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A Robust RF-based Wireless Charging System for Dockless Bike-Sharing

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Abstract—In the past few years, dockless bike-sharing has become a popular means of public transportation and brought significant convenience to millions of citizens. As one of the key components of a shared bike, the smart locking/unlocking module has proposed a new challenge of how to provide robust power supplement for them. Current charging solutions for shared bikes are mainly based on mechanical power and solar power, and rarely take user experience and charging delay into consideration. In this paper, we design a robust RF-based wireless charging system for dockless bike-sharing. Our system utilizes radio frequency (RF) power to provide stable charging service while preserving the quality of service. In our system, an RF wireless charging sensing node is integrated on the bike's basket, so that the mutual interference during charging process and space occupation can be reduced. In order to reduce charging delay, we first design an efficient charging direction scheduling algorithm for a single charger. Then, we extend the solution to multiple-charger scenarios via dynamic programming. Our system has been successfully implemented on a dockless bike-sharing system. The experimental results verify that our design can satisfy the charging demands of shared-bikes and achieve 85% of the optimal solution.

Index Terms—dockless bike-sharing, wireless charging system, radio frequency, wireless power transfer.

1 Introduction

As one of the most popular means of zero-emission public transportation, bike-sharing provides significant convenience to citizens. Since 2014, dockless bike-sharing has attracted great attention all over China. More than 20 million shared-bikes have been deployed nationwide by dozens of companies [2]. And this trend is soon spreading across hundreds of cities worldwide, such as Washington, Singapore, etc. Compared with traditional bike-sharing systems, dockless bike-sharing replaces the docking station with a smart lock module. This design makes it possible for users to remotely lock/unlock bikes via APPs so that shared-bikes can be rented/returned more flexibly. In particular, removing docking stations can reduce the deployment and management costs of the whole system.

Power supplement is a new challenge while implementing the smart lock module on bike-sharing systems. To sustain the daily operation of the smart lock module, a robust charging solution to bike-sharing systems is necessary. On the existing dockless bike-sharing systems, there are three main charging methods. *1) Battery replacement*. When the energy level is low, the smart lock sends a request to the server. Then the batteries are replaced manually. Apparently, this method has high management costs. *2) Pedal power (Mobike)*. The mechanical energy is harvested to recharge the battery in user riding. This method increases the system complexity and decreases user experience as well. *3) Solar power (Hello Bike and Mobike)*. This is one of the most popular charging methods for bike-sharing systems. In such systems, a solar panel is implemented on the bottom of a bike's basket to harvest solar energy. However, in practical operation, solar power is not stable and can not satisfy smart lock's charging demands since the charging efficiency is usually affected by the weather or covering of the solar penal. Moreover, solar power can not be harvested during the nighttime. Most sharing bikes are not in use at nighttime, which is the perfect time for recharging batteries. Therefore, a new system that can provide robust charging services for dockless bike-sharing systems is in pressing demand.

In recent years, thanks to the effort from both academia and industry [3], [4], [5], Radio Frequency (RF) wireless charging technology has become a reliable, safe, and low-cost solution to providing sustainable energy for low-power electronic devices. Various RF-based wireless charging applications have been developed for different scenarios, such as smart home [6], electric vehicle (EV) charging [7], access control [8], etc. And it also has potential applications in sensor networks [47], [48], [49]. Thus, we propose to address the energy supplement issue of dockless bike-sharing systems by RF wireless charging. Various wireless charging experimental platforms have been launched for developers. The most typical one is Powercast [4]. Powercast is a pioneering battery-free wireless charging and sensing platform. It is based on electromagnetic radiation RF wireless charging technology, which can provide wireless power for multiple devices simultaneously via radio waves from 40-50 feet in the unlicensed $915\,$MHz ISM band [9].

In this paper, we design a robust RF-based wireless charging system for dockless shared bikes based on the Powercast platform. Our system consists of an RF wireless charging transmitter, a receiver node, and a joint direction

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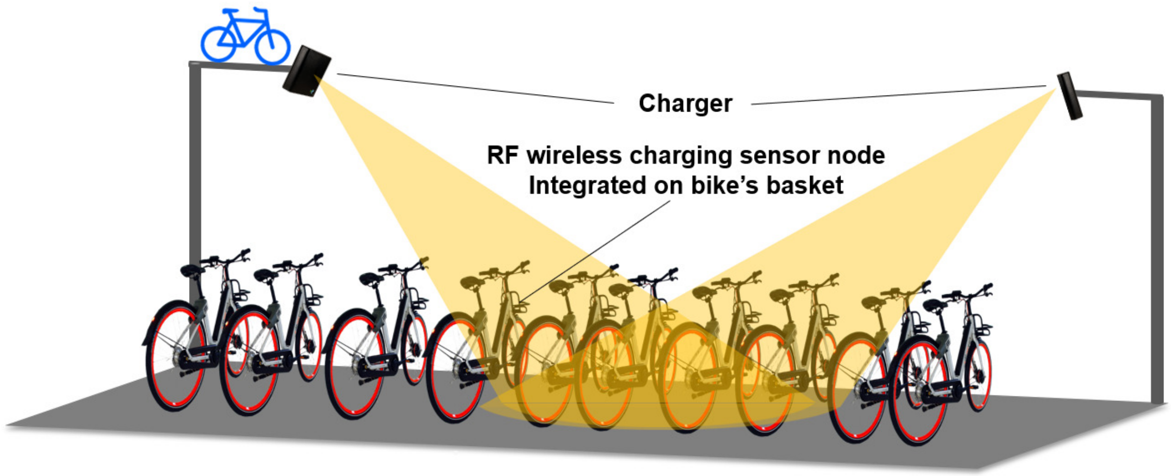

Fig. 1. A sketch of RF-Based wireless charging system.

scheduling algorithm for multiple chargers. Fig. 1 presents the sketch of our RF-based wireless charging system. The receiver node, which integrates with the energy harvesting and management module, is specially designed to be implemented on the bottom of a shared-bike's basket. This design can significantly reduce mutual interference during the charging process and space occupation.

In order to standardize the management of shared-bikes, governments have planned specific areas for parking. Thereby, we propose to implement chargers on the parking area sign to provide RF power for the shared bikes. Each charger has a fixed covering angle, and its orientation can be controlled to cover different regions in the parking area. To reduce the charging delay, we propose a joint direction scheduling problem of multiple chargers and provide efficient solutions with a proven worst-case bound.

1.1 Contributions

The main contributions of this paper are summarized as follows:

- To the best of our knowledge, this is the first work that introduces RF wireless charging technology as a solution to the energy supplement of dockless bike-sharing systems. A practical system is designed to provide a robust wireless charging service with minimum charging delay for dockless bike-sharing.
- We design an RF wireless charging transmitter and a receiver node based on the Powercast platform. The energy harvesting antenna is specially designed to be integrated into the shared-bike's basket. Our design achieves a 9.67 dBi antenna gain and a 53.8 m maximum charging range.
- To minimize the total charging delay, we first design an efficient charging direction scheduling algorithm for a single charger in small-scale scenarios. Then, we extend the solution to multiple charger joint direction scheduling in large-scale scenarios based on dynamic programming. Our algorithm terminates in polynomial time with a $log\frac{e}{\epsilon}$ worst-case bound.
- We implement the proposed charging system on a real-world bike-sharing system. Extensive experiments verify that our algorithm achieves an efficient solutions, and our system shows robust performance under different parameter settings.

1.2 Related Work

RF wireless charging technology has shown great potential to solve the energy supplement problem in Internet of Things (IoT) and Cyber-Physical System (CPS) [10], [11], [12]. Typically, most mobile device manufacturers, including Apple, Huawei, Samsung, etc, are working with Qi to provide standardized wireless charging service on their products [13]. Moreover, Guntupalli *et al*. designed an on-demand energy requesting mechanism that improves the charging delay performance of an RF-powered IoT. Two associated discrete time Markov chain models were proposed to verify the performance of the scheme [14]. Zhang *et al*. investigated the charger deployment optimization and optimal charging power selection problems to maximize the total received power of sensor nodes [15]. Wang *et al*. developed an optimal recharging scheme to maximize the amount of harvested energy, while reducing the number of deployed mobile chargers [16]. Shu *et al*. solved the optimal velocity control problem of mobile chargers, while the route is supposed to be known. By obtaining the optimal velocity via dynamic programming, the network lifetime was maximized [17]. Fu *et al*. discretized the area by concentric circles, and further optimized the charger deployment location to minimize system charging delay [18]. Dai *et al*. first noticed the directional problem, and proposed a charger deployment optimization model to fulfill the charging demands of the whole network [19]. Li *et al*. deployed wireless charging in a Cloud-Radio Access Network with multiple enhanced remote radio heads and achieves minimizing the weighted sum of energy transfer time [42]. Yu *et al*. considered energy delivery by a hybrid access point to one or more RF-energy harvesting devices and they considered imperfect and causal channel state information and probabilistic constraints that ensure devices receive their required amount of energy over a given planning horizon [46].

