Understanding Wireless Charger Networks: Concepts, Current Research, and Future Directions

Meixuan Ren, *Student Member, IEEE*, Haipeng Dai, *Senior Member, IEEE*, Tang Liu, *Member, IEEE*, Xianjun Deng, *Senior Member, IEEE*, Wanchun Dou, *Member, IEEE*, Yuanyuan Yang, *Life Fellow, IEEE*, and Guihai Chen, *Fellow, IEEE*

***Abstract*—Wireless Charger Network (WCN) emerges as a promising networking paradigm, employing wireless chargers with Wireless Power Transfer (WPT) technology to provide long-term and sustainable energy supply for future networks. Although extensive research has been conducted in this area over the last decade, there is currently no comprehensive survey to compile the latest literature and provide insights into future research directions. To fill this gap, our survey explores the recent developments in the active research area of WCNs. This paper starts by providing a framework of WCNs in detail, covering aspects of network architecture, various charging models, network design issues, and typical applications of WCNs. Then, we give an overview of charger deployment schemes, focusing on omnidirectional, directional, non-radiative, and heterogeneous charger deployments. We also provide an overview of charging scheduling schemes, encompassing power control, time allocation, energy beamforming, and multi-resource scheduling. Moreover, we explore communication optimization schemes, including Medium Access Control (MAC) protocols, routing protocols, broadcast transmission, and data collection. Finally, we highlight some future research directions and present corresponding open issues to advance the research on WCNs.**

***Index Terms*—Wireless power transfer, wireless charger networks, deployment, scheduling, communication optimization.**

I. INTRODUCTION

WIRELESS Power Transfer (WPT) [1] has emerged as a viable commercial power supply solution. By transmitting electromagnetic energy through the air, WPT eliminates the need for interconnecting wires, effectively overcoming limitations such as restricted device mobility, the high time and cost of wiring, and safety hazards associated with exposed cables. Up to 2024, more than 350 companies, including industry giants such as Microsoft, Qualcomm, Samsung, Huawei, and Google, have participated in the Wireless Power Consortium (WPC) [2], an organization dedicated to standardizing WPT and driving its development. Moreover, the wireless power transmission market has reached \$31.1 billion and is expected to exceed \$185 billion by 2030 [3].

In conventional battery-powered networks, relying solely on manual battery replacement cannot guarantee the long-term and sustainable operation of electronic devices, especially those distributed in harsh environments such as forests, bridges, and volcanic areas [4]. To address this limitation, some studies have proposed energy harvesting, leveraging ambient energy sources such as solar [5], vibration [6], and wind [7], to supplement device power. Despite its potential, energy harvesting's effectiveness is significantly hampered by its dependence on environmental conditions, which can be highly variable and uncontrollable. Recently, benefiting from the development of the WPT technology, Wireless Charger Networks (WCNs) [8] have emerged as a superior choice for providing stable, reliable, and controllable energy supplies for electronic devices. WCNs overcome the limited energy bottleneck of electronic devices and have found widespread applications in various fields, including smart homes [9], medical systems [10], precision agriculture [11], and Wireless Identification and Sensing Platform (WISP) [12].

A WCN typically consists of a number of wireless chargers working together to ensure the long-term and sustainable operation of electronic devices within the network. Specifically, these chargers use WPT technology to transmit energy to devices equipped with an energy harvesting unit. The harvested energy is then stored in a rechargeable battery to sustain the operation of electronic devices. Depending on the WPT technology employed, wireless chargers can be categorized into two categories, *i.e.,* radiative chargers (omnidirectional and directional) and non-radiative chargers (inductive coupling and magnetic resonance coupling) [13]. Radiative chargers emit electromagnetic waves that operate in the far-field region, creating charging areas with complex energy distribution, especially in overlapping areas of multiple chargers. These

Manuscript received June 1, 2024; revised October 9, 2024; accepted October 22, 2024. This work was supported in part by the National Key R&D Program of China under Grant No. 2023YFB4502400; in part by the National Natural Science Foundation of China under Grant 62272223, U22A2031, 62072320, 62272182; in part by the Collaborative Innovation Center of Novel Software Technology and Industrialization, Nanjing University; in part by the Jiangsu High-level Innovation and Entrepreneurship (Shuangchuang) Program; in part by the Shenzhen Science and Technology Program under Grant JCYJ20220530161004009; in part by the Natural Science Foundation of Sichuan Province (2022NSFSC0569); and in part by the Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX24_0234).
(Corresponding author: Haipeng Dai.)

M. Ren, H. Dai, W. Dou, and G. Chen are with the State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing 210023, China (e-mail: meixuanren@smail.nju.edu.cn; {haipengdai, douwc, gchen}@nju.edu.cn).

T. Liu is with the College of Computer Science, Sichuan Normal University, Chengdu, Sichuan 610101, China, and also with the Visual Computing and Virtual Reality Key Laboratory of Sichuan Province, Sichuan Normal University, Chengdu, Sichuan 610068, China (e-mail: liutang@sicnu.edu.cn).

Xianjun Deng is with the School of Cyber Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China (e-mail: dengxj615@hust.edu.cn).

Yuanyuan Yang is with the Department of Electrical and Computer Engineering, Stony Brook University, Stony Brook, New York 11794, United States. (e-mail: yuanyuan.yang@stonybook.edu).

chargers are well-suited for powering low-power devices [10], [14]. In contrast, non-radiative chargers rely on magnetic field coupling for energy transmission, operating in the near field and limiting transmission distance. Due to their high transmission efficiency, non-radiative chargers are widely used in our daily lives, such as providing energy for smartphones [15], electric toothbrushes [13], and electric vehicles [16].

Constructing effective and efficient WCNs involves addressing the following key challenges: 1) *where should wireless chargers be strategically deployed?* Strategic deployment of wireless chargers is fundamental to WCNs. Deploying radiative chargers requires consideration of factors such as device coverage, charging efficiency, and radiation characteristics. Deploying non-radiative chargers necessitates attention to charging efficiency and multi-hop charging scenarios. Therefore, optimizing the deployment of various types of chargers to enhance network charging performance is extremely challenging; 2) *how can limited wireless charger resources be effectively scheduled?* Following charger deployment, another critical challenge is the effective scheduling of charger resources such as power, time, and energy beams. With a constrained resource budget, devising a rational scheduling strategy is essential for maintaining charging performance, coordination, and security of the WCN; and 3) *how can the charging process be coordinated to optimize communication in WCNs?* The integration of wireless charging brings new demands on the network's communication mechanisms. To ensure the long-term coordinated development of WCNs, MAC protocol, routing protocol, broadcast transmission, and data collection need to be optimized to adapt to the charging process.

To the best of our knowledge, we are the first to conduct a comprehensive review of state-of-the-art techniques for constructing effective and efficient WCNs. Our work systematically explores how to leverage static wireless chargers, progressing from physical deployment and resource scheduling to communication coordination, ultimately building a complete and innovative network paradigm.

TABLE I
LIST OF ABBREVIATIONS

Abbreviations	Meanings
BF-WSN	Battery-free wireless sensor network
BS	Base station
CH	Cluster head
CPP	Cluster point process
CSI	Channel state information
CSMA/CA	Carrier sense multiple access with collision avoidance
EM	Electromagnetic wave
EMR	Electromagnetic radiation
EV	Electric vehicle
HAP	Hybrid access point
ILP	Integer linear programming
IRS	Intelligent reflecting surface
LOS	Line-of-sight
MC	Mobile charger
MDK	Multidimensional 0/1 knapsack
MEC	Mobile edge computing
MIMO	Multiple-input multiple-output
MISO	Multiple-input single-output
ML	Machine learning
mmWave	Millimeter-wave
RFID	Radio frequency identification
RHAP	Relay-hybrid access point
SINR	Signal-to-interference-and-noise ratio
SIR	Signal-to-interference ratio
SNR	Signal-to-noise ratio
TDMA	Time division multiple access
UAV	Unmanned aerial vehicle
WCN	Wireless charger network
WISP	Wireless identification and sensing platform
WPCN	Wireless powered communication network
WPT	Wireless power transfer
WRSN	Wireless rechargeable sensor network

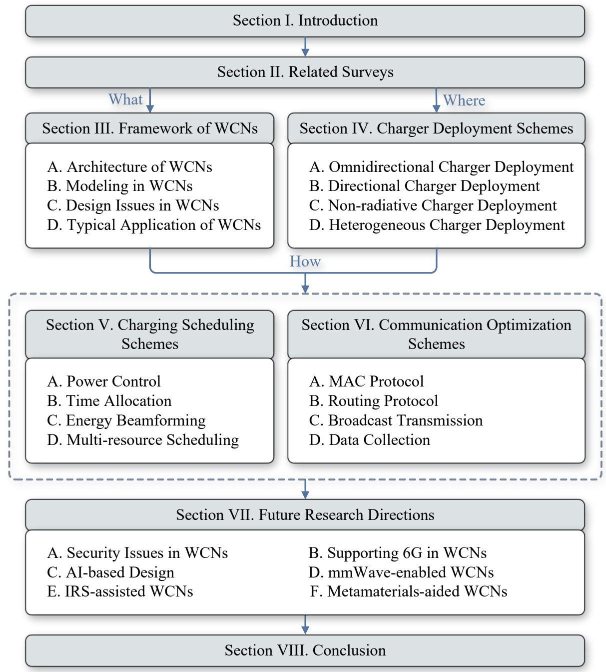


Fig. 1. Main structure of this paper.

The key contributions are summarized as follows:

- We introduce the detailed framework of WCNs, including network architecture, models, design issues, and typical applications, to provide a foundational understanding of how different components interact within WCNs.
- We conduct a comprehensive review of charger deployment schemes in WCNs, covering omnidirectional, directional, non-radiative, and heterogeneous deployments, and explore how the physical placement of wireless chargers affects charging coverage and performance.
- We present an in-depth study of charging scheduling schemes in WCNs, addressing power control, time allocation, energy beamforming, and multi-resource scheduling, with a focus on optimizing the limited resources of wireless chargers to improve charging efficiency.
- We review communication optimization schemes, focusing on MAC protocols, routing protocols, broadcast transmission, and data collection methods, to ensure seamless integration and efficient coordination between charging and communication processes within WCNs.
- Finally, we offer discussions on open issues and promising research directions for WCNs.

The remainder of this paper is organized following the structure as shown in Fig. 1. Section II provides an overview of related surveys. Section III offers an in-depth discussion covering the architecture, charging models, design issues, and typical applications of WCNs. Section IV presents a thorough discussion of charger deployment schemes in WCNs. Section V and Section VI review charging scheduling schemes and communication optimization schemes in WCNs, respec-

TABLE II
COMPARISON OF OUR SURVEY WITH EXISTING SURVEYS
('CDS': CHARGER DEPLOYMENT SCHEMES; 'CSS': CHARGING SCHEDULING SCHEMES;'COS': COMMUNICATION OPTIMIZATION SCHEMES; 'C': THE TOPIC IS FULLY COVERED; 'P': THE TOPIC IS PARTIALLY COVERED; AND 'N': THE TOPIC IS NOT COVERED)

Networks	Network features	Charging models	CDS	CSS	COS
WRSNs (*e.g.,* [17]–[21])	Power the network with a dynamic wireless charger.	C	N	N	N
BF-WSNs (*e.g.,* [22]–[24])	Equip devices with a capacitor for indefinite energy storage.	N	N	N	C
WPCNs (*e.g.,* [25]–[29])	Harness wireless chargers to facilitate energy and information transmission to/from devices.	N	N	P	P
WCNs (our paper)	Employ wireless chargers to provide a sustained and stable power supply, ensuring the permanent operation of the network.	C	C	C	C

tively. Section VII outlines open issues and future research directions, Section VIII concludes this paper. For convenience, abbreviations used in this paper are listed in Table I.

II. RELATED SURVEYS

With the rapid advancement of WPT technology, several network paradigms incorporating WPT have emerged, including Wireless Rechargeable Sensor Networks (WRSNs) [17]–[21], Battery-Free Wireless Sensor Networks (BF-WSNs) [22]–[24], and Wireless Powered Communication Networks (WPCNs) [25]–[29]. Table II compares existing surveys on WRSNs, BF-WSNs, WPCNs, and WCNs.

We begin by reviewing survey papers on the WRSN paradigm, where Mobile Chargers (MCs) equipped with WPT technology wirelessly charge devices in a designated order. Earlier in 2015, Hu *et al.* [17] provided a comprehensive review of charging schemes in WRSNs from six dimensions, covering the number of MC, charging range, charging capability, service station deployment scheme, optimization objectives, and charging cycle. In 2018, Prakash *et al.* [18] conducted a detailed investigation of WRSNs, offering a comparison of employed techniques and analyzing the advantages and disadvantages of the relevant research. Subsequently, Fan *et al.* [19] categorized and compared existing periodic charging scheduling schemes, evaluating them from six perspectives: the number of MCs, driving speed, charging range, charging power, driving path, and charging cycle. In 2022, Kaswan *et al.* [20] provided a detailed survey of mobile charging techniques based on various design attributes and then reviewed the literature by categorizing it into periodic and on-demand charging techniques. Qureshi *et al.* [21] defined basic terms of WRSNs and summarized mobile charging schemes according to charging cycle, scheduling scheme, charging range, charging mode, and the number of MCs. Existing survey articles on WRSN mainly focus on the charging path planning of MCs. While these studies describe radiative and non-radiative charging models, they do not consider the impact of wave interference, as well as the deployment, charging scheduling, and communication of fixed chargers.

Some survey papers focus on the BF-WSN paradigm, in which each device is equipped with a capacitor capable of indefinite charging for energy storage, and the energy supply of the network is unlimited. In 2021, Khalid *et al.* [22] investigated various components of wireless sensor devices in BF-WSNs. Their research surveys five main topologies used to transform simple Radio Frequency Identification (RFID) chips into battery-free wireless sensor devices, along with recent implementations of these topologies. Subsequently, Cai *et al.* [23] reviewed aspects of energy replenishment scheduling, communication and networking, data acquisition, and applications in BF-WSNs. In 2023, Jiang *et al.* [24] conducted a comprehensive survey of backscatter communication-enabled BF-WSNs. The study introduces the hardware architecture and key components of these networks and discusses four fundamental issues: link performance enhancement, multi-device concurrent transmission, security guarantee, and the interplay between BF-WSNs and services. Unlike the focus on optimizing charging schemes in WCNs, surveys on BF-WSNs emphasize enhancing the composition and communication of battery-free sensors. Due to the absence of external energy supplies, there has been little exploration of charging models, charger deployment schemes, or charging scheduling schemes.

Several contributions survey different issues in the WPCN paradigm, in which Hybrid Access Points (HAPs) support the energy/information transmission to/from wireless devices. In 2016, Bi *et al.* [25] provided an overview of the key networking structures of WPCNs and performance-enhancing techniques, which cover energy beamforming, joint communication and energy scheduling, wireless powered cooperative communication, and multi-node cooperation. Niyato *et al.* [26] reviewed performance improvement methods in WPCNs from three aspects: backscatter communications with energy harvesting, duty-cycle based energy management, and transceiver design for self-sustainable communications. In 2020, large-scale WPCNs are discussed in [27], specifically focusing on signal processing aspects, network design issues, and efficient communication techniques. In 2022, Huda *et al.* [28] conducted an in-depth survey on WPCNs in terms of critical design parameters and performance factors. In 2023, Wang *et al.* [29] provided a comprehensive review of WPCNs, integrating Mobile Edge Computing (MEC) and WPT technologies, and addressing computation offloading and resource allocation. In WPCNs, wireless chargers typically handle both power and information transmission. Existing research primarily focuses on coordinating these two functions, so relevant surveys emphasize communication optimization and certain charging scheduling schemes, with less focus on charging models and the deployment of dedicated chargers.

In summary, although extensive surveys have been conducted in the paradigms of WRSNs, BF-WSNs, and WPCNs, there are still gaps in the optimization of fixed charging. Specifically, the impact of wave interference on charging models, the deployment of fixed chargers, and charging scheduling have not been fully explored. This paper integrates comprehensive charging models, charger deployment schemes, charging scheduling strategies, and communication optimization schemes, offering a systematic explanation of WCNs from deployment to integration with existing networks.

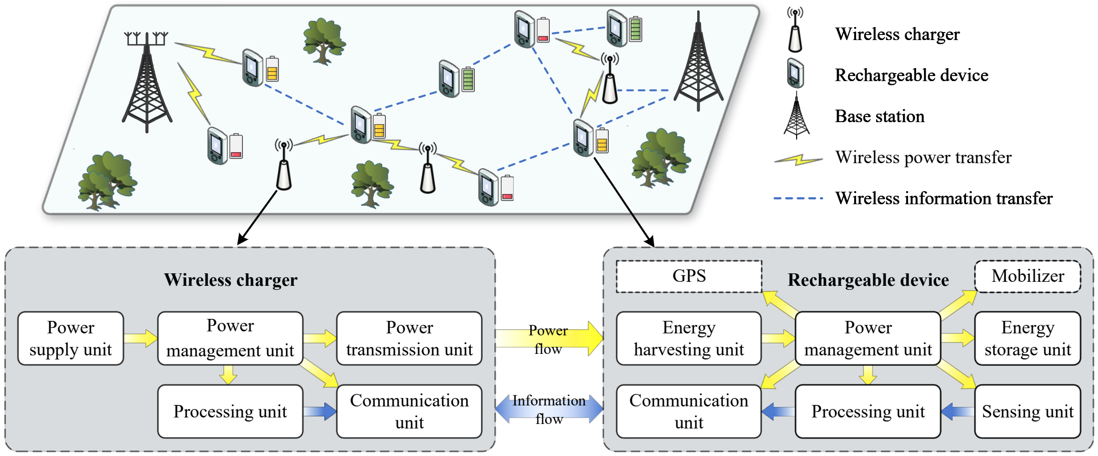


Fig. 2. WCN infrastructure architecture and basic components of wireless chargers and rechargeable devices.

III. Framework of WCNs

This section introduces the framework of WCNs. Specifically, we first present the network architecture and basic components of WCNs. Then, we give various charging models and corresponding energy distributions. Next, we discuss the design issues of WCNs, encompassing aspects such as charger deployment, charging scheduling, and communication optimization. Finally, we highlight typical applications of WCNs.

A. Architecture of WCNs

A Wireless Charger Network (WCN) consists of a group of wireless chargers, denoted as $S = \{s_1, s_2, ..., s_n\}$. These chargers are randomly or manually deployed in proximity to rechargeable devices, denoted as $O = \{o_1, o_2, ..., o_m\}$, to support the wireless charging process. Multiple chargers and Base Stations (BSs) can communicate wirelessly to exchange information. The upper portion of Fig. 2 depicts the network architecture of WCNs, while the lower portion provides detailed views of the basic components of chargers and devices.

The basic components of a WCN are as follows.

Wireless Chargers: the architecture of wireless chargers comprises five key components: the power supply unit, power management unit, power transmission unit, processing unit, and communication unit. The power supply unit serves as the charger's energy source, delivering power to the remaining components [1]. The power management unit manages the distribution of power among various components of the charger. The power transmission unit generates an electromagnetic field, facilitated by a coil [30] or an antenna [31], to enable the wireless power transfer to devices. Additionally, the processing unit is employed for localized information processing, while the communication unit facilitates wireless information transfer (WIT) with other components within the network.

Rechargeable Devices: similar to wireless chargers, a rechargeable device also has an energy harvesting unit, power management unit, processing unit, and communication unit. Additionally, it has an energy storage unit, a sensing unit, and in certain cases, a Global Positioning System (GPS) and a mobilizer unit. Rechargeable devices extract power from the electromagnetic field using the energy harvesting unit, typically a coil or antenna that corresponds to the charger. The power management unit strategically allocates the harvested energy to the energy storage unit (*e.g.,* lithium-ion and alkaline rechargeable batteries [32]), while also supporting various device functions such as sensing, computing, communication, positioning, and mobility. Within the network, these rechargeable devices collect essential information through the sensing unit, perform localized computations via the processing unit, and communicate either among each other or directly to external BSs. For mobile rechargeable devices, it is essential to include GPS and mobilizer units to support mobility.

Base Stations (BSs): BSs are responsible for collecting sensing data and managing the network. Each BS has high processing capability and network data storage function, allowing it to maintain all information about rechargeable devices and wireless chargers, including their status, location, and energy consumption. This information is crucial for accurately modeling the power transmission process and devising appropriate charging schemes. In certain specific WCNs, BSs may also have WPT technology, enabling them to function as multifunctional chargers that can transmit both information and power to rechargeable devices [33].

In WCNs, the interaction between wireless chargers, rechargeable devices, and BSs forms the basis for efficient power and information transmission. Wireless chargers transmit power wirelessly to rechargeable devices, which capture and store it to support functions like communication, sensing, and mobility. BSs interact with chargers and devices through wireless information transmission to coordinate charging schemes and information transmission. Consequently, WCNs can provide a stable, continuous, and controllable energy supply for a large number of devices without the need for wired connections. This ensures uninterrupted operation, improves energy efficiency, and enhances the overall flexibility and scalability of the network.

B. Models in WCNs

In WCNs, as shown in Fig. 2, energy is transferred from the charger to the rechargeable device, where it is harvested by the energy harvesting unit and stored to support functions such as sensing and communication. This process involves three models: the charging model, energy harvesting model, and energy consumption model. Firstly, the charging model varies depending on the WPT technology used. WPT technologies

TABLE III
COMPARISON OF DIFFERENT WIRELESS CHARGING METHODS

	Methods	Advantages	Drawbacks
Radiative	Omni-directional	Wide charging coverage; supports multiple devices.	Lower charging efficiency; potential safety concerns.
	Directional	Higher efficiency than omnidirectional; targeted energy transfer.	Limited charging angle; potential safety concerns.
Non-radiative	Inductive Coupling	High charging efficiency; widely used in consumer electronics.	Short charging range; requires physical proximity;
	Magnetic Resonance	Longer range than inductive; supports multi-hop charging.	Complex implementation; needs specific resonant frequencies.

are broadly categorized into two types: radiative and non-radiative techniques. Radiative techniques can be subcategorized into omnidirectional and directional techniques, both work on the far field, where the electromagnetic field generated is predominant at greater distances. In contrast, non-radiative techniques can be further divided into inductive coupling and magnetic resonance coupling, both work on the near field, where the generated electromagnetic field dominates the area close to the wireless charger or rechargeable device. Table III summarizes the various wireless charging methods and compares their advantages and drawbacks.

1) Radiative Charging Models: for radiative technologies, power is transferred via electromagnetic waves, encompassing various types such as infrared, X-ray, and Radio Frequency (RF). Due to safety considerations, RF waves are commonly used. Recent commercial RF-based wireless chargers, including the Cota system [34], PRIMOVE [35], and Powercast transmitter [36], exemplify this trend. Fig. 3 illustrates the power transfer process. On the charger side, a DC/RF converter module transforms the direct current (DC) voltage from an external source to RF power. The power is then transmitted via a transmit antenna, radiating RF waves through free space in a specified radiation pattern, enabling low-power charging over distances of up to several meters. The rechargeable device captures these RF waves through its receive antenna and converts them into storable power in the rechargeable battery by a power processing unit.

Radiative chargers are designed with either an omnidirectional transmit antenna, emitting RF waves uniformly in all directions, or a directional antenna, focusing the RF waves in a specific direction. For omnidirectional chargers, the power density is uniform in all directions, resulting in a spherical charging area. According to the widely accepted empirical charging model described in [31], and depicted in Fig. 4. Hence, the omnidirectional charging model is

$$P_r(d) = \frac{P_t G_t G_r \eta}{L_p}\left(\frac{\lambda}{4\pi(d+\beta)}\right)^2, \quad (1)$$

where d is the distance between the charger and device, P_t refers to the transmission power of the charger, G_t and G_r represent the transmit gain and the receive gain, respectively, η is the rectifier efficiency, L_p is the polarization loss, λ is the average wavelength, and β is a parameter to adjust the Friis's free space equation for the short distance transmission.

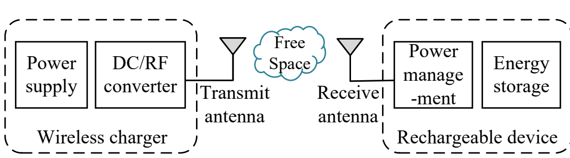


Fig. 3. The basic principle of a radiative charging system.

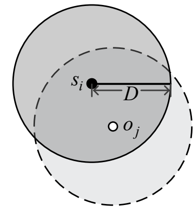


Fig. 4. Omnidirectional charging model.

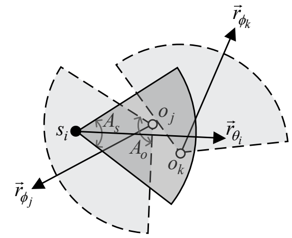


Fig. 5. Directional charging model.

Notably, when the rechargeable device is too far away from the charge, *i.e.,* $d > D$, it cannot receive non-negligible energy. The received power transmitted from omnidirectional charger s_i to rechargeable device o_j is simplified to

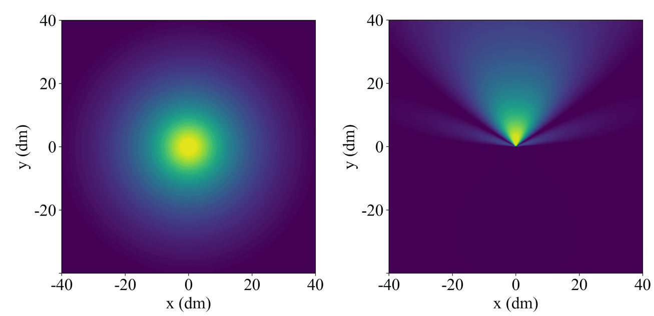
$$P_r(s_i, o_j) = \begin{cases} \frac{\alpha}{(||s_i o_j||+\beta)^2}, & 0 \le ||s_i o_j|| \le D, \\ 0, & \text{otherwise}, \end{cases} \quad (2)$$

where $\alpha = \frac{G_t G_r \eta}{L_p}(\frac{\lambda}{4\pi})^2 P_t$ (for simplicity), α, β, and D are constants determined by the experimental environment and the hardware parameters of wireless chargers. Note that charging power varies nonlinearly with distance in the continuous space.

