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Review

On-Demand Energy Provisioning Scheme in Large-Scale WRSNs: Survey, Opportunities, and Challenges

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Abstract: Wireless rechargeable sensor networks (WRSNs) have emerged as a critical infrastructure for monitoring and collecting data in large-scale and dynamic environments. The energy autonomy of sensor nodes is crucial for the sustained operation of WRSNs. This paper presents a comprehensive survey on the state-of-the-art approaches and technologies in on-demand energy provisioning in large-scale WRSNs. We explore various energy harvesting techniques, storage solutions, and energy management strategies tailored to the unique challenges posed by the dynamic and resource-constrained nature of WRSNs. This survey categorizes existing literature based on energy harvesting sources, including solar, kinetic, and ambient energy, and discusses advancements in energy storage technologies such as supercapacitors and rechargeable batteries. Furthermore, we investigate energy management techniques that adaptively balance energy consumption and harvesting, optimizing the overall network performance. In addition to providing a thorough overview of existing solutions, this paper identifies opportunities and challenges in the field of on-demand energy provisioning for large-scale WRSNs. By synthesizing current research efforts, this survey aims to provide insight to researchers and policymakers in understanding the landscape of on-demand energy provisioning in large-scale WRSNs. The insights gained from this study pave the way for future innovations and contribute to the development of sustainable and self-sufficient wireless sensor networks, critical for the advancement of applications such as environmental monitoring, precision agriculture, and smart cities.

Keywords: wireless rechargeable sensor networks; energy harvesting; on-demand energy provisioning; energy management; energy consumption; wireless charging; supercapacitors

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1. Introduction

Wireless rechargeable sensor networks (WRSNs) have emerged as a transformative paradigm in the domain of wireless sensor networks, enabling long-term and autonomous operation through the integration of energy harvesting and rechargeable energy storage technologies. Large-scale WRSNs, deployed in diverse environments ranging from environmental monitoring to industrial automation, face unique challenges in maintaining sustained and reliable energy provision. The dynamic and often unpredictable nature of the deployment environments, coupled with the resource constraints of sensor nodes, necessitates innovative approaches for on-demand energy provisioning. Recent advancements in energy harvesting techniques, coupled with the evolution of energy storage technologies, have opened new avenues for enhancing the autonomy and operational efficiency of WRSNs. This paper presents a comprehensive survey of the current state of the art in on-demand energy provisioning for large-scale WRSNs, examining the latest developments in energy harvesting, storage, and management strategies.

The significance of on-demand energy provisioning in WRSNs lies in its ability to address the fundamental challenge in mitigating the finite energy resources of sensor nodes. As emphasized by the authors in [1,2], the autonomy of energy-harvesting wireless sensor nodes is pivotal for extending the network's operational lifetime, reducing maintenance costs, and enabling autonomous and sustainable deployment in remote and inaccessible locations. The advent of energy-harvesting technologies, such as solar and kinetic energy harvesting, has empowered sensor nodes to extract energy from the surrounding environment, diminishing their reliance on conventional power sources and enabling long-term autonomy [2].

While the literature on energy harvesting and storage for WRSNs has seen significant contributions, there exists a need for a comprehensive survey that consolidates the diverse approaches, assesses their strengths and limitations, and identifies avenues for future research. Motivated by the imperative to address the complexities of large-scale WRSNs, this survey seeks to fill a critical gap in the literature. While various studies have explored components of on-demand energy provisioning, a comprehensive survey that synthesizes these contributions, assesses their efficacy, and identifies avenues for further research is conspicuously absent. This paper addresses this gap by presenting a systematic survey of on-demand energy provisioning in large-scale WRSNs, emphasizing the evolving landscape of energy harvesting technologies, storage solutions, and energy management strategies. This paper endeavors to bridge this gap by providing an in-depth examination of existing on-demand energy provisioning schemes, shedding light on their strengths, limitations, and potential improvements.

On-demand energy provisioning is a strategy that addresses energy depletion in large-scale WRSNs by deploying mobile energy sources, such as wireless charging vehicles (WCVs) or drones, to deliver energy to sensor nodes based on their real-time needs. This method leverages advanced technologies such as machine learning, optimization algorithms, and clustering to ensure energy-efficient routing, scheduling, and charging. Wireless charging strategies for WRSNs are critical for maintaining the functionality of sensor nodes, which are often deployed in remote or inaccessible areas. Two primary approaches are ***on-demand (demand-driven) charging*** and ***periodic charging***, each with distinct methodologies, benefits, and challenges. The theoretical research identifies charging planning as a crucial problem and presents more difficulties and challenges for multiple mobile chargers. The authors in [3] addressed a charging planning problem for multiple chargers in WRSNs, proving its NP-hardness. They aimed to maximize the energy efficiency of the charging process by optimizing the charging amounts and planning efficient charging paths. Two charging strategies were identified in the literature, namely, demand-driven charging strategies [4–8] and periodic charging strategies [9–12]. Demand-driven and periodic charging strategies are two distinct approaches for managing energy consumption and sensor recharging in WRSNs. Both strategies aim to optimize sensor energy usage and maintain efficient network operations. The demand-driven charging strategy recharges sensors based on their individual energy levels and operational needs, focusing on providing energy only when necessary. This approach prevents sensors from depleting their energy completely and going offline. Some key aspects of this strategy include the following:

- *Individualized recharging*: sensors are charged on an as-needed basis, prioritizing those with low energy or critical tasks.
- *Real-time monitoring*: sensors continuously track their energy levels and request recharging when energy falls below a defined threshold.

A key advantage of this method is its ability to keep sensors operational for as long as possible, thereby preventing network downtime caused by drained batteries. Additionally, it optimizes energy utilization and prolongs the overall network lifespan [13]. Conversely, the periodic charging strategy involves recharging sensors at fixed intervals or scheduled times, regardless of their individual energy levels or activity [12,14,15]. While this approach simplifies scheduling and maintenance, it may result in energy wastage and network downtime if sensor needs are not effectively addressed. Table 1 provides a summary comparing demand-driven and periodic charging strategies.

Table 1. A comparative summary of demand-driven and periodic charging strategies [16,17].

Aspect	Demand-Driven Charging	Periodic Charging
Responsiveness	Reactive to real-time energy demands.	Follows fixed schedules, regardless of energy levels.
Efficiency	Focuses on nodes with critical needs, avoiding waste.	May result in overcharging or delayed recharging.
Scalability	Faces challenges in large-scale networks.	Easier to scale with predictable paths.
Complexity	Requires advanced algorithms for scheduling and routing.	Simpler due to pre-determined paths.
Adaptability	Adapts to dynamic network conditions.	Limited adaptability to unexpected demands.
Energy Utilization	More efficient due to priority-based charging.	Risk of resource wastage from unnecessary charging.

The authors in [18] conducted a comprehensive survey on mobile charging techniques (MCTs) in WRSNs. They introduced the network model of a WRSN, as depicted in Figure 1, and outlined the basic architectures of various wireless power transfer (WPT) techniques. The study also discussed the fundamental design challenges associated with MCTs and presented a taxonomy of mobile charging techniques based on key design attributes.

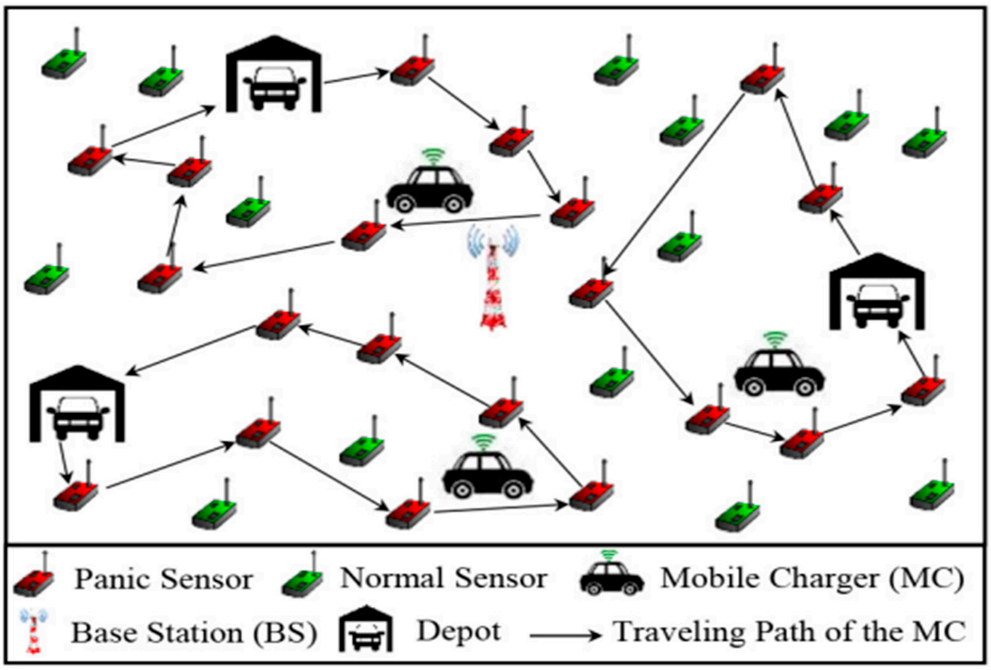

Figure 1. A typical WRSN architecture with multiple MCs and depots [17,18].

In the subsequent sections, we delve into the recent developments in on-demand energy provisioning in WRSNs, categorization and analysis of various energy harvesting sources, explore cutting-edge developments in energy storage technologies, and examine adaptive energy management strategies designed to optimize energy utilization in large-scale WRSNs. Additionally, this paper critically evaluates the current opportunities and challenges in the field, paving the way for future research directions. Through this survey, we aim to provide a comprehensive resource for researchers, practitioners, and policymakers engaged in the design and development of large-scale WRSNs, fostering a deeper understanding of the current state of on-demand energy provisioning and inspiring innovations that propel the sustainability of and effectiveness of wireless rechargeable sensor networks.

The motivation behind this study was to explore recent advancements in on-demand energy provisioning strategies, focusing on energy harvesting techniques, storage solutions, and energy management strategies designed to address the dynamic and resource-constrained nature of wireless rechargeable sensor networks (WRSNs). A comprehensive review of state-of-the-art approaches and technologies is presented, with a focus on large-scale WRSNs. This survey categorizes existing literature by energy sources, including solar, kinetic, and ambient energy, and highlights advancements in energy storage technologies such as supercapacitors and rechargeable batteries. Additionally, energy management techniques that adaptively balance energy consumption and harvesting to optimize network performance are examined.

In providing an extensive overview of existing solutions, this paper identifies key challenges and opportunities in on-demand energy provisioning for large-scale WRSNs. By synthesizing current research efforts, it aims to guide researchers and policymakers in understanding the evolving landscape of on-demand energy provisioning. The insights gained contribute to the development of sustainable and self-sufficient WRSNs, essential for applications such as environmental monitoring, precision agriculture, and smart cities.

To the best of our knowledge, this is the first comprehensive review to critically evaluate advancements in on-demand energy provisioning for large-scale WRSNs, emphasizing energy management strategies, storage solutions, and future trends. The paper is structured as follows: Section 2 provides an overview of recent developments in on-demand energy provisioning in large-scale WRSNs, while Section 3 outlines the challenges of on-demand wireless charging in WRSNs. Section 4 discusses energy management strategies, energy harvesting techniques, and energy storage solutions in WRSNs. Section 5 explores future trends and opportunities in on-demand wireless power transfer (WPT) for WRSNs, and Section 6 concludes the paper.

2. Recent Developments in On-Demand Energy Provisioning in Large-Scale WRSNs

This section presents an overview of recent developments in on-demand energy provisioning in large-scale WRSNs. On-demand energy provisioning in large-scale wireless rechargeable sensor networks (WRSNs) is a dynamic approach to ensuring that the energy needs of distributed sensors are met efficiently through wireless power transfer (WPT). This concept is especially vital for large-scale deployments where traditional methods like battery replacements are impractical due to high costs, logistical challenges, and environmental impact. In WRSNs, numerous sensor nodes are deployed over large areas to monitor and report data. These nodes are often placed in hard-to-access locations, making regular battery replacement or wired charging impossible. On-demand energy provisioning allows energy to be supplied to these sensors wirelessly only when they need it, extending the network's lifetime and supporting sustainable operation. This approach is critical in applications like environmental monitoring, military surveillance, and disaster response.

Figure 2 depicts a typical on-demand single mobile charging scheme, while Figure 3 illustrates a typical on-demand multiple mobile charging model for WRSNs.

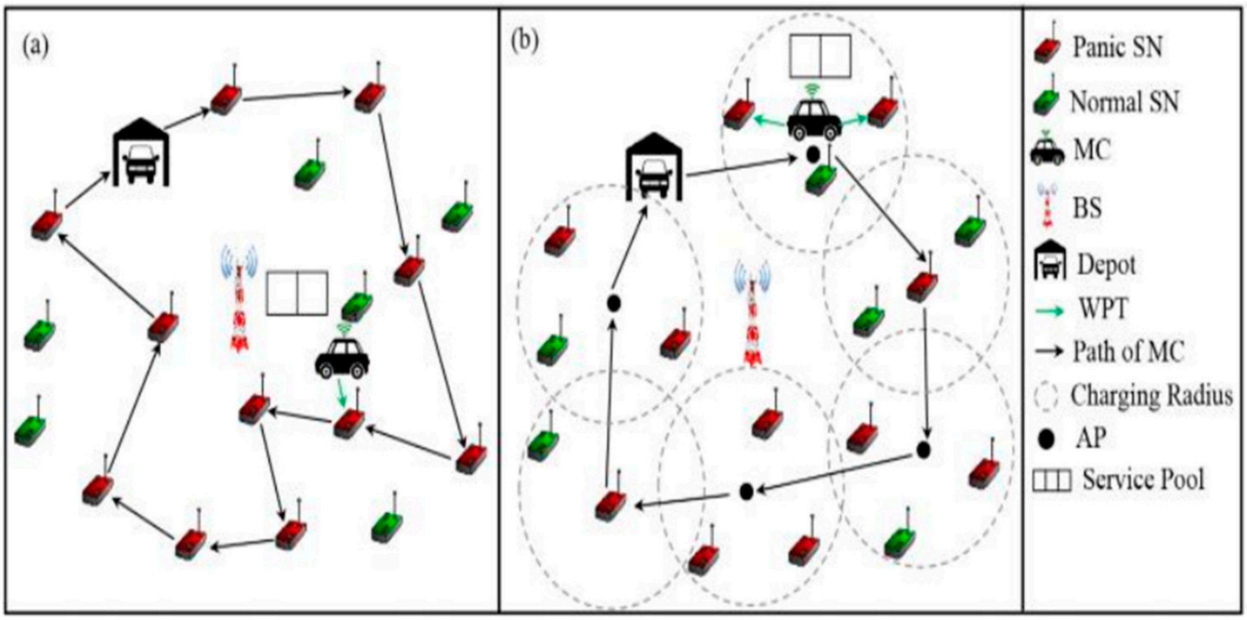

Figure 2. A typical on-demand single mobile charging model for WRSNs. (**a**) Single-node charging (P2P); (**b**) multi-node charging [16].

