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A Survey on Mobile Charging Techniques in Wireless Rechargeable Sensor Networks

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***Abstract*—The recent breakthrough in wireless power transfer (WPT) technology has empowered wireless rechargeable sensor networks (WRSNs) by facilitating stable and continuous energy supply to sensors through mobile chargers (MCs). A plethora of studies have been carried out over the last decade in this regard. However, no comprehensive survey exists to compile the state-of-the-art literature and provide insight into future research directions. To fill this gap, we put forward a detailed survey on mobile charging techniques (MCTs) in WRSNs. In particular, we first describe the network model, various WPT techniques with empirical models, system design issues and performance metrics concerning the MCTs. Next, we introduce an exhaustive taxonomy of the MCTs based on various design attributes and then review the literature by categorizing it into periodic and on-demand charging techniques. In addition, we compare the state-of-the-art MCTs in terms of objectives, constraints, solution approaches, charging options, design issues, performance metrics, evaluation methods, and limitations. Finally, we highlight some potential directions for future research.**

***Index Terms*—Wireless rechargeable sensor networks, mobile charging problem, mobile charging techniques, periodic charging, on-demand charging.**

I. Introduction

The past decade has witnessed a rapid growth of wireless sensor networks (WSNs) in a wide variety of applications ranging from environmental monitoring, military applications, industrial automation, health care, and smart cities [1]. A WSN comprises of hundreds or thousands of battery-powered sensors that monitor the physical conditions of the surroundings and transmit the sensed data to a base station (BS) (also called sink), via single-hop or multi-hop communication. However, the network lifetime of WSNs is restricted by the limited battery capacity of the sensors. In recent years, many studies [2]–[12] have been conducted to prolong the network lifetime, which can be classified into two basic categories, i.e., energy conservation and energy provisioning. The former approach includes the cross-layer resource allocation [2], clustering and routing [3], data aggregation [4], sleep scheduling [5], and mobile data collection [6]–[9]. Although energy conservation enhances the network lifetime significantly, it does not ensure perpetual network operation. This is because the sensors will eventually exhaust their limited battery energy and become non-functional. In contrast, energy provisioning methods such as renewable energy harvesting (REH) [10] and wireless power transfer (WPT) [13] can restore the battery power of the sensors (periodically or on-demand) for perpetual operation.

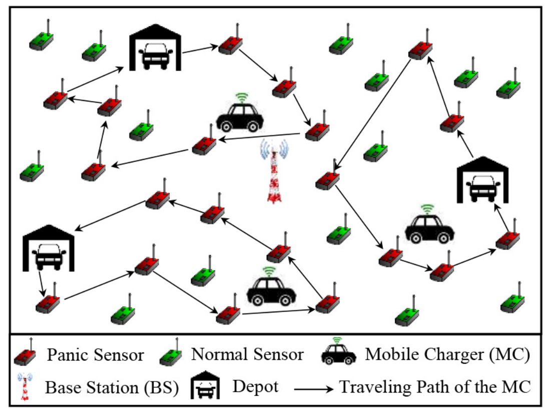

Fig. 1. An example of a WRSN with multiple MCs and depots.

Energy provisioning has led to the development of wireless rechargeable sensor networks (WRSNs) in which sensors are equipped with a rechargeable lithium-ion battery and an energy harvesting module [11]. In WRSNs, the sensors recharge their batteries by harvesting renewable energy from ambient sources (wind, solar, etc.) or electrical power from wireless chargers. However, the success of REH for rechargeable sensor networks remains very limited in practice. This is because the amount of energy harvested from REH is a function of the deployment environment. In contrast, the WPT decouples the locations of the energy sources from sensing locations and allows to move energy from energy-rich regions to energy-poor ones. Hence, the WPT has garnered much attention for enabling stable and reliable energy supplies to the rechargeable sensors.

The existing works employ static chargers (SCs) [14], [15] or mobile chargers (MCs) [16]–[18] for wireless energy provisioning. The SCs are deployed at different network locations and remain stationary to recharge the sensors. However, this is very expensive as we require to deploy many SCs to cover the whole network since the effective charging coverage of WPT is only a few meters. In contrast, WPT using MCs is very effective with respect to cost as well as coverage. The

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reason is that there can be the use of a single MC or a limited number of MCs (NoM) that can roam around the network and recharge the sensors. In particular, the MCs start from depots, reach the sensors, and recharge them periodically or on an on-demand basis. The configuration of the MC model is depicted in Fig. 1 in which solid lines indicate the paths of the MCs.

In general, the problem of recharging sensors using one or more MCs is concerned with the following fundamental questions: 1) Is it possible to recharge all the sensors before they exhaust their battery power? 2) How many MCs are required to ensure the perpetual network operation? 3) When should the MCs recharge the sensors? 4) Which MCs should recharge which sensors and in what sequence? 5) Will the sensors be recharged fully, partially or in a hybrid mode? In this paper, we refer to this problem as *mobile charging problem* (MCP) and its solution as *mobile charging technique* (MCT).

To the best of our knowledge, none of the existing survey papers provides an overall understanding of the MCTs by 1) presenting various quantitative models, 2) identifying the most critical system design issues, 3) describing the various performance metrics, and 4) introducing a complete taxonomy based on several design attributes. This motivates us to present a comprehensive survey on the fundamental aspects of various state-of-the-art MCTs. The key contributions of this survey are summarized as follows.

- We describe the basic architectures of different network components and the quantitative models of sensor's flow routing and energy consumption, MC's charging behavior, and WPT.
- We present an inclusive knowledge on fundamental system design issues addressed by the MCTs and various performance metrics used to analyze them.
- We introduce an exhaustive taxonomy of MCTs based on various design attributes and then review the literature by categorizing it into periodic and on-demand schemes.
- Finally, we convey some future research directions to design efficient MCTs for sustainable WRSNs.

The remainder of this paper is organized as follows. Section II presents an overview of the related survey articles. Section III confers a detailed discussion on the network model, WPT techniques with empirical models, design issues, and performance metrics. Section IV introduces a detailed taxonomy for the MCTs. Section V and Section VI present a thorough discussion on the existing periodic and on-demand MCTs, respectively. Section VII provides future research directions and Section VIII concludes this survey paper. Table I presents a list of frequently used acronyms in the survey.

TABLE I
SUMMARY OF ACRONYMS USED IN THIS PAPER

Acronym	Full Name
AP	Anchor Point
BS	Base Station
CC	Coverage and Connectivity
CD	Charging Delay
CHT	Charging Throughput
CT	Charging Time
CS	Collaboration Strategy
CU/CR	Charging Utility/Reward
CYT	Cycle Time
DTR	Docking Time Ratio
EHN	Energy Harvesting Network
EUE	Energy Usage Efficiency
EEP	Exclusive Energy Provisioning
FR	Failure Rate
FLR	Flow Routing
FDA	Fully-Dynamic Approach
IoT	Internet of Things
JDCEP	Joint Data Collection and Energy Provisioning
LP	Linear Programming
MCP	Mobile Charging Problem
MCT	Mobile Charging Technique
MS	Mobile Sink
MC	Mobile Charger
MNC	Multi-Node Charging
MMT	Multiple MCs-based Techniques
NL	Network Lifetime
NLP	Non-Linear Programming
NoD	Number of Depots
NoM	Number of MCs
MNoM	Minimum Number of MCs
PoI	Points of Interest
QoM	Quality of Monitoring
QDA	Quasi-Dynamic Approach
QL	Queue Length
RF	Radio Frequency
REC	Renewable Energy Cycle
RT	Response Time
RF-EHN	RF-Energy Harvesting Network
SC	Static Charger
SED	Smallest Enclosing Disk
SMT	Single MC-based Techniques
SNC	Single-Node Charging
SR	Survival Rate
SRC	Service Cost
SS	Sleep Scheduling
ST	Service Time
STS	Space-Time Scheduling
SWIPT	Simultaneous Wireless Information and Power Transfer
TEC	Total Energy Consumption
TP	Travling Path
TSP	Traveling Salesman Problem
TT	Traveling Time
VC	Velocity Control
WPT	Wireless Power Transfer
WRSN	Wireless Rechargeable Sensor Network
WSN	Wireless Sensor Network
WT	Waiting Time

II. RELATED SURVEY ARTICLES

In recent years, many surveys have appeared on mobility management and energy harvesting in networking paradigms, such as wireless sensor networks, Internet of things (IoT), and unmanned aerial vehicle (UAV) networks.

We first present works devoted to energy harvesting and its applications in the aforementioned paradigms. In [19], the authors presented a detailed survey on radio frequency energy harvesting networks (RF-EHNs) with a focus on the receiver-side designs. The same authors have also reviewed different types of WPT technologies, viz. magnetic inductive coupling, magnetic resonance coupling, and radio frequency (RF) radiation, from the perspective of transmitter-side designs in [12]. In addition, they conferred a synopsis of representative works on charger deployment and scheduling. Krikidis *et al.* [20] outlined various simultaneous wireless information and power transfer (SWIPT) techniques with hardware implementations.

TABLE II
COMPARISON OF CONTRIBUTIONS OF RELATED SURVEY PAPERS, WHERE "COVERED (C)," "PARTIALLY COVERED (P)," AND "NOT COVERED (N)"

Contributions	[Ours]	[12]	[20]–[43]	[19], [44]–[46]	[47]	[48]	[49]	[50]
Empirical models of flow routing and WPT	C	P	N	N	N	N	N	N
Identification of system design issues	C	N	N	N	P	P	N	N
Review of quality of service metrics	C	N	N	N	N	N	N	N
Taxonomy of system design alternatives	C	P	N	N	N	N	N	P
Detailed discussion on state-of-the-art	C	P	N	P	P	P	P	P
Status-quo and future research directions	C	N	N	N	P	N	P	P

In [21], the authors presented a comprehensive survey on different emerging technologies for 5G wireless communication networks using the SWIPT/WPT.

Alsaba *et al.* [22] studied different beamforming methods to implement the SWIPT in the multi-antenna energy harvesting networks (EHNs). Ku *et al.* [23] reviewed the most critical aspects of EHNs concerning energy sources and models, energy scheduling and optimization, energy harvesting and usage protocols, and other related issues. Barman *et al.* [24] discussed the magnetic resonant coupling-based mid-range WPT and its consumer and non-consumer applications. Huang *et al.* [25] summarized the recent advances in both REH and WPT technologies with their potential applications in device-to-device communication.

Some survey papers [26]–[33] focused on integrating energy harvesting into IoT and UAV networks. A survey on energy harvesting wireless communications from transmission scheduling, resource allocation, networking, medium access, and information-theoretic viewpoints is presented in [26]. Kamalinejad *et al.* [27] briefly outlined various technological advancements for efficient WPT in IoT devices. Ma *et al.* [28] presented a survey on energy harvesting-IoT from standards, hardware, applications, commercial products, and services perspectives. Sandhu *et al.* [29] reviewed various state-of-the-art task scheduling algorithms in energy harvesting-IoT. Sharma *et al.* [30] suggested insights into recent UAV communication techniques by studying antennas, network architectures, task modules, and resource handling platforms. Besides, they also discussed different encryption and optimization methods for secure communication, path planning, and power management methods for UAV communications. Li *et al.* [31] delivered a review on different 5G and beyond 5G UAV communications. Lu *et al.* [32] and Xie *et al.* [33] reviewed various WPT techniques and mobility models in UAV networks, respectively.

The papers [10], [11], [34]–[37], [45]–[48] classified and compared different renewable energy sources and wireless charging methods with their fundamentals and applications in WRSNs. In particular, the papers [10], [34], [35] presented various energy management and harvesting mechanisms. Sudevalayam and Kulkarni [11] studied different characteristics of energy harvesting sensors, energy storage methods, and energy sources. Akhtar and Rehmani [45] presented brief notes on diverse energy storage methods. Bhatti *et al.* [37] put forward a discussion for identifying the most suitable REH/WPT technology based on the application at hand. The surveys [46]–[48] provided short reviews on periodic mobile charging scheduling along with some design issues.

Several contributions such as [6], [7], [38]–[44], [49], [50] preliminary surveyed different issues in WSNs with mobile nodes. In [6], [7], the authors provided extensive reviews on different aspects of data collection using mobile sinks (MSs). Similarly, the article [38] provided insights on various state-of-the-art routing algorithms by summarizing their main characteristics, advantages, and disadvantages. The papers [39], [44], [49], [50] reviewed mobility-assisted network lifetime maximization techniques. The authors in [40], [41] surveyed the works on overall mobility management with their key features and limitations. Dong and Dargie [40] delivered a comparative investigation of mobility-aware medium access control protocols. In [42], [43], the authors presented exhaustive studies on various localization algorithms by classifying them based on node's information state, mobility state, and localization technique. We compare and summarize the contributions of the related survey papers in Table II.

III. SYSTEM DESCRIPTION

This section will help readers understand how to model the MCP for designing efficient MCTs. In particular, we first describe the basic network model of WRSNs with the architectures of different network components and the quantitative models of sensor's flow routing and energy consumption, and MC's charging behavior. Next, we report various WPT techniques with their empirical models. Then, we discuss the fundamental design issues that the research community has solved. Finally, we define different performance metrics used to analyze the state-of-the-art MCTs.