For directional chargers, power density varies with direction, meaning the received power by the rechargeable device depends on both distance and angle. As illustrated in Fig. 5, the charging regions of the directional charger and device are modeled as sectors with angles A_s and A_o and radius D. The device only receives power when both it and the charger are within each other's charging areas, as seen with device o_j, whereas device o_k cannot receive energy. Let $\overrightarrow{r_{\theta_i}}$ and $\overrightarrow{r_{\phi_j}}$ denote the orientations of the charger and device, respectively, the received power is expressed as follows [37]:

$$P_r(s_i, \theta_i, o_j, \phi_j) = \begin{cases} \frac{\alpha}{(||s_i o_j||+\beta)^2}, & 0 \le ||s_i o_j|| \le D, \\ & \overrightarrow{s_i o_j} \cdot \overrightarrow{r_{\theta_i}} - (||s_i o_j|| cos(A_s/2), \\ & \text{and } \overrightarrow{o_j s_i} \cdot \overrightarrow{r_{\phi_j}} - (||o_j s_i|| cos(A_o/2), \\ 0, & \text{otherwise}. \end{cases} \quad (3)$$

Fig. 6 illustrates simulated radiation patterns of both omnidirectional and directional chargers, showcasing the distinct charging areas characteristic of each type. Omnidirectional chargers enable rechargeable devices to receive energy from



(a) Omnidirectional charger. (b) Directional charger.

Fig. 6. Simulated charging power heatmaps: omnidirectional charger vs directional charger. Simulated results are based on (a) $\alpha = 2.175, \beta = 0.1$, and (b) $\alpha = 3.893$, $\beta = 0.1$.

all directions. However, they offer lower power density and shorter charging distances, making them more suitable for dense, small-scale networks. In contrast, directional chargers concentrate energy in specific directions, enabling higher power density and longer charging distances, ideal for sparse, large-scale networks. As shown in Fig. 6b, the charging power of directional chargers, unlike the omnidirectional chargers, is anisotropic. Besides the energy beam with the highest power intensity, known as the main lobe, there are additional and undesired energy beams in other directions, referred to as side lobes. These side lobes, resulting from interference during the antenna design process, are unavoidable [38], [39].

For radiative chargers, RF waves propagate in the network, and the presence of overlapping areas is inevitable. Within these overlapping areas, rechargeable devices can be charged by multiple chargers simultaneously. To simplify the calculation, some studies assume that the accumulated power received by rechargeable devices is additive [8], [31]. In fact, due to wave interference, the cumulative power is determined by the amplitude and phase of the waves emitted by multiple chargers [40], [41]. Specifically, constructive interference occurs when the emitted waves are in phase, resulting in a combined wave with increased power intensity. Conversely, destructive interference happens when the waves are out of phase, leading to a combined wave with reduced power intensity. The RF wave arriving at device o_j from charger s_i can be expressed in the form of a sinusoidal wave:

$$A(t) = \frac{A_0}{\hat{d_{ij}}} cos\left(2\pi f t - \frac{2\pi}{\lambda} d_{ij}\right), \tag{4}$$

where A_0 and f are the amplitude and frequency of RF waves, respectively, $\hat{d_{ij}} = \frac{d_{ij}+\beta}{\sqrt{\alpha}}$ is the attenuation factor for wave propagation, and $\alpha = \frac{G_t G_r \eta}{L_p}(\frac{\lambda}{4\pi})^2$.

When multiple chargers charge device o_j simultaneously, the combined wave arrives at o_j can be written as

$$A(t) = \sum\nolimits_{j=1}^{n} \frac{A}{\hat{d_{ij}}} cos\left(2\pi f t - \frac{2\pi}{\lambda} d_{ij}\right), \tag{5}$$

where $A = [mA_0^2 + 2A_0^2 \sum_{j>k}^{m} \sum_{k=1}^{m} cos\left(2\pi \frac{d_{ij}-d_{ik}}{\lambda}\right)]^{\frac{1}{2}}$.

Hence, the cumulative power from multiple chargers at the device o_j is

$$\begin{aligned} P_r(o_j) &= \sum_{j=1}^{n} P_r(s_i, o_j) \\ &= \frac{A_0^2}{2}\left(\sum_{j=1}^{n} \frac{1}{\hat{d_{ij}}^2} + \sum_{j=1}^{n}\sum_{k>i}^{n} \frac{2cos(2\pi\frac{d_{ij}-d_{ik}}{\lambda})}{\hat{d_{ij}}\hat{d_{ik}}}\right). \end{aligned} \tag{6}$$

Fig. 7 depicts the simulated power distribution emitted by the four omnidirectional chargers according to Eq. (6). It can be observed that the network displays alternating light (*i.e.,* constructive interference) regions and dark (*i.e.,* destructive interference) regions of different shapes and sizes. Within these overlapping areas, even a slight shift in a device's location can lead to significant changes in the received charging power. Consequently, this complexity necessitates more sophisticated charging scheme designs. Additionally, the interference phenomenon caused by directional chargers is explored in [42].

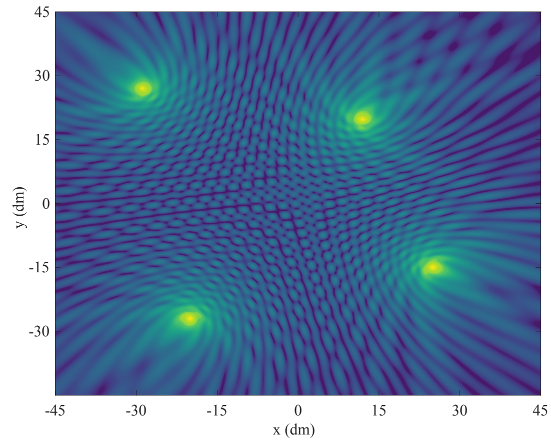


Fig. 7. Charging power heatmap of four omnidirectional chargers.

In this study, directional chargers are deployed within the network and their directionals are freely adjustable. Fig. 8 illustrates how charging power distribution changes when the orientations of directional chargers are adjusted, disregarding the anisotropy of their power [43]. The directivity of these chargers clearly has a significant impact on power distribution.

Radiative Charging Standardization: beyond the charging models discussed, standardization plays a crucial role in advancing WCNs. For radiative charging, particularly using RF technology, the focus is primarily on Electromagnetic Radiation (EMR) safety and equipment authorization regulations.

- EMR Safety: Radiative wireless charging relies on electromagnetic waves to transfer power, which inevitably impacts the surrounding environment. High EMR exposure is recognized as a potential threat to human health, with risks such as tissue damage, cardiovascular disease, and brain tumors [44]. To mitigate these risks, standards like the IEEE C95.1 [45] and the International Commission on Non-Ionizing Radiation Protection (ICNIRP) guidelines [46] set limits on EMR exposure.
- Equipment Authorization: As early as 2017, the Federal Communications Commission (FCC) certified the first mid-field RF wireless power transmitter, followed by the certification of a wireless charging system using both near-field and far-field methods in 2021. Currently, wireless chargers operating at frequencies above 9 kHz must comply with FCC's Part 15 and/or Part 18 regulations [47]. These regulations cover the emission power of devices, operational frequency ranges, and EMR exposure limits when in close proximity to the human body.

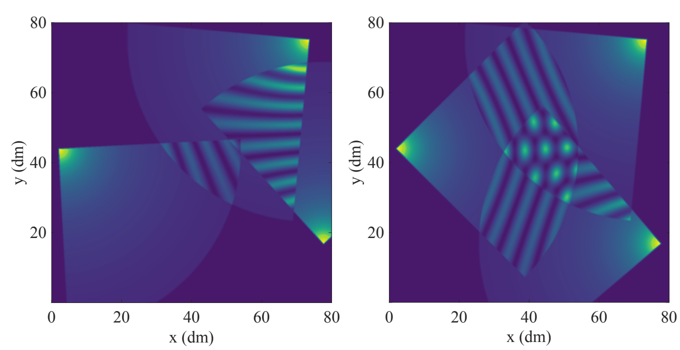


Fig. 8. Charging power heatmaps under different chargers' directions.

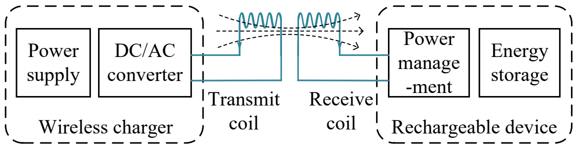


Fig. 9. The basic principle of a non-radiative charging system.

2) Non-radiative Charging Models: for non-radiative technologies, power is transmitted over short distances through magnetic field coupling between two coils, as shown in Fig. 9. The most widely applied technologies corresponding to this classification are inductive coupling and magnetic resonant coupling. Laboratory wireless chargers such as MagMIMO [48] and WiTricity [30], serve as examples of these technologies, employing inductive coupling and magnetic resonance coupling, respectively. Inductive coupling occurs when an alternating current in the transmitter coil generates a varying magnetic field, inducing a voltage across the receiver coil within the field. Optimal charging performance is achieved when the charger is close to the rechargeable device (typically within a few centimeters) and the coils are precisely aligned. In comparison, magnetic resonance coupling relies on aligning coils at the same resonant frequency, creating a strong non-radiative magnetic resonance induction. This allows for high power transfer efficiency over longer distances (typically within tens of centimeters), with multi-hop power transmission achievable using resonant repeaters [49]. Operating in the near field, non-radiative technologies produce a magnetic field that dominates close to the charger or device, resulting in higher charging efficiency.

The received power can be expressed as [13]:

$$P_r(d) = \begin{cases} P_t Q_t Q_r \eta_t \eta_r k^2(d), & 0 \leq d \leq D, \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where Q_t and Q_r represent the quality factors of the charger and device, respectively, while η_t and η_r denote their respective efficiencies. Additionally, $k^2(d)$ refers to the coupling coefficient between the transmit and receive coils. The closer and more accurately aligned the coils are, the higher the coupling coefficient and power transfer efficiency.

The coupling coefficient k is determined by the mutual inductance M and the self-inductance of transmit coil L_t and receive coils L_r, as shown in the following expression:

$$k = \frac{M}{\sqrt{L_t L_r}}. \tag{8}$$

Given the radii of the transmit and receive coils (r_t and r_r) and the distance d between them, the coupling coefficient, which reflects the alignment and distance between coils, can also be described by the following equation:

$$k^2(d) = \frac{r_t^3 r_r^3 \pi^2}{(d^2 + r_t^2)^3}. \tag{9}$$

Consequently, the received power for non-radiative charging, incorporating the coupling coefficient, is calculated as

$$P_r(d) = \begin{cases} P_t Q_t Q_r \eta_t \eta_r \frac{r_t^3 r_r^3 \pi^2}{(d^2 + r_t^2)^3}, & 0 \leq d \leq D, \\ 0, & \text{otherwise}. \end{cases} \tag{10}$$

Non-radiative Charging Standardization: in addition to adhering to EMR safety and equipment authorization regulations, the commercialization and widespread adoption of non-radiative charging technologies have led to the development of wireless charging standards like Qi [2], Rezence [50], PMA [51], and AirFuel Resonant [52] to ensure compatibility.

- Qi: developed by the WPC, Qi is the most widely adopted standard for inductive charging, commonly used in portable devices. Qi supports short-range charging, typically within a few centimeters, ensuring compatibility across various devices from different manufacturers.
- Rezence: initially developed by the Alliance for Wireless Power (A4WP) and now part of the AirFuel Alliance, Rezence uses magnetic resonance to provide greater flexibility in device positioning, support charging over several centimeters, and support multiple devices simultaneously.
- PMA: the Power Matters Alliance (PMA), a global non-profit organization, focused on developing standards and protocols for inductive charging similar to Qi, aiming to advance wireless power solutions for mobile devices.
- AirFuel Resonant: formed by the merger of PMA and Rezence, the AirFuel Alliance focuses on resonant charging technology, enabling longer charging distances than inductive systems like Qi, and supporting multiple devices without requiring precise alignment.

3) Energy Harvesting and Consumption Models: in WCNs, rechargeable devices capture charging energy via an energy harvesting unit. The maximum energy harvested by a device o_i is constrained by its battery capacity b_i. Let the corresponding charging time of the device be t_i, then the harvested energy of device o_i is given by

$$E_h(o_i) = \begin{cases} P_r(o_i) t_i, & E_i^{res} + P_r(o_i) t_i \leq b_i, \\ b_i - E_i^{res}, & \text{otherwise}, \end{cases} \tag{11}$$

where E_i^{res} is the residual energy of rechargeable device o_i before charging, *i.e.,* $0 \leq E_i^{res} \leq b_i$.

When rechargeable devices have harvested a certain amount of energy, they perform sensing, processing, and communication tasks. Assuming that each device o_i produces its sensing data at a constant rate R_i (in b/s), it then transmits the processed data to the BS via one-hop or multi-hop communication. Let the data transmission rate from device o_i to device o_j be f_{ij}, and to the BS be f_{iB}, respectively. Thus, the following flow conservation holds at each device o_i:

$$\sum\nolimits_{o_k \in O}^{o_k \neq o_i} f_{ki} + R_i = \sum\nolimits_{o_j \in O}^{o_j \neq o_i} f_{ij} + f_{iB}. \tag{12}$$

For rechargeable devices, we assume that communication is the main source of the device's energy consumption. Let C_{ij} and C_{iB} represent the energy consumption rate for transferring one unit of data to device o_i and the BS, respectively, and are given by [53]

$$C_{ij} = \beta_1 + \beta_2 d_{ij}^{\alpha}, \tag{13}$$

$$C_{iB} = \beta_1 + \beta_2 d_{iB}^{\alpha}, \tag{14}$$

where β_1 and β_2 are constants, α is the path loss index, and d_{ij} and d_{iB} are the distance from device o_i to device o_j and the BS, respectively. Notably, the energy consumption rate is influenced by the distance raised to the power of α.

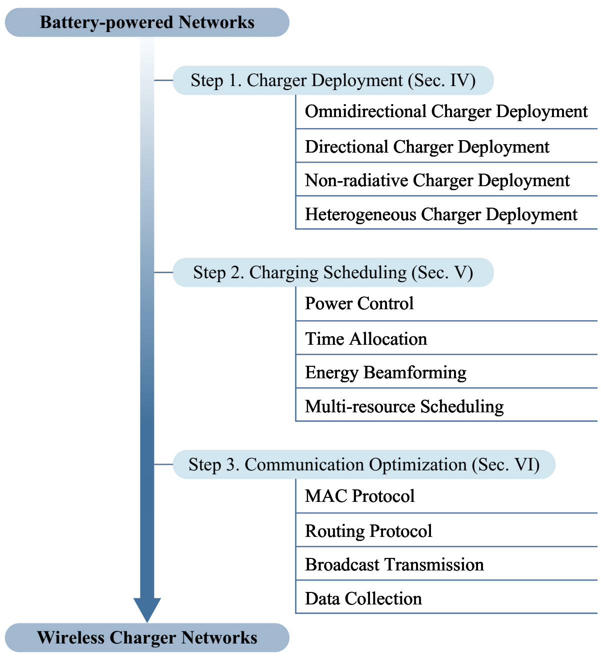


Fig. 10. Taxonomy of design issues.

Similarly, let ρ represent the energy consumption rate for receiving one unit of data. Then, the total energy consumption rate for both transmission and reception at device o_i is

$$E_c(o_i) = \rho \sum\nolimits_{o_k \in O}^{o_k \neq o_i} f_{ki} + \sum\nolimits_{o_j \in O}^{o_j \neq o_i} C_{ij} f_{ij} + C_{iB} f_{iB}. \quad (15)$$

C. Design Issues in WCNs

This section outlines the fundamental design issues in transitioning conventional battery-powered networks into efficient and effective WCNs. These considerations are categorized into three main aspects: charger deployment, charging scheduling, and communication optimization. This categorization reflects the essential steps in establishing WCNs—beginning with the physical deployment of charging infrastructure, progressing through the efficient management of charging processes, and culminating in optimizing communication protocols that support and enhance overall network functionality. Each aspect is crucial for ensuring the seamless operation and performance of WCNs, as illustrated in Fig. 10 and detailed below.

1) Charger Deployment Schemes (CDS): strategic deployment of wireless chargers is fundamental to constructing WCNs, as it directly affects charging coverage [31], efficiency [54], and network connectivity [55]. Deployment strategies vary depending on charging models, considering factors such as coverage area, efficiency, and power distribution. These strategies can be categorized into omnidirectional, directional, non-radiative, and heterogeneous deployments based on the type of chargers used. Omnidirectional and directional deployment schemes focus on reducing the number of chargers [31], maximizing charging utility [37], [56], or achieving multi-objective optimization [11]. Given their radiation properties, EMR safety [57], [58] and wave interference [40], [41] are also key considerations during deployment. Non-radiative charger deployment schemes prioritize ensuring a continuous energy supply for critical devices through single- or multi-hop power transmission [59], [60]. Heterogeneous charger deployments, as studied in [61], leverage the characteristics of different charger types through collaborative strategies to optimize performance.

Fundamental problem of CDS

Given a set of rechargeable devices, how can we determine the deployment schemes for the chargers (including charger location and orientation) to

- minimize the number of chargers, maximize charging utility, or achieve multi-objective optimization.
- subject to constraints such as coverage quantity, energy provision, and radiation properties.

2) Charging Scheduling Schemes (CSS): effectively scheduling the limited resources of wireless chargers is crucial for the sustainable operation of WCNs, including optimizing power control, time allocation, energy beamforming, and multi-resource coordination. Power control schemes focus on enhancing charging efficiency by adjusting the power received by devices [62], [63] or the charging area of chargers [64], [65]. Moreover, multifunctional chargers that handle both power and information transmission require strategies to balance these functions [66]. Time allocation schemes typically involve allocating charging duration [15], scheduling power transmission [67], [68], and coordinating power and information transfer [69] to either maximize efficiency or minimize energy consumption. Energy beamforming maximizes transmission efficiency by focusing power delivery on specific targets [10], [70]. Multi-resource scheduling further optimizes multiple objectives by coordinating resource allocation [71].

Fundamental problem of CSS

Given a set of rechargeable devices and wireless chargers, how can we determine the scheduling schemes for the chargers (including determining power control, time allocation, and energy beamforming) to

- maximize charging efficiency and fairness among devices, minimize energy consumption, or achieve multi-objective optimization.
- subject to constraints such as power budget, time duration, and energy provision.

3) Communication Optimization Schemes (COS): beyond the above schemes focusing on charging performance optimization, the researchers also explored communication optimization schemes in WCNs, including optimizing MAC protocols, routing protocols, broadcast transmission, and data collection. Among them, the MAC protocol controls access to shared wireless media and coordinates power transmission with communication processes [72], [73]. Routing protocol optimization aims to identify the best route to transmit data from source to destination, considering devices with additional power supply [74]. Broadcast transmission optimization focuses on enhancing transmission reliability [75], [76] and reducing broadcast latency [77], while ensuring collision-free transmission and maintaining charging performance. Additionally, it is crucial to consider how to utilize mobile [78] or fixed sinks [79] to collect data, ensuring timely data collection.

Fundamental problem of COS

Given a set of rechargeable devices and wireless chargers, how can we optimize the communication schemes of the network (including MAC protocol, routing protocol, broadcast transmission, and data collection) to

- maximize transmission reliability and throughput, minimize latency, or achieve multi-objective optimization.
- subject to constraints such as energy conservation, flow conservation, collision-free transmission, and tolerant delay.

D. Typical Applications of WCNs

WCNs provide a contactless, continuous, and controllable energy supply, seamlessly integrating into our daily lives. This section outlines typical applications of WCNs, including wireless sensors, medical implants, portable electronics, Unmanned Aerial Vehicles (UAVs), home appliances, and Electric Vehicles (EVs), organized by increasing power requirements.

1) Wireless Sensors: wireless sensors, designed for environmental data sensing, play pivotal roles in industrial automation, environmental monitoring, and military surveillance. These sensors have low charging power requirements, typically ranging from microwatts to milliwatts, making them ideal for large-scale charging via radiated chargers such as Powercast's transmitters [36] and Energous's WattUp [80]. The charging durations are relatively short, from minutes to a few hours. WCNs can remotely charge sensors in vast or hard-to-reach areas like oceans, forests, or bridges, ensuring a stable energy supply for real-time monitoring and rapid response [81]–[83]. Due to the limitation of the charging efficiency and radiation safety of the radiation charger, higher requirements are put forward for the deployment and scheduling strategy of its WCNs to achieve full device coverage and maintain EMR safety.

2) Medical Implants: medical implants are devices implanted in the patient's body to monitor, treat, or aid physiological functions. Due to safety concerns, their charging power is rigorously restricted to milliwatt levels, typically using non-radiated chargers like the prototype developed by Fan *et al* [10] for precise, localized charging. Integration with WCNs effectively avoids potential risks associated with surgical battery replacements [84]. Additionally, the WCN can monitor medical implants wirelessly, providing doctors with real-time data for remote monitoring and adjustments to treatment plans. Real-time monitoring and remote management are crucial for patients with chronic diseases or those requiring long-term monitoring [85]. Since the implants are situated within the human body, WCNs must deliver energy with precise transmission angles and intensity to ensure sufficient power while preventing overheating of surrounding tissues.

3) Portable Electronics: portable electronic devices, such as smartphones, tablets, and Bluetooth headphones, which users frequently carry, typically require charging powers ranging from several watts to tens of watts. Non-radiative chargers using inductive coupling technology, such as Duracell's Powermat [86], Google's Nexus Wireless Charger [87], and Samsung's Wireless Charger Duo Pad [88], efficiently meet these needs. Devices must remain on the charging pads for several hours to fully charge. In WCNs, these devices can achieve continuous power supply, eliminating concerns about battery depletion and greatly improving travel convenience [15]. WCNs also remove the need for cables and are compatible with various portable electronics, providing a cleaner, more organized service environment [89]. Despite these advantages, the short-range nature of non-radiative chargers imposes spatial limitations on device placement.

4) UAVs: UAVs are designed for aerial photography, communication, and other tasks, requiring charging power ranging from tens to hundreds of watts. Non-radiated chargers using resonant coupling, capable of providing longer charging distances and higher charging efficiency, are ideally suited to meet these requirements. Examples include Powermat's wireless charging solution [86], Bumblebee Power [90], and WiBotic's PowerPad Pro [91]. UAVs can either dock with chargers or charge mid-air, completing the process within a few hours. In WCNs, UAVs do not have to land frequently to replace their batteries. This enables them to perform missions more efficiently and have longer flight ranges [92], [93]. In addition, when a natural disaster strikes, those UAVs can be easily and quickly deployed to establish communication links. Through wireless charging technology, these UAVs ensure the continuous operation of communication links, effectively facilitating rescue missions [94], [95]. However, current wireless charging solutions for UAVs are limited by range and charging time, restricting their operational flexibility.

5) Home Appliances: with rising demand for convenience, WPT technology has found extensive applications in home appliances, including LED TVs, kitchen appliances, and lighting systems. Non-radiated chargers using inductive coupling, like Fulton's eCoupled [96] and Semtech's LinkCharge [97], offer the highest charging efficiency and can meet power requirements of up to several kilowatts. The elimination of wires not only significantly enhances the flexibility of placing home appliances but also contributes to a more organized and tidy appearance throughout the entire home [98]. Furthermore, WCNs turn ordinary appliances into smart appliances, enhancing their control and safety features [99]. However, the high energy consumption of home appliances themselves continues to limit the widespread adoption of WCNs.

6) EVs: certain EVs, e-bikes, and e-scooters are now wireless charging-capable, demanding power from tens of watts to tens of kilowatts. Products like WiTricity's Wireless Charging System [100], Qualcomm's Halo WEVC [101], and Evatran's Plugless Power [102] fulfill these needs using large transmission coils, with charging times of several hours. The emergence of WCNs enables EVs to eliminate the inconvenience of wires, with no plugs or ports worn or damaged by repeated connections to chargers. This advancement ensures safe charging, even in wet environments [16]. Moreover, the establishment of two-way communication between EVs and wireless chargers enables seamless integration of intelligent functions, such as automatic parking payments and repair reports [103]. However, the widespread adoption of WCNs is hindered by several challenges, including the high cost of infrastructure deployment and the need for standardization across different vehicle manufacturers.

By introducing the architecture of WCNs, we clarify the network structure and basic components. The explanation of models reveals the energy conversion processes within WCNs, while the discussion of design issues highlights key challenges in network construction. Typical applications demonstrate the practical value of WCNs, establishing a solid framework for understanding their complexities and real-world applications.

IV. Charger Deployment Schemes

Charger deployment schemes are fundamental to constructing WCNs, directly influencing the network's charging coverage and efficiency. Due to the distinct characteristics of different wireless charger types, customized optimization strategies are essential for effective deployment. To meet diverse wireless charging requirements, charger deployment schemes can be classified into four main types: 1) omnidirectional charger deployment, where electromagnetic waves are broadcast equally in all directions, creating a circular charging area suitable for simultaneously providing energy to multiple devices within a wide coverage (Sec. IV.A); 2) directional charger deployment, which focuses energy in a specific direction using beamforming to form a sector-shaped charging area, ideal for scenarios requiring concentrated power delivery and enhanced energy efficiency for targeted devices (Sec. IV.B); 3) non-radiative charger deployment, characterized by short-range but high-efficiency energy transfer, making it suitable for point-to-point charging scenarios where precision is crucial (Sec. IV.C); and 4) heterogeneous charger deployment, which combines different types of wireless chargers to offer flexible and efficient charging services, meeting diverse device needs within the network (Sec. IV.D).