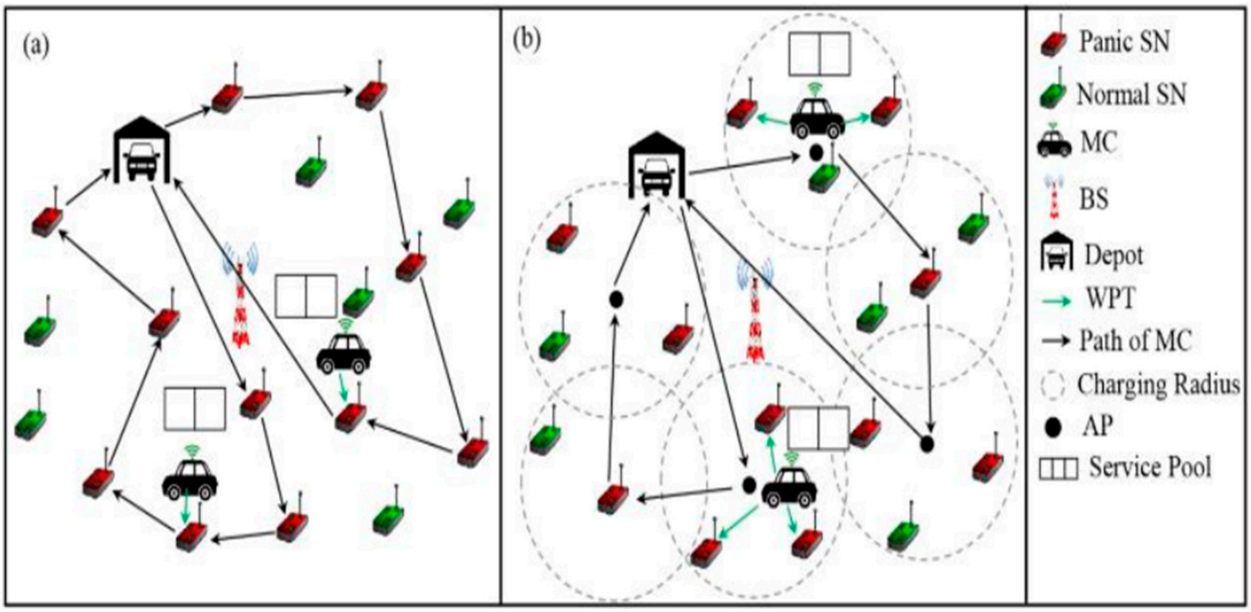

Figure 3. A typical on-demand multiple mobile charging model for WRSNs. (**a**) Single-node charging; (**b**) multi-node charging [16].

On-demand charging involves dynamically responding to the energy needs of sensor nodes. Charging requests are initiated based on real-time energy thresholds, ensuring critical nodes are recharged as needed. Key features include the following:

- *Dynamic nature:* nodes or clusters request energy replenishment only when required.
- *Energy thresholds:* charging is triggered when energy falls below a predefined level, preventing node failures.
- *Priority-based scheduling:* critical nodes (e.g., those with higher data traffic or strategic locations) are prioritized for charging.

The paper [19] addresses energy constraints in wireless sensor networks and proposes three on-demand charging schemes including Pcharge, Bcharge, and Fcharge. The Pcharge scheme employs a priority-based charging strategy, the Bcharge scheme utilizes a best-fit approach, and the Fcharge scheme adopts the first-fit decreasing strategy. The schemes are designed to optimize mobile charger capacity utilization and minimize tour length. By employing multiple mobile chargers with limited capacities, the simulation results demonstrate the effectiveness of the proposed approaches. The proposed schemes outperform the state-of-the-art NJNP scheme, with Pcharge achieving the shortest tour length among all evaluated approaches and significantly enhancing the capacity utilization of mobile chargers (MCs). However, certain limitations remain. The limited capacity of MCs in WRSNs poses challenges in meeting large-scale energy demands, and inefficient scheduling of MCs can further hinder optimal performance. While the proposed schemes address some of these issues, a single MC is insufficient for large-scale WRSNs, and existing research, including the current work, still lacks a comprehensive focus on advanced MC scheduling strategies to fully overcome these challenges. The paper [16] explores on-demand wireless charging for sensor networks, focusing on mobile charging techniques that employ single or multiple chargers to address energy constraints in wireless sensor networks (WSNs). Mobile chargers operate by recharging sensors based on energy requests, and the study delves into various on-demand wireless recharging schemes.

Key design issues affecting recharging efficiency and system performance are identified, with scalability and energy consumption optimization highlighted as critical challenges. However, the paper acknowledges several limitations, including the following:

- Scalability issues in on-demand recharging schemes;
- High energy consumption of mobile chargers;
- Prolonged recharging delays for sensor nodes.

These limitations underscore the need for further research to improve the scalability, efficiency, and responsiveness of wireless recharging strategies in WSNs. The papers [20–22] propose innovative on-demand wireless charging schemes for WRSNs, focusing on reducing charging latency [23], increasing active nodes, and addressing energy constraints through techniques like real-time scheduling, heap-based structures, and optimization algorithms. They improve performance compared to existing methods but face common limitations, including scalability challenges, inefficiencies in uneven charging requests, preemption issues, and impracticality in large networks. Future work should focus on integrating multiple mobile chargers [24–26], adaptive scheduling [13,27], and robust preemption strategies to enhance efficiency and scalability.

Figure 4 shows an illustration of mobile charger scheduling in a WRSN scenario, while Figure 5 shows a typical on-demand charging scheme in a WRSN scenario.

The model in Figure 4 illustrates the schedulability of a network comprising three groups (g_1, g_2, g_3) and five clusters $(c_1, c_2, c_3, c_4, c_5)$. Notably, clusters c_3 and c_4 may share nodes. The model assumes that a total of N sensor nodes is distributed across various groups and clusters within the network. A mobile charger (MC) is scheduled to recharge energy-constrained sensor nodes based on their charging requests. The MC's route begins at the base station (BS), traverses designated anchor points (APs) and returns to the BS for energy replenishment or battery replacement, preparing for the next recharging cycle. The BS acts as the central controller, dynamically scheduling the MCs to provide on-demand energy to the sensor nodes.

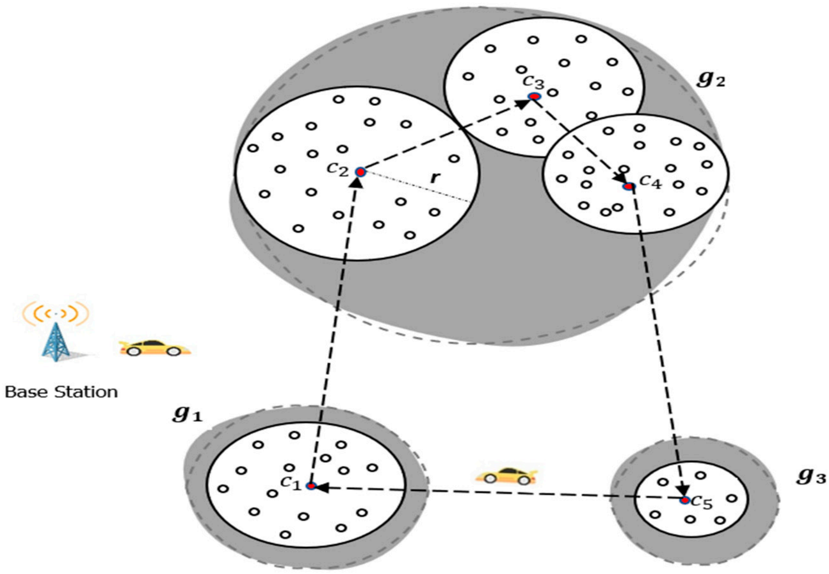

Figure 4. An illustration of MC scheduling in a WRSN scenario.

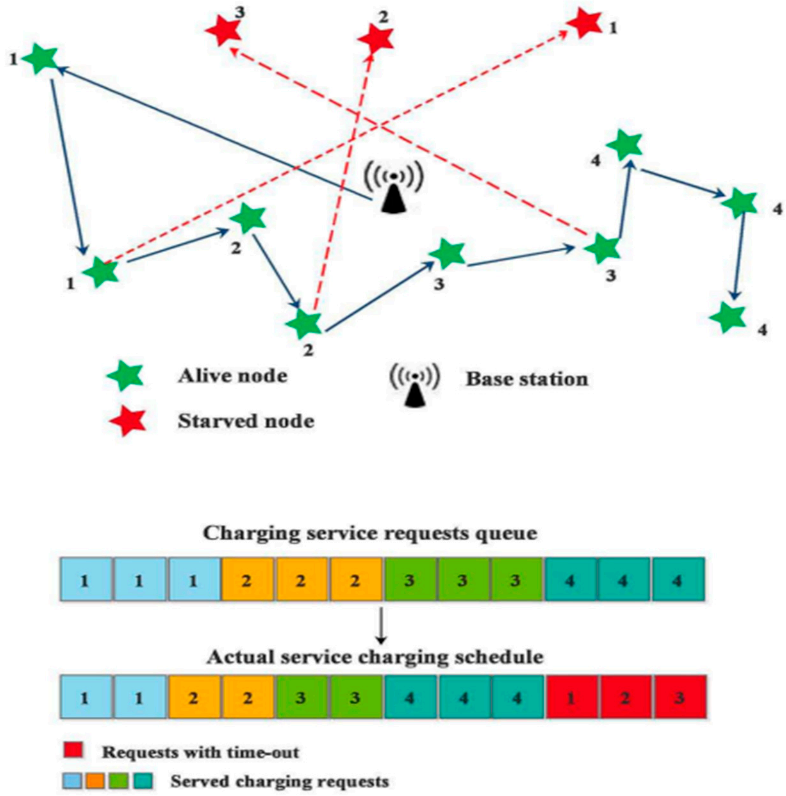

Figure 5. A typical on-demand charging scheme in a WRSN scenario [21].

The authors in [20] propose a novel on-demand charging scheduling scheme for WRSNs that prioritizes scheduling using multiple network parameters and incorporates real-time information to ensure fairness. It is designed for high-demand scenarios with spatial and temporal constraints [28] and leverages multi-node charging [14] to reduce delays. While effective, the scheme has limitations, including its reliance on a single mobile charger, which is inadequate for large-scale networks, and increased delays in time-critical applications. In [21], the authors introduce an on-demand charging scheme for WRSNs using a heap-based energy replenishment approach. This scheme addresses energy starvation in dynamic sensor node scenarios and reduces computational and storage overhead, improving scalability in large networks. It outperforms the existing Nearest-Job-Next with Preemption (NJNP) scheme by reducing charging latency and increasing the number of active nodes. However, it has limitations, such as its inability to adapt to uneven charging requests, the risk of energy starvation due to untimely responses, and the lack of support for preemption of wireless charging vehicles (WCVs).

The papers [29,30] address collaborative charging scheduling challenges in WRSN by proposing a Temporal–Spatial Charging Scheduling Algorithm (TSCA) and a Game Theoretical Collaborative Charging Scheduling (GTCCS) algorithm, respectively. The TSCA tackles collaborative charging in WRSNs by optimizing spatial–temporal scheduling to minimize dead nodes and maximize energy efficiency by computing feasible movement solutions for wireless charging vehicles (WCVs) [31] through path planning and optimization techniques [32]. It employs path planning and clustering techniques, outperforming existing methods. In contrast, the GTCCS algorithm leverages game theory to resolve charging conflicts among WCVs, treating them as players striving to maximize energy efficiency. It also introduces dynamic thresholds and a sacrifice-charge mechanism to reduce dead nodes and enhance energy management. However, the TSCA faces scalability challenges in large networks.

The authors of [4,33] propose innovative approaches to enhance the energy efficiency and network lifetime of WRSNs. While Nguyen et al. [4] propose an on-demand charging algorithm using fuzzy logic and Q-learning to optimize charging time and location for mobile chargers, thereby extending monitoring time by 6.8 times on average and improving network lifetime by 1.9 times compared to Q-charging, Habibi et al. [33] introduce a demand-based charging method using UAVs. This approach employs K-means clustering to group sensors for efficient energy management and uses fuzzy logic to rank clusters based on battery life and distance. Combined with a gradient-based optimization algorithm for UAV routing, it extends network lifetime and reduces total energy consumption by 26%, travel distance by 17.2%, and travel delay by 25.4%, with optimal performance achieved using four clusters. Both approaches significantly enhance WRSN performance by improving energy efficiency and network lifetime. While fuzzy Q-charging focuses on leveraging machine learning and logic-based optimization for mobile chargers, the UAV-based method prioritizes efficient sensor clustering and UAV routing. Together, these techniques highlight the potential for combining on-demand charging algorithms with advanced clustering and routing methods to address key limitations, such as target coverage, connectivity, and charging time constraints.

Figure 6 shows the network model of a typical on-demand charging scheme in WRSNs utilizing fuzzy logic and Q-learning, while Figure 7 shows an overview of the Q-learning environment, which presents a reinforcement learning model that is widely used in decision-making.

Q-learning is a widely used reinforcement learning technique for decision-making. Its core principle is to achieve specific goals by learning from past experiences. The standard Q-learning framework comprises four key components: an environment, one or more agents, a state space (S_t), and an action space (A_t), as illustrated in Figure 7. The Q-value represents the estimated effectiveness of an action in relation to the agent's objective. Agents select actions based on a policy and the corresponding Q-values. After executing an action, the agent updates its policy to better achieve its goal. R_t denotes the reward received for performing action A_t in state S_t.

