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

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***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], as an innovative energy transfer technology, has revolutionized the way electronic devices are powered. This technology allows electromagnetic energy to be transmitted through the air to electronic devices, eliminating the need for interconnecting wires. 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 [2], an organization dedicated to driving the standardization of WPT, to jointly promote WPT 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], [5]. To address this limitation, some studies have proposed energy harvesting, leveraging ambient energy sources such as solar [6], vibration [7], and wind [8], 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) [9] 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 [10], medical systems [11], precision agriculture [12], and Wireless Identification and Sensing Platform (WISP) [13].

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) [14]. 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 chargers are well-suited for powering low-power devices. In

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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], [16], electric toothbrushes [14], and electric vehicles [17].

Constructing effective and efficient WCNs involves addressing the following key challenges:1) *how to strategically deploy wireless chargers?* 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 to effectively schedule limited wireless charger resources?* 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 to coordinate the charging process to optimize the communication of 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 wireless 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. Specifically, our survey provides a thorough overview of WCNs, including: 1) an introduction to the framework of WCNs, 2) a discussion of charger

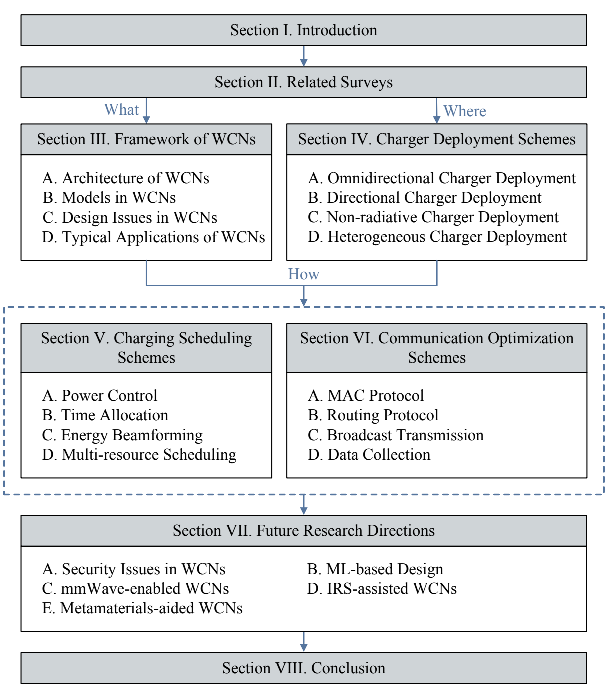


Fig. 1. Main structure of this paper.

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
EMI	Electromagnetic interference
EMR	Electromagnetic radiation
EV	Electric vehicle
GPS	Global positioning system
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

deployment schemes utilizing different WPT technologies, 3) an investigation of various charging scheduling schemes, and 4) a review of communication optimization schemes to coordinate the charging process. The key contributions of this survey are summarized as follows.

- We introduce the framework of WCNs, including network architecture and basic components, omnidirectional and directional charging models, non-radiative charging models, design issues, and typical applications of WCNs.
- We conduct a comprehensive, in-depth review of existing charger deployment schemes in WCNs, which includes omnidirectional, directional, non-radiative, and heterogeneous charger deployments.
- We conduct an in-depth study of charging scheduling schemes in WCNs, covering power control, time allocation, energy beamforming, and multi-resource scheduling.
- We conduct a literature review on communication optimization schemes, focusing on MAC protocols, routing protocols, broadcast transmission, and data collection.
- 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, respectively. Section VII outlines open issues and future research

TABLE II
COMPARISON OF OUR SURVEY WITH EXISTING SURVEYS
('C': THE TOPIC IS FULLY COVERED; 'P': THE TOPIC IS PARTIALLY COVERED; AND 'N': THE TOPIC IS NOT COVERED)

Networks	**Network features**	**Architecture**	**Charging modeling**	**Charger deployment schemes**	**Resource scheduling schemes**	**Communication optimization schemes**
WRSNs (*e.g.,* [18])	Power the network with a dynamic wireless charger.	C	C	N	N	N
BF-WSNs (*e.g.,* [19])	Equip devices with a capacitor for indefinite energy storage.	C	N	N	N	C
WPCNs (*e.g.,* [20])	Harness wireless chargers to facilitate energy and information transmission to/from devices.	C	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	C

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) [18], [21]–[24], Battery-Free Wireless Sensor Networks (BF-WSNs) [19], [25], [26], and Wireless Powered Communication Networks (WPCNs) [20], [27]–[30]. Table II summarizes and compares the existing survey works on WRSNs, BF-WSNs, WPCNs, and WCNs.

We begin by presenting survey papers focusing on the WRSN paradigm. In WRSNs, Mobile Chargers (MCs) equipped with WPT technology visit devices in the network in a certain order to charge them wirelessly. Earlier in 2015, Hu *et al*. [21] 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*. [22] 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*. [23] 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*. [18] 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*. [24] 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. Research on WRSNs primarily focuses on planning the charging paths of MCs, rather than the deployment of fixed chargers or the scheduling of charging resources.

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*. [25] 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*. [26] reviewed aspects of energy replenishment scheduling, communication and networking, data acquisition, and applications in BF-WSNs. In 2023, Jiang *et al*. [19] 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. Diverging from the focus on optimizing charging schemes for wireless chargers in WCNs, research on BF-WSNs prioritizes enhancing the composition and communication of battery-free wireless sensors.

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*. [27] 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*. [28] 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 [29], specifically focusing on signal processing aspects, network design issues, and efficient communication techniques. In 2022, Huda *et al*. [30] conducted an in-depth survey on WPCNs in terms of critical design parameters and performance factors. In 2023, Wang *et al*. [20] offered a comprehensive review of wireless powered mobile edge computing networks, integrating Mobile Edge Computing (MEC) and WPT technologies. The study summarizes solutions for computation offloading and resource allocation to solve critical issues in these networks. In WPCNs, wireless chargers typically handle both energy and information transmission. Research in this field primarily emphasizes the coordination of energy and information transmission functions, with less attention to optimizing the spatial deployment of chargers or their charging schedules.

III. FRAMEWORK OF WCNs

This section introduces the framework of WCNs. Specifically, we first present the network architecture and basic

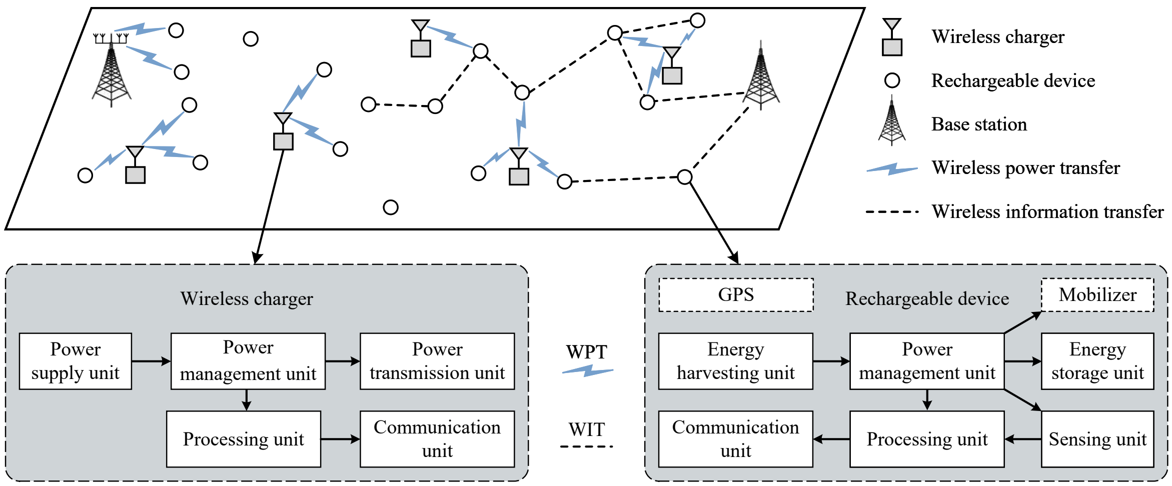


Fig. 2. WCN infrastructure architecture and basic components of wireless chargers and rechargeable devices.

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 [31] or an antenna [32], 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 [33]), 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 [34].

B. Models in WCNs

In WCNs, wireless chargers with different WPT technologies exhibit distinct charging performance. In practice, WPT technologies can be broadly categorized into two groups: 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.

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 [35], PRIMOVE [36], and Powercast transmitter [37], exemplify this trend. Fig. 3 illustrates

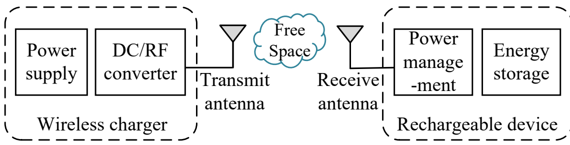


Fig. 3. The basic principle of a radiative charging system.