A. Omnidirectional Charger Deployment

In WCNs, the problem of omnidirectional charger deployment is how to determine the locations and the numbers of omnidirectional chargers to meet various objectives. These objectives include minimizing deployment costs, maximizing charging utility, achieving multi-objective optimization, and enhancing charging performance by considering device mobility and charger radiation characteristics [11], [31], [31], [40], [41], [44], [54], [58], [61]–[63], [104]–[129]. For better comprehension, Fig. 11 illustrates an omnidirectional charger deployment scheme. Additionally, Table IV presents a comprehensive overview of related studies, detailing their comparison in terms of objectives, constraints, device mobility, approaches, performance metrics, and Evaluation Methods (EVM).

1) Deployment Cost Minimization: in the past decade, extensive efforts [31], [104]–[111] have been made to reduce deployment costs for recharging devices. Chargers are usually much more expensive than rechargeable devices, about 100 times the price difference [31], so it is a great concern to cover more rechargeable devices with as few chargers and deployment costs as possible.

In WCNs, He *et al.* [31] utilized WISP [12] and commercial off-the-shelf omnidirectional chargers to achieve full coverage of the network. Specifically, the WISP integrates devices with

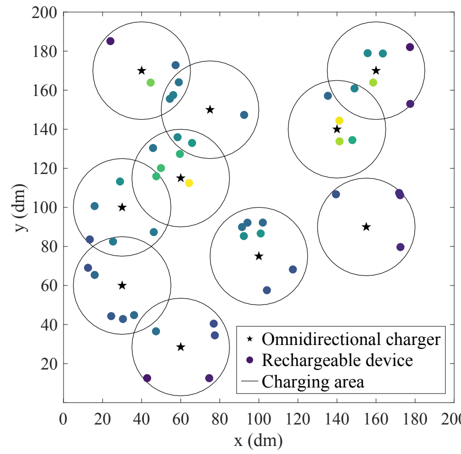


Fig. 11. Illustration of an omnidirectional charger deployment scheme within a network comprising 50 rechargeable devices and 10 omnidirectional chargers, each having an effective charging distance of 25dm.

sensing and computing components. These devices are capable of harvesting energy from the charger and storing it in a capacitor, which powers data sensing, logging, and computing. To ensure that these devices can have continuous operation, they considered a point provisioning problem, that is, how to strategically deploy the minimum number of omnidirectional chargers to ensure full coverage across the network. To tackle this problem, they exploited the triangular deployment technique proposed in [130], providing the upper-bound asymptotic approximation ratios of the proposed solutions to the optimal ones.

Some papers [104]–[109] investigate the approach to partial coverage, aiming to provide power to devices or selected areas within the network, using a minimum number of omnidirectional chargers. Pang *et al.* [104] designed a partition algorithm to reduce the number of chargers covering static devices. The algorithm divides the entire spatial plane into smaller partitions, solving them independently within each partition, and then combines these solutions to create an approximate solution for the original problem. Wan *et al.* [105] proposed two algorithms to minimize the number of chargers, by combining the solution of the Fermat point problem with the advantages of the greedy algorithm. Subsequently, Wan *et al.* [106] proposed a charger deployment algorithm based on a greedy algorithm and position relationship between sensor nodes, which utilizes the local search capability to avoid exponential growth in the number of chargers (*i.e.,* combinatorial explosion). Ding *et al.* [107] concentrated on minimizing the deployment costs while satisfying the energy supply requirements. They introduced an approximation algorithm that greedily selects locations to maximize the energy supply.

Diverging from certain greedy-based techniques, Chien *et al.* [108] proposed a metaheuristic-based algorithm to find the optimization charger deployment. Notably, metaheuristic algorithms typically demand more computational time for convergence. In response to this challenge, they effectively tackled it by pruning redundant solutions from the solution space, thus significantly reducing the required computational time. Simulation results show that the metaheuristic-based algorithm can use a minimized number of chargers to cover all static

TABLE IV
COMPARISON OF OMNIDIRECTIONAL CHARGER DEPLOYMENT SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Omnidirectional Charger Deployment	[31]	Minimum number of chargers	Energy provision constraints	Static; mobile	Approximation	Approximation ratio; average consumption power	TA; NS
	[104]	Minimum number of chargers	Coverage constraints	Static	Approximation	Approximation ratio	TA
	[105], [106]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Number of chargers; number of candidate chargers	NS
	[107]	Minimum deployment cost	Energy provision constraints	Static	Approximation	Deployment cost	TA; NS
	[108]	Minimum number of chargers	Energy provision constraints	Static	Metaheuristic	Number of chargers; running time	NS
	[109]	Minimum number of chargers	Coverage constraint	Static	Heuristic	Coverage quality	NS
	[124]	Minimum number of chargers	Energy provision constraints	Static	Heuristic; metaheuristic	Number of chargers	NS
	[110]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Harvested power; convergence rate; number of chargers	TA; NS
	[111]	Minimum number of chargers	Flow conservation constraints; energy provision constraints	Static	Approximation	Number of chargers; harvested power	TA; NS
	[54]	Maximum charging utility	Coverage constraints	Mobile	Heuristic	Survival rate	NS
	[112]	Maximum charging utility	Coverage constraints	Mobile	Approximation	Coverage rate; coverage efficiency	TA; NS
	[62], [63]	Maximum charging utility	Power budget constraints	Static	Approximation	Coverage quality; running time	TA; NS
	[113]	Maximum task utility	Deployment cost budget	Static	Approximation	Task utility; harvested power	TA; NS
	[11]	O1: Maximum charging utility O2: Maximum charging efficiency	Coverage quantity constraint	Static	Metaheuristic	Accuracy; convergence rate	NS
	[114]	O1: Maximum charging utility O2: Maximum fairness O2: Minimum number of chargers	Energy provision constraints	Static	Heuristic	Average harvested power; number of chargers	NS
	[115]	O1: Maximum harvested power O2: Maximum fairness O3: Minimum number of chargers O4: Minimum energy consumption	Energy provision constraints	Static	Heuristic	Average harvested power; number of chargers; energy consumption	NS
	[116]	O1: Maximum network lifetime O2: Minimum number of chargers	Coverage constraints	Mobile	Heuristic	Number of chargers; survival rate	NS
	[117]	Minimum number of chargers	Energy provision constraints	Mobile	Heuristic; metaheuristic	Number of chargers	NS
	[118]	Minimum number of chargers	Non-overtime stay probability requirement	Mobile	Heuristic; metaheuristic	Number of chargers; number of devices	NS
	[119]	Assess the impact of mobility	Energy provision constraints	Mobile	Bound analysis	Quality of energy provisioning	TA; NS
	[120]	Minimum number of chargers	Energy provision constraints	Mobile	Exact	Number of chargers and discrete grids; overhead of running	NS
	[121]	Minimum number of chargers	Non-overtime updating probability requirement	Mobile	Heuristic; metaheuristic	Number of chargers; success rate; running time	NS; FE
	[44], [58]	Maximum charging utility	EMR safety constraints; charger location constraints	Static	Approximation	Harvested power	TA; NS; FE
	[122], [123]	Maximum charging utility	EMR safety constraints	Static	Approximation	Harvested power	TA; NS; FE
	[125]	Optimal distributions of power	EMI impact constraints	Static	Distribution fitting	Harvested power	NS; FE
	[126]	Maximum charging utility	Energy provision constraints	Static	Heuristic	Harvested power	NS
	[127]	Maximum charging utility	Placement constraints	Static	Heuristic	Harvested power	NS
	[40], [128]	Maximum charging utility	Deployment area constraint	Static	Approximation	Harvested power	TA; NS; FE
	[129]	Maximum charging utility	Deployment area constraint	Static	Approximation	Harvested power	TA; NS; FE

devices in the indoor scenario. Arivudainambi *et al.* [109] leveraged a Daubechies wavelet algorithm to identify the optimal locations for omnidirectional chargers, with the goal of minimizing the number of chargers. Additionally, they took into account the improvement in device coverage by optimizing the charger locations.

In addition to charger deployment, some papers [110], [111] also consider BS deployment for data collection, with the aim of balancing energy supply and information transmission. In the case where the charger and BS are separated, the study in [110] first proposes an efficient cluster-based greedy algorithm to optimize the locations of chargers given fixed BS locations. Then, a trial-and-error algorithm for BS location optimization is proposed. On this basis, an effective method to optimize the charger and BS location alternately is proposed. In the case where each pair of the charger and BS are co-located, an efficient greedy algorithm is proposed. Li *et al.* [111] investigated a similar co-deployment problem, that is, how to minimize the number of BSs and chargers given two sets of candidate locations for placing them while satisfying flow constraints. To tackle this problem, they first transformed the co-deployment problem into two max-flow sub-problems. Then they designed a greedy-based algorithm for each sub-problem with $ln\frac{R}{\epsilon}$ worst-case bound, where R is the required data flow rate and ϵ is a small enough number. Further, they designed an iterative algorithm that solves two subproblems alternatively to achieve a near-optimal performance.

2) Charging Utility Maximization: the research [54], [62], [63], [112], [113] on the omnidirectional charger deployment also focuses on maximizing the charging utility, which can refer to either the received power of device or the coverage quantity. Charging utility is a crucial optimization metric that can directly reflect the quality of the deployment scheme.

Some papers [54], [112] explore omnidirectional charger deployment using a binary model, where charging utility only indicates whether a device is covered, regardless of the power received Chiu *et al*. [54] tackled the problem of optimizing the charging utility for mobile devices. They first divided the sensing area into different grids for deploying wireless chargers. By analyzing human movement patterns, they identified grid areas where mobile devices were more susceptible to battery drain and placed chargers accordingly. This strategic placement aimed to maximize the survival rate of devices, ensuring they maintain sufficient power for uninterrupted operation. Rao *et al*. [112] focused on urban environments, where they deployed a limited number of chargers to maximize charging utility, considering pre-known device trajectories and bounded detouring costs. They addressed the problem using a greedy algorithm with an approximation factor of $(1-1/e)$ and further improved it to account for detouring, achieving an approximation factor of $1-\ 1/\sqrt{e}$.

Other studies [62], [63], [113] quantify charging utility based on the amount of power received by the device. For instance, Zhang *et al*. [62] defined charging utility as being proportional to the power received by a device, with a set maximum received power acting as the upper limit. They addressed a P^3 problem, that is, given a set of candidate locations for placing omnidirectional chargers, how to find a charger deployment, and a corresponding power allocation to maximize the charging utility, subject to a power budget. Based on the greedy strategy, they proposed a $(1-1/e)$-approximation algorithm to solve the charger deployment problem with a fixed power level, and an approximation algorithm with a ratio of $\frac{(1-1/e)}{2L}$ for the P^3 problem, where L is the maximum received power. In addition, the expansion of the P^3 problem via relaxing several assumptions is investigated in [63], including mobile device, reconfiguration, and arbitrary candidate locations. In addition, Ding *et al*. [113] investigated the deployment of wireless chargers in a task-driven context, proposing an approximation algorithm to maximize total task utility within a limited deployment cost budget.

3) Multi-Objective Optimization: some works [11], [114]–[116] study how to deploy omnidirectional chargers to achieve multi-objective optimization. Different from the single-objective optimization problem, multi-objective optimization deployment needs to consider the relationship between multiple objectives, which may be competitive, cooperative, tradeoff, and constrained.

Sun *et al*. [11] propose an improved firefly algorithm to solve a multi-objective optimization problem to maximize the number of devices covered by each charger and enhance charging efficiency simultaneously. Ejaz *et al*. [114] studied the charger deployment problem of software-defined WSNs. The deployment problem is how to determine the optimal location and minimum number of chargers to maximize the charging energy and fair distribution of energy among all devices. They proposed a utility function to represent a tradeoff between the maximum energy charged in the network and the fair distribution of energy. The optimization problem is formulated and solved while satisfying the constraint on minimum energy charged by each device. They also proposed an energy-efficient scheduling scheme [115], which aims to reduce the energy consumption of the chargers. In addressing the challenge of supplying power to non-deterministic mobile nodes, the work in [116] introduces a multi-objective optimization scheme based on a genetic algorithm to extend network life and reduce deployment costs. The proposed scheme constructs a D-dimensional vector, where D is the cardinality of the candidate set, to depict the candidate chargers. These candidates are iteratively optimized, and a dual indicator selection method is employed to determine the ultimate deployment solution.

4) Mobile Device Service: in WCNs, there are various mobile devices (*e.g.,* smart bracelets, medical devices, and smart cameras) carried by mobile agents (*e.g.,* humans and animals). Unlike the deployment optimization of static devices, it is critical to consider the mobility patterns and trajectories of these mobile devices [31], [117]–[121].

Regarding the mobility trajectories of these mobile devices, various studies adopt different assumptions. Some studies [117], [118] assume that specific stops exist along the trajectory. In [117], mobile devices have a specific stay-move behavior pattern, which is characterized by the distribution of trajectory, stay points, and residence time. The optimization problem is to minimize the number of chargers, subject to the power non-outage probability requirement of the mobile device. A similar problem is also explored in [118], that is, given static task points and the directed trajectory of a mobile device, how to deploy a minimum number of chargers and receivers subject to the non-overtime stay probability requirement in all task points. The mobile device is assumed to update information to the nearest receiver when it is fully charged at each task point. Considering the interaction effect between the deployment of chargers and receivers, greedy heuristic and particle swarm optimization solutions are proposed.

Some studies [31], [119]–[121] assume that mobile devices can stop at any point along the trajectory. He *et al*. [31] employed the mobility of devices to reduce the number of required chargers. As the power around the charger is higher than the marginal part of the charging area, mobile devices can harvest more energy in the power-rich areas. Assuming a uniform distribution of devices, they proposed a triangular deployment method to ensure the accumulated energy exceeds a specified threshold over time. Dai *et al*. [119] investigated the impact of mobility on energy provisioning. They provided the upper and lower bounds of the expected duration that mobile devices could sustain normal operation in single and multiple charger situations. Li *et al.* [120] tackled the problem of deploying omnidirectional chargers on a two-dimensional (2D) plane, considering the trajectory of mobile devices. They discretized the continuous plane into grids and segmented the corresponding trajectory. The optimization problem is transformed into a binary integer programming problem that can be easily solved by existing methods. Additionally, Yao et al. [121] employed trajectory discretization to decrease computational demands, proposing heuristic algorithms based on greedy and particle swarm optimization techniques to reduce the number of chargers.

5) Radiation Characteristics: several studies have explored the radiation characteristics of omnidirectional chargers, focusing on the effects of electromagnetic radiation (EMR), interference, and penetration on deployment strategies [40], [41], [44], [58], [61], [122]–[129].

Given the widely recognized health risks associated with high EMR exposure, ensuring EMR safety in charger deployment schemes is crucial [44], [58], [122], [123]. Dai *et al.* [44], [58] focused on the safe charging problem of activating omnidirectional chargers to maximize charging utility while ensuring EMR safety. Since EMR constraints are imposed on every point in the plane, this inevitably leads to an infinite number of constraints. By proper discretization, the problem is transferred to a Multidimensional 0/1 Knapsack (MDK) problem [131] and a Fermat-Weber problem [132]. Subsequently, Dai *et al.* [122], [123] extended the safe charging problem to charger deployment on a 2D continuous plane. To address this problem, they discretized the continuous plane such that the problem can be formulated into the MDK problem. Recognizing the inadequacy of existing MDK approximation algorithms in terms of speed, they introduced a fast approximation algorithm tailored for MDK problems. Furthermore, they optimized the charger deployment scheme to further improve speed by double partitioning the plane.

The studies mentioned above assume that the cumulative charging power from multiple chargers is simply additive. However, wave interference significantly impacts power distribution [40], [41], [124]–[128]. Li *et al.* [124] introduced a charging model that accounts for the multipath effect. Based on the proposed charging model, they explored the problem of how to deploy a minimal number of chargers to guarantee the duty cycle of devices. To solve the problem, they proposed both greedy and particle swarm optimization-based heuristic algorithms. Naderi *et al.* [125] discussed the impact of wave interference on power distribution in both 2D and 3D spaces. The study provides closed matrix formulas for calculating received power at any given point in space. It reveals that both received power and interference power over the network exhibit Log-Normal distributions, while harvested voltage follows a Rayleigh distribution.

Katsidimas *et al.* [126] presented a vector model to describe interference phenomena. They proposed two optimization problems: maximizing the power and maximizing the minimum cumulative power across all device subsets of size k. To tackle these problems, they proposed heuristic approaches. In their subsequent work [127], they extended their study by assuming that omnidirectional chargers can be slightly moved around the initial deployment location. They proposed two heuristic methods for 1D and 2D spaces, optimizing charger positions to enhance charging utility. In addition, Ma *et al.* [40], [41] modeled the cumulative power of multiple chargers using cosine waves, illustrating the energy distribution of five concurrently active chargers. Their findings revealed alternating zones of enhanced and weakened energy due to constructive and destructive interference. To maximize charging utility, a heuristic algorithm is proposed to optimize charger and device deployment. Similarly, Xue *et al.* [128] developed a two-step charger placement scheme, also considering wave interference, to determine the charger locations.

Radiation characteristics in scenarios with obstacles have also been investigated [61], [129]. Wang *et al.* [61] assumed that obstacles completely block charging power and explored the optimal deployment of heterogeneous chargers under this assumption. However, You *et al.* [129] found through experiments that obstacles do not fully block energy but cause attenuation instead. Their study comprehensively considered the material, size, and location of obstacles to optimize the omnidirectional charger deployment, aiming to maximize charging utility. Considering the shadow fading caused by obstacles, they established a practical charging model and verified the correctness of the model by experiments. Based on the established model, the plane is first discretized to solve the problem of infinite candidate locations on the 2D continuous plane. Then, a dominating coverage set extraction algorithm is proposed to select candidate points with the largest number of covers on the plane, Finally, a greedy algorithm with an approximation ratio of $1 - 1/e - \epsilon$ is designed.

B. Directional Charger Deployment

Compared with omnidirectional chargers, directional chargers have a narrower charging angle, demanding greater precision in their deployment, encompassing not only their physical location but also their specific direction, as shown in Fig. 12. The core challenge in deploying directional chargers is strategically determining their location and direction to minimize deployment costs, maximize charging utility, achieve multi-objective optimization, and enhance charging performance by utilizing directional radiation characteristics [8], [37], [55], [56], [67], [68], [133]–[155]. Table V provides a comparison of various directional charger deployment schemes.

1) Deployment Cost Minimization: some works [133]–[141] focus on the directional charger deployment with a primary objective of cost reduction. Unlike omnidirectional chargers, which emit energy uniformly in all directions, directional chargers concentrate energy and allow for flexible adjustments in their charging direction. This makes them more efficient at covering devices spread across different heights and positions in three-dimensional (3D) scenarios. Additionally, directional chargers can adapt to varying device energy consumption, adjusting orientation to further optimize deployment costs.

Liao *et al.* [133] conducted a study on the deployment of directional chargers in a 3D scenario, where directional chargers are assumed to be on grid points at a fixed height to maintain the energy supply for devices located below it. Notably, in this configuration, the energy beam emitted by the

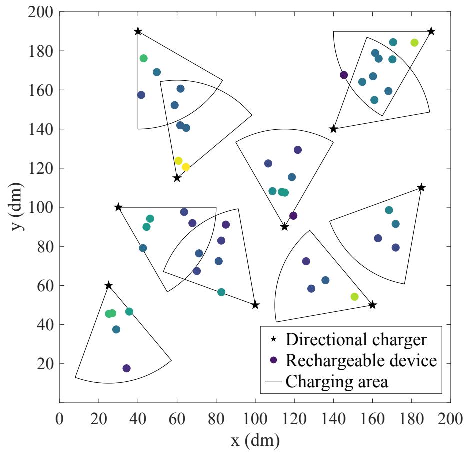


Fig. 12. Illustration of a directional charger deployment scheme within a network comprising 50 rechargeable devices and 10 directional chargers, each with an effective charging distance of 50dm and a charging angle of $60°$.

directional charger is projected onto the device's plane, presenting a circular charging area. They proposed two heuristic algorithms to optimize the number of chargers that can cover all devices, one based on device location and the other on device pairs. Analysis results show that the latter is superior in the number of chargers, while the former has lower time complexity. Subsequently, they modeled the transmitted energy based on the Friis propagation model in [134] to reduce the number of chargers with a more accurate energy estimate. Jiang *et al*. [135] addressed the problem of directional charger deployment in similar scenarios. They introduced two heuristic algorithms, one greedy and the other adaptive, to minimize the number of chargers. While the greedy approach prioritizes covering most devices, the adaptive strategy selects directions that provide higher charging power.

In addition to heuristic algorithms, several studies [136], [137] propose metaheuristic-based deployment algorithms for 3D scenarios. In [136], a particle swarm charger deployment algorithm is presented. Specifically, on the basis of the particle swarm algorithm, the local optimal results and global optimal results are used to adjust the locations and directions of directional chargers. The primary goal is to minimize the number of chargers required to supply energy to the devices effectively. Furthermore, Jiang *et al*. [137] enhanced the particle swarm charger deployment algorithm by employing genetic algorithms for parameter encoding and optimization. This enhanced algorithm builds upon the particle swarm optimization concept, utilizing parameters generated by the genetic algorithm to optimize the directional charger deployment, thereby further reducing the number of chargers.

In a WCN, devices perform various tasks, leading to varying levels of energy consumption. The impact of this diverse energy consumption on the number of directional chargers is also studied in [138]–[141]. Due to frequent data forwarding, devices near the BS consume more energy than those away from the BS. To solve this problem, Lin *et al*. [138] designed a novel hybrid search and removal strategy to optimize charger deployment. This approach involves strategically placing the directional charger near a device, followed by rotating it to identify the coverage dominating set. It accounts for the device mobility and energy consumption of the BS. Additionally, Jaiswal *et al*. [139] also considered the impact of data traffic distribution on device energy consumption. An optimal charger deployment scheme based on a transferable belief model is proposed to find the optimal number of chargers. Furthermore, the charger deployment problem of satisfying the individual energy supply requirements for each device is investigated in [140]. The spatial occupation of mobile devices is considered in [141]. This study first investigates the properties of the optimal arrangement of mobile devices for a directional charger. Subsequently, an angle discretization method is applied to obtain the finite candidate charging directions and their corresponding approximate charging power. To optimize the charging cost, a $(\ln n + 1)(1 + \epsilon)$-approximation algorithm based on the greedy approach is proposed.

2) Charging Utility Maximization: several studies focus on how adjusting the direction of directional chargers can significantly enhance charging utility, optimizing energy distribution to better meet device-specific demands [8], [37], [55], [56], [67], [68], [142]–[148].

Dai *et al*. [37], [56] established the directional charging model through field experiments, modeling charger and sensor charging areas as sector areas of $60°$ and $120°$ angles, respectively. To maximize charging utility, they employed techniques for approximating nonlinear charging power and expected utility, transforming the problem into an almost linear one. Subsequently, they designed a dominating coverage set extraction method to reduce the search space without performance loss and proposed a $(1 - 1/e - \epsilon)$-approximation algorithm to solve the problem. Additionally, they investigated a direction scheduling problem for charging tasks [67], [68]. To address this problem, a centralized offline algorithm and a distributed online algorithm are proposed to maximize the overall task utility. Ding *et al*. [142] delved into solving the charging utility maximum problem subject to the deployment cost budget constraint. The problem is solved by an approximation algorithm that maximizes charging utility.

The optimization of charging utility for devices with diverse energy consumptions is explored in [143]–[145]. Devices closer to the BS exhibit higher energy consumption, leading to higher charging demands. Lin *et al*. [143] discretized the charging demand based on the distance between the device and the BS, which resulted in the charging area being divided into sub-areas with distinct charging power and charging demand. Each sub-area is further analyzed to determine the coverage dominating set, from which the solution set is selected to minimize the difference between its charging demand and charging power. The study in [144] focuses on the energy consumption of task loading. To balance energy supply and task loads, they designed an approximation algorithm to optimize the direction of directional chargers and the energy transferred by devices to tasks. He *et al*. [145] studied a small-scale WCN for dockless shared bikes, which includes Powercast wireless chargers and the receiving antenna integrated into the shared bike's basket. To minimize total charging delay, they first proposed an efficient charging direction scheduling algorithm for a single charger in small-scale scenarios. Then, they extended the solution to multiple charger joint direction scheduling in large-scale scenarios based on dynamic programming.