A. Network Model

In WRSNs, a mobile charging system usually comprises of four key components: a set of n rechargeable sensors $S = \{s_1, s_2, \ldots, s_n\}$, a set of m MCs $V = \{v_1, v_2, \ldots, v_m\}$, a set p depots $D = \{d_1, d_2, \ldots, d_p\}$, and a base station (BS) B. All the sensors are deployed randomly (or sometimes manually) in the area of interest, which are aware of their physical locations. As shown in Fig. 2a, a rechargeable sensor s_i consists of a sensing unit, a processing unit, a short-range transceiver unit, an energy harvesting unit, a small energy storage unit, and a power management unit. The sensing unit of a sensor s_i generates sensory data for user applications with a data rate of R_i and feeds it into the processing unit. The processing unit then processes this data and forwards it to the BS via single-hop or multi-hop communication using a short-range

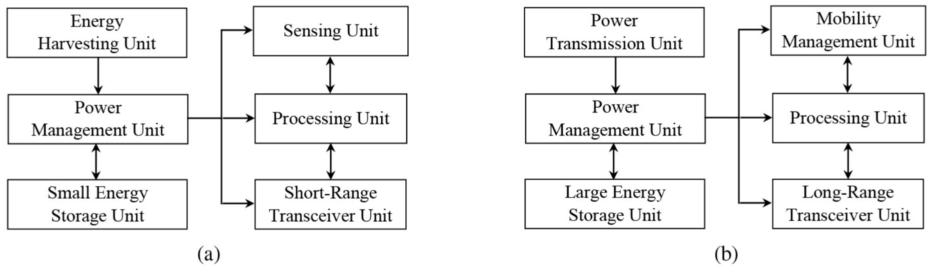

Fig. 2. Block diagram of basic components with their connectivity in (a) rechargeable sensor and (b) mobile charger (MC).

transceiver unit of range r_i^s. Let the data transmission rate from sensor s_i to sensor s_j and the BS *B* are denoted by f_{ij} and f_{iB}, respectively. Then there exists a flow rate balance at each sensor s_i, i.e., the sum of data reception rate and data generation rate of s_i is equal to its data outflow rate which is expressed as [51]–[54]:

$$\Sigma_{s_k \in S}^{s_k \neq s_i} f_{ki} + R_i = \Sigma_{s_j \in S}^{s_j \neq s_i} f_{ij} + f_{iB} \tag{1}$$

The energy consumption rate E_i^{rx} of sensor s_i for data reception is calculated as:

$$E_i^{rx} = \rho \cdot \Sigma_{s_k \in S}^{s_k \neq s_i} f_{ki} \tag{2}$$

where ρ denotes the energy consumption rate of sensor s_i for receiving one unit of data.

Similarly, the energy consumption rate E_i^{tx} of sensor s_i for data transmission is expressed as:

$$E_i^{tx} = \Sigma_{s_j \in S}^{s_j \neq s_i} C_{ij} \cdot f_{ij} + C_{iB} \cdot f_{iB} \tag{3}$$

where C_{ij} and C_{iB} denote the energy consumption rates of sensor s_i for transferring one unit of data to sensor s_j and the BS *B*, respectively and are defined as:

$$C_{ij} = \beta_1 + \beta_2 \cdot D_{ij}^{\alpha} \tag{4}$$
$$C_{iB} = \beta_1 + \beta_2 \cdot D_{iB}^{\alpha} \tag{5}$$

where β_1 and β_2 are constants and α is the path loss index. D_{ij} and D_{iB} are the distance from sensor s_i to sensor s_j and the BS *B*, respectively.

Therefore, the total energy consumption rate p_i of sensor s_i for both data reception and transmission is:

$$p_i = E_i^{rx} + E_i^{tx} \tag{6}$$

The energy harvesting unit of sensor s_i is equipped with a receiving coil or an antenna for harvesting the electrical energy transmitted by the power transmission unit of the MCs. The harvested energy is then stored in a small energy storage unit (i.e., rechargeable batteries or super-capacitors [11]) of capacity $E_i^s(full)$. Note that the energy storage unit of sensor s_i is fully charged initially and requires minimum $E_i^s(min)$ energy to remain operational. The power management unit manages the storage of harvested energy and the distribution of stored energy among various sensor components.

Likewise, all the MCs are initially stationed at their depots. As depicted in Fig. 2b, an MC v_i comprises of a mobility management unit, a processing unit, a long-range transceiver unit, a power transmission unit, a large energy storage unit, and a power management unit. The mobility management unit consists of a global positioning system, navigation protocols, and a mobilizer. It helps MC v_i traverse through the network region at a velocity of s_i^v by finding the locations of energy-critical sensors and performing the navigation operations. The processing unit of MC v_i performs local information processing and communicates with other network components using a long-range transceiver unit of range r_i^v. Also, MC v_i is equipped with a large energy storage unit (i.e., high-density batteries) of capacity $E_i^v(full)$ to power its components and recharge the sensors. Note that the MC v_i requires $E_i^v(min)$ energy to travel back to its depot. The power management unit of MC v_i handles the dispersal of energy among different components of the MC. The power transmission unit of MC v_i recharges the energy-deficit sensors by transmitting wireless electrical energy using a transmitting coil [13] or an antenna [19].

In general, an MC v_i takes either a periodical or on-demand approach to recharge the sensors in a series of recharging rounds. In each round, the MC v_i traverses a traveling path $P_i = \{\pi_0, \pi_1, \ldots, \pi_k, \pi_0\}$ that starts from the depot π_0, passes via *k* anchor points (APs), i.e., $\pi_j, 1 \leq j \leq k$, and ends at the depot π_0. When v_i arrives at an AP, say π_j, it wirelessly recharges the batteries of nearby sensors for τ_j time. Let D_{P_i} denote the length of the path P_i, then the traveling time of MC v_i for traveling a distance of D_{P_i} is given as:

$$\tau_{P_i} = \frac{D_{P_i}}{s_i^v} \tag{7}$$

Once MC v_i visits all the APs, it returns to the depot for own maintenance (e.g., recharging or replacing its battery) and get ready for the next tour. The amount of time that MC v_i spends at depot is called vacation time and is denoted by τ_{vac_i}. Then, the cycle time (CYT), i.e., the total time taken by MC v_i for completing its charging tour is defined as:

$$\tau_i = \tau_{P_i} + \sum_{j=1}^{k} \tau_j + \tau_{vac_i} \tag{8}$$

In periodical charging [52], the charging tour P_i of an MC v_i is prepared only once during the network initialization using a priori network information, i.e., energy profiles and physical locations of the sensors. Then, the MC v_i traverses the tour P_i after every τ_i time to recharge the sensors belonging to its tour. This is because the energy profiles and locations of the sensors are assumed to remain fixed throughout the network operation period. In contrast, the controller (i.e., BS or MC) dynamically

decides the charging tour P_i of MC v_i based on the charging requests of the sensors in on-demand charging [16], [17]. Note that a sensor sends a charging request to the controller if its residual energy drops below a specific threshold value.

Besides, a depot is the place where the MCs are sheltered and serviced when they are not on charging missions. It has sufficiently large energy reserves to support several charging missions of the MCs. Usually, the system administrator commands an MC via BS to complete a charging tour. When an MC arrives at the depot after finishing the charging tour, its batteries are quickly replaced (or recharged) before the next trip. Note that the depot can also be co-located with the BS. However, the primary role of the BS is to collect sensory data and manage the overall working of the network. To do so, it is equipped with high processing capabilities and a continuous power supply. The BS maintains the global information about the locations, energy consumption rates, energy levels, and energy capacities of all the sensors and the MCs. The administrator can ask sensors and MCs to send this information remotely through the BS or they themselves send it in the form of charging requests [17] and beacons [16], respectively. This information is then used to model the MCP and determine the space-time scheduling of the MCs.

B. WPT Techniques and Empirical Models

In practice, the WPT techniques fall into two major classes: radiative [19] and non–radiative [13]. The radiative methods work on far-field and transmit energy based on electric field of radio-frequency (RF) waves. In general, the transmitter first converts the alternating current into direct current and then transforms the direct current into RF wave using a magnetron. It then transmits the RF wave to the receiver, which the receiver later rectifies into the direct current using a rectenna. PRIMOVE [55], Powercast [56], and Cota system [57] are recent commercialized RF-based wireless charging systems.

The non-radiative methods operate on near-field and transfer energy based on the magnetic field coupling between two coils [12]. In magnetic inductive coupling, an alternating current is applied to the transmitter coil that forms a varying magnetic field across the receiver coil and therefore induces electrical energy between two coils. However, the transmitter and receiver coils in inductive coupling need to be within a few centimetres distance and accurately aligned. In contrast, these coils are strongly coupled at the same resonate frequency using compensation capacitors in magnetic resonant coupling [13]. Hence, the resonant coupling enables wireless transmission of energy to longer distance with higher energy transfer efficiency than the inductive coupling. Besides, it enables transmission of wireless power from one transmitter to multiple receivers simultaneously [58]. MagMIMO [59] and Witricity [13] are recent mid-range wireless charging systems based on inductive coupling and resonant coupling, respectively. The readers can find a detailed discussion on hardware designs, architectures, and implementations of these methods in [12], [19]. We now define various empirical models used to simulate wireless charging in WRSNs. Let *r* denote the charging range (radius) of an MC and *d* denote the distance between a sensor and an MC. Likewise, let P_{rx} and P_{tx} denote the power reception and power transmission rate of a sensor and an MC, respectively.

1) RF-Based Omnidirectional WPT Model: The Friis's free space equation-based omnidirectional WPT model is given by [60]:

$$P_{rx} = \frac{G_{tx} G_{rx} \eta}{L_p} \left(\frac{\lambda}{4\pi(d+\beta)} \right)^2 P_{tx} \tag{9}$$

where G_{tx} is the MC antenna gain, G_{rx} is the sensor antenna gain, η is the rectifier efficiency, L_p is the polarization loss, λ is the wavelength of RF signal, and β is an adjustable parameter for Friis's free space equation.

This may be noted that when MC is too far away from the sensor, the sensor's power reception rate would be too low to be rectified. Therefore, the aforesaid model is simplified as:

$$P_{rx} = \begin{cases} \frac{\alpha}{(d+\beta)^2}, & \text{if } d \le r \\ 0, & \text{if } d > r \end{cases} \tag{10}$$

where $\alpha = \frac{G_{tx} G_{rx} \eta}{L_p} (\frac{\lambda}{4\pi})^2 P_{tx}$.

2) RF-Based Directional WPT Model: Let θ represent the charging orientation angle between a sensor and an MC, then the Friis's free space equation-based directional WPT model [61] is expressed as:

$$P_{rx}(d,\theta) = \frac{\eta A_{rx} A_{tx}^{max} (\cos\theta + c)}{L_p \lambda^2 (d+\beta)^2} P_{tx} \tag{11}$$

where A_{rx} and A_{tx}^{max} are the effective power receiving area and the maximum power transferring area of sensor and MC, respectively, and c and β are constants.

$$P_{rx}(d,\theta) = \begin{cases} \gamma \frac{\cos\theta + c}{(d+\beta)^2}, & \text{if } d \le r \text{ and } -\frac{\pi}{2} \le \theta \le \frac{\pi}{2} \\ 0, & \text{if } d > r \end{cases} \tag{12}$$

where $\gamma = \frac{\eta A_{rx} A_{tx}^{max}}{L_p \lambda^2} P_{tx}$.

3) Resonant Coupling-Based Single-Hop WPT Model: The resonant coupling-based single-hop WPT model is given by [53]:

$$P_{rx} = \mu(d) P_{tx} \tag{13}$$

where $\mu(d)$ is the efficiency of WPT between a sensor and an MC at distance *d*, which is expressed as:

$$\mu(d) = \begin{cases} -0.0958 d^2 - 0.0377 d + 1, & \text{if } d \le r \\ 0, & \text{if } d > r \end{cases} \tag{14}$$

4) Resonant Coupling-Based Multi-Hop WPT Model: Herein, the sensors act as repeaters to relay excessive energy to their neighboring sensors. The resonant coupling-based multi-hop WPT model [62] is defined as:

$$P_{rx} = \mu_k(d) P_{tx} \tag{15}$$

where $\mu_k(d)$ is the charging efficiency of the k^{th} repeater sensor, which is given by:

$$\mu_k(d) = \begin{cases} \frac{I_k^2}{\sum_{j=1}^{k} I_j^2}, & \text{if } d \le r \\ 0, & \text{if } d > r \end{cases} \tag{16}$$

where I_k is the current on k^{th} repeater sensor.

C. Design Issues

This section presents the fundamental system design issues that the researchers have taken care of while addressing the MCP. In particular, these matters involve ensuring continuous coverage of points of interest (PoI) by sensors and connectivity among the sensors by utilizing the redundancy in sensor deployment for long-run network operation. Similarly, determining the minimum number of MCs (MNoM) to ensure perpetual network operation and their collaboration strategies are also vital. The other pressing matters are finalizing the sensor's flow routing and MC's space-time scheduling, including traveling path, charging time, and velocity control. We now discuss each of these issues in detail as follows.

1) Coverage and Connectivity (CC): Like the conventional WSNs, the PoI in WRSNs needs to be adequately covered by sensors and connectivity among the sensors must be ensured. Typically, the sensing coverage of a sensor is characterized by a circular disk [63], i.e., the PoI within the circular range of the sensors is considered covered. We can obtain the minimum number of sensors for ensuring coverage of PoI by positioning them on the vertices of equilateral triangles [63]. However, deploying sensors by providing coverage and connectivity is insufficient to guarantee continuous monitoring of PoI as sensors will eventually drain their batteries and become dead. Under these circumstances, it is essential to plan the charging schedule of the sensors by considering the coverage and connectivity issues [64], [65]. Apart from ensuring coverage and connectivity of the PoI, the charging coverage of sensors, i.e., recharging as many panic sensors as possible before their energy exhaustion, is an equally important issue [66], [67].