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There are also an amount of RF wireless charging applications in IoT and CPS [20], [21]. A multi-spot charging system for smart homes was designed by Shi *et al*. [6] which can provide wireless charging service for multiple mobile devices. Considering the large-scale sensing applications, Chen *et al*. [22] integrated RF wireless charging system with a quadcopter to provide sufficient charging power. RF wireless charging technology is also applied to the medical field. Agrawal *et al*. [23] designed conformal phased surfaces to enhance the performance of wireless power transfer for bioelectronic devices. Lukic *et al*. [24] considered RF wireless charging technology as a solution for electric vehicle (EV) charging. An inductive power transfer (IPT) system was proposed for static and dynamic vehicle charging scenarios. Electromagnetic radiation (EMR) is another critical issue. Dai *et al*. [25], [26] noticed this safety problem during the wireless power transfer process. An adjustable power charging system was designed to restrict EMR intensity under a specified threshold. Shu *et al*. introduced time of charge to address localization problems. By estimating the distance via time of charge, they designed a novel localization system [27]. Smith *et al*. developed a wireless identification and sensing platform for human activity detection [28]. Shu *et al*. designed an access control system based on wireless rechargeable sensors to maintain access security [8], [29]. Jiang *et al*. designed a lightweight magnetic coupler to harvest wireless power for a 360 kW wireless charging tram [30]. Hejazi *et al*. designed a highly efficient wireless charging chip that achieves a maximum power conversion efficiency of 53.8% [31]. Based on the wireless charging hardware, Li *et al*. proposed a charging efficiency tracking algorithm for supercapacitors and improved the maximum efficiency to 81% [32]. Rong *et al*. presented an optimization process of the coupling mechanism in 100 W power transfer with an efficiency of 92.41% [33]. Zhu *et al*. designed an NFC-connected coupler wireless charging system for metal-cover smartphone applications [34] and Vital *et al*. designed an ergonomic wireless charging platform to supply power for the emerging wearable medical, Internet of Things, and portable devices [35]. Zhang *et al*. minimized the total energy consumption of the unmanned aerial vehicle (UAV) by determining the trajectory and charging power of the UAV in the UAV-enabled IoT network [43]. Lawton *et al*. presented a high-power IPT magnetic design suitable for wirelessly charging an EV at 50 kW using a heuristic approach [44]. Liu *et al*. proposed a two-step green energy wireless charging algorithm to efficiently power the IoT devices for the multiple-green base stations-to-multiple IoT devices charging scenarios [45].

These systems have proved that RF wireless charging technology has reliable and sufficient performance in low-power scenarios. Thus, we consider providing an RF-based charging solution, including RF wireless charging transmitter, receiver node, and charger scheduling algorithm design, to dockless bike-sharing so that the bike-sharing systems can benefit from the robust charging service.

1.3 Paper Organization

The rest of the paper is organized as follows: The detailed design of the RF wireless charging transmitter and node is presented in Section 2. Then we provide the joint direction scheduling algorithm of multiple chargers in Section 3. In Section 4, our system is implemented on a real-world bike-sharing system, and our design is evaluated via both field experiments and numerous simulations. Finally, we conclude this paper in Section 5.

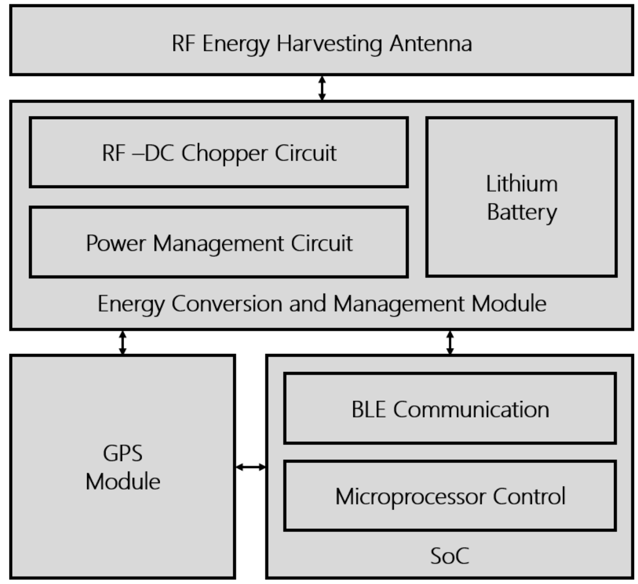

Fig. 2. Architecture of the proposed RF Wireless charging sensor node.

2 RF Wireless Charging System Design

The RF wireless charging receiver node is implemented to harvest RF power to recharge the battery of shared-bike's smart lock module. Our design must satisfy the practical requirements during the charging process, which are summarized as follows:

- The most important factor is charging power. The energy harvesting module should achieve sufficiently high charging power to recharge batteries in time and a sufficiently long charging range to accommodate the size of the parking area.
- In order to further optimize the scheduling of chargers, the sensor node should be able to upload shared-bike's location and energy level. Thus, the sensing module and communication module are necessary.
- Since the battery capacity is limited, the low-power design of sensing and communication processes must be taken into consideration.
- The implementation of the sensor node should not affect the user experience. Thereby, the RF wireless charging sensor node should not take extra space occupation and be convenient for integration.

Fig. 2 presents the architecture of our RF wireless charging receiver node, which consists of the following four components: RF energy harvesting antenna, energy conversion and management module, controller and low-power Bluetooth communication module, and GPS module.

There are three types of RF wireless charging technologies: inductive coupling [3], magnetic resonant coupling [36], and electromagnetic radiation [37]. In our design,

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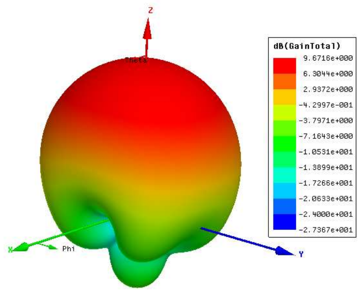

Fig. 3. Electromagnetic simulation of the RF energy harvesting antenna.

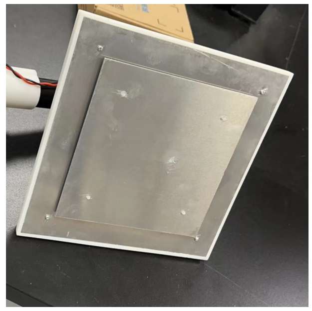

Fig. 4. Front view of the antenna.

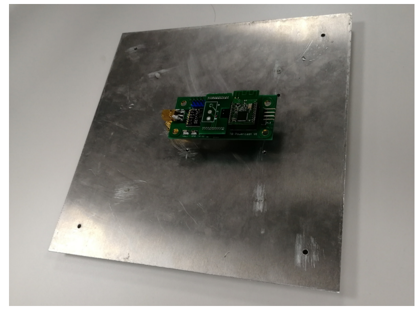

Fig. 5. The RF wireless charging receiver node

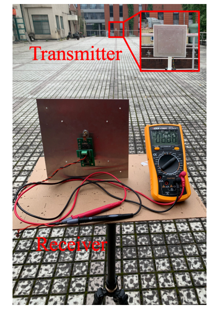

Fig. 6. Experiment.

shared-bikes are recharged when they are in the parking areas. Thus, the charging range is meter-level. Furthermore, since the density of parked bikes is usually high, if our system can recharge multiple bikes simultaneously, the charging efficiency can increase dramatically. Thereby, electromagnetic radiation technology is more suitable for our system. We design the RF energy conversion and management module based on the Powercast wireless charging platform, which can provide meter-level RF power for multiple devices simultaneously and support various wireless communication modules. On our RF wireless charging receiver node, the energy harvesting antenna harvests the RF energy broadcasted by the charger within the wireless regulation (3 W 915 MHz). Then the energy is converted into a continuous DC pulse. For the convenience of integration on bikes, the antenna is designed the same as the shape of the bike's basket board. This design can reduce the mutual interference during the charging process, since there is no overlapping among the baskets when bikes are parking. Moreover, such integration on a shared-bike's basket does not require any extra space occupation. It should be noted that since the antenna design is a one-time effort and our paper only provides a prototype, the antennas could be redesigned according to the environmental factors in the actual deployment, such as the size limitation of the antenna, the parking size, the number of parking bikes, covering angle, and so on.

