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An Overview of On-Demand Wireless Charging as a Promising Energy Replenishment Solution for Future Wireless Rechargeable Sensor Networks

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ABSTRACT

The rapid advancement in the emerging technology of wireless power transfer (WPT) has enabled energy-constrained wireless sensor networks (WSNs) to operate perpetually through the mobile charging robot scheduled to recharge the sensors' batteries. In contrast to previous schemes where the mobile charger (MC) is scheduled to periodically visit and recharge every sensor node (SN) in the network irrespective of their energy status, the current trend is using a more efficient recharging scheme called on-demand. In the on-demand recharging scheme, the MC is scheduled to visit and recharge only a few SNs that have forwarded a recharging request after their battery energies lessen below a preset threshold. However, due to the energy consumption dynamicity of WSNs, designing an on-demand wireless recharging scheme is still a challenging research problem. This article explores some of the recent design issues of on-demand wireless recharging scheme and corresponding performance evaluation metrics. Although recently, researchers have proposed many efficient on-demand recharging schemes, there are still some limitations, such as scalability, high MCs' energy consumption, and prolonged SNs' recharging delay, which, if not adequately addressed through research, may limit the network's performance efficiency as well as lifetime.

1. Introduction

Wireless sensor networks (WSN) have been widely deployed in military, civil, environmental, and industrial applications for remote detection of targets or monitoring of special events. Advances in wireless microelectronics technology have motivated research interests in enhancing fine-grained metering and controlling environments, systems, and structures using WSNs. However, due to the finite battery energy of the sensor nodes (SNs), the lifetime and performance of WSNs designed for long-term operation are constrained.

Credence to wireless power transfer (WPT) technology, a new energy replenishment method using wireless charging, has emerged as the current research trend in solving the energy problem of WSNs [1]. In this new method, a robotic car bearing a wireless charger is employed to recharge the network sensors, a model termed "wireless rechargeable sensor network" (WRSN) [2].

Compared to previous methods, wireless charging technology replenishes SNs' energy more controllably, does not require precise localization or bodily alignment to the SN, and is not subject to weather or seasonal fluctuations [3]. However, due to space-time constraints and nonlinear energy consumption, designing an optimal charging trajectory for the MC in WRSNs is still a challenging research problem.

The drawbacks of the previous charging schemes drive research for a more energy-efficient solution called "on-demand" [4]. In on-demand recharging scheme, the mobile charger (MC) is scheduled to only visit and recharge those sensors that used their battery energy below a preset threshold and requested to be recharged. Thus, it is more flexible, adaptive, and energy-efficient [5].

In general, the development of wireless recharging of energy-constrained WSNs employing one or more MCs is usually related to the following critical research issues: Is it realistic to recharge the entire network SNs before exhausting their energy? How many MCs will be needed to guarantee continuous network operation? When is the appropriate time for the MCs to recharge the network SNs? Which of the MCs should be scheduled to recharge which of the SNs? Should the sensors be fully or partially recharged? Thus, providing valuable insights into these unresolved research problems remains this article's ultimate goal.

The rest of the paper is structured as follows: section 2 is an overview of the existing energy replenishment solutions in WRSN. Section 3 discusses some significant attributes of on-demand wireless recharging schemes. In section 4, some basic performance evaluation metrics for WRSNs are defined. Network models (architectural and mathematical) of on-demand wireless recharging techniques are discussed in section 5. Section 6 explores some recent design issues of on-demand recharging schemes, while section 7 recommends some future research directions. The article is concluded in section 8.

2. Existing Energy Replenishment Solutions in WRSNs

Notably, replacing batteries from trillion sensors could be a prohibitive feat, incredibly when inaccessible. Previous research [6, 7] revealed that transforming such WSNs to conserve energy, self-powered or wirelessly rechargeable, seems to be the right approach to tackle such a challenge. This development has been known for a long in the sensor network community, and thus, many solutions have been researched. The recent state-of-the-art approach to energy restoration uses a robot to serve as a mobile charger (MC) which cruises around the network area to wirelessly replenish the energy of the nodes, either periodically or on-demand.