2) Sleep Scheduling (SS): Once the coverage and connectivity assured deployment is achieved, the network operation period can be divided into time slots. Due to redundancy in the deployment pattern, the sensors can be duty-cycled and alternate between sleep and active modes [68]. In the sleep mode, the sensors turn off their communication and sensing devices and consume a negligible amount of energy. As a result, the network requires one or more sensors to remain in inactive mode from the overlapped areas at any point in time, while other sensors remain in sleep mode for conserving energy. When the first batch of sensors exhausts their battery power, another batch of sensors with full energy is appointed to take their sensing responsibility [65]. Thus, this strategy results in balanced energy consumption among the sensors. However, the sensors of a batch require to be recharged before they take back the sensing responsibility from another batch. Therefore, the space-time scheduling of the MCs is usually designed as per sensor's sleep scheduling [69] and vice versa.

3) Flow Routing (FLR): Sensors usually send their sensory data to the BS using multi-hop data flow routing to conserve energy [70], [71]. There are two types of data flow routing, i.e., static [72], [73] and dynamic [74]. In the former, the data routing paths are determined only once during the setup phase and retained throughout the network lifetime, while they are dynamically adjusted in the latter. Since the data generation rate of sensors is time-dependent and can be non-linear, a static data flow routing may not be suitable for real-time applications. Therefore, it is vital to utilize a dynamic flow routing strategy to relay the sensory data to the BS. In addition, the data sampling and energy consumption rates of the sensors require to be adjusted as per their residual energy [75]. Note that the flow routing mechanism and the mobile charging policies are closely related. In particular, there exists two alternatives to incorporate the flow routing with the space-time scheduling of the MCs. First, each of the two problems can be solved independently, one after another. Second, these two problems can be combined for solving them simultaneously such that no sensor becomes dead and all the sensory data is transmitted to the BS. In general, the flow routing scheme should be designed such that the sensors closer to the APs of the MCs take more routing load than the others and vice-versa. Similarly, MC's space-time scheduling should allocate more charging time to the sensors that are closer to the BS and APs as they tend to deplete more energy than other sensors [76].

4) Minimum Number of MCs (MNoM): In small-scale networks, a single MC has been shown to perform well since the network contains a limited number of sensors and has a small deployment area [17]. However, a single MC is not enough to recharge all energy-critical sensors in a large-scale network due to its limited battery capacity and nontrivial charging time of the sensors [16]. As a result, many panic sensors will die, and the perpetual network operation can no longer be achieved. Hence, it is essential to deploy multiple MCs with limited energy capacities, ensuring that each panic sensor's energy is restored before it becomes dead [66], [77], [78]. This enables recharging multiple sensors simultaneously and thus, reduces charging delay. However, using multiple MCs for energy replenishment is usually cost-inefficient as an MC is much more expensive than a sensor. Besides, this has been shown that finding the minimum number of MCs to keep the network perpetually operational is an NP-hard problem [67], [79]–[83].

5) Space-Time Scheduling (STS): The movement of MCs is usually constrained by both space and time. For instance, the chargers in structural health monitoring applications are usually mounted on the existing infrastructures, such as public transport vehicles (treated as MCs) traveling through fixed paths [84]. In contrast, the MC must complete each charging task within a specified deadline in a mission-critical practice [85]. In general, MC's space-time scheduling comprises of three sub-design issues: 1) What should the traveling path of the MCs be? 2) What should the charging time of the sensors be? and 3) What should the velocity of the MCs be? A brief note on the each of the issues mentioned above is given as follows.

a) Traveling path (TP): Most pressing issue to address the MCP is to construct the traveling path of the MCs [65], [86]. Usually, the traveling path is determined for periodic timeline [70], [84] and on-demand timeline [87], [88]. In the first situation, the controller first determines a charging path for each MC, and then each MC periodically repeats the same path throughout the network operation period. In the second case, the controller frequently updates MC's traveling path as per the sensors' energy demands. In general, the controller selects a set of sensors to be recharged and obtains some APs near those sensors. Based on the APs, the controller finalizes

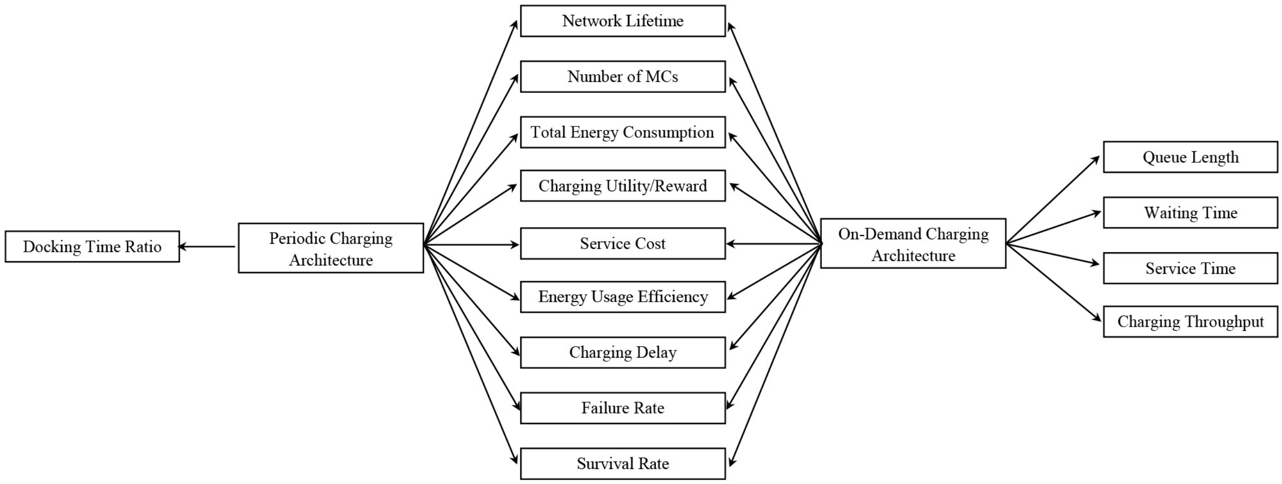

Fig. 3. Performance metrics to quantify the quality of service provided by the MCTs.

MC's traveling path to optimize a given objective function within the underlined constraints. After that, each MC starts traveling from its depot with full energy and sojourns its APs to recharge sensors along its traveling path. The MC returns to the depot for maintenance after completing its charging tour or when its remaining energy is too low.

b) Charging time (CT): Even though the traveling path of an MC is obtained, the determination of charging time (or energy) allocated to the selected energy-critical sensors remain unsolved. The naive idea is to allocate an identical charging time to all the sensors following a full [17] or partial [89] charging policy. However, in real-time applications, the charging time of sensors differs from each other due to their non-deterministic energy consumption rates [16]. In addition, the energy received by the sensors from MCs is also influenced by the distance between sensors and MCs [12], [13]. In particular, the charging time increases with the increase in distance between the sensors and the MCs as the efficiency of WPT decreases as the distance increases. Hence, it is desirable that an MC recharges a sensor from the nearest possible location to it and as long as possible. Note that the amount of energy provisioned to a critical sensor during a charging tour must be greater than or equal to the amount of energy consumed by the sensors till it gets recharged again to ensure its perpetual operation [52].

c) Velocity control (VC): Velocity control [90]–[92] of the MC has a crucial act in reducing the total time taken by the MC to complete its charging tour. The total time is made up of two quantities: traveling time and charging time. The former is the time incurred by the MC to restore the energy of all the sensors in the charging tour, while the latter is the time required by the MC to travel through the same charging tour. Typically, the MC can change its velocity during the charging process. Note that the velocity control mechanism can notably decrease both the traveling and charging time. The charging tour of the MC can be discretized in various segments to enable the benefits of velocity control. On the one hand, MC's traveling time can be reduced by assigning a high velocity to the segments in which MC travels between two stop locations. On the other hand, when MC's velocity is low, sensors' charging time can be reduced by realizing the concept of charging on the move. However, these two strategies are conflicting, and thus, the traveling and charging time cannot be optimized simultaneously with velocity control. Further, it is non-trivial to regularly change the velocity of MC along its charging tour to reduce the charging completion time. Thus, a trade-off between traveling and charging time requires to be achieved for efficient energy replenishment.

6) Collaboration Strategy (CS): In a large-scale network, when multiple MCs work independently, their energy consumption rate may not be identical [16], [93]. This is because non-deterministic data generation and transmission rates of the sensors usually leads to unbalanced charging load distribution among the MCs. In other words, some MCs can be burdened more than others. Further, individual MCs having limited energy can barely travel to and recharge the farthest sensors [61], [94]. Hence, it is necessary to rely on a collaborative charging paradigm to eliminate the influence of uncertainties described above. In collaborative charging [80], [82], the MCs cooperate to ensure the continuous operation of sensors. This cooperation can be of two types. First, energy can be transferred from one MC to another MC to improve the network coverage [93]. Second, the charging load of MCs with low residual energy can be transferred to the MCs having high residual energy [16]. These new flexibilities given to the MCs enable effective exploitation of limited power sources and result in increased charging coverage and energy usage efficiency.

D. Performance Metrics

This section describes various performance metrics used to measure the performance of the MCTs, as shown in Fig. 3. Typically, an MCT optimizes one or more metrics and satisfies a few metrics as the constraints. It is worthwhile to mention that some of the metrics are conflicting in nature; for instance, when the sensors conceive a short charging delay, the service cost of the MCs may increase. Similarly, when fewer MCs are

employed, the network lifetime may decrease. We now briefly describe these metrics as follows.

1) Docking Time Ratio (DTR): In WRSNs, the MCs have limited energy capacity to support their traveling and charging operations. The energy consumed by an MC is directly related to the time spent by it in the sensor field, i.e., cycle time. Therefore, it is vital to minimize the MC's cycle time to minimize its total energy consumption and maximize energy usage efficiency. Although reducing the cycle time is equivalent to enhancing the docking time ratio (DTR) [52], [53], which is defined as the ratio of MC's vacation time and cycle time, i.e.,

$$DTR = \frac{\tau_{vac_i}}{\tau_i} \tag{17}$$

where τ_{vac_i} and τ_i are the vacation time and traveling time of the MC v_i, respectively.

2) Network Lifetime (NL): Network lifetime [65], [95], [96] is a crucial performance metric since the sensors are equipped with small batteries. Several definitions of the network lifetime are suggested in the existing works. For example, it is the time till the last sensor dies or the first sensor dies, or a certain percentage of sensors die. This may be noted that a sensor is treated as dead if its energy falls below the minimum energy required to be operational. In some situations, the network lifetime is also considered as the period until the first coverage hole occurs [65]. In this survey, we define the network lifetime *NL* as the time till the first sensor dies, and it is obtained as:

$$NL == \min_{1 \leq i \leq n} NL_i^s \tag{18}$$

where *n* is the total number of sensors and NL_i^s denotes the lifespan of sensors s_i.

3) Number of MCs (NoM): In multiple MCs-based charging techniques, it is desirable to deploy the minimum number of MCs for ensuring perpetual network lifetime [66], [67], [77]–[83]. This is because the monetary cost of a mobile charging system is directly proportional to the number of MCs employed. Let the charging period $\mathcal{T}$ be divided into *r* equal sized time slots, then the number of MCs *NoM* used during the charging process can be calculated as:

$$NoM == \max_{1 \leq i \leq r} NoM_i^v \tag{19}$$

where NoM_i^v is the number of MCs used in i^{th} time slot.

4) Total Energy Consumption (TEC): The operating cost of an MCT is directly associated with the total energy consumption [94], [97]. An MCT having a low total energy consumption is said to be cost-efficient. The amount of energy consumed by an MC v_i can be divided into three parts: the energy transferred to the sensors, the energy spent by the MC for traveling, and the energy loss during wireless charging. The first part is regarded as the payload energy E_i^p, and the sum of the remaining two parts is treated as the overhead energy E_i^o. Therefore, the total energy consumption *TEC* is obtained as:

$$TEC = \sum_{i=1}^{m} E_i^p + E_i^o \tag{20}$$

where *m* is the total number of MCs.

5) Charging Utility/Reward (CU/CR): The charging utility/reward [83], [98], [99] helps us measure the effectiveness of a mobile charging system. Intuitively, the sensors having low residual energy should be recharged with higher priority to minimize the number of dead sensors. Therefore, the charging utility/reward gained by recharging a critical sensor is defined as a sub-modular function $f(.)$, which implies that the utility gained by recharging a sensor having low residual energy is higher than that of reviving a sensor with high residual energy. In other words,

$$f\left(s_j\right) = E_j^s(full) - E_j^s(res) \tag{21}$$

where $E_j^s(full)$ and $E_j^s(res)$ are the initial and residual energy of sensor s_j, respectively.

Then, the charging utility/reward *CU/CR* received by an MC is determined as:

$$CU/CR = \sum_{\forall s_j \in P_i} f\left(s_j\right) \tag{22}$$

where P_i is the traveling path of the MC v_i.

6) Service Cost (SRC): Some researchers [100]–[102] evaluated the performance of the MCTs based on the service cost, which is defined as the total distance traveled by the MCs during the charging process. Typically, it is observed that the service cost linearly increases with the increase in the number of to-be-charged sensors, number of MCs, and network size. An MCT with a low service cost is desirable since the energy consumed for traveling is considered overhead. The service cost *SRC* is evaluated as:

$$SRC = \sum_{i=1}^{m} TT_i^v \times s_i^v \tag{23}$$

where TT_i^v and s_i^v are the traveling time and speed of MC v_i, respectively.

