Wireless Rechargeable Sensor Networks: Energy Provisioning Technologies, Charging Scheduling Schemes, and Challenges

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Abstract—Recently, a plethora of promising green energy provisioning technologies has been discussed in the orientation of prolonging the lifetime of energy-limited devices (e.g., sensor nodes). Wireless rechargeable sensor networks (WRSNs) have emerged among other fields that could greatly benefit from such technologies. Such an ad-hoc network comprises a base station(s) and multiple sensor nodes, which are primarily deployed in harsh environments, meeting the requirements of transmitting, receiving, collecting, and processing data. Unlike existing works, this survey paper focuses on energy provisioning technologies within the context of WRSNs by reviewing two interrelated domains. First, we introduce various energy provisioning techniques and their associated challenges, including conventional energy harvesting methods (e.g., solar, thermal, and mechanical). We highlight wireless power transfer (WPT) as one of the most applicable technologies for WRSNs, covering both radiative and non-radiative WPT. Additionally, we present radio frequency (RF) energy harvesting, including simultaneous wireless information and power transfer (SWIPT) and wireless powered communication networks (WPCNs), as well as backscatter communications. Furthermore, we compare hybrid energy harvesting techniques (e.g., solar-RF, vibro-acoustic, solar-thermal, etc.). Second, we introduce the fundamentals of wireless charging, reviewing various charger types (static and mobile), charging policies (including full and partial charging), charging modes (offline and online), and charging schemes (periodic and on-demand). We also present the collaborative charging mechanisms. Additionally, we address several key challenges facing WRSNs, such as energy consumption, multi-charger coordination, dynamic network recharging, monitoring & security threats, vehicle-to-vehicle (V2V) charging, and hybrid WRSNs Finally, we highlight trends and future directions for integrating advanced artificial intelligence (AI) technologies into WRSNs.

Index Terms—charging scheduling schemes, charging policy, energy provisioning techniques, collaborative charging mechanisms, wireless rechargeable sensor networks.

1 Introduction

Recently, due to the difficulties that researchers encounter with energy-depleted sensor nodes, the WRSN technology was developed. One of the most popular research areas is WPT, which is also one of the most commercialized technologies as a new promising technology that could potentially solve the energy limitation for the Internet of Things (IoTs), 5G, and 6G devices [1]. In particular, WPT has rapidly increased in mobile phone chargers, stationary electric vehicle (EV) chargers, and dynamic EV chargers, also known as road-powered EV (RPEVs) chargers [2]. The energy used in the WPT can be transferred through various technologies. These approaches can be divided into radiative RF-based charging and nonradiative coupling-based charging. There are three types of non-radiative coupling-based technologies [3]: magnetic inductive coupling [4], magnetic resonance coupling [5], and capacitive coupling [6]. Radiative RF-based technologies use both non-directional RF power transmission [7] and directive RF power beamforming. Capacitive coupling and directional RF power beamforming techniques rarely find use in practice due to various constraints. Consequently, WPT technology is potentially paving the way for solving energy limitations. The story starts with the creation of WSN, moves on to energy harvesting, and ends with WRSN. Within the WSN, the system consists of multiple small-scale sensor nodes. Sensor nodes have the following advantages: being lightweight, having restricted battery capacity, and being cost-efficient. The sensor nodes are strategically placed within predefined regions through random or systematic distribution. The primary responsibilities of these sensor nodes include data collection, neighbor monitoring, data transmission to a central server, and data receipt for subsequent processing.

However, due to the limited battery capacity, WSN faces challenges, especially in expansive and challenging environments. Sensor nodes endowed with a limited battery capacity and tasked with enduring severe conditions over

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Manuscript received December 20, 2022; accepted March 5, 2025.

extended periods can only sustain a reduced data rate. This limitation can lead to data packet loss or exhaustion of the sensor nodes' energy reserves.

Indeed, extending the network lifetime and minimizing the survival rate of inactive sensor nodes have emerged as key challenges in WSNs [8]. Despite significant efforts to extend the lifetime of WSNs, there is still a need for improved solutions to tackle this issue. The extension of network lifetime is recognized as a primary factor impeding system performance in a large environment [9].

Natural sources, such as solar, wind, tidal, renewable, biomass, hydroelectricity, and thermal, have served as energy harvesting techniques for further supplying WSN with energy to prolong the network lifetime (i.e., the WSN environment is influenced by the natural sources surrounding it). Photovoltaic energy harvesting, thermal energy harvesting, and vibration energy harvesting are all examples of energy harvesting techniques suitable for various applications.

Unlike the aforementioned energy-generating techniques, RF energy harvesting techniques are widely adopted for supplying energy to next-generation wireless networks. This method can harness energy from the surrounding ambient RF waves [10]. Wireless devices can use RF energy harvesting techniques to draw power from RF signals and use it to power tasks such as information processing, transmission, and sensing. Consequently, RF energy harvesting is particularly well suited for wireless networks with limited power, such as the IoTs and WSNs. Moreover, active RF data transmission necessitates intricate circuit designs and uses much energy. To overcome these restrictions and greatly enhance network performance, ambient backscatter communications provides the solution [11].

Recent breakthroughs of a new expenditure of wireless charging technology have been considered promising techniques for extending the network lifetime [12], [13], [14]. This direction has paved a new way for WRSNs to work by replenishing the energy of sensor nodes. Such a system contains three main components: (a) the sensor nodes, (b) the mobile charger (MC), and (c) the sink/base station (BS) [15]. Static charger deployment within the network restricts mobility to the surrounding area, leading to high costs. Therefore, MC is a more feasible alternative to static charger (SC) deployment. MC's extensive and free mobility facilitates the recharging of designated sensor nodes from any location within the network [16].

1.1 Applications of WRSNs

WRSN is a choice for extending the network lifetime. Wireless charging technologies mitigate harsh environmental factors, harsh cleaning products, substantial soiling, and significant mechanical stress. It has various applications in various fields, including intelligent traffic monitoring, smart household, industrial monitoring [17], educational, environmental [18], [19], commercial field, health care monitoring, agriculture field [20], [21], earthquake monitoring, smart cities [22]. These include robot manipulation applications, robotic underwater vehicles, induction motors, and generators. As a result, we showcase several intriguing applications that focus on extending and optimizing the network lifetime. More applications and details are provided in the supplementary material **Subsection (1.1)**.

1.2 Related Surveys

A plethora of studies have been introduced on energy harvesting and WRSNs over the last decade. This subsection reviews numerous survey papers published between 2011 and 2024, focusing on their scope, main contributions, and differences between our work and previous surveys. Some studies in [23], [24], [10], [25] focused on energy harvesting. Sudevalayam et al. [23] reviewed energy harvesting models (Harvest-Use, Harvest-Store-Use), energy sources (solar, wind, RF, human movement), and storage options like Lithium Ion (Li-ion) batteries, highlighting how recharge opportunities improve sensor design and networks. Prasad et al. [24] reviewed sensor deployment growth due to miniaturization and communication advances, exploring energy harvesting methods, storage (e.g., supercapacitors), models (Markov chain, leaky bucket), and efficient energy conversion hardware. They reviewed protocols for energy-harvested WSNs, including MAC, routing, relay selection & cooperative communication, and challenges. Adu-Manu et al. built on the work of Sudevalayam et al. [23] by reviewing radiant, mechanical, and thermal energy sources, hybrid systems, energy prediction, and management. They addressed challenges like universal harvester design and network optimization, proposing future trends in protocol design, wearable devices, and non-RF communication technologies.

The rapid growth in WPT has led to studies such as [26], [27], [13] to focus on WRSNs, which provide detailed insights into how these networks overcome energy limitations in traditional networks by enabling wireless recharging of sensor nodes. In 2015, Lu et al. [26] discussed wireless charging methods and advancements in network applications and technical standards. The static scheduling algorithms, mobile charger dispatch strategies, wireless charger deployment, challenges in implementation, and future directions. In our previous study [13], we reviewed WRSNs, highlighting their role in extending WSN lifetime through WPT. We discussed charging cycles, scheduling, multi-vehicle strategies, energy optimization (e.g., UAVs), and security risks, proposing directions for improving charging strategies and efficiency. Building on this, our current work comprehensively studies WRSNs, including energy provisioning techniques, applications, wireless charging fundamentals, challenges, and future directions. However, in [27], Kaswan et al. studied mobile charging techniques in WRSNs, covering network models, WPT technologies, system performance, and design challenges. They classified and compared periodic and on-demand charging methods, highlighting objectives, constraints, solutions, and limitations. Our study builds on this by incorporating recent advancements in WRNs, collaborative charging, energy harvesting, RF, and backscatter communications. Alabsi et al. [28] provided a comprehensive review of WPT technologies and proposed a classification framework for various charging schemes. The field of WRSNs is rapidly growing, with new technologies and applications constantly emerging. Consequently, to help researchers explore recent techniques, schemes, challenges, and advancements in WRSNs, we provide a detailed review of recent studies on energy provisioning and WRSNs in the following sections.