2.1. Periodic Charging

In periodic charging, the MC has a static or pre-optimized recharging schedule that repeats periodically. Recharging schemes in this category are generally referred to as deterministic since the MC maintains a fixed charging trajectory, taking into account every node in the network regardless of the network energy heterogeneity [8]. This results in performance inefficiency, which limits the applicability of this recharging scheme. Moreover, periodic strategies are vulnerable to fluctuations in the network conditions, showing a lack of adaptability, and can easily suffer from perennial performance degradation as they are blind to real-time events and future changes in the network [9].

2.2. On-Demand Charging

In on-demand charging, the recharging schedule for the MC is designed in real time, considering the residual energy of the SNs and their physical locations [10]. Whenever the residual energy of an SN falls below a preset threshold value, it forwards a recharging request to the base station (BS). The BS then computes the charging schedule and dispatches the MC to serve the requests.

The earliest work in this regard is a first-come-first-served (FCFS) model reported in [11]. The authors first argued that the solution to the energy problem in WSNs relies on the networks' topology and traffic loads. Then, they demonstrated a first-come-first-served-based energy restoration model that can mitigate the networks' total energy consumption. In the FCFS model, the MC serves the charging requests according to their arrival time (temporal property). Unfortunately, the MC may have to unnecessarily travel back and forth since the recharging schedule was planned by neglecting the physical locations of the requesting nodes. Moreover, it may also increase the average charging latency, thereby degrading the charging efficiency of the network.

To address the highlighted drawbacks of the FCFS model, a nearest-job-next-with-preemption (NJNP) model was proposed in [12]. In the NJNP scheme, the MC can switch over the next to be recharged SN with the nearest requesting SN. However, the SN located far from the MC's current location may suffer energy shortage due to the repeated preemption operation, leading to the network SNs' premature death, thereby making the NJNP model deficient. Recently, in WRSNs, as an attempt to improve the earlier FCFS and NJNP, enormous studies have been conducted based on an on-demand approach with different objectives and methodologies [13, 14]. Table 1 below provides a summary of a few of such research works.

TABLE 1: Summary of Existing On-Demand Research Works

Reference	**Objective**	**Methodology**	**Limitation**
Rahaman *et al.* 2020 [2]	Minimize SNs' failure rates. Minimize charging latency	The priority scheduling algorithm (PSA) is based on spatial-temporal factors and the remaining lifetime of SNs. Single MC. P2P power transfer	The scheme behaves as NJNP with increased network size, which is not desired.
Mukase *et al.* 2022 [4]	Minimize total distance covered by MC. Maximize MC's vacation time ratio	PSO-based algorithm using two threshold variables. Single MC. P2P power transfer	High speed reduces the MC's travel time, consequently increasing its energy consumption.
Zhou *et al.* 2021 [6]	Improve charging efficiency. Reduce network energy consumption.	Integrates multiple energy harvesting sources (solar and wind) with wireless charging to achieve a self-sustained WSN. Single MC. P2P power transfer	Wind- and solar-powered SNs are not feasible in real WSNs since the charging mechanisms are much larger and more expensive than those of SNs.
Wang *et al.* 2021 [7]	Maximize received power. Minimize the number of MCs	Improve Cuckoo Search (ICS) algorithm-based solution. Multiple MCs. P2M power transfer	Did not consider energy consumed by the MCs, which contradicts real-life application.

3. Taxonomy of On-Demand Wireless Charging Technology

This section examines the various attributes for classifying and comparing on-demand wireless charging techniques.