The performance of the RF energy conversion and management module is tested via both simulations and experiments. Fig. 3 shows the electromagnetic simulation of the RF energy harvesting antenna, which achieves gain of 9.67 dBi, and 53.8 m maximum charging range. The energy charging model is usually described by Friis space equation, which has been verified by He *et al*. [5] and commonly applied:

$$P_R = \frac{G_T G_R \eta_0}{L}\left(\frac{\lambda_0}{4\pi(d+\epsilon_0)}\right)^2 P_T, \tag{1}$$

where P_R is the received power at the shared-bike side, d is the Euclidean distance between the bike and the charger, P_T is the transmitting power, G_T is the transmitting antenna gain, G_R is the received antenna gain, η_0 is the transmission efficiency, L is the polarization loss, λ_0 is the wavelength, ϵ_0 is a parameter to adjust the model for extremely short-range transmission. In the practical charging process, the transmitting power P_T is fixed. Thus, in order to simplify the expression, we combine all the constant parameters and Eq. 1 can be expressed as $P_R = \frac{\alpha_0}{(d+\beta_0)^2}$.

To achieve a longer charging distance and coverage than the Powercast platform, we design a new patch antenna and a receiver node. In particular, the TX antenna's power gain is increased to 9.67 dB from 8 dB (the antenna's gain of Powercast). Meanwhile, the RX antenna's power gain is increased to 9.67 dB from 1 dB. Specifically, as shown in Fig. 4 and Fig. 5, the antenna consists of two aluminum squares with different side lengths, where the larger square measures 200 mm and the smaller one measures 150 mm, both with a thickness of 2 mm. The squares are aligned at their centers and held together at four points near right angles, with a gap thickness of 3 mm. The antenna feed point is located 3.5 mm above the center of the square on the back of the antenna. In our prototype, we remove the plastic shell of the transmitter and the receiver, which decreases the blocks between the antennas and saves about 2 dB attenuation experimentally. Those efficient power designs save about 12 dB from the link budget, which helps to extend the charging range. According to the Friis space propagation model Eq. 1. The path loss can be further derived as

$$P_L\,(dB) = -20log\left(\frac{\lambda_0}{4\pi\,(d+\epsilon_0)}\right). \tag{2}$$

As we increase 12 dB in the link budget, the maximum charging range can be calculated by

$$d_{max} = 10^{\frac{12}{20}}\,(d+\epsilon_0) - \epsilon_0. \tag{3}$$

Based on the Powercast platform, we have $\epsilon_0 = 0.315$. Thus, the maximum range is extended to more than 60 meters from 15 meters with the 3-watt transmitting power.

We conduct experiments to measure the maximum charging distance of our prototype. As illustrated in Fig. 6, we place the transmitter and the receiver on two tripods, respectively. We fix the receiver and move the transmitter to increase the distance between them. We stop moving the transmitter when the voltage is less than the charging threshold. From our measurements, the maximum charging distance is 53.8 m. Specifically, after harvesting by the antenna, the power is transmitted to the power conversion and management module as DC pulses. Firstly, an RF-DC chopper circuit converts the DC pulse to DC voltage. Then it is maintained by the regulator circuit as a 4.2 V stable output voltage and stored in the lithium battery via a power management circuit.

Fig. 7. Implementation on the Hello-bike platform.

To further optimize the charger schedule, we need to know the location of the bike and its energy lever. We can know the location of the bike from the GPS module on it. Together with the power level information, the sensor node uploads the data to the charger. Due to the low-power limitation, we select Bluetooth Low Energy (BLE) as our communication protocol. BLE is a new protocol designed and marketed by the Bluetooth Special Interest Group, which is intended to provide considerably reduced power consumption and cost while maintaining a similar communication range [38]. The BLE module can work under 20 μA and achieve about 100 m communication range. Both features make it quite suitable for our design. The control SoC is also specially designed for our wireless charging system. We apply the framework of TI-RTOS (Real-Time Operating System) in CCS (Code Composer Studio) for the sensor node. The firmware consists of the user App and the Bluetooth stack. The user App runs in *Cortex-M3* core, processing the controlling task of the system. The Bluetooth stack runs in *Cortex-M0* core, which handles the communication tasks between the sensor node and charger. So far, the firmware design has been simplified. And the working current is limited within 2μA in the TI-RTOS sleep mode.

The four modules compose the RF wireless charging receiver node, which is shown in Fig. 5. Then, we implement it on the basket of a shared-bike. As presented in Fig. 7, the RF energy harvesting antennas obtain a good power receiving angle when the bikes are parking. And there is almost no overlap among different antennas. Thus the mutual interference during the charging process is significantly reduced. Furthermore, the implementation on the basket does not require any extra space. Our design of the RF wireless charging sensor node can provide an automatic charging environment for shared-bikes without affecting the user experience.

3 Joint Charger Direction Scheduling

Multiple chargers with a fixed covering angle are deployed in the parking area to provide RF power for shared-bikes. Therefore, designing an optimal joint scheduling algorithm for multiple chargers is another critical issue to provide a robust wireless charging service. Moreover, the renting and returning of bikes introduce strong dynamics to the charging system. Thus, real-time performance should also be taken into consideration. In this section, we minimize the charging delay of shared-bikes by joint scheduling each charger's rotation angle optimally to get ready for the users as soon as possible. In this section, we first illustrate the joint charger direction scheduling model, then we provide complexity analysis for the joint charger direction scheduling problem. Finally, for clarity, we provide a two-step solution to the problem, analyze it from the perspective of the special case and general situations, and provide progressive solutions for the problem.

TABLE 1
Summary of Notations

Symbol	Definiton
e_k^{int}	initial energy level of bike k
$\gamma_k^n(t)$	index to denote the coverage of bike k
T_k	charging delay of bike k
P_k^n	charging power from charger n to bike k
τ_0	length of time slot
e^{full}	full energy which equals to battery capacity
$\mathcal{F}_i$	charging family of charger i
S_i^m	charging set in $\mathcal{F}_i$
$\{\mathcal{F}_i\}$	combined charging family of all the chargers
ξ	threshold that energy demanded is satisfied
$P_t(i, \{\mathcal{F}_i\})$	charging power contribution of first i chargers
$p_{max}(i, m)$	maximum power contribution from charging sets

3.1 Joint Charger Direction Scheduling Model

Assuming that there are K bikes in the parking area, each bike $k \in \{1, 2, \cdots, K\}$ is charged by N chargers with a fixed covering angle (30° in the Powercast platform). Each charger $n \in \{1, 2, \cdots, N\}$ is deployed to provide RF power and about $1.5 - 1.8m$ over the ground, as shown in Fig. 1.

During the charging process, we suppose that the whole system operates in a finite-horizon period $\mathcal{T} \overset{def}{=} \{1...T\}$ with time slot length τ_0. In every time slot, each charger $i \in \{1, 2, \cdots, N\}$ rotates its orientation to cover a specific area $m = \{p, q, r\} \subseteq \{1, 2, \cdots, K\}$, which can be described as $S_i^m(p, q, r) \subseteq \{1, 2, \cdots, K\}$. Say, when charger i covers area m, bike p, q and r can receive the RF power from it. Also, we define a charging family for charger i as $\mathcal{F}_i \overset{def}{=} \{S_i^1(1, 2), ..., S_i^m(p, q, r), ..., S_i^M(K-1, K)\}$. However, bike k might not need to be charged even though it is in the charging field generated by the charger n. The index $\gamma_k^n(t)$ is set to denote whether bike k can receive power from charger n in time slot t ($\gamma_k^n(t) = 0$ for no, $\gamma_k^n(t) = 1$ for yes). The received power of bike k from charger n is presented as P_k^n, which follows the Friis space equation as shown in Eq. 1.