7) Energy Usage Efficiency (EUE): Many studies [71], [93], [103] regarded energy usage efficiency as a crucial performance parameter since the MCs carry only a limited amount of energy. An MCT with a high energy usage efficiency is the most cost-effective way to replenish the energy of panic sensors. The energy usage efficiency is defined as the ratio of payload energy to the total energy consumption and calculated as:

$$EUE = \frac{\sum_{i=1}^{m} E_i^p}{\sum_{i=1}^{m} E_i^p + E_i^o} \tag{24}$$

where E_i^p and E_i^o are the payload energy and overhead energy of MC v_i, respectively.

8) Queue Length (QL): In on-demand scenario, the performance of an MCT is analyzed based on the queue length [104], [105], which refers to the average number of charging requests recorded during the charging process. It reflects MC's operational capability and sensor's energy state. A mobile charging system having a shorter queue length indicates a higher successful charging rate and energy usage efficiency. Contrarily, a longer queue length leads to higher waiting time (WT) and response time (RT) and a higher

charging latency. The average queue length *QL* is defined as:

$$QL = \frac{\sum_{i=1}^{r} QL_i^s}{r} \tag{25}$$

where QL_i^s denotes the waiting queue length at i^{th} time slot.

9) Waiting Time (WT): In on-demand charging, the waiting time [106]–[108] relates to the time spent by a charging request in the request queue (or service pool) before an MC decides to serve it. A mobile charging system with a short waiting time is desirable since it yields a quick response time and thus enhances the network lifetime. Let WT_i^s denote the waiting time of sensor s_i, then the average waiting time *WT* is calculated as:

$$WT = \frac{\sum_{i=1}^{n} WT_i^s}{n} \tag{26}$$

where

$$WT_i^s = \sum_{\forall s_j \in Prev_i} TT_j^s + CT_j^s \tag{27}$$

Here $Prev_i$ denotes the set of sensors recharged before sensor s_i. TT_j^s and CT_j^s denote the time taken by MC for traveling to and charging the sensor s_j, respectively.

10) Service Time (ST): The time taken by an MC for traveling to a sensor from its current location and subsequently recharging that sensor is known as the service time [71], [109]. Typically, an MCT with a short service time is favored because more sensors can be covered with a lower service cost and total energy consumption. Let ST_i^s denote the service time of a sensor s_i, then the average service time is defined as:

$$ST = \frac{\sum_{i=1}^{n} ST_i^s}{n} \tag{28}$$

where

$$ST_i^s = TT_i^s + CT_i^s \tag{29}$$

Here TT_i^s and CT_i^s are the time taken by MC for traveling to and charging the sensor s_i, respectively.

11) Charging Delay (CD): Charging delay [17], [71], [102], [106] is the most salient metric to analyze the performance of an energy replenishment scheme.It is defined as the average time taken by the MC to recharge the panic sensors. Note that the charging delay is also referred as the response time or the charging latency. In general, an MCT having a short charging delay is preferred as it expedites the energy restoration process and recharges more sensors in time. The average charging delay *CD* is calculated as:

$$CD = \frac{\sum_{i=1}^{n} WT_i^s + ST_i^s}{n} \tag{30}$$

where WT_i^s and ST_i^s are the waiting time and service time of sensor s_i, respectively.

12) Charging Throughput (CHT): Charging throughput is a vital performance metric to keep track of network stability. It depicts the average number of sensors served by the MCs in each time slot. Ideally, a higher charging throughput indicates that more sensors are being recharged and thereby enhancing the network lifetime. The average charging throughput *CHT* is defined as:

$$CHT = \frac{\sum_{i=1}^{m} rc_i}{r} \tag{31}$$

where rc_i denotes the number of sensors recharged by MC v_i.

13) Failure Rate (FR): The failure rate [110], [111] reflects the energy replenishment capability of an MCT to prevent sensors from running out of energy. Note that a sensor ceases functioning once its energy level falls below the minimum energy required to be operational and remains nonfunctional until its energy is replenished. A system with a low failure rate is preferred for achieving a high network lifetime. The failure rate is measured as the ratio of the number of dead sensors to the total number of sensors, i.e.,

$$FR = \frac{\sum_{i=1}^{n} b_i}{n} \tag{32}$$

where b_i is a Boolean variable defined as:

$$b_i = \begin{cases} 1, & \text{if sensor } s_i \text{ is dead} \\ 0, & \text{otherwise} \end{cases} \tag{33}$$

14) Survival Rate (SR): The survival rate [85], [112], [113] is a metric to characterize the efficiency of the MCTs. It refers to the ratio of the number of alive sensors to the total number of sensors. Note that a sensor is said to be alive if its battery power is above the minimum energy level required to be functional. A system with a high survival rate is encouraged for improving network's reliability. The survival rate *SR* is defined as:

$$SR = \frac{\sum_{i=1}^{n} c_i}{n} \tag{34}$$

where c_i is a Boolean variable defined as:

$$c_i = \begin{cases} 1, & \text{if sensor } s_i \text{ is alive} \\ 0, & \text{otherwise} \end{cases} \tag{35}$$

IV. Taxonomy of Mobile Charging Techniques

We now consider a large number of attributes and present an exhaustive taxonomy to classify and compare the existing MCTs, as shown in Fig. 4. In particular, we categorise the literature based on service timeline, number of MCs, control structure, charging options, design issues, design objectives, and design constraints. This taxonomy will permit us to group similar works and review them together as they deal with similar challenges and constraints. Besides, these suggested design attributes will be used as comparison criteria to compare and contrast different MCTs.

We consider service timeline as the primary criterion for classifying the MCT literature as periodic charging schemes [81] and on-demand charging schemes [93]. In periodical charging, it is assumed that residual energy level of the sensors follows a cyclic trend with time and can be recharged in a deterministic manner. Periodic schemes can be divided into two groups depending on the tasks of the MCs. The first group includes methods for exclusive energy provisioning (EEP) [114] in which MCs' job is only to recharge the sensors. The second group comprises strategies for joint data collection and energy provisioning (JDCEP) [115] in which the MCs perform two tasks, i.e., data collection and energy provisioning.

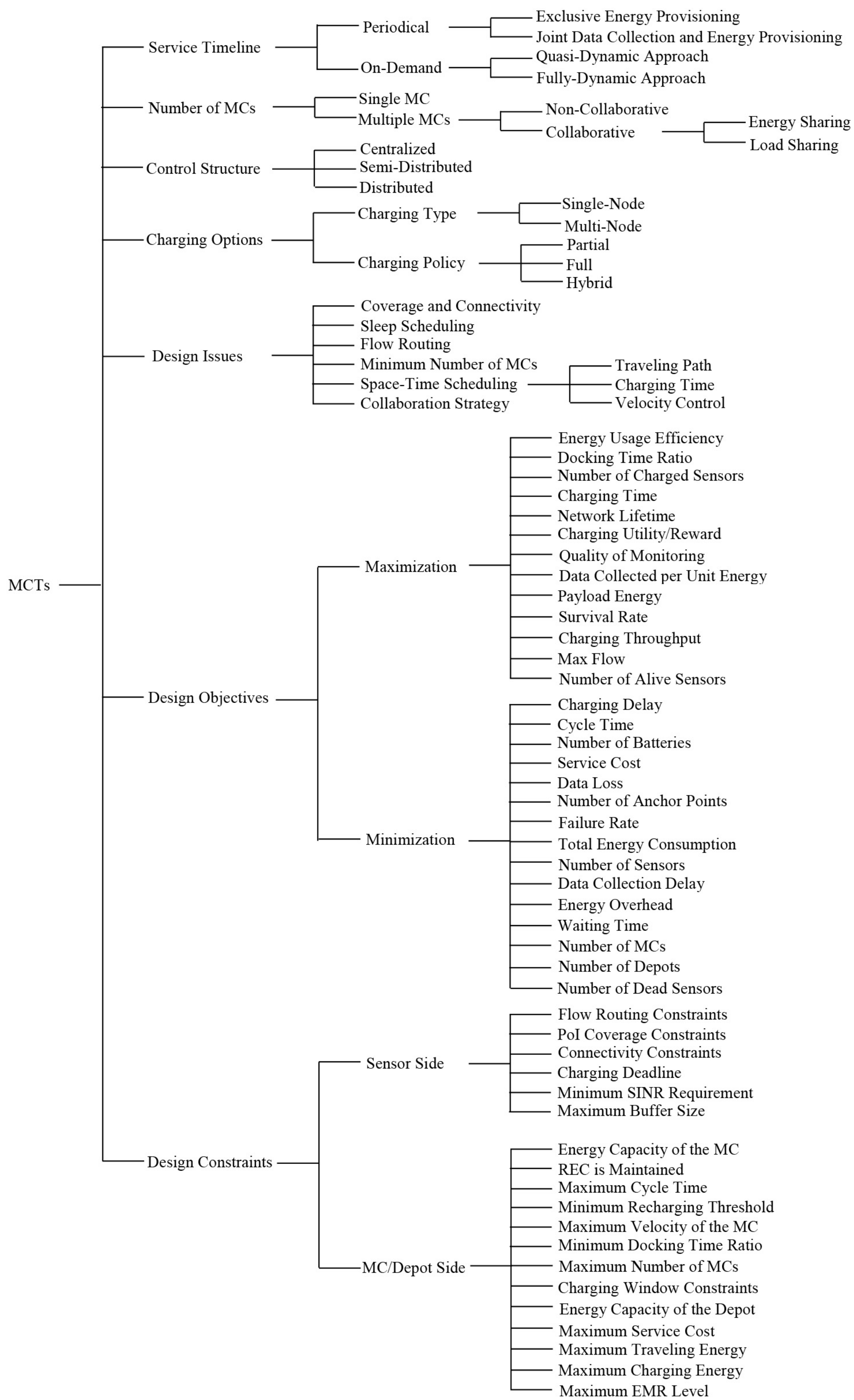

Fig. 4. Taxonomy of mobile charging techniques.

In general, the space-time scheduling of MCs is determined by converting the MCP into the travelling salesman problem (TSP) and then obtaining the shortest Hamiltonian cycle as the charging tours of those MCs. Once the charging tours are formulated, the MCs periodically traverse them to recharge the sensors.

The periodic charging schemes are better suited for sensor networks having fixed energy consumption profiles due to the assumptions that the sensors consume their energy at a constant rate and a priori global information of the network is available. However, the sensors can have diverse energy profiles in event-driven applications. In addition, a

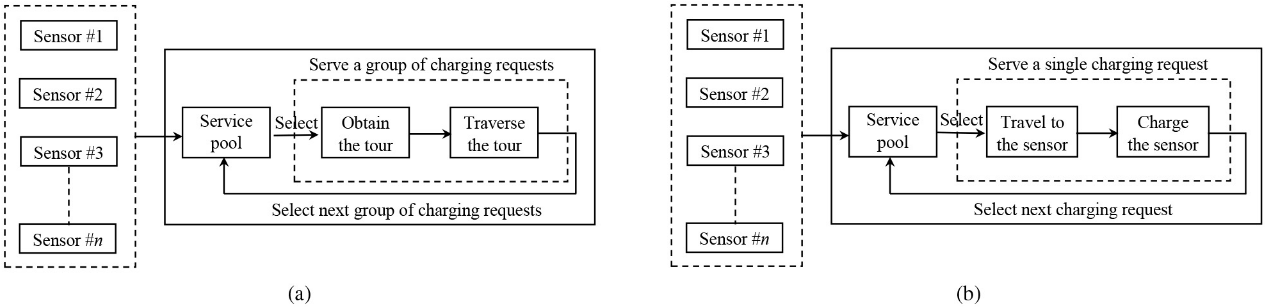

Fig. 5. Queuing models for (a) QDA and (b) FDA [116].

prior information may not always be available in practice due to connectivity issues like disconnected networks. Also, such techniques usually recharge all the sensors irrespective of their energy level. In that case, the MCs visit many energy-sufficient sensors unnecessarily, which is not desirable. Therefore, the periodic schemes are vulnerable to small changes in network dynamics and lack adaptability.

In contrast to periodical charging, the sensors are recharged based on their charging requests to the MCs in on-demand charging. In general, each sensor monitor its energy level and send a charging request to the MCs when its energy level drops below a given threshold value. The MCs wait for the charging requests from the sensors and accumulates them in a request queue implemented using the $M/G/1/N/3DC$ queuing model [116]. The MCs then take a quasi-dynamic approach (QDA) [109] or a fully-dynamic approach (FDA) [116] in order to fulfill the energy demands of sensors. In QDA, the controller periodically selects a group of charging requests from the request queue and then determines the space-time scheduling of the MCs, as shown in Fig. 5a. The MCs then traverse their charging tours and restore the energy of the selected sensors. Note that the remaining charging requests and the requests received when the MCs are on a charging mission are served in the subsequent recharging rounds.

Unlike QDA, the controller selects only a single charging request from the request queue at a time and commands an MC to recharge the selected sensor in the FDA, as shown in Fig. 5b. The controller re-determines a next-to-be-served charging request once the MC has finished the current charging task and the MC then fulfills it. This process is repeated till all the charging requests are served. In other words, the charging tours of the MCs are dynamically updated to accommodate the newly received energy demands in the FDA. In this way, the requirement of a priori global knowledge is relaxed, and the MCs do not visit any energy-sufficient sensors unnecessarily. In addition, the controller can adjust the space-time scheduling of the MCs depending on sensors' criticality. Hence, the on-demand charging architecture is more flexible and adaptive.