3.1. Classification Based on Number of Mobile Chargers

The first criterion for classifying mobile charging techniques is the number of MCs employed: single-MC and multiple-MC techniques. The former uses only one MC to serve the charging requests of all the nodes in small-scale networks [15], as illustrated in Figure 1. Although the single-MC technique is simple and cost-effective to implement, it is not recommended for large-scale WSNs because of the limited energy of the MC. A multiple-MCs approach is employed to ensure perpetual operation in large scale WSNs. In this approach, the MCs cruise around the network area to recharge the nodes using collaborative or non-collaborative methods [16], as illustrated in Figure 2.

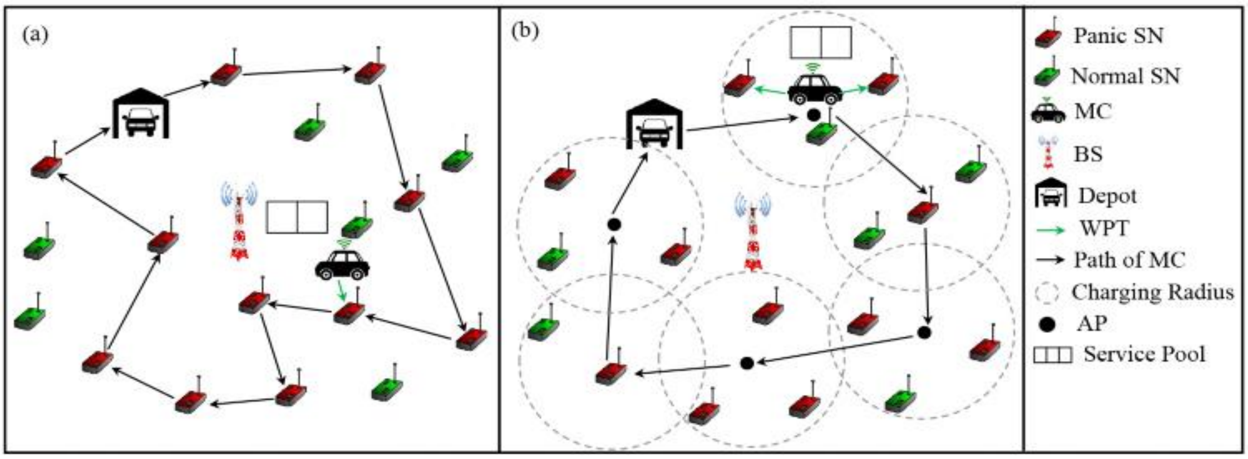

Figure 1. On-Demand Recharging Model for Single-MC Approach: (a) Single-Node Charging (P2P) and (b) Multiple-Node Charging (P2M) [1].