In our system, the charging time difference of multiple chargers is very short. When the transmitter starts charging, the power amplifier is waked up at the same time. Further, the wireless energy is sent out via the antenna. The energy of the signal arrives at the receiver at the speed of light. The distance to each bike may be different, and we assume

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that the charging time difference can be ignorable in the charging area. Specifically, each charger changes direction in a fixed period and then starts charging at the same time. We define the charging delay of bike k, T_k, as the total time slots required to recharge bike k from its initial energy to full (i.e., Eq. 4).

$$e_k^{int} + \sum_{t=1}^{T_k} \sum_{n=1}^{N} \gamma_k^n(t) P_k^n \tau_0 \geq e^{full}. \tag{4}$$

We select the maximum charging delay among all bikes to ensure that every bike can be fully recharged as our optimization objective. Our joint charger direction scheduling problem is defined as:

Joint Charger Direction Scheduling Problem:

$$\begin{aligned} & min \quad \max_{k \in \mathcal{K}} \; T_k \tau_0 \\ & s.t. \quad \begin{cases} (1), (4) \\ \gamma_k^n(t) \in \{0, 1\} \end{cases} \quad \forall k \in \mathcal{K}, n \in \mathcal{N}. \end{aligned} \tag{5}$$

3.2 Complexity Analysis

In this section, we provide a complexity analysis for the joint charger direction scheduling problem.

Theorem 1. The joint charger direction scheduling problem is NP-hard.

Proof. We first prove that the joint charger direction scheduling problem is NP. Given a specific charging direction scheduling strategy, we should verify whether it is a feasible solution in polynomial time. In our problem, it is easy to calculate the charging power for each bike in every time slot via Eq. 1. Then, according to Eq. 4, we can calculate the charging delay for each bike in polynomial time. Therefore, the primal problem is an NP problem.

To further prove that the joint charger direction scheduling problem is NP-hard, we prove that the Multi-Set Multi-Cover (MSMC) Problem, known to be NP-hard, is equal to our primal problem.

Multi-Set Multi-Cover Problem: Suppose we have a finite set $\mathcal{U} = \{u_1, ...u_{|\mathcal{U}|}\}$. Every element has a coverage requirement $b(u_i)$. A collection of multi-sets $\mathcal{C} = \{S_1, ..., S_{|\mathcal{C}|}\}$ is defined over $\mathcal{U}$, where any multi-set in $S \in \mathcal{C}$ may contain a number of copies of elements in $\mathcal{U}$. The objective of the Multi-Set Multi-Cover Problem is to find the minimum number of multi-sets in $\mathcal{C}$, so that the coverage requirement of every element in $\mathcal{U}$ can be satisfied.

In our joint charger direction scheduling problem, let the set of bikes be $\mathcal{U}$. The covering set $S_n^m(p, q, r)$ is the set over $\mathcal{U}$. In every time slot, each charger $\mathcal{F}_n$ covers one set, and all these selected sets combined form the corresponding multi-set. The combinations are various and defined as the collection of multi-sets $\mathcal{C}$. We intend to obtain the minimum total number of time slots. This is equal to minimizing the number of multi-sets selected from $\mathcal{C}$. So far, we have proved that the Multi-Set Multi-Cover Problem is equal to our Joint Charger Scheduling Problem. And the Multi-Set Multi-Cover Problem is known to be NP-hard [39], [40]. Therefore, the joint charger direction scheduling problem is proved to be NP-hard. □

3.3 Joint Direction Scheduling Algorithm

Due to the NP-hardness of the joint charger direction scheduling problem, we provide a two-step solution with a proven performance guarantee in this section. Firstly, we consider a special case of the primal problem. The charging families for different chargers $\{\mathcal{F}_n\}$ are combined as one single family. The primal problem is that we select this new family's most minor set combination to recharge bikes from their initial energy levels to full. This special case can be formulated as a set multi-cover problem. In order to generalize the special case to the multiple-charger scenario, we provide a coverage scheduling algorithm among different chargers with an optimal solution based on dynamic programming.

3.3.1 Special Case Solution

We first investigate a special case of the joint charger direction scheduling problem. That is, we consider the multiple chargers as a whole, then the charging families $\{\mathcal{F}_n\}$ are combined as a new one. The problem becomes that, in every time slot, we select a proper charging set from this new charging family to provide wireless power for bikes in the specific charging set, and minimum selected charging sets are required to minimize the total charging delay.

We design a greedy-based approximation algorithm to solve the special case of joint charger direction scheduling problem in polynomial time. As shown in Algorithm 1, in every time slot, we select the charging set $S \in \{\mathcal{F}_n\}$ that provides the maximum total charging power for all shared-bikes. The chargers are scheduled to cover the selected sets, and each bike's energy level is updated, respectively. We repeat this process, until all the bikes are fully recharged. In Algorithm 1, there are two loops: one is for selecting a charging set to be provided the maximum total charging power, and the other is for updating energy e^k of all bikes and charging family F_n. Regarding to time complexity, Algorithm 1 of time complexity is $O(n^2)$.

Theorem 2. The special case of joint charger direction scheduling problem is NP-hard.

Proof. Recall the definition of Set Multi-Cover Problem: Suppose we have a universe $\mathcal{U}$ of $|\mathcal{U}|$ elements and a collection $\mathcal{C}$ of $|\mathcal{C}|$ sets whose union equals the universe. The objective is to select the minimum number of sets in $\mathcal{C}$ so that each element $u_i \in \mathcal{U}$ is covered $b(u_i)$ times.

In the special case of the joint charger direction scheduling problem, we define the set of bikes as the finite set $\mathcal{U}$. Each bike $u_k \in \mathcal{U}$ has a charging requirement $b(u_k)$. The coverage range of different chargers does not overlap. Thus the combined charging family $(F)_n$ is defined as the collection of sets $\mathcal{C}$. The charger will charge (cover) the target bikes for τ_0 length of time within every time slot. To minimize the total number of time slots, we select the minimum number of charging sets to supply the charging requirements of all bikes. This special case of the joint charger direction scheduling problem is equal to the set multi-cover problem, which is known to be NP-hard [39]. Therefore, we have proved that this special case is NP-hard. □

Theorem 3. Compared with the optimal solution, our greedy-based algorithm has an approximation ratio of

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Algorithm 1: Single Charger Direction Scheduling

Input: initial energy level e_k^{int}, charging family $\mathcal{F}_n$, time slot τ_0;
Output: charging set combination of $\{\mathcal{F}_n\}$, minimum charging delay $\max\limits_{k\in\mathcal{K}} T_k\tau_0$;
while *any* $e_k < e^{full}$ **do**
  for *all the* $\mathcal{F}_n$ **do**
    calculate the contribution to total charging power $\sum\limits_{k\in\mathcal{K}} \gamma_k^n(t)P_k^n\tau_0$;
  end
  select the charging set S with the maximum $\sum\limits_{k\in\mathcal{K}} \gamma_k^n(t)P_k^n\tau_0$;
  update all the e_k and $\mathcal{F}_n$;
end

$log\frac{e_0}{\xi}$. e_0 is the initial total energy demanded to recharge all the bikes fully. ξ is the threshold parameter. If the total energy demanded is smaller than ξ, all the bikes are regarded as fully recharged.

Lemma 1: Assume that the optimal solution is F^*, x_i is the remaining energy demand before the iteration i, y_i is the maximum energy supply that can be provided in iteration i based on the greedy algorithm, then $\frac{x_i}{F^*} \leq y_i$.