1.3 Motivations & Contributions

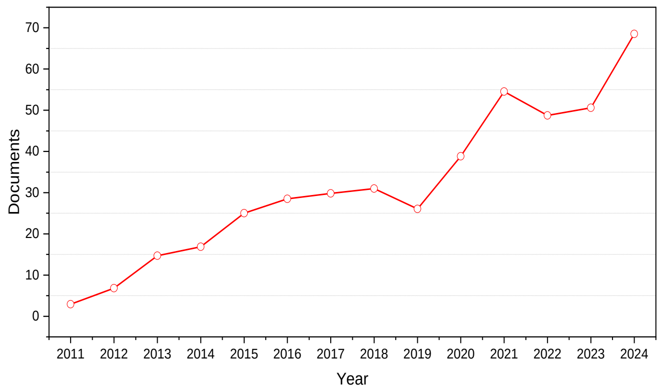

Fig. 1: Year-rate of related publications in WRSNs according to Scopus database.

WRSNs have emerged as transformative technologies, enabling long-term monitoring in challenging environments such as disaster response, environmental sensing, and health monitoring. Powered by advancements in WPT, these systems consist of sensor nodes, a BS, and MCs that replenish energy in sensor nodes, ensuring continuous operation and significantly extending the network's lifetime. As WRSNs gain recognition for providing sustainable energy solutions to IoT and WSN devices, we believe this critical domain still requires further synergistic efforts. While the rapid advancements, researchers face several challenges, including minimizing energy consumption, reducing sensor node failures, optimizing the number and location of MCs, improving charging efficiency, maximizing the number of charged nodes, lowering service costs, optimizing charging trajectories, addressing security risks, and enhancing overall energy efficiency. These challenges have motivated us to present this comprehensive survey paper, which serves as a guiding light for researchers in WRSNs, inspiring new ideas and solutions. Furthermore, an analysis of approximately 425 WRSNs-related publications indexed in the Scopus database (from 2011 to the present) shows a growing interest in addressing these challenges, as shown in Fig. 1. Thus, herein, we highlight the following main contributions:

- We provide an overview of energy provisioning techniques, starting with conventional energy harvesting methods like solar, thermal, and mechanical, as well as WPT in both radiative and non-radiative forms. RF energy harvesting techniques are introduced technologies such as simultaneous wireless information and power transfer (SWIPT) and wireless-powered communication networks (WPCNs). Additionally, we discuss backscatter communications, compare different energy harvesting techniques, explore hybrid approaches, and outline challenges in energy provisioning.
- We introduce the fundamentals of wireless charging, providing an overview of previous work on wireless charging techniques and ranges, including key constraints, decision variables, highlights, techniques, and control methods, as shown in Table 1. We discuss types of chargers, including mobile and static, as well as full and partial charging ways. Additionally, we outline charging modes, covering both offline and online modes. We present various charging scheduling schemes, including periodic and on-demand, with a comparison and summary of previous studies as shown in Table 2. Finally, we introduce collaborative charging mechanisms.
- Finally, we introduce the challenges of wireless charging with solutions, followed by a discussion of trends and future directions in WRSNs.

1.4 Paper Organization

This survey's structure is depicted in Fig. 2. Table 1. provided in the supplementary materials **Section (1)** provides the notation definitions in our work. We organize the remainder of this paper as follows: Section 2 offers a brief overview of energy provisioning techniques, including conventional energy harvesting, WPT, RF, and backscatter communications. In this section, we also introduced a brief of hybrid energy harvesting techniques and then discussed the challenges researchers face when using these techniques. Section 3 offers an in-depth discussion on the fundamentals of wireless charging. Subsection 3.1 presents a comprehensive summary of charger types, including static and mobile chargers. In subsection 3.2, full and partial charging policies are introduced. Subsection 3.3 covers the charging modes, including offline and online charging modes. Subsection 3.4 furnishes detailed insights into periodical and on-demand charging schemes, respectively. Finally, subseection 3.5 introduces collaborative charging mechanisms. Section 4 introduces the prominent challenges researchers face with solutions in this field, followed by trends and future directions in WRSNs in Section 5. Finally, Section 6 offers a concluding perspective for this survey paper.

2 The Energy Provisioning Techniques

Traditionally, batteries have served as the primary power source for sensor nodes. However, placing these devices in remote or inaccessible locations makes changing the battery laborious. Consequently, it has become essential to seek practical solutions with advanced techniques to address the energy challenges faced by these devices. Harvesting energy from the surrounding environment or delivering energy wirelessly to these devices are currently available solutions. Energy harvesting enhances the capability of sensor networks by providing a sustainable solution to energy challenges. Unlike batteries, which have a finite energy storage capacity, energy harvesting sources are limited by their energy consumption rate, ensuring a more consistent energy supply despite fluctuations in availability over time. While a deterministic metric like residual battery life is suitable for describing energy availability in battery-powered systems, energy-harvesting systems require a more nuanced approach. This complexity is essential to our research, particularly because energy harvesting opportunities vary across network nodes, posing significant challenges [29]. Thus, this section provides an overview of energy provisioning technologies in the following subsections.

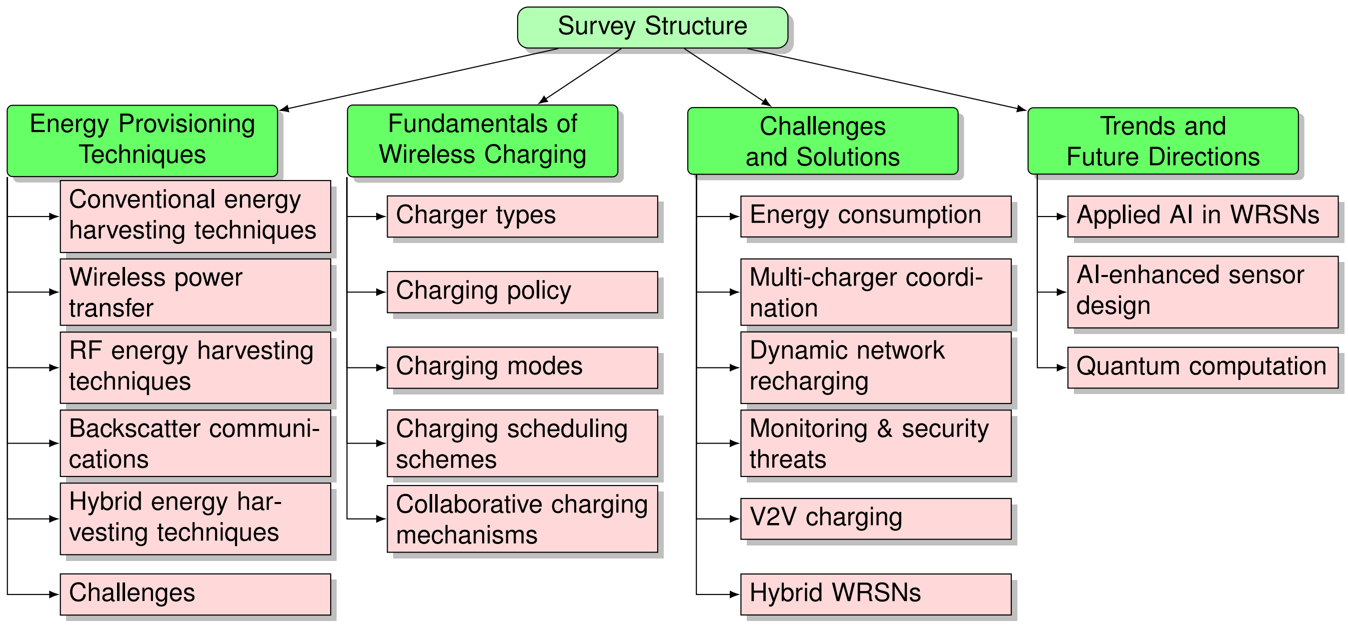

Fig. 2: Survey Organization

2.1 Conventional Energy Harvesting Techniques

Sensor nodes can obtain their energy from external environments using harvesting techniques such as solar, thermal, and mechanical energy. These sources store accumulated energy in batteries or capacitors to support operations like processing and communication. This subsection introduces solar, thermal, and mechanical energy harvesting techniques.