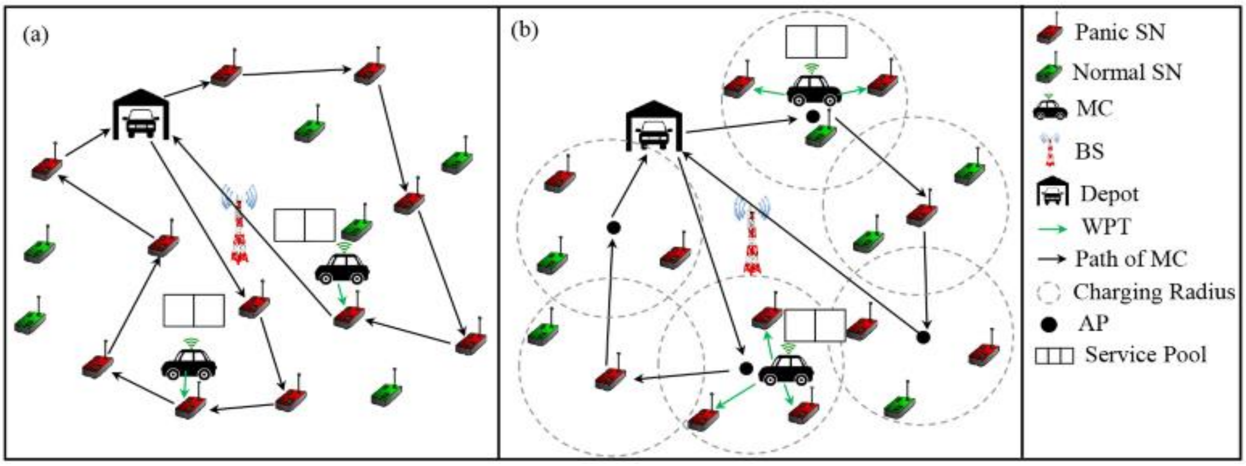

Figure 2. On-Demand Recharging Model for Multiple-MC Approach: (a) Single-Node Charging (P2P) and (b) Multiple-Node Charging (P2M) [1].

3.2. Classification Based on Adopted Control Structure

Alternative classification is based on the employed control structure. Three basic types of control structures can be adopted to implement a mobile charging system: centralized [17], semi-distributed [18], and distributed [19]. In a centralized control structure, one central entity (base station/controller) usually performs all the necessary communication and computing tasks. In contrast, in a semi-distributed control structure, a central entity first divides the network area (or the SNs) amongst the MCs, and then each MC recharges the SNs assigned to it. However, in a distributed control structure, all the MCs work independently.

3.3. Classification Based on Charging Policy

Another vital classification of the mobile charging scheme is based on the different charging operations. The MCs use single-node charging [4] or multiple-node charging [18] to restore the energy of the network SNs, as illustrated in Figures 1(b) and 2(b), respectively. Similarly, the MC can implement partial, complete, or hybrid charging policy to recharge the SNs. The paper [20] assumed that the MC must recharge all the energy-critical SNs to their total battery ratings. However, if each node must be fully recharged, some nodes may not be recharged before their deadline. Reference [21] reported a reinforcement learning-based algorithm for charging reward maximization through partial charging of SNs.

4. Performance Evaluation Metrics for WRSNs

Designing an effective and efficient wireless charging scheme (WCS) requires a good knowledge of the primary network parameters. In this section, some performance evaluation metrics for WRSNs relevant to this study are briefly defined:

Traveling time **($\boldsymbol{T_{t,\ MC \to s_i}}$):** traveling time is defined as the time spent by the MC in moving to the location of an SN s_i From its present location. It is the ratio of the Euclidean distance between the MC's current location and the sensor. s_i To MC's velocity of travel, given by [16, 22]:

$$\boldsymbol{T_{t,\ MC \to s_i}} = \frac{dist(S_i,\ MC)}{v},\ \forall s_i \in C_s \tag{1}$$

Charging time **($\boldsymbol{C_{t,\ MC \to s_i}}$):** charging time is defined as the time spent by the mobile charger to charge an SN s_i. It is the ratio of the energy received to the power received by the sensor, given by [16, 22]:

$$\boldsymbol{C_{t,\ MC \to s_i}} = \frac{\boldsymbol{e_i - e_{ress_i}}}{\boldsymbol{P_r}},\ \forall s_i \in C_s \tag{2}$$

Where; e_i and e_{ress_i}Denote the initial and the residual energy of SN, respectively.

Service time ($\boldsymbol{S_{t,\ MC \to s_i}}$)**:** Service time is when the mobile charger travels to the sensor node location from its present location and later charges it. Hence, it is the sum of traveling and charging times, given by [1, 22]:

$$\boldsymbol{S_{t,}}\ _{MC \to s_i} = \boldsymbol{T_{t,}}\ _{MC \to s_i} + \boldsymbol{C_{t,}}\ _{MC \to s_i}, \forall s_i \in C_s \quad (3)$$

Waiting time ($\boldsymbol{W_{t,\ MC \to s_i}}$)**:** waiting time is defined as the time spent by the mobile charger in charging all the sensors with charging requests before the sensor s_i In the schedule given by [1, 22]:

$$W_{\boldsymbol{t},\ MC \to s_i} = \sum \left(\boldsymbol{T_{t,}}\ _{MC \to s_j} + \boldsymbol{C_{t,}}\ _{MC \to s_j} \right), \forall s_j \in prevs_i \quad (4)$$