TABLE V
COMPARISON OF DIRECTIONAL CHARGER DEPLOYMENT SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Directional Charger Deployment	[133]	Minimum number of chargers	Coverage constraints	Static	Heuristic	Number of chargers	NS
	[134]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Number of chargers	NS
	[135]	Minimum number of chargers	Coverage constraints; energy provision constraints	Static	Heuristic	Charging power; number of chargers; execution time	NS; FE
	[136]	Minimum number of chargers	Energy provision constraints	Static	Metaheuristic	Number of chargers	NS; FE
	[137]	Minimum number of chargers	Energy provision constraints	Static	Metaheuristic	Number of chargers	NS
	[138]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Number of chargers; execution time; charging demand	NS
	[139]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Average harvested power; number of chargers	NS
	[140]	Minimum number of chargers	Energy provision constraints	Static	Approximation	Number of chargers	TA; NS
	[141]	Minimum deployment cost	Coverage constraints; spatial occupation issue	Mobile	Approximation	Deployment cost; running time	TA; NS; FE
	[37], [56]	Maximum charging utility	Charger direction constraints	Static	Approximation	Harvested power	TA; NS; FE
	[67], [68]	Maximum task utility	Charger direction constraints	Static	Approximation	Charging utility	TA; NS; FE
	[142]	Maximum charging utility	Deployment cost budget	Static	Approximation	Deployment cost; charging levels	TA; NS
	[143]	Maximum charging efficiency	Energy consumption constraints	Static	Heuristic	Charging efficiency; number of chargers	NS
	[144]	Maximum task utility	Energy consumption constraints	Static	Approximation	Task utility; energy consumption	TA; NS
	[145]	Minimum charging delay	Energy provision constraints	Static	Heuristic	Charging delay	NS
	[146], [55]	Maximum charging utility	Connectivity constraints	Static	Approximation	Charging utility	TA; NS; FE
	[8]	Maximum charging utility	Charging power jittering; device drifting constraint	Static	Approximation	Charging utility	TA; NS; FE
	[147], [148]	Maximum charging utility	Charger mobility constraints	Static	Approximation	Charging utility	TA; NS; FE
	[149], [150]	O1:Maximum charging efficiency O2: Maximum energy balance	Charger capacity constraint	Mobile	Heuristic	Charging efficiency; energy balance; lifetime of the chargers	NS
	[151]	O1: Maximum received power O2: Maximum survival probability	Energy provision constraints	Static	Heuristic	Received power; survival probability	TA; NS
	[152], [153]	Maximum omnidirectional charging proportion	Energy provision constraints	Static	Heuristic	Omnidirectional charging proportion	TA; NS; FE
	[154]	Maximum charging utility	Charger location constraints; charger direction constraints	Static	Approximation	Harvested power	TA; NS; FE
	[155]	Minimum energy consumption	Energy provision constraints	Static	Heuristic; metaheuristic	Energy consumption	TA; NS

Some studies focus on the connectivity, robustness, and limited mobility of the directional charging deployment [8], [55], [146]–[148]. Yu *et al*. [55], [146] focused on the problem of connected directional charger deployment, that is, given candidate locations, how to determine the location and direction of directional chargers under connectivity constraints, such that overall charging utility is maximized. They proposed a constant approximation algorithm to solve the problem. Wang *et al*. [8] considered the problem of robust charger deployment, that is, given a number of rechargeable devices, each of which may drift within a certain range, how to determine the directions of directional chargers to maximize the charging utility considering the charging power jitter. To address this problem, they developed a probabilistic model for charging power, applied area and direction discretization, and proposed a $(1/2-\epsilon)$-approximation algorithm. Dai *et al*. [147], [148] studied the problem of deploying directional chargers with limited mobility, that is, how to determine deployment locations, stop locations and directions, and portions of time for all directional chargers with limited mobility, such that overall charging utility of devices is maximized.

3) Multi-Objective Optimization: multi-objective optimization has been explored in the deployment of directional chargers, with a focus on strategically adjusting charger orientations to simultaneously enhance charging efficiency, energy distribution, and other key performance metrics [149]–[151].

Nikoletseas *et al*. [149], [150] investigated mobile ad hoc networks with multiple directional chargers. Under the constraint of limited charger battery energy, they proposed two heuristic algorithms. These algorithms are designed to determine, in each charging cycle, which directional chargers should be activated, with the respective objectives of maximizing charging efficiency and balancing the residual energy of the chargers. Wang *et al*. [151] proposed an adaptive directional charging scheme for a large-scale sensor network. The scheme utilizes energy beamforming strategies to charge nearby sensors. they derived closed-form expressions for the distribution metrics of the aggregate received power at a typical sensor using stochastic geometry. They also analyzed the optimal charging radius for maximizing the average received power and the sensor active probability. Simulation results demonstrated that the proposed adaptive directional charging scheme is more energy-efficient than conventional omnidirectional charging schemes.

4) Directional Radiation Characteristics: some studies explore the radiation characteristics of directional chargers to achieve full-view coverage and multi-directional deployment, and accounting for anisotropic energy distribution [152]–[155].

Full-view coverage of the charging area can be achieved using directional chargers [152], [153]. Dai *et al*. [152] introduced the concept of omnidirectional charging, defining it as an area where any device, regardless of orientation, receives power not lower than a specified threshold. For deterministic charger deployments, they developed a fast detection algorithm to verify omnidirectional charging coverage. For random deployments, they calculated the probability of achieving such coverage. Their subsequent work, detailed in [153], extends this work by designing a charger deployment scheme that satisfies omnidirectional charging. By strategically deploying chargers at the points of a triangular lattice, they estimated the optimal length of the lattice side that satisfies omnidirectional charging and derived the corresponding error bound.

To expand the charging angle of directional chargers, Dai *et al*. [154] introduced the use of a specialized charger equipped with multiple directional antennas. They delved into the deployment problem of these multi-directional chargers, that is, how to determine the optimal locations for the chargers and directions for their multiple antennas, such that the charging utility is maximized. Jia *et al*. [155] considered the anisotropic energy receiving property of directional charging, which is the charging power related to not only distance but also angle. Based on this property, they studied the energy-saving problem in WCNs. They assumed that the charging demand distribution follows a Gaussian distribution, and designed a charger direction scheduling scheme to minimize energy consumption.

C. Non-radiative Charger Deployment

In contrast to radiative chargers, non-radiative chargers operate in the near field, offering higher charging efficiency, particularly well-suited for one-to-one charging scenarios.

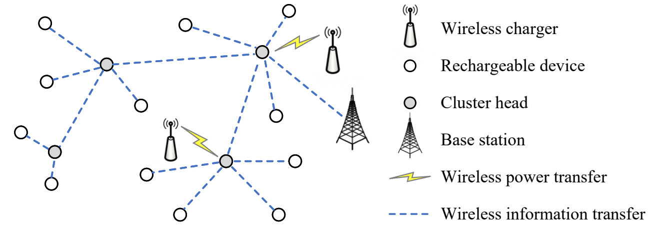


Fig. 13. Illustration of a non-radiative charger deployment scheme in a clustered network.

Consequently, the non-radiative charger deployment primarily focuses on efficiently allocating chargers to charge fixed or mobile devices, as well as improving charging performance through the multi-hop charging feature [15], [59], [60], [94], [95], [156]–[160]. Fig. 13 illustrates an example of a non-radiative charger deployment scheme in a clustered network, where devices are organized into clusters and communicate with a BS through designated Cluster Heads (CHs). Non-radiative chargers are strategically deployed near CHs with high energy consumption to wirelessly charge them. Moreover, Table VI summarizes and compares various non-radiative charger deployment schemes.

1) Single-hop Charging: several studies [15], [59], [94], [95], [156]–[158] investigate single-hop charging, where non-radiative chargers are deployed to provide efficient one-to-one energy transfer to devices.

Some research [59], [156], [157] focuses on deploying non-radiative chargers for stationary devices. He *et al.* [156] aimed to increase the network's maximum flow rate by strategically placing a limited number of chargers near bottleneck devices. They formulated the problem as a Mixed Integer Linear Programming (MILP) model, solving it optimally for small-scale networks and using heuristic algorithms for larger ones. In their subsequent work [157], they designed a meta-heuristic to search for a neighboring solution that yields a higher max flow rate. Moghadam *et al*. [59] investigated the joint optimization of magnetic charger locations to maximize the minimum harvested power of devices. They presented an adaptive magnetic

TABLE VI
COMPARISON OF NON-RADIATIVE CHARGER DEPLOYMENT SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Charging types	Approaches	Performance metrics	EVM
Non-radiative Charger Deployment	[156], [157]	Maximum flow rate	Flow conservation constraints; charger capacity constraints; link capacity constraints; charger quantity constraint	Static	Single-hop	Exact; heuristic; metaheuristic	Max flow	NS
	[59]	Maximum minimum received power	Power budget constraint	Static	Single-hop	Heuristic	Receive power	TA
	[15]	Maximum charging satisfaction	Charger quantity constraint	Mobile	Single-hop	Approximation; heuristic	Residual lifetime distribution; charging satisfaction	TA; NS
	[158]	Minimum number of chargers	Energy provision constraints	Mobile	Single-hop	Heuristic	Number of chargers; network lifetime	NS
	[94]	Minimum delivery time	Energy provision constraints; UAV capacity constraint	Mobile	Single-hop	Heuristic	Coverage rate	NS
	[95]	Minimum number of chargers	Coverage constraints	Mobile	Single-hop	Heuristic	Number of chargers	NS
	[159]	Minimum number of chargers	Energy provision constraints	Static	Multi-hop	Exact	Number of chargers	NS
	[60], [160]	Minimum deployment cost	Energy provision constraints; charger capacity constraint	Static	Multi-hop	Approximation; heuristic	Number of chargers; energy consumption; deployment cost; running time	TA; NS

beamforming approach and developed an iterative algorithm for solving the problem approximately. The iterative algorithm leverages the symmetry principle, strategically placing chargers symmetrically over the midpoint of the target line.

The deployment of non-radiative chargers for mobile devices (especially UAVs) is investigated in [15], [94], [95], [158]. Xu *et al*. [15] focused on the optimal allocation of non-radiative chargers for mobile devices, such that overall charging satisfaction is maximized. For known and unknown motion trajectories of mobile devices, they presented an approximate algorithm and a heuristic algorithm to solve them, respectively. The optimization of non-radiative charger deployment for UAVs is investigated in [158]. To minimize the number of chargers required to create at least one viable routing path for each BS within a specified network, four heuristic algorithms are proposed to solve the optimization problem. Arafat *et al*. [94] explored the joint optimization of charger deployment, flight segmentation, and route planning for UAV delivery, aiming to maximize the number of customers delivered within the shortest possible time. Famili *et al*. [95] explored a charger deployment scheme to ensure the continuous flight of UAVs. They proposed a solution based on evolutionary algorithms to minimize the number of chargers.

2) Multi-hop Charging: in multi-hop charging, non-radiative chargers transmit power to remote devices using magnetic resonance. The deployment of non-radiative chargers in this scenario is studied in [60], [159], [160].

Rault *et al*. [159] investigated the optimization of charger deployment to minimize the number of chargers required for energy supply in multi-hop scenarios. To achieve this, they obtained different disjoint charging trees, so that a charger located at a root can recharge all the nodes of the charging tree. Wu *et al*. [60] explored the deployment cost optimization problem for multi-hop chargers. To minimize deployment cost under charger capacity constraints, they presented a $(\ln n + 1)$-approximation algorithm, where n is the number of rechargeable devices. Moreover, they presented a cost sharing mechanism to balance the cost budget, and conflict avoidance schemes to schedule charging tasks. Furthermore, Wu *et al*. [160] decomposed the deployment cost optimization problem into two sub-problems, solving them with a greedy algorithm and a $(1/2)$-approximation algorithm.

D. Heterogeneous Charger Deployment

In addition to homogeneous WCNs, researchers have explored the deployment of heterogeneous WCNs [61], [161], [162]. A heterogeneous WCN typically includes at least two different types of wireless chargers, including a variety of dedicated chargers as well as BSs with WPT technology. This diversity in charger types introduces new challenges to their deployment. Table VII summarizes and compares various heterogeneous charger deployment schemes.

Erol *et al*. [161] investigated a heterogeneous WCN, wherein a mix of macro and small cell BSs are available and power can be scavenged from the already existing small cell base stations in addition to the dedicated chargers. They proposed Integer Linear Programming (ILP) models that select active BSs and chargers, such that the received energy is maximized while the numbers of BSs and chargers are maximized. They employed state-of-the-art ILP solvers, such as CPLEX [163], for an efficient solution. Lin *et al*. [162] studied the deployment of a mix of directional and omni-directional chargers, assuming both have the same charging efficiency but different ranges. The optimization objective is to deploy a minimum number of two chargers on a continuous 2D plane so that all devices are covered and the charging power is maximized. Given the infinite potential locations for deployment, they discretized the continuous plane based on charging power to simplify the search for optimal locations Subsequently, they proposed an exhaustive search for minimal dominating sets, which are sets of chargers that collectively guarantee coverage. Finally, they leveraged a greedy algorithm to identify the optimal charger deployments.

Wang *et al*. [61] addressed the problem of heterogeneous charger deployment in WCNs with obstacles. They assumed that the charging power could not penetrate these obstacles, nor could it be reflected from the surface of the obstacles, which means the determination of the location and direction of the heterogeneous charger needs to take into account the location, size, and shape of the obstacles. To address this, they used multi-feasible geometric area discretization and a practical dominating coverage set extraction algorithm to reduce the infinite solution space to a finite one. They then formulated the optimization as a submodular function maximization problem, subject to a partition matroid constraint, which can be solved using an approximation algorithm.

In summary, charger deployment schemes are crucial in determining the charging efficiency and coverage of WCNs. By flexibly deploying omnidirectional, directional, non-radiative, and heterogeneous chargers to meet various charging needs, a solid physical foundation is established for constructing effective and efficient WCNs.

TABLE VII
COMPARISON OF HETEROGENEOUS CHARGER DEPLOYMENT SCHEMES
('HCD': HETEROGENEOUS CHARGER DEPLOYMENT; 'EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
HCD	[161]	O1: Maximum received power O2: Minimum number of chargers	Energy provision constraints; charging area restrictions	Static	Exact	Number of chargers; received power	NS
	[162]	O1: Maximum charging power O2: Minimum number of chargers	Full coverage constraints	Static	Heuristic	Charging power	NS
	[61]	Maximum charging utility	Charger location constraints; charger direction constraints	Static	Approximation	Charging utility	TA; NS; FE

V. Charging Scheduling Schemes

Once charger deployment is determined, the next critical step is efficiently scheduling charger resources to enhance charging services. This process relies on four key factors: power control, time allocation, energy beamforming, and multi-resource optimization, which collectively manage the power, time, and spatial resources of wireless chargers. Power control adjusts charging power dynamically based on device needs and environmental factors, ensuring efficient energy transfer without overcharging or underutilizing resources (Sec. V.A). Time allocation manages the charging duration for each device, promoting fairness and timely charging (Sec. V.B). Energy beamforming enhances efficiency by accurately directing electromagnetic energy toward target devices (Sec. V.C). Finally, multi-resource optimization synchronizes power, time, and spatial energy distribution, ensuring efficient resource utilization, minimizing conflicts, and maximizing network performance (Sec. V.D).

A. Power Control

Generally, the power control scheme in WCNs refers to the strategic control of charging power that wireless chargers deliver to multiple devices [62]–[66], [164]–[182]. This scheme aims to manage and optimize charging power to various devices based on their individual requirements, charging states, and prioritization, ensuring effective energy transfer while maintaining overall system performance and efficiency. The wireless charger can either be a dedicated charger or a multifunctional charger. The latter, such as BSs, CHs, and Hybrid Access Points (HAPs), are capable of transmitting both information and power. The power control scheme for dedicated chargers emphasizes optimizing charging performance by adjusting the received energy of devices or the charging area of chargers (as depicted in Fig. 14) [62]–[65], [165]–[176]. In contrast, the power control scheme for multifunctional chargers must simultaneously optimize wireless information and power transfer [66], [177]–[182]. Table VIII summarizes various power control schemes.

1) Charging Performance Optimization: some papers [62], [63], [164], [165] explore methods to control charging power in order to provide efficient charging services to both stationary and mobile devices. These methods focus on optimizing charging performance by adjusting power according to device needs, locations, and movement trajectories.

Zhang *et al*. [62] developed an approximation algorithm to control charging power in a pre-determined charger deployment, while later work [63] expanded the problem by considering mobile device scenarios and flexible charger locations. Niyato *et al*. [164] investigated a competitive charging scenario. To maximize charging utility, they proposed a non-cooperative game to analyze the competitive bidding of charging power by devices, and considered the Nash equilibrium as a solution. Yu *et al*. [165] designed a novel attack scheme under charger capture attack, that is, an intelligent adversary captures a limited number of chargers and adjusts the charging power of chargers to maximize attack utility. To achieve this, they proposed an attacking algorithm with a constant approximation ratio and lightweight timing complexity.

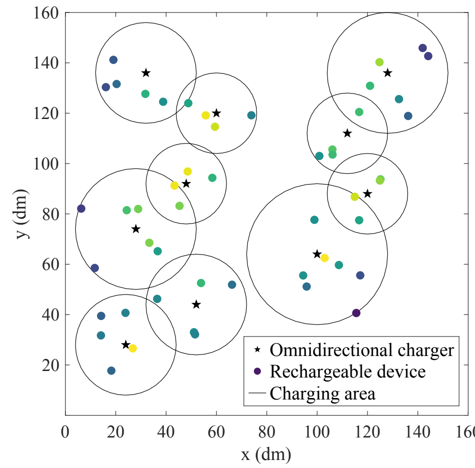


Fig. 14. Illustration of a power control scheme: adjusting the radius of omnidirectional chargers.

The charging power control scheme for mobile devices is studied in [166], [167]. Madhja *et al*. [166] considered a mobile ad hoc network consisting of mobile devices and a single static charger with limited energy. Utilizing real-time data on the mobility and energy consumption patterns of mobile devices, they studied the dynamically adjustment charging power, which directly influences the charging area. The aim is to efficiently compute the appropriate range of the charger with the goal of prolonging the network lifetime. Wu *et al*. [167] studied tunable charger scheduling for mobile devices, aiming to optimize overall charging utility. By approximating the charging power as piecewise constant power, they partitioned the moving trajectory of devices. Then, they proposed a $\frac{1-1/e}{2}$-approximation algorithm for scheduling charging on/off at a fixed power level and a $\frac{1-1/e}{2(1+\epsilon)T}$-approximation algorithm for scheduling charging with tunable power levels, where T is the maximum power level.

2) EMR Safety Considerations: certain power control schemes [64], [65], [168]–[176] aim to improve charging performance while adhering to EMR exposure limits, which are crucial for protecting human health.

Dai *et al*. [168], [169] explored how to adjust charger power to maximize charging utility while adhering to EMR safety constraints, transforming the problem into a Linear Programming (LP) model and developing distributed algorithms to achieve approximation ratios. In their subsequent research [170], [171], they explored EMR jitter, which may lead to exceeding the threshold even when the expected EMR remains below it. The problem of robustly safe charging considering EMR jitter is studied. This involves strategically scheduling charger power to maximize charging utility for all rechargeable devices while ensuring that the probability of EMR exceeding the threshold is no less than the given confidence. In addition, Li *et al*. [172], [173] focused on the fairness of charging. Specifically, their work centers on the radiation-constrained fair charging problem, where the objective is to maximize the minimum charging utility. This is accomplished through adjustments to the power of wireless chargers while ensuring EMR safety. Ma *et al*. [174] explored a more accurate EMR computing model and studied the problem of maximizing charging power while ensuring EMR safety. This problem

TABLE VIII
COMPARISON OF POWER CONTROL SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Power Control	[31]	Minimum number of chargers	Energy provision constraints	Static; mobile	Approximation	Approximation ratio; average consumption power	TA; NS
	[62], [63]	Maximum charging quality	Power budget constraints	Static	Approximation	Charging quality; average running time	TA; NS
	[164]	Maximum charging utility	Energy provision constraints	Static	Heuristic	Strategy probabilities	NS
	[165]	Maximum attacking utility	Energy provision constraints	Static	Approximation	Attacking utility	TA; NS
	[166]	O1: Maximum coverage quality O2: Maximum network lifetime	Power budget constraint	Mobile	Heuristic	Survival quantity	NS
	[167]	Maximum charging utility	Power budget constraint	Mobile	Approximation	Charging utility	TA; NS; FE
	[168]–[171]	Maximum charging utility	EMR intensity constraints	Static	Approximation	Charging utility	TA; NS; FE
	[172], [173]	Maximum minimum charging utility	EMR intensity constraints	Static	Approximation	Minimum charging utility; communication cost	TA; NS; FE
	[174]	Maximum harvested power	EMR intensity constraints	Static	Exact	harvested power	NS
	[64], [65]	Maximum charging efficiency	EMR intensity constraints	Static	Heuristic	Charging efficiency; maximum radiation; energy balance	NS
	[175]	Minimum radiation degree	Energy provision constraints; power budget constraints	Mobile	Approximation	Radiation degree; communication interval	NS
	[176]	Optimizing trade-off between EMR and charging efficiency	Energy provision constraints	Mobile	Heuristic	EMR; charging efficiency	TA
	[66]	Maximum energy efficiency	Energy provision constraints; power budget constraints minimum data rate requirement	Static	Heuristic	Energy efficiency; average harvested energy	NS
	[177]	O1: Minimum transmission power O2: Maximum charging ratio	Energy provision constraints	Static	Heuristic	Transmission power; charging ratio	NS
	[178]	Maximum minimum transmission rate	Power budget constraints	Static	Exact	Average scheduling rates; residual power	NS
	[179]	Maximum network throughput	Outage constraints	Static	Exact	Transmission probability; outage probability	TA; NS
	[180]	Maximum rate coverage	Energy provision constraints	Mobile	Exact	Rate coverage	TA; NS
	[181]	Maximum charging efficiency	Energy provision constraints	Static	Exact	Average harvested power; charging efficiency	TA; NS
	[182]	Maximum sensing rate	Power budget constraints	Static	Exact	Network sensing rate	TA; NS

is an LP problem with infinite constraints. To convert the problem into a typical LP problem with finite constraints, they introduced a sampling safety charging algorithm.

Some papers [64], [65], [175], [176] modify the charging area by controlling the charging power to ensure EMR safety. Nikoletseas *et al*. [64], [65] investigated a low radiation efficient charging problem, which aims to optimize the amount of energy transferred while limiting radiation levels. They proposed a charging model that takes into account the hardware constraints of chargers and devices, as well as non-linear constraints in the time domain. An iterative local improvement heuristic is proposed to solve the problem. They also introduced a relaxation of the problem and provided an integer program for finding the optimal solution. Zhu *et al*. [175] proposed a real-time power control scheme to minimize the maximal radiation degree among mobile devices while maintaining the normal operation of devices. They first discretized the users' moving trajectories and transformed the real-time problem into a tractable one. Then, they proposed an efficient distributed algorithm with an approximation ratio $(1+\epsilon)$ to solve the transformed problem. Filios *et al*. [176] used a vector model to accurately represent the degree of radiation. To optimize the trade-off between the radiation levels and the power transfer efficiency, they presented heuristic algorithms to efficiently control EMR in WCNs.

3) Multifunctional Charger Power Control: in addition to dedicated chargers, several papers delve into power control schemes for multifunctional chargers that transmit both power and information [66], [177]–[182]. These schemes require coordination of both functions to ensure efficient operation.

Guo *et al*. [66] considered cooperative clustered WCNs, where CHs serve as both power and information transmitters, and can communicate directly with each other or facilitate one- or multi-hop communication via relaying. To maximize energy efficiency, they proposed a distributed iterative algorithm for power allocation, power segmentation, and relay selection by exploiting fractional programming and dual decomposition. Multi-hop wireless charging is explored in [177]. The study focuses on the multi-hop power flow problem, introducing heuristic algorithms to determine optimal configurations for power flow and the joint data and power flows. Roh *et al*. [178] addressed a fair charging problem, which seeks to balance available power among devices at varying distances from chargers. They transformed this problem into an equivalent LP problem, employing an LP solver to achieve joint routing, MAC, and power control.

Some papers study the power control schemes in some special network scenarios [179]–[182]. Building upon cognitive radio networks, Lee *et al*. [179] proposed a method for wireless network coexistence where secondary chargers harvest

TABLE IX
COMPARISON OF TIME ALLOCATION SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Time Allocation	[15]	Maximum charging satisfaction	Charger quantity constraint	Mobile	Approximation; heuristic	Residual lifetime distribution; charging satisfaction	TA; NS
	[183]	Maximum operator profit	Charger capacity constraint; energy provision constraints	Mobile	Heuristic	Charging rate; operator profit; average queue backlog	NS
	[149], [150]	O1:Maximum charging efficiency O2: Maximum energy balance	Charger capacity constraint	Mobile	Heuristic	Charging efficiency; energy balance; lifetime of the chargers	NS
	[67], [68]	Maximum task utility	Charger direction constraints	Static	Approximation	Charging utility	TA; NS; FE
	[155]	Minimum energy consumption	Energy provision constraints	Static	Heuristic; metaheuristic	Energy consumption	TA; NS
	[184]	Minimum charging periods	Energy provision constraints	Static	Approximation	Number of fully charged devices; harvested energy; charging periods	TA; NS
	[185]	Maximum charging efficiency	Coverage constraints; power budget constraints	Static	Heuristic	Number of fully charged devices; harvested energy; charging efficiency; charging periods	NS
	[69]	Maximum network throughput	Total time constraint	Static	Exact	Total throughput	TA; NS
	[186]	Maximum coverage probability	Energy provision constraints; minimum SINR requirement	Static	Exact	Uplink/downlink coverage probability	TA; NS
	[187]	Maximum network throughput	Device distribution constraints	Static	Exact	Coverage probability; average network throughput	TA; NS
	[188], [189]	Maximum network lifetime	Energy provision constraints	Static	Heuristic	Average network lifetime	NS

energy as well as reuse the spectrum of primary chargers. To avoid interference, each primary charger is associated with a guard zone, and at the same time rechargers to secondary chargers secondary chargers located within its harvesting zone. Based on this, they developed a model to determine the transmission probability of a secondary transmitter, and characterized the maximum throughput of the secondary network under specified outage constraints for both primary and secondary devices. In addition, Kim *et al*. [180] introduced a spatial attraction cellular network consisting of macro cells overlaid with small cell BSs equipped with beamforming antennas for wireless charging. In this network, mobile devices with depleting batteries actively move toward the proximity of BSs for recharging. Through meticulous adjustment of the charging power, this spatial attraction not only enhances spectral efficiency but also load balancing. They employed a stochastic geometric approach to derive the optimal charging power in a closed-form expression.