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. 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, as described in [32], [38], the received power transmitted from the omnidirectional charger to the rechargeable device 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.

Notably, when the rechargeable device is too far away from the charge, *i.e.,* $d > D$, it cannot receive non-negligible energy. Hence, the omnidirectional charging model is simplified as

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

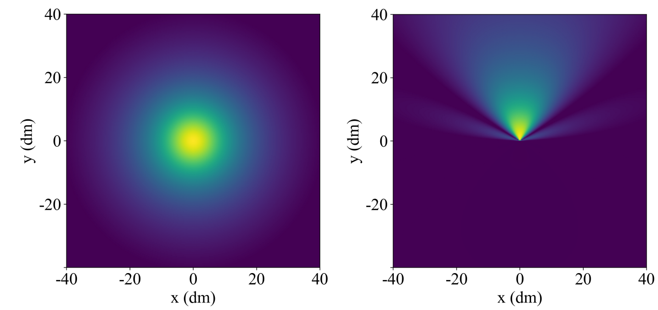
where $\alpha = \frac{G_t G_r \eta}{L_p} (\frac{\lambda}{4\pi})^2 P_t$ (for simplicity). Note that α, β, and D are constants determined by the experimental environment and the hardware parameters of wireless chargers.

For directional chargers, the power density varies across different directions, and the received power by the rechargeable device is not only related to the distance, but also to the angle. Let θ represent the related angle between a charger and a device, the received power is expressed as follows [39]:

$$P_r(d, \theta) = \begin{cases} \mu \frac{cos\theta + c}{(d+\beta)^2}, & 0 \le d \le D, \ -\frac{\gamma}{2} \le \theta \le \frac{\gamma}{2}, \\ 0, & \text{otherwise}, \end{cases} \quad (3)$$

where $\mu = \frac{A_t^{max} A_r \eta}{L_p \lambda^2} P_t$, A_t^{max} and A_r represent the maximum transmitting area of the wireless charger and the effective receiving area of the rechargeable device, respectively. Additionally, c is a parameter to adjust the equation for a vertical situation, *i.e.,* $\theta = \pm\frac{\pi}{2}$, and γ denotes the beamwidth, indicating the angle from where most of the power is transmitted.

Fig. 4 illustrates simulated radiation patterns of both omnidirectional and directional chargers, showcasing the distinct



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

Fig. 4. Simulated charging power heatmaps: omnidirectional charger vs directional charger. Simulated results are based on (a) $\alpha = 2.175, \beta = 0.1$, and (b) $\mu = 3.893$, $c = 0.1161$, $\beta = 0.1$.

charging areas characteristic of each type. Omnidirectional chargers enable rechargeable devices to receive energy from 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 focus energy supply in limited directions, which allows for higher power density and longer charging distances, making them ideal for sparse and large-scale networks. Furthermore, as depicted in Fig. 4b, 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 [40], [41].

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 [9], [32], [38]. In fact, due to Electromagnetic Interference (EMI), the cumulative power is determined by the amplitude and phase of the waves emitted by multiple chargers [42]. 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_i from charger s_j can be expressed in the form of a sinusoidal wave:

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

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_i simultaneously, the combined wave arrives at o_i can be written as

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

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

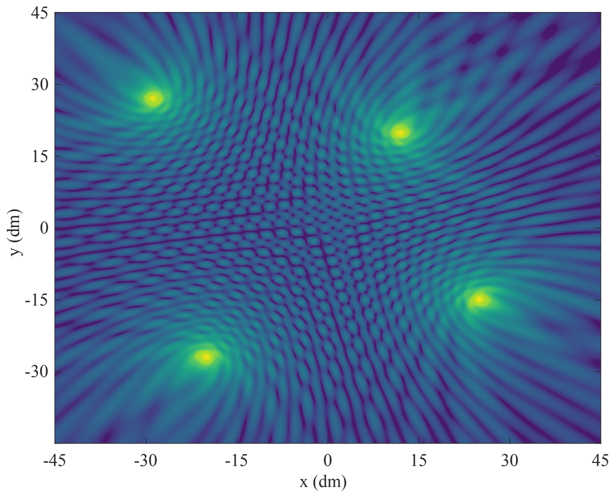


Fig. 5. Charging power heatmap of four omnidirectional chargers.

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

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

Fig. 5 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 [43]. In this study, directional chargers are deployed within the network and their directionals are freely adjustable. Fig. 6 demonstrates the changes in charging power distribution when the directionals of these chargers are altered, without considering the anisotropy of their charging power. It is evident that the directivity of directional chargers significantly influences the power distribution.

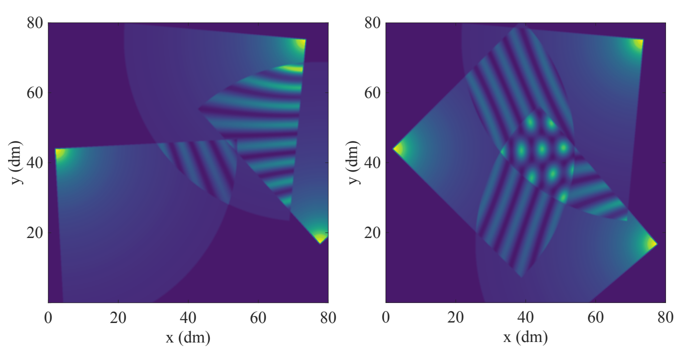


Fig. 6. Charging power heatmaps under different chargers' directions.

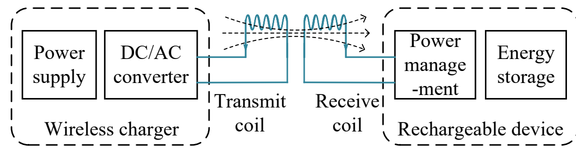


Fig. 7. The basic principle of a non-radiative charging system.

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. 7. The most widely applied technologies corresponding to this classification are inductive coupling and magnetic resonant coupling. Laboratory wireless chargers such as MagMIMO [44] and WiTricity [31], 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. Consequently, optimal charging performance is achieved when the charger is close to the rechargeable device (typically within the coil diameter, such as in the centimeter range) and when the coils are precisely aligned. In contrast, magnetic resonance coupling works by aligning magnetic resonance coils at the same resonant frequency, creating a strong non-radiative magnetic resonance induction. High power transfer efficiency can be achieved over relatively long distances, and multi-hop power transmission can be achieved using resonant repeaters [45]. Non-radiative technologies work on the near field, and the generated magnetic field dominates the area close to the charger or device, resulting in shorter charging distances and higher charging efficiency. The received power can be expressed as [14]:

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

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 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 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

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

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 [46]

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

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

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.

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

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

C. Design Issues in WCNs

This section outlines the fundamental design issues that researchers are concerned with when constructing effective and efficient WCNs. These issues include the strategic deployment of diverse chargers to guarantee extensive coverage and continuous energy supply for rechargeable devices within the network. Another issue is efficiently scheduling the various limited resources of wireless chargers to improve charging performance. Moreover, optimizing communication in WCNs while ensuring efficient charging is also an issue that needs attention. Fig. 8 illustrates the taxonomy of these design issues, and each is discussed in detail in the following.

1) Charger Deployment Schemes (CDS): the strategic deployment of wireless chargers constitutes a fundamental aspect of constructing WCNs. Charger deployment significantly influences the charging coverage [32], [38], charging efficiency [47], and connectivity [48] of the network. As previously discussed, the deployment strategies for wireless chargers vary due to differences in their charging models, which include aspects such as charging area, efficiency, and power distribution. These strategies can be categorized based on the type of chargers employed into omnidirectional, directional, non-radiative, and heterogeneous charger deployments. Omnidirectional and directional charger deployment schemes focus on optimizing charging coverage to reduce the number of chargers [32], [38] and maximize charging utility [49], [50]. Due to their radiation properties, Electromagnetic Radiation (EMR) safety [51], [52] and Electromagnetic Interference (EMI) [42] 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 [53], [54]. Furthermore, the deployment of heterogeneous chargers is studied in [55], [56], leveraging the charging characteristics of different charger types through collaborative deployment to further optimize charging performance.

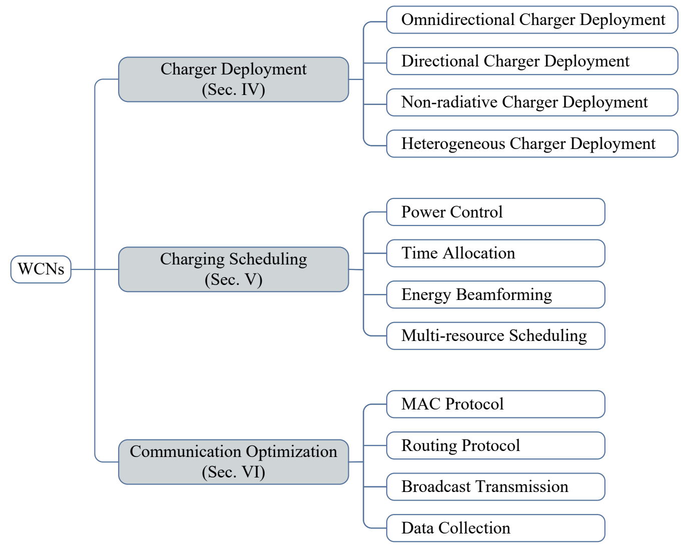


Fig. 8. Taxonomy of design issues.