Where; $prevs_i$ Denote the set of sensor nodes served before the sensor. s_i

Charging latency $\boldsymbol{C_l}$: The charging latency metric is defined as the average time the mobile charger spends serving each request present in the request pool. It is simply the sum of waiting time and service time, given by [1, 22]:

$$\boldsymbol{C_l} = \frac{1}{w} \sum_{i=1}^{w} \left(W_{\boldsymbol{t},\ MC \to s_i} + \boldsymbol{T_{t,}}\ _{MC \to s_i} + \boldsymbol{C_{t,}}\ _{MC \to s_i} \right),\ \forall s_i \in C_s \quad (5)$$

Where; $W_{\boldsymbol{t},} T_{t,}$ *and* $C_{t,}$ Denotes the waiting time, traveling time, and charging time of i[th] SN s_i, respectively while C_s is the charging schedule.

Total energy consumption (TEC): usually, the MC consumed has three parts: the energy used in charging the SNs, the energy lost during charging, and the energy used for traveling. The first part is called payload energy $E^{PL,}$ while the sum of the last two parts is regarded as overhead energy E^{OH}. Thus, TEC is given by [1]:

$$TEC = E^{PL} + E^{OH} \quad (6)$$

Energy usage efficiency (EUE): EUE (also called energy usage effectiveness in [22]) is defined as the ratio of the payload energy to the TEC of the MC, calculated as [1]:

$$EUE = \frac{E^{PL}}{TEC} = \frac{E^{PL}}{E^{PL} + E^{OH}} \quad (7)$$

Where: E^{PL} and E^{OH} Are respectively the payload energy and the overhead energy. Thus, a mobile recharging scheme with a higher EUE value is most desirable in WRSN.

5. Modeling of On-Demand Wireless Charging Scheme

This section briefly describes the architectural and empirical models as fundamental tools for designing on-demand wireless recharging systems.

5.1. Network Model

A typical on-demand wireless recharging scheme consists of the following entities: a set of rechargeable SNs randomly dispersed over a 2D monitoring region, single or multiple mobile chargers, single or multiple service stations, and an immobile base station. Figure 3 depicts the block diagram showing the essential components with their Interconnectivity for the SN and the MC wirelessly interfaced by the base station (BS).

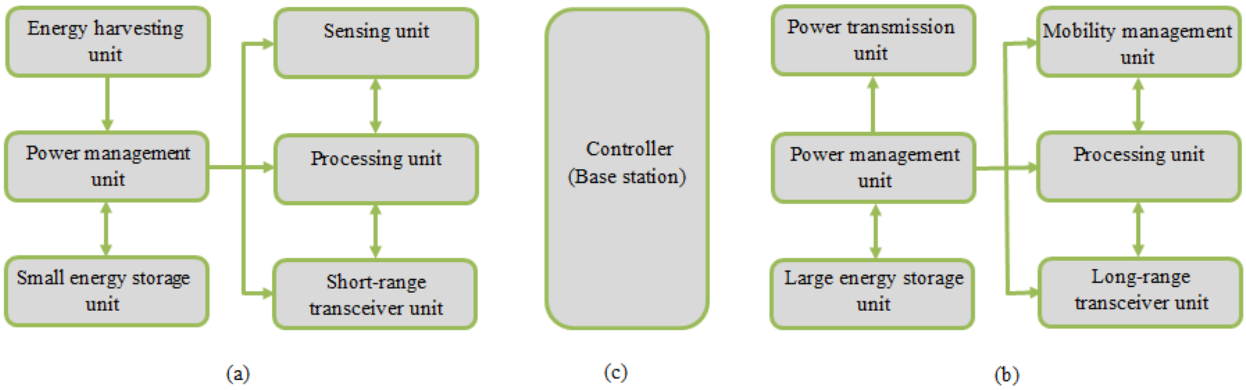

Figure 3. Block Diagram of the System's Basic Units with their Interconnectivity in (a) Rechargeable SN, (b) Mobile Charger, and (c) Controller / Base Station