The number of MCs employed is the next criterion to classify MCTs as single MC-based techniques (SMT) [52], and multiple MCs-based techniques (MMT) [117]. The former employs a single MC to recharge all the sensors in a small-scale network. Although such schemes are easy to implement and cost-effective, they are unsuitable for large-scale networks. The reason is that a single MC can carry a limited amount of energy and recharge only a few sensors in a charging tour, i.e., the MC would frequently return to the depot to replenish its own power. However, several sensors may require energy replenishment simultaneously in a large-scale network, which a single MC cannot fulfil. As a result, the number of dead sensors will drastically increase, and hence, the perpetual network operation can no longer be achieved. In contrast, the latter method employs multiple MCs to ensure continuous network operation in large-scale networks. In particular, multiple MCs travel across the network region and recharge the sensors using a collaborative or non-collaborative approach. Collaborative charging strategies focus on the MCs' cooperation and allow them to share their energy or charging loads while they work independently in a non-collaborative setup.

Alternatively, the literature can be classified based on the adopted control structure. In particular, we can embrace three types of control structures to implement the MCTs, i.e., centralized [118], or semi-distributed [85], or distributed [81]. In a centralized control structure, a single entity (usually BS) is responsible for performing all the necessary communication and computing activities, such as obtaining the energy status of network components and preparing space-time scheduling of the MCs. Similarly, in a semi-distributed control, a central entity first divides the network (or sensors) among the MCs, and then the MCs recharge the sensors assigned to them in a distributed manner. On the other hand, all the MCs work independently in a distributed control structure.

Similarly, we can categorize the MCTs based on different charging options, including charging type and charging policy. The MCs follow single-node charging (SNC) or multi-node charging (MNC) to replenish the energy of the sensors. In SNC, an MC recharges a single sensor at a time using point-to-point charging [13], while it revives multiple sensors simultaneously using point-to-multipoint charging in the MNC [119]. Also, the MC can adhere to a partial, or full, or hybrid charging policy for recharging the sensors. The partial and full charging policies replenish sensors' battery energy partially [120] and fully [121], respectively. In contrast, the hybrid charging policy recharges some sensors partially and some fully [122].

Another class of attributes for classifying the MCTs include design issues, design objectives, and design constraints. In particular, the design issues are coverage and connectivity [64], sleep scheduling [68], flow routing [74], minimum number of MCs [77], collaboration strategy [93], space-time scheduling.

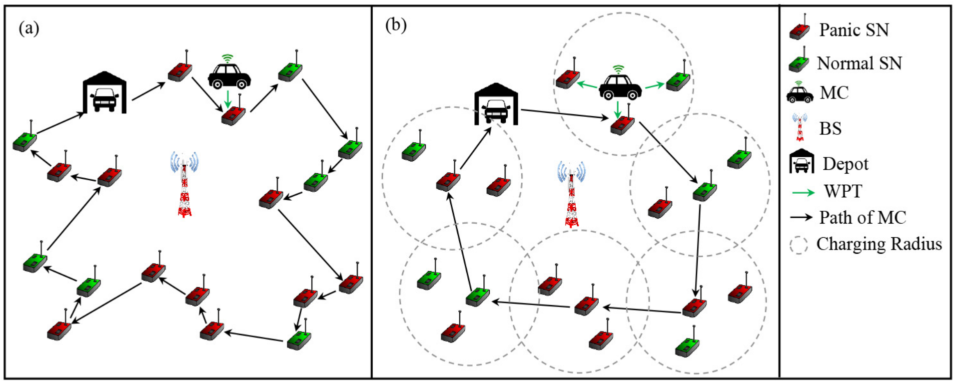

Fig. 6. Reference models of single MC-based periodic techniques for EEP with (a) SNC and (b) MNC approaches.

In fact, space-time scheduling has three sub issues: traveling path [65], charging time [123] and velocity control [91]. We can also classify the literature from the design objectives viewpoint. The maximization objectives are energy usage efficiency [124], docking time ratio [52], number of charged sensors [125], charging time [67], network lifetime [126], charging utility/reward [98], quality of monitoring [64], data collected per unit energy [115], payload energy [127], survival rate [126], charging throughput [113], max flow [128], and number of alive sensors [129]. In contrast, the minimization objectives are charging delay [130], cycle time [52], number of batteries [131], service cost [88], data loss [132], number of anchor points [133], failure rate [134], total energy consumption [135], number of sensors deployed [136], energy overhead [121], waiting time [122], number of MCs [77], number of depots (NoD) [83], and number of dead sensors [137].

We consider the design constraints as the last attribute for categorization. These constraints can be divided into sensor side and MC/depot side constraints. The former constraints are flow routing constraints [97], PoI coverage constraints [138], sensor connectivity constraints [135], charging deadline [139], minimum SINR requirement [140], and maximum buffer size [123]. Whereas the latter constraints comprise of energy capacity of the MC [95], renewable energy cycle (REC) is maintained [52], maximum cycle time [123], minimum recharging threshold [76], maximum velocity of the MC [91], minimum docking time ratio [138], maximum number of MCs [141], charging window constraints [142], energy capacity of the depot [83], maximum service cost [98], maximum traveling energy [143], maximum charging energy [124], and maximum electromagnetic radiation (EMR) level [144].

This may be noted that these categories and sub-categories of the taxonomy are not mutually exclusive, i.e., some of the MCTs belong to more than one category or sub-category. Therefore, in this paper, we review the literature by dividing it into two major categories: periodic charging schemes and on-demand charging schemes. In these categories, we first review the SMT and then discuss the MMT by illustrating their reference models. In addition, we compare and contrast the state-of-the-art MCTs through tables by specifying design objectives, design constraints, solution approaches, charging options, performance metrics, evaluation methods, and limitations.

V. PERIODIC CHARGING SCHEMES

In this section, we present a detailed discussion on various periodical SMT and MMT by illustrating the EEP and JDCEP techniques with single and multiple MCs. As stated earlier, most of the literature on periodic charging determines MC's space-time scheduling by converting the MCP into the TSP. Indeed, the charging tour of the MC is obtained by finding the solution to the TSP, i.e., the shortest Hamiltonian cycle through the designated APs. Further, we summarize and compare various periodic techniques in each subsection based on the proposed taxonomy.

A. Single MC-Based Techniques (SMT)

1) Exclusive Energy Provisioning (EEP): Fig. 6 portrays reference models of single MC-based EEP techniques with SNC and MNC approaches. Here, the green and red sensors depict the normal and panic sensors, respectively. The panic sensors are the sensors which are low on energy and require recharging, while the normal sensors have adequate battery power. Besides, the black and green lines denote the traveling path of the MC and the WPT link between the MC and sensors, respectively. In Fig. 6a, the MC starts traveling from the BS, visits each sensor to revive it through the SNC approach, and then returns to the BS. In contrast, in the MNC approach, the MC recharges the sensors by visiting some APs, as shown in Fig. 6b in which dotted circles represent MC's charging radius and the APs are co-located with the sensors.

In the past decade, a plethora of researches [52]–[54], [64], [65], [68], [71]–[74], [76], [86], [88], [90]–[92], [112], [114], [124], [125], [130]–[133], [136], [138], [145]–[159] have been published on single MC-based periodic EEP techniques. The papers [52], [54], [64], [65], [68], [72]–[74], [76], [88], [112], [114], [125], [130]–[132], [136], [138], [145]–[148], [150], [151], [154], [158], [160], [161] employed the SNC approach to recharge the sensors. In particular, the authors [72]–[74], [76] studied the MCP by jointly considering the flow routing and MC's trajectory design. To the best of our knowledge, Li *et al.* [72] are the first authors to use a wireless MC with the SNC approach. The same authors developed the first proof-of-concept to evaluate the

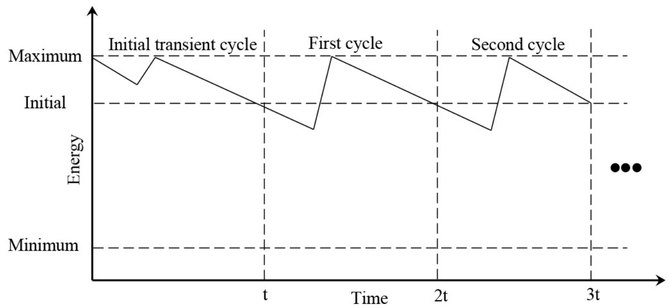

Fig. 7. An example of energy behavior during initial transient cycle and the first two RECs [52].

feasibility of real-time implementation of point-to-point charging in [73]. They examined the impact of routing algorithms, wireless charging efficiency, and various design parameters. However, both [72], [73] did not consider MC's service cost. Li *et al.* [74] proposed a joint routing and charging scheme by considering the energy-minimum and energy-balanced routing for balancing the routing load among the sensors and recharging the critical sensors in time. They also carried out real-time experiments on a small-network of TelosB motes. Han *et al.* [76] divided the network region into multiple equal-sized grids and treated the vertices of grid cells as the APs of the MC. They then presented a routing algorithm based on MC's charging behavior and determined its charging tour.

The [52], [54], [130], [145], [148] aimed to minimize the cycle time. Xie *et al.* [52] introduced the concept of renewable energy cycle, which is defined as the duration for which a sensor meets the following two conditions: (i) its energy level starts and ends with the same level in each cycle, and (ii) its energy level never drops below a given threshold value for the duration of the cycle. The energy levels of a sensor during the initial transient cycle and the first two renewable energy cycles are shown in Fig. 7. They established that minimizing the cycle time is similar to maximizing the ratio of MC's vacation time to the cycle time, i.e., docking time ratio. They then jointly optimized the flow routing, charging tour, and charging time allocation to maximize the docking time ratio. However, they did not consider the heterogeneous energy consumption rate of sensors and unreliable wireless communication link quality. In contrast, Shi *et al.* [54] considered a dynamic multi-hop routing arrangement to maximize the docking time ratio. Rao *et al.* [145] solved an optimization problem using CPLEX to minimize the cycle time.

The studies [125], [130], [132], [147], [148] put forward various algorithms to design the traveling path of the MC for different objectives. Zhu *et al.* [130] reported an ellipse-based discretization scheme to determine the trajectory of the MC and a greedy algorithm to find the depot's location. Lyu *et al.* [148] proposed a hybrid particle swarm optimization genetic algorithm-based solution to maximize the docking time ratio. Chen *et al.* [125] proposed a poly-logarithmic approximation algorithm to maximize the number of recharged sensors in each charging round. Han *et al.* [147] exploited four space-filling curves, i.e., Z-Curve, HILBERT, SRCAN, and S-Curves(ad), to form MC's traveling path, whereas Sangare *et al.* [132] devised a Markov decision process for the same. Hu *et al.* [88] used a charging vehicle with k removable wireless chargers to recharge the sensors with charging window constraints. The vehicle initially visits k sensors, places one charger near each sensor, collects the chargers, and puts them near the next k sensors after fully recharging the first batch of sensors. This process is repeated till the energy of all the sensors in MC's tour is restored.

The papers [64], [65], [68], [136], [138], [149] studied the coverage and connectivity issues and traveling path planning combinedly. The paper [149] focused on charging-oriented sensors placement and flexible charging instead of a full or nothing charging policy to ensure coverage of all the PoI. They proposed an approximation algorithm to solve a sub-modular function maximizing problem to maximize the charging utility under the constraint of flow routing. Zhu *et al.* [138] devised two algorithms to find the minimum number of sensors required to ensure perpetual target coverage with their locations and routing paths. Wang *et al.* [136] envisioned deploying sensors with dual-energy harvesting capabilities, i.e., solar and wireless power. In particular, they solved a minimum number of sensors' perpetual coverage of targets problem using two heuristic algorithms. The first algorithm minimizes the number of sensors by discretizing the network area. In contrast, the second algorithm initially places a sensor near each PoI and then lessens the number of sensors. In addition, the authors used an MC to ensure sensors' continuous operation when solar energy is insufficient.

The proposals [64], [65], [68], [158] considered the sensor's sleep scheduling and MC's space-time scheduling simultaneously. Shu *et al.* [65] proposed a provable sub-optimal heuristic to maximize the network lifetime by ensuring full coverage of the sensing field. Kan *et al.* [158] proposed a two-phase scheme to maximize the surveillance quality measured in terms of the number of sensors connected to the BS. The works [64], [68], [154] studied the problem of stochastic event capturing with different objectives. Cheng *et al.* [68] solved the problem of efficient event capturing along with the MCP to maximize the quality of monitoring (QoM). However, they assumed that the charging time of each sensor is identical, and a single sensor monitors each PoI. In contrast, Dai *et al.* [64] solved a charging and scheduling problem to maximize QoM, such that multiple sensors can monitor the same PoI. Sun *et al.* [154] focused on the charging exclusivity issue (i.e., charging and sensing cannot exist simultaneously) and solved a combinatorial optimization problem to maximize the charging utility with flow routing constraints.

The papers [112], [114], [133], [146] employed a UAV to recharge the sensors in harsh terrains. Johnson *et al.* [146] examined the feasibility of reviving the sensors of a bridge monitoring system. Wang *et al.* [133] jointly optimized the sensor's activation scheduling and the UAV's trajectory to maximize the payload energy. Jin *et al.* [112] presented a bus network-assisted UAV-based energy replenishment scheme in which the UAV starts flying from a bus, recharges the sensors, and returns to the nearest bus for its own recharge. Wu *et al.* [114] optimized UAV's flight and hovering times to minimize the number of APs and cycle time while maximizing

the charging time. Ding *et al.* [131] assumed that the MC could visit multiple depots to replace its battery and devised two approximation algorithms to minimize the number of batteries used by the MC to recharge all the sensors fully.

This is worth noting that the papers discussed above adhere to a centralized control structure in which the controller requires global knowledge of the network components. However, global information may not always be available in practice. In contrast, Angelopoulos *et al.* [150], [151] proposed various distributed algorithms to solve the MCP. In [150], they devised a fully distributed charging algorithm, which is restricted to a network with uniform node deployment and does not take flow routing into account. To fill this gap, they put forward three novel charging algorithms by considering diverse levels of network information in [151].