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

- maximize charging performance,
- subject to constraints such as coverage quantity, energy provision, and radiation properties.

2) Charging Scheduling Schemes (CSS): effectively scheduling various limited resources of wireless chargers is essential for the sustainable operation of WCNs. This includes optimizing power control, time allocation, energy beamforming, and multi-resource scheduling. Power control schemes concentrate on dynamically allocating power based on demand [57], [58], prioritizing the charging of energy-critical devices [59], and maximizing charging efficiency [60]. Moreover, for multi-functional chargers that transmit both information and power, power control schemes must meticulously balance wireless information transmission and power transfer [61]. Time allocation schemes typically involve allocating charging duration [15], [16], scheduling power transmission [62], [63], and coordinating power and information transfer [64], aiming to maximize charging efficiency or network throughput. Energy beamforming involves directing wireless power transmission in a specific direction to enhance transmission efficiency. The scheme is designed to focus energy transfer on target devices, minimizing energy waste [11], [65]. Finally, multi-resource scheduling aims to maximize charging efficiency through the coordinated optimization of various resources [66].

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,
- 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 not only controls the access to the shared wireless media between devices, but also coordinates the power transmission process and the communication process [67], [68]. Routing protocol optimization aims to identify the best route to transmit data from source to destination, considering devices with additional power supply [69]. Broadcast transmission optimization focuses on enhancing transmission reliability [70], [71] and reducing broadcast latency [72], while ensuring collision-free transmission and maintaining charging performance. Additionally, it is crucial to consider how to utilize mobile [73] or fixed sinks [74] (or BSs) to collect data, ensuring timely data collection for subsequent analysis.

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 communication performance,
- 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. With low charging power requirements, typically ranging from microwatts to milliwatts, they are suitable for large-scale charging using radiated chargers. In WCNs, these sensors can be placed remotely and distributed without concerns about energy supply limitations [75], which is essential for extensive or hard-to-reach areas like oceans, forests, or bridges [76], [77]. Moreover, the reliable power supply ensures continuous data collection, essential for real-time monitoring and rapid environmental response [78]. Furthermore, by eliminating battery replacements, the network's maintenance costs are significantly reduced, enhancing its cost-effectiveness. In brief, WCNs enhance wireless sensor deployment with improved flexibility, reliability, and reduced maintenance costs.

2) Medical Implants: medical implants are devices implanted in the patient's body to monitor, treat, or aid physiological functions. Due to safety considerations, their charging power is strictly limited to the milliwatt level, typically employing non-radiated chargers. Integration with WCNs effectively avoids potential risks associated with surgical battery replacements [11], [79]. 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 [80]. Overall, WCNs offer several advantages for medical implants, including enhanced convenience, improved maintainability, and remote monitoring capabilities.

3) Portable Electronics: portable electronic devices, such as smartphones, tablets, and Bluetooth headphones, can be carried by users. These devices typically require charging power ranging from several watts to tens of watts, which can be efficiently provided through non-radiative chargers using inductive coupling. In WCNs, these devices can achieve continuous power supply, eliminating concerns about battery depletion and greatly improving travel convenience [15]. Moreover, WCNs enable users to freely position their devices in areas that support wireless charging. This not only eliminates the limitations of charging locations but also effectively reduces cable clutter, creating a cleaner, more organized environment [81]. In summary, WCNs provide a convenient, flexible, and stable wireless charging service for portable electronic devices, greatly improving user experience and device usability.

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. 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 [82]. 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 [83], [84]. This convenient and flexible energy supply method propels further development and application of UAV technology in various fields.

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 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 [85]. Furthermore, WCNs turn ordinary appliances into smart appliances, enhancing their control and safety features [86].

6) EVs: Certain EVs, e-bikes, and e-scooters are now wireless charging-capable, demanding power from tens of watts to tens of kilowatts. 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 [17]. 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 [87]. Another notable benefit is the ability of the WCN to facilitate wireless charging of various models of EVs, simplifying the charging process and promoting interoperability within the EV ecosystem [88].

IV. Charger Deployment Schemes

For charger deployment schemes, generally, a set of rechargeable devices equipped with an energy harvesting unit is deployed in a network, and a set of fixed chargers equipped with a power transmission unit is responsible for providing these rechargeable devices with the necessary energy supply. Since the efficiency of energy transmission is influenced by the relative positions of chargers and devices, strategically deploying wireless chargers becomes a critical consideration.

Given the distinct charging models of each charger type, tailored optimization strategies are necessary for their deployment. Hence, charger deployment schemes can be categorized into four main types based on the type of wireless charger employed: 1) omnidirectional charger deployment, wherein electromagnetic waves broadcast equally in all directions from wireless chargers, forming a circular charging area with the charger at its center and the maximum charging distance as its radius; 2) directional charger deployment, wherein energy is concentrated in a predetermined narrow direction of wireless chargers via energy beamforming, forming a sector charging area with the charger at its center, the maximum charging distance as its radius, and the beamwidth as its central angle; 3) non-radiative charger deployment, characterized by a short charging distance and high efficiency, suitable for point-to-point charging scenarios; and 4) heterogeneous charger deployment, which employs different types of wireless chargers to provide charging services for the network, catering to various charging needs.

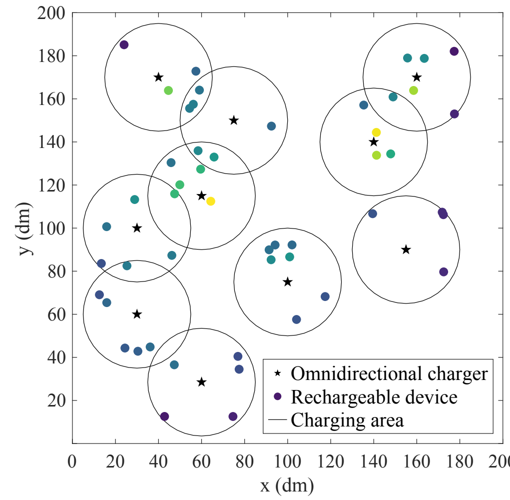


Fig. 9. Illustration of an omnidirectional charger deployment scheme within a network comprising 50 rechargeable devices and 10 omnidirectional chargers, each having an effective charging distance of 25dm.

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 satisfy different optimization objectives (*e.g.,* reducing deployment cost, enhancing charging utility, and achieving multi-objective optimization) [12], [32], [38], [42], [47], [51], [52], [57], [58], [89]–[114]. For better comprehension, Fig. 9 illustrates an omnidirectional charger deployment scheme. Additionally, Table III presents a comprehensive overview of related studies, detailing their comparison in terms of objectives, constraints, device mobility, approaches, performance metrics, and Evaluation Methods (EVM).

In the past decade, extensive efforts [32], [38], [89]–[98], [101], [102] have been made to reduce deployment costs for recharging static or mobile devices. Chargers are usually much more expensive than rechargeable devices, about 100 times the price difference [32], so it is a great concern to cover more rechargeable devices with as few chargers and deployment costs as possible.

In WCNs, a large number of static devices are often deployed to perform some long-term tasks such as data monitoring and communication. How to deploy a minimum number of omnidirectional chargers to maintain the continuous and permanent operation of these static devices has been deeply studied in [32], [38], [89]–[95]. He *et al.* [32], [38] introduced a WCN constructed from the WISP [13] and commercial off-the-shelf omnidirectional chargers. Specifically, the WISP integrates devices with 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 [115], providing the upper-bound asymptotic approximation ratios of the proposed solutions to the optimal ones.

Some papers [89]–[93] 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*. [89] 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*. [90] 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*. [91] 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*. [116] 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*. [92] 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 devices in the indoor scenario. Arivudainambi *et al*. [93] 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.

The studies mentioned above assume that the cumulative charging power from multiple chargers is simply additive. However, in real-world scenarios, each electromagnetic wave reaches the device with distinct time delays, amplitudes, and phases. In recognition of this complexity, Li *et al*. [94] introduced a charging model that takes into account 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. In addition to charger deployment, some papers [95], [96] also consider the deployment of BSs responsible 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 [95] 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*. [96] 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 subproblem 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.

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. This aspect has been discussed in [32], [38], [97]–[102].