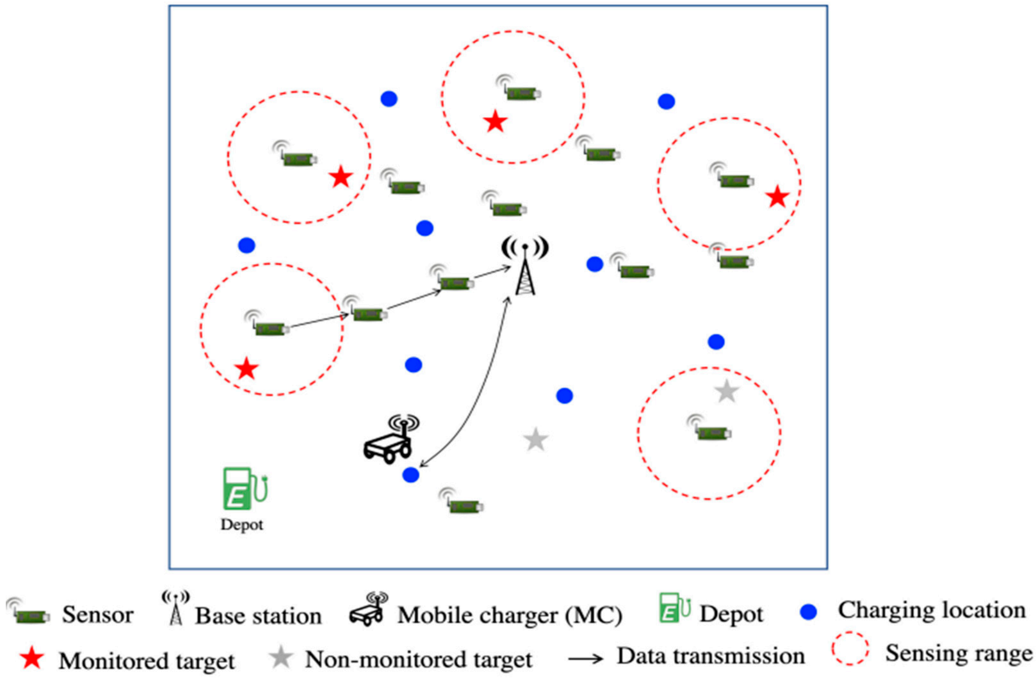

Figure 6. A typical on-demand charging in WRSNs using fuzzy logic and Q-learning [4].

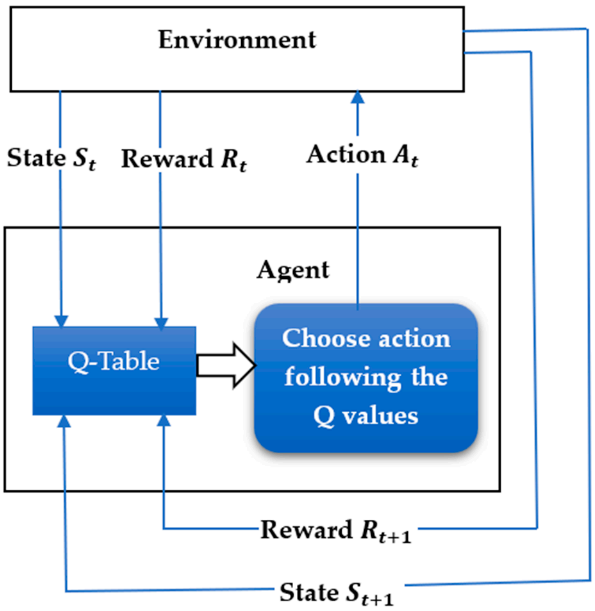

Figure 7. An overview of the Q-learning environment [4].

2.1. "One-to-One" and "One-to-Many" On-Demand Charging Schemes in WRSNs

In WRSNs, mobile chargers provide flexibility and adaptability to network energy management by wirelessly recharging energy-constrained sensor nodes. Two common charging schemes have been identified in the literature: "*One-to-One*" and "*One-to-Many*" wireless charging [23,34–41]. These schemes define how mobile chargers interact with sensor nodes and also determine the efficiency and scalability of energy replenishment within the network. In the "One-to-One" charging scheme, a single sensor is charged by one mobile charger (MC) at a time. Each MC is dedicated to recharging a specific sensor node, creating a direct and exclusive connection between the MC and the sensor. In contrast, the "One-to-Many" charging scheme allows a single MC to recharge multiple sensor nodes simultaneously during a single operation. The advantages of "One-to-One" charging scheme include the following [17]:

- *Precise energy distribution:* this scheme ensures that individual sensors receive the exact amount of energy required, minimizing wastage.
- *Individualized charging*: sensors with varying energy needs are recharged based on their specific requirements, ensuring optimal energy replenishment.
- *High transfer efficiency*: the direct proximity between the MC and sensor node ensures efficient energy transfer and maximizes network uptime.

Despite its advantages, the "One-to-One" charging scheme faces several challenges, particularly in scalability and cost-efficiency [34,36]. The limitations of this approach are further highlighted in [17] and include the following:

- *Higher hardware costs*: Setting up dedicated charging for each sensor node is expensive and infrastructure-intensive. If MCs are limited, some sensors may experience delays in recharging. Compared to "One-to-Many" schemes, this approach incurs significantly higher costs.
- *Scalability challenges*: in large-scale WRSNs, deploying a single MC for each sensor is impractical, leading to potential bottlenecks and leaving many sensors energy-deprived.
- *Navigation complexity*: MCs must navigate efficiently to reach target nodes, which can be challenging in dynamic environments.
- *Management overhead:* managing multiple MCs becomes increasingly complex as the network scales, unlike the simpler management associated with the "One-to-Many" scheme.

To overcome these scalability and efficiency bottlenecks, the "*One-to-Many*" charging scheme was proposed [34,36]. In this approach, a single MC recharges multiple sensor nodes simultaneously via wireless energy transmission, also referred to as the multi-node wireless energy charging scheme. The authors [36] proposed a single MC to replenish multiple sensor nodes within the range of its energy transmission. This concept was extended in [34], whereby two MCs were deployed to simultaneously recharge multiple sensors, enhancing charging efficiency and scalability. Figure 8 illustrates an example of a multi-node energy charging scheme utilizing two mobile chargers. As highlighted in [34], the multi-node wireless energy charging scheme effectively addresses the challenges of charging efficiency and scalability in large-scale WRSNs. Its advantages include the following [17]:

- *Cost-efficiency:* fewer MCs are required to service multiple sensor nodes, optimizing resource utilization and reducing infrastructure and hardware costs.
- *Reduced charging time:* the simultaneous charging of multiple nodes significantly decreases the overall time needed for energy replenishment.
- *Balanced energy distribution*: excess energy from one sensor can be redistributed to others, ensuring more equitable energy availability across the network.
- *Stable energy supply*: sensors receive consistent energy replenishment without requiring a line-of-sight (LoS) connection, as long as they are within the MC's transmission range.

However, using a mobile charger (MC) to simultaneously recharge multiple sensor nodes in a WRSN introduces several challenges, primarily related to efficiency, scheduling, and energy distribution. Key issues are highlighted in [17] and include the following:

- Efficient energy utilization: how to best allocate the MC's limited energy to replenish the most energy-deficient sensors, minimizing the risk of sensor failures.
- Optimizing movement energy consumption: how to plan the MC's movements to reduce energy consumption, assuming the MC has sufficient energy to recharge all sensors.

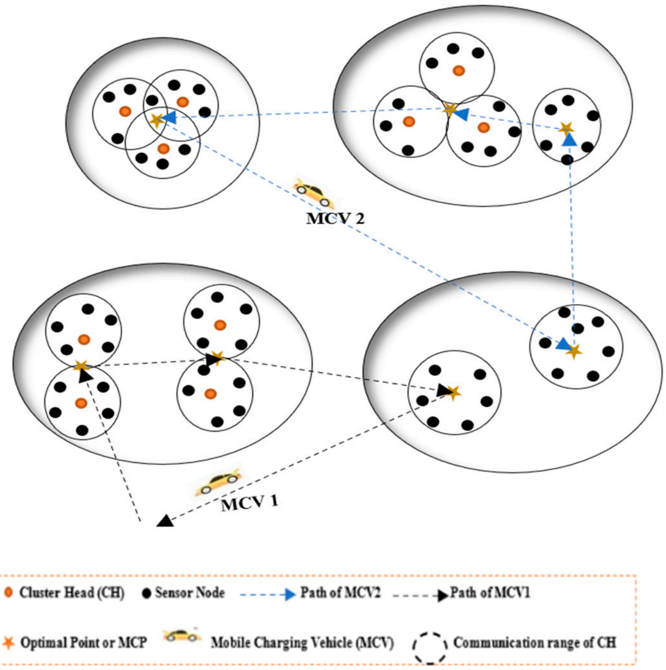

Figure 8. The architecture of multi-node energy charging with two MCs [13].

These challenges involve critical trade-offs that require further exploration. Additionally, charging scheduling poses unique difficulties due to spatial and temporal constraints [18,20,23,42]. Other key trade-offs are highlighted in [17,34] and include the following:

- Efficient scheduling of multiple MCs: ensuring all energy-constrained nodes are replenished promptly while minimizing scheduling delays.
- Avoiding simultaneous charging conflicts: preventing a sensor node from being recharged by multiple MCs simultaneously, as overcharging could damage the battery.
- Determining charging duration: deciding the optimal charging time at each location to ensure all nodes within an MC's transmission range are sufficiently charged.

The scalability of single mobile charging schemes remains a significant limitation, as these schemes are suited only for small-scale networks. In large-scale networks, the limited energy capacity of an MC renders this approach ineffective. While the "*One-to-Many*" charging scheme improves efficiency, it also faces notable constraints as highlighted in [17], which include the following:

- Energy imbalance: Ensuring equitable energy distribution is challenging. Sensors with critical energy needs may receive insufficient replenishment if others consume more power.
- Interference: charging multiple nodes in close proximity can result in interference, reducing charging efficiency for some sensors.
- Energy inefficiency: some sensors may receive more energy than required, leading to wastage.
- Reduced precision: the energy delivered to each sensor is less precise compared to the "One-to-One" scheme, potentially compromising optimal replenishment.

Addressing these challenges is essential to enhance the scalability, efficiency, and reliability of multi-node wireless energy charging in WRSNs.

To tackle the challenges of energy consumption and the limitations of the multi-node charging approach in large-scale WRSNs with a single mobile element, researchers [13,23,27,43,44] proposed leveraging multiple mobile elements (MMEs) for wireless charging. The paper [13] proposes a Deadline-Based Multiple Mobile Elements (DB-MMEs) scheme for energy optimization in large-scale wireless rechargeable sensor networks (LS-WRSNs). This approach utilizes multifunctional mobile charging vehicles (MCVs) that integrate charging and data collection functionalities to enhance operational efficiency, particularly for delay-intolerant applications. The method also explores optimal energy allocation and MCV deployment strategies to address key challenges in wireless charging and data collection. Figure 9 shows the architecture of the proposed model.

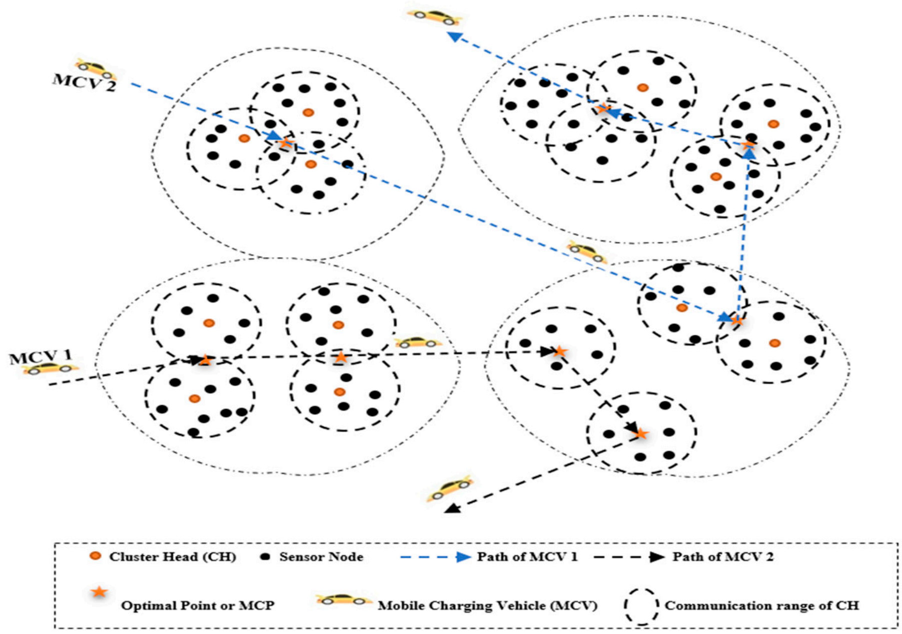

Figure 9. The typical architecture of the proposed DB-MMEs scheme for WRSNs [13].

One of the most challenging issues in the deployment of MCs is finding an efficient charging schedule for MCs to replenish the sensors [20,22,45,46]. The absence of proper scheduling evaluation in previous charging schemes for WRSNs reduces charging efficiency, ultimately resulting in sensor node exhaustion [47]. The paper [47] proposes an Optimal Path Planning Charging (OPPC) scheme for on-demand charging architectures. The scheme evaluates the schedulability of charging missions, making charging schedules more predictable, while providing an optimal charging path to maximize efficiency. To address the challenges of coordination and scheduling in multi-charger wireless charging systems, the papers [27,48] propose the application of swarm intelligence techniques for mobile wireless charging in large-scale networks. The studies explore critical trade-offs in charging strategies and energy availability and introduce a node-partition algorithm for efficiently scheduling multiple mobile chargers. The key contributions include the following:

- Energy-efficient route planning and coordination: developing strategies to optimize charger routes and improve coordination among multiple chargers.
- Optimization problem formulation: establishing the multi-charger recharge optimization problem as NP-hard.
- Node-partition algorithm: designing an algorithm to efficiently schedule chargers across the network.
- Performance evaluation: validating the proposed scheme through detailed simulations, demonstrating its effectiveness.

Figure 10 depicts coordination and scheduling of a single MC, while Figure 11 illustrates coordination and scheduling of multiple MCs.

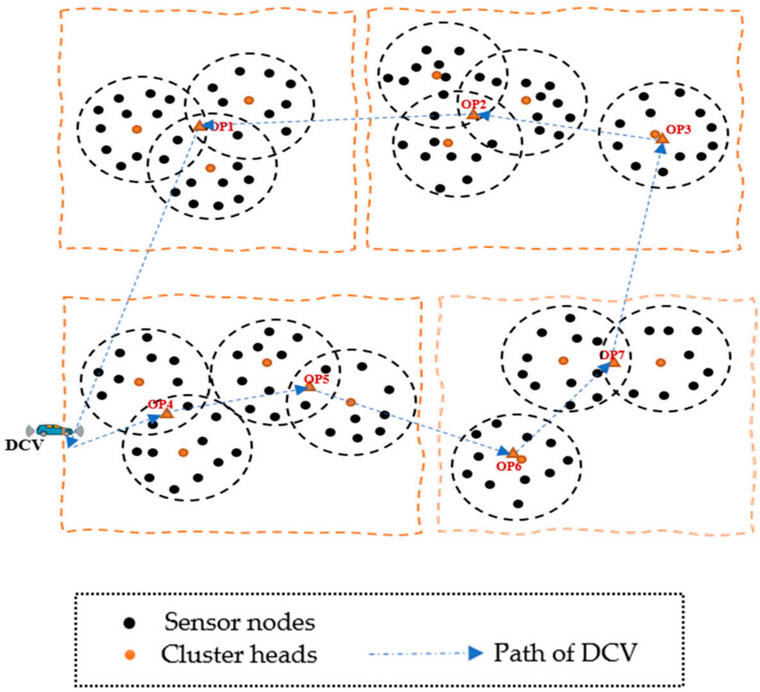

Figure 10. Coordination and scheduling of a single charger [48].