1) **Solar energy harvesting:** Photovoltaic (PV) technology converts light into electricity through semiconducting materials. PV systems consist of solar panels made of multiple solar cells, which are classified into four types: silicon, multi-compound, polymer photovoltaic cells (PPVC), and nanocrystalline solar cells [25]. These cells differ in efficiency: silicon cells range from 15% to 22%, multi-compound cells exceed 40% under concentrated sunlight, PPVC typically have less than 5%, and nanocrystalline cells around 10%. Researchers use quantum efficiency and volt-ampere testing to assess spectral response and short-circuit current. PV technology is used in applications like rooftop systems, power plants, transportation, and telecommunications [30]. The rapid growth of IoT has enhanced connectivity but faces challenges for sustainable power supply [30]. Indoor photovoltaics (IPV) offer a reliable energy source, though their effectiveness is limited by nighttime unavailability and manufacturing complexities [31]. To address this, IPV materials and manufacturing processes must be eco-friendly and low-toxic, providing a sustainable solution for powering IoT devices.
2) **Thermal energy harvesting:** It uses thermoelectric generators (TEGs) to convert heat into electricity via the Seebeck or Thomson effect. Heat can come from natural sources or machinery, engines, and other systems [30]. TEGs are reliable when there is a temperature difference or heat flow, offering advantages like compact size, safety, and high reliability. However, they have relatively low efficiency (5–8%) [30] and struggle to maintain significant temperature gradients in small devices, limiting power output. Recent advances in thermoelectric technology focus on optimizing materials, exploring new thermoelectric materials, creating functionally graded materials, and reducing material dimensions to increase power output. Despite losses from electrical interconnections, contact heat resistance, and other factors, TEGs remain viable for powering devices in WSNs, especially in environments with consistent heat sources [32]. Multiple thermocouples are often required to increase efficiency, as single units generate minimal power. Consequently, thermal energy harvesting is better suited for large-scale applications like steam turbines.
3) **Mechanical energy harvesting:** Vibration energy harvesting converts kinetic energy from vibrations into electricity using electromagnetic induction, piezoelectric fibers, and capacitive devices [33]. Applications include agriculture [34] and livestock farming [35]. For example, a system harnessed elephant movement to generate 88.91 J daily, powering a tracking unit. Piezoelectric harvesters generate high voltage without external power, with materials like PZT and polyvinylidene fluoride (PVDF) offering efficiency and mechanical strength [36]. However, they face limitations like depolarization and brittleness [37]. Electromagnetic harvesters use induction and NdFeB magnets to capture energy from vibrations [38], though output can decrease with size reduction. Researchers are improving coil designs and resonance frequency to enhance efficiency. Capacitive harvesters convert mechanical energy by altering capacitance due to vibrations, powering sensor devices [39]. Challenges include generating enough power and reducing reliance on external charging. Efforts focus on improving electret materials for better efficiency and stability.

2.2 Wireless Power Transfer (WPT)

WPT technology enables energy delivery from a power source to a target without physical wires, using air as the transmission medium [40]. The transmitter, receiver, and coupling devices are the main parts of WPT. The transmitter produces and sends energy wirelessly, while the receiver captures it and converts it into usable power for devices like phones. Coupling devices, such as inductive coils, capacitive plates, or antennas, facilitate energy transfer between the transmitter and receiver. Recent advancements in WPT have optimized energy efficiency, mobility, and extended network lifetime, surpassing conventional energy harvesting techniques. WPT revolutionizes smart homes, healthcare, and industries by enabling wireless, cord-free energy solutions. It powers home appliances, medical devices, and industrial systems, enhancing convenience, safety, and efficiency while reducing downtime. It also presents promising for solving power challenges in WSNs and is increasingly used in applications such as smartphone charging, EVs, and UAVs.

WPT technologies are widely classified into radiative and non-radiative transmissions [3]. Non-radiative-WPT is suitable for short-range energy transfer, relying on magnetic resonance coupling for mid-range applications [4]. Key techniques in this category include inductive coupling and capacitive induction [6]. However, radiative-WPT transmits energy over long distances using electromagnetic waves. This category includes several techniques, including RF, optical, ultrasonic, and microwave-based power transfer. Non-radiative WPT, also known as near-field WPT, is primarily used for short-range energy transfer [41]. The main challenge is that energy transfer becomes less efficient as the distance increases, making it hard to power devices that are far away. This technology is further categorized into inductive and capacitive coupling, each with different operational principles.

1) **Inductive coupling:** It uses a magnetic field generated between a transmitter and receiver coil to transfer energy efficiently over short distances, typically within 20 cm and at kilohertz frequencies. This method is commonly found in consumer electronics, such as wireless phone chargers and RFID systems, due to its low cost, simplicity, and high efficiency.
2) **Magnetic resonance coupling:** It extends the energy transfer range, enabling the simultaneous charging of multiple devices over greater distances. Its flexible configurations allow it to adapt to various applications. However, energy transfer efficiency decreases as the distance between the transmitter and receiver increases [41].
3) **Capacitive coupling:** It uses electric fields to transfer energy over very short distances [42]. The challenge is that the amount of power transferred depends on the capacitance between the plates, which limits efficiency and performance, especially as the distance between the plates increases. Thus, the authors in [43] considered that the most widely used technologies in this field are inductive coupling and magnetic resonance coupling.

Radiative WPT transmits energy using carriers such as acoustic waves, optical signals, and microwaves [44]. It can transfer energy over several meters through RF signals and laser beams, making it suitable for applications like SWIPT and WPCNs [7]. This method covers a wider area than traditional antennas, enabling broader deployment. However, it faces challenges such as RF safety concerns and limited range, which require advanced techniques like beamforming to improve performance. While these solutions enhance efficiency, they also increase the system's complexity.

2.3 RF Energy Harvesting Techniques

As shown in Fig. 3, RF energy harvesting is a type of radiative WPT that captures energy from ambient or transmitted RF signals and converts it into usable power. It collects electromagnetic waves, such as Wi-Fi or cellular signals, and converts them into direct current (DC) power using a rectifier circuit [45]. The process starts with an antenna receiving these signals as alternating current (AC), which the rectifier transforms into DC. These antennas can operate on multiple frequencies and transmit signals either omnidirectionally (in all directions) for low-intensity broadcasts or in a focused beam (directed) for high-intensity, typically using antenna arrays. Since the energy harvested is limited, it is stored in capacitors or batteries to power small devices, supporting applications in WSNs and IoTs.

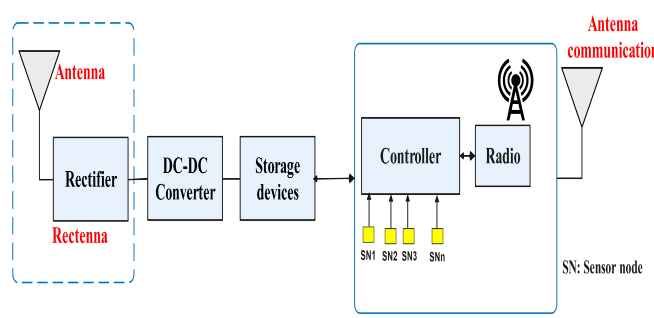

Fig. 3: RF energy harvesting sensor node.

Recent advancements in WPT integrate power and data transfer, inspired by Nikola Tesla's experiments [41]. These innovations aim to make future wireless networks faster, more reliable, and with lower latency. WPT shows significant promise to support advanced wireless powered networks technologies like SWIPT, WPCN, and Backscatter Communications. Thus, WPT can be used to power either wireless information transmitters or receivers. When the harvested energy powers the transmitters, the system is known as SWIPT [46]. Alternatively, the system is known as a WPCN when it powers the receivers [47]. Despite challenges due to signal degradation from path loss and fading, these techniques show promise, especially in urban areas with abundant ambient RF energy. More details are provided in the supplementary materials **Subsection (2.1)**.

2.4 Backscatter Communications

In 1948, Stockman introduced the modulated backscatter method [11], which enables data transmission by modulating and reflecting received RF signals without generating active RF signals. Building upon our previous work [48], we highlight the three primary techniques of backscatter communications: monostatic backscatter communication systems (Mon-BackComs) [49], bistatic backscatter communication systems (Bis-BackComs) [50], and ambient backscatter communication systems (Amb-BackComs) [51].

Amb-BackComs holds several advantages over Mon-BackComs and Bis-BackComs. First, they capitalize on nearby available RF sources, negating the necessity of deploying and managing discrete RF sources. This translates to reduced costs and energy consumption, as the components of backscatter devices are low-cost and energy-efficient [52]. Second, Amb-BackComs leverages existing ambient RF signals, obviating the need for allocating a fresh frequency spectrum. This optimized spectrum resource utilization is achieved by modifying and reflecting current ambient RF signals instead of actively generating signals in the licensed spectrum, rendering Amb-BackComs virtually interference-free to licensed devices. Consequently, Amb-BackComs functions without requiring dedicated frequency spectrums, further trimming down system expenses. Finally, Amb-BackComs adheres to existing spectrum utilization regulations [52]. However, Amb-BackComs have their drawbacks. Firstly, intense direct interference from ambient RF sources can impact the system performance of Amb-BackComs. Secondly, the simple analog construction of backscatter devices raises various security concerns for Amb-BackComs. Moreover, these devices utilize ambient RF waves for their internal operations and transmission, posing challenges in coordinating ambient RF sources' frequencies, scheduling, and transmission power. Furthermore, since the energy harvested from ambient RF sources is often minimal, backscatter devices may require substantial time to accumulate enough energy to sustain their operations and transmissions [53].