Proof. When $i = 1$, the selected charging set can charge at least $\frac{1}{F^*}$ of the total charging energy demand, i.e. $\frac{x_1}{F^*} \leq y_1$. The remaining charging energy demand becomes $e_0(1-\frac{1}{F^*})$. When $i > 1$, we assume a subproblem where the charging family $\hat{\mathcal{F}}$ contains the charging sets from $\mathcal{F}$ apart from those already selected in the previous iterations. At the $1st$ iteration of this subproblem, since our algorithm greedily selects the charging set $\mathcal{S} \in \hat{\mathcal{F}}$ which can provide the maximum charging power. We have $\frac{\hat{x_1}}{\hat{F^*}} \leq \hat{y_1}$. $\hat{F^*}$ is the optimal solution for this subproblem, $\hat{x_1} = x_{i+1}$, $\hat{y_1} = y_{i+1}$. Also, it is obvious that the optimal solution for the original problem F^* is at least $\hat{F^*}$, i.e. $F^* \geq \hat{F^*}$. Therefore, we have $\frac{x_{i+1}}{F^*} \leq \frac{x_{i+1}}{\hat{F^*}} = \frac{\hat{x_1}}{\hat{F^*}} \leq \hat{y_1} = y_{i+1}$, i.e. $\frac{x_i}{F^*} \leq y_i$. Lemma 1 is proved.

Suppose the total number of iterations is k, when the bikes are fully recharged, we have $e_0(1-\frac{1}{F^*})^k < \xi$ and $e_0(1-\frac{1}{F^*})^{(k-1)} > \xi$, thus $\frac{e_0}{\xi}(1-\frac{1}{F^*})^k \approx 1$. This indicates that our greedy-based algorithms achieve a $log\frac{e_0}{\xi}$ ratio when compared with the optimal solution. □

3.3.2 Solution Generalization

In the last section, we design a greedy-based algorithm for the special case of the primal problem. The solution is suitable for the one-charger scenario. In this section, we provide a generalization to make it suitable for multiple-charger scenarios.

In the multiple-charger scenario, chargers should work jointly. Thus, the charging families can not be combined. In every time slot, we should select a charging set from each charger's charging family $\mathcal{F}_n$ properly, so that the total charging power for all the bikes is maximized. In order to solve this problem, an algorithm based on dynamic programming is proposed.

Algorithm 2: Joint Charger Direction Scheduling

Input: initial energy level e_k^{int}, charging family $\mathcal{F}_n$, time slot τ_0;
Output: charging set combination of $\{\mathcal{F}_n\}$, minimum charging delay $\max\limits_{k\in\mathcal{K}} T_k\tau_0$;
while *any* $e_k < e^{full}$ **do**
  for *all the* $\mathcal{F}_n$ **do**
    for *all the* S_n^m *in* $\mathcal{F}_n$ **do**
      calculate the contribution to total charging power $\sum\limits_{k\in\mathcal{K}} \gamma_k^n(t)P_k^n\tau_0$;
    end
    add the S_n^m with the maximum power contribution to the subsequence according to (6);
  end
  select the charging set combination with the maximum $\sum\limits_{n\in\mathcal{N}}\sum\limits_{k\in\mathcal{K}} \gamma_k^n(t)P_k^n\tau_0$;
  update all the e_k and $\mathcal{F}_n$;
end

Dynamic programming is a general approach to solving control or optimization problems in a "divide-and-conquer" way. It requires two properties, that is: (1) Optimal substructure. In each iteration, the substructure should be solved optimally. (2) Subproblem overlap. The solutions of subproblems have overlap so that the solution space becomes smaller in each iteration. With the advantage of optimal substructure and subproblem overlap, dynamic programming can efficiently obtain optimal solutions to specific problems [41].

In our problem, we add one charger in every iteration, and select one charging set from its charging family $\mathcal{F}_i$, which can achieve the maximum total charging power P_t. Then, the remaining charging families are updated according to the real-time energy level of each bike. Thus, the problem becomes a smaller one with new total charging power and available charging families. The subproblem has overlapped. In our algorithm, the charger selection subsequence according to

$$P_t(n, \{\mathcal{F}_n\}) = p_{max}(n, m) + P_t(n-1, \{\mathcal{F}_{n-1}\}), \quad (6)$$

where $P_t(n, \{\mathcal{F}_n\})$ is the charging power contribution of first n chargers, $\{\mathcal{F}_n\}$ is the combined charging family of the first n chargers, $p_{max}(n, m)$ is the maximum power contribution from charging sets, and $P_t(n-1, \{\mathcal{F}_{n-1}\}$ is the charging power contribution of the updated $n-1$ chargers with the charger selected in the last iteration eliminated.

This indicates that, in every iteration, one charger is added to the sequence. We select the charging set for the specific charger that leads to the maximum charging power under the current charging family settings. Therefore until all the chargers are considered, our algorithm terminates, and the optimal charging set combination for the maximum total charging power is achieved. Comparing with algorithm 1, algorithm 2 has one more loop for selecting one charger. In algorithm 1, all charging families are combined as a new one, but algorithm 2 distinguishes them from each other. One more loop means that the time complexity of

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algorithm 1 and algorithm 2 is not the same. Algorithm 2 of time complexity is $O(n^3)$.

We summarize our joint charger direction scheduling algorithm in Algorithm 2. The energy level e_k^{int}, charging family $\mathcal{F}_n$, time slot τ_0 are initialized firstly. In every time slot, we calculate the contribution to the total charging power of each charging set. Add the charging set with the maximum power contribution to the subsequence. Then select the charging set combination that has the maximum total charging power and provides wireless power for the bikes. The bikes in the specific charging sets receive the power and update their energy levels and charging families. The algorithm terminates in polynomial time when the total energy demand is satisfied.

3.4 Discussion about Dynamic Issues

In the practical operation of bike-sharing systems, bikes can be rented or returned at any time. Thereby, the set of bikes $\mathcal{K}$ is dynamic. Accordingly, it might affect the scheduling results. In our design, we take the dynamic issue into consideration, and provide relative compensation mechanisms. In our system, the locations of bikes are reported to the chargers in real-time. If the rent or return of bikes is detected, the set of bikes $\mathcal{K}$ and the combination of charging families $\{\mathcal{F}_i\}$ are reconstructed. Then, our system runs the algorithms again to compute the real-time joint charger direction scheduling strategy. Our algorithms terminate in polynomial time. Thus, this design can compensate for the dynamic issues.

4 System Evaluation

In this section, we verify the effectiveness of our system via both field experiments and extensive simulations.

4.1 Field Experiments

4.1.1 System Implementation

Our system is implemented on Hello Bike dockless bike-sharing system. We design a wireless transmitter and receiver node based on the Powercast platform. The transmitter works at the frequency from 902 MHz to 928 MHz and the center frequency is 915 MHz. The RF signal is first generated by an oscillator VC0190-915T, and then is sent to the power amplifier (PA) RA13H8891MB. The PA connects the patch antenna via a match network and transmits the wireless energy via the antenna. The power components LT1084CT-12 and 78M05 supply 12 and 5 voltages for the transmitting system. The charger structure is presented in Fig. 8(a).

When the wireless signal is harvested by the receiver node antenna, it will be sent to the boosting module via the match network. The boosting module is based on diode circuits and transforms the AC signal into DC signal. Further, the boosted DC signal is sent to the power management chip that stores the energy in the battery.

To rotate the charger to cover nodes in different time slots, we design a controller based on the VIM3 board computer [9] and prototype a 3D-printed rotary head to switch the chargers. The charger's patch antenna is fixed on a rotary head driven by a motor. The motor is controlled by VIM3 and the angle is collected via the embedded encoder. The controller receives the battery and charging status from the nodes via BLE. When the controller updates the charging status, it changes the motor angle via the Pulse Width Modulation signal. The system implementation is illustrated in Fig. 8(b).

As presented in Fig. 8(c), two transmitters are deployed in the parking area to provide wireless power for five bikes. We first conduct experiments to fit the parameters in Eq. 1, which provide $a = 17.911\,\mathrm{mW/m^2}$, and $b = 0.315\,\mathrm{m}$. The five bikes' horizontal distances to the charger are $0.75\,\mathrm{m}$, $1.07\,\mathrm{m}$, $1.54\,\mathrm{m}$, $2.08\,\mathrm{m}$, and $2.61\,\mathrm{m}$. The distance between two chargers is $3.13\,\mathrm{m}$. Each charger is deployed on the tripod that is set at the same height of the prompt stop sign at $1.76\,\mathrm{m}$ above the ground. In the actual deployment, the height is usually fixed and it should be considered and decided according to the parking area size, the number of parking bikes, covering angle, and other factors. We adopt a fixed and same parameter value for all the chargers just to deploy the prototype and clarify the principle in our paper. This parameter is selected according to experience and may not be optimal, and it should be recalculated in the actual deployment. The chargers are switched every $30\,\mathrm{s}$ according to the results of the scheduling algorithm in a rotating clamp. Five bikes implemented with RF wireless charging receiver nodes are parked in a specific area of length L waiting for charging service. The battery capacity of the smart lock on the bike is $80\,\mathrm{mAh}$, and the initial energy level is set randomly without loss of generality. Field experiments are conducted to test the system performance.