Power control schemes in massive antenna systems are explored in [181], [182]. Khan *et al*. [181] studied a massive Multiple-Input Multiple-Output (MIMO) system consisting of a BS with multiple antennas and single-antenna users. The BS transmits energy to users on the downlink and the users exploit the received energy to transmit information with the BS on the uplink. They studied power transfer efficiency and energy efficiency. Using a piecewise linear energy collection model, they derived the average harvested power. For wireless energy transfer, they characterized the optimal number of BS antennas and devices to maximize the efficiency of energy transmission. Additionally, for wireless power and information transmission, they analyzed and determined the optimal BS transmit power for an energy-efficient system. Du *et al*. [182] focused on energy beamforming in a massive MIMO system. They investigated the optimal power allocation for channel estimation and energy transmission to each device that maintains a required monitoring performance throughout the network.

B. Time Allocation

In WCNs, the coordination and organization of charging activities in the time domain are crucial to ensure optimal energy transfer and network performance. Time allocation schemes typically involve allocating charging duration, scheduling energy transmission, and coordinating energy and information transfer. The goal is to maximize the charging efficiency, minimize interference, and guarantee the energy supply, among other things [15], [67], [68], [149], [150], [155], [183]–[191]. Table IX summarizes different time allocation schemes.

1) Charging Performance Optimization: given their flexibility and the necessity for effective scheduling in the time domain, charging time allocation problems frequently emerge in research involving mobile devices and directional chargers [15], [67], [68], [149], [150], [155], [183].

Xu *et al*. [15] studied the charging time allocation for mobile devices. To optimize the charging satisfaction of mobile devices, they introduced an approximate algorithm for the case where the travel trajectory of each mobile device is given. For dynamic charging requests, they proposed an online algorithm. Moreover, they proposed a non-trivial distributed scheduling algorithm for unknown global knowledge of device energy information. Lyu *et al*. [183] proposed a charging time scheme for UAVs based on Lyapunov optimization. This scheme not only improves operator revenue but also prevents congestion at wireless chargers. Nikoletseas *et al*. [149], [150] explored the scenario of using directional chargers to charge mobile devices. Directional chargers are fixed in the network, and the problem is how to determine which directional chargers should be activated during each charging cycle to maximize charging efficiency and balance the residual energy of the chargers. Dai *et al*. [67], [68] investigated a direction scheduling problem for charging tasks, where directional chargers are capable of rotation. To maximize the utility of the task, they proposed both a centralized offline algorithm and a distributed online algorithm to schedule the direction of all chargers over time.

Jia *et al*. [155] studied a similar direction scheduling problem. Leveraging the anisotropic energy receiving property of directional charging, they focused on minimizing the energy consumption of directional chargers.

2) Wave Interference Effect: wave interference between wireless chargers requires scheduling tasks to minimize conflicts or leveraging interference to enhance charging performance [184], [185], [190], [191].

Since nonlinear superimposed charging effects are caused by wave interference, the charging utility of each charger cannot be calculated independently, Guo *et al*. [184] established a concurrent charging model and focused on a concurrent charging scheduling problem to quickly fill all sensor nodes in the shortest possible time. They proposed two efficient greedy algorithms and gave an approximate ratio of one of them. The charging time scheduling problem impacted by interference is also considered in [190], [191], that is, how to optimize the scheduling of chargers in the time domain, so as to minimize the total charging time while ensuring energy supply. The research builds a nonlinear superposition model, exploring both one- and two-dimensional scenarios. Liu *et al*. [185] used a vector model to represent cumulative power influenced by wave interference. To enhance charging efficiency, they proposed a two-step algorithm. First, they introduced a charging threshold model with an effective schedule. Then, they proposed a multi-charger joint accumulative charging scheme for devices that were not yet fully charged.

3) Multifunctional Charger Time Allocation: in WCNs with multifunctional chargers, time is divided into slots, with some designated for wireless power transmission and others for information transmission or additional functions. Efficient time allocation between these functions is crucial for optimizing network performance [69], [186]–[189].

Some papers [69], [186], [187] explore the coordination of energy and information transfer to maximize network throughput. Ju *et al*. [69] considered a WCN where a BS coordinates wireless energy/information transmissions to/from a set of distributed devices. To maximize network throughput, they jointly optimized the time allocated to power transmission and data transmission given a total time constraint. Kishk *et al*. [186] considered a cellular-based WCN. Each time slot is assumed to be partitioned into charging, downlink, and uplink sub-slots. Within each time slot, devices first harvest energy from BSs and then use this energy to perform downlink and uplink communication in subsequent sub-slots. For this setup, they derived a combined probability that the device will obtain sufficient energy in the charging sub-slots and obtain a sufficiently high Signal-to-Interference-Noise Ratio (SINR) in the following two sub-slots. The optimal slot partitioning that maximizes throughput is also studied. The study [187] analyzes a large-scale WCN. Considering the inefficiency of wireless charging, the spatial distribution of devices is modeled as a Cluster Point Process (CPP). The study introduces truncated Matern CPP and Thomas CPP, considering the practical transmission range. The performances of coverage probability and average received SINR are derived. Through pseudo-convexity optimization, the time allocation for energy and information transmission is optimized.

Some works [188], [189] delve into the coordination of energy and information transfer with the goal of extending the network lifetime. Du *et al*. [188] explored the problem of scheduling the transmission of energy beams in the time domain. They explored critical factors such as energy transfer efficiency and packet generation rates necessary to achieve sustained network immortality. For larger network sizes or packet generation rates, they further studied the lifetime maximization problem and proposed a solution algorithm. To make the WCN immortal, in their subsequent work [189], they tried to alleviate the problem of insufficient power supply by deploying redundant devices, which not only increases the total harvested energy, but also reduces the energy consumption of devices.

C. Energy Beamforming

In WCNs, energy beamforming significantly enhances the charging power transferred to devices [10], [33], [59], [70], [192]–[201]. The energy beamforming schemes in WCNs are mainly categorized into two types: distributed and centralized beamforming schemes. Distributed beamforming schemes control the phase and relative amplitude of signals transmitted by multiple chargers distributed in the network [10], [59], [70], [192]–[194]. Centralized beamforming schemes control the phase and relative amplitude of signals transmitted by multiple antennas of a single charger [33], [195]–[201]. As shown in Fig. 15, the centralized beamforming scheme allows the control of multiple transmitted signals from a transmitter to efficiently transmit energy to specified receivers. Table X provides a summary of energy beamforming schemes.

1) Distributed Beamforming: distributed beamforming schemes coordinate the transmit antennas of multiple chargers [10], [70], [192], [193] to ensure that electromagnetic waves emitted by the antennas reach the receiver in phase, enabling coherent superposition to maximize charging efficiency. This process is achieved by adjusting the phase and amplitude of the signal of transmit antennas.

Fan *et al*. [70] designed a distributed beamforming scheme that concentrates energy around a target while minimizing energy density in surrounding areas. They achieved this by arranging a set of distributed chargers around the device and coherently combining their phases. In their follow-up study [10], they introduced a flexible far-field charging system to satisfy the continuous energy supply of medical implants. Leveraging a distributed beamforming scheme, energy can be precisely focused on medical implants inside the human body, with no energy dispersed elsewhere, ensuring the safety of the human body. In [192], the study investigates distributed WPT with or without frequency and phase synchronization.

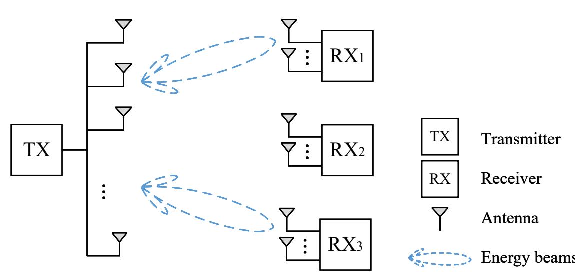


Fig. 15. Illustration of an energy beamforming scheme.

TABLE X
COMPARISON OF ENERGY BEAMFORMING SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	CSI	Performance metrics	EVM
Energy Beamforming	[70], [10]	Maximum receive power	EMR intensity constraints	Mobile	Adaptive Beamforming	N.A.	Receive power	NS; FE
	[192]	Maximum receive power	Energy provision constraints	Static	Adaptive Beamforming	Perfect	Receive power	NS; FE
	[193]	Maximum receive power	Phase constraint	Static	Heuristic	N.A.	Receive power	NS
	[59]	Maximum receive power	Power budget constraint	Static	Adaptive Beamforming	N.A.	Receive power	TA
	[194]	Minimum transmit power	Power provision constraints	Static	Exact; approximation	Imperfect	Outage probabilitiy; power efficiency	TA; NS
	[33]	Maximum receive power	Average power constraint	Static	Exact	N.A.	Rate-energy region	TA; NS
	[195]	Maximum receive power	Individual SINR constraints; power budget constraint	Static	Approximation	Perfect	Average harvested power; running time	TA; NS
	[196]	Maximum charging efficiency	Energy provision constraints	Static	Zero-forcing beamforming	Perfect	Charging efficiency	NS
	[197]	Minimum transmit power	Energy provision constraints; power budget constraint	Static	Exact Approximation	Perfect	Transmit power	TA; NS
	[198]	Maximum receive power	Individual SINR constraints	Static	Zero-forcing beamformingt	Perfect/ imperfect	Receive power; SINR	NS
	[199]	Maximum receive power	Power budget constraint	Static	Asymptotically optimal	Imperfect	Receive power	TA; NS
	[200]	Minimum transmit power	Individual SINR constraints; energy provision constraints	Mobile	Approximation	Imperfect	Average harvested power; running time	TA; NS
	[201]	Maximum average receive power	Energy provision constraints; power budget constraint	Static	Approximation	Imperfect	Average receive power	TA; NS

Three beamforming schemes, namely optimal, static, and random, are analyzed in terms of receiving power and coverage probability. Additionally, Katsidimas *et al*. [193] explored a distributed beamforming scheme to maximize charging power. They used a vector model to represent the superposition of electromagnetic waves radiated by multiple chargers. By adjusting the phases among multiple chargers, constructive interference is formed at devices to maximize charging power.

For non-radiative WPT, distributed beamforming ensures that magnetic fields from multiple chargers constructively combine at the receiving device, enhancing magnetic beamforming gain. This process is done by adjusting the current (or equivalent source voltage) of the transmission coils. Moghadam *et al*. [59] investigated magnetic beamforming in a Multiple-Input Single-Output (MISO) WCN, in which a BS is equipped with multiple antennas, and each device is equipped with a single antenna. To maximize the harvested power subject to power budget constraints, they proposed an optimal magnetic beamforming solution in closed form, which involves jointly assigning currents at different chargers. Zhang *et al*. [194] explored a robust magnetic beamforming solution, to minimize transmit power while ensuring an adequate energy supply to devices. For a single device, they used Semidefinite Relaxation (SDR) to achieve optimal beamforming. For multiple devices, they obtained an approximately optimal solution by combining SDR with randomization techniques.

2) Centralized Beamforming: these schemes centrally control the phases and amplitudes of signals from a charger's multiple antennas, forming sharp beams aimed at specific devices to maximize charging efficiency [33], [195]–[201].

Zhang *et al*. [33] investigated a MIMO wireless broadcast system where a multi-antenna BS simultaneously transmits information and energy to a pair of energy and information receivers. They developed optimal energy beamforming designs for scenarios where the information and energy receivers are either separate or co-located, aiming to balance information and energy transmission. A multiuser MISO broadcast system is explored in [195]. The joint information and energy transmission beamforming problem is formulated to a non-convex quadratically constrained quadratic program, and the optimal solution is obtained by applying a semidefinite relaxation technique. Sheng *et al*. [196] studied energy-efficient beamforming in MISO heterogeneous cellular networks. They devised two beamformers, which are zero-forcing and mixed beamforming, and proposed an efficient algorithm to obtain the optimal power under both beamformers. López *et al*. [197] leveraged energy beamforming for powering multiple devices in an indoor distributed massive MIMO system. Employing techniques such as semi-definite programming, successive convex approximation, and maximum ratio transmission, they derived optimal and suboptimal precoders to minimize transmit power while satisfying energy and power constraints.

3) Beamforming under Imperfect CSI: accurate Channel State Information (CSI) measurement is crucial for energy beamforming, as it directly influences the precision of beamforming vectors and overall transmission performance. However, achieving perfect CSI is challenging due to estimation and quantization errors. Several studies address beamforming under imperfect CSI conditions [198]–[201].

Son *et al*. [198] proposed a joint beamforming algorithm for multiuser MIMO systems that maximizes total harvested energy while satisfying SINR constraints. When the beamforming vector serves both data collection and energy transfer devices, harvested energy increases at the cost of SINR loss for the data collection device. The sum rate and harvested energy are analyzed under both perfect and imperfect CSI

TABLE XI
COMPARISON OF MULTI-RESOURCE SCHEDULING SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Multi-resource Scheduling	[71]	Maximum charging satisfaction	Charger quantity constraint	Mobile	Approximation; heuristic	Residual lifetime distribution; charging satisfaction	TA; NS
	[199]	Maximum minimum uplink rate	Power budget constraint	Static	Asymptotically optimal	Maximum minimum uplink rate	TA; NS
	[202]	Maximum uplink rate	Downlink rate constraint	Static	Exact	Uplink rate	TA; NS
	[203]	Maximum network throughput	Time duration constraint	Static	Heuristic	Network throughput	NS
	[204]	Maximum charging efficiency	Energy provision constraints; time duration constraint; power budget constraint	Static	Exact	Charging efficiency; network throughput	TA; NS
	[205]	Minimum transmit power	Task constraints	Mobile	Exact	Average minimum transmit energy and power	TA; NS
	[206]	Minimum energy consumption	Latency constraints; energy provision constraints	Static	Exact	Average energy consumption	TA; NS
	[207]	Maximum energy effciency	Energy consumption constraint	Mobile	Metaheuristic	Energy effciency; received energy	TA; NS
	[208]	O1: Minimum energy consumption O2: Maximum received energy	Power budget constraint; latency constraints	Static	Exact	Received energy	TA; NS
	[209]	Minimum energy consumption	Power budget constraint; latency constraints	Static	Exact	Received energy	TA; NS

conditions. Yang *et al*. [199] explored large-scale MIMO systems with imperfect CSI, employing time division duplexing to separate information and energy transmission, and proposed an asymptotically optimal beamforming scheme to maximize energy gain. Zhu *et al*. [200] designed simultaneous robust information and energy beamforming for a multiuser massive MIMO system. The objective is to minimize the transmit power of the BS subject to individual SINR and the energy provision constraints under imperfect CSI. Lastly, López *et al*. [201] introduced a low-complexity beamforming scheme for a multi-antenna BS to wirelessly power single-antenna devices, relying only on average CSI, *i.e.,* first-order channel statistics of the channel.

D. Multi-resource Scheduling

In WCNs, effective scheduling of individual resources is crucial, but equally important is the concurrent scheduling of multiple resources. This entails strategically scheduling and coordinating various resources, including charging power, charging time, and energy beamforming, to enhance network performance and charging efficiency [71], [199], [202]–[209]. Table XI compares various multi-resource scheduling schemes.

Some papers explore multi-resource scheduling in massive MIMO systems [71], [199], [202]–[204]. In [71], wireless information and power transmission in massive MIMO systems are considered. Subject to a delay constraint, a resource allocation scheme is proposed to jointly optimize charging time and transmission power. In [199], a WPT-enabled massive MIMO system is studied. To optimize network throughput and achieve device fairness, the study maximizes the minimum rate for all users, by optimizing channel estimation time, charging time, energy-splitting fraction, and energy allocation vector. Gong *et al*. [202] explored the optimal design of a partially WCN, where some devices are wirelessly powered. The network operates in two phases: during the downlink phase, the BS simultaneously transfers power and information to devices; in the uplink phase, devices transmit sensing data back to the BS. To maximize the uplink sum rate while meeting the downlink rate constraint, the study jointly optimizes downlink beamforming, uplink beamforming, and time allocation.

To improve charging efficiency, an Intelligent Reflecting Surface (IRS) is employed in massive MIMO systems [203], [204]. Zhang *et al*. [203] explored an IRS-assisted WCN. The IRS panel consists of low-cost, adaptable elements capable of intelligently reflecting transmitted signals through phase shift adjustments, thereby significantly enhancing charging efficiency. In such a network, a BS transmits power to multiple clustered devices, and these devices transmit information back to the BS in the uplink. To maximize network throughput, they studied optimizing the reflect beamforming by the IRS and time allocation for the power transfer and information transmission from different device clusters. Furthermore, Zargari *et al*. [204] leveraged the capabilities of the RIS to maximize energy efficiency. They proposed a joint optimization of charging time and transmission power, backscattering coefficients, local computing frequencies, execution times, and RIS phase shifts.

Several studies address multi-resource scheduling in WCNs combined with Mobile Edge Computing (MEC) [205]–[209]. The paper [205] discusses an MEC system where a BS acts as an energy source and assists two mobile devices with their computation-intensive, latency-critical tasks. The objective is to minimize the total transmit energy of the BS through jointly optimal power and time allocation. The optimization problem is equivalent to a min-max problem and can be solved using a two-phase method. Wang *et al*. [206] developed a multiuser MEC-WPT design framework with joint energy beamforming, offloading, and computing optimization. To minimize the total energy consumption subject to users' individual computation latency constraints, they obtained an optimal solution in a semi-closed form by leveraging the Lagrange duality method. The study in [207] explores the mobility of mobile devices, employing a random motion model to describe their movement and an integral expression for the charging model. To optimize energy efficiency, they employed a quantum-behaved particle swarm optimization algorithm, determining optimal subcarrier and power allocation schemes. Malik *et al*. [208] studied

TABLE XII
COMPARISON OF MAC PROTOCOL SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Protocol types	Performance metrics	EVM
MAC Protocol	[72], [73]	Maximum receive power	Frequency constraint	CSMA/CA	Receive power; network throughput	TA; NS; FE
	[210]	Maximum throughput and energy efficiency	Collision probability	CSMA/CA	Network throughput; energy efficiency	TA; NS
	[211]	Maximum network throughput	SNR constraints	Slotted ALOHA	Network throughput; optimal number of random access slots	TA; NS
	[212]	Trade-off delivery probability and time efficiency	SIR constraints	TDMA	Asymptotic delivery probability; asymptotic time efficiency	TA; NS
	[69]	Maximum network throughput	Individual throughput constraints	TDMA	Network throughput	TA; NS
	[213]	Maximum network throughput	Time constraint	TDMA; CSMA	Network throughput; total harvested energy	TA; NS
	[214]	Maximum network throughput	Harvested energy and time constraints	TDMA	Network throughput; packet reception rate; average transmission frequency	TA; NS

a multi-access edge computing system with a BS equipped with a massive MIMO antenna array. They aimed to minimize energy consumption for computation offloading while maximizing the received energy from wireless charging. The proposed solution involves data partitioning, time allocation, and optimal energy beamforming. A similar system configuration is explored in [209], where an efficient nested algorithm is designed to minimize energy consumption under charging power and latency constraints by dividing the problem into convex subproblems, addressing data partitioning, time allocation, power control, and energy beamforming.

By focusing on power control, time allocation, energy beamforming, and multi-resource optimization, we can dynamically manage the limited resources of wireless chargers. This approach ensures efficient energy transfer, promotes fairness, and maximizes network performance, striving to enhance the efficient operation of WCNs.

VI. COMMUNICATION OPTIMIZATION SCHEMES

As WPT integrates into existing wireless networks, optimizing key protocols and mechanisms is essential for ensuring normal operation and sustained energy supply. Enhancements to the MAC protocol, routing protocol, broadcast transmission, and data collection are critical for coordinating wireless power and data transmission. MAC protocol optimization is crucial for managing energy and data reception, minimizing interference during simultaneous transmissions (Sec. VI.A). Efficient routing protocols must prioritize paths that balance energy consumption and data transmission, ensuring network sustainability (Sec. VI.B). Broadcast transmission must be refined to accommodate additional energy supply, ensuring synchronization between power transfer and communication (Sec. VI.C). Finally, data collection processes must be optimized for real-time monitoring of energy usage and network performance, enabling dynamic adjustments that enhance efficiency and reliability (Sec. VI.D).

A. MAC Protocol

In WCNs, the MAC protocol not only controls access among devices to the shared wireless medium, but also coordinates the power transmission process and communication process [69], [72], [73], [210], [212]–[215]. The challenge lies in the diversity of the charging processes among devices, attributed to factors like charger types and charging distances. The MAC protocol can adopt a contention-based approach, exemplified by Carrier Sensing Multiple Access/Collision Avoidance (CSMA/CA), where each device competes for the wireless medium, optimizing both power transfer and communication. Alternatively, a contention-free approach can be employed, assigning devices to specific time slots, frequency channels, or codes to avoid the collision, exemplified by Time Division Multiple Access (TDMA). Table XII briefly summarizes various MAC protocols.

1) Contention-based Protocols: some studies [72], [73], [210], [211], [215] optimize contention-based MAC protocols. Naderi *et al*. [215] explored the concurrent transmission of power and information in WCNs. Key parameters such as wireless charging, communication, and interference range are quantified, and the impacts of frequency separation between power and information transmission, as well as multiple concurrent power transfers, are investigated. Based on this, in [72], [73], they optimized the CSMA/CA protocol. This protocol allows a device with lower energy to broadcast its Request for Energy (RFE) packet. Upon receiving the RFE packet, nearby wireless chargers send Cleared for Energy (CFE) packets, and the device may receive multiple CFE packets. Depending on the distance between the device and the chargers, nearby chargers are divided into two groups and assigned slightly different peak transmission frequencies, facilitating the constructive interference of the transmitted energy at the device. Iqbal *et al*. [210] proposed a CSMA/CA protocol in a relay-enabled WCN, where devices receive energy from a Relay-Hybrid Access Point (RHAP) and transmit information to BSs via the RHAP. In the proposed protocol, devices and the RHAP compete for access channels through different contention mechanisms. The RHAP is given a higher priority, ensuring more frequent access to the channel. Choi *et al*. [211] introduced a harvest-or-access protocol based on slotted ALOHA, where HAPs perform WPT during idle slots.

2) Contention-free Protocols: contention-free MAC protocols in WCNs are investigated in [69], [212]–[214]. Iannello *et al*. [212] studied a TDMA-based MAC protocol and analyzed the trade-off between power delivery probability and data col-

TABLE XIII
COMPARISON OF ROUTING PROTOCOL SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Protocol types	Performance metrics	EVM
Routing Protocol	[74]	Maximum energy efficiency	Energy budget constraints	Hierarchical routing	Average residual energy; traffic load	NS
	[216]	Maximum energy efficiency	Energy budget constraints	Opportunistic routing	Delivery ratio; transmission delay; average residual energy	NS
	[217]	Maximum energy efficiency	Delays constraints; throughput constraints; packet loss constraints	Opportunistic routing	Energy efficiency; delay; network throughput; packet loss ratio	NS
	[218]	Maximum network throughput	Energy budget constraints	Online routing	Network throughput	TA; NS
	[219]	Maximum system utility	Energy budget constraints	Online routing	System utility	TA; NS
	[220]	Minimum energy consumption	Energy budget constraints	Routing tree	Total charging cost	NS
	[221]	Maximum minimum fair rate	Flow conservation constraints; energy budget constraints	Routing tree; unsplittable routing; fractional routing	Maximum minimum fair rate	TA

lection efficiency. Ju *et al*. [69] studied a TDMA-based MAC protocol to maximize network throughput. A hybrid MAC protocol that utilizes both TDMA and CSMA is introduced in [213]. The protocol involves a dual WPT method at the BS, with the main WPT performed in TDMA mode, and the other WPT performed at space holes in CSMA mode, thus improving channel utilization and harvested energy. In addition, Hu *et al*. [214] designed a TDMA-based MAC protocol to avoid transmission conflicts and idle interception. They proposed a modified superframe structure to optimize network traffic throughput and ensure communication reliability.

B. Routing Protocol

The routing protocol delineates the procedure for finding the best route to transmit data from the source to the destination. In WCNs, rechargeable devices feature an additional power supply, making it imperative for routing protocols to incorporate this factor into their design. The optimization goals of routing protocols in WCNs prioritize achieving maximum energy efficiency and optimizing network throughput, among other considerations [74], [79], [216], [218]–[221]. A comparison of various routing protocols is presented in Table XIII.

1) Energy-efficient Protocols: many research efforts are dedicated to developing energy-efficient routing protocols [74], [216], [217]. Cao *et al*. [74] designed an energy harvesting routing protocol, which takes energy harvesting as a critical factor in routing design to improve energy efficiency. To efficiently select the next hop, they introduced an information updating mechanism to periodically update the routing table without extra overhead. Bouachir *et al*. [216] presented an opportunistic routing and data dissemination protocol designed for WCNs, based on cross-layer constructs that enable synchronization and coordination between application layer services and the routing protocol. In this routing protocol, each device transmits its sensing data only when it has enough residual energy, and it selects a relay node among its neighbors to transmit data based on the number of hops by creating the forwarder list and the residual energy of its neighbors. Nguyen *et al*. [217] designed a routing protocol for heterogeneous WCNs to address issues of variations in traffic load and energy availability conditions. They developed an energy back-off mechanism, which can be integrated into the proposed routing protocol and the IEEE 802.15.4 CSMA/CA mechanism. By leveraging the proposed mechanism, optimal routes for efficiently forwarding data packets from source nodes to their destinations are obtained.