The works reviewed so far are not suitable for dense and large-scale networks. The is because they used the SNC approach that leads to increase in the charging latency and reduction in the energy usage efficiency. In contrast, the references [53], [70], [86], [90]–[92], [95], [115], [124], [133], [149], [152], [153], [155]–[157], [162], [163] exploited the MNC approach that allows the MCs to recharge multiple sensors simultaneously. Hence, the charging latency can be reduced and the energy usage efficiency can be increased significantly. Xie *et al.* [53] divided the network region into a hexagonal grid and considered the center point of each grid cell as an AP to extend their idea of REC [52] for the MNC approach. They solved a joint nonlinear optimization problem for flow routing, traveling path, and charging time, with the aim of maximizing the docking time ratio. However, the sensors need to frequently transmit their energy status to the depot using a multi-hop routing, which incurs a significant portion of network energy.

On the other hand, Lin *et al.* [153] proposed a hybrid clustering charging algorithm by creating a virtual backbone using a minimum connected dominating set. They combined $k-$means and hierarchical clustering algorithms to deal with the energy awareness and location relationship. Further, they proposed another algorithm for splitting the mobile charging process into several tasks and sub-tasks. The work [155] first predicted the energy consumption rate of sensors and clustered them into specific groups using an improved $k-$means algorithm. The charging tour of the UAV is then determined by finding the shortest path through the cluster centers. Further, they modeled the interference mitigation problem as a mean-field game and then devised a finite difference algorithm using the upwind scheme to obtain the optimal power control policy for sensors to minimize communication interference and improve the energy usage efficiency.

Similarly, Moraes *et al.* [156] divided the charging process into two phases. The first phase groups the sensors into some clusters, and an MC periodically recharges all the cluster heads and the sensors in their vicinity. In the second phase, the sensors revived in the first phase act as the seller sensors, while the remaining sensors become the buyer sensors for energy trading among themselves. The seller sensors transmit surplus energy to the buyer sensors via many-to-one correspondences to bring their power to the desired level. The work [86] proposed an approximation algorithm based on the smallest enclosing disk (SED) to determine the minimum number of APs and MC's sojourn time at the selected APs. Wang *et al.* [133] also used the concept of the SED to find the minimum number of APs. Further, they optimized the traveling path to obtain a trade-off between the service cost and efficiency of WPT.

The papers [90]–[92] considered a fixed periodic trajectory and proposed their schemes to obtain MC's optimal velocity along its path for various objectives. In particular, Shu *et al.* [90] aimed to maximize the network lifetime under time-bound charging and acceleration limit. Chen *et al.* [91] devised a heuristic to solve the TSP with velocity variations while minimizing the charging delay. Unlike [90], [91], Dong *et al.* [92] presented an online task assignment algorithm to assign a set of sensing and computing tasks to the sensors such that the charging delay is minimized. They also provide a quantitative lower bound for MC's velocity by ensuring that the energy transferred to sensors is sufficient to finish the assigned tasks.

Some researchers [124], [152], [157] have exploited metaheuristic algorithms to address the MCP with the MNC approach. They first determined the minimum number of APs using different methods and then utilized metaheuristic algorithms to obtain MC's trajectory. Li *et al.* [152] exploited the notion of intersecting circles to select the APs. Lyu *et al.* [124] obtained the APs by partitioning the network region into hexagonal grids. Jia *et al.* [157] used the in-degree of sensors to find the APs. After that, the paper [152] used particle swarm optimization for path planning. Jia *et al.* [157] used the genetic algorithm to deal with both flow routing and the trajectory design, and Lyu *et al.* [124] employed a hybrid simulated annealing discrete fireworks algorithm for trajectory design. Unlike [124], [152], [157], Liu *et al.* [159] used the particle swarm optimization to solve a multi-objective optimization problem to minimize the number of APs, number of repeatedly charged sensors, and the service cost simultaneously.

2) Joint Data Collection and Energy Provisioning (JDCEP): As mentioned earlier, the MC has dual responsibility in the JDCEP, i.e., it restores the energy of sensors and gathers sensory data from them. Fig. 8 illustrates the reference models of single MC-based JDCEP schemes based on SNC and MNC approaches. The readers should interpret these reference models as explained in Section V-A1, except that the red lines depict the data transmission between an MC and a sensor.

The studies [70], [71], [160]–[162] employed the SNC approach. Zhao *et al.* [162] are the first authors to introduce the idea of JDCEP. In particular, they aimed to attain energy-efficient data collection and ensure steady and high sensor recharging rates. To begin with, they obtained MC's traveling path such that the length of the path does not surpass a given limit. They then presented a method to determine the optimal data rates, link scheduling, and flow routes of the sensors to maximize the network utility defined in terms of the total amount of data collected from sensors. However, they assumed that the energy consumed for sensing and data reception is negligible. Besides, they also ignored the charging time of sensors. In contrast, the paper [70] considered different

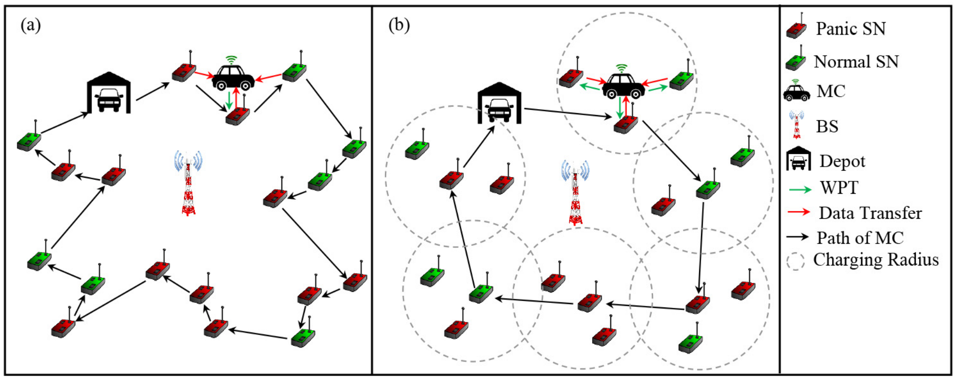

Fig. 8. Reference models of single MC-based periodic techniques for JDCEP with (a) SNC and (b) MNC approaches.

causes of energy depletion and time-varying characteristics of energy provisioning. The authors then proposed a distributed algorithm comprising sub-algorithms for flow routing, cross-layer data control, scheduling of sensed data, and determining the sojourn time of MC at the APs.

Liu *et al.* [71] devised two dynamic distributed algorithms to update the cluster-based network topology regularly. After that, they obtained MC's charging tour by finding the shortest Hamiltonian cycle through the cluster heads and sensors having low residual energy. Wei *et al.* [160] devised an elitist strategy-based multi-objective ant colony optimization algorithm to maximize the energy usage efficiency and minimize the data collection delay (DCD). Liu *et al.* [161] proposed an optimal joint data gathering and energy harvesting algorithm to optimize the relay selection, link scheduling, and power allocation for maximizing the network utility calculated based on data transmission and energy consumption models. They also presented a near-optimal buffer-battery-aware adaptive scheduling algorithm based on the real-time status of the battery and data buffer of the sensors for the same objective.

Different from [70], [71], [160]–[162], the works [95], [115], [163] utilized the MNC approach for energy provisioning. Similar to [52], [53], Xie *et al.* [163] solved a joint nonlinear optimization problem for flow routing, AP selection, and traveling path to maximize the docking time ratio. Lyu *et al.* [115] put forward a discrete-fireworks algorithm based on population entropy to formulate MC's traveling path, such that the amount of data gathered per unit energy consumption of the MC is maximized. Malebary [95] first divided the network into several charging regions and then optimized the MC's traveling path and charging time simultaneously to maximize the network lifetime. Table III summarizes and compares various single MC-based periodic charging techniques.

B. Multiple MCs-Based Techniques (MMT)

In periodic MMT, multiple MCs roam around the network and visit all the sensors or a set of APs for the EEP or JDCEP. In general, the literature on the MMT adheres to a partition-based approach or a non-partition-based approach. The former arrangement divides the sensors into groups using an area partitioning or clustering method. It then assigns an MC to each group to perform the intended task. Herein, an MC can serve only the sensors allocated to it. In contrast, an MC can recharge any sensor in the latter strategy. Besides, the MCs can collaborate to share their energy and charging loads for mutual benefits. Usually, the periodic MMT deals with 1) finding the charging tours for a given number of MCs such that some objective functions are optimized, 2) finding the minimum number of MCs required to ensure perpetual network operation, and 3) designing efficient collaboration strategies for MCs for load or energy sharing.

1) Exclusive Energy Provisioning (EEP): We show the reference models of multiple MCs-based periodic EEP techniques with SNC and MNC approaches in Fig. 9. Herein, the sensors are divided between two MCs to recharge them in time. Like the single MC-based EEP techniques, most of the multiple MCs-based EEP techniques also adhere to the SNC approach and periodically recharge all the sensors. Madhja *et al.* [164], [165] followed the partition-based approach to group and recharge the sensors. In particular, they presented a partition-based coordination model using different levels of network information and proposed four algorithms. The first two algorithms work without prior knowledge of the network, whereas the other two exploit limited and global information, respectively. The same authors presented a hierarchical collaborative model in [165]. In this model, they classified the MCs into two groups. The first group forms the lower layer of the hierarchy and includes the MCs that recharge the sensors. The second group forms the upper layer and comprises of some special MCs that recharge the MCs of the first group.

The studies [166], [167] divided a mine roadway or tunnel into multiple regions and employed an MC in each region. Liu *et al.* [166] formulated a charging time distribution problem that ensures a perpetual network lifetime. Herein, they considered that the MC could travel across all the regions in different rounds and solved their problem in a centralized manner. In contrast, Hu *et al.* [167] determined each roadway region's length and the MC's battery capacity. It is worth noting that an MC working in a region closer to the BS has a higher capacity than an MC in a distant region. The reason is that i^{th} MC not only recharges the sensors from the i^{th} region but also recharges the $(i+1)^{th}$ MC.

TABLE III
COMPARISON OF DIFFERENT SINGLE MC-BASED TECHNIQUES FOR PERIODIC CHARGING ARCHITECTURE, WHERE "CHARGING POLICY (CP)," "TYPE OF CHARGING (ToC)," "DESIGN ISSUES (DI)," "PERFORMANCE METRICS (PM)," "EVALUATION METHODS (EVM)," "THEORETICAL ANALYSIS (TA)," "NUMERICAL SIMULATIONS (NS)," AND "FIELD EXPERIMENTS (FE)"