4.1.2 Experimental Results

We first consider a small-scale scenario that only has one charger. Our charger direction scheduling method (CDS) is tested and compared with the optimal solution (OPT). Since the charger scheduling problem is proved to be NP-hard, the optimal solution is obtained via an exhaustive search. Thereby, it can not respond to the dynamic issue of real-time rent and return. The experimental results are shown in Fig. 9. Our scheduling method achieves good performance, which is about 85% of the optimal solution. And notice that our system can fully recharge all the bikes in 20 hours. A fully charged battery can power a bike's lock/unlock module for about one week.

We also test the performance of multiple-charger joint scheduling in our experiments. As presented in Fig. 10, our design still performs quite close to the optimal solution. And more chargers can significantly reduce the charging delay.

4.2 Extensive Simulations

In order to verify the robustness of our wireless charging system for shared-bikes, we further conduct extensive simulations in different scenarios. We consider a shared-bike parking area with length L, and suppose there are N bikes, whose locations are set randomly, parking in this area. L and N are variable parameters in our simulations. The length of the time slot is $30\,\mathrm{s}$. In every time slot, bikes are allowed to be rented from or returned to the parking area. Four chargers are supposed to be deployed in the parking area to provide a joint charging service. Each of them is $1.5\,\mathrm{m}$

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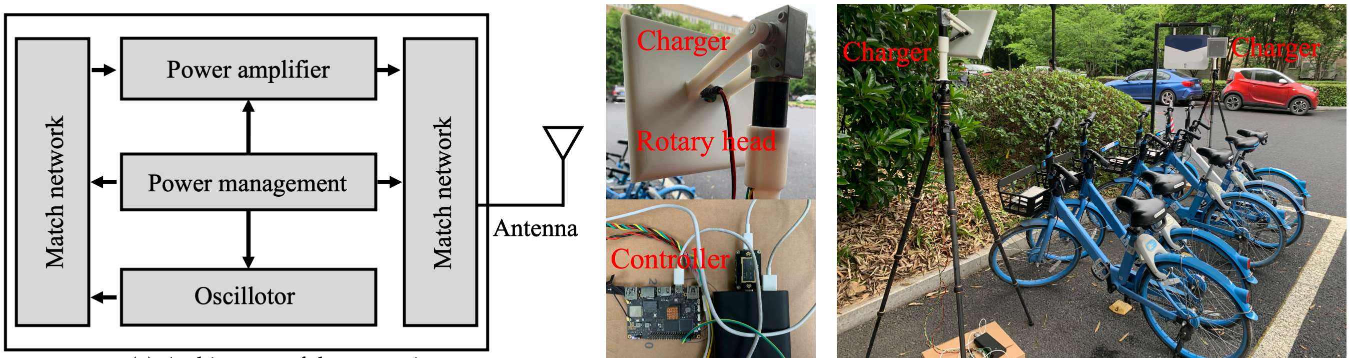

(a) Architecture of the transmitter. (b) Charger design. (c) System implementation.

Fig. 8. Prototype design and implementation.

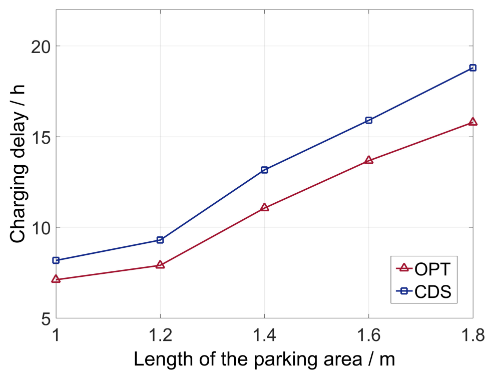

Fig. 9. Single-charger scheduling.

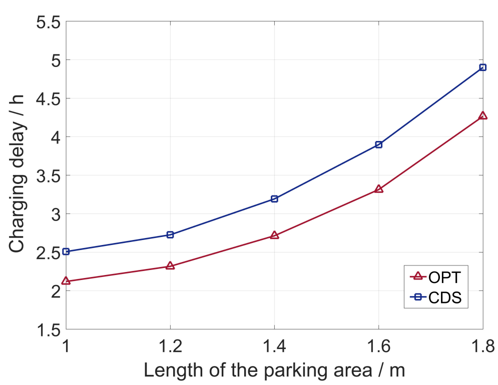

Fig. 10. Multiple-charger joint scheduling.

above the ground and has a covering angle of $30°$. The parameters of the charging model (Eq. 1) are set according to our pre-experiments. We have $\alpha_0 = 17.911\,\mathrm{mW/m^2}$, and $\beta_0 = 0.315\,\mathrm{m}$. Based on our hardware, the battery capacity is set as $80\,\mathrm{mAh}$. And each shared-bike's initial energy level is set randomly.

4.2.1 Baseline Settings

Since this is the first work to consider the joint charger direction scheduling problem, we compare the simulation results of our algorithm (CDS) with the optimal solution and a heuristic method. The optimal solution (OPT) is solved via an exhaustive search. Assume that there are n chargers, and each charger can choose from m directions of rotation, and the time slot is t. Apparently, the time complexity of OPT is $O(mnt)$ and the time will increase dramatically with the increase of the directions of rotation and the time slot. The time complexity is extremely high, making it impossible to meet the dynamic issues. The heuristic method (MIN) schedules chargers to cover the set which contains the bike with the minimum energy level in every time slot. Assume c is the number of the bikes, then the time complexity of MIN is $O(c)$.

4.2.2 Comparison with Different Scheduling Algorithms

We run the simulations multiple times under different parking area sizes, the number of parking bikes, and the number of chargers and obtain the following simulation results.

We first test the performance with different scales of the parking area. Ten bikes are assumed to be parked in the area, where the length of the parking area is changed during experiments. We run three charging scheduling methods mentioned above. As presented in Fig. 11, it is clear that our design performs better than MIN, and achieves about 85% of the optimal solution. Notice that, when the length of the parking area is set to $3\,\mathrm{m}$, our system can fully recharge all the bikes in 9.2 hours. A fully charged battery can power the smart lock of the shared-bike for about a week. Thus, our system can satisfy the charging demands in different scales of the parking area. We can also see that when the size of the parking area gets larger, the charging delay increases faster. This is because the wireless charging process is quite "distance-sensitive" since the wireless charging power is inversely proportional to the $2nd$ power of charging distance.

The influence of the number of bikes should also be taken into consideration. We test three methods in a $3\,\mathrm{m}$-long parking area with varying numbers of bikes. As shown in Fig. 12, our system still has good robustness under different shared-bike settings. The performance outperforms MIN and is quite close to the optimal solution. We also notice that when the number of parking bikes increases to a certain amount, the charging delay tends to be stable. This indicates that the charging delay is not "number-sensitive". This is because when the number of shared-bikes increases, the distances between any pair of them get smaller, it only increases the density of shared-bikes in the parking area. Resultantly, the chargers can recharge more shared-bikes simultaneously, and the persistent increase of shared-bikes does not affect the charging delay dramatically. Thus, our wireless charging system can perform better when a large number of bikes are parked for charging.

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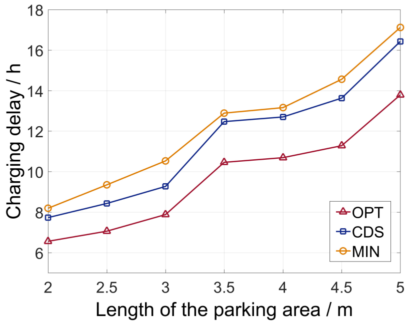

Fig. 11. Charging delay v.s. length of parking area.

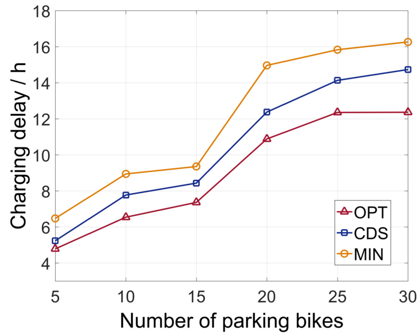

Fig. 12. Charging delay vs. number of bikes.