2.5 Hybrid Energy Harvesting Techniques

This subsection introduces hybrid energy harvesting (HEH) techniques, which combine multiple energy sources, such as ambient light, RF signals, and vibrational energy, to develop autonomous power systems for active RFID tags. HEH techniques are essential for enhancing the energy sustainability of WSNs. They are applied in various applications, including environmental monitoring, industrial automation, wearable devices, power devices, truck recognition, organic fertilizer plants, agriculture, and the automobile industry, in both indoor and outdoor environments [54]. More details about the hybrid energy harvesting techniques are provided in the supplementary materials **Subsection (2.2).**

2.6 Challenges of Energy Provisioning Techniques

While energy harvesting and hybrid techniques can extend WSN lifetimes, they face significant challenges. Energy sources like solar and RF signals are highly variable, leading to inconsistent power output [55]. Solar energy depends on weather and time of day, with cloudy conditions and nighttime drastically reducing efficiency. Similarly, ambient RF signals vary in availability and strength, limiting their energy-harvesting potential. These factors often result in low power output and insufficient for high-energy WSN operations. Additionally, the conversion efficiency of ambient energy to electricity, particularly with RF and thermal energy harvesting, remains low, hindering performance and reliability. High material costs, IoT integration challenges, and managing multiple energy sources further complicate HEH in large, remote WSNs.

Unlike energy provisioning techniques that depend on changing environmental factors, WRSNs utilize controlled and predictable WPT. MCs or unmanned aerial vehicles (UAV) can be deployed to recharge sensor nodes as needed, ensuring consistent power without being affected by weather or RF conditions. This capability meets the energy demands of applications that require higher power levels. By integrating WRSNs into the system, the limitations of traditional energy provisioning techniques are overcome, leading to extended network lifetime and improved performance. Thus, in the following sections, We introduce a brief overview of the fundamentals of wireless charging.

3 Fundamentals of Wireless Charging

WRSNs are an advanced type of WSNs that integrate the ability to recharge sensor nodes wirelessly, extending their operational lifetime without needing battery replacement. They can increase energy efficiency by scheduling charging based on the network's needs. WRSNs have three main components: chargers, sensor nodes, and BS. Each component is essential for the network's functionality and efficiency, and they can differ based on whether the environment is 2-D or 3-D. Our focus in this review is on wireless charging, where scheduling can be categorized as centralized or distributed, depending on the route control where the charging requests are collected. In centralized scheduling, requests are gathered at the BS. However, in distributed scheduling, MCs collect requests within sub-regions for localized management. To clarify the fundamentals, technologies, and challenges of wireless charging, we review the main concepts, such as charger types, charging policy, charging modes, charging scheduling schemes, and charger modes. Table 1 shows related wireless charging work based on centralized and distributed control.

3.1 Charger Types (CTs)

In WRSNs, energy replenishment is crucial to ensure sensor nodes remain active. One of the critical components in WRSNs is the charger type, which ensures that nodes have sufficient energy to perform sensing and communication tasks. Charger types in WRSNs are typically divided into mobile and static chargers, each offering unique benefits and challenges. This subsection introduces static and mobile chargers in 3.1.1 and 3.1.2, respectively.

3.1.1 Static Charger Type (SCT)

In SCT, wireless charging devices are commonly and strategically positioned at identified and fixed locations within the network [74]. This type faces the problem of figuring out where to place chargers within the network to maximize coverage and replenish all sensor nodes with enough energy. Liao et al. introduced a greedy algorithm called adaptive pair-based greedy cone selection (APB-GCS), which utilized the Friis propagation model [75]. It

TABLE 1: Examples of Related Work of Wireless Charging Based on Centralized And Distributed Control

Ref	Highlighted	Decision Variables	Key Constraints	Control Method
[56], (2011)	Prolong the network lifetime	Charging sequence, data routing	Time limit for total energy	Centralized
[57], (2012)	Maximize the ratio of charger's vacation time	Cycle time, traveling path	Energy consumption rate of sensor nodes	Centralized
[58], (2013)	Reducing the number of MCs	Charging sequence of each MC, number of chargers	Eternal WSN operation, MC energy capacity	Centralized
[59], (2013)	Maximize the network lifetime	Charging trajectory of each MC	MC energy capacity	Distributed
[60], (2014)	Maximize the ratio of charger's vacation time	Cycle time, traveling path	Charging range	Centralized
[16], (2017)	Maximize coverage and charging efficiency	Charging range, adaptive attractiveness, dynamic location update	Sensor node locations, unrestricted energy	Distributed
[61], (2017)	Optimize path planning and MES scheduling, minimize data loss	Traveling time, charging range, number of paths	MES energy capacity	Centralized
[62], (2018)	Maximize energy efficiency, survival rate	Charging schedule trajectory, distances	Temporal and spatial correlation	Distributed
[63], (2018)	Maximize charging coverage utility	Charging routes, charging time, node association	Limited energy capacity, traveling energy consumption, charging consumption	Centralized
[64], (2018)	Minimize the maximize moving time	Number of chargers, service cost, energy consumption	Charger velocity, distances, number of chargers	Distributed
[65], (2019)	Minimize the cost deployment of rechargeable directional sensor network	Number of deployed sensor nodes	Sensing angles of directional sensors and MC energy capacity	Centralized
[66], (2019)	Optimize the service process	Residual energy information, traveling distance, charging time	MC energy capacity, flow routing	Distributed
[67], (2020)	Static node energy consumption	Random node distribution, charging distance, distance to BS	Node density	Centralized
[68], (2020)	Minimize the number of used batteries	Distance between two service stations, charging tour	MC energy capacity	Centralized
[69], (2020)	Enhance energy efficiency, reducing charging latency, maximize network lifetime	Moving trajectory, charging time	MC energy capacity, routing flow	Centralized
[70], (2020)	Minimize the number of chargers	Number of chargers	MC energy capacity	Centralized
[71], (2020)	Maximize the energy usage efficiency, reduce the charging frequency	Location, energy consumption	Routing flow	Centralized
[72], (2021)	Maximize the charging utility/reward	Sensing range, charging range, sensor nodes	Routing flow, MC energy capacity	Centralized
[73], (2021)	Minimize charging delay	Distance, angle, search space	MC energy capacity	Centralized

assumed that chargers with directional antennas were fixed at specific heights on a grid while sensors were placed on the ground. They showed that APB-GCS effectively reduced the number of chargers needed while keeping complexity manageable. However, using static chargers is unsuitable for dynamic and large-scale networks. Zhang et al. were the first to explore charging non-deterministic mobile nodes with static chargers [76]. They optimized charging quality in a 2-D area by selecting optimal charger placements and power allocations under a budget, proving the problem to be NP-complete, and developing approximation algorithms. In 2018, they extended their work with stationary devices (SP^3), mobile devices (MP^3), and cost-constrained reconfiguration (CRP) [1]. Simulations showed that their algorithms performed close to optimal, with performance gaps of 4.5%, 4.4%, and 5.0%, outperforming baseline methods. However, Zhong et al. addressed charging nodes with unpredictable mobility while minimizing the number of static chargers (SCs) [77]. The charger selection problem (CSP) was proven to be NP-hard. CSP involved selecting the smallest subset of candidate locations for placing chargers, ensuring that each node in the network was covered by at least one charger, and maximizing the network's energy gain. This problem can be reformulated as a minimum weight set cover problem (MWSCP), a well-known NP-hard problem. Since MWSCP is NP-hard, CSP is also NP-hard by reduction. They demonstrated that finding the optimal solution to CSP, in terms of the minimal number and placement of chargers while ensuring full network coverage and maximizing energy efficiency, is computationally intractable for large instances. This justified the need for heuristic or approximation algorithms, such as the proposed greedy algorithm, to solve the problem efficiently.

3.1.2 Mobile Charger Type (MCT)

The mobile charger type is one of the critical keys in WRSNs, and mobile devices travel from the BS or their current locations to their destination to recharge the batteries of hanger nodes. These mobile devices may be vehicles, robots, or UAVs, and they distribute energy among sensor nodes to extend the network's lifetime. The network can use either a single or multiple chargers. Thus, we now introduce the prior works using mobile chargers type by either single or multiple chargers.