	Paper	Objectives	Constraints	Approaches	CP	ToC	DI	PM	EVM	Limitations
Periodic SMT for EEP	[73]	Minimization of SRC	Energy capacity of the MC	Centralized, Greedy	Full	SNC	TP	NL	FE	Perpetual NL is not guaranteed
	[159]	**O1:** Minimization of number of APs **O2:** Minimization of repeated charging **O3:** Minimization of SRC	A sensor belongs only one AP	Centralized, Metaheuristic	Full	MNC	TP	Fitness value	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[150]	Optimize different critical aspects	Energy capacity of the MC	Centralized, Semi-Distributed Heuristic	Hybrid	SNC	TP	Number of alive sensors, SRC	NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[130]	Minimization of CD	Energy capacity of the MC	Centralized, Discretization	Full	SNC	TP	-	-	Perpetual NL is not guaranteed
	[148]	Maximization of DTR	REC is maintained	Centralized, Metaheuristic	Full	SNC	TP	CYT, DTR, SRC	NS	No constraint on MC's energy capacity
	[147]	Assess the impact of different traveling paths	MC follows certain curves	Centralized, Space Filing Curves	Full	SNC	TP	CD, NL, SRC	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[125]	Maximization of number of charged sensors	**C1:** Energy capacity of the MC **C2:** Maximum CYT	Centralized, Approximation	Hybrid	SNC	TP	Number of charged sensors	TA	Perpetual NL is not guaranteed
	[114]	**O1:** Minimization of CYT **O2:** Maximization of CT **O3:** Minimization of number of APs	Energy capacity of the MC	Centralized, Approximation	Full	SNC	TP	Coverage ratio, EUE, SRC	NS	Same energy consumption rate of sensors
	[131]	Minimization of number of batteries used	Energy capacity of the MC	Centralized, Approximation	Full	SNC	TP	Number of batteries	TA, NS	Perpetual NL is not guaranteed
	[112]	**O1:** Minimization of CYT **O2:** Maximization of number of charged sensors	Energy capacity of the MC	Centralized, Approximation	Full	SNC	TP	SR, CYT	FE, TA, NS	Perpetual NL is not guaranteed
	[152]	Minimization of SRC	Energy capacity of the MC	Centralized, Metaheuristic	Full	MNC	TP	Coverage ratio, SRC	NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[88]	Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Charging window constraints	Centralized, Heuristic	Full	SNC	TP, CT	CYT	NS	Fixed energy consumption rate of sensors
	[132]	Minimization of data loss	**C1:** Maximum CYT **C2:** Energy capacity of the MC	Centralized, Heuristic	Full	SNC	TP, CT	Data loss	TA, NS, FE	Perpetual NL is not guaranteed
	[153]	Minimization of CYT	A sensor belongs to only one AP	Centralized, Markov model	Full	MNC	TP, CT	CT, CYT, SRC	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[133]	**O1:** Minimization of number of APs **O2:** Minimization of TEC	**C1:** A sensor belongs at least one AP **C2:** Minimum recharging threshold	Centralized, Clustering	Full	MNC	TP, CT	Number of APs, SRC, TEC	TA, NS, FE	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[145]	Minimization of CYT	REC is maintained	Centralized, Heuristic	Hybrid	SNC	TP, CT	TT, CT, EUE	TA, NS	**L1:** Fixed energy consumption rate of sensors **L2:** No constraint on MC's energy capacity
	[124]	Maximization of EUE	**C1:** Maximum traveling energy **C2:** Maximum charging energy	Centralized, Metaheuristic	Hybrid	MNC	TP, CT	EUE	TA, NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[156]	Minimization of CYT	A sensor belongs to only one AP	Centralized, LP Solver	Hybrid	MNC	TP, CT	CT	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[86]	Minimization of CD	**C1:** A sensor belongs to only one AP **C2:** REC is maintained **C3:** Minimum recharging threshold	Centralized, Approximation	Hybrid	MNC	TP, CT	CD, Number of APs	TA, NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[155]	**O1:** Maximization of EUE **O2:** Minimization of data loss	**C1:** A sensor belongs to only one AP **C2:** Minimum SINR requirement	Semi-Distributed, Mean-Field Game	Hybrid	MNC	TP, CT	Data loss, Average SINR	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[91]	Minimization of CD	**C1:** A sensor belongs to only one AP **C2:** Minimum recharging threshold **C3:** Maximum velocity of the MC	Centralized, Heuristic	Full	MNC	TP, CT, VC	CD, CYT	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[90]	Maximization of NL	**C1:** Maximum acceleration **C2:** Energy capacity of the MC	Centralized, Approximation	Hybrid	MNC	TP, CT, VC	Average charged energy, NL	TA, NS	**L1:**: Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[92]	Minimization of CD	**C1:** A task belongs to at most one sensor **C2:** Each task must be executed **C3:** Charging deadline	Centralized, Approximation	Hybrid	MNC	TP, CT, VC	Payload energy	TA, NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[72], [146]	Maximization of NL	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Heuristic	Full	SNC	TP, FLR	NL	NS	**L1:** Fixed energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[151]	Optimize several critical aspects	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Semi-Distributed, Heuristic	Hybrid	SNC	TP, FLR	Number of alive sensors, SRC	NS	Perpetual NL is not guaranteed
	[52]	Maximization of DTR	**C1:** REC is maintained **C2:** FLR constraints	Centralized, Approximation	Full	SNC	TP, CT, FLR	CYT, SRC	TA, NS	**L1:** Same energy consumption rate of sensors **L1:** No constraint on MC's energy capacity
	[54]	Maximization of DTR	**C1:** REC is maintained **C2:** FLR constraints	Centralized, Approximation	Full	SNC	TP, CT, FLR	CYT, SRC	TA, NS	No constraint on MC's energy capacity
	[53]	Maximization of DTR	**C1:** A sensor belongs only one AP **C2:** REC is maintained **C3:** FLR constraints	Centralized, Reformulation-Linearization	Full	MNC	TP, CT, FLR	CYT, SRC	TA, NS	No constraint on MC's energy capacity
	[74]	Maximization of NL	FLR constraints	Centralized, Heuristic	Partial	SNC	TP, CT, FLR	NL	NS, FE	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[76]	Achieve local energy balance	**C1:** FLR constraints **C2:** Minimum recharging threshold	Centralized, Heuristic	Partial	SNC	TP, CT, FLR	SRC, SR	NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[136]	Minimization of number of sensors deployed	**C1:** Energy capacity of the MC **C2:** PoI coverage constraints	Centralized, Approximation	Hybrid	SNC	TP, CC	Number of deployed sensors	TA, NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[138]	Minimization of number of sensors deployed	**C1:** Energy capacity of the MC **C2:** PoI coverage constraints **C3:** FLR constraints **C4:** Minimum DTR	Centralized, Heuristic	Hybrid	SNC	TP, FLR, CC	Number of deployed sensors	TA, NS	Perpetual NL is not guaranteed
	[149]	Maximization of CU/CR	**C1:** Energy capacity of the MC **C2:** PoI coverage constraints **C3:** FLR constraints	Centralized, Approximation	Hybrid	MNC	TP, CT, CC, FLR	CU/CR	TA, NS, FE	Perpetual NL is not guaranteed
	[68]	Maximization of QoM	PoI coverage constraints	Centralized, Approximation	Hybrid	SNC	TP, CT, CC, SS	QoM	TA, NS	**L1:** Same energy consumption rate of sensors **L2:** No constraint on MC's energy capacity
	[64]	Maximization of QoM	**C1:** PoI coverage constraints **C2:** Maximum CYT	Centralized, Approximation	Hybrid	SNC	TP, CT, CC, SS	QoM	TA, NS	No constraint on MC's energy capacity
	[158]	Maximization of surveillance quality	Sensor state transition constraints	Centralized, Greedy Heuristic	Full	SNC	TP, CC, SS	Network coverage	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[133]	**O1:** Maximization of payload energy **O2:** Maximization of minimum payload energy	Maximum SRC	Centralized, Approximation	Hybrid	MNC	TP, SS	Payload energy	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[65]	Maximization of NL	**C1:** Energy capacity of the MC **C2:** PoI coverage constraints	Centralized, Heuristic	Hybrid	SNC	TP, CT, CC, SS	Energy utility, NL	TA, NS	**L1:** Uniform sensor deployment **L2:** Charging and Traveling time are ignored **L3:** Perpetual NL is not guaranteed
	[154]	Maximization of CU/CR	**C1:** Energy capacity of the MC **C2:** PoI coverage constraints **C3:** FLR constraints	Centralized, Greedy Approximation	Full	SNC	TP, CC, FLR	CU/CR	TA, NS, FE	Perpetual NL is not guaranteed
Periodic SMT for JDCEP	[71]	**O1:** Minimization of CD **O2:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** FLR constraints **C3:** Maximum CYT	Distributed, Approximation	Full	SNC	TP, FLR	CD, CYT, EUE, SRC	TA, NS	Perpetual NL is not guaranteed
	[162]	Maximization of network utility	**C1:** FLR constraints **C2:** Maximum SRC	Centralized, Distributed, Heuristic, Approximation	Full	MNC	TP, FLR	Network utility	TA, NS	**L1:** No constraint of MC's energy capacity **L2:** Charging Time is ignored
	[70]	Maximization of network utility	**C1:** FLR constraints **C2:** Maximum DCD	Centralized, Distributed, Heuristic, Approximation	Full	MNC	TP, CT, FLR	Network utility	TA, NS	No constraint of MC's energy capacity
	[160]	**O1:** Maximization of EUE **O2:** Minimization of DCD	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Metaheuristic	Full	SNC	TP, CT, FLR	DCD, EUE	NS	**L1:** Data collection time is not considered **L2:** Perpetual NL is not guaranteed
	[161]	Maximization of network utility	**C1:** FLR constraints **C2:** Buffer size	Centralized, Lyapunov optimization	Hybrid	SNC	TP, CT, FLR	Network utility and throughput	TA, NS	**L1:** No energy constraint on MC's energy **L2:** Same data generation rate of sensors
	[95]	Maximization of NL	**C1:** Energy capacity of the MC **C1:** FLR constraints	Centralized, Greedy Heuristic	Full	MNC	TP, CT, FLR	Energy level of sensors, NL	NS	**L1:** Same data generation rate of sensors **L2:** Perpetual NL is not guaranteed
	[163]	Maximization of DTR	**C1:** REC is maintained **C1:** FLR constraints	Centralized, Approximation	Full	MNC	TP, CT, FLR	CYT, SRC	TA, NS	No constraint on MC's energy capacity
	[115]	Maximization of data collected per unit energy	**C1:** A sensor belongs to only one AP **C2:** REC is maintained **C3:** FLR constraints	Centralized, Heuristic, Metaheuristic	Full	MNC	TP, CT, FLR	CYT, Data collected per energy unit	TA, NS	No constraint on MC's energy capacity

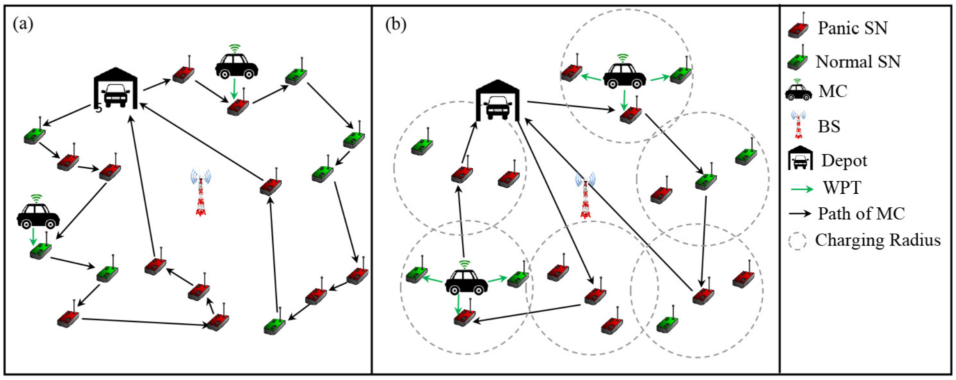

Fig. 9. Reference models of multiple MCs-based periodic techniques for EEP with (a) SNC and (b) MNC approaches.

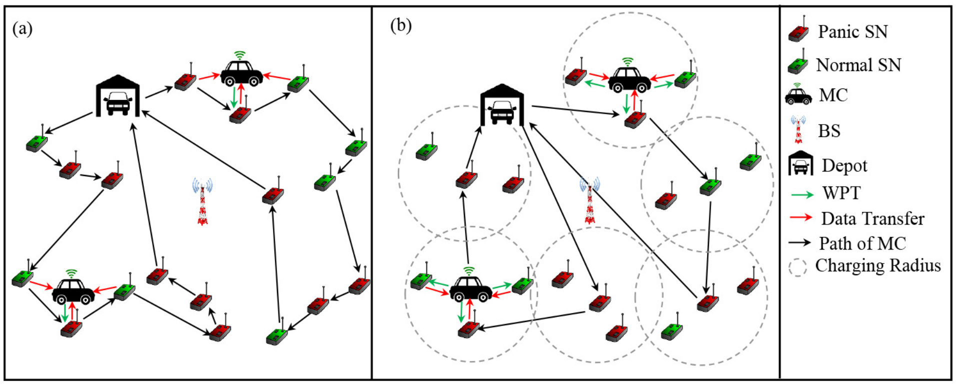

Fig. 10. Reference models of multiple MCs-based periodic techniques for JDCEP with (a) SNC and (b) MNC approaches.

The papers [103], [117], [118], [121], [168] proposed various approximation algorithms to solve the MCP. Xu *et al.* [118] designed a 2-approximation algorithm to minimize the service cost. The studies [103], [121] addressed the common problem of selecting traveling paths of the MCs from a set of candidate paths and associating sensors with the paths chosen. Zhang *et al.* [121] devised an approximation algorithm and a practical heuristic algorithm based on the set cover problem to minimize the total overhead energy consumption. Wu *et al.* [103] proposed an approximation algorithm to solve a monotone sub-modular function that maximizes the charging coverage. Chen *et al.* [168] put forward a suite of recursive approximation algorithms to maximize the number of charged sensors under maximum cycle time and total energy consumption constraints. Xu *et al.* [117] devised an iterative approximation algorithm for a generalized team orienting problem to maximize the number of charged sensors.

Gharaie *et al.* [122] employed two MCs. The first MC is dispatched when the variance of the residual lifetime of the sensors exceeds a given threshold. The second MC is used when the remaining energy of any sensors falls below another threshold. Wei *et al.* [141] formulated a multi-MC scheduling problem to minimize the service cost and proposed an improved genetic algorithm coupled with the 2-opt strategy to solve the said problem. Lin *et al.* [61] derived a directional energy transfer model by considering the transmission distance and orientation angle between the MC and sensors. They then proposed two algorithms to plan the MC's charging activities such that the charging delay is minimized.

The references [84], [94] minimized the maximum cycle time. Zhu *et al.* [84] devised an efficient distributed algorithm for solving a tractable velocity control problem. Mo *et al.* [94] jointly optimized the charging time, traveling time, and total energy consumption under limited time and energy constraints. Han *et al.* [143] considered both mobile and static sensors and used a set of UAVs and terrestrial MCs to recharge them, respectively. In particular, they first employed a deep learning method to cluster mobile sensors and deployed one UAV within each cluster to fulfill the energy demands of the member sensors. Next, they determined a set of APs where both UAVs and mobile sensors can stay to recharge the latter's batteries. Finally, the charging tours of the terrestrial MCs are formed using a genetic algorithm. Lin *et al.* [127] proposed a cost-efficient algorithm to maximize the payload energy with flow routing and energy capacity constraints. Liang *et al.* [169] solved the MCP using an improved firefly algorithm for maximizing the number of charged sensors and charging efficiency while minimizing the service cost.

Different from [61], [84], [94], [103], [117], [118], [121], [122], [127], [141], [143], [164]–[167], [169], the works [15], [66], [67], [77]–[83] studied the common problem of finding the minimum number of MCs and their trajectories such that no sensor dies. The authors in [78] reported a novel collaborative mobile charging paradigm to enable WPT among the MCs and maximize the energy usage efficiency.