Regarding the mobility trajectories of these mobile devices, various studies adopt different assumptions. Some studies [97], [98] assume that specific stops exist along the trajectory. In [97], 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 [98], 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 [32], [38], [99]–[102] assume that mobile devices can stop at any point along the trajectory. He *et al*. [32], [38] 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. Consider the case where mobile devices follow a uniform distribution, they tried to ensure that the accumulated energy over a period of time is greater than a certain threshold and proposed a method based on triangular deployment. Dai *et al*. [99], [100] 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*. [101] tackled the problem of deploying omnidirectional chargers on a two-dimensional 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. Furthermore, the research in [102] also introduces a trajectory discretization approach to reduce computational complexity. Then, heuristic algorithms based on greedy and particle swarm optimization are proposed to minimize the number of chargers.

The research [42], [47], [51], [52], [57], [58], [103]–[110] on the omnidirectional charger deployment also focuses on

TABLE III
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	[32], [38]	Minimum number of chargers	Energy provision constraints	Static; mobile	Approximation	Approximation ratio; average consumption power	TA; NS
	[89]	Minimum number of chargers	Coverage constraints	Static	Approximation	Approximation ratio	TA
	[90], [91]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Number of chargers; number of candidate chargers	NS
	[116]	Minimum deployment cost	Energy provision constraints	Static	Approximation	Deployment cost	TA; NS
	[92]	Minimum number of chargers	Energy provision constraints	Static	Metaheuristic	Number of chargers; running time	NS
	[93]	Minimum number of chargers	Coverage constraint	Static	Heuristic	Coverage quality	NS
	[94]	Minimum number of chargers	Energy provision constraints	Static	Heuristic; metaheuristic	Number of chargers	NS
	[95]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Harvested power; convergence rate; number of chargers	TA; NS
	[96]	Minimum number of chargers	Flow conservation constraints; energy provision constraints	Static	Approximation	Number of chargers; harvested power	TA; NS
	[97]	Minimum number of chargers	Energy provision constraints	Mobile	Heuristic; metaheuristic	Number of chargers	NS
	[98]	Minimum number of chargers	Non-overtime stay probability requirement	Mobile	Heuristic; metaheuristic	Number of chargers; number of devices	NS
	[99], [100]	Assess the impact of mobility	Energy provision constraints	Mobile	Bound analysis	Quality of energy provisioning	TA; NS
	[101]	Minimum number of chargers	Energy provision constraints	Mobile	Exact	Number of chargers and discrete grids; overhead of running	NS
	[102]	Minimum number of chargers	Non-overtime updating probability requirement	Mobile	Heuristic; metaheuristic	Number of chargers; success rate; running time	NS; FE
	[47]	Maximum charging utility	Coverage constraints	Mobile	Heuristic	Survival rate	NS
	[103]	Maximum charging utility	Coverage constraints	Mobile	Approximation	Coverage rate; coverage efficiency	TA; NS
	[57], [58]	Maximum charging utility	Power budget constraints	Static	Approximation	Coverage quality; running time	TA; NS
	[104]	Maximum task utility	Deployment cost budget	Static	Approximation	Task utility; harvested power	TA; NS
	[51], [52]	Maximum charging utility	EMR safety constraints; charger location constraints	Static	Approximation	Harvested power	TA; NS; FE
	[105], [106]	Maximum charging utility	EMR safety constraints	Static	Approximation	Harvested power	TA; NS; FE
	[107]	Maximum charging utility	Deployment area constraint	Static	Approximation	Harvested power	TA; NS; FE
	[108]	Optimal distributions of power	EMI impact constraints	Static	Distribution fitting	Harvested power	NS; FE
	[109]	Maximum charging utility	Energy provision constraints	Static	Heuristic	Harvested power	NS
	[110]	Maximum charging utility	Placement constraints	Static	Heuristic	Harvested power	NS
	[42]	Maximum charging utility	Deployment area constraint	Static	Approximation	Harvested power	TA; NS; FE
	[12], [111]	O1: Maximum charging utility O2: Maximum charging efficiency	Coverage quantity constraint	Static	Metaheuristic	Accuracy; convergence rate	NS
	[112]	O1: Maximum charging utility O2: Maximum fairness O2: Minimum number of chargers	Energy provision constraints	Static	Heuristic	Average harvested power; number of chargers	NS
	[113]	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
	[114]	O1: Maximum network lifetime O2: Minimum number of chargers	Coverage constraints	Mobile	Heuristic	Number of chargers; survival rate	NS

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 [47], [103] explore the omnidirectional charger deployment using a binary model to represent charging utility. In this case, regardless of the amount of power received by the device, the charging utility only reflects whether the device is covered. Chiu *et al*. [47] 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*. [103] specifically concentrated on urban environments. In this context, with pre-known device trajectories and a given number of chargers, they deployed limited chargers to maximize the charging utility with consideration of bounded detouring cost. The problem is addressed using a greedy-based algorithm with an approximation factor of $(1-1/e)$. Furthermore, they examined the detouring mode's impact and proposed an improved algorithm with an approximation factor of $1- 1/\sqrt{e}$.

Other studies [42], [51], [52], [57], [58], [104]–[110] quantify charging utility based on the amount of power received by the device. For instance, Zhang *et al.* [57] 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 [58], including mobile device, reconfiguration, and arbitrary candidate locations. In addition, Ding *et al.* [104] 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.

The optimization of charging efficiency, considering the radiation properties such as electromagnetic radiation, penetration, and interference, is explored in [42], [51], [52], [105]–[107], [110]. Given the widely recognized threat of high EMR exposure to human health, charger deployment schemes ensuring EMR safety are of significant importance [51], [52], [105], [106]. Dai *et al.* [51], [52] 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 [117] and a Fermat-Weber problem [118]. Subsequently, Dai *et al.* [105], [106] extended the safe charging problem to charger deployment on a two-dimensional 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.

You *et al.* [107] investigated the effect of electromagnetic penetration on charging utility in WCNs with obstacles. Their study involves a comprehensive consideration of the material, size, and location of obstacles to place omnidirectional chargers, 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 two-dimensional 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.

Furthermore, the omnidirectional charger deployment considering EMI is studied in [42], [108]–[110]. Naderi *et al.* [108] discussed the impact of EMI on power distribution in both two-dimensional and three-dimensional 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.* [109] 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 [110], they extended their study by assuming that omnidirectional chargers can be slightly moved around the initial deployment location. They introduced two heuristic approaches for scenarios involving one- and two-dimensional deployments, carefully adjusting charger locations to maximize charging utility. In addition, Ma *et al.* [42] used the form of cosine waves to represent the cumulative power of multiple chargers. They presented the energy distribution of five chargers simultaneously emitting energy, revealing alternating zones of enhanced and weakened energy caused by constructive and destructive interference. To maximize charging utility, a heuristic algorithm is proposed to optimize charger and device deployment.

Some works [12], [111]–[114] 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.

The work in [12], [111] proposes 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.* [112] 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 [113], 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 [114] 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.

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. 10. Therefore, the problem with directional charger deployment is how to strategically determine both their location and direction to achieve different goals (such as reducing deployment costs and enhancing charging utility) [9], [48], [49], [49], [50], [62], [63], [119]–[144]. A comprehensive overview and comparison of various directional charger deployment schemes are presented in Table IV.

Some works [119]–[127] focus on the directional charger deployment with a primary objective of cost reduction. Liao *et al*. [119] conducted a study on the deployment of directional chargers in a three-dimensional 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 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 [120] to reduce the number of chargers with a more accurate energy estimate. Jiang *et al*. [121] addressed the problem of directional charger deployment in similar scenarios. To minimize the number of chargers, they introduced two heuristic algorithms based on greedy and adaptive strategies. Unlike the greedy approach, which prioritizes covering most devices, the adaptive strategy focuses on selecting directions that offer higher charging power for devices.

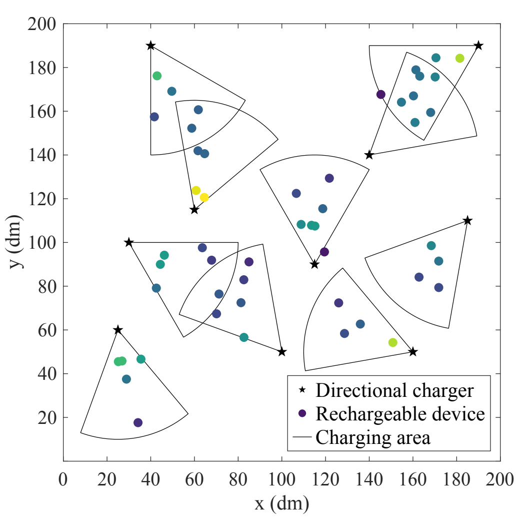


Fig. 10. Illustration of a directional charger deployment scheme within a network comprising 50 rechargeable devices and 10 directional chargers, each with an effective charging distance of 50dm and a charging angle of 60°.

In addition to heuristic algorithms, several studies [122]–[124] propose deployment algorithms based on meta-heuristics. In [122], [123], 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*. [124] 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 [125]–[127]. 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*. [125] 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*. [126] 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 [127].