Several studies use a single charger that is suitable for small networks with simple setups, offering easy operation and low cost [78], [5], [62], [56], [67]. However, they are limited to large-scale networks. To overcome this limitation, the J-RoC scheme integrated routing and charging, guiding both activities proactively [56]. By delivering energy where needed and optimizing energy consumption, J-RoC enhances network performance and prolongs its lifetime. Fu et al. proposed the ESync protocol to reduce charger travel distance and node charging delays by creating nested TSP tours based on energy levels and synchronizing charging requests [79]. They demonstrated a 30% reduction in travel distance and a 40% decrease in charging delays. One key challenge for a single charger is handling unpredictably moving nodes. The predicting-scheduling-tracking (PST) method [80] and the charging reward maximization problem (CRMP) approach [81] improved single MC by addressing the challenge of unpredictable node movement. PST focused on predicting node locations using an improved LSTM algorithm [80] and tracked them with a Kalman filter [82] for accurate charging. On the other hand, CRMP used reinforcement learning (RL) [83] to prioritize nodes based on their remaining energy, ensuring efficient charging. While PST relied on prediction and scheduling, CRMP focused on adaptive learning to make better real-time charging decisions. Lin et al. in [67] proposed the circular-density charging cluster division method (CDCCDM) to extend network lifetime by forming circular clusters based on node density, reducing clusters, and optimizing the MC's path. In [84], the authors proposed to minimize the energy consumption and the covered distance in the network. However, their efficiency still faces the limitation of using a single charger. These approaches show that a single charger is inefficient for large-scale networks with limited MC energy, leading to increased charging delays, higher energy consumption, and lower survival rates. Thus, increasing the number of chargers in the network is a crucial key. Then, the researchers turned to using multiple chargers to address these challenges [16], [58], [59]. Dai et al. addressed the minimum number of energy-constrained MCS (MinMCP) problem, designing optimal paths for continuous operation [58]. They showed that: (1) no $(2-\epsilon)$-approximation algorithm exists for DVRP in broad metric spaces, (2) MinMCP is NP-hard, and (3) MinMCP matches DVRP complexity through reduction. Wang et al. addressed the recharge scheduling problem under energy consumption and capacity constraints. They achieved 30-50% less transient energy depletion, 10-20% energy savings, and 30% energy savings with latency reduced by two orders of magnitude [85]. Liang et al. optimized multiple charger scheduling, minimizing charger deployment while considering energy capacity constraints [86]. Although researchers have increased network lifetime and energy efficiency, they are still working to optimize charging paths, coverage, and energy consumption while addressing the challenges of static and mobile chargers.

3.2 Charging Policy

Energy consumption in WRSNs is crucial for researchers to enhance network efficiency and extend its lifetime. Both chargers and sensor nodes are the main reasons for energy consumption. Sensor nodes consume energy for continuous monitoring, location tracking, communication with the BS, and chargers for traveling to recharge nodes, along with tasks like route discovery and data collection in dynamic networks. To manage this, charging tours operate in two ways for energy transfer: partial charging [87], [73], [88], [89], [90], [91], [92], and full charging [66], [93], [70], [94], [95], [96], [69], [97], [71], [98], [68], [61], [99], [72], [100] , each significantly impacting network efficiency and longevity. Thus, we now discuss partial and full policies as follows.

3.2.1 Full Charging Policy

During each charging tour, full charging uses MC to recharge the hanger sensor nodes completely [97]. It ensures that the charger fully recharges each sensor node before moving on to the next. This guarantees that each sensor node can operate longer before needing another recharge. However, this way is challenging with a single charger, as it takes time to recharge each sensor node fully, risking energy loss in other nodes before the charger reaches them. This works better with multiple MCs, allowing them to balance the workload and efficiently keep nodes powered. Several studies employed a full charging policy to optimize charging efficiency and paths [101], [102]. Fu et al. introduced a method to charge RFID-based sensor nodes to a required energy level efficiently, improving charging efficiency by 24.7% [101]. Chen et al. investigated how to determine a charging path that maximizes the number of nodes charged within a specified time limit, proving that this problem is APX-hard [102]. One of the challenges is reducing dead sensor nodes and energy consumption. Lin et al. addressed these challenges by optimizing the charging schedule to avoid conflicts [62] and managing device sleep time [103]. In [62], a joint optimization problem was addressed using a real-time scheduling strategy, dividing the system into subdomains to simplify MC arrangement. This approach enabled efficient travel and energy replenishment for critical sensor nodes while managing computational complexity to optimize performance. However, in [103], they proposed a 3-D dynamic collaborative scheduling scheme (3DCS) using UAVs and MCs to divide the network into regions, optimize charging sequences, and enable cross-region collaboration. Lyu et al. proposed a periodic charging scheme to prevent sensor node failures and maximize docking time using a hybrid particle swarm optimization genetic algorithm, outperforming GA and PSO [100]. Ding et al. reduced battery needs for MCs by optimizing algorithms for single and multiple service stations [68]. Malebary extended network lifetime by partitioning networks into charging regions, optimizing MC routes and durations [69]. Liu et al. optimized CUAV scheduling and trajectory in 3-D networks, minimizing hovering points and flight distances with particle swarm optimization [104].

3.2.2 Partial Charging Policy

Due to challenges with full charging, such as charging delay and high energy consumption, the researchers direct their interest to partial charging, where the MC recharges sensor nodes partially during each tour [105], [56]. This way involves charging sensor nodes only to a specific level rather than to full capacity, which quickly provides enough energy to keep the sensor nodes operational until the next charging tour. Its advantages reduce the time and energy consumed by the MCs, allowing them to recharge more sensor nodes quickly. However, this way requires careful balancing of the energy needs of multiple nodes with varying charge levels, making them particularly suitable for networks with a single charger [106], [107], [108]. For example, an MC that uses 20% of its energy for travel and 80% for recharging four sensor nodes can provide partial charging. While this doesn't fully recharge the nodes, it ensures they stay operational and allows the MC to complete its tour and return to the BS, helping to extend the network's lifetime. Han et al. addressed energy issues in industrial WRSNs with a grid-based joint routing and charging algorithm, improving local energy distribution and balancing energy consumption, which increased node survival rates [87]. Meanwhile, Feng et al. introduced the Mobile Energy Replenishment Scheme (MERSH), which combined online and offline modes to adapt to changing energy needs and improve energy supply. [91]. MERSH enabled nodes to request charging from an MC and optimized paths and durations to prevent node failures. Xu et al. proposed a partial charging strategy to maximize sensor lifetime while minimizing the charger's travel distance [107]. Wang et al. addressed varying energy consumption rates with partial charging [109]. In [88], the authors aimed to optimize the scheduling, movement, and charging times for multiple mobile chargers with limited resources. Liu et al. created the multi-node temporal-spatial partial charging algorithm (MTSPC) to balance minimizing dead sensors and maximizing energy efficiency [106]. Liu et al. focused on the challenge of unpredictable mobility of mobile devices by formalizing it as a charging reward maximization problem (CRMP) [89]. They considered the energy capacity of the charger and developed a reinforcement learning (RL)-based algorithm to improve charging efficiency. Priyadarshani et al. developed an on-demand, multi-node charging approach using the NSGA-II genetic algorithm and multi-attribute decision-making (MADM) to optimize charging schedules [90]. Lin et al. enhanced energy efficiency and reduced delays by applying partial charging with single and multiple chargers [73]. Kaswan et al. introduced the Distributed Mobile Charging Protocol (DMCP) to improve partial charging in large WSNs [110]. By focusing on sensor energy needs and charger idle times, and using game theory to prioritize critical nodes, DMCP reduced charging delays by 44% and increased coverage and survival rates. Despite efforts to improve partial and full charging policies, challenges remain. Partial charging can result in uneven energy distribution, causing some nodes to deplete faster and leading to coverage gaps. On the other hand, full charging requires more energy and time, making it less sustainable for large-scale networks.

3.3 Charging Modes

In WRSNs, the charging modes are divided into (a) offline charging mode (deterministic techniques) and (b) online charging mode (non-deterministic techniques). In this section, we now review offline and online charging modes. Chargers proceed to this stage to determine the paths that directly lead to the requested nodes; as a result, the path definition for the offline mode consists of predefined or fixed paths, which is different from the online charging mode.

3.3.1 Offline Charging Mode

In the offline charging mode, decisions are made before the system operates, with BSs and MCs having prior knowledge of sensor information like location information for required nodes, energy levels, and energy consumption rate. Some researchers [61],[18] employ the offline mode in their research. However, several assumptions, such as network topology, location information for required nodes, and energy consumption rate, constrain offline path planning for MCs. The charger's route is crucial in transforming the charging method into a traveling salesman problem (TSP) and identifying the appropriate Hamiltonian cycle. TPS aims to find the shortest path so that, through it, the MC visits each node exactly once and returns to the BS. The Hamiltonian cycle strives to ensure that MC visits each sensor node exactly once in a cycle, avoiding any node duplication. Although the offline model may appear similar to a periodic charging scheme, the key difference is that in offline scheduling, the MCs, sensor nodes, and BSs are all coordinated and planned in advance. In contrast, the periodic charging scheme involves only the MCs, which follow a fixed path throughout the network to recharge sensor nodes. Using single or multiple MCs is considered in online and offline modes, as employing a single MC in a vast and harsh area can lead to several issues. Despite offline scheduling solutions' contributions, unanticipated changes in network topology remain a performance barrier in a dynamic system. Consequently, offline scheduling may not be suitable for several real-world applications. Shi et al., for example, addressed the charging problem of an MC as an optimization problem [14]. Their goal was to increase the MC's vacation time ratio relative to tour time. Furthermore, they showed that the shortest Hamiltonian cycle was the optimal path for the MC to take on each recharging tour. Then, by enhancing a verifiable near-optimal solution, they tackled the problem of flow routing, total cycle time, and individual charging time at each node as a joint optimization problem, which was a non-linear problem. They also demonstrated that the typical minimal energy routing wasn't the best option. The authors in [111] designed a hybrid clustering charging algorithm to reduce charging time, travel duration, and average delay. They created a network backbone with a minimum connected dominating set, utilized hierarchical clustering, and incorporated a k-means algorithm for energy awareness. They improved the HCCA to develop HCCA-TS for enhanced performance.