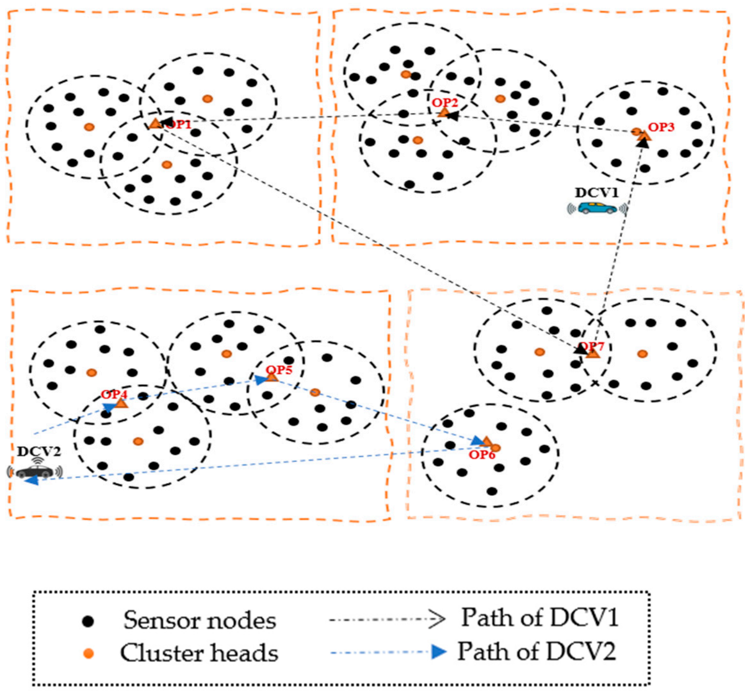

Figure 11. Coordination and scheduling of multiple chargers [48].

In large-scale WRSN scenarios with extensive sensor-based data systems and numerous sensor nodes, scheduling a single mobile charger (MC) for energy provisioning becomes both challenging and inefficient. The time required for a single MC to traverse the entire network leads to significant delays and the risk of energy depletion, resulting in operational bottlenecks. To address these scalability issues, deploying multiple MCs is more effective. However, this approach introduces additional challenges, such as increased costs and network complexity [13]. Therefore, it is crucial to strike a balance between cost and delay by implementing effective coordination and scheduling techniques that utilize optimal points (OPs) as shown in Figures 10 and 11 for energy provisioning, thus ensuring stable and efficient network operations.

2.2. On-Demand Wireless Power Transfer (WPT) in WRSNs

This section presents a detailed discussion of on-demand WPT in wireless rechargeable sensor networks (WRSNs). WRSNs are an integral part of modern technology, enabling applications like environmental monitoring, disaster management, healthcare, smart cities, and military surveillance. However, their functionality depends heavily on the energy available to the sensor nodes. Traditional battery-powered sensors face energy depletion over time, posing significant challenges to the network's lifetime and operational efficiency. Conventional power supply systems using cords and wires have become increasingly obsolete due to their limitations in supporting large-scale deployment, utilization, and mobility [49,50]. Battery replacements for such systems are also suboptimal, as batteries have a short operational lifespan and impose cost and weight constraints on hardware. Moreover, the operational costs associated with frequent battery charging or replacement make these solutions impractical.

Recent advancements have introduced the use of electromagnetic (EM) waves for wirelessly transferring power from a source (transmitter) to a destination (receiver), a breakthrough known as wireless power transfer (WPT) technology. The paper [50] highlights recent applications of WPT across various domains, including medical implants, unmanned aerial vehicles (UAVs), mobile phones, wireless sensor networks (WSNs), electric vehicles, and audio players. For an in-depth review of near-field WPT, refer to [50].

To overcome these limitations, on-demand WPT and energy harvesting (EH) have emerged as critical solutions, enabling sustainable energy replenishment without manual intervention. These approaches aim to maximize the operational lifetime of WRSNs, ensuring efficient, uninterrupted, and scalable functionality. On-demand WPT involves transferring energy wirelessly to sensor nodes as and when needed. The energy is delivered through specialized wireless charging vehicles (WCVs) [46,47,51,52] or mobile charging vehicles (MCVs) [13,23], which travel to sensor nodes to replenish their energy wirelessly via electromagnetic induction, magnetic resonance, or microwave transmission. The core principles of on-demand WPT include the following:

- Dynamic energy requests: nodes initiate charging requests when their battery levels fall below a predefined threshold.
- Mobile charging vehicles (MCVs): equipped with wireless charging equipment and a limited energy reservoir, MCVs navigate through the network to fulfill charging requests.
- Charging scheduling and routing: algorithms prioritize which nodes to charge first, optimize MCV routes, and ensure efficient energy utilization.
- Multi-node charging: advanced WPT techniques allow simultaneous charging of multiple nearby nodes, reducing charging delays and MCV travel costs.

2.2.1. Classification of On-Demand WPT Technology for WRSNs

This section reviews classifications of on-demand WPT technology for WRSN scenarios. On-demand WPT can be categorized into the following: radiative vs. non-radiative, near-field vs. far-field, and charging frame-based classifications.

A. *Radiative and Non-radiative Techniques*

Wireless power transfer (WPT) technologies are broadly classified into two categories: radiative and non-radiative techniques [49,53]. Radiative techniques utilize electromagnetic (EM) waves, particularly radio frequency (RF) waves, to transfer power over longer distances, while non-radiative techniques rely on methods such as inductive coupling and resonant coupling to transfer power over short distances, catering to a wide range of appliances. Table 2 provides a classification of WPT technologies based on radiative and non-radiative approaches for WRSN scenarios. Figure 12 depicts a classification of WPT technology based on radiative and non-radiative techniques.

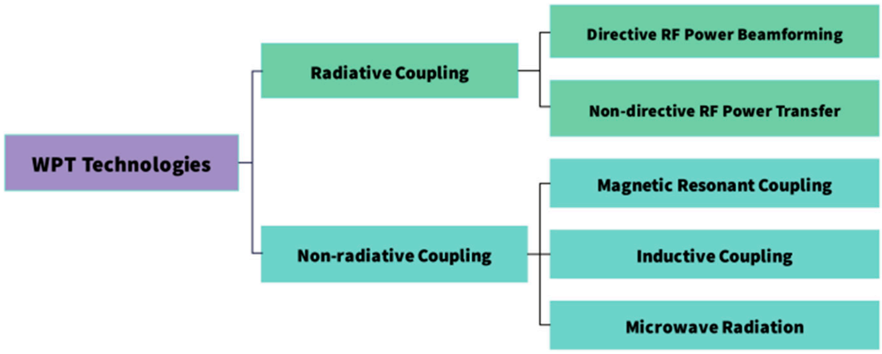

Figure 12. Classification of radiative and non-radiative WPT [53].

B. *Near-Field and Far-Field WPT Technologies*

WPT technologies may also be classified as near-field and far-field WPT [50,54–56]. Near-field WPT is a technique that transfers power using magnetic or electric fields within a distance shorter than the wavelength of the electromagnetic (EM) signal. It occurs when the transfer distance is shorter than the wavelength of the EM signal. This technique typically operates at resonant frequencies below 5 MHz and achieves a short transfer distance, approximately 5 cm, delivering power to nearby devices. Examples include magnetic inductive coupling [57–59], magnetic resonant coupling [60–62], capacitive coupling [63,64], and magneto dynamic coupling [54]. Conversely, the far-field WPT technique uses EM waves (such as microwaves, RF, or lasers) to transmit power over distances longer than the wavelength of the EM signal. It involves transfer distances greater than the wavelength of the EM signal, enabling power delivery to far-reaching or remote devices. Examples include radio waves and microwaves [50,54,65]. Far-field RF energy transfer faces challenges such as significant path loss, reducing power efficiency at the rectifying antenna (rectenna). The paper [66] proposed optimizing propagation channels and rectenna subsystems to improve RF energy transport. The paper [67] introduced the In-N-Out scheme, a flexible far-field WPT system combining software and hardware, addressing the drawbacks of near-field systems, such as reduced efficiency with smaller coils and limited flexibility. Their system eliminates the need for cumbersome devices and enables the continuous charging of medical implants deep within human tissue. The paper [54] highlights recent advancements in WPT technology, including energy harvesting, millimeter-wave/THz rectennas, MIMO-WPT, and near-field applications, emphasizing that inductive coupling remains the most efficient approach, followed by radio wave-based WPT. The commercialization of near-field WPT is more advanced, with public buses in Europe and China using wireless chargers at 20 kHz/85 kHz frequencies and 60–200 kW power. Additionally, Apple's adoption of the Qi standard in 2017 popularized cordless wireless phone chargers.

C. *Classification based on Charging Frameworks*

WRSNs rely on efficient WPT methods to maintain sensor operation in remote or inaccessible environments. The charging frameworks for WPT in WRSNs can be classified into three main types: omni-directional [68,69], directional, and bi-directional WPT. Each framework has distinct characteristics and applications based on the nature of the deployment and the specific energy requirements. In directional WPT, RF energy signals are transmitted directly toward the locations of power receivers, ensuring targeted energy delivery. In omnidirectional WPT, RF energy signals are broadcast to sensors for energy harvesting, often using energy beamforming. This method is particularly useful when sensor locations are indeterminate or uncontrollable. For example, the paper [70] applied this approach in WSNs using wireless chargers and mobile robots to harvest RF energy signals. In bidirectional WPT, power flows in both directions, meaning the transmitter can also act as a receiver, and vice versa. This method enables simultaneous charging of two sensor devices without compromising power transfer efficiency. Each WPT technique has its strengths and limitations. Omni-directional WPT is flexible and easy to deploy but inefficient. Directional WPT offers high efficiency but demands precise alignment and specialized hardware. Bidirectional WPT provides flexibility in energy sharing but is best suited for shorter ranges. Among non-radiative methods, inductive coupling is highly efficient at short distances, while magnetic resonance extends the range but may experience interference and slightly reduced efficiency.

Wireless charger networks (WCNs) have emerged as a promising solution leveraging wireless power transfer (WPT) technology to extend network lifetimes and provide sustainable energy for future systems. WCNs facilitate energy transfer from wireless chargers to rechargeable devices, where it is harvested by an energy-harvesting unit and stored to support operations such as sensing, mobility, and communication. This process is characterized by three key models: the charging model, energy harvesting model, and energy consumption model, which vary based on the WPT technology employed. A comprehensive survey in [68] explores WCNs, detailing their architecture, charging models, and associated design challenges. The authors classify WPT techniques into two broad categories: radiative and non-radiative. Radiative techniques are further divided into omni-directional and directional methods, while non-radiative techniques include inductive coupling and magnetic resonance coupling. Table 3 summarizes the charging frameworks for WPT in WRSNs.

Figure 13 illustrates the architecture of a WCN, depicting the fundamental components: wireless chargers, rechargeable devices, and a base station (BS). It also demonstrates the energy transmission pathway from chargers to rechargeable devices.

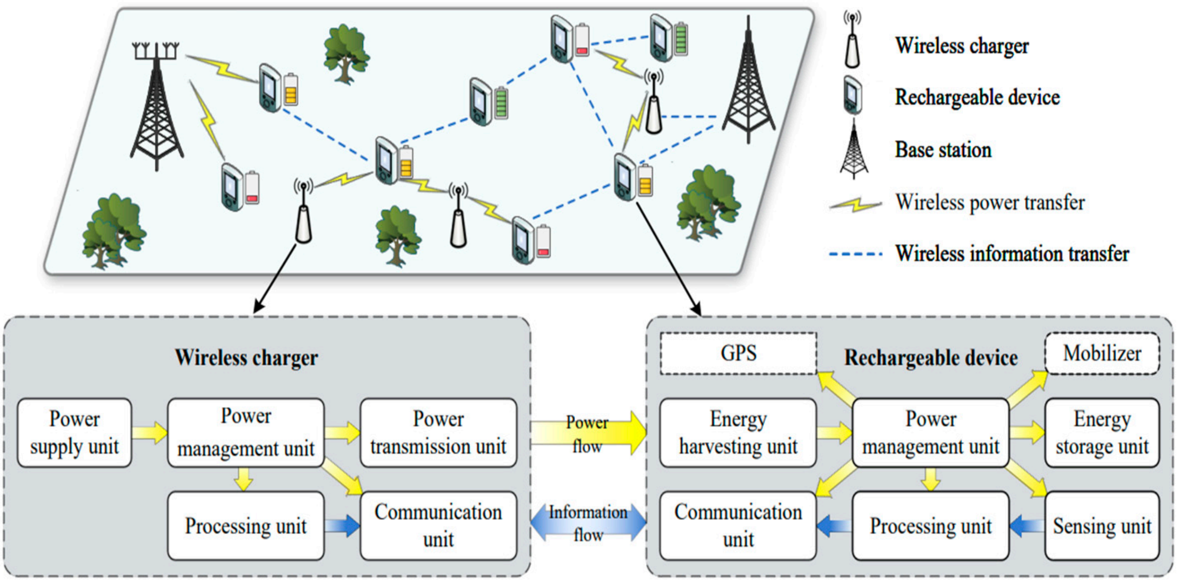

Figure 13. Architecture of a typical WCN showing the basic components [68].

Table 2. Classification of on-demand WPT based on radiative and non-radiative technologies [49,53,54,63–65].

Technique	Category	Field	Method	Efficiency	Distance	Power	Applications	Safety	Future Applications
Microwave Power Transfer (MPT)	Radiative	Electromagnetic	Microwave beams	Medium to high	Long	High	Space solar power, long-distance energy transfer	Moderate concerns	Space solar power, remote military bases
Laser-based power transfer	Radiative	Optical	Laser beams	High	Long	High	Space communication, power beaming	High concerns	Long-range wireless power
Radio frequency (RF)	Radiative	Electromagnetic	Ambient RF waves	Low	Short to medium	Low	IoT devices, small electronics	Low concerns	Ubiquitous IoT, low-power sensors
Inductive coupling	Non-radiative	Magnetic	Magnetic induction	High	Short	Medium	Consumer electronics, medical devices	Low concerns	Wireless charging pads
Resonant inductive coupling	Non-radiative	Magnetic	Magnetic resonance	Medium to high	Medium	Medium	EV charging, industrial applications	Low concerns	EV charging, industrial robots
Capacitive coupling	Non-radiative	Electric	Electric fields	Low to medium	Short	Low	Wearable devices, small sensors	Moderate concerns	Biomedical implants
Magnetic resonant coupling	Non-radiative	Magnetic	Magnetic induction	Medium to high	Medium	Medium	Medical implants, consumer electronics	Moderate concerns	Advanced medical devices, smart homes
Magnetic field power transfer	Non-radiative	Magnetic	Magnetic resonance	High	Short	Medium	Smartphones, wearable devices	Low concerns	Integrated consumer electronics

Table 3. WPT-based charging frameworks for WRSN scenarios.

