with joint optimization of angle and distance. (c) The random location for charging comparing with joint optimization of angle and distance.**



(a) (b) (c)

FIGURE 9. **The impacts of different parameters. (a) The variation tendency of charging time and traveling time by number of nodes. (b) The variation tendency of charging time and traveling time by speed of WCV. (c) The variation tendency of charging time and traveling time by number of nodes at different way of height distribution.**

result, we get the cycle time $T = 1638.9s$, and the charging time and locations of nodes are shown by a three-dimensional diagram Fig. 7a.

In Fig. 7a, we also can get the variation tendency of charging time and location in terms of height. By increasing of height, firstly, the effects of angle occupy the leading role. Then WCV must increase the charging distance to decrease effects of charging angle for improving charging efficiency. Secondly, the effects of distance occupy the leading role. Then WCV must cut down the charging distance. In Fig. 7b, we use the size of circle to denote the quantity of charging time at nodes. More bigger sizes of circles mean greater charging time. we can see some nodes need more time to recharge energy for its lower charging efficiency.

For showing the significance of our work, we also conduct additional experiments. In the results of Fig. 8, we compare our optimal model for angle and distance with other three cases, that are optimization only for angle or distance and random selection optimal location for charging nodes. In Fig. 8, Fig. 8a shows that the optimization for distance comparing with joint optimization of angle and distance, Fig. 8b shows that the optimization for angle comparing with joint optimization of angle and distance, and Fig. 8c shows that the random location for charging comparing with joint optimization of angle and distance. In Fig. 8, we can see that the joint optimization of angle and distance can decrease around half of time spent on charging nodes at least, especially in terms of increasing the number of nodes. It indicates that our optimal model would decrease much charging time in recharging sensor network with large amounts of nodes.

Fig. 9a shows the variation tendency of charging time and traveling time in terms of the number of sensor nodes. Fig. 9b shows the variation tendency of charging time and traveling time in terms of the speed of WCV. And Fig. 9c shows The variation tendency of charging time and traveling time in terms of number of nodes at different way of height distribution. We can see, in Fig. 9a, that the increasing range of charging time is faster than increasing range of traveling time, then joint optimization for angle and distance is serious. Fig. 9b shows us a way of that charging time and traveling time can be decreased in terms of increasing the speed of WCV. Fig. 9c shows us that the variation tendency of charging time would not be affected much in terms of different way of height of node z_i distribution.

VI. CONCLUSION

In our paper, we consider that a mobile wireless charging vehicle travels across the WSNs and charges nodes one by one to achieve a rechargeable wireless sensor network. For each node, the power of wireless charging varies from different wireless charging distances and angles. We exploit some effects of distance and angle efficiency factors on efficiency of wireless charging. Our goal is to achieve an optimal cycle time over a cycle, thus the efficiency of wireless charging at each node should be maximized under restraints of distance and angle. We aim to find the optimal location for the WCV to charge nodes with maximum charging efficiency under the constraints of charging angle and distance. On the other hand, we show that the optimal traveling path for WCV is the shortest Hamiltonian cycle. Lastly, we develop a solution for traveling path of WCV, optimal power of wireless charging and optimal charging position of WCV for sensor nodes, and individual charging time at each node. Extensive simulation results show us that total charging time can be decreased by more than half.

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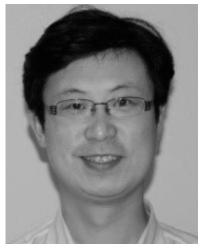

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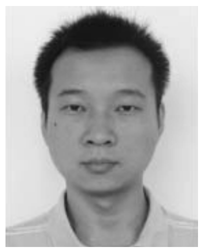

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