3.3.2 Online Charging Mode

In the online charging mode, recharging decisions are made in real-time without prior knowledge of new requests or task completion. This mode, often using on-demand or collaborative scheduling schemes, is more practical than the offline mode, which struggles with tracking sensor locations and maintaining balanced energy levels. Therefore, the limitations of MCs constrained offline path planning through several assumptions, including network topology, location data for necessary nodes, and energy consumption rate. Some online modes were suggested. These needed to send information about requested sensor nodes to MCs or BSs when a warning message had the rate of remaining energy dropped below a certain level [112], [113]. BS or MC would then decide on the charging schedule method plan based on predetermined algorithms after receiving the gathered information from the requested sensor nodes (such as location information, remaining energy rate, and consumption energy rate). For example, the authors in [114] addressed maximizing covering utility in WRSNs by using an online charging scheduling for MCs. The MC autonomously moved upon receiving a recharge request.

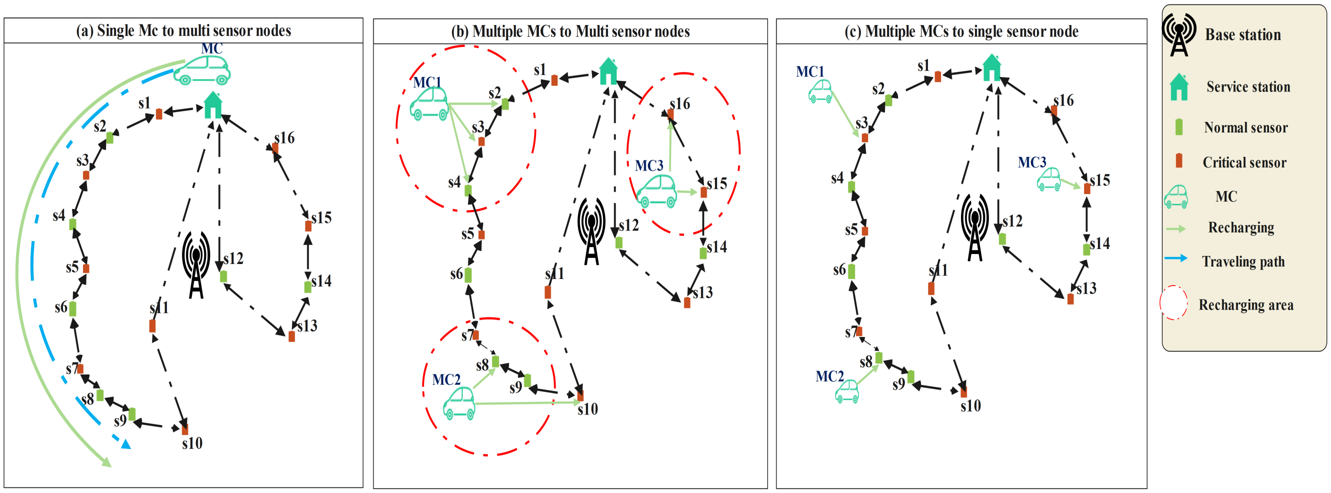

Fig. 4: Scenarios of periodic charging scheme: (a) A single MC is deployed within the network to recharge multi-sensor nodes periodically; (b) Multiple MCs are deployed within the network, where each MC can periodically recharge multi-sensor nodes in the same coverage area; (c) Multiple MCs are deployed within the network, where each MC can recharge only one sensor node periodically.

They formulated the scheduling problem as an optimization task and proposed three heuristic algorithms, leveraging the spatial redundancy of WRSNs to solve the NP-complete problem. The solution was also extended to scenarios with multiple MCs. Ouyang et al. [115] introduced utility-based collaborative charging (UBCC) to optimize MC performance by merging paths, balancing workloads, and reducing idle time. Simulations showed a 25% reduction in required MCs and a 35% increase in charging efficiency. Additionally, in [116], they improved charging utility and reduced data loss using multiple MCs.

3.4 Charging Scheduling Schemes

This section introduces a brief review of charging scheduling schemes, categorizing them into periodic and on-demand schemes. Subsections 3.4.1 and 3.4.2 review periodic and on-demand charging schemes, respectively, and previous works are summarized in Table 2.

3.4.1 Periodic Charging Scheme

In this scheme, the MC operates periodically to continually charge each deployed sensor node across the environment, subject to predetermined conditions [111], [57], [117], [118]. These factors include the charging duration at each node, the route the MC takes, and the charging sequence. These schemes transform the charging problem into a TSP to determine the shortest Hamiltonian cycle, which is regarded as a solution. The energy distribution and consumption model serve as the foundation for their calculation. This scheme has the following benefits: (a) adapting to deployed nodes while maintaining balanced energy consumption; (b) fixing the nodes' energy consumption. However, its limited charging capacity is inappropriate for dynamic networks, as it assumes a fixed network topology. Therefore, this scheme may be more effective in large-scale environments where other approaches are not feasible.

We divided these schemes into two categories based on the number of chargers that can operate to replenish sensor nodes. The categories are single-MC-based and multiple-MC-based. Single-MC-based uses one MC to recharge all sensor nodes within a network. However, multiple-MC-based uses multiple MCs to recharge sensor nodes simultaneously across a network. Fig. 4 shows the scenarios of periodic charging schemes: (a) A single MC is deployed within the network to recharge multi-sensor nodes periodically, (b) Multiple MCs are deployed within the network, where each MC can periodically recharge multi-sensor nodes in the same coverage area, and (c) Multiple MCs are deployed within the network, where each MC can recharge only one sensor node periodically. Unfortunately, working with a single-MC-based has low charging efficiency and is inappropriate for large-scale networks compared to multiple-MC-based. More related work of periodical charging schemes based on using a single and multiple MCs are provided in the supplementary material **Subsection(3.1)**.

3.4.2 On-demand Charging Scheme

This scheme relies on determining which node needs to be replenished first in each round based on priority[96],[138], [105]. Thus, it relies on non-deterministic characteristics, such as dynamic changes in network topology, network connectivity, and varying energy consumption for each node across the network. Therefore, it is particularly suitable for dynamic networks. The system of this scheme operates based on a predefined threshold for remaining energy [139]. When the energy level falls below this threshold, the MC or BS receives a recharging request warning message. The MC or BS then takes over the charging priority and selects the node that requires recharging first. Once the MC identifies the designated node, it promptly recharges its energy. In the network, either a single MC or multiple MCs are deployed to recharge sensor nodes. A single MC can charge multiple