References	Classification	Explanation	Example Scenario	Limitations
[71–75]	Omni-directional	• RF energy is broadcast uniformly in all directions, allowing energy harvesting over a broader area. • Characterized by its ability to charge multiple devices simultaneously without precise alignment.	In a densely deployed WRSN for agricultural monitoring, omni-directional WPT ensures that multiple sensor nodes scattered across the field receive energy without the need for precise alignment.	Lower efficiency and energy wastage due to non-targeted power distribution.
[54,76–81]	Directional	• RF energy is transmitted directly toward the targeted device. • Utilizes narrow beams to deliver energy, enhancing efficiency and range.	In a coastal environmental monitoring system, directional WPT can be used to efficiently transfer energy to sensor nodes positioned along a distant shoreline, ensuring sustained operation with minimal energy loss.	Requires precise alignment, more complex deployment, and safety concerns due to concentrated energy.
[82–86]	Bi-directional	• Allows energy transfer in both directions between the charger and the sensor node. • This framework supports two-way communication for optimized energy management.	In a smart city deployment, bi-directional WPT can enable adaptive energy transfer to mobile sensor nodes that monitor traffic and pollution levels.	Complexity in implementation, requiring sophisticated control systems.

2.2.2. Applications of On-Demand WPT in WRSNs

On-demand WPT has emerged as a transformative solution for addressing energy constraints in WRSNs, enabling continuous operation and enhancing network reliability. Conventional wireless sensor networks (WSNs) are inherently energy-constrained, with limited operational lifetimes that require optimization to maximize network performance. In contrast, WPT in WRSNs aims to achieve energy neutrality, enabling a theoretically unlimited operational lifetime when deployed with a constant energy supply. This transformative capability has facilitated numerous practical applications of WPT in WRSNs, including environmental monitoring, which includes air quality and water monitoring [49]; healthcare applications, which include continuous patient health monitoring through wearable and implantable sensors [17]; smart agriculture, which includes precision farming through real-time soil, crop, and environmental monitoring [48]; industrial automation, which includes machinery and environmental monitoring in complex or hazardous facilities [49]; disaster management, which includes sensor deployment in disaster-hit areas for hazard detection and rescue operations; safety, security, and military applications, which include surveillance, battlefield monitoring, and security systems [56]; urban and smart city infrastructure, which includes traffic, pollution, and energy metering in smart city systems; and Internet of Things (IoT) integration, which includes seamless energy management across IoT-enabled devices and networks [87]. The authors in [49,53] reviewed studies on WPT, covering its classifications, advantages, disadvantages, and primary application domains. They highlighted recent advancements in WPT, including resonance-based WPT, magnetic resonance coupling, beamforming, and high-power WPT. These innovations have improved efficiency, convenience, and cost-effectiveness, driving increased adoption of WPT in applications such as smartphones, smart homes, electric vehicles, and wearable devices. A comprehensive study of the applications of WPT can be found in [17,49,53]. Table 4 gives a comparative summary of On-demand WPT technologies for WRSN scenarios. On-demand WPT technologies for WRSN scenarios offer various strengths and weaknesses based on the specific application and environmental conditions. Each WPT technology offers trade-offs between efficiency, range, and complexity, making their selection dependent on specific WRSN deployment requirements and constraints.

Table 4. A comparative summary of on-demand WPT technology for WRSNs.

References	WPT Technologies	Strengths	Weaknesses
[50,57,58,88–90]	Magnetic inductive coupling	• Short energy-transfer distance • It is simple and non-radiative • High power transfer eff. (95%) at short-ranges • Simple implementation • Most widely used as charging pad for all phones and electric toothbrushes	• The power transfer efficiency is drastically reduced as the distance between Tx and Rx widens apart • Requires accurate alignment in charging • Produces heating effect over metal • Short charging distance • Inappropriate for mobile use
[50,60,64,65]	Magnetic resonant coupling	• Long energy-transfer distance • LoS is not needed • High power transfer eff. using omnidirectional antenna • Unaffected by weather conditions • Suitable for everyday use/mobile apps • No alignment is required in the charging direction • Multiple devices can be charged concurrently on different power	• Low transfer power for consumer devices • Low efficiency due to axial mismatch btw receiver and transmitter coils • Not applicable for long-range charging • Axial mismatch b/w transmitter and receiver and interference • Efficiency decreases as distance increases • Complex implementation
[65,91–93]	Microwave Power Transfer (MPT)	• LoS is needed to transfer energy through EM radiation successfully • Radio frequency (RF) waves are used to recharge the battery • Have large charging coverage	• Requires a clear line-of-sight b/w Tx and Rx • Weather and physical objects can obstruct the LoS b/w Tx and Rx and prevent the transfer of power • Suffers from propagation loss due to long distance transmission • RF exposure can cause health impairments • Power transfer is difficult at longer distances with a highly directional antenna
[94–96]	RF-energy transfer	• Can be used to achieve far-field WPT in inaccessible environments • Can reduce the energy consumption in smart buildings and can achieve RF to DC conversion efficiency • Energy is provided to many receivers at the same time	• Low RF energy transfer efficiency • RF power transfer efficiency diminishes over increasing distance • Required sophisticated tracking mechanism • Sensitive to obstructions • Raises strong safety concerns

3. Challenges of On-Demand Wireless Charging in WRSNs

This section presents a study of the challenges of on-demand wireless charging in WRNSs. Recent research focuses on improving charging efficiency, optimizing MCV routes using AI and machine learning, and developing lightweight protocols that enable fast and reliable communication. Multi-MCV systems and cooperative energy sharing between nodes are other emerging solutions to address scalability issues. On-demand energy provisioning in WRSNs opens up possibilities for sustainable and autonomous operations in areas where human intervention is minimal, such as remote environmental monitoring, smart agriculture, and urban infrastructure management. An energy management system utilizing particle swarm optimization (PSO) is proposed in [97]. This system leverages minimum and threshold energy levels to guide the charging process, improving network performance while maintaining lower complexity compared to previous approaches. However, this scheme faces several challenges, including the following:

- *Energy consumption variations:* differences in energy usage among sensor nodes increase travel distances for mobile chargers, while unnecessary visits to energy-sufficient nodes waste time and resources.
- *Scheduling complexity*: coordinating charging in large-scale networks is inherently complex, further compounded by limited computing resources, which restrict the ability to develop optimal charging schedules.
- *Dynamic energy consumption*: fluctuating energy demands make it challenging to create efficient charging paths and adapt to the network's evolving needs.

The authors of [26,41,98,99] propose a schedulability evaluation mechanism for partial-charging scheduling in WRSNs. They introduce a Partial Charging Scheme (PCS) tailored for on-demand charging and compare its efficiency against traditional full-charging schemes. The study includes testbed experiments to validate the proposed approach, demonstrating that partial charging offers significant advantages over full charging. Results show that the PCS outperforms previous algorithms in efficiency and feasibility. Unlike full charging, which degrades efficiency and reduces network lifetime, partial charging enhances performance and extends the operational lifespan of the network [27].

The authors of [16,97,100,101] investigate critical research challenges in wireless recharging, focusing on architectural and mathematical models for on-demand recharging in wireless sensor networks (WSNs). It highlights key limitations in existing schemes, including scalability issues and high energy consumption. To address these challenges, the paper explores design considerations and performance metrics for recharging strategies, emphasizing the need for the following:

- *Efficient charging delay management*: minimizing delays to ensure timely energy replenishment.
- *Optimization of mobile charger energy usage*: enhancing efficiency in energy consumption during recharging operations.
- *Scalability in dense deployments:* ensuring effective performance in large-scale, densely populated networks.

The studies underscore the importance of developing solutions that address these limitations to improve the feasibility and performance of on-demand wireless recharging schemes. Table 5 summarizes the challenges of on-demand wireless recharging for WRSNs as outlined in studies [16,22,102–108].

Table 5. Challenges of on-demand wireless charging in WRSNs.

Techniques	Advantages	Challenges
• ***Clustering-based approaches:*** nodes are grouped to reduce charging trips.	• ***Efficient resource utilization:*** chargers are deployed only when and where needed, avoiding unnecessary energy use.	• ***Scalability:*** managing large-scale networks can lead to increased charging delays, complexity of scheduling and routing, leading computational overhead.
• ***Machine learning models:*** techniques like fuzzy logic and Q-learning optimize charging schedules.	• ***Improved network lifetime:*** prevents critical nodes from failing while focusing on high-priority energy demands.	• ***Real-time decision-making:*** requires fast, efficient algorithms to handle complex scheduling problems.
• ***Collaborative strategies:*** multiple mobile chargers (MCVs or drones) coordinate charging tasks to minimize delays and improve efficiency.	• ***Flexibility:*** adaptable to dynamic network conditions, such as uneven energy consumption or node failures.	• ***Path optimization complexity:*** mobile chargers must minimize travel distance while meeting energy demands but determining the shortest and most efficient path is computationally challenging, especially in dynamic or dense networks.

Table 5. *Cont.*

Techniques	Advantages	Challenges
• ***Heuristic and metaheuristic approaches:*** Genetic algorithms (GAs), particle swarm optimization (PSO), and ant colony optimization (ACO). • ***Machine learning and reinforcement learning:*** deep reinforcement learning (DRL) and predictive models. • ***Energy-aware clustering:*** clusters nodes dynamically based on energy consumption rates and geographic proximity, ensuring priority charging for critical clusters. • ***Collaborative multi-charger systems:*** multiple chargers work together to divide charging tasks, reducing response time and improving scalability. • ***Mobile charging path optimization:*** dynamic path replanning and spatial–temporal algorithms.	• ***Energy efficiency:*** Chargers only operate when required, reducing unnecessary energy expenditure. Prioritization ensures critical nodes receive energy, avoiding network partitioning. • ***Enhanced network lifetime:*** focuses on maintaining operational nodes, prolonging the overall functionality of the network. • ***Scalability with machine learning:*** advanced algorithms enable efficient management of larger networks with high energy demands. • ***Reduced node downtime:*** rapid response to low-energy nodes minimizes the chances of sensor failures. • ***Flexibility and adaptability:*** adapts to changing network conditions, such as uneven energy consumption or node failures. • ***Support for dynamic networks:*** handles mobile or dynamic sensor nodes by continuously reevaluating energy needs and paths.	• ***Energy consumption of chargers:*** MCs expend significant energy while traveling between nodes, potentially limiting their operational range and effectiveness. • ***Real-time decision-making:*** requires rapid computation of scheduling and routing decisions, which may become impractical in high-demand scenarios. • ***Uneven energy demand*:** nodes with disproportionately high energy consumption can monopolize the charger's resources, leaving other nodes at risk. • ***Hardware limitations:*** the energy storage capacity and recharging speed of mobile chargers can restrict the number of nodes that can be serviced in a single tour. • ***Coverage and connectivity constraints:*** focus on charging critical nodes might lead to neglect of connectivity requirements, impacting data transmission reliability. • ***Integration with existing networks:*** implementing on-demand systems in pre-existing WRSNs might require significant infrastructure changes.

3.1. Design Challenges of Wireless Mobile Charging Techniques in WRSNs

Mobile charging techniques in WRSNs involve the deployment of mobile chargers or vehicles that traverse through the network to recharge sensors. While these techniques offer advantages like flexibility and adaptability, they also come with certain design challenges that need to be addressed for effective implementation [17]. Thus, designing wireless mobile charging techniques for WRSNs using mobile chargers involves several challenges that need to be addressed to ensure efficient and effective energy replenishment for sensor nodes. This section presents some of the key design challenges associated with mobile charging techniques in WRSNs. Table 6 presents a survey of design issues associated with on-demand energy replenishment strategies for WRSNs. The survey explores critical challenges and considerations for optimizing mobile energy replenishment. Key design issues include *charging path optimization, scheduling and coordination, energy efficiency, scalability, communication overhead, and cost and complexity.* This survey highlights the importance of integrated strategies that address these issues, promoting efficient and sustainable energy management in WRSNs. It is instructive to note that efficient methods that jointly solve these challenges are generally lacking in the literature. Thus, this research is conducted with the aim of contributing to the solutions of some of the design issues associated with wireless mobile charging in a large-scale WRSNs. Addressing these design challenges is crucial to developing robust and efficient wireless mobile charging techniques for WRSN scenarios. Solutions should consider the specific requirements of the WRSNs, the characteristics of the sensor nodes, and the operational dynamics of the network.

Table 6. A survey of design issues associated with on-demand mobile charging techniques in WRSNs.

References	Design Challenges	Explanation
[109–111]	• Optimal route planning	• One of the primary challenges is to determine the optimal routes for the mobile chargers. Efficient route planning is crucial to ensure that MCs can cover a maximum number of sensors in the network while minimizing travel time and energy consumption.
[110,112,113]	• Charger mobility and navigation: ✓ Path planning ✓ Obstacle avoidance	• Designing efficient algorithms for MCs to navigate through the network and reach sensor nodes in need of charging. • Ensuring that MCs can navigate around obstacles and barriers without compromising their effectiveness.
[114–116]	• Energy transfer efficiency: ✓ Wireless charging range ✓ Charging rate	• Defining the effective charging range between the MC and the sensor nodes to achieve optimal energy transfer efficiency is a challenge. • Determining the rate at which energy can be transferred wirelessly to maximize charging speed while avoiding overheating. • The MCs themselves require energy to operate. Balancing the energy consumption of the MCs with the energy they provide to sensors is a challenge.
[29,110,117–119]	• MC deployment and scheduling: ✓ Charger density ✓ Charger scheduling ✓ Collision avoidance	• Coordinating the scheduling of mobile charging operations is complex. Determining when and where to deploy MCs to provide sufficient energy to sensors without causing disruptions to the network's operations requires careful planning. Deciding the number and deployment locations of MCs to ensure adequate coverage and minimize delays. • Developing strategies for coordinating the movements of multiple MCs to avoid collisions and congestion is a big challenge. incorporating collision avoidance mechanisms is essential to prevent disruptions and accidents.
[18,120,121]	• Coverage and capacity ✓ Charging coverage and efficiency ✓ Energy distribution	• Ensuring adequate coverage of the entire network and having sufficient capacity to charge multiple sensors simultaneously are challenges. The design should accommodate different charging requirements across sensors.
[22,43,122,123]	• Dynamic network changes: ✓ Node mobility ✓ Charger replenishment	• WRSNs are dynamic environments where sensors can move, fail, or be added or removed. Mobile charging techniques must be adaptable to these changes to ensure that sensors are effectively charged despite the network's fluctuations. • Addressing challenges posed by dynamic node movements, which can affect the accuracy of node location prediction and MC navigation. • Ensuring that MCs themselves have sufficient energy to perform charging operations and navigate the network.
[109,117,124]	• Charging infrastructure: ✓ Charging time ✓ Charger localization ✓ Location prediction	• Predicting the optimal charging time and locations for sensors is a challenge. Factors such as sensor energy levels, mobility patterns and traffic conditions need to be considered to make accurate predictions. • Implementing accurate localization techniques to determine the positions of both the MCs and the sensor nodes is a challenge. • Designing the infrastructure required for wireless charging, including charging stations, power management, and comm protocols.
[122]	• Energy consumption trade-offs: ✓ Charging overhead	• Evaluating the energy consumption required for MC's navigation and wireless charging operations compared to the energy gained by sensor nodes.
[18,117,124]	• Communication and coordination	• Effective communication and coordination among the MCs and with the network infrastructure are crucial. Overcoming this challenge and ensuring seamless coordination are design priorities.
[49,124]	• Security and privacy: ✓ Authentication ✓ Data privacy	• Implementing authentication mechanisms to prevent unauthorized MCs from accessing the network. • Ensuring that sensitive data, such as charging schedules and energy levels remain secure during wireless charging operations.
[125,126]	• Energy distribution and allocation: ✓ Fair energy distribution ✓ Prioritization	• Developing algorithms to ensure equitable energy distribution among sensor nodes during group charging (one-to-many scheme). • Defining criteria for prioritizing sensor nodes based on their energy levels, criticality, or operational requirements.