Some papers study the directional charger deployment with an emphasis on enhancing charging utility [9], [48]–[50], [62], [63], [128]–[144]. Dai *et al*. [49], [50] 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. To expand the charging angle of directional chargers, Dai *et al*. [128] 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. Additionally, they investigated a direction scheduling problem for charging tasks [62], [63]. To address this problem, a centralized offline algorithm and a distributed online algorithm are proposed to maximize the overall task utility. Ding *et al*. [129] delved into solving the charging utility maximum

TABLE IV
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	[119]	Minimum number of chargers	Coverage constraints	Static	Heuristic	Number of chargers	NS
	[120]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Number of chargers	NS
	[121]	Minimum number of chargers	Coverage constraints; energy provision constraints	Static	Heuristic	Charging power; number of chargers; execution time	NS; FE
	[122], [123]	Minimum number of chargers	Energy provision constraints	Static	Metaheuristic	Number of chargers	NS; FE
	[124]	Minimum number of chargers	Energy provision constraints	Static	Metaheuristic	Number of chargers	NS
	[125]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Number of chargers; execution time; charging demand	NS
	[126]	Minimum number of chargers	Energy provision constraints	Static	Heuristic	Average harvested power; number of chargers	NS
	[127]	Minimum number of chargers	Energy provision constraints	Static	Approximation	Number of chargers	TA; NS
	[49], [50]	Maximum charging utility	Charger direction constraints	Static	Approximation	Harvested power	TA; NS; FE
	[128]	Maximum charging utility	Charger location constraints; charger direction constraints	Static	Approximation	Harvested power	TA; NS; FE
	[62], [63]	Maximum task utility	Charger direction constraints	Static	Approximation	Charging utility	TA; NS; FE
	[129]	Maximum charging utility	Deployment cost budget	Static	Approximation	Deployment cost; charging levels	TA; NS
	[130]	Maximum charging efficiency	Energy consumption constraints	Static	Heuristic	Charging efficiency; number of chargers	NS
	[131]	Maximum task utility	Energy consumption constraints	Static	Approximation	Task utility; energy consumption	TA; NS
	[132]	Minimum energy consumption	Energy provision constraints	Static	Heuristic; metaheuristic	Energy consumption	TA; NS
	[133], [134]	O1:Maximum charging efficiency O2: Maximum energy balance	Charger capacity constraint	Mobile	Heuristic	Charging efficiency; energy balance; lifetime of the chargers	NS
	[135]	Minimum deployment cost	Coverage constraints; spatial occupation issue	Mobile	Approximation	Deployment cost; running time	TA; NS; FE
	[136], [48]	Maximum charging utility	Connectivity constraints	Static	Approximation	Charging utility	TA; NS; FE
	[9]	Maximum charging utility	Charging power jittering; device drifting constraint	Static	Approximation	Charging utility	TA; NS; FE
	[137], [138]	Maximum charging utility	Charger mobility constraints	Static	Approximation	Charging utility	TA; NS; FE
	[139], [140]	Maximum omnidirectional charging proportion	Energy provision constraints	Static	Heuristic	Omnidirectional charging proportion	TA; NS; FE
	[141], [142]	O1: Maximum received power O2: Maximum survival probability	Energy provision constraints	Static	Heuristic	Received power; survival probability	TA; NS
	[143], [144]	Minimum charging delay	Energy provision constraints	Static	Heuristic	Charging delay	NS

problem subject to the deployment cost budget constraint. The problem is solved by an approximation algorithm that maximizes energy supply per unit deployment cost.

The optimization of charging utility for devices with diverse energy consumptions is explored in [130]–[132]. Devices closer to the BS exhibit higher energy consumption, leading to higher charging demands. Lin *et al*. [130] 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 [131] 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. Jia *et al*. [132] considered the anisotropic energy receiving property of directional charging, which is the charging power not only related to 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.

The directional charger deployment for mobile devices is studied in [133]–[135]. Nikoletseas *et al*. [133], [134] 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. The spatial occupation of mobile devices is considered in [135]. 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.

Some studies focus on the connectivity, robustness, and limited mobility of the directional charging deployment [9], [48], [136]–[138]. Yu *et al*. [48], [136] 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*. [9] 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*. [137], [138] 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.

Full-view coverage of the charging area can also be achieved by using directional chargers [139], [140]. Dai *et al*. [139] introduced the concept of omnidirectional charging, defining an area as achieving omnidirectional charging if any device within it, regardless of its orientation, can be charged with power not lower than a given threshold. For deterministic charger deployments, they designed a fast detection algorithm to detect whether the area achieves omnidirectional charging. For random charger deployments, they provided a probability of achieving omnidirectional charging. Their subsequent work, detailed in [140], 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.

Several papers investigate directional charger deployments in networks of various scales [141]–[144]. Wang *et al*. [141], [142] 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 show that the proposed adaptive directional charging scheme is more energy efficient than the omnidirectional charging scheme. He *et al*. [143], [144] 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.

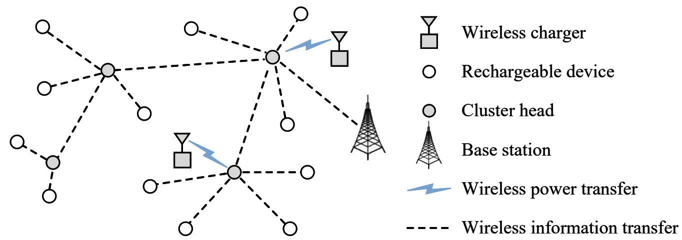


Fig. 11. Illustration of a non-radiative charger deployment scheme in a clustered network.

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. 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], [16], [53], [54], [83], [84], [145]–[150]. Fig. 11 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 V summarizes and compares various non-radiative charger deployment schemes.

Several studies [53], [145]–[147] explore efficient allocation strategies for non-radiative chargers to charge fixed devices. He *et al*. [145], [146] tried to deploy a limited number of non-radiative chargers next to bottleneck devices to increase the maximum flow rate of the network. The maximum flow optimization problem is formulated as a Mixed Integer Linear Programming (MILP), which can be optimally solved for small-scale networks. For large-scale networks, they proposed heuristic algorithms to solve it. In their subsequent work [147], they designed a meta-heuristic to search for a neighboring solution that yields a higher max flow rate. Moghadam *et al*. [53] investigated the joint optimization of magnetic charger locations to maximize the minimum harvested power of devices. They presented an adaptive magnetic 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], [16], [83], [84], [148]. Xu *et al*. [15], [16] 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 [148]. 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

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

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Non-radiative Charger Deployment	[145]–[147]	Maximum flow rate	Flow conservation constraints; charger capacity constraints; link capacity constraints; charger quantity constraint	Static	Exact; heuristic; metaheuristic	Max flow	NS
	[53]	Maximum minimum received power	Power budget constraint	Static	Heuristic	Receive power	TA
	[15], [16]	Maximum charging satisfaction	Charger quantity constraint	Mobile	Approximation; heuristic	Residual lifetime distribution; charging satisfaction	TA; NS
	[148]	Minimum number of chargers	Energy provision constraints	Mobile	Heuristic	Number of chargers; network lifetime	NS
	[83]	Minimum delivery time	Energy provision constraints; UAV capacity constraint	Mobile	Heuristic	Coverage rate	NS
	[84]	Minimum number of chargers	Coverage constraints	Mobile	Heuristic	Number of chargers	NS
	[149]	Minimum number of chargers	Energy provision constraints	Static	Exact	Number of chargers	NS
	[54], [150]	Minimum deployment cost	Energy provision constraints; charger capacity constraint	Static	Approximation; heuristic	Number of chargers; energy consumption; deployment cost; running time	TA; NS

problem. Arafat *et al*. [83] 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*. [84] 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.

Additionally, power can be transmitted to remote devices via multi-hop transmission based on magnetic resonance. The deployment of chargers in this scenario is studied in [54], [149], [150]. Rault *et al*. [149] 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*. [54] 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*. [150] 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 [55], [56], [151], [152]. 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 VI summarizes and compares various heterogeneous charger deployment schemes.

Erol *et al*. [151] 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 [153], for an efficient solution. Lin *et al*. [152] considered the deployment problem of a mixture of directional and omnidirectional chargers. In this scenario, they assumed both types of chargers exhibit identical charging efficiency, the only distinction lying in their charging ranges. The optimization objective is to deploy a minimum number of two chargers on a continuous two-dimensional plane so that all devices are covered and the charging power is maximized. Given the infinite potential locations for deployment, they

TABLE VI
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	[151]	O1: Maximum received power O2: Minimum number of chargers	Energy provision constraints; charging area restrictions	Static	Exact	Number of chargers; received power	NS
	[152]	O1: Maximum charging power O2: Minimum number of chargers	Full coverage constraints	Static	Heuristic	Charging power	NS
	[56]	Maximum charging utility	Charger location constraints; charger direction constraints	Static	Approximation	Charging utility	TA; NS; FE

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*. [55], [56] 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 complex problem, they used multi-feasible geometric area discretization and a practical dominating coverage set extraction algorithm to reduce the infinite solution space to a limited one. Subsequently, they formulated the optimization problem as the maximization of a submodular function, subject to a partition matroid constraint, which can be solved by an approximation algorithm.