2) Multi-objective Protocols: some studies [218]–[221] explore additional optimization goals beyond energy efficiency. Lin *et al*. [218] presented a routing protocol designed for WCNs, with prior knowledge of the power supply. This protocol computes the lowest-cost path to accommodate each task in the network, with the cost being an exponential function of the residual energy. The throughput of this protocol is proven to achieve an asymptotically optimal competitive ratio as the number of devices in the network grows to infinity. Furthermore, the routing protocol is easily integrated into existing routing protocols. Chen *et al*. [219] studied the joint optimization problem of energy allocation and routing protocol in WCNs. They characterized an upper bound for the optimal network utility, by constructing an infeasible scheme that outperforms the optimal scheme. Based on this, they developed a low-complexity online solution and showed that the long-term performance of the online solution approaches the upper bound. Tong *et al*. [220] were concerned with the simultaneous determination of network deployment and routing arrangements in WCNs. They introduced various heuristic algorithms to minimize charging costs. Marašević *et al*. [221] explored max-min fair rate allocation and routing in WCNs with a predictable energy profile. Specifically, for the unsplittable routing and routing tree, they developed a fully combinatorial algorithm applicable in both time-variable and time-invariable settings. For fractional routing, they developed an approximation algorithm and a full combinational algorithm for time-variable and time-invariable settings, respectively.

C. Broadcast Transmission

Broadcast is a fundamental operation in WCNs, disseminating data from a source sensor node to the whole network. The investigation into the impact of WPT technology on broadcasting aims to optimize broadcast reliability and latency. These studies typically revolve around single-hop or multi-hop network topologies [75]–[77], [222]–[229]. Table XIV summarizes and compares different broadcast transmission schemes.

TABLE XIV
COMPARISON OF BROADCAST TRANSMISSION SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Network topologies	Performance metrics	EVM
Broadcast Transmission	[75], [76]	O1: Maximum transmission reliability O2: Maximum network throughput O2: Maximum eclectic utility	Throughput constraints; transmission reliability constraints	Single-hop network	Successful reception probability; network throughput	NS
	[222], [223]	O1: Minimum broadcast overhead O2: Minimum broadcast latency	Energy provision constraints	Single-hop network	Broadcast latency; number of missed nodes; received energy	TA; NS
	[224]	Maximum throughput region	Power budget constraint	Single-hop network	Optimal throughput region	TA; NS
	[225], [226]	Minimum broadcast latency	Harvested energy constraints	Single-hop network	Broadcast latency	TA; NS
	[77]	Minimum broadcast latency	Collision-free constraints	Multi-hop network	Broadcast latency	TA; NS
	[227]	Minimum broadcast latency	Collision-free constraints; harvested energy constraints	Multi-hop network	Broadcast latency; communication overhead	TA; NS
	[228]	Minimum broadcast latency	Collision-free constraints; harvested energy constraints	Multi-hop network	Broadcast latency; total number of transmissions	TA; NS
	[229]	Minimum broadcast latency	Harvested energy constraints	Multi-hop network	Broadcast latency; energy usage ratio	TA; NS

1) Single-hop Networks: several studies [75], [76], [222]–[226] explore broadcast transmission in single-hop networks. Kuan *et al*. [75] took both transmission error and energy deficiency into account and proposed a reliable broadcast transmission mechanism. To reduce energy consumption, they adopted an erasure-based forward error correction scheme to deal with transmission errors. Considering diverse requirements, they proposed reliability-first and throughput-first broadcast policies, respectively. Furthermore, in their subsequent work [76], they proposed an eclectic policy that considers both throughput and reliability, aiming to maximize the sum of the eclectic utility. In [222], [223], a fast and reliable broadcast mechanism without disturbing upstream communications is proposed. During the broadcast process, the BS dynamically selects the broadcast slot to synchronize with the charging activity cycle. Meanwhile, devices adapt their schedules to enable optimal selection of broadcast time slots, minimizing both the number of broadcasts per message and the latency. Baknina *et al*. [224] studied online transmission schemes where devices know energy arrivals only as they occur. They considered scenarios where the arriving energy follows a Bernoulli distribution or independent and identically distributed, and proposed optimum and sub-optimum online schemes respectively. In [225], [226], broadcast transmission over an additive white Gaussian noise channel is studied. To minimize latency, they proposed offline schemes tailored to devices with either unlimited or finite battery capacity.

2) Multi-hop Networks: the studies [77], [227]–[229] extensively explore broadcast transmission in multi-hop networks, with a common objective of minimizing broadcast latency. Zhu *et al*. [77] addressed this optimization objective by proposing three approximate algorithms and analyzing the latency bound of the broadcast schedules generated by these algorithms. Yao *et al*. [227] explored a method for calculating end-to-end transmission latency. Based on the consideration of energy supply and conflict, they proposed centralized and distributed algorithms for constructing conflict-free multicast trees. Chen *et al*. [228] investigated the construction of broadcast trees combined with the computation of energy-satisfied and collision-free schedules. They introduced two scheduling algorithms that are mindful of latency and energy considerations, enabling adaptive construction of the broadcast tree. Moreover, a delayed broadcasting technique is proposed to tradeoff between the number of transmissions and latency. Yao *et al*. [229] proposed an energy-adaptive, bottleneck-aware scheduling algorithm to minimize latency, with a thorough analysis of its correctness and average latency performance.

D. Data Collection

The ultimate critical communication process in WCNs is data collection, wherein devices gather sensing data and transmit it either directly or through multi-hop relays to a sink or BS for further processing. Research on this process can be categorized based on the mobility of the sink [78], [230], [231], and Table XV compares data collection schemes.

1) Mobile Sink: some studies [78], [230], [231] delve into scheduling mobile sinks to collect delay-tolerant data. Mehrabi *et al*. [78] addressed the problem of maximizing data collection throughput in WCNs with a mobile sink, where the mobile sink follows a fixed pattern to collect data on a pre-specified path. They introduced an optimization model that considers the effective and heterogeneous duration of sensor transmissions with the energy harvesting aspect of the problem. Subsequently, they devised an online centralized algorithm with polynomial run-time complexity to handle the problem. In [230], the mobile sink travels along a trajectory of data collection and is constrained by a specified tolerance delay. The optimization problem is to find an optimal closed trajectory for the mobile sink, including both the sojourn locations and the corresponding sojourn time, to maximize network throughput. Under the assumption that the mobile sink can only collect data from one-hop devices, a heuristic algorithm is proposed to address this optimization problem. Ren *et al*. [231] focused on the problem of maximizing data collection. Assuming that global knowledge of the network is available, they presented an offline approximation algorithm with a guaranteed approximation ratio. Additionally, for practical networks without the global knowledge assumption, they proposed a fast and scalable online distributed algorithm.

2) Static Sink: the other category of studies uses a static sink to collect data [79], [232]–[235]. The monitoring quality max-

TABLE XV
COMPARISON OF DATA COLLECTION SCHEMES
('EVM': EVALUATION METHODS; 'TA': THEORETICAL ANALYSIS; 'NS': NUMERICAL SIMULATIONS; AND 'FE': FIELD EXPERIMENTS)

	Paper	Objectives	Constraints	Sinks	Network topologies	Performance metrics	EVM
Data Collection	[78]	Maximum network throughput	Energy budget constraints	Mobile	Single-hop network	Network throughput; data collection latency	TA; NS
	[230]	Maximum network throughput	Tolerant delay constraint	Mobile	Single-hop network	Network throughput ratio	NS
	[231]	Maximum data collection	Energy provision constraints	Mobile	Single-hop network	Network throughput	TA; NS
	[79]	Maximum monitoring quality	Energy budget constraints	Static	Single-hop network	Data collection quality; running time	TA; NS
	[232]	Maximum data collection	Flow conservation constraints; energy conservation constraints	Static	Multi-hop network	Network utility; energy utilization ratio	TA; NS
	[233]	Minimum data collection latency	Individual SINR constraints; energy budget constraints	Static	Multi-hop network	Data collection latency	TA; NS
	[234]	Minimum data collection latency	Individual SINR constraints; energy budget constraints	Static	Multi-hop network	Data collection latency; energy utilization ratio	TA; NS
	[235]	Maximum data collection	Individual SINR constraints; energy budget constraints	Static	Multi-hop network	Network throughput	TA; NS

imization problem is explored in [79]. A fast approximation algorithm with a provable approximation ratio is presented, such that the weighted, fair data rate allocation and flow routing problem is solved. Zhang *et al*. [232] designed a data acquisition optimization algorithm for dynamic sensing and routing. They first devised a balanced energy distribution scheme for the device to manage its energy. Subsequently, they proposed a distributed sensing rate and routing control algorithm that together optimizes data sensing and data transmission, thereby effectively improving the data gathering process. Zhu *et al*. [233] focused on the problem of generating data collection schedules with minimum latency for WCNs. Their research covers both linear and general network configurations, wherein devices are distributed along a line or arbitrarily dispersed across a 2D plane. They proposed distributed algorithms to generate data collection schedules. The work in [234] regards data collection latency as a design parameter and proposes a distributed data collection framework. The framework enables devices to select receivers based on their state, and more devices per time slot have the opportunity to transmit, resulting in high spatial parallelism. Song *et al*. [235] studied data collection in WCNs, where a HAP employs switched beamforming for downlink power transmission and concurrent decoding of multiple uplink transmissions. To maximize the number of data transmissions, they proposed an approach enabling the HAP to proactively determine the mode of future time slots.

Overall, as WPT integrates with wireless networks, optimizing MAC, routing, broadcast transmission, and data collection is crucial for seamless operation. These optimizations enhance power and information coordination, minimize interference, and ensure efficient and reliable performance of WCNs.

VII. FUTURE RESEARCH DIRECTIONS

This survey discusses charger deployment, charging scheduling, and communication optimization in WCNs. However, there are still some open issues. In this section, we outline some potential research directions for WCNs, including security issues, supporting sixth generation (6G) networks, the role of Artificial Intelligence (AI), millimeter-wave (mmWave)-enabled WCNs, Intelligent Reflecting Surfaces (IRS)-assisted WCNs, and metamaterials-aided WCNs.

A. Security Issues in WCNs

In WCNs, wireless chargers are commonly deployed in remote environments to supply power to rechargeable devices engaged in various monitoring tasks, such as forest fire detection and illegal activity surveillance. Unfortunately, the absence of tamper-resistant hardware makes wireless chargers vulnerable to capture or destruction by malicious attackers. Once captured, these malicious attackers can take control of the charger, adjusting transmission power, charging times, charger direction, and other parameters [165]. In such cases, rechargeable devices may either receive insufficient power, hampering their functionality, or too much power, potentially causing damage to their circuits. Therefore, addressing security issues in WCNs becomes imperative. Several fundamental issues require more attention and further studies, such as:

1) Investigating attacking schemes is of fundamental importance as it can offer valuable attack models for developing security schemes. Therefore, the key problems in the design of the attack scheme are how to control the various parameters of captured chargers to maximize the attacking utility, and how to disguise the existence of the attack without being detected.

2) Researching security schemes is pivotal for effectively addressing security issues in WCNs. This involves determining how to modify charging schemes to ensure adequate power supply, and how to design attack detection schemes that can identify captured chargers. These efforts are crucial for fortifying the security of WCNs.

B. Supporting 6G in WCNs

The forthcoming mobile network generation, 6G, demands nearly unlimited battery life for devices to achieve near-instant, seamless wireless connectivity [236]. As 6G deployment progresses, WCNs will play a critical role in meeting this requirement by enabling continuous and efficient energy replenishment for a vast array of devices. Supporting 6G in WCNs involves addressing several fundamental issues:

1) With 6G supporting billions of connected devices, WCNs must efficiently manage power delivery across a massive network. Wireless charging schemes should consider device

priorities, energy requirements, *etc.,* to achieve dynamic energy management in large-scale WCNs.

2) To achieve near-instant communication, 6G requires fast and efficient energy transfer. This necessitates advanced communication optimization schemes within WCNs to ensure that devices receive sufficient power promptly without compromising communication quality.

C. AI-based Design

In WCNs, AI can predict dynamic charging demands and device states, enabling real-time adjustments to charging schemes based on network load and topology changes, maximizing energy efficiency [237], [238]. Additionally, generative AI enhances network robustness by generating simulated interference, attack, and failure data, supporting the design of fault-tolerant and resilient mechanisms that account for various anomalies. By analyzing user behavior, AI can also offer personalized charging designs, with adaptive learning capabilities that adjust schemes according to user habits and preferences, improving user satisfaction. Future research will continue to deepen the application of AI in WCNs, driving the network towards higher levels of intelligence and stability. However, some fundamental problems are still open, for example:

1) How to accurately predict various dynamic parameters like charging demands, device states, and topological changes in complex networks, providing essential insights for optimizing subsequent charging schemes.

2) How to leverage generative AI to adaptively modify charging schemes, enabling WCNs to better respond to network changes and improve overall reliability and stability.

D. mmWave-enabled WCNs

The mmWave frequencies (30-300 GHz), along with the potential extension into terahertz (THz) frequencies (300 GHz to 10 THz), offer promising solutions for improving both energy transfer and data transmission in WCNs. The growing demand for data transmission has led to increasingly congesting traditional spectrum resources. Leveraging mmWave frequencies can effectively address the requirements for gigabit-level information transmission [239]. Compared with traditional WPT, mmWave WPT provides more focused energy with smaller relative antennas, large spectrum resources, and less interference to other networks [240]–[242]. But there are some fundamental problems that need more attention and research, for example:

1) The wavelength of mmWave shrinks by an order of magnitude compared to microwave frequencies, leading to greater attenuation through diffraction and material penetration. This increases the importance of Line-of-Sight (LOS) transmission. In this case, addressing how to strategically deploy wireless chargers to optimize mmWave benefits while ensuring LOS transmission poses a complex challenge.

2) Moreover, the adoption of mmWave with shorter wavelengths leads to larger path loss. Therefore, mmWave-enabled WCNs require a combination of beamforming technology to improve the directivity and efficiency of power transmission. Consequently, how to design beamforming with higher gain to compensate for the larger path loss is a critical consideration.

E. IRS-assisted WCNs

The IRS, consisting of a large number of low-cost reflecting elements, is capable of reflecting incident RF signals [243]. In IRS-assisted WCNs, the IRS can greatly improve the performance of WCNs by smartly adjusting the phase shift of each of the reflecting elements. It captures the RF signal, optimally reflecting it to achieve improved charge efficiency and interference suppression within a specific area [244], [245]. Additionally, in cases where the LOS path between the charger and the device is obstructed, the IRS can be utilized to create alternative LOS charging schemes, further enhancing network performance [246]. However, some fundamental issues still require further study, such as:

1) The IRS controls the amplitude, phase, and propagation direction of the RF signal by intelligently adjusting the phase of each reflecting element. So, how to adjust these phases to maximize charging efficiency and coverage area is essential.

2) How to deploy wireless chargers and IRSs to solve non-line-of-sight charging scenarios, such that the overall charging utility of the network is maximized.

F. Metamaterials-aided WCNs

Metamaterials are artificially engineered materials that exhibit unique electromagnetic properties, including evanescent wave amplification and negative refractive characteristics. These properties can be harnessed to enhance near-field WPT [247]–[249]. In metamaterials-aided WCNs, placing the metamaterial slab between the transmission coil and receiving coil can effectively improve charging efficiency or increase charging distance by leveraging the properties of the metamaterial slab. However, there are still some fundamental problems that require further study:

1) In metamaterial-aided WCNs, metamaterial slabs are usually larger than or at least equal to the size of the transmission coil and the receiving coil, but this undoubtedly reduces the convenience of the network. Therefore, a key challenge is how to minimize the size of the metamaterial slab while ensuring charging efficiency.

2) Since charging efficiency is influenced by the relative position of the metamaterial slabs, transmission coil, and receiving coil, it is necessary to consider how to deploy wireless chargers and metamaterial slabs to maximize the overall charging utility of the network.

VIII. Conclusion

This survey paper provides a comprehensive study of the state-of-the-art of WCNs. We first introduce WCNs in detail, covering aspects such as network architecture, basic composition, various charging modes, network design issues, and typical applications. Then, we provide a summary and analysis of existing research in WCNs, focusing on three key aspects: charger deployment, charging scheduling, and communication optimization. In particular, we provide information tables summarizing these optimization strategies in WCNs. We also list some important open issues and indicate potential research directions for WCNs. We hope that this survey paper will help readers understand the general architecture and the holistic knowledge of WCNs.

References

[1] Z. Zhang, H. Pang, A. Georgiadis, and C. Cecati, "Wireless power transfer—An overview," *IEEE Trans. Ind. Electron.*, vol. 66, no. 2, pp. 1044–1058, 2018.

[2] "Wireless Power Consortium," Accessed: 2024. [Online]. Available: https://www.wirelesspowerconsortium.com.

[3] Statistica, "Size of wireless charging market worldwide from 2020 to 2030," Accessed: 2024. [Online]. Available: https://www.statista.com/statistics/1256342/worldwide-wireless-charging-market-revenues/.

[4] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Comput. Netw.*, vol. 52, no. 12, pp. 2292–2330, 2008.

[5] C. Wang, J. Li, Y. Yang, and F. Ye, "Combining solar energy harvesting with wireless charging for hybrid wireless sensor networks," *IEEE Trans. Mobile Comput.*, vol. 17, no. 3, pp. 560–576, 2017.

[6] C. Wei and X. Jing, "A comprehensive review on vibration energy harvesting: Modelling and realization," *Renew. Sust. Energ. Rev.*, vol. 74, pp. 1–18, 2017.

[7] D. Ma, G. Lan, M. Hassan, W. Hu, and S. K. Das, "Sensing, computing, and communications for energy harvesting IoTs: A survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 1222–1250, 2019.

[8] X. Wang, H. Dai, H. Huang, Y. Liu, G. Chen, and W. Dou, "Robust scheduling for wireless charger networks," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2019, pp. 2323–2331.

[9] L. Shi, Z. Kabelac, D. Katabi, and D. Perreault, "Wireless power hotspot that charges all of your devices," in *Proc. ACM Annu. Int. Conf. Mobile Comput. Netw. (MobiCom)*, 2015, pp. 2–13.

[10] X. Fan, L. Shangguan, R. Howard, Y. Zhang, Y. Peng, J. Xiong, Y. Ma, and X. Li, "Towards flexible wireless charging for medical implants using distributed antenna system," in *Proc. ACM Annu. Int. Conf. Mobile Comput. Netw. (MobiCom)*, 2020, pp. 1–15.

[11] G. Sun, Y. Liu, M. Yang, A. Wang, and Y. Zhang, "Charging nodes deployment optimization in wireless rechargeable sensor network," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2017, pp. 1–6.

[12] "WISP," Accessed: 2024. [Online]. Available:https://sensor.cs.washington.edu/research/wisp_1.

[13] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, "Wireless charging technologies: Fundamentals, standards, and network applications," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1413–1452, 2015.

[14] X. Jing, J. Jing, L. Yan, and L. Changjun, "Microwave wireless power transmission inside a closed cavity based on novel frequency controlling," *Acta Electron. Sin.*, vol. 52, no. 7, pp. 2257–2261, 2024.

[15] W. Xu, W. Liang, J. Peng, Y. Liu, and Y. Wang, "Maximizing charging satisfaction of smartphone users via wireless energy transfer," *IEEE Trans. Mobile Comput.*, vol. 16, no. 4, pp. 990–1004, 2016.

[16] A. Ahmad, M. S. Alam, and R. Chabaan, "A comprehensive review of wireless charging technologies for electric vehicles," *IEEE Trans. Transp. Electrif.*, vol. 4, no. 1, pp. 38–63, 2017.

[17] C. Hu, Y. Wang, and H. Wang, "Survey on charging programming in wireless rechargeable sensor networks," *J. Softw.*, vol. 27, no. 1, pp. 72–95, 2015.

[18] S. Prakash and V. Saroj, "A review of wireless charging nodes in wireless sensor networks," *Data Science and Big Data Analytics: ACM-WIR 2018*, pp. 177–188, 2018.

[19] Z. Fan, Z. Jie, and Q. Yujie, "A survey on wireless power transfer based charging scheduling schemes in wireless rechargeable sensor networks," in *Proc. IEEE Int. Conf. Control Sci. Syst. Eng. (ICCSSE)*, 2018, pp. 194–198.

[20] A. Kaswan, P. K. Jana, and S. K. Das, "A survey on mobile charging techniques in wireless rechargeable sensor networks," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 3, pp. 1750–1779, 2022.

[21] B. Qureshi, S. A. Aziz, X. Wang, A. Hawbani, S. H. Alsamhi, T. Qureshi, and A. Naji, "A state-of-the-art survey on wireless rechargeable sensor networks: Perspectives and challenges," *Wireless Netw.*, vol. 28, no. 7, pp. 3019–3043, 2022.

[22] N. Khalid, R. Mirzavand, and A. K. Iyer, "A survey on battery-less RFID-based wireless sensors," *Micromachines*, vol. 12, no. 7, p. 819, 2021.

[23] Z. Cai, Q. Chen, T. Shi, T. Zhu, K. Chen, and Y. Li, "Battery-free wireless sensor networks: A comprehensive survey," *IEEE Internet Things J*, vol. 10, no. 6, pp. 5543–5570, 2022.

[24] T. Jiang, Y. Zhang, W. Ma, M. Peng, Y. Peng, M. Feng, and G. Liu, "Backscatter communication meets practical battery-free Internet of Things: A survey and outlook," *IEEE Commun. Surveys Tuts.*, vol. 25, no. 3, pp. 2021–2051, 2023.

[25] S. Bi, Y. Zeng, and R. Zhang, "Wireless powered communication networks: An overview," *IEEE Wireless Commun.*, vol. 23, no. 2, pp. 10–18, 2016.

[26] D. Niyato, D. I. Kim, M. Maso, and Z. Han, "Wireless powered communication networks: Research directions and technological approaches," *IEEE Wireless Commun.*, vol. 24, no. 6, pp. 88–97, 2017.

[27] F. Rezaei, C. Tellambura, and S. Herath, "Large-scale wireless-powered networks with backscatter communications—A comprehensive survey," *IEEE Open J. Commun. Soc.*, vol. 1, pp. 1100–1130, 2020.

[28] S. A. Huda, M. Y. Arafat, and S. Moh, "Wireless power transfer in wirelessly powered sensor networks: A review of recent progress," *Sensors*, vol. 22, no. 8, p. 2952, 2022.

[29] X. Wang, J. Li, Z. Ning, Q. Song, L. Guo, S. Guo, and M. S. Obaidat, "Wireless powered mobile edge computing networks: A survey," *ACM Computing Surveys*, vol. 55, no. 13s, pp. 1–37, 2023.

[30] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljacic, "Wireless power transfer via strongly coupled magnetic resonances," *Science*, vol. 317, no. 5834, pp. 83–86, 2007.

[31] S. He, J. Chen, F. Jiang, D. K. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE Trans. Mobile Comput.*, vol. 12, no. 10, pp. 1931–1942, 2012.

[32] G. K. Ijemaru, K. L.-M. Ang, and J. K. Seng, "Wireless power transfer and energy harvesting in distributed sensor networks: Survey, opportunities, and challenges," *Int. J. Distrib. Sens. Netw.*, vol. 18, no. 3, p. 15501477211067740, 2022.

[33] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 1989–2001, 2013.

[34] "Cota," Accessed: 2024. [Online]. Available: https://www.ossia.com.

[35] "PRIMOVE," Accessed: 2024. [Online]. Available: https://primove.bombardier.com.

[36] "Powercast," Accessed: 2024. [Online]. Available:https://www.powercastco.com.

[37] H. Dai, X. Wang, A. X. Liu, H. Ma, and G. Chen, "Optimizing wireless charger placement for directional charging," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2017, pp. 1–9.

[38] M. Ren, D. Wu, J. Xue, W. Xu, J. Peng, and T. Liu, "Utilizing the neglected back lobe for mobile charging," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2023, pp. 1–10.

[39] T. Liu, M. Ren, D. Wu, J. Xue, J. Li, S. Mao, and W. Xu, "Utilizing the neglected back lobe for directional charging scheduling," *IEEE Trans. Mobile Comput.*, no. 01, pp. 1–14, 2023.

[40] Y. Ma, D. Wu, M. Ren, J. Peng, J. Yang, and T. Liu, "Concurrent charging with wave interference," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2023, pp. 1–10.

[41] T. Liu, Y. Ma, M. Ren, J. Yang, J. Peng, J. Yang, and D. Wu, "Concurrent charging with wave interference for multiple chargers," *IEEE/ACM Trans. Netw*, vol. 32, no. 3, pp. 2525–2538, 2024.

[42] Y. Ma, D. Wu, J. Gao, S. Wen, J. Yang, and T. Liu, "Dynamic power distribution controlling for directional chargerse," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2024, pp. 1–10.

[43] C. Lin, Z. Yang, H. Dai, L. Cui, L. Wang, and G. Wu, "Minimizing charging delay for directional charging," *IEEE/ACM Trans. Netw*, vol. 29, no. 6, pp. 2478–2493, 2021.

[44] H. Dai, Y. Liu, G. Chen, X. Wu, and T. He, "Safe charging for wireless power transfer," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2014, pp. 1105–1113.

[45] Institute of Electrical and Electronics Engineers, *IEEE standard for safety levels with respect to human exposure to radio frequency electromagnetic fields, 3 kHz to 300 GHz*. IEEE, 2006.