Table 6. *Cont.*

References	Design Challenges	Explanation
[42,118,124]	• Minimum number of MCs	• Determining the minimum number of MCs to keep the network perpetually operational is an N-P hard problem.
[22,117,124,127]	• Space–time scheduling: ✓ Traveling path ✓ Charging time	• The movement of MCs is usually constrained by both space and time. For instance, in a mission-critical scenario, the MC must accomplish each charging task within a given deadline. The following are some of the trade-offs that need to be addressed. (1) How to determine the travelling path of the MCs; (2) How to find the charging time of the sensors; (3) How to find the speed of the MCs. • Constructing the travelling path and determining the optimal trajectory of the MCs is a challenge. • The naïve idea is to allocate an identical charging time to all the sensors following a full or partial charging policy. However, in real-time scenarios, the charging time of sensors differs from each other due to their non-deterministic energy consumption rates. In addition, since energy consumption of the sensor nodes is proportional to the distance between the sensors and the MCs, charging time will increase as the distance increases and WPT efficiency decreases.

3.2. Security Challenges in WRSNs

WRSNs are inherently more susceptible to security threats compared to the traditional wireless sensor network (WSNs) due to the open nature of their transmission medium. This increased vulnerability arises due to the additional complexity introduced by WPT mechanisms and the dynamic nature of energy provisioning in WRSNs. This vulnerability becomes even more critical in large-scale deployments where the stakes of compromised data or operations are significantly higher. As WRSNs are utilized across diverse applications, ensuring data confidentiality is vital to secure communication between sensor devices within the network and between sensors and the sink node [128]. Furthermore, it is essential to verify transmitted information to ensure that adversaries have not compromised the transmission channel.

A range of security threats can affect WRSN applications, including spoofing attacks, denial of service (DoS), node subversion, sinkhole attacks, jamming, and Sybil attacks, among others. Comprehensive studies on the security threats, challenges, and issues in WRSNs are available in the literature [17,49,68,129–132]. The need for mobility, sustainability, and large-scale distribution of sensor devices has rendered conventional power cords obsolete as they fail to meet these demands. Additionally, battery replenishment is often infeasible and incurs significant costs. This has led to the emergence of energy harvesting (EH) and wireless power transfer (WPT) technologies. However, the adoption of RF-based WPT technologies for powering cyber-physical systems (CPSs) introduces its own set of challenges. A major challenge of RF-based WPT is ensuring the security of data transmitted over the network. The free-space nature of WPT communication makes it vulnerable to adversaries who can interfere with the charging operation, potentially stealing sensitive information or exposing the system to safety and security vulnerabilities. CPSs, defined as smart systems integrating cyber technologies with physical components [133,134] face unique security challenges. Key challenges for CPSs are discussed by Leitao et al. [134], while Radanliev et al. [133] propose security measures tailored to these systems. To address CPS vulnerabilities, the authors advocate for anti-malicious and anti-tamper system engineering, along with the development of unique security solutions that address gaps not covered by traditional IT approaches. These measures are critical for ensuring the safe and reliable operation of CPSs in the context of WPT networks.

Key factors contributing to the susceptibility of WRSNs to security threats are further highlighted in [129,132,135,136] and include the following:

- Open nature of communication and power transfer: Like WSNs, WRSNs rely on wireless communication, making them vulnerable to traditional security threats such as eavesdropping, spoofing, and denial of service (DoS). WPT introduces a new channel for adversaries to exploit. For example, an attacker could intercept or manipulate the charging process, potentially leading to unauthorized energy harvesting, charging disruptions, or data breaches.

- Dependency on wireless power transfer (WPT): The open space used for WPT can be intercepted by malicious actors to harvest energy illegitimately or disrupt power delivery to legitimate sensors. Adversaries can deliberately force WRSNs to use their limited energy reserves, compromising both data transmission and system stability.
- Cyber-physical system (CPS) integration: WRSNs, as part of cyber-physical systems, integrate with physical components (e.g., actuators, environmental sensors). This introduces vulnerabilities not only in the communication layer but also in the physical domain, where adversaries can tamper with or destroy nodes. Many WRSNs are used in time-sensitive applications. Attackers exploiting timing vulnerabilities can cause delays or failures in critical processes, leading to cascading system disruptions.
- Security threats unique to WRSNs: Battery exhaustion attacks pose a significant threat to WRSNs, as malicious entities target nodes with excessive energy requests, forcing them to remain active and prematurely depleting their energy reserves. Adversaries may also spoof energy requests, diverting critical resources away from legitimate nodes, leading to system inefficiencies or even node failure. Furthermore, WPT channels can unintentionally reveal sensitive information, such as the network's energy topology, the locations of critical nodes, or the routes of mobile charging vehicles (MCVs), providing adversaries with valuable insights to launch strategic attacks.
- Increased complexity of network management: WRSNs dynamically adapt to varying energy demands, requiring frequent communication for energy requests. This creates opportunities for adversaries to exploit vulnerabilities by injecting malicious data, launching man-in-the-middle (MITM) attacks, or overwhelming the system with false energy requests, such as energy-depletion attacks. Additionally, the network's reliance on nodes to report their energy status makes it vulnerable to false data injection, which can result in inefficient energy allocation and potential system disruptions.
- Mobility of charging vehicles and routing vulnerabilities: Mobile charging vehicles (MCVs) or drones play a crucial role in WRSNs, but they also present significant security risks. If an adversary gains control of an MCV, they can disrupt the entire energy provisioning process, disable sensor nodes, or steal sensitive data. Moreover, predictable routes or schedules used by MCVs can be exploited, enabling targeted attacks that compromise the network's stability and efficiency.

In summary, while WRSNs offer significant advantages over traditional WSNs, their reliance on WPT, integration with mobility systems, and dynamic energy management make them inherently more susceptible to security threats. Addressing these vulnerabilities requires a holistic approach that combines traditional WSN security measures with specialized protections for the energy provisioning and physical components unique to WRSNs.

3.3. Charging Conflicts Due to Improper Coordination

In WRSNs, efficient energy provisioning is critical for maintaining uninterrupted network functionality. Improper coordination in the charging process can lead to charging conflicts, which negatively affect the system's performance and reliability. These conflicts typically arise due to overlapping charging demands, limited energy resources, inadequate scheduling, or communication breakdowns between network components.

In environments with multiple energy transmitters and receivers, malicious or greedy energy receivers can disrupt the energy replenishment process. A fully charged malicious receiver might falsely report high RF values, causing transmitters to reduce or cease power transmission, depriving nearby nodes of energy. Additionally, such receivers can inject malicious feedback to undermine transmission efficiency. Greedy receivers may repeatedly send charging requests to monopolize resources, starving neighboring nodes of energy. This issue is exacerbated when transmitters use directional antennas, further concentrating energy on dishonest nodes and worsening network imbalance.

Charging conflicts in WRSNs, stemming from improper coordination, pose a significant challenge to efficient energy provisioning. By implementing robust scheduling, real-time communication protocols, and adaptive management strategies, these conflicts can be minimized, ensuring the stability, efficiency, and longevity of the network.

4. Energy Management Strategies in WRSNs

This section presents a survey of energy management strategies in WRSNs. Effective energy management is critical to the operation of WRSNs, as these networks rely on constrained energy resources for continuous functioning. Managing energy efficiently ensures prolonged network lifespan, reduced downtime, and enhanced reliability. Major energy management strategies include energy harvesting, energy scheduling, energy allocation, and energy optimization, each tailored to address the unique challenges of WRSNs. Effective energy management is crucial for optimizing the performance of on-demand energy provisioning schemes in WRSNs. Key energy management strategies also include the following [13,55,97,137]:

- *Clustering and grouping:* Nodes are grouped into clusters based on their energy levels, locations, or tasks. Techniques like K-means clustering improve charging efficiency and reduce travel delays.
- *Energy-efficient routing:* advanced routing algorithms minimize the travel distance of WCVs and avoid unnecessary energy consumption.
- *Dynamic prioritization*: nodes with critical energy levels or higher importance (e.g., nodes covering essential targets) are prioritized for charging.
- *Multi-WCV coordination*: synchronizing the actions of multiple WCVs ensures balanced energy distribution and minimizes conflicts.
- *Integration with energy harvesting*: combining on-demand charging with ambient energy harvesting reduces dependence on external charging, creating a hybrid energy provisioning model.

WRSNs frequently utilize energy harvesting technologies to replenish sensor nodes and ensure sustainable operation. Energy harvesting can be broadly categorized into ambient energy harvesting and on-demand wireless power transfer (WPT). In ambient energy harvesting, nodes capture energy from naturally available sources, such as solar, thermal, or kinetic energy, to complement WPT systems. This reduces reliance on external chargers and enables continuous operation in resource-constrained environments. On the other hand, in on-demand WPT, energy is delivered directly to nodes using WPT technologies such as RF-based methods or magnetic resonance coupling. This approach allows for targeted energy replenishment of nodes with critical energy needs.

4.1. Energy Harvesting Strategies in WRSNs

Energy harvesting techniques, sometimes referred to as ambient resource techniques, generate energy sources that power the sensor network, supporting uninterrupted functionality. Examples of energy harvesting schemes in WRSNs include *solar, wind, thermal, mechanical, and RF-based sources* [138,139]. The fundamental goal is to convert energy from one form to another that can be utilized to power electronic devices effectively.

By leveraging these diverse energy harvesting approaches, WRSNs can enhance their energy sustainability, reduce operational dependency on external infrastructure, and expand their applicability to a variety of scenarios. The authors in [138] discussed four renewable energy harvesting strategies namely solar, wind, mechanical, and thermal. They presented an architecture of the renewable energy harvesting schemes as shown in Figure 14.

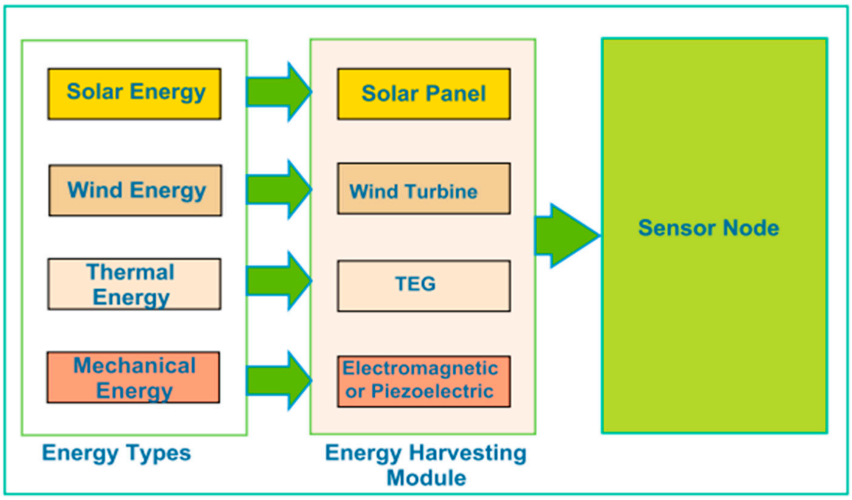

Figure 14. A typical energy harvesting scheme for WRSN scenarios [138].

4.1.1. Solar-Based Energy Harvesting and Management Strategy

This is one of the most efficient and widely adopted methods for powering WRSNs. It utilizes sunlight, a renewable and abundant energy source, to generate electricity, ensuring the sustainable operation of sensor nodes. This approach is particularly well-suited for outdoor deployments in applications such as environmental monitoring, smart agriculture, and disaster response [138,140]. A practical example of the effectiveness of a solar energy-based harvesting and management strategy can be observed in urban smart lighting systems. In this scenario, a smart city deploys solar-powered sensor nodes to manage streetlights based on ambient light levels and pedestrian traffic. During the day, these nodes harvest solar energy and store it in energy storage systems, ensuring sufficient power for streetlights at night. Energy management circuits optimize usage by activating lights only when needed, significantly reducing energy waste. This approach highlights both reliability and sustainability, allowing the system to operate autonomously while reducing the city's reliance on grid power. A comprehensive survey of solar energy harvesting is presented in [141]. Figure 15 shows the basic internal block diagram of a solar energy harvesting model.

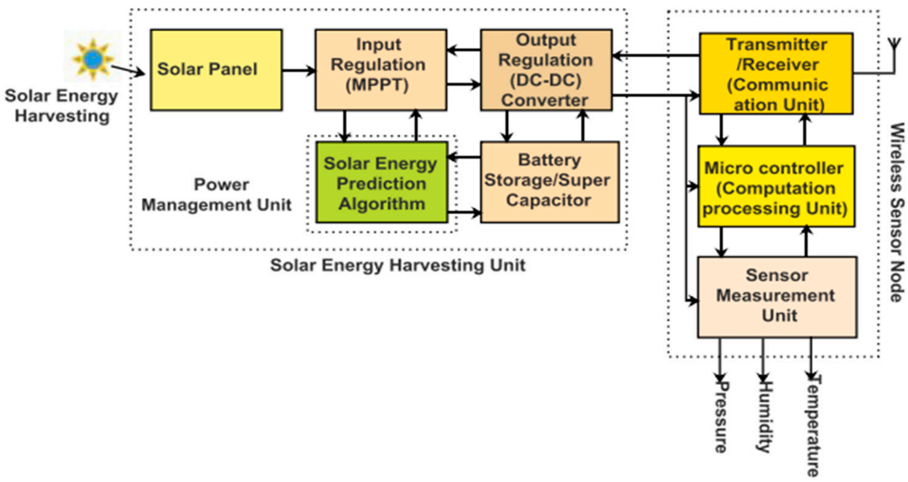

Figure 15. Basic internal block diagram of a solar energy harvesting scheme [141].