V. Charging Scheduling Schemes

Once the charger deployment is determined, the most important issue is how to efficiently schedule all kinds of limited charger resources to provide better charging services. This includes the scheduling of power control, charge duration, energy beamforming, and multi-resource optimization. Effective scheduling of these resources is crucial for ensuring the overall effectiveness and sustainability of WCNs, preventing unnecessary resource wastage.

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 [57]–[61], [154]–[173]. This scheme aims to manage and optimize charging power to various devices based on their individual requirements, charging

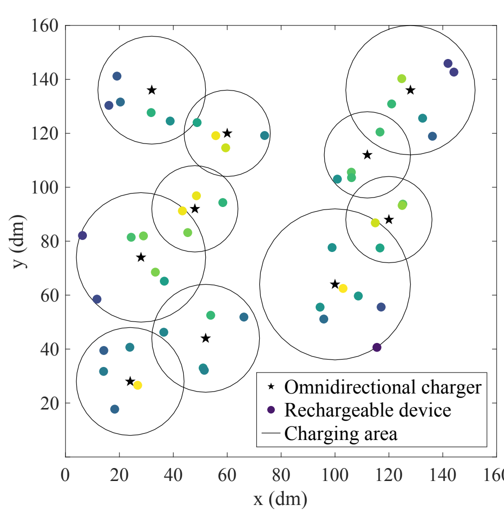


Fig. 12. Illustration of a power control scheme: adjusting the radius of omnidirectional chargers.

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. 12) [57]–[60], [155]–[164], [172], [173]. In contrast, the power control scheme for multifunctional chargers must simultaneously optimize wireless information and power transfer [61], [165]–[171]. Table VII summarizes various power control schemes.

Some papers [57], [58], [154], [155] focus on controlling charging power for fixed devices. To maximize charging quality, Zhang *et al*. [57] designed an approximation algorithm for controlling the charging power associated with a pre-determined deployment of chargers. Furthermore, the study in [58] explores the expansion of the problem by relaxing several assumptions, incorporating factors such as mobile device scenarios, reconfiguration, and arbitrary candidate charger locations. Niyato *et al*. [154] 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*. [155] 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.

The charging power control scheme for mobile devices is studied in [59], [60]. Madhja *et al*. [59] 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*. [60] 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.

Certain power control schemes [156]–[164], [172], [173] prioritize not only charging efficiency but also EMR safety. Dai *et al*. [156], [172] investigated a safe charging problem with adjustable power, *i.e.,* how to adjust the power of chargers to maximize the charging utility under the EMR safety constraint. They proposed techniques to reformulate the original problem into a Linear Programming (LP) problem and developed distributed algorithms that achieve approximation ratios. In their subsequent research [157], [173], they explored

TABLE VII
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	[32], [38]	Minimum number of chargers	Energy provision constraints	Static; mobile	Approximation	Approximation ratio; average consumption power	TA; NS
	[57], [58]	Maximum charging quality	Power budget constraints	Static	Approximation	Charging quality; average running time	TA; NS
	[154]	Maximum charging utility	Energy provision constraints	Static	Heuristic	Strategy probabilities	NS
	[155]	Maximum attacking utility	Energy provision constraints	Static	Approximation	Attacking utility	TA; NS
	[59]	O1: Maximum coverage quality O2: Maximum network lifetime	Power budget constraint	Mobile	Heuristic	Survival quantity	NS
	[60]	Maximum charging utility	Power budget constraint	Mobile	Approximation	Charging utility	TA; NS; FE
	[156]–[157]	Maximum charging utility	EMR intensity constraints	Static	Approximation	Charging utility	TA; NS; FE
	[158], [159]	Maximum minimum charging utility	EMR intensity constraints	Static	Approximation	Minimum charging utility; communication cost	TA; NS; FE
	[160]	Maximum harvested power	EMR intensity constraints	Static	Exact	harvested power	NS
	[161], [162]	Maximum charging efficiency	EMR intensity constraints	Static	Heuristic	Charging efficiency; maximum radiation; energy balance	NS
	[163]	Minimum radiation degree	Energy provision constraints; power budget constraints	Mobile	Approximation	Radiation degree; communication interval	NS
	[164]	Optimizing trade-off between EMR and charging efficiency	Energy provision constraints	Mobile	Heuristic	EMR; charging efficiency	TA
	[61]	Maximum energy efficiency	Energy provision constraints; power budget constraints minimum data rate requirement	Static	Heuristic	Energy efficiency; average harvested energy	NS
	[165]	O1: Minimum transmission power O2: Maximum charging ratio	Energy provision constraints	Static	Heuristic	Transmission power; charging ratio	NS
	[166]	Maximum minimum transmission rate	Power budget constraints	Static	Exact	Average scheduling rates; residual power	NS
	[167]	Maximum network throughput	Outage constraints	Static	Exact	Transmission probability; outage probability	TA; NS
	[168]	Maximum rate coverage	Energy provision constraints	Mobile	Exact	Rate coverage	TA; NS
	[169], [170]	Maximum charging efficiency	Energy provision constraints	Static	Exact	Average harvested power; charging efficiency	TA; NS
	[171]	Maximum sensing rate	Power budget constraints	Static	Exact	Network sensing rate	TA; NS

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*. [158], [159] 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*. [160] explored a more accurate EMR computing model and studied the problem of maximizing charging power while ensuring EMR safety. This problem 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 [161]–[164] modify the charging area by controlling the charging power to ensure EMR safety. Nikoletseas *et al*. [161], [162] 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*. [163] 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*. [164] 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.

In addition to dedicated chargers, several papers delve into power control schemes for multifunctional chargers that transmit both power and information [61], [165]–[171]. Guo *et al*. [61] 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 [165]. 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*. [166] 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 [167]–[171]. Building upon cognitive radio networks, Lee *et al*. [167] proposed a method for wireless network coexistence where secondary chargers harvest 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*. [168] 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 [169]–[171]. Khan *et al*. [169], [170] 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*. [171] 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 energy efficiency of the system, minimize interference, and guarantee the energy supply of devices, among other things [15], [16], [62], [63], [132]–[134], [174]–[182]. Table VIII briefly summarizes different time allocation schemes.

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], [16], [62], [63], [132]–[134], [174]. Xu *et al*. [15], [16] 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

TABLE VIII
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], [16]	Maximum charging satisfaction	Charger quantity constraint	Mobile	Approximation; heuristic	Residual lifetime distribution; charging satisfaction	TA; NS
	[174]	Maximum operator profit	Charger capacity constraint; energy provision constraints	Mobile	Heuristic	Charging rate; operator profit; average queue backlog	NS
	[133], [134]	O1:Maximum charging efficiency O2: Maximum energy balance	Charger capacity constraint	Mobile	Heuristic	Charging efficiency; energy balance; lifetime of the chargers	NS
	[62], [63]	Maximum task utility	Charger direction constraints	Static	Approximation	Charging utility	TA; NS; FE
	[132]	Minimum energy consumption	Energy provision constraints	Static	Heuristic; metaheuristic	Energy consumption	TA; NS
	[175]	Minimum charging periods	Energy provision constraints	Static	Approximation	Number of fully charged devices; harvested energy; charging periods	TA; NS
	[176]	Maximum charging efficiency	Coverage constraints; power budget constraints	Static	Heuristic	Number of fully charged devices; harvested energy; charging efficiency; charging periods	NS
	[64]	Maximum network throughput	Total time constraint	Static	Exact	Total throughput	TA; NS
	[177]	Maximum coverage probability	Energy provision constraints; minimum SINR requirement	Static	Exact	Uplink/downlink coverage probability	TA; NS
	[178]	Maximum network throughput	Device distribution constraints	Static	Exact	Coverage probability; average network throughput	TA; NS
	[179], [180]	Maximum network lifetime	Energy provision constraints	Static	Heuristic	Average network lifetime	NS

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.* [174] 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.* [133], [134] 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.* [62], [63] 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.* [132] 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.

Due to interference between different wireless chargers, it is necessary to schedule these chargers chronologically [175], [176], [181], [182]. Since nonlinear superimposed charging effects are caused by radio interference, the charging utility of each charger cannot be calculated independently, Guo *et al.* [175] 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 EMI is also considered in [181], [182], 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.* [176] employed a vector model to represent the cumulative power affected by EMI. To improve charging efficiency, they proposed a two-step algorithm. Initially, they provide a charging threshold model alongside an effective charging schedule. Subsequently, they propose a multi-charger joint accumulative charging scheme for devices that have yet to reach full charge.