TABLE IV
COMPARISON OF DIFFERENT MULTIPLE MCS-BASED TECHNIQUES FOR PERIODIC CHARGING ARCHITECTURE, WHERE "CHARGING POLICY (CP)," "TYPE OF CHARGING (TOC)," "DESIGN ISSUES (DI)," "PERFORMANCE METRICS (PM)," "EVALUATION METHODS (EVM)," "THEORETICAL ANALYSIS (TA)," "NUMERICAL SIMULATIONS (NS)," AND "FIELD EXPERIMENTS (FE)"

	Paper	Objectives	Constraints	Approaches	CP	ToC	DI	PM	EVM	Limitations
Periodic MMT for EEP	[167]	Maximization of EUE	**C1:** Energy capacity of the MC **C2:** REC is maintained	Distributed, Heuristic	Full	SNC	TP, CC, CS	EUE	NS	Uniform sensor deployment
	[166]	Maximization of payload energy	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Clustering	Full	SNC	TP, CT, CC, CS	Payload energy	TA, NS	Fixed energy consumption rate of sensors
	[121]	Minimization of energy overhead	Energy capacity of the MC	Centralized, Heuristic, Approximation	Full	SNC	TP, CT, CC	CT, Energy overhead	TA, NS, FE	Same energy consumption rate of sensors
	[103]	Maximization of number of charged sensors	Energy capacity of the MC	Centralized, Approximation	Hybrid	SNC	TP, CT, CC	Number of charged sensors, EUE, TEC	TA, NS	Same energy consumption rate of sensors
	[168]	Maximization of number of charged sensors	**C1:** Energy capacity of the MC **C2:** Maximum CYT or TEC	Centralized, Approximation	Hybrid	SNC	TP, CT	Number of charged sensors	TA, NS	**L1:** Fixed trajectory of mobile sensors **L2:** Perpetual NL is not guaranteed
	[118]	Minimization of SRC	REC is maintained	Centralized, Approximation	Full	SNC	TP, CS	SRC	TA, NS	**L1:** No constraint on MC's energy capacity **L2:** Fixed energy consumption rate of sensors
	[164], [165]	Maximization of NL	Energy capacity of the MC	Centralized, Semi-Distributed, Approximation	Full	MNC	TP, CS	Number of alive sensors	NS	Perpetual NL is not guaranteed
	[94]	Minimization of TEC	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Heuristic	Partial	MNC	TP, CT, CS	TEC	TA, NS	Perpetual NL is not guaranteed
	[61]	Minimization of CD	Energy capacity of the MC	Centralized, LP Solver	Partial	MNC	TP, CT, CS	CD	TA, NS, FE	Perpetual NL is not guaranteed
	[117]	Maximization of number of charged sensors	Energy capacity of the MC	Centralized, Approximation	Full	SNC	TP	Number of charged sensors	NS	Perpetual NL is not guaranteed
	[141]	Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Maximum NoM **C3:** Charging window constraints	Centralized, Metaheuristic	Full	SNC	TP, CT	NoM, SRC	NS	Constant energy consumption rate of sensors
	[122]	Minimization of WT	Energy capacity of the MC	Centralized, Heuristic	Hybrid	SNC	TP, CT	Payload energy, NL	NS	**L1:** MC's movement energy not considered **L2:** Perpetual NL is not guaranteed
	[127]	Maximization of payload energy	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Approximation	Full	MNC	TP, CT	Payload energy	TA, NS, FE	Perpetual NL is not guaranteed
	[143]	**O1:** Minimization of traveling energy **O2:** Maximization of payload energy	**C1:** Maximum charging energy **C2:** Maximum traveling energy	Centralized, Metaheuristic, Deep learning	Full	SNC	TP, CT, VC, CS, CC	Payload energy	NS	**L1:** Fixed trajectory of mobile sensors **L2:** Perpetual NL is not guaranteed
	[169]	**O1:** Maximization of number of charged sensors **O2:** Maximization of charging efficiency **O3:** Minimization of SRC	Energy capacity of the MC	Centralized, Metaheuristic	Full	MNC	TP, CC	Fitness value	NS	Perpetual NL is not guaranteed
	[77]	Minimization of NoM	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Metaheuristic	Full	SNC	TP, CC, MNoM	NoM	TA, NS	Fixed energy consumption rate of sensors
	[78]	Maximization of EUE	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Approximation	Full	SNC	TP, CC, CS, MNoM	EUE	TA, NS	Uniform sensor deployment
	[82]	Minimization of NoM	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Clustering, Heuristic	Full	SNC	TP, CC, CS, MNoM	EUE, NoM	TA, NS	Uniform sensor deployment
	[80]	**O1:** Minimization of NoM **O2:** Minimization of TEC	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Approximation	Full	SNC	TP, CC, CS, MNoM	EUE, NoM, Cost	TA, NS	Uniform sensor deployment
	[79]	Minimization of NoM	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Approximation	Hybrid	SNC	TP, CC, CT, MNoM	NoM, SRC, TEC	TA, NS	Fixed and same energy consumption rate of sensors
	[84]	Minimization of CYT	**C1:** Maximum NoM **C2:** REC is maintained **C3:** Maximum velocity of the MC	Distributed, Approximation	Hybrid	MNC	TP, CT, CS, VC	CT	TA, NS	No constraint on MC's energy capacity
	[83]	**O1:** Minimization of NoM **O2:** Minimization of NoD	**C1:** Energy capacity of the MC **C2:** Energy capacity of depots **C3:** REC is maintained	Centralized, Approximation	Full	SNC	TP, CC, MNoM	NoM, NoD	TA, NS	Same energy consumption rate of sensors
	[66]	Minimization of NoM	**C1:** Energy capacity of the MC **C2:** REC is maintained	Centralized, Metaheuristic	Full	SNC	TP, CC, CS, CT, MNoM	NoM, EUE	TA, NS	**L1:** Same energy consumption rate of sensors **L2:** Uniform sensor deployment
	[67]	Minimization of NoM	**C1:** Energy capacity of the MC **C2:** REC is maintained **C3:** FLR constraints **C4:** Maximum SRC	Semi-Distributed, Heuristic	Hybrid	SNC	TP, CC, CS, CT, MNoM	CD, CT, TEC, Number of dead sensors	NS	Same data generation rate of sensors
	[15]	**O1:** Maximization of surplus energy **O2:** Minimization of NoM	**C1:** Energy capacity of the MC/SC **C2:** Charging deadline	Centralized, Approximation	Full	SNC MNC	TP, CC, CS, MNoM	EUE, saved energy	TA, NS, FE	**L1:** Uniform sensor deployment **L2:** Fixed energy consumption rate of sensors
	[81]	**O1:** Minimization of NoM **O2:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Charging deadline	Semi-Distributed, Approximation	Full	SNC	TP, CT, CC, MNoM	Payload energy, TEC	TA, NS	Uniform sensor deployment
Periodic MMT for JDCEP	[170]	Maximization of total weight of charged sensors	**C1:** Energy capacity of the MC **C2:** FLR constraints	Semi-Distributed, Greedy	Full	SNC	TP, FLR	Total weight of charged sensors	NS	**L1:** Perpetual NL is not guaranteed **L2:** Uniform sensor deployment
	[171]	**O1:** Minimization of DCD **O2:** Maximization of EUE	**C1:** Energy capacity of the MC **C2:** FLR constraints	Semi-Distributed, Metaheuristic	Full	SNC	TP, FLR	DCD, TEC	NS	Uniform sensor deployment
	[172]	Minimization of DCD	**C1:** Energy capacity of the MC **C2:** REC is maintained **C3:** FLR constraints	Centralized, Clustering, Heuristic	Full	SNC	TP, FLR, CS, MNoM	NoM, DCD	NS	**L1:** Same data generation rate
	[173]	Minimization of CD	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Clustering, Markov Model	Hybrid	MNC	TP, FLR	Average residual energy	TA, NS, FE	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[174], [175]	Maximization of EUE	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Clustering, Heuristic, Metaheuristic	Partial	MNC	TP, FLR, MNoM	CD, CT, TEC, EUE, SRC	NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[120]	Minimization of CD	**C1:** Energy capacity of the MC **C2:** Minimum recharging threshold **C3:** FLR constraints	Centralized, Clustering, Convex Hull	Partial	MNC	TP, CC, CT, MNoM	Average residual energy, CD	NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed

However, the number of MCs in their scheme drastically increases with the network size. In contrast, Liu *et al.* [80] introduced the notion of shuttling, allowing an MC to travel between its previous and current locations to carry additional energy to minimize the number of MCs. Wang *et al.* [81] leveraged the concept of named data networking for real-time collection of sensor's energy status to adapt to uncertain network conditions. The authors designed a hierarchical framework for aggregating the energy information in a bottom-up fashion. In general, they proposed a heuristic to achieve an infinite network lifetime using a minimum number of MCs with the minimum service cost. Dai *et al.* [79] proposed two approximation algorithms to find the minimum number of MCs, their traveling path and charging time.

Chen *et al.* [82] proposed a hop-based mobile charging policy algorithm to minimize the number of MCs through a collaborative charging model. They also devised a hop-based mobile charging policy plus to reduce the service cost via a non-collaborative charging paradigm. Jiang *et al.* [83] proposed a three-phase charging scheme. The first phase plans the traveling paths of the MCs. The second phase identifies and reduces the candidate locations of depots. The third phase deploys the depots and assigns traveling paths to them. Ouyang *et al.* [66] devised a utility-based collaborative charging scheme for maximizing energy usage efficiency with three modules. The first module merges opposite paths to reduce the number of MCs and lengths of their traveling paths. The second module alleviates the vacation time of the MCs to improve their utilization. The third module minimizes the energy wastage of the MCs by distributing the charging tasks among themselves.

Nguyen *et al.* [77] utilized the average energy consumption ratio per unit distance for fairly recharging the sensors. Sha *et al.* [67] divided the panic sensors into different sets

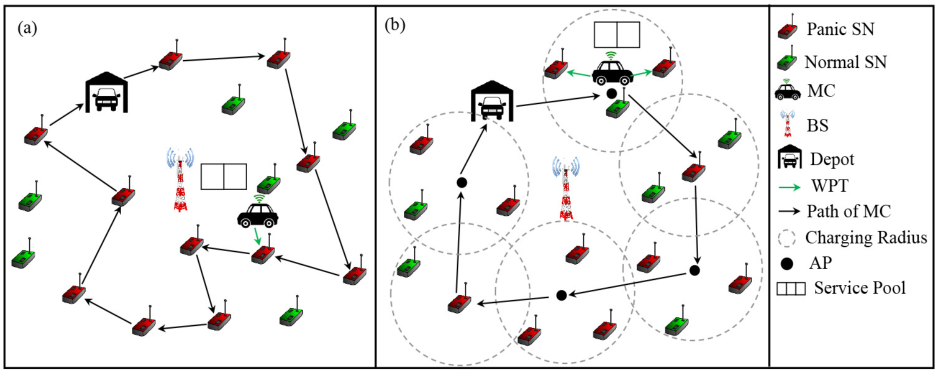

Fig. 11. Reference models of single MC-based on-demand techniques for QDA with (a) SNC and (b) MNC approaches.

of to-be-recharged sensors to obtain the minimum number of requisite MCs. They then proposed two semi-distributed charging tour allocation algorithms with the service cost constraints. Further, they optimized these tours by calculating the charging time of each sensor to reduce the total energy consumption. Different from [66], [67], [77]–[83], Sun *et al.* [15] initially deployed a set of SCs such that all the sensors were covered. However, they found that the energy usage efficiency of SCs is significantly low as most of their energy is wasted during the wireless charging of sensors. With this motivation, they replaced a few SCs with freeloading MCs that can harvest SC's wastage energy to recharge some undercharged sensors, thereby reducing the system's total energy consumption.

2) Joint Data Collection and Energy Provisioning (JDCEP): The models of multiple MCs-based JDCEP methods with the SNC and MNC approaches are shown in Fig. 10. The studies [170]–[172] used the SNC approach. Nguyen *et al.* [170] assigned higher recharging weights to the sensors monitoring critical areas than those in other areas. They then devised a greedy scheduling algorithm to maximize the total weight of the recharged sensors. Farris *et al.* [172] employed two types of MCs: cluster MCs and bus MCs. Each cluster MC collects the sensory data from sensors of a specific cluster and recharges them. In contrast, the bus MCs transport the data collected by the cluster MCs to the BS. Wu *et al.* [171] investigated the joint optimization problem of finding hovering locations and trajectories of the UAVs to maximize the energy usage efficiency.

Unlike [170]–[172], the studies [120], [173]–[175] used the MNC approach. The papers [120], [173] grouped the sensors using the *k*-means algorithm and then selected an AP in each cluster. The authors then configured the charging tours by obtaining the shortest Hamiltonian cycle through these APs in [173] and two convex hulls in [120]. They then used two MCs in each tour to traverse it in opposite directions. Besides, they also utilized a few spare MCs to replace an MC when its energy is exhausted before completing the charging tour. Boukerche *et al.* [174], [175] first divided the sensors into some clusters and selected a cluster head. After that, they utilized the minimum spanning tree to obtain the minimum number of MCs and their traveling paths to maximize the energy usage efficiency in a delay-sensitive environment. Table IV summarizes and compares various multiple MCs-based periodic charging techniques.

VI. On-Demand Charging Schemes

In this section, we deliver a meticulous study on different on-demand SMT and MMT. Unlike periodic charging, the MC recharges only those sensors that have sent a charging request to the controller in on-demand charging. We exhibit visual demonstrations of the QDA and FDA techniques using single and multiple MCs and compare various on-demand MCTs based on the proposed taxonomy.

A. Single MC-Based Techniques (SMT)

1) Quasi-Dynamic Approach (QDA): As mentioned before, the recharging process of sensors is carried out in a series of recharging round. In each round, the controller selects some (or all) charging requests from the request queue and determines MC's charging tour. Fig. 11 shows the reference models of single MC-based on-demand QDA techniques with SNC and