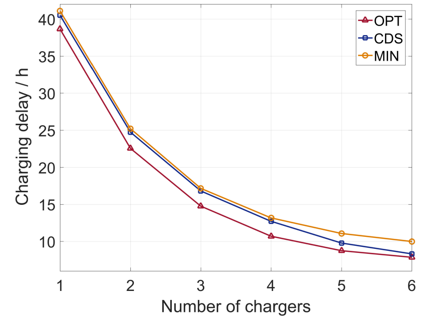

Fig. 13. Charging delay vs. number of chargers.

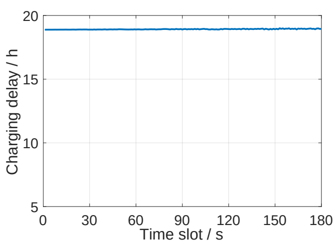

Fig. 14. Charging delay vs. time slot.

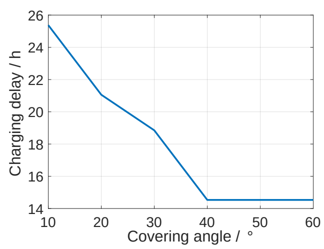

Fig. 15. Charging delay vs. covering angle.

The influence of different chargers on the charging performance has also been tested. Ten shared-bikes are supposed to be parked in a 6 m-long area. The four chargers are positioned in the east, south, west, and north directions. The distance between two chargers on opposite sides is slightly greater than the corresponding length of the parking area. For additional chargers, we evenly distribute them along the long sides of the parking area. Fig. 13 compares the performance of three methods. We can see that our system has good robustness under different charger settings. It still performs better than MIN and is quite close to the optimal solution. The simulation results also indicate that when the number of chargers increases, the charging delay decreases remarkably. This can also be explained by the "distance-sensitive" of the wireless charging process. More chargers mean a shorter charging distance for each bike so that the charging delay can be significantly reduced.

4.2.3 *Impact of Covering Angle and Time Slot*

We also conduct simulations to verify the impacts of the covering angle and time slot length. The results show that the direction-changing period has little impact on performance. However, the covering angle parameter can change the charging performance. Specifically, based on the small-scale scenario experiment results with one charger in 1.8 meters parking area, we first change the time slot length from 1 second to 180 seconds and keep other parameters similar to the experiments. The charging delay is almost constant with different time slot lengths as illustrated in Fig. 14. This is because the time slot length is far less than the maximum charging delay, which is several hours. Thus, the harvested energy difference could be compensated in the different time slots during the charging.

We further conduct the simulations for different covering angles. The time slot length is 30 seconds and the covering changes from 10 degrees to 60 degrees. The charging delay is presented in Fig. 15. As the larger covering angle helps more bikes harvest the wireless energy in each time slot, the maximum charging delay is decreased from 10 degrees to 60 degrees. However, the charging delay could not be reduced anymore when the covering angle is bigger than a threshold which is determined by the bike location.

We select the angle according to the practical charger hardware coverage performance and the time slot is selected based on the bike borrowing and returning process that a user operates on the bike.

5 Conclusion

In this paper, we designed a robust RF-based wireless charging system for dockless shared bikes. Our system consists of an RF wireless charging transmitter, a receiver node, and a joint direction scheduling algorithm for multiple chargers. The hardware system was designed based on the Powercast wireless charging platform, integrated with the energy harvesting and management module. We provided a specific design for implementation on the bottom of a bike's basket. This design can significantly reduce the mutual interference during the charging process and space occupation. Moreover, we first designed an efficient direction scheduling algorithm for a single charger in small-scale scenarios to reduce the system charging delay. Then, we extended it to multiple charger joint direction scheduling in large-scale scenarios based on dynamic programming. Our algorithm achieves an efficient solution with a proven worst-case bound in polynomial time. Finally, the whole system is implemented on a practical bike-sharing system. We conduct field experiments and extensive simulations to verify the effectiveness and robustness of our design.

References

[1] S. Li, K. Hu, S. He, L. Fu and J. Chen, "RWC: A Robust Wireless Charging System for Dockless Bike-Sharing", *In Proceedings of IEEE RFID-TA*, Macau, Sept. 2018.
[2] https://news.cgtn.com/news/2019-08-11/Bike-sharing-industry-seeks-ways-for-sustainability-J4TrlnJiRW/index.html.
[3] A. Kurs, A. Karalis, R. Moffatt, J. Joannopoulos, P. Fisher and M. Soljacic, "Wireless Power Transfer via Strongly Coupled Magnetic Resonances", *Science*, vol. 317, no. 5834, pp. 83-86, 2007.
[4] http://www.powercastco.com/.

This article has been accepted for publication in IEEE Transactions on Mobile Computing. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TMC.2023.3255980

[5] S. He, J. Chen, F. Jiang, D. Yau, G. Xing and Y. Sun, "Energy Provisioning in Wireless Rechargeable Sensor Networks", *IEEE Transactions on Mobile Computing*, vol. 12, no. 10, 2013.

[6] L. Shi, Z. Kabelac, D. Katabi and D. Perreault, "Wireless Power Hotspot that Charges All of Your Devices", *In Proceedings of ACM MobiCom*, Paris, Sept. 2015.

[7] L. Zhao, D. Thrimawithana and U. Madawala, "Hybrid Bidirectional Wireless EV Charging System Tolerant to Pad Misalignment", *IEEE Transactions on Industrial Electronics*, vol. 64, no. 9, pp. 7079-7086, 2017.

[8] Y. Shu, Y. Gu and J. Chen, "Dynamic Authentication with Sensory Information for the Access Control Systems", *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 2, pp. 427-436, 2014.

[9] https://www.powercastco.com/products/rfid-sensor-tags/.

[10] S. Guo, Y. Shi, Y. Yang and B. Xiao, "Energy Efficiency Maximization in Mobile Wireless Energy Harvesting Sensor Networks", *IEEE Transactions on Mobile Computing*, vol. 17, no. 7, pp. 1524-1537, 2017.

[11] B. Gurakan, O. Ozel and S. Ulukus, "Optimal Energy and Data Routing in Networks with Energy Cooperation", *IEEE Transactions on Wireless Communications*, vol. 15, no. 2, pp. 857-870, 2016.

[12] C. M. Angelopoulos, S. Nikoletseas, T. P. Raptis, C. Raptopoulos and F. Vasilakis, "Efficient Energy Management in Wireless Rechargeable Sensor Networks", *In Proceedings of ACM MSWiM*, New York, USA, Oct. 2012.

[13] http://www.qiwireless.com/.

[14] L. Guntupalli, M. Gidlund and F. Li, "An On-Demand Energy Requesting Scheme for Wireless Energy Harvesting Powered IoT Network", *IEEE Internet of Things Journal*, vol. 5, no. 4, pp. 2868-2879, 2018.

[15] S. Zhang, Z. Qian, F. Kong, J. Wu and S. Lu, "P3: Joint Optimization of Charger Placement and Power Allocation for Wireless Power Transfer. *In Proceedings of IEEE INFOCOM*, Hong Kong, China, Aug. 2015.

[16] C. Wang, J. Li, F. Ye, and Y. Yang, "Recharging Schedules for Wireless Sensor Networks with Vehicle Movement Costs and Capacity Constraints", *In Proceedings of IEEE SECON*, Singapore, June. 2014.

[17] Y. Shu, H. Yousefi, P. Cheng, J. Chen, Y. Gu, T. He and K. G. Shin, "Near-optimal Velocity Control for Mobile Charging in Wireless Rechargeable Sensor Networks", *IEEE Transactions on Mobile Computing*, vol. 15, no. 7, pp. 1699–1713, 2015.

[18] L. Fu, P. Cheng, Y. Gu, J. Chen and T. He, "Minimizing Charging Delay in Wireless Rechargeable Sensor Networks", *In proceedings of IEEE INFOCOM*, Turin, Italy, July. 2013.

[19] H. Dai, X. Wang, A. Liu, H. Ma, G. Chen and W. Dou, "Wireless Charger Placement for Directional Charging", *IEEE/ACM Transactions on Networking*, vol. 26, no. 4, pp. 1865-1878, 2018.