[46] International Commission on Non-Ionizing Radiation Protection, "Guidelines for limiting exposure to electromagnetic fields (100 kHz to 300 GHz)," *Health Physics*, vol. 118, no. 5, pp. 483–524, 2020.

[47] Federal Communications Commission, "Equipment authorization of wireless power transmission devices," Publication 680106, Rule Parts: 18, 15B, 2023.

[48] J. Jadidian and D. Katabi, "Magnetic MIMO: How to charge your phone in your pocket," in *Proc. ACM Annu. Int. Conf. Mobile Comput. Netw. (MobiCom)*, 2014, pp. 495–506.

[49] C. Wang, J. Li, F. Ye, and Y. Yang, "A novel framework of multi-hop wireless charging for sensor networks using resonant repeaters," *IEEE Trans. Mobile Comput.*, vol. 16, no. 3, pp. 617–633, 2016.

[50] "Rezence," Accessed: 2024. [Online]. Available: https://www.rezence.com.

[51] "Power Matters Alliance," Accessed: 2024. [Online]. Available: https://powermatters.org.

[52] “Airfuel resonant,” Accessed: 2024. [Online]. Available: https://airfuel.org/airfuel-resonant.

[53] D. Lin, Q. Wang, W. Min, J. Xu, and Z. Zhang, “A survey on energy-efficient strategies in static wireless sensor networks,” *ACM Trans. Sens. Netw.*, vol. 17, no. 1, pp. 1–48, 2020.

[54] T. Chiu, Y. Shih, A. Pang, J. Jeng, and P. Hsiu, “Mobility-aware charger deployment for wireless rechargeable sensor networks,” in *Proc. IEEE Asia–Pac. Netw. Oper. Manag. Symp (APNOMS)*, 2012, pp. 1–7.

[55] N. Yu, H. Dai, G. Chen, A. X. Liu, B. Tian, and T. He, “Connectivity-constrained placement of wireless chargers,” *IEEE Trans. Mobile Comput.*, vol. 20, no. 3, pp. 909–927, 2019.

[56] H. Dai, X. Wang, A. X. Liu, H. Ma, G. Chen, and W. Dou, “Wireless charger placement for directional charging,” *IEEE/ACM Trans. Netw*, vol. 26, no. 4, pp. 1865–1878, 2018.

[57] W. Zhou, X. Wang, H. Zhou, S. Jiang, Z. Liu, and Y. Ji, “Safety guaranteed power-delivered-to-load maximization for magnetic wireless power transfer,” in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*. IEEE, 2024, pp. 2049–2058.

[58] H. Dai, Y. Liu, G. Chen, X. Wu, T. He, A. X. Liu, and H. Ma, “Safe charging for wireless power transfer,” *IEEE/ACM Trans. Netw*, vol. 25, no. 6, pp. 3531–3544, 2017.

[59] M. R. V. Moghadam and R. Zhang, “Node placement and distributed magnetic beamforming optimization for wireless power transfer,” *IEEE Trans. Signal Inf. Process. Netw.*, vol. 4, no. 2, pp. 264–279, 2017.

[60] S. Wu, H. Dai, L. Xu, L. Liu, F. Xiao, and J. Xu, “Comprehensive cost optimization for charger deployment in multi-hop wireless charging,” *IEEE Trans. Mobile Comput.*, 2022.

[61] X. Wang, H. Dai, W. Wang, J. Zheng, N. Yu, G. Chen, W. Dou, and X. Wu, “Practical heterogeneous wireless charger placement with obstacles,” *IEEE Trans. Mobile Comput.*, vol. 19, no. 8, pp. 1910–1927, 2019.

[62] S. Zhang, Z. Qian, F. Kong, J. Wu, and S. Lu, “P^3: Joint optimization of charger placement and power allocation for wireless power transfer,” in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2015, pp. 2344–2352.

[63] S. Zhang, Z. Qian, J. Wu, F. Kong, and S. Lu, “Wireless charger placement and power allocation for maximizing charging quality,” *IEEE Trans. Mobile Comput.*, vol. 17, no. 6, pp. 1483–1496, 2017.

[64] S. Nikoletseas, T. P. Raptis, and C. Raptopoulos, “Low radiation efficient wireless energy transfer in wireless distributed systems,” in *Proc. IEEE Int. Conf. Distrib. Comput. Syst. (ICDCS)*, 2015, pp. 196–204.

[65] ——, “Radiation-constrained algorithms for wireless energy transfer in ad hoc networks,” *Comput. Netw.*, vol. 124, pp. 1–10, 2017.

[66] S. Guo, F. Wang, Y. Yang, and B. Xiao, “Energy-efficient cooperative tfor simultaneous wireless information and power transfer in clustered wireless sensor networks,” *IEEE Trans. Commun.*, vol. 63, no. 11, pp. 4405–4417, 2015.

[67] H. Dai, K. Sun, A. X. Liu, L. Zhang, J. Zheng, and G. Chen, “Charging task scheduling for directional wireless charger networks,” in *Proc. Int. Conf. Parallel Process. (ICPP)*, 2018, pp. 1–10.

[68] ——, “Charging task scheduling for directional wireless charger networks,” *IEEE Trans. Mobile Comput.*, vol. 20, no. 11, pp. 3163–3180, 2021.

[69] H. Ju and R. Zhang, “Throughput maximization in wireless powered communication networks,” *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 418–428, 2013.

[70] X. Fan, H. Ding, S. Li, M. Sanzari, Y. Zhang, W. Trappe, Z. Han, and R. E. Howard, “Energy-ball: Wireless power transfer for batteryless internet of things through distributed beamforming,” *ACM Interact. Mobile Wear. Ubiquit. Technol.*, vol. 2, no. 2, pp. 1–22, 2018.

[71] X. Chen, X. Wang, and X. Chen, “Energy-efficient optimization for wireless information and power transfer in large-scale MIMO systems employing energy beamforming,” *IEEE Wireless Commun. Lett.*, vol. 2, no. 6, pp. 667–670, 2013.

[72] P. Nintanavongsa, M. Y. Naderi, and K. R. Chowdhury, “Medium access control protocol design for sensors powered by wireless energy transfer,” in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2013, pp. 150–154.

[73] M. Y. Naderi, P. Nintanavongsa, and K. R. Chowdhury, “RF-MAC: A medium access control protocol for rechargeable sensor networks powered by wireless energy harvesting,” *IEEE Trans. Wireless Commun.*, vol. 13, no. 7, pp. 3926–3937, 2014.

[74] Y. Cao, X. Liu, L. Kong, M. Wu, and M. K. Khan, “EHR: Routing protocol for energy harvesting wireless sensor networks,” in *Proc. IEEE Int. Conf. Parallel Distrib. Syst. (ICPADS)*, 2016, pp. 56–63.

[75] C. Kuan and H. Wei, “Design and analysis for reliable broadcast transmission in energy harvesting networks,” in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2012, pp. 1745–1750.

[76] C. Kuan, G. Lin, H. Wei, and R. Vannithamby, “Reliable multicast and broadcast mechanisms for energy-harvesting devices,” *IEEE Trans. Veh. Technol.*, vol. 63, no. 4, pp. 1813–1826, 2013.

[77] T. Zhu, J. Li, H. Gao, and Y. Li, “Broadcast scheduling in battery-free wireless sensor networks,” *ACM Trans. Sens. Netw.*, vol. 15, no. 4, pp. 1–34, 2019.

[78] A. Mehrabi and K. Kim, “Maximizing data collection throughput on a path in energy harvesting sensor networks using a mobile sink,” *IEEE Trans. Mobile Comput.*, vol. 15, no. 3, pp. 690–704, 2015.

[79] W. Liang, X. Ren, X. Jia, and X. Xu, “Monitoring quality maximization through fair rate allocation in harvesting sensor networks,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 9, pp. 1827–1840, 2013.

[80] “Energous,” Accessed: 2024. [Online]. Available:https://energous.com.

[81] Y. Sun, C. Lin, W. Yang, J. Ren, L. Wang, G. Wu, and Q. Zhang, “Charging dynamic sensors through online learning,” in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2023, pp. 1–10.

[82] K. W. Choi, L. Ginting, A. A. Aziz, D. Setiawan, J. H. Park, S. I. Hwang, D. S. Kang, M. Y. Chung, and D. I. Kim, “Toward realization of long-range wireless-powered sensor networks,” *IEEE Wireless Commun.*, vol. 26, no. 4, pp. 184–192, 2019.

[83] M. Z. Hasan, H. Al-Rizzo, and F. Al-Turjman, “A survey on multipath routing protocols for QoS assurances in real-time wireless multimedia sensor networks,” *IEEE Commun. Surveys Tuts.*, vol. 19, no. 3, pp. 1424–1456, 2017.

[84] T. Shaw, G. Samanta, and D. Mitra, “Efficient wireless power transfer system for implantable medical devices using circular polarized antennas,” *IEEE Trans. Antennas Propagat.*, vol. 69, no. 7, pp. 4109–4122, 2020.

[85] S. R. Khan, S. K. Pavuluri, G. Cummins, and M. P. Desmulliez, “Wireless power transfer techniques for implantable medical devices: A review,” *Sensors*, vol. 20, no. 12, p. 3487, 2020.

[86] “Powermats,” Accessed: 2024. [Online]. Available:https://powermat.com.

[87] “Nexus,” Accessed: 2024. [Online]. Available:https://support.google.com/nexus.

[88] “Wireless Charger Duo,” Accessed: 2024. [Online]. Available:https://www.samsung.com.

[89] J. Liu, J. Peng, W. Xu, W. Liang, T. Liu, X. Peng, Z. Xu, Z. Li, and X. Jia, “Maximizing sensor lifetime via multi-node partial-charging on sensors,” *IEEE Trans. Mobile Comput.*, vol. 22, no. 11, pp. 6571–6584, 2023.

[90] “Bumblebee Power,” Accessed: 2024. [Online]. Available:https://bumblebeepower.com.

[91] “WiBotic,” Accessed: 2024. [Online]. Available:https://www.wibotic.com.

[92] M. Simic, C. Bil, and V. Vojisavljevic, “Investigation in wireless power transmission for UAV charging,” *Procedia Comput. Sci.*, vol. 60, pp. 1846–1855, 2015.

[93] Z. Yi, C. Xiang, S. Huaguang, J. Zhanqi, N. Nianwen, and L. Fuqiang, “Multi-objective coordinated optimization for UAV charging scheduling in intelligent aerial-ground perception networks,” *Chinese J. Electron.*, vol. 32, no. 6, pp. 1203–1217, 2023.

[94] M. Y. Arafat and S. Moh, “JRCS: Joint routing and charging strategy for logistics drones,” *IEEE Internet Things J*, vol. 9, no. 21, pp. 21 751–21 764, 2022.

[95] A. Famili and A. Stavrou, “Eternal flying: Optimal placement of wireless chargers for nonstop drone flights,” in *Proc. IEEE Int. Conf. Electr., Comput. Energy Technol. (ICECET)*, 2022, pp. 1–6.

[96] “eCoupled,” Accessed: 2024. [Online]. Available:https://www.ecoupled.com.

[97] “LinkCharge,” Accessed: 2024. [Online]. Available:https://www.semtech.com.

[98] H. A. Fadhil, S. G. Abdulqader, and S. Aljunid, “Implementation of wireless power transfer system for smart home applications,” in *Proc. IEEE GCC Conf. Exhib. (GCC)*, 2015, pp. 1–4.

[99] L. Xie, Y. Shi, Y. T. Hou, and A. Lou, “Wireless power transfer and applications to sensor networks,” *IEEE Wireless Commun.*, vol. 20, no. 4, pp. 140–145, 2013.

[100] “WiTricity,” Accessed: 2024. [Online]. Available:https://witricity.com/wireless-charging-solutions.

[101] “Qualcomm,” Accessed: 2024. [Online]. Available:https://www.qualcomm.com.

[102] “Plugless Power,” Accessed: 2024. [Online]. Available:https://pluglesspower.com.

[103] A. O. El Meligy, E. A. Elghanam, M. S. Hassan, and A. H. Osman, "Deployment optimization of dynamic wireless chargers for electric vehicles," in *Proc. IEEE Transp. Electrification Conf. Expo. (ITEC)*, 2021, pp. 113–118.

[104] Y. Pang, Z. Lu, M. Pan, and W. W. Li, "Charging coverage for energy replenishment in wireless sensor networks," in *Proc. IEEE Int. Conf. Netw. Sens. Control. (ICNSC)*, 2014, pp. 251–254.

[105] P. Wan, B. Wu, Y. Cheng, and G. Wang, "Charging base stations deployment algorithms for wireless rechargeable sensor networks," in *Proc. IEEE Wireless Power Transf. Conf. (WPTC)*, 2019, pp. 475–478.

[106] P. Wan, Y. Cheng, B. Wu, and G. Wang, "An algorithm to optimize deployment of charging base stations for WRSN," *EURASIP J. Wirel. Commun. Netw.*, vol. 2019, pp. 1–9, 2019.

[107] X. Ding, G. Sun, Y. Wang, C. Luo, D. Li, W. Chen, and Q. Hu, "Cost-minimum charger placement for wireless power transfer," in *Proc. Int. Conf. Comput. Commun. Netw. (ICCCN)*, 2019, pp. 1–9.

[108] W. Chien, H. Cho, H. Chao, and T. K. Shih, "Enhanced SA-based charging algorithm for WRSN," in *Proc. Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, 2016, pp. 1012–1017.

[109] D. Arivudainambi and S. Balaji, "Optimal placement of wireless chargers in rechargeable sensor networks," *IEEE Sensors J.*, vol. 18, no. 10, pp. 4212–4222, 2018.

[110] S. Bi and R. Zhang, "Placement optimization of energy and information access points in wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 2351–2364, 2015.

[111] S. Li, L. Fu, S. He, and Y. Sun, "Near-optimal co-deployment of chargers and sink stations in rechargeable sensor networks," *ACM Trans. Embed. Comput. Syst.*, vol. 17, no. 1, pp. 1–19, 2017.

[112] X. Rao, Y. Yan, M. Zhang, W. Xu, X. Fan, H. Zhou, and P. Yang, "You can recharge with detouring: Optimizing placement for roadside wireless charger," *IEEE Access*, vol. 6, pp. 47–59, 2017.

[113] X. Ding, J. Guo, Y. Wang, D. Li, and W. Wu, "Task-driven charger placement and power allocation for wireless sensor networks," *Ad Hoc Netw.*, vol. 119, p. 102556, 2021.

[114] W. Ejaz, S. Kandeepan, and A. Anpalagan, "Optimal placement and number of energy transmitters in wireless sensor networks for RF energy transfer," in *Proc. IEEE Annu. Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, 2015, pp. 1238–1243.

[115] W. Ejaz, M. Naeem, M. Basharat, A. Anpalagan, and S. Kandeepan, "Efficient wireless power transfer in software-defined wireless sensor networks," *IEEE Sensors J.*, vol. 16, no. 20, pp. 7409–7420, 2016.

[116] H. Liu, L. Zhong, Z. Liu, and F. Lin, "A multi-objective genetic optimization algorithm for charger selection in static charger deployment scheme for WRSN," in *Proc. IEEE Int. Conf. Adv. Infocomm Technol. (ICAIT)*, 2022, pp. 230–235.

[117] Y. Li, Y. Chen, C. S. Chen, Z. Wang, and Y. Zhu, "Charging while moving: Deploying wireless chargers for powering wearable devices," *IEEE Trans. Veh. Technol.*, vol. 67, no. 12, pp. 11 575–11 586, 2018.

[118] H. Yao, C. Zheng, X. Fu, Y. Yang, and I. Ungurean, "Charger and receiver deployment with delay constraint in mobile wireless rechargeable sensor networks," *Ad Hoc Netw.*, vol. 126, p. 102756, 2022.

[119] H. Dai, G. Chen, C. Wang, S. Wang, X. Wu, and F. Wu, "Quality of energy provisioning for wireless power transfer," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 2, pp. 527–537, 2014.

[120] M. Li, L. Liu, Y. Wang, J. Peng, J. Xi, and L. Wang, "Efficient wireless static chargers deployment for UAV networks," in *Proc. IEEE Int. Conf. Big Data Cloud Comput. (BdCloud)*, 2021, pp. 1483–1490.

[121] H. Yao, Q. Zhang, X. Fu, Y. Yang, and I. Ungurean, "Charger and receiver deployment for trajectory coverage with delay constraint in mobile wireless rechargeable sensor networks," *Ad Hoc Netw.*, p. 103237, 2023.

[122] H. Dai, Y. Liu, A. X. Liu, L. Kong, G. Chen, and T. He, "Radiation constrained wireless charger placement," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2016, pp. 1–9.

[123] H. Dai, Y. Liu, N. Yu, C. Wu, G. Chen, T. He, and A. X. Liu, "Radiation constrained wireless charger placement," *IEEE/ACM Trans. Netw*, vol. 29, no. 1, pp. 48–64, 2020.

[124] Y. Li, L. Fu, M. Chen, K. Chi, and Y.-h. Zhu, "RF-based charger placement for duty cycle guarantee in battery-free sensor networks," *IEEE Commun. Lett.*, vol. 19, no. 10, pp. 1802–1805, 2015.

[125] M. Y. Naderi, K. R. Chowdhury, and S. Basagni, "Wireless sensor networks with RF energy harvesting: Energy models and analysis," in *Proc. IEEE Wireless Commun. Netw. (WCNC)*, 2015, pp. 1494–1499.

[126] I. Katsidimas, S. Nikoletseas, T. P. Raptis, and C. Raptopoulos, "Efficient algorithms for power maximization in the vector model for wireless energy transfer," in *Proc. Int. Conf. Distrib. Comput. Netw. (ICDCN)*, 2017, pp. 1–10.

[127] I. Katsidimas, E. Kerimakis, and S. Nikoletseas, "Placement optimization in wireless charging systems under the vector model," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, 2019, pp. 473–480.

[128] J. Xue, D. Wu, J. Peng, W. Xu, and T. Liu, "Charger placement with wave interference," *IEEE Trans. Mobile Comput.*, 2024, Early Access.

[129] W. You, M. Ren, Y. Ma, D. Wu, J. Yang, X. Liu, and T. Liu, "Practical charger placement scheme for wireless rechargeable sensor networks with obstacles," *ACM Trans. Sens. Netw.*, vol. 20, no. 1, pp. 1–23, 2023.

[130] H. Zhang, J. C. Hou *et al.*, "Maintaining sensing coverage and connectivity in large sensor networks." *Ad Hoc Sens. Wirel. Networks*, vol. 1, no. 1-2, pp. 89–124, 2005.

[131] A. Fréville, "The multidimensional 0–1 knapsack problem: An overview," *Eur. J. Oper. Res.*, vol. 155, no. 1, pp. 1–21, 2004.

[132] P. Bose, A. Maheshwari, and P. Morin, "Fast approximations for sums of distances, clustering and the Fermat–Weber problem," *Comput. Geom.*, vol. 24, no. 3, pp. 135–146, 2003.

[133] J. H. Liao and J. R. Jiang, "Wireless charger deployment optimization for wireless rechargeable sensor networks," in *Proc. Int. Conf. Ubi-Media Comput. (Ubi-Media)*. IEEE, 2014, pp. 160–164.

[134] J. Liao, C. Hong, and J. Jiang, "An adaptive algorithm for charger deployment optimization in wireless rechargeable sensor networks," in *IOS Press Intelligent Systems and Applications*, 2015, pp. 2080–2089.

[135] J. Jiang and J. Liao, "Efficient wireless charger deployment for wireless rechargeable sensor networks," *Energies*, vol. 9, no. 9, p. 696, 2016.

[136] J. Jiang, Y. Chen, and T. Lin, "Particle swarm optimization for charger deployment in wireless rechargeable sensor networks," *Int. J. Parallel Emergent Distrib. Syst.*, vol. 36, no. 6, pp. 652–667, 2021.

[137] J. Jiang, Y. Chen, C. Tsai, and Z. Wu, "Meta-optimization for charger deployment in wireless rechargeable sensor networks," in *Proc. IEEE Int. Conf. Knowl. Innov. Invent. (ICKII)*, 2020, pp. 185–188.

[138] T.-L. Lin, H.-Y. Chang, and Y.-H. Wang, "A novel hybrid search and remove strategy for power balance wireless charger deployment in wireless rechargeable sensor networks," *Energies*, vol. 13, no. 10, p. 2661, 2020.

[139] A. Jaiswal, P. Kashyap, and S. Kumar, "Green communication: Optimal charger deployment based on TBM (OCD-TBM) in IoT," in *Proc. IEEE Int. Conf. Comput. Power Commun. Technol. (GUCON)*, 2021, pp. 1–6.

[140] X. Ding, J. Guo, D. Li, and W. Wu, "Optimal wireless charger placement with individual energy requirement," *Theor. Comput. Sci.*, vol. 857, pp. 16–28, 2021.

[141] S. Wu, H. Dai, L. Liu, L. Xu, F. Xiao, and J. Xu, "Cooperative scheduling for directional wireless charging with spatial occupation," *IEEE Trans. Mobile Comput.*, vol. 23, no. 1, pp. 286–301, 2022.

[142] X. Ding, Y. Wang, G. Sun, C. Luo, D. Li, W. Chen, and Q. Hu, "Optimal charger placement for wireless power transfer," *Comput. Netw.*, vol. 170, p. 107123, 2020.

[143] T. Lin, S. Li, and H. Chang, "A power balance aware wireless charger deployment method for complete coverage in wireless rechargeable sensor networks," *Energies*, vol. 9, no. 9, p. 695, 2016.

[144] J. Zhang, H. Gao, Q. Chen, and J. Li, "Task-oriented energy scheduling in wireless rechargeable sensor networks," *ACM Trans. Sens. Netw.*, vol. 19, no. 4, pp. 1–32, 2023.

[145] S. He, K. Hu, S. Li, L. Fu, C. Gu, and J. Chen, "A robust RF-based wireless charging system for dockless bike-sharing," *IEEE Trans. Mobile Comput.*, vol. 23, no. 3, pp. 2395–2406, 2024.

[146] N. Yu, H. Dai, A. X. Liu, and B. Tian, "Placement of connected wireless chargers," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2018, pp. 387–395.

[147] H. Dai, C. Wu, X. Wang, W. Dou, and Y. Liu, "Placing wireless chargers with limited mobility," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2020, pp. 2056–2065.

[148] H. Dai, X. Wang, X. Lin, R. Gu, S. Shi, Y. Liu, W. Dou, and G. Chen, "Placing wireless chargers with limited mobility," *IEEE Trans. Mobile Comput.*, vol. 22, no. 6, pp. 3589–3603, 2021.

[149] S. Nikoletseas, T. P. Raptis, A. Souroulagkas, and D. Tsolovos, "An experimental evaluation of wireless power transfer protocols in mobile ad hoc networks," in *Proc. IEEE Wireless Power Transf. Conf. (WPTC)*, 2015, pp. 1–3.

[150] ——, "Wireless power transfer protocols in sensor networks: Experiments and simulations," *J. Sens. Actuator Netw.*, vol. 6, no. 2, p. 4, 2017.

[151] Z. Wang, L. Duan, and R. Zhang, "Adaptively directional wireless power transfer for large-scale sensor networks," *IEEE J. Select. Areas Commun.*, vol. 34, no. 5, pp. 1785–1800, 2016.

[152] H. Dai, X. Wang, A. X. Liu, F. Zhang, Y. Zhao, and G. Chen, "Omnidirectional chargability with directional antennas," in *Proc. IEEE Int. Conf. Netw. Protocols (ICNP)*, 2016, pp. 1–10.

[153] H. Dai, Y. Zhang, X. Wang, A. X. Liu, and G. Chen, "Omnidirectional chargability with directional antennas," *IEEE Trans. Mobile Comput.*, vol. 23, no. 5, pp. 4483–4500, 2023.

[154] H. Dai, Y. Zhao, W. Wang, R. Gu, Y. Qu, C. Lin, L. Xu, and W. Dou, "Placing wireless chargers with multiple antennas," in *Proc. IEEE Int. Conf. Sens. Commun. Netw. (SECON)*, 2022, pp. 479–487.

[155] R. Jia, J. Lu, J. Wu, X. Wang, Z. Zheng, and M. Li, "Geometric analysis of energy saving for directional charging in WRSNs," *IEEE Internet Things J*, vol. 8, no. 6, pp. 4697–4710, 2020.

[156] T. He, K.-W. Chin, and S. Soh, "On maximizing min flow rates in rechargeable wireless sensor networks," *IEEE Trans Ind. Informat.*, vol. 14, no. 7, pp. 2962–2972, 2017.

[157] ——, "On wireless power transfer and max flow in rechargeable wireless sensor networks," *IEEE Access*, vol. 4, pp. 4155–4167, 2016.

[158] J. Chen, C. W. Yu, and W. Ouyang, "Efficient wireless charging pad deployment in wireless rechargeable sensor networks," *IEEE Access*, vol. 8, pp. 39 056–39 077, 2020.

[159] T. Rault, A. Bouabdallah, and Y. Challal, "Multi-hop wireless charging optimization in low-power networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2013, pp. 462–467.

[160] S. Wu, L. Xu, H. Dai, L. Liu, F. Xiao, and J. Xu, "Optimizing comprehensive cost of charger deployment in multi-hop wireless charging," *ACM Trans. Sens. Netw.*, vol. 19, no. 4, pp. 1–24, 2023.

[161] M. Erol-Kantarci and H. T. Mouftah, "Radio-frequency-based wireless energy transfer in LTE-A heterogenous networks," in *Proc. IEEE Symp. Computer and Commun. (ISCC)*, 2014, pp. 1–6.