In Figure 3, the sensing unit of the rechargeable SN generates the sensory data at a preset rate. It relays it to the processing unit, which computes the sensed data and transfers it to the controller via single-hope or multi-hope transmission protocol through a short-range transceiver unit. The BS then runs the charging algorithm to generate the recharging schedule and communicates the same to the MC for implementation. The energy harvesting unit of the SN is enhanced with a wireless power receiving coil or a rectenna for harvesting the power radiated by the power transmission unit of the MC [1].

The mobility management unit of the MC comprises a Global Positioning System (GPS), a navigation protocol, and a mobilizer. These components help the MC navigate the network area and locate the energy-critical sensors [1].

5.2. Charging Model

A charging model used for RF radiation by omnidirectional chargers as used in [23] is described in equation (8):

$$P_r(S_i,\ MC) = \frac{G_t G_r \eta}{L_p}\left(\frac{\lambda}{4\pi(dist(S_i,\ MC)+\delta)}\right)^2 P_t \tag{8}$$

Where; P_t does the MC transmit the power, P_r is the power received by the SN, $dist(S_i,\ MC)$ is the Euclidean distance between the SN s_i and the MC, G_t is the antenna gain of MC, G_r Is the antenna gain of the SN, L_p is the antennas polarization loss, λ is the wavelength of the RF radiation, η is the efficiency of the rectifier and δ is the parameter for adjusting the Friis' free space equation in short distance radio link. The experimental value of δ is 0.2316 [24].

It is worth noting that when MC and SN are very far away, the power received by the SN will be too weak to be rectified. Assuming that R is the maximum charging radius of the charger, except the parameter $dist(S_i,\ MC)$The remaining terms are all constants determined by the environment and the devices. Merging all these constants into α, the model in equation (8) can be simplified as [5]:

$$P_r(S_i,\ MC) = \begin{cases} \frac{\alpha}{(dist(S_i,\ MC)+\delta)^2}, & dist(S_i,\ MC) \le R \\ 0, & dist(S_i,\ MC) > R \end{cases} \tag{9}$$

$$\Rightarrow \alpha = \frac{G_t G_r \eta}{L_p}\left(\frac{\lambda}{4\pi}\right)^2 P_t \tag{10}$$

5.3. Energy Consumption Model

In sensor nodes, significant energy is consumed during the transmission and reception operations, thereby neglecting consumptions due to sensing and computing. Thus, the power dissipated by the transmitter for transmitting k-bits data packet to a distance l is found in [25] given as:

$$E_t(k,\ l) = \begin{cases} kE_{elec} + kE_{fs}l^2, & l \le l_0 \le r_c \\ kE_{elec} + kE_{mp}l^4, & l_0 < l \le r_c \\ \infty, & r_c < l \end{cases} \tag{11}$$

Where $l_0 = \sqrt{\frac{E_{fs}}{E_{mp}}}$ is the threshold distance for swapping amplification models while r_c Denote the maximum range over which an SN can communicate. The parameter $E_{elec} = 50\ nJ/bit$ is the energy dissipated in running the transmitter or receiver circuits per bit; $E_{fs} = 10\ pJ/bit/m^2$ and $E_{mp} = 1.3 \times 10^{-3}\ pJ/bit/m^4$ are the energy expenditures in transmitting one bit of data over a short (free space) and a long (multipath) distance respectively, in achieving an acceptable bit error rate [26]. On the other hand, the energy consumption of the receiver in receiving a k-bits packet is determined as follows:

$$E_r(k) = kE_{elec} \tag{12}$$

Therefore, the energy dissipated by a SN in receiving η packets and transmitting them to another node is calculated by the equation:

$$E_{SN}(\eta, \zeta, l, k) = \eta E_r(k) + (\eta + \zeta)E_t(k, l) \tag{13}$$

Where, $E_t(k,l)$, $E_r(k)$ They are determined as in equations (11) and (12), respectively. The parameter ζ denotes the number of targets surrounding an SN, while l is the transmission distance.