4.1.2. Wind-Based Energy Harvesting and Management Strategy

This is an effective solution for powering WRSNs, particularly in environments where consistent wind flow is available, such as coastal regions, plains, or elevated terrains. This approach leverages wind turbines or micro wind generators to convert kinetic energy from wind into electrical energy, supporting sustainable operation and reducing dependence on traditional power sources. Wind energy is a form of kinetic energy derived from the movement of large air masses. It is influenced by solar energy, as factors such as temperature, air density, and pressure interact to drive wind patterns. Approximately 2% of all solar radiation reaching the Earth's surface is converted into the kinetic energy of atmospheric movement [138]. Wind energy is widely used for electricity generation and is considered one of the fastest-growing renewable energy sources [142]. A practical example of the effectiveness of a wind energy-based harvesting and management strategy can be found in remote environmental monitoring along coastal areas. Sensor nodes are deployed along the coastline to track environmental parameters such as wind speed, temperature, and humidity. These nodes are powered by wind energy harvested through micro-turbines, taking advantage of the consistent coastal winds. Energy sharing mechanisms enable nodes with surplus power to distribute excess energy to neighboring nodes, ensuring a balanced energy supply. This strategy offers a sustainable solution in areas where solar energy is unreliable due to frequent overcast conditions, while the energy sharing capability enhances the resilience and reliability of the network.

In the context of wind-powered sensor nodes, the system consists of three primary components namely an energy harvester that incorporates a wind turbine coupled with an electrical generator to capture and convert wind energy into electricity, a power management unit that regulates and optimizes the harvested energy for efficient use, and a wind turbine generator that converts the mechanical energy from the turbine into electrical energy for powering sensor nodes [143]. This setup enables sensor networks to leverage wind as a sustainable energy source for continuous operation in various applications. Figure 16 shows a typical wind energy-based harvesting model that can be exploited for WRSN applications.

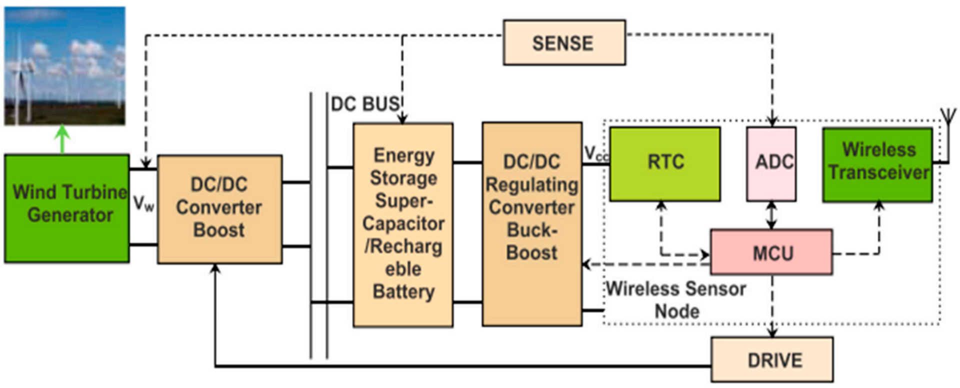

Figure 16. A typical wind energy-based harvesting model for WRSNs [138].

Charging scheduling mechanism: In the context of wind-powered sensor nodes, charging is typically scheduled based on the availability of wind energy, the energy demands of the sensor nodes, and the capacity of the energy storage system. The energy harvesting monitoring system continuously monitors wind speed and energy generation. The energy harvester (wind turbine coupled with an electrical generator) captures wind energy, converting it into electrical power. The power management unit (PMU) plays a crucial role in regulating and optimizing the use of harvested energy. It assesses the current energy levels of the sensor nodes and prioritizes charging based on real-time needs. Nodes with critical energy levels or higher importance in the network (e.g., those managing crucial data) are prioritized. Depending on wind conditions, the PMU adapts the charging schedule. In times of high wind energy availability, excess energy is stored in batteries or supercapacitors, ensuring availability during low-wind periods. Conversely, during low wind conditions, stored energy is utilized to maintain network operation.

Wind turbine's role: In scenarios where the wind turbine is solely dedicated to serving wireless sensor networks (WSNs), it is optimized specifically for powering the nodes. The entire energy harvested is allocated for the network's operational needs, ensuring continuous monitoring and data transmission. In some setups, the wind turbine may serve multiple purposes, such as powering other local applications (e.g., lighting, small appliances) alongside the WSNs. In such cases, the PMU must balance and allocate energy between the different uses, potentially prioritizing critical operations like sensor network maintenance during periods of limited wind energy.

This flexible and adaptive charging scheduling ensures the sustainability and reliability of wind-powered WRSNs, making them suitable for remote and environmentally sensitive applications.

4.1.3. RF-Based Energy Harvesting and Management Strategy

Radio frequency (RF)-based energy harvesting is a promising method for powering WRSNs. It involves capturing electromagnetic waves from ambient or dedicated RF sources and converting them into electrical energy for sensor operation. This technology is particularly advantageous in urban areas and environments with high RF signal density, where ambient RF energy is abundant [17]. RF-based energy harvesting leverages electromagnetic waves to generate electrical energy, providing a viable power solution for WRSNs. This method captures energy from ambient or dedicated RF sources, such as Wi-Fi routers, cellular towers, or RF transmitters, and converts it into usable power for sensor nodes [49]. RF-based energy harvesting (EH) captures and converts ambient RF signals into usable electrical energy using rectifying antennas (rectennas). These antennas harvest electromagnetic (EM) signals from sources like mobile phones, TV broadcasts, and radio stations, generating DC voltage. The harvested energy can be stored in batteries or directly power low-energy devices. A practical example of the effectiveness of an RF-based energy harvesting and management strategy is seen in smart agriculture for crop monitoring. IoT sensors are deployed across a large agricultural field to track soil moisture, temperature, and crop health. In this approach, RF energy is harvested from dedicated transmitters strategically placed around the field. AI-driven energy allocation prioritizes energy distribution based on node criticality and real-time monitoring needs. This strategy ensures the continuous operation of essential sensors, providing accurate data for efficient water and resource management, ultimately improving crop yields and agricultural productivity.

The process involves three main components, namely, antennas, used to capture RF signals across specific frequencies; rectifiers (rectennas), which convert the alternating current (AC) RF signal into direct current (DC); and energy storage and management, used to store harvested energy in batteries or supercapacitors and regulate its distribution [17]. Among various EH mechanisms, RF-based EH has emerged as a promising alternative despite its low power density [144,145]. This is due to the ubiquity of RF energy signals, which enable the harvesting of sufficient energy to power numerous sensor devices. Consequently, RF energy harvesters are a viable energy source for WRSN applications. A detailed review is provided in [145,146]. RF-based EH is particularly suitable for low-power applications [147]. Figure 17 presents the circuit diagram of an RF energy harvesting system, highlighting its key components.

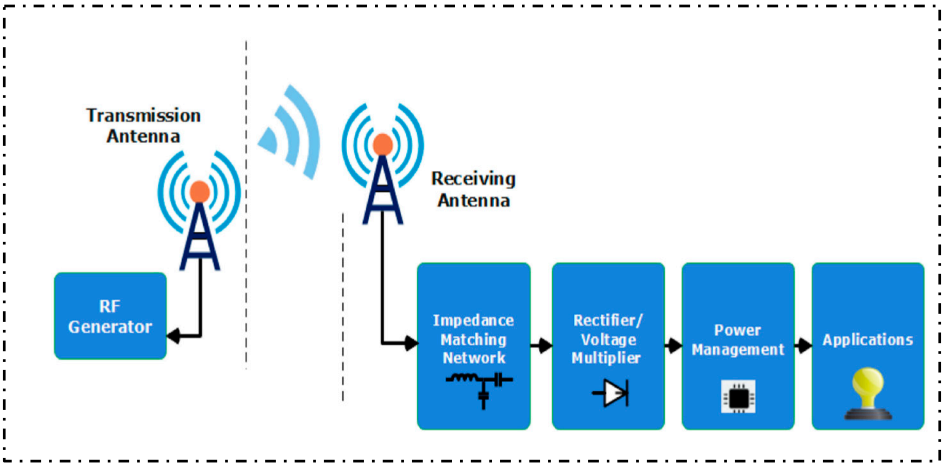

Figure 17. A typical RF-based energy harvesting system [17].

There are two models for RF power harvesting and communication with other sensor nodes: single-radio and dual-radio systems [139]. In the dual-radio model, one radio receives RF signals for energy harvesting, while the other handles communication. In the single-radio model, a single radio performs both functions, simplifying the harvesting and communication software.

A key limitation of RF power sources is the rapid signal attenuation with distance, resulting in very low power levels for harvesting [148]. Other limitations of RF include low power density [146], interference risks [49], and regulatory restrictions [145]. However, the growing presence of wireless communication and broadcasting infrastructure (e.g., analog/digital TV, AM/FM radio, and Wi-Fi networks) is steadily increasing ambient RF energy density, particularly in urban areas [95].

RF-based energy harvesting has several advantages over solar, thermal, and wind-based sources, particularly its wide availability indoors [139]. Additional benefits include on-demand power delivery, where dedicated RF transmitters can target specific nodes for energy replenishment, and seamless integration in environments with limited natural energy sources such as solar or wind [146]. Potential applications include smart homes [95], smart cities [17], health monitoring [145], remote sensing [66], and environmental monitoring (e.g., pollution and agriculture) [144,145].

In summary, RF-based EH is a promising technique for sustaining WRSNs in energy-constrained environments. While it faces challenges like low power density and regulatory limits, recent advancements are steadily improving its practicality. By complementing other harvesting methods, RF-based systems can enhance the resilience and autonomy of WRSNs in diverse applications.

Table 7 shows a summary of the energy harvesting strategies in WRSNs.

4.2. Energy Storage Techniques in WRSNs

Energy storage is a critical aspect of WRSNs, as the lifetime, efficiency, and reliability of these networks depend heavily on the energy storage capabilities of individual sensor nodes. Efficient energy storage systems ensure that nodes can perform their tasks, maintain connectivity, and participate in the network's charging protocols without frequent failures. This discussion outlines the key considerations, challenges, and advancements related to energy storage in WRSNs. Sensor nodes typically rely on rechargeable batteries such as lithium-ion (Li-ion) or lithium-polymer (Li-Po) due to their high energy density, long cycle life, and reliability. Supercapacitors are also being explored for their rapid charging capabilities and durability. The energy storage capacity of a node's battery must be sufficient to support its sensing, communication, and computational tasks, while accommodating irregular charging intervals.

Table 7. Energy harvesting strategies in WRSNs.

Technique	Energy Source	Power Density	Advantages	Challenges	Applications	Recent Advancements
Solar energy harvesting [140,149–151]	Sunlight	15 mW/cm^2	• Renewable and abundant • High efficiency • Low operational cost	• Weather and time-dependent • Requires energy storage • Reduced efficiency in shaded areas	• Environmental monitoring • Smart agriculture • disaster response	• High efficiency PV cells • Flexible and light weight panels • Self-cleaning technologies
Wind energy-based harvesting [139,143]	Wind motion or air flow	28.5 mW/cm^2	• Renewable • Works at night • Complements solar energy	• Highly dependent on wind availability • Maintenance of moving parts • Noise and integration issues	• Costal monitoring • Remote environmental sensors • Smart cities	• Micro wind turbines • Aerodynamic turbine designs • Hybrid solar-wind systems
Mechanical energy-based harvesting [138,152,153]	Vibrations, structural movement	250 µW/cm^3	• Utilizes ambient vibrations • Compact and scalable	• Limited to vibration-prone environments • Low energy output per node	• Structural health monitoring • Industrial equipment monitoring	• Piezoelectric materials • Wideband energy harvester
Thermal energy-based harvesting [138,139]	Temperature or heat	15 mW/cm^2	• Ideal for temperature-variable environments • Continuous source	• Requires substantial temperature differences • Low energy conversion efficiency	• Industrial processes • Building management • Space and deep-sea exploration	• Thermoelectric materials with high Seebeck coefficient • Improved heat dissipation designs
RF-based energy harvesting [139]	Ambient RF signals	12 nW/cm^2 0.2 mW/cm^2	• Ubiquitous in urban areas • Supports on-demand WPT	• Limited energy density • Interference with RF communication • Requires precise alignment	• Urban IoT devices • Smart homes • Medical implants	• Beamforming and directional antennas • High efficiency-RF rectifiers • Adaptive frequency harvesting

Energy storage refers to technologies that convert energy from a form that is difficult to store (e.g., electrical energy) into a storable form (e.g., chemical energy) and later reconvert it into a directly usable form [139]. Various energy storage technologies differ in terms of capacity, power, and charge/discharge rates, with the choice depending on application requirements. For environmental monitoring, energy storage units must meet specific criteria, including compact size, adequate capacity, and minimal environmental impact. In RF energy harvesting systems, supercapacitors and rechargeable batteries are commonly used to store harvested energy, enabling extended operation of wireless sensor nodes [145,148]. Energy storage in sensor nodes is typically classified into two categories [139,148]: (1) ***supercapacitors***, which excel in quick charge/discharge cycles and high cycling efficiency, and (2) ***rechargeable batteries***, known for their higher energy density and longer energy storage capabilities. Selecting an energy storage mechanism involves balancing factors such as lifespan, cycling efficiency, charging/discharging speed, energy density (size), and material density (weight), depending on the application [154].

4.2.1. Advancements in Energy Storage Technologies

Energy storage technologies have advanced significantly in response to the growing demand for efficient, durable, and high-performance solutions in applications such as

WRSNs, electric vehicles, renewable energy systems, and consumer electronics. Among these advancements, *rechargeable batteries and supercapacitors* stand out as two key areas of innovation [139,145,154]. These technologies have undergone significant development to address limitations related to energy density, charging speed, durability, and scalability.

A. Rechargeable Batteries

Rechargeable batteries store energy via reversible chemical reactions. They are widely used in WRSNs due to their high energy density, ability to supply consistent power, and compatibility with wireless charging technologies. Batteries can be classified as primary (non-rechargeable) or secondary (rechargeable) [139,154]. Primary batteries offer advantages such as higher capacity and better temperature stability, but their main drawback is the need for periodic maintenance and replacement once they reach the end of their life. In contrast, secondary batteries are rechargeable but are limited by their cycling capacity, which determines the number of charge/discharge cycles. As their capacity decreases over time, they eventually need to be replaced when they can no longer meet application requirements [154].

Batteries serve as an alternative to supercapacitors for energy storage and can also function as rechargeable power supplies in energy harvesting circuits. Various types of batteries are available, including nickel–cadmium (NiCd), sealed lead acid (SLA), nickel-metal hydride (NiMH), lithium (Li), and lithium-ion (Li-ion). Lithium and lithium alloy batteries are particularly advantageous due to their higher efficiency compared to other types [145,146,154]. The equivalent model of a battery is typically represented as a series connection of an ideal voltage source and internal resistance [155].