TABLE 2: Summary of Previous Works of Charging Scheduling Schemes

Ref	Scheme Type	Focus/Highlights	Charging Capacity	Device Used
[99], 2016	On-demand	Improving the efficiency and scalability of recharge in WRSNs, handling dynamic energy demands and reducing service interruption time	One-to-one	Multiple SenCars
[119], 2017	On-demand	Improving efficiency, maximizing survival rate and throughput	One-to-one	Single MC
[120], 2017	On-demand	Optimizing energy consumption, minimizing battery depletion, and reducing the movement costs in WSNs	Multi-to-one	Multiple MCs
[61], 2017	Periodic	Optimizing path planning and scheduling	One-to-one	Single MES
[121], 2017	Periodic	Reducing energy latency, predicting anchor points	One-to-multi	Multiple MCs
[108], 2017	On-demand	Maximizing the total reward collected from the charged sensors	One-to-one	Single MC
[62], 2018	On-demand	Maximizing energy usage and node survival rate	One-to-one	Multiple MCs
[93], 2018	On-demand	Reducing MC operating costs, optimizing routes	One-to-one	Single MC
[63], 2018	Periodic	Maximizing coverage and balancing travel/charging energy	One-to-multi	Multiple drones
[122], 2018	Periodic	Reducing energy use, improving charging efficiency and path optimization	One-to-multi	Single MC
[107], 2018	On-demand	Maximizing sensor lifetime, minimizing MC travel distance	One-to-one	Single MC
[65], 2019	Periodic	Minimizing required sensor nodes for effective coverage	One-to-one	Single MC
[123], 2019	On-demand	Increasing efficiency, improving reliability and performance	One-to-one	Single UAV
[91], 2019	On-demand	Optimizing the charger path and reducing the whole charging cost	One-to-one	Single MC
[92], 2020	On-demand	Maximizing the overall task utility	One-to-multi	Single MC
[70], 2020	Periodic	Minimizing the number of MCs	One-to-one	Multiple MCs
[124], 2020	Periodic	Maximizing data collection, reducing energy use	One-to-multi	Single MD
[69], 2020	Periodic	Optimizing routes, enabling multi-node charging	One-to-multi	Single WMC
[125], 2020	On-demand	Optimizing scheduling, maximizing survival rate	One-to-one	Single robot
[115], 2020	Periodic	Improving charger energy use and cost	One-to-one	Multiple MCs
[126], 2020	Periodic	Reducing dead nodes, maximizing energy efficiency	One-to-multi	Multiple MCs
[71], 2020	On-demand	Reducing charger journey length and charging frequency while balancing energy consumption across the network	One-to-one	Single WCE
[90], 2021	On-demand	Improving charging performance and energy consumption	Multi-to-multi	Multiple MCs
[127], 2021	Periodic	Minimizing the number of sensor nodes required for effective coverage	One-to-one	Single MC
[128], 2021	On-demand	Extending the network lifetime and reducing the cost	One-to-one	Single MC
[72], 2021	Periodic	Improving charging utility and network performance	One-to-one	Single MC
[129], 2022	Periodic	Increasing the number of nodes within the charging range, minimizing MCVs' moving distance, giving high priorities to sensors with low battery levels, making the MCV closer to the sensor nodes to improve the efficiency, and maximizing the network lifetime.	One-to-multi	Multiple MCs
[130], 2023	On-demand	Minimizing energy consumption and data delivery latency	One-to-multi	Multiple MCs
[131], 2023	On-demand	Improving energy consumption and provisioning for wireless charging and data collection on a large scale, Minimizing latency, optimal amount of energy of MCVs, optimal number of MCs, and optimal number of data collection and charging points	On-to-multi	Multiple MCs
[132],2023	On-demand	Enhancing energy efficiency, response time, and reducing dead nodes and queuing delay	One-to-multi	Multiple MCs
[133], 2023	On-demand	Increasing system efficiency, extending network lifetime, and ensuring optimal performance for WRSNs in dynamic environment (smart cities)	One-to-multi	Single MC
[134], 2023	On-demand	Maximizing surveillance quality	One-to-multi	Multiple MCs
[135], 2023	Periodic	Maximizing network lifetime and reducing the number of mobile devices	One-to-multi	Multiple MDs
[136], 2024	Periodic	Minimizing charging delays in a WRSN with automatic landing pad (PADs)	One-to-one	Single UAV
[137], 2024	On-demand & semi-on-demand	Improving charging efficiency and network performance, optimizing charging time, energy usage, and network lifetime, and minimizing charging latency	One-to-multi	Multiple MCs

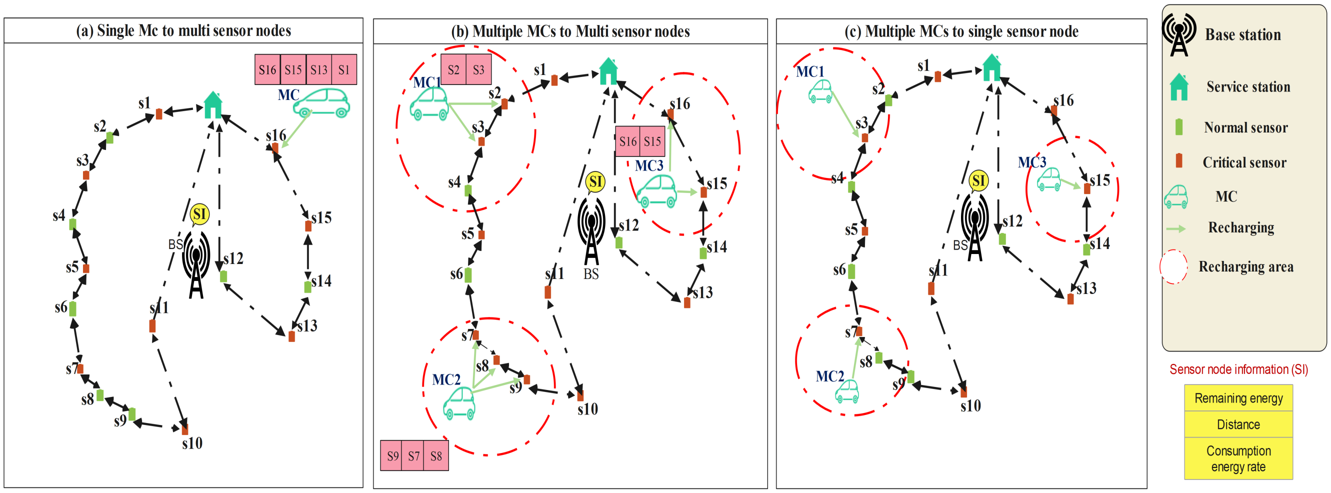

Fig. 5: Scenarios of on-demand charging schemes within the network that prioritize sensor nodes based on their recharge needs (a) A single MC is deployed to recharge multiple sensor nodes simultaneously, based on their priority; (b) Multiple MCs are deployed, and each MC can recharge multiple sensor nodes simultaneously according to their priority; (c) Multiple MCs are deployed, but each MC can recharge only one sensor node at a time.

sensor nodes, while multiple MCs can charge one or multiple sensor nodes simultaneously. Fig. 5 shows scenarios of on-demand charging schemes within the network that prioritize sensor nodes based on their recharge needs; (a) A single MC is deployed to recharge multiple sensor nodes sequentially in the order of priority (S16, S15, S13, S1); (b) Multiple MCs are deployed, and each MC can recharge multiple sensor nodes sequentially based on priority: MC1 charges S2 and S3; MC2 charges S9, S7, and S8; MC3 charges S16 and S15; (c) Multiple MCs are deployed, but each MC can recharge only one sensor node at a time.

However, when multiple sensor nodes send requests for recharging, the MCs follow the closest sensor node and adhere to the current charging path (resulting in suboptimal paths). The supplementary material **Subsection (3.2)** provides more related work on the on-demand charging scheme.

3.5 Collaborative Charging Mechanisms

The collaborative charging mechanisms are designed to manage the distribution of charging tasks among multiple MCs in large-scale WRSNs. MCs work together to minimize energy consumption and dead sensor nodes and increase survival rates. There are two types of collaborative charging mechanisms. The first type is based on dividing the network into areas, with specific MCs (maybe only one MC or more than one MC) responsible for each area. The idea is to reduce overlap by ensuring each MC only works within its designated area. This way, MCs are not competing for the same tasks, and the energy distribution is more efficient. The preemptive collaborative mechanism uses a utility function, allowing different MCs to compete for charging tasks based on the values of the function [115]. The advantage of this approach is its ability to effectively engage all MCs in the network, enhancing the overall charging efficiency. Liu et al. studied the costs of building and operating WRSNs with energy-limited MCs and introduced ”shuttling” to minimize MCs [95]. They developed the Push-Shuttle-Back (PSB) solution for 1D shuttling with minimal energy loss, and later extended it to 2D with a ”shortcutting” scheme. Simulations demonstrated reduced costs. Lin et al. developed a Game Theoretical Collaborative Charging Scheduling (GTCCS) scheme to address limited battery energy, using a non-cooperative game model with Nash Equilibrium to optimize charging decisions for multiple MCs [97]. They improved energy efficiency, reduced dead nodes, and enhanced system performance with features like warning thresholds and sacrifice charges. Wang et al. proposed a partial charge scheduling scheme to reduce dead time and extend network lifetime by prioritizing core nodes with a preemptive algorithm (MCDE) and excluding inefficient ones [105]. They improved service time, survival rate, and queue size. However, in [140], a Collaborative Charging Scheduling Algorithm (CCSA) was introduced, using two MCs to maximize sensor survival by classifying nodes and adapting charging strategies. They outperformed in reducing node mortality and effectively managing charging uncertainties and coordination complexities.

Additionally, in a collaborative charging process, sensor nodes, and MCs can work together to complete the charging process. Periodic charging schemes, which assume unrealistic certainty and regularity, cannot account for the unpredictable network factors that affect energy demand and supply [141]. Therefore, collaborative charging mechanisms address varying demands and dynamic conditions. Lin et al. proposed an online collaborative charging schedule using the mTS design, dividing the network into subdomains for specific MCs, with each MC prioritizing charging requests based on deadlines and distances [62]. Han et al. [142] introduced a collaborative charging algorithm that used density clustering to divide the network into areas. A mean-shift approach guided the deployment of sub-vehicles (SWCVs) by the mother wireless charger vehicle (MWCV), with optimal MWCV deployment and traversal order determined by the virtual field intensity technique. Chen et al. proposed a WRSN model combining MCs, MC-carried drones, and independent drones, organizing charging zones to schedule their cooperation, aiming to extend network lifetime and minimize charging time [143]. Qureshi et al. [144] developed a partial and full charging scheduling scheme that divides the network into areas and uses a layered collaborative mechanism to improve charging efficiency and network lifetime. Zeng et al. [145] addressed dynamic charging scheduling in WRSNs with obstacles and multiple MCs, using the Fresnel Diffraction Model (FDM) to account for obstacle effects. They grouped nodes for simultaneous charging, defined charging spot ranges, and used a dynamic scheme to balance charging loads and reduce sensor failures.