6. Current Design Issues in On-Demand Wireless Charging Schemes

This section briefly discusses the fundamental issues of the WRSN system design. To guarantee the charging efficiency of the requesting SNs and the MC, the design procedure of an on-demand mobile charging scheme must consider the following issues:

6.1. Bounded Charging Delay (Charging Latency)

For each requesting SN, the charging delay measures when it forwarded the charging request to when it is fully recharged [22]. Hence, an efficient WCS should ensure that every requesting SN is served within a limited delay to avoid a high failure rate due to battery energy exhaustion.

6.2. Optimized Mobile Charger's Energy Consumption

From the MC's perspective, achieving an efficient WCS will require optimization of its energy consumption profile [2]. This consists of the charging energy (energy expended in recharging requesting nodes), and the corresponding moving energy necessary to visit such nodes.

6.3. Scalability and Collaborative Strategy

Mostly, WSN real-life applications envisage a highly dense (large-scale) deployment. Thus, a viable recharging scheme must ensure a scalable performance when applied in those application scenarios where the workload is expected to be very high. One naive solution to improve scalability characteristics in on-demand wireless charging is to adopt cooperative multiple MCs, similar to [27] in which the MCs cooperate to guarantee the continuous operation of the SNs. In a cooperation strategy, energy can be shared among MCs [28] or through charging load swapping among MCs [29]. Generally, achieving the scalability objective is more challenging using a single-MC approach.

7. Future Research Directions

Although enormous research has been conducted on energy provisioning in WRSNs, some vital methodologies are still underexplored and could thus serve as a potential research hub.

7.1. Application of Artificial Intelligence (AI)

Application of AI-based techniques, including machine learning (ML), reinforcement learning (RL), artificial neural network (ANN), and deep learning (DL), requires higher computing power and more significant memory than the conventional methods. However, it yields new potential for WRSNs: It makes the available network components more intelligent with self-adaptation features that enable the system to predict dynamic network parameters for sustained operation. Recently, very few researchers [29] have explored reinforcement learning in solving wireless charging problems, hence the need for future researchers to revisit the on-demand wireless charging solutions from a deeper AI perspective.

7.2. Application of Mobile Edge Computing (MEC)

Mobile Edge Computing is a three-layer computing paradigm with a cloud server occupying the topmost layer, mobile and static edge devices occupying the middle layer, and the user devices occupying the base layer [30]. The potential of MEC may be explored to design an efficient, less complex, and distributed AI-based wireless recharging scheme to solve energy problems in WRSNs. The topmost layer may consist of the cloud servers, the middle layer may compose the MCs as the mobile edge devices, and the service station and base stations may serve as the static edge devices. The base layer may then consist of stationary or mobile sensors. Hence, with this type of framework, the middle layer can link the base layer to the cloud server of the topmost layer to execute any complex AI-based solution with less computing power and memory.

8. Conclusion

The article briefly discussed various research efforts to address the energy constraint of WSNs. The multiple attributes for classifying on-demand wireless recharging schemes have also been discussed. The advantages and effectiveness of the on-demand recharging scheme over its periodic counterpart in improving the performance and extending the lifetime of WSNs have been highlighted. However, despite the numerous advantages of the on-demand wireless charging scheme, its design and implementation are still experiencing some challenges that cannot be ignored. Thus**,** some of the current design issues of on-demand wireless charging schemes and corresponding performance evaluation metrics were discussed to guide future WRSN researchers. Finally, future research directions are recommended.

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