[162] T. Lin, S. Li, H. Chang, W. Chang, and Y. Lin, "An effective wireless charger deployment method for complete coverage in wireless chargeable sensor networks," in *Proc. Int. Conf. Netw. Netw. Appl. (NaNA)*, 2016, pp. 379–382.

[163] "IBM ILOG CPLEX Optimizer," Accessed: 2024. [Online]. Available: https://www.ibm.com/products/ilog-cplex-optimization-studio.

[164] D. Niyato and P. Wang, "Competitive wireless energy transfer bidding: A game theoretic approach," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2014, pp. 1–6.

[165] N. Yu, X. Wang, H. Dai, and G. Chen, "A novel strategy under charger capture attack in wireless rechargeable sensor networks," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, 2020, pp. 356–361.

[166] A. Madhja, S. Nikoletseas, and A. A. Voudouris, "Adaptive wireless power transfer in mobile ad hoc networks," *Comput. Netw.*, vol. 152, pp. 87–97, 2019.

[167] T. Wu, P. Yang, and H. Dai, "Charging on the Move: Scheduling Static Chargers with Tunable Power for Mobile Devices," in *Proc. IEEE/ACM Int. Symp. Qual. Serv. (IWQOS)*, 2021, pp. 1–10.

[168] H. Dai, Y. Liu, G. Chen, X. Wu, and T. He, "SCAPE: Safe charging with adjustable power," in *Proc. IEEE Int. Conf. Distrib. Comput. Syst. (ICDCS)*, 2014, pp. 439–448.

[169] H. Dai, Y. Liu, G. Chen, X. Wu, T. He, A. X. Liu, and Y. Zhao, "SCAPE: Safe charging with adjustable power," *IEEE/ACM Trans. Netw*, vol. 26, no. 1, pp. 520–533, 2018.

[170] H. Dai, Y. Zhao, G. Chen, W. Dou, C. Tian, X. Wu, and T. He, "Robustly safe charging for wireless power transfer," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, 2018, pp. 378–386.

[171] H. Dai, Y. Xu, G. Chen, W. Dou, C. Tian, X. Wu, and T. He, "Rose: Robustly safe charging for wireless power transfer," *IEEE Trans. Mobile Comput.*, vol. 21, no. 6, pp. 2180–2197, 2020.

[172] L. Li, H. Dai, G. Chen, J. Zheng, Y. Zhao, and P. Zeng, "Radiation constrained fair wireless charging," in *Proc. IEEE Int. Conf. Sens. Commun. Netw. (SECON)*, 2017, pp. 1–9.

[173] L. Li, H. Dai, G. Chen, J. Zheng, W. Dou, and X. Wu, "Radiation constrained fair charging for wireless power transfer," *ACM Trans. Sens. Netw.*, vol. 15, no. 2, pp. 1–33, 2019.

[174] F. Ma, X. Liu, and N. Ansari, "Electromagnetic radiation safety on far-field wireless power transfer in IoT," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2022, pp. 4995–5000.

[175] Y. Zhu, X. Tian, K. Chi, C. Wen, and Y.-h. Zhu, "Real-time power control of wireless chargers in battery-free body area networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2019, pp. 1–6.

[176] G. Filios, A. Madhja, S. Nikoletseas, and C. Raptopoulos, "Characteristic models and algorithmic methods for efficient electromagnetic radiation control in wirelessly powered adhoc communication networks," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, 2019, pp. 487–494.

[177] L. Xiang, J. Luo, K. Han, and G. Shi, "Fueling wireless networks perpetually: A case of multi-hop wireless power distribution," in *Proc. IEEE Annu. Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, 2013, pp. 1994–1999.

[178] H.-T. Roh and J.-W. Lee, "Cross-layer optimization for wireless sensor networks with RF energy transfer," in *Proc. IEEE Int. Conf. Inf. Commun. Technol. Convergence. (ICTC)*, 2014, pp. 919–923.

[179] S. Lee, R. Zhang, and K. Huang, "Opportunistic wireless energy harvesting in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4788–4799, 2013.

[180] J. Kim, J. Park, S.-W. Ko, and S.-L. Kim, "User attraction via wireless charging in downlink cellular networks," in *Proc. Int. Symp. Model. Optim. Mobile Ad Hoc Wireless Netw. (WiOpt)*, 2016, pp. 1–8.

[181] T. A. Khan, A. Yazdan, and R. W. Heath, "Optimization of power transfer efficiency and energy efficiency for wireless-powered systems with massive MIMO," *IEEE Trans. Wireless Commun.*, vol. 17, no. 11, pp. 7159–7172, 2018.

[182] R. Du, H. Shokri-Ghadikolaei, and C. Fischione, "Wirelessly-powered sensor networks: Power allocation for channel estimation and energy beamforming," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 2987–3002, 2020.

[183] L. Lv, C. Zheng, L. Zhang, C. Shan, Z. Tian, X. Du, and M. Guizani, "Contract and Lyapunov optimization-based load scheduling and energy management for UAV charging stations," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 3, pp. 1381–1394, 2021.

[184] P. Guo, X. Liu, S. Tang, and J. Cao, "Concurrently wireless charging sensor networks with efficient scheduling," *IEEE Trans. Mobile Comput.*, vol. 16, no. 9, pp. 2450–2463, 2016.

[185] X. Liu, N. Ansari, Q. Sha, and Y. Jia, "Efficient green energy far-field wireless charging for Internet of Things," *IEEE Internet Things J*, vol. 9, no. 22, pp. 23 047–23 057, 2022.

[186] M. A. Kishk and H. S. Dhillon, "Joint uplink and downlink coverage analysis of cellular-based RF-powered IoT network," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 2, pp. 446–459, 2017.

[187] L. Chen, W. Wang, and C. Zhang, "Stochastic wireless powered communication networks with truncated cluster point process," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 11 286–11 294, 2017.

[188] R. Du, C. Fischione, and M. Xiao, "Lifetime maximization for sensor networks with wireless energy transfer," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2016, pp. 1–6.

[189] R. Du, M. Xiao, and C. Fischione, "Optimal node deployment and energy provision for wirelessly powered sensor networks," *IEEE J. Select. Areas Commun.*, vol. 37, no. 2, pp. 407–423, 2019.

[190] Z. Ma, J. Wu, S. Zhang, and S. Lu, "Fast interference-aware scheduling of multiple wireless chargers," in *Proc. Int. Conf. Mobile Adhoc Sens. Syst. (MASS)*, 2018, pp. 344–352.

[191] Z. Ma, S. Zhang, J. Wu, Z. Qian, Y. Zhao, and S. Lu, "Fast charging scheduling under the nonlinear superposition model with adjustable phases," *ACM Trans. Sens. Netw.*, vol. 15, no. 4, pp. 1–23, 2019.

[192] K. W. Choi, A. A. Aziz, D. Setiawan, N. M. Tran, L. Ginting, and D. I. Kim, "Distributed wireless power transfer system for Internet of Things devices," *IEEE Internet Things J*, vol. 5, no. 4, pp. 2657–2671, 2018.

[193] I. Katsidimas, S. Nikoletseas, and C. Raptopoulos, "Power efficient algorithms for wireless charging under phase shift in the vector model," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, 2019, pp. 131–138.

[194] Y. Zhang, D. Chen, and T. Jiang, "Robust beamforming design for magnetic MIMO wireless power transfer systems," *IEEE Trans. Signal Processing*, vol. 69, pp. 5066–5077, 2021.

[195] J. Xu, L. Liu, and R. Zhang, "Multiuser MISO beamforming for simultaneous wireless information and power transfer," *IEEE Trans. Signal Processing*, vol. 62, no. 18, pp. 4798–4810, 2014.

[196] M. Sheng, L. Wang, X. Wang, Y. Zhang, C. Xu, and J. Li, "Energy efficient beamforming in MISO heterogeneous cellular networks with wireless information and power transfer," *IEEE J. Select. Areas Commun.*, vol. 34, no. 4, pp. 954–968, 2016.

[197] O. L. López, D. Kumar, R. D. Souza, P. Popovski, A. Tölli, and M. Latva-Aho, "Massive MIMO with radio stripes for indoor wireless energy transfer," *IEEE Trans. Wireless Commun.*, vol. 21, no. 9, pp. 7088–7104, 2022.

[198] H. Son and B. Clerckx, "Joint beamforming design for multi-user wireless information and power transfer," *IEEE Trans. Wireless Commun.*, vol. 13, no. 11, pp. 6397–6409, 2014.

[199] G. Yang, C. K. Ho, R. Zhang, and Y. L. Guan, "Throughput optimization for massive MIMO systems powered by wireless energy transfer," *IEEE J. Select. Areas Commun.*, vol. 33, no. 8, pp. 1640–1650, 2015.

[200] F. Zhu, F. Gao, Y. C. Eldar, and G. Qian, "Robust simultaneous wireless information and power transfer in beamspace massive MIMO," *IEEE Trans. Wireless Commun.*, vol. 18, no. 9, pp. 4199–4212, 2019.

[201] O. L. López, F. A. Monteiro, H. Alves, R. Zhang, and M. Latva-Aho, "A low-complexity beamforming design for multiuser wireless energy transfer," *IEEE Wireless Commun. Lett.*, vol. 10, no. 1, pp. 58–62, 2020.

[202] S. Gong, S. Ma, C. Xing, and G. Yang, "Optimal beamforming and time allocation for partially wireless powered sensor networks with downlink SWIPT," *IEEE Trans. Signal Processing*, vol. 67, no. 12, pp. 3197–3212, 2019.

[203] D. Zhang, Q. Wu, M. Cui, G. Zhang, and D. Niyato, "Throughput maximization for IRS-assisted wireless powered hybrid NOMA and TDMA," *IEEE Wireless Commun. Lett.*, vol. 10, no. 9, pp. 1944–1948, 2021.

[204] S. Zargari, C. Tellambura, and S. Herath, "Energy-efficient hybrid offloading for backscatter-assisted wirelessly powered MEC with reconfigurable intelligent surfaces," *IEEE Trans. Mobile Comput.*, vol. 22, no. 9, pp. 5262–5279, 2022.

[205] X. Hu, K. Wong, and K. Yang, "Wireless powered cooperation-assisted mobile edge computing," *IEEE Trans. Wireless Commun.*, vol. 17, no. 4, pp. 2375–2388, 2018.

[206] F. Wang, J. Xu, X. Wang, and S. Cui, "Joint offloading and computing optimization in wireless powered mobile-edge computing systems," *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 1784–1797, 2017.

[207] Y. Zhao, V. C. Leung, H. Gao, Z. Chen, and H. Ji, "Uplink resource allocation in mobile edge computing-based heterogeneous networks with multi-band RF energy harvesting," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2018, pp. 1–6.

[208] R. Malik and M. Vu, "On-request wireless charging and partial computation offloading in multi-access edge computing systems," *IEEE Trans. Wireless Commun.*, vol. 20, no. 10, pp. 6665–6679, 2021.

[209] ——, "Energy-efficient joint wireless charging and computation offloading in MEC systems," *IEEE J. Sel. Top. Sign. Proces.*, vol. 15, no. 5, pp. 1110–1126, 2021.

[210] A. Iqbal, Y. Kim, and T. Lee, "Access mechanism in wireless powered communication networks with harvesting access point," *IEEE Access*, vol. 6, pp. 37 556–37 567, 2018.

[211] H. Choi, W. Shin, M. Levorato, and H. V. Poor, "Harvest-or-access: Slotted ALOHA for wireless powered communication networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 11, pp. 11 394–11 398, 2019.

[212] F. Iannello, O. Simeone, and U. Spagnolini, "Medium access control protocols for wireless sensor networks with energy harvesting," *IEEE Trans. Commun.*, vol. 60, no. 5, pp. 1381–1389, 2012.

[213] S. Cho, K. Lee, B. Kang, and I. Joe, "A hybrid MAC protocol for optimal channel allocation in large-scale wireless powered communication networks," *EURASIP J. Wirel. Commun. Netw.*, vol. 2018, pp. 1–13, 2018.

[214] J. Hu, G. Xu, L. Hu, S. Li, and Y. Xing, "An adaptive energy efficient MAC protocol for RF energy harvesting WBANs," *IEEE Trans. Commun.*, vol. 71, no. 1, pp. 473–484, 2022.

[215] M. Y. Naderi, K. R. Chowdhury, S. Basagni, W. Heinzelman, S. De, and S. Jana, "Experimental study of concurrent data and wireless energy transfer for sensor networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2014, pp. 2543–2549.

[216] O. Bouachir, A. B. Mnaouer, F. Touati, and D. Crescini, "Opportunistic routing and data dissemination protocol for energy harvesting wireless sensor networks," in *Proc. IEEE Int. Conf. New Technol. Mobil. Secur. (NTMS)*, 2016, pp. 1–5.

[217] T. D. Nguyen, J. Y. Khan, and D. T. Ngo, "A distributed energy-harvesting-aware routing algorithm for heterogeneous IoT networks," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 4, pp. 1115–1127, 2018.

[218] L. Lin, N. B. Shroff, and R. Srikant, "Asymptotically optimal energy-aware routing for multihop wireless networks with renewable energy sources," *IEEE/ACM Trans. Netw*, vol. 15, no. 5, pp. 1021–1034, 2007.

[219] S. Chen, P. Sinha, N. B. Shroff, and C. Joo, "A simple asymptotically optimal joint energy allocation and routing scheme in rechargeable sensor networks," *IEEE/ACM Trans. Netw*, vol. 22, no. 4, pp. 1325–1336, 2013.

[220] B. Tong, Z. Li, G. Wang, and W. Zhang, "How wireless power charging technology affects sensor network deployment and routing," in *Proc. IEEE Int. Conf. Distrib. Comput. Syst. (ICDCS)*, 2010, pp. 438–447.

[221] J. Marašević, C. Stein, and G. Zussman, "Max-min fair rate allocation and routing in energy harvesting networks: Algorithmic analysis," in *Proc. ACM Int. Symp. Mobile Ad Hoc Netw. Comput. (MobiHoc)*, 2014, pp. 367–376.

[222] K. Mustapha and D. Djenouri, "ADABCAST: Adaptive broadcast approach for solar energy harvesting wireless sensor networks," in *Proc. Wirel. Opt. Commun. Conf. (WOCC)*, 2017, pp. 1–6.

[223] M. Khiati and D. Djenouri, "Adaptive learning-enforced broadcast policy for solar energy harvesting wireless sensor networks," *Comput. Netw.*, vol. 143, pp. 263–274, 2018.

[224] A. Baknina and S. Ulukus, "Optimal and near-optimal online strategies for energy harvesting broadcast channels," *IEEE J. Select. Areas Commun.*, vol. 34, no. 12, pp. 3696–3708, 2016.

[225] J. Yang, O. Ozel, and S. Ulukus, "Broadcasting with an energy harvesting rechargeable transmitter," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 571–583, 2011.

[226] O. Ozel, J. Yang, and S. Ulukus, "Optimal broadcast scheduling for an energy harvesting rechargeable transmitter with a finite capacity battery," *IEEE Trans. Wireless Commun.*, vol. 11, no. 6, pp. 2193–2203, 2012.

[227] B. Yao, H. Gao, and J. Li, "Multicast scheduling algorithms for battery-free wireless sensor networks," in *Proc. Int. Conf. Mobile Adhoc Sens. Syst. (MASS)*, 2019, pp. 398–406.

[228] Q. Chen, Z. Cai, L. Cheng, and H. Gao, "Low latency broadcast scheduling for battery-free wireless networks without predetermined structures," in *Proc. IEEE Int. Conf. Distrib. Comput. Syst. (ICDCS)*, 2020, pp. 245–255.

[229] B. Yao, H. Gao, Q. Chen, and J. Li, "Energy-adaptive and bottleneck-aware many-to-many communication scheduling for battery-free WSNs," *IEEE Internet Things J*, vol. 8, no. 10, pp. 8514–8529, 2020.

[230] X. Ren and W. Liang, "Delay-tolerant data gathering in energy harvesting sensor networks with a mobile sink," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, 2012, pp. 93–99.

[231] X. Ren, W. Liang, and W. Xu, "Data collection maximization in renewable sensor networks via time-slot scheduling," *IEEE Trans. Comput.*, vol. 64, no. 7, pp. 1870–1883, 2014.

[232] Y. Zhang, S. He, and J. Chen, "Data gathering optimization by dynamic sensing and routing in rechargeable sensor networks," *IEEE/ACM Trans. Netw*, vol. 24, no. 3, pp. 1632–1646, 2015.

[233] T. Zhu, J. Li, H. Gao, and Y. Li, "Latency-efficient data collection scheduling in battery-free wireless sensor networks," *ACM Trans. Sens. Netw.*, vol. 16, no. 3, pp. 1–21, 2020.

[234] J. Zhang, H. Gao, K. Zhang, Q. Chen, and J. Li, "A distributed framework for low-latency data collection in battery-free wireless sensor networks," *IEEE Internet Things J*, vol. 9, no. 11, pp. 8438–8453, 2021.

[235] X. Song and K. Chin, "Maximizing packets collection in wireless powered IoT networks with charge-or-data time slots," *IEEE Trans. Cogn. Commun. Netw.*, vol. 9, no. 4, pp. 1067–1079, 2023.

[236] K. David and H. Berndt, "6G vision and requirements: Is there any need for beyond 5G?" *IEEE Veh. Tech. Mag.*, vol. 13, no. 3, pp. 72–80, 2018.

[237] T. Liu, B. Wu, W. Xu, X. Cao, J. Peng, and H. Wu, "RLC: A reinforcement learning-based charging algorithm for mobile devices," *ACM Trans. Sens. Netw.*, vol. 17, no. 4, pp. 1–23, 2021.

[238] S. Zhang, B. Yin, W. Zhang, and Y. Cheng, "Topology aware deep learning for wireless network optimization," *IEEE Trans. Wireless Commun.*, vol. 21, no. 11, pp. 9791–9805, 2022.

[239] X. Wang, L. Kong, F. Kong, F. Qiu, M. Xia, S. Arnon, and G. Chen, "Millimeter wave communication: A comprehensive survey," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 1616–1653, 2018.

[240] L. Wang, K.-K. Wong, R. W. Heath, and J. Yuan, "Wireless powered dense cellular networks: How many small cells do we need?" *IEEE J. Select. Areas Commun.*, vol. 35, no. 9, pp. 2010–2024, 2017.

[241] L. Dai, B. Wang, M. Peng, and S. Chen, "Hybrid precoding-based millimeter-wave massive MIMO-NOMA with simultaneous wireless information and power transfer," *IEEE J. Select. Areas Commun.*, vol. 37, no. 1, pp. 131–141, 2018.

[242] A. Khazali, D. Tarchi, M. G. Shayesteh, H. Kalbkhani, and A. Bozorgchenani, "Energy efficient uplink transmission in cooperative mmWave NOMA networks with wireless power transfer," *IEEE Trans. Veh. Technol.*, vol. 71, no. 1, pp. 391–405, 2021.

[243] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surface-aided wireless communications: A tutorial," *IEEE Trans. Commun.*, vol. 69, no. 5, pp. 3313–3351, 2021.

[244] Z. Feng, B. Clerckx, and Y. Zhao, "Waveform and beamforming design for intelligent reflecting surface aided wireless power transfer: Single-

user and multi-user solutions," *IEEE Trans. Wireless Commun.*, vol. 21, no. 7, pp. 5346–5361, 2022.
[245] W. Shi, Q. Wu, D. Wu, F. Shu, J. Wang, and R. He, "Joint transmit and reflective beamforming design for active irs-aided swipt systems," *Chinese J. Electron.*, vol. 33, no. 2, pp. 536–548, 2024.
[246] Q. Yue, J. Hu, K. Yang, and K. Wong, "Intelligent reflecting surface aided wireless power transfer with a DC-combining based energy receiver and practical waveforms," *IEEE Trans. Veh. Technol.*, vol. 71, no. 9, pp. 9751–9764, 2022.
[247] K. Sun, R. Fan, X. Zhang, Z. Zhang, Z. Shi, N. Wang, P. Xie, Z. Wang, G. Fan, H. Liu *et al.*, "An overview of metamaterials and their achievements in wireless power transfer," *J. Mater. Chem. C*, vol. 6, no. 12, pp. 2925–2943, 2018.
[248] C. Rong, C. Lu, Y. Zeng, X. Tao, X. Liu, R. Liu, X. He, and M. Liu, "A critical review of metamaterial in wireless power transfer system," *IET Power Electron.*, vol. 14, no. 9, pp. 1541–1559, 2021.
[249] J. Zhou, P. Zhang, J. Han, L. Li, and Y. Huang, "Metamaterials and metasurfaces for wireless power transfer and energy harvesting," *Proc. IEEE Inst. Electr. Electron. Eng.*, vol. 110, no. 1, pp. 31–55, 2021.

Meixuan Ren (Student Member, IEEE) received the B.S. degree from the Department of Mathematics, Sichuan Normal University, China, in 2020, and the M.S. degree from the Department of Computer Science and Technology, Sichuan Normal University, China, in 2023. She is working towards the Ph.D. degree in the Department of Computer Science and Technology, Nanjing University, China. Her research interests include wireless charging, Internet of Things, and wireless sensor networks.

Haipeng Dai (Senior Member, IEEE) received the B.S. degree in the Department of Electronic Engineering from Shanghai Jiao Tong University, Shanghai, China, in 2010, and the Ph.D. degree in the Department of Computer Science and Technology in Nanjing University, Nanjing, China, in 2014. His research interests are mainly in the areas of Internet of Things and mobile computing. He is an associate professor in the Department of Computer Science and Technology in Nanjing University. His research papers have been published in many prestigious conferences and journals such as ACM MobiSys, ACM MobiHoc, ACM UbiComp, IEEE INFOCOM, ACM SIGMETRICS, IEEE ICDCS, IEEE ICNP, IEEE TMC, IEEE JSAC, IEEE/ACM TON, and IEEE TPDS. He serves/ed as TPC Chair of the IEEE ISPA'22, TPC Vice-Chair of the IEEE HPCC'21, Poster Chair of the IEEE ICNP'14, Track Chair of the ICCCN'19 and the ICPADS'21, TPC member of ACM MobiHoc'20-22 and IEEE INFOCOM'20-23. He received Best Paper Award from IEEE ICNP'15, Best Paper Award Runner-up from IEEE SECON'18, and Best Paper Award Candidate from IEEE INFOCOM'17.

Tang Liu (Member, IEEE) received the B.S. degree in computer science from University of Electronic and Science of China, China, in 2003, and the M.S. and Ph.D. degree in computer science from Sichuan University in 2009 and 2015, respectively. Since 2003, he has been with the College of Computer Science, Sichuan Normal University, where he is currently a professor. He has authored more than 50 scientific papers in several journals and conferences, including IEEE INFOCOM, IEEE TMC, IEEE/ACM TON, IEEE TWC, ACM TOSN and IEEE IPDPS. His research interests include wireless charging, Internet of Things, and wireless sensor networks.

Xianjun Deng (Senior Member, IEEE) received the Ph.D. degree from Huazhong University of Science and Technology in 2014. He is currently a Professor with the School of Cyber Science and Engineering, HUST. He has authored or coauthored more than 50 technical papers in international top journals and conferences. His research interests include security and reliability, coverage optimization, parallel and distributed computing in wireless sensor networks (WSNs), and the Internet of Things (IoT). He was a recipient of the IEEE TCSC Award.

Wanchun Dou (Member, IEEE) received the Ph.D. degree in mechanical and electronic engineering from the Nanjing University of Science and Technology, China, in 2001. He is currently a full professor of the State Key Laboratory for Novel Software Technology, Nanjing University. From April 2005 to June 2005 and from November 2008 to February 2009, he respectively visited the Department of Computer Science and Engineering, Hong Kong University of Science and Technology, Hong Kong, as a visiting scholar. Up to now, he has chaired three National Natural Science Foundation of China projects and published more than 100 research papers in international journals and international conferences. His research interests include workflow, cloud computing, and service computing. He is a member of the IEEE.

Yuanyuan Yang (Life Fellow, IEEE) received the B.Eng. and M.S. degrees in computer science and engineering from Tsinghua University, Beijing, China, and the M.S.E. and Ph.D. degrees in computer science from Johns Hopkins University, Baltimore, MD, USA. She is currently a SUNY Distinguished Professor of computer engineering and computer science with Stony Brook University, Stony Brook, NY, USA. She is also on leave with the National Science Foundation as the Program Director. She has published more than 460 papers in major journals and refereed conference proceedings and holds seven U.S. patents in these areas. Her research interests include edge computing, data center networks, cloud computing, and wireless networks. She is currently the Editor-in-Chief for IEEE Transactions on Cloud Computing and an Associate Editor for IEEE Transactions on Parallel and Distributed Systems and *ACM Computing Surveys*. She has served as the Associate Editor-in-Chief for IEEE Transactions on Cloud Computing, the Associate Editor-in-Chief and an Associate Editor of IEEE Transactions on Computers, and an Associate Editor of IEEE Transactions on Parallel and Distributed Systems. She has also served as the general chair, program chair, or vice chair for several major conferences, and a program committee member for numerous conferences.

Guihai Chen (Fellow, IEEE) received B.S. degree in computer software from Nanjing University in 1984, M.E. degree in computer applications from Southeast University in 1987, and Ph.D. degree in computer science from the University of Hong Kong in 1997. He is a professor and deputy chair of the Department of Computer Science, Nanjing University, China. He had been invited as a visiting professor by many foreign universities including Kyushu Institute of Technology, Japan in 1998, University of Queensland, Australia in 2000, and Wayne State University, USA during Sept. 2001 to Aug. 2003. He has a wide range of research interests with focus on sensor networks, peer-to-peer computing, high-performance computer architecture and combinatorics.