4 Challenges and Solutions

Researchers in WRSNs focus on extending network lifetime by recharging sensor nodes using various charging devices. However, several challenges hinder efficient energy transfer, including energy consumption, security, charging conflicts, multi-charger coordination, dynamic network recharging, and environmental interference. To overcome these challenges, innovative strategies and new research directions have emerged. We now discuss each of these challenges in detail as follows.

1) **Energy Consumption (EC):** Energy consumption remains a major challenge in wireless charging. Jia et al. optimized WPT to reduce energy consumption while ensuring full sensor node charging, but managing directional energy in large-scale networks remains difficult [146]. Lin et al. used UAVs for IoT applications to improve energy efficiency by 18.2%, but their method faces challenges like high costs and weather impacts [147]. Chen et al. developed a dynamic energy model using ant systems and particle swarm optimization to enhance energy efficiency, but clustering complexity limits flexibility [148].

2) **Charging Conflict (CC):** Charging conflict occurs when multiple chargers attempt to recharge the same sensor nodes simultaneously, leading to energy consumption, delays, and increased node failure, which reduce network performance and lifetime. One solution is the mobile-to-cluster (M2C) scheme [66], where nodes are grouped by energy levels, prioritizing low-energy nodes to prevent delays and conflicts. This scheme reduces charging delays by 50% and travel distance by 10%, enhancing network reliability. Alternatively, [98] ensures that no node is charged by more than one charger at a time, avoiding energy consumption and battery damage. This approach optimizes charger scheduling to reduce overlaps and delays, improving charging efficiency and extending network lifetime.

3) **Multi-charger Coordination (MCC):** In multi-UAV systems, researchers face high latency and data interference. In [149], a high-level architecture for multi-UAV systems is proposed, with UAVs equipped with integrated sensor nodes, computing, and modules for coordination, communication, and networking. Real-world tests highlight the importance of addressing communication and coordination issues for dynamic multi-UAV applications. In [88], the focus is on optimizing scheduling, movement, and charging times for multiple MCs with limited resources, aiming to minimize energy consumption while preventing sensor node power depletion. The authors use MILP to coordinate multiple MCs and introduce a decomposition technique to break the problem into subproblems, MC scheduling, movement time, and charging time and solving them iteratively to find an optimal solution.

4) **V2V Charging:** In WRSNs, one key challenge is recharging mobile chargers effectively. A study [94] proposed a collaborative mobile charging approach where chargers transfer energy to each other. The PushWait algorithm optimized scheduling to prevent sensor nodes from depleting their power. Simulations showed that this collaborative charging improves energy efficiency and coverage and extends network lifetime, even in complex network scenarios.

5) **Dynamic Network Recharging (DNR):** Dynamic network recharging adjusts energy delivery in real-time based on node locations, energy levels, and network demands. AI algorithms optimize charging routes and reduce energy consumption, with UAVs providing on-demand energy replenishment and maintenance tasks like battery replacement [150]. As AI and UAV technologies advance, recharging efficiency and network uptime will improve [151]. In [152], the authors introduced a dynamic charging-recycling scheduling (DCRS) problem using deep reinforcement learning (DRL) with double deep Q-networks (DDQN), reducing dead nodes and delays. Similarly, Yang et al. [125] used actor-critic reinforcement learning (ACRL) and Gated Recurrent Units (GRUs) to optimize dynamic charging, selecting the best sensor node to charge and adjusting strategy based on tour length and node survival as rewards.

6) **Monitoring & Security Threats:** Most WRSN research has focused on scheduling and energy optimization, neglecting security, which exposes networks to attacks. Two main types of threats are software and interference attacks. For software attacks, the Denial of Charge (DoC) attack [153] uses fake requests to drain energy from legitimate nodes, causing them to miss events. In 2022, the MDoC attack [154] manipulated charger routes to overload nodes, draining 20% more nodes undetected. For interference attacks, the Charging Spoofing Attack (CSA) [155] involves a charger pretending to provide power but blocking energy transfer with electromagnetic interference, depleting 80% of nodes undetected. These threats highlight the need for improved security in WRSNs.

7) **Hybrid WRSNS (HWRSNs):** WRSNs have become crucial for various applications, but they face challenges such as limited battery life, energy inefficiency, high costs, delays, and charger management [120]. A hybrid design offers a promising solution, combining renewable energy sources (RES) like solar, wind, and thermal energy to ensure reliability. Solar technologies, including PV panels and thermal harvesting, play a key role. While wireless charging is effective, it raises safety concerns

regarding electromagnetic exposure, requiring FCC compliance. High-traffic nodes, like cluster heads, demand more power, risking battery depletion and network issues [156]. A hybrid framework combining solar energy with wireless charging optimizes energy use, balances power, and schedules data collection, reducing battery depletion by 20% and cutting costs by 25%. The hybrid WRSN faces challenges related to costs, safety, and energy management despite its potential. Research is ongoing to improve efficiency and reliability.

5 Trends and Future Directions in WRSNs

WRSNs are evolving rapidly to address challenges related to energy consumption and network lifetime. Emerging technologies such as artificial intelligence (AI), autonomous UAVs, and renewable energy integration are transforming WRSNs, offering new possibilities for dynamic recharging. We now introduce the key trends and future directions shaping the development of WRSNs as follows.

1) **Applied AI in WRSN:** AI techniques such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) optimize WRSNs by predicting maintenance, scheduling charging, and managing energy consumption, thereby extending network lifetime. RL algorithms, for example, determine optimal paths for MCs and UAVs, reducing travel time and energy consumption while maximizing recharged nodes [113], [157], [158]. Zhang et al. [159] enhanced MC efficiency and minimized data delays by integrating energy replenishment with data collection through a deep reinforcement learning (DRL)-powered path planning algorithm. Meanwhile, Wang et al. [160] addressed optimal charger placement by clustering nodes using K-Means++ and refining locations through an RL-based charging cluster algorithm enhanced by an experience-strengthening mechanism. However, these approaches face high computational demands, large data requirements, and security risks [161]. AI-powered systems also facilitate improved collaboration among network components and enable proactive maintenance through predictive models.
2) **AI-Enhanced Sensor Design for WRSNs:** Integrating AI-driven sensor design can significantly enhance WRSN performance and extend network lifetime. Zhang et al. [162] used inverse design and machine learning to optimize sensor hardware, improving energy efficiency. These enhanced nodes predict energy consumption, optimize charging schedules for MCs, and maximize data collection, contributing to a more sustainable and efficient WRSN.
3) **Quantum Sensor Technology in WRSNs:** Quantum sensors enhance WRSNs by detecting magnetic fields and other physical quantities with high sensitivity, improving performance, energy efficiency, and security, which extends network lifetime [163]. Rydberg sensors, for example, improve RF signal detection with lower energy consumption than traditional antennas, enabling longer operation on harvested energy [164]. Their ability to capture weak signals at longer wavelengths provides a more accurate and energy-efficient alternative.

6 Conclusion

This paper provides a comprehensive survey of WRSNs, considering wireless charging technologies as promising techniques to reduce energy consumption and maximize WRSN network lifetime. We have conducted a detailed study of energy provisioning techniques. Due to the importance of determining which wireless charging technique is adaptable to the environment, a table is established for summarizing the highlighted/focused, decision variables, key constraints, techniques, and control methods within 2011–2024. We also discuss related works based on charger types, including static and mobile chargers. The paper introduces partial and full charging policies, as well as offline and online charging modes. Furthermore, we cover periodic and on-demand charging schemes alongside the collaborative charging mechanism. WRSNs face several challenges during the wireless charging process, such as energy consumption, multi-charger coordination, dynamic network recharging, and monitoring & security threats. We also present V2V charging and hybrid WRSNs as emerging challenges in the field. Finally, we highlight trends and future directions for integrating advanced AI technologies into WRSNs. This comprehensive study of WRSNs offers insights that could lead to the optimization of network performance, extend network lifetime, and enhance resource utilization through the adoption of optimized or newly discovered techniques.

Acknowledgments

This paper is supported by the Innovation Team and Talents Cultivation Program of the National Administration of Traditional Chinese Medicine (No. ZYYCXTD-D-202208). Samah Abdel Aziz is grateful for financial support from CAS-TWAS Fellowship. She also extends her gratitude to Dr. Youssef A. Youssef from Nile University, Egypt, for his valuable assistance in reorganizing and revising the content of the article survey.

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