[20] B. H. Waters, A. P. Sample, P. Bonde and J. R. Smith, "Powering a Ventricular Assist Device (VAD) With the Free-Range Resonant Electrical Energy Delivery (FREE-D) System", *Proceedings of the IEEE*, vol. 100, no. 1, pp. 138-149, 2012.

[21] S. Roy, V. Jandhyala, J. R Smith, D. J. Wetherall, B. P Otis, R. Chalaaboriy, M. Buettner, D. J. Yeager, Y-C Ko and A. P. Sample, "RFID: From Supply Chains to Sensor Nets", *Proceedings of the IEEE*, vol. 98, no. 9, pp. 1583-1592, 2010.

[22] J. Chen, S. Li, S. Chen, S. He and Z. Shi, "Q-Charge: A Quadcopter-Based Wireless Charging Platform for Large-Scale Sensing Applications", *IEEE Network*, vol. 31, no. 6, pp. 56-61, 2017.

[23] D. R. Agrawal, Y. Tanabe, D. Weng, et al., "Conformal Phased Surfaces for Wireless Powering of Bioelectronic Microdevices", *Nature Biomedical Engineering*, vol. 1, no. 3, pp. 0043, 2017.

[24] S. Lukic and Z. Pantic, "Cutting the Cord: Static and Dynamic Inductive Wireless Charging of Electric Vehicles", *IEEE Electrification Magazine*, vol. 1, no. 1, pp. 57-64, 2013.

[25] H. Dai, Y. Liu, G. Chen, X. Wu, T. He, A. X. Liu and H. Ma, "Safe Charging for Wireless Power Transfer", *IEEE/ACM Transactions on Networking*, vol. 25, no. 6, pp. 3531-3544, 2017.

[26] H. Dai, Y. Liu, G. Chen, X. Wu, T. He, A. X. Liu and Y. Zhao, "SCAPE: Safe Charging With Adjustable Power", *IEEE/ACM Transactions on Networking*, vol. 26, no. 1, pp. 520-533, 2018.

[27] Y. Shu, P. Cheng, Y. Gu, J. Chen and T. He, "TOC: Localizing Wireless Rechargeable Sensors with Time of Charge", *ACM Transactions on Sensor Networks*, vol. 11, no. 3, 2015.

[28] J. R. Smith, K. P. Fishkin, B. Jiang, A. Mamishev, M. Philipose, A. D. Rea, S. Roy and K. Sundara-Rajan, "RFID-based Techniques for Human-Activity Detection", *ACM Communications*, vol. 48, no. 9, pp. 39-44, 2005.

[29] Y. Shu, Y. Gu and J. Chen, "Sensory-data-enhanced Authentication for RFID-based Access Control Systems", *In proceedings of IEEE MASS*, Las Vegas, USA, Oct. 2012.

[30] Y. Jiang, K. Chen, Z. Zhao, L. Yuan, T. Tan and Q. Lin, "Designing an M-Shape Magnetic Coupler for the Wireless Charging System in Railway Applications", *IEEE Transactions on Power Electronics* , vol. 37, no. 1, pp. 1059-1073, 2022.

[31] A. Hejazi, B. Jang, R. E. Rad, J. W. Jo, B. S. Rikan, Y. Pu and K. Y. Lee, "A 2.4 GHz Power Receiver Embedded With a Low-Power Transmitter and PCE of 53.8%, for Wireless Charging of IoT/Wearable Devices", *IEEE Transactions on Microwave Theory and Techniques*, vol. 69, no. 9, pp. 4315-4325, 2021.

[32] Z. Li, K. Song, J. Jiang and C. Zhu, "Constant Current Charging and Maximum Efficiency Tracking Control Scheme for Supercapacitor Wireless Charging", *IEEE Transactions on Power Electronics*, vol. 33, no. 10, pp. 9088-9100, 2018.

[33] C. Rong, X. He, Y. Wu, Y. Qi, R. Wang, Y. Sun and M. Liu, "Optimization Design of Resonance Coils With High Misalignment Tolerance for Drone Wireless Charging Based on Genetic Algorithm", *IEEE Transactions on Industry Applications*, vol. 58, no. 1, pp. 1242-1253, 2022.

[34] J. Q. Zhu, Y. L. Ban, R. M. Xu and C. C. Mi, "An NFC-Connected Coupler Using IPT-CPT-Combined Wireless Charging for Metal-Cover Smartphone Applications", *IEEE Transactions on Power Electronics*, vol. 36, no. 6, pp. 6323-6338, 2021.

[35] D. Vital, P. Gaire, S. Bhardwaj and J. L. Volakis, "An Ergonomic Wireless Charging System for Integration With Daily Life Activities", *IEEE Transactions on Microwave Theory and Techniques*, vol. 69, no. 1, pp. 947-954, 2021.

[36] B. Cannon, J. Hoburg, D. Stancil and S. Goldstein, "Magnetic Resonant Coupling as a Potential Means for Wireless Power Transfer to Multiple Small Receivers", *IEEE Transactions on Power Electronics*, vol. 24, no. 7, pp. 1819, 2009.

[37] C. Mikeka and H. Arai, "Design Issues in Radio Frequency Energy Harvesting System", *INTECH Open Access Publisher*, 2011.

[38] R. Heydon, "Bluetooth Low Energy: The Developer's Handbook", *Upper Saddle River: Prentice Hall*, Vol. 1, 2013.

[39] Q-S. Hua, D. Yu, F. Lau and Y. Wang, "Exact Algorithms for Set Multicover and Multiset Multicover Problems", *International Symposium on Algorithms and Computation*, Berlin, 2009.

[40] Q-S. Hua, Y. Wang, D. Yu and F. Lau, "Dynamic Programming based Algorithms for Set Multicover and Multiset Multicover Problems", *Theoretical Computer Science*, vol. 411, no. 26-28, pp. 2467-2474, 2010.

[41] J. Xie, L. Lyu, Y. Deng and L. Yang, "Improving Routing Performance via Dynamic Programming in Large-Scale Data Centers", *IEEE Internet of Things Journal*, vol. 2, no. 4, pp. 321-328, 2015.

[42] Li, Ruijing and Tang, Lan and Bai, Yechao and Lou, Mengting and Zhang, Xinggan, "Computation Offloading and Resource Allocation in C-RAN Supporting Wireless Charging", *IEEE Internet of Things Journal*, 2022.

[43] Zhang, Shuai and Liu, Weiqi and Ansari, Nirwan, "Joint Wireless Charging and Data Collection for UAV-Enabled Internet of Things Network", *IEEE Internet of Things Journal*, vol. 9, no. 23, pp. 23852-23859, 2022.

[44] Lawton, Patrick A. J. and Lin, Feiyang J. and Covic, Grant A., "Magnetic Design Considerations for High-Power Wireless Charging Systems", *IEEE Transactions on Power Electronics*, vol .37, no. 8, pp. 9972-9982, 2022.

[45] Liu, Xilong and Ansari, Nirwan and Sha, Qiuyu and Jia, Yongxing, "Efficient Green Energy Far-Field Wireless Charging for Internet of Things", *IEEE Internet of Things Journal*, vol. 9, no. 22, pp. 23047-23057, 2022.

[46] H. Yu, K. -W. Chin and S. Soh, "Charging RF-Energy Harvesting Devices in IoT Networks With Imperfect CSI", *IEEE Internet of Things Journal*, vol. 9, no. 18, pp. 17808-17820, 2022.

[47] Deng, Xianjun and Wang, Bang and Liu, Wenyu and Yang, Laurence T., "Sensor Scheduling for Multi-Modal Confident Information Coverage in Sensor Networks", *IEEE Transactions on Parallel and Distributed Systems*, vol. 26, no. 3, pp. 902-913, 2022.

[48] Xianjun Deng and Yalan Jiang and Laurence T. Yang and Man Lin and Lingzhi Yi and Minghua Wang, "Data fusion based coverage optimization in heterogeneous sensor networks: A survey", *Information Fusion*, vol. 52, pp. 90-105, 2019.

[49] S. He, K. Shi, C. Liu, B. Guo, J. Chen and Z. Shi, "Collaborative Sensing in Internet of Things: A Comprehensive Survey", IEEE Communications Surveys Tutorials, vol. 24, no. 3, pp. 1435-1474, 2022.