In WCNs employing multifunctional chargers, time is partitioned into slots. Specific slots are designated for wireless power transmission to devices, while others are dedicated to information transmission and other functions. Consequently, the efficient allocation of time for power and information transmission emerges as a critical factor in optimizing network performance [64], [177]–[180].

Some papers [64], [177], [178] explore the coordination of energy and information transfer to maximize network throughput. Ju *et al.* [64] 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.* [177] 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 [178] 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 [179], [180] delve into the coordination of energy and information transfer with the goal of extending the network lifetime. Du *et al.* [179] 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 [180], 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 [11], [34], [53], [65], [75], [183]–[191]. 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 [11], [53], [65], [75], [183], [184]. Centralized beamforming schemes control the phase and relative amplitude of signals transmitted by multiple antennas of a single charger [34], [185]–[191]. As shown in Fig. 13, the centralized beamforming scheme allows the control of multiple transmitted signals from a transmitter to efficiently transmit energy to specified receivers. Table IX provides a summary of energy beamforming schemes.

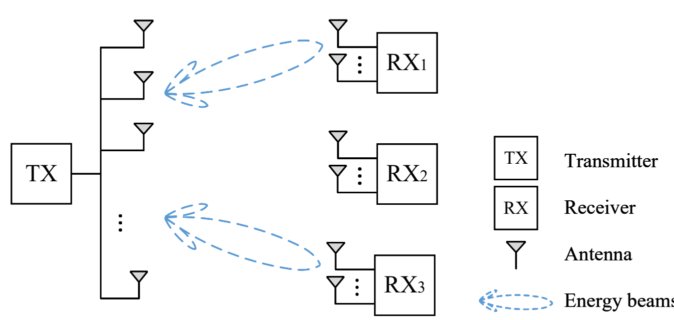


Fig. 13. Illustration of an energy beamforming scheme.

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

	Paper	Objectives	Constraints	Devices	Approaches	Performance metrics	EVM
Energy Beamforming	[65], [11]	Maximum receive power	EMR intensity constraints	Mobile	Adaptive Beamforming	Receive power	NS; FE
	[75]	Maximum receive power	Energy provision constraints	Static	Adaptive Beamforming	Receive power	NS; FE
	[183]	Maximum receive power	Phase constraint	Static	Heuristic	Receive power	NS
	[53]	Maximum receive power	Power budget constraint	Static	Adaptive Beamforming	Receive power	TA
	[184]	Minimum transmit power	Power provision constraints	Static	Exact; approximation	Outage probabilitiy; power efficiency	TA; NS
	[34]	Maximum receive power	Average power constraint	Static	Exact	Rate-energy region	TA; NS
	[185]	Maximum receive power	Individual SINR constraints; power budget constraint	Static	Approximation	Average harvested power; running time	TA; NS
	[186]	Maximum charging efficiency	Energy provision constraints	Static	Zero-forcing beamforming	Charging efficiency	NS
	[187]	Minimum transmit power	Energy provision constraints; power budget constraint	Static	Exact Approximation	Transmit power	TA; NS
	[188]	Maximum receive power	Individual SINR constraints	Static	Zero-forcing beamformingt	Receive power; SINR	NS
	[189]	Maximum receive power	Power budget constraint	Static	Asymptotically optimal	Receive power	TA; NS
	[190]	Minimum transmit power	Individual SINR constraints; energy provision constraints	Mobile	Approximation	Average harvested power; running time	TA; NS
	[191]	Maximum average receive power	Energy provision constraints; power budget constraint	Static	Approximation	Average receive power	TA; NS

Distributed beamforming schemes involve coordinated adjustments among the transmit antennas of multiple chargers [11], [65], [75], [183]. For radiative WPT, distributed beamforming ensures that electromagnetic waves emitted from transmit antennas arrive at the receiver antenna in the same phase, allowing for 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*. [65] 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 [11], 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 [75], the study investigates distributed WPT with or without frequency and phase synchronization. Three beamforming schemes, namely optimal, static, and random, are analyzed in terms of receiving power and coverage probability. Additionally, Katsidimas *et al*. [183] 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*. [53] 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*. [184] 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.

Centralized beamforming schemes centrally control the phase and relative amplitude of signals transmitted by multiple antennas, forming sharp energy beams toward devices to improve charging efficiency [34], [185]–[191]. Zhang *et al*. [34] initially 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 [185]. 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*. [186] 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*. [187] leveraged energy beamform-

TABLE X
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	[66]	Maximum charging satisfaction	Charger quantity constraint	Mobile	Approximation; heuristic	Residual lifetime distribution; charging satisfaction	TA; NS
	[189]	Maximum minimum uplink rate	Power budget constraint	Static	Asymptotically optimal	Maximum minimum uplink rate	TA; NS
	[192]	Maximum uplink rate	Downlink rate constraint	Static	Exact	Uplink rate	TA; NS
	[193]	Maximum network throughput	Time duration constraint	Static	Heuristic	Network throughput	NS
	[194]	Maximum charging efficiency	Energy provision constraints; time duration constraint; power budget constraint	Static	Exact	Charging efficiency; network throughput	TA; NS
	[195]	Minimum transmit power	Task constraints	Mobile	Exact	Average minimum transmit energy and power	TA; NS
	[196]	Minimum energy consumption	Latency constraints; energy provision constraints	Static	Exact	Average energy consumption	TA; NS
	[197]	Maximum energy effciency	Energy consumption constraint	Mobile	Metaheuristic	Energy effciency; received energy	TA; NS
	[198]	O1: Minimum energy consumption O2: Maximum received energy	Power budget constraint; latency constraints	Static	Exact	Received energy	TA; NS
	[199]	Minimum energy consumption	Power budget constraint; latency constraints	Static	Exact	Received energy	TA; NS

ing 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 sub-optimal precoders aimed at minimizing transmit power under the constraints of energy supply and power budget.

Some works address centralized beamforming schemes in scenarios where perfect Channel State Information (CSI) cannot be obtained due to channel estimation and quantization errors [188]–[191]. Imperfect CSI can hinder the effectiveness of beamforming, resulting in degraded power transfer performance. For a multiuser MIMO system, Son *et al*. [188] proposed a joint beamforming algorithm to maximize the total harvested energy while satisfying SINR constraints. When the beamforming vector serves both data collection and energy transfer devices, harvested energy can be increased at the cost of SINR loss for the data collection device. The sum rate and harvested energy obtained from the proposed algorithm are analyzed under perfect/imperfect CSI conditions. The large-scale MIMO system is studied in [189]. Using a time division duplex to transmit information and energy separately, the study obtains an asymptotically optimal energy beamforming device to maximize energy gain. Zhu *et al*. [190] 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*. [191] introduced a low-complexity beamforming scheme for a multi-antenna BS to wirelessly power a set of single-antenna devices. This scheme allows the BS to fairly power a set of single-antenna devices using only the first-order statistics of the channels, catering to the needs of low-power transmission.

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 [66], [189], [192]–[199]. Table X summarizes and compares different multi-resource scheduling schemes.

Some papers explore multi-resource scheduling in massive MIMO systems [66], [189], [192]–[194]. In [66], 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 [189], 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*. [192] studied the optimal design for a partially WCN in which some devices are wirelessly powered. In such a network, two different phases are involved for power transfer and communications. In the downlink phase, a BS simultaneously transfers power and information to devices. Following this, in the uplink phase, all devices transmit sensing data back to the BS. To maximize the uplink sum rate while satisfying the downlink rate constraint, the study jointly designs downlink beamforming, uplink beamforming, and time allocation.

To improve charging efficiency, an Intelligent Reflecting Surface (IRS) is employed in massive MIMO systems [193], [194]. Zhang *et al*. [193] 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 trans-

TABLE XI
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	[67], [68]	Maximum receive power	Frequency constraint	CSMA/CA	Receive power; network throughput	TA; NS; FE
	[200]	Maximum throughput and energy efficiency	Collision probability	CSMA/CA	Network throughput; energy efficiency	TA; NS
	[201]	Maximum network throughput	SNR constraints	Slotted ALOHA	Network throughput; optimal number of random access slots	TA; NS
	[202]	Trade-off delivery probability and time efficiency	SIR constraints	TDMA	Asymptotic delivery probability; asymptotic time efficiency	TA; NS
	[64]	Maximum network throughput	Individual throughput constraints	TDMA	Network throughput	TA; NS
	[203]	Maximum network throughput	Time constraint	TDMA; CSMA	Network throughput; total harvested energy	TA; NS
	[204]	Maximum network throughput	Harvested energy and time constraints	TDMA	Network throughput; packet reception rate; average transmission frequency	TA; NS

mission from different device clusters. Furthermore, Zargari *et al*. [194] 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 papers study the multi-resource scheduling problem in WCNs, combined with Mobile Edge Computing (MEC) [195]–[199]. The paper [195] 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*. [196] 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 [197] 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*. [198] considered a multi-access edge computing system with a BS equipped with a massive MIMO antenna array. The objective is to minimize energy consumption for computation offloading while simultaneously maximizing received energy from wireless charging. Their proposed solution involves data partitioning, time allocation, and optimal energy beamforming. The same system configuration is also explored in [199]. To minimize energy consumption subject to charging power and latency constraints, an efficient nested algorithm is designed by optimally dividing it into convex subproblems to solve data partitioning, time allocation, power control, and energy beamforming.