When used as a load in energy harvesting circuits, the charging efficiency of a battery depends on the charging current, with an optimal current that maximizes charging efficiency [145]. While batteries offer higher energy density than supercapacitors and conventional capacitors, they have lower power density and shorter lifespans. To address some of these limitations, a new energy storage device called a "supercapattery" has recently been developed [145]. A supercapattery is a hybrid energy storage device that combines the properties of supercapacitors and batteries, aiming to leverage the strengths of both technologies. It integrates the high energy density of batteries with the high power density and long cycle life of supercapacitors [156].

B. Supercapacitors

Addressing the limitations of rechargeable batteries, such as cycling capacity and lifespan, has led to the development of battery-free nodes that eliminate the need for frequent battery replacement. Supercapacitors have gained significant interest in energy harvesting systems as either replacements for or supplements to batteries to overcome their limitations [154,157]. Supercapacitors, also known as ultracapacitors or electrochemical capacitors, are energy storage devices that store energy through electrostatic charge separation, rather than chemical reactions as in traditional batteries. This fundamental difference provides them with unique advantages in terms of rapid charging and high durability. Supercapacitors are distinguished by their high-power density compared to batteries and conventional capacitors.

Supercapacitors, a type of electrochemical double-layer capacitor, offer high energy storage capacity with greater power density than batteries and higher energy density than conventional capacitors. These characteristics position them between conventional capacitors and rechargeable batteries. Their fast charging, excellent discharge performance, and long lifespan make them ideal for storing harvested energy [154,158].

Unlike batteries, supercapacitors operate based on an electrochemical mechanism that allows them to quickly store large amounts of energy. While their energy density is lower than that of batteries, it is significantly higher than that of conventional capacitors, and they exhibit superior charging efficiency, enabling faster charging [154]. Compared to rechargeable batteries, supercapacitors offer several advantages for energy harvesting sensor nodes [139,145,154], including the following:

- Extremely long lifespans (over one million charge–discharge cycles);
- High charging and discharging efficiency;
- Broad operating temperature ranges;
- Minimal aging and degradation over time;
- Eco-friendlier material composition.

Recent advancements have improved the energy density of supercapacitors to levels comparable to rechargeable batteries, making them practical for energy storage applications [154]. However, they cannot directly replace batteries without considering their distinct charging and discharging characteristics. Supercapacitors differ from batteries in several major ways, including the following [154,159]:

- *Lower energy density:* while improving, their energy density remains less than that of batteries, necessitating careful capacitance optimization to store sufficient energy.
- *High self-discharge rates:* they can lose 60% of their charge per month or 11% per day [159], which may reduce operational efficiency during extended periods of low ambient energy availability.
- *Fast discharge:* once fully charged, they discharge at much higher rates than traditional batteries, which can be problematic for sustaining loads over long durations during energy shortages [160].

To fully utilize supercapacitors in energy harvesting systems, addressing self-discharge and optimizing energy storage capacity are critical.

Supercapacitors are categorized into three types based on their energy storage mechanisms: *electrochemical double-layer capacitors (EDLCs), pseudo-supercapacitors, and hybrid supercapacitors* [139,154,159,161]. Each type can be constructed from a variety of materials, which influence their specific properties. A comprehensive summary of these material types, their impact on specific capacitance, and detailed information about each supercapacitor type is provided by the authors in [161]. EDLCs (ultracapacitors) operate on electrochemical principles, storing electric charge between electrodes with high surface area and thin electrolytic dielectrics. Their maximum operating voltage is limited by the breakdown properties of the dielectric material, with a safety margin incorporated into the rated voltage to prevent electrolyte decomposition and short circuits [148]. EDLCs are the most widely used and commercially dominant supercapacitors due to their lower cost compared to other types. They offer good durability, energy density, and cycling stability, enduring millions of charge/discharge cycles [159,161]. Pseudo-supercapacitors, also known as *Faradaic Supercapacitors*, operate via fast and reversible redox reactions, making their principle of operation more similar to that of batteries than capacitors. They achieve greater energy density and capacitance (10–100 times higher than EDLCs). However, they have drawbacks such as lower power density, reduced cycling stability, lower charging efficiency, slower discharge rates, and faster component degradation compared to EDLCs [159–163]. Hybrid supercapacitors are the most recent innovation in supercapacitor technology by combining components of both EDLCs and pseudo-supercapacitors. This design enables higher energy density, power density, cycling efficiency, and voltage, along with the ability to deliver higher currents than other supercapacitor types. Structurally and operationally, they resemble lithium-ion batteries but with higher power density and lower energy density, while retaining the general benefits of capacitors [159,161].

4.2.2. Collaborative Benefits of Rechargeable Batteries and Supercapacitors in WRSNs

In WRSNs, the collaboration between rechargeable batteries and supercapacitors offers a powerful energy storage solution that enhances the system's efficiency, longevity, and adaptability to varying power demands. This hybrid energy storage system leverages the strengths of both components to address the inherent limitations of each, ensuring optimal energy management in resource-constrained and dynamic environments. The combination allows supercapacitors to handle short-term, high-power demands, reducing the strain on batteries and preventing deep discharges. This leads to more efficient energy usage and less energy wastage. By offloading peak power demands to supercapacitors, batteries are subjected to fewer charge/discharge cycles and can operate within a more stable range. This reduces wear and tear, significantly extending the operational life of the batteries. In terms of scalability and adaptability, this combination is particularly useful in large-scale WRSNs where energy demands can vary widely. The hybrid system can adapt to diverse power requirements across different nodes, enhancing the overall scalability and resilience of the network. In summary, the collaboration of rechargeable batteries with supercapacitors in WRSNs provides a balanced and efficient energy storage solution, addressing both short-term and long-term energy needs while improving the overall reliability and longevity of the network. Table 8 provides a summary of the comparative advantages of supercapacitors and rechargeable batteries.

Table 8. Comparative advantages of supercapacitors and rechargeable batteries.

Reference	Feature	Supercapacitors	Rechargeable Batteries
[156,162]	Energy density	Low–moderate	High
[155,161]	Power density	Very high	Moderate
[162,163]	Cycle life	Over 1,000,000 cycles	Typically, 500–3000 cycles
[158,159]	Charging speed	Seconds	Minutes
[139,154]	Cost	Higher per energy unit	Lower per energy unit
[145,154]	Durability	Excellent (low degradation)	Moderate to good (degrades over time)
[139,145,154,159]	Applications	High-power, short-duration needs	Long-duration, steady power needs

5. Future Trends and Opportunities in On-Demand WPT for WRSNs

On-demand energy provisioning in large-scale wireless rechargeable sensor networks (WRSNs) is a dynamic approach to ensuring that the energy needs of distributed sensors are met efficiently through wireless power transfer (WPT). This concept is especially vital for large-scale deployments where traditional methods like battery replacements are impractical due to high costs, logistical challenges, and environmental impact. The evolving demands of WRSNs necessitate innovations in on-demand WPT technologies. These advancements aim to enhance efficiency, scalability, security, and sustainability to address challenges such as dynamic energy requirements, security vulnerabilities, and the limitations of existing technologies. Future advancements in WPT technologies and AI-driven management algorithms are expected to increase the efficiency and feasibility of large-scale WRSNs, enabling broader adoption across industries. Below are some key future trends:

- ***Advanced energy harvesting and transmission techniques***: This involves adopting multi-modal energy harvesting and advanced WPT technologies. By integrating various energy harvesting modalities, such as RF, solar, and kinetic, energy availability can be enhanced while reducing reliance on a single power source. Hybrid systems enable nodes to harvest ambient energy alongside on-demand power, fostering a more sustainable energy ecosystem. Emerging WPT technologies, including laser-based and millimeter-wave power transfer, offer improved efficiency and extended transmission ranges compared to traditional RF and inductive methods. Additionally, magnetic resonant coupling with optimized alignment mechanisms enhances mid-range energy transfer while minimizing power loss [164,165].

- ***Intelligent charging management:*** This approach leverages AI-driven energy allocation and decentralized coordination protocols. Artificial intelligence and machine learning algorithms can predict energy demands, optimize charging schedules, and dynamically prioritize nodes based on real-time network needs. Predictive analytics further minimizes charging latency and maximizes resource utilization. Meanwhile, decentralized energy management using blockchain [166] or distributed ledger technology [167] provides secure, tamper-proof coordination between charging devices and sensor nodes. Autonomous, self-organizing protocols eliminate dependence on central controllers, improving scalability and enhancing network robustness.
- ***Enhanced security mechanisms:*** This approach focuses on securing WPT channels and implementing trust and reputation systems. Cryptographic solutions and robust communication protocols safeguard WPT channels from threats such as eavesdropping, spoofing, and energy theft [17,49,168]. Anti-tampering technologies further protect energy transmitters and receivers from physical and cyber-attacks. Additionally, trust-based frameworks can evaluate the behavior of energy receivers, mitigating risks like false reporting and energy monopolization by malicious or greedy nodes.
- ***Energy-aware network architectures:*** This approach emphasizes energy-aware network architectures, incorporating energy-optimal node deployment and inter-node energy sharing. Adaptive node placement strategies can minimize energy consumption while maximizing WPT efficiency [169]. Deploying relay nodes or energy hubs strategically extends WPT coverage and reduces power loss. Additionally, peer-to-peer energy sharing via short-range WPT enables nodes to distribute surplus energy, decreasing reliance on central transmitters and improving network resilience.
- ***Integration with next-generation technologies:*** This approach focuses on integration with next-generation technologies, including IoT and 6G networks. The convergence of WRSNs with IoT will require WPT solutions that support high-density, heterogeneous devices with diverse energy needs. Edge computing in IoT-enabled WRSNs can further reduce the energy overhead associated with data processing and communication [170]. Additionally, advanced wireless networks like 6G will provide ultra-reliable, low-latency WPT communication, enabling real-time energy management for WRSNs. These networks will also enhance the precision of mobile charging vehicle (MCV) navigation and facilitate dynamic power adjustments for improved efficiency.
- ***Environmental and economic sustainability:*** This approach prioritizes environmental and economic sustainability through green energy integration and cost-effective WPT solutions. Utilizing renewable energy sources, such as solar-powered charging stations for MCVs [171], can significantly reduce the environmental impact of WRSNs. Additionally, designing energy-efficient WPT devices with minimized electromagnetic interference supports eco-friendly objectives. Developing affordable WPT infrastructure and devices will further enhance accessibility, enabling diverse applications such as smart agriculture and disaster response.
- ***Application-specific customizations:*** This approach emphasizes application-specific customizations, catering to mission-critical applications and high-mobility environments. WPT technologies designed for mission-critical scenarios, such as healthcare monitoring and military surveillance [49,138,172] will prioritize reliability, robust security, and minimal downtime. In high-mobility settings like transportation and smart cities, advancements in mobile charging vehicles (MCVs), including autonomous navigation and obstacle avoidance, will enhance WPT efficiency and ensure seamless energy delivery.

- ***Multi-charger optimization:*** develop algorithms for collaborative charging among multiple MCs to reduce delays and improve scalability.
- ***Hybrid approaches:*** combine on-demand and periodic strategies to balance real-time responsiveness and predictable energy management.
- ***Energy harvesting integration:*** supplement wireless charging with renewable energy sources like solar panels on nodes to reduce dependency on MCs.
- ***Hierarchical scheduling models***: implement hierarchical frameworks that divide networks into smaller clusters, each managed by local MCs to reduce scheduling complexity.
- ***Dynamic clustering techniques:*** use adaptive clustering algorithms that evolve with network conditions to ensure efficient grouping of nodes.
- ***Intelligent algorithms:*** employ AI-driven optimization to improve decision-making under dynamic and resource-constrained conditions.

The future of on-demand WPT for WRSNs lies in the convergence of advanced technologies, sustainable practices, and intelligent management systems. By addressing current limitations and leveraging innovations like AI, blockchain, and next-generation wireless networks, WPT can revolutionize energy provisioning in WRSNs, making them more efficient, scalable, and adaptable to a wide range of applications. In summary, on-demand energy provisioning in large-scale WRSNs is a transformative approach that enables sustainable, flexible, and cost-effective sensor network operation through intelligent, wireless energy delivery systems. The ongoing development of more sophisticated WPT, routing algorithms, and energy management protocols will further optimize this technology's implementation. By addressing the challenges of scalability, optimization complexity, and resource limitations, on-demand wireless charging can evolve into a robust and adaptable solution for energy management in WRSNs.

6. Conclusions

This paper has presented a comprehensive review of on-demand energy provisioning strategies for large-scale wireless rechargeable sensor networks (WRSNs), encompassing energy harvesting techniques, storage solutions, and energy management strategies. These approaches are crucial to addressing the dynamic and resource-constrained nature of WRSNs, ensuring their viability for a range of applications such as environmental monitoring, precision agriculture, and smart cities. Our analysis has highlighted advancements in energy harvesting technologies, including solar, kinetic, and ambient sources, as well as innovations in energy storage devices like supercapacitors and rechargeable batteries. These solutions provide essential building blocks for creating sustainable and self-sufficient WRSNs. Furthermore, this review has emphasized adaptive energy management strategies that balance energy consumption and harvesting, optimizing network performance under varying operational conditions. Despite these advancements, this study has identified several challenges, including the efficiency of wireless charging in dynamic environments, the limitations of existing energy storage technologies, and the need for improved energy management techniques. Addressing these challenges is critical for unlocking the full potential of WRSNs. This review has also identified opportunities for future research, such as the development of hybrid energy storage devices like supercapatteries, more efficient energy transfer protocols, and intelligent algorithms for real-time energy optimization. By synthesizing current research efforts, this paper has aimed to provide valuable insights for researchers and policymakers, fostering innovation and progress in on-demand energy provisioning for WRSNs. The findings lay the groundwork for future advancements that will enable robust, sustainable, and scalable WRSNs capable of meeting the demands of emerging applications.

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Abbreviations

WRSNs	Wireless Rechargeable Sensor Networks
WCVs	Wireless Charging Vehicles
MCTs	Mobile Charging Techniques
WPT	Wireless Power Transfer
MCs	Mobile Chargers
WSNs	Wireless Sensor Networks
TSCA	Temporal–Spatial Charging Scheduling Algorithm
GTCCS	Game Theoretical Collaborative Charging Scheduling
UAVs	Unmanned Aerial Vehicles
LoS	Line-of-Sight
DB-MMEs	Deadline-Based Multiple Mobile Elements
LS-WRSNs.	Large-Scale Wireless Rechargeable Sensor Networks
OPPC	Optimal Path Planning Charging
EH	Energy Harvesting
MCVs	Mobile Charging Vehicles
EM	Electromagnetic
RF	Radio Frequency
MIMO-WPT	Multiple-Input Multiple-Output Wireless Power Transfer
WCNs	Wireless Charger Networks
BS	Base Station
RFID	Radio Frequency Identification
PSO	Particle Swarm Optimization
PCS	Partial Charging Scheme
DoS	Denial of Service
CPSs	Cyber Physical Systems
AC	Alternating Current
DC	Direct Current
AM	Amplitude Modulation
FM	Frequency Modulation
Li-Po	Lithium-Polymer
EDLCs	Electrochemical Double-Layer Capacitors

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