VI. COMMUNICATION OPTIMIZATION SCHEMES

As the WPT process is introduced, it becomes imperative to conduct further optimization of the MAC protocol, routing protocol, and information processing of devices in the original wireless network. This optimization is crucial to ensure the normal operation and sustained energy supply of the network.

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 [64], [67], [68], [200], [202]–[205]. 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 XI briefly summarizes various MAC protocols.

The papers [67], [68], [200], [201], [205] focus on optimizing competition-based MAC protocols. Naderi *et al*. [205] initially 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 [67], [68], 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*. [200] 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

TABLE XII
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	[69]	Maximum energy efficiency	Energy budget constraints	Hierarchical routing	Average residual energy; traffic load	NS
	[206]	Maximum energy efficiency	Energy budget constraints	Opportunistic routing	Delivery ratio; transmission delay; average residual energy	NS
	[207]	Maximum energy efficiency	Delays constraints; throughput constraints; packet loss constraints	Opportunistic routing	Energy efficiency; delay; network throughput; packet loss ratio	NS
	[208]	Maximum network throughput	Energy budget constraints	Online routing	Network throughput	TA; NS
	[209]	Maximum system utility	Energy budget constraints	Online routing	System utility	TA; NS
	[210]	Minimum energy consumption	Energy budget constraints	Routing tree	Total charging cost	NS
	[211]	Maximum minimum fair rate	Flow conservation constraints; energy budget constraints	Routing tree; unsplittable routing; fractional routing	Maximum minimum fair rate	TA

compete for access channels through different contention mechanisms. Notably, the RHAP is given a higher priority, ensuring more frequent access to the channel. In addition, the work in [201] considers a harvest-or-access protocol based on slotted ALOHA, where HAPs randomly perform WPT during idle slots to replenish the energy of wireless devices.

In [64], [202]–[204], contention-free MAC protocols in WCNs are investigated. Iannello *et al*. [202] studied a TDMA-based MAC protocol and analyzed the trade-off between power delivery probability and data collection efficiency. Ju *et al*. [64] studied a TDMA-based MAC protocol to maximize network throughput. A hybrid MAC protocol that utilizes both TDMA and CSMA is introduced in [203]. 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*. [204] 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 [69], [74], [206], [208]–[211]. A comprehensive overview and comparison of various routing protocols is presented in Table XII.

Many research efforts are dedicated to developing energy-efficient routing protocols [69], [206], [207]. Cao *et al*. [69] 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*. [206] 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*. [207] 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.

Additionally, some studies [208]–[211] consider other optimization goals. Lin *et al*. [208] 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*. [209] 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*. [210] 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*. [211] explored max-min fair rate allocation and routing in WCNs with a predictable energy profile. They devised algorithms that obtain a max-min fair rate assignment for various routing. Specifically, for the unsplittable routing and

TABLE XIII
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	[70], [71]	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
	[212], [213]	O1: Minimum broadcast overhead O2: Minimum broadcast latency	Energy provision constraints	Single-hop network	Broadcast latency; number of missed nodes; received energy	TA; NS
	[214]	Maximum throughput region	Power budget constraint	Single-hop network	Optimal throughput region	TA; NS
	[215], [216]	Minimum broadcast latency	Harvested energy constraints	Single-hop network	Broadcast latency	TA; NS
	[72]	Minimum broadcast latency	Collision-free constraints	Multi-hop network	Broadcast latency	TA; NS
	[217]	Minimum broadcast latency	Collision-free constraints; harvested energy constraints	Multi-hop network	Broadcast latency; communication overhead	TA; NS
	[218]	Minimum broadcast latency	Collision-free constraints; harvested energy constraints	Multi-hop network	Broadcast latency; total number of transmissions	TA; NS
	[219]	Minimum broadcast latency	Harvested energy constraints	Multi-hop network	Broadcast latency; energy usage ratio	TA; NS

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 [70]–[72], [212]–[219]. Table XIII summarizes and compares different broadcast transmission schemes.

Several studies [70], [71], [212]–[216] explore broadcast transmission in single-hop networks. Kuan *et al*. [70] 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 [71], they proposed an eclectic policy that considers both throughput and reliability, aiming to maximize the sum of the eclectic utility. In [212], [213], 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*. [214] focused on online transmission schemes where the device knows the energy arrivals only causally 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 addition, the broadcast transmission for single-hop networks over an additive white Gaussian noise broadcast channel is studied in [215], [216]. To minimize broadcast latency, the work in [215], [216] proposes offline schemes for devices with unlimited and finite battery capacity, respectively.

The studies [72], [217]–[219] extensively explore broadcast transmission in multi-hop networks, with a common objective of minimizing broadcast latency. Zhu *et al*. [72] 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*. [217] 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*. [218] 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*. [219] proposed an energy-adaptive and bottleneck-aware scheduling algorithm to minimize latency. The correctness and average latency of the proposed algorithm are thoroughly analyzed.

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 [73], [220], [221], and Table XIV provides a comparison of data collection schemes.

Some studies [73], [220], [221] delve into scheduling mobile sinks to collect delay-tolerant data. Mehrabi *et al*. [73] 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

TABLE XIV
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	[73]	Maximum network throughput	Energy budget constraints	Mobile	Single-hop network	Network throughput; data collection latency	TA; NS
	[220]	Maximum network throughput	Tolerant delay constraint	Mobile	Single-hop network	Network throughput ratio	NS
	[221]	Maximum data collection	Energy provision constraints	Mobile	Single-hop network	Network throughput	TA; NS
	[74]	Maximum monitoring quality	Energy budget constraints	Static	Single-hop network	Data collection quality; running time	TA; NS
	[222]	Maximum data collection	Flow conservation constraints; energy conservation constraints	Static	Multi-hop network	Network utility; energy utilization ratio	TA; NS
	[223]	Minimum data collection latency	Individual SINR constraints; energy budget constraints	Static	Multi-hop network	Data collection latency	TA; NS
	[224]	Minimum data collection latency	Individual SINR constraints; energy budget constraints	Static	Multi-hop network	Data collection latency; energy utilization ratio	TA; NS
	[225]	Maximum data collection	Individual SINR constraints; energy budget constraints	Static	Multi-hop network	Network throughput	TA; NS

energy harvesting aspect of the problem. Subsequently, they devised an online centralized algorithm with polynomial runtime complexity to handle the problem. In [220], 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*. [221] 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.

The other category of studies uses a static sink to collect data [74], [222]–[225]. The monitoring quality maximization problem is explored in [74]. 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*. [222] 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*. [223] 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 two-dimensional plane. They proposed distributed algorithms to generate data collection schedules. The work in [224] 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*. [225] 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.

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 list some potential research directions for WCNs, including security issues, the role of Machine Learning (ML), 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 [155]. 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. ML-based Design

In WCNs, ML can predict the dynamic charging demand and device states of rechargeable devices. This prediction enables the network to adjust charging schemes in advance, effectively avoiding energy waste [226], [227]. Moreover, by employing ML techniques, WCNs can dynamically adjust their charging schemes in response to real-time changes in network load and topology [228]. This approach not only ensures the provision of sufficient energy during peak demand periods but also enhances the adaptability of WCNs in complex and ever-changing environments. Furthermore, by using ML techniques to analyze user behavior data, WCNs can provide more personalized services by adjusting charging schemes based on user habits and preferences. Future research will continue to deepen the application of ML, pushing the WCN towards more intelligence and stability. 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 utilize ML to adaptively modify charging schemes, enabling WCNs to better accommodate changes in the network, thereby enhancing the overall reliability and stability of the network.

C. mmWave-enabled WCNs

The mmWave frequencies, spanning from 30-300 GHz, offer a promising solution for enhancing both power and information transmission in WCNs. The escalating demand for data transmission has led to traditional spectrum resources becoming increasingly congested. Leveraging mmWave frequencies can effectively address the requirements for gigabit-level information transmission [229]. Compared with traditional WPT, mmWave WPT provides more focused energy with smaller relative antennas, large spectrum resources, and less interference to other networks [230]–[232]. 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.

D. IRS-assisted WCNs

The IRS, consisting of a large number of low-cost reflecting elements, is capable of reflecting incident RF signals [233]. 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 [234]. 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 [235]. 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.

E. 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 [236]–[238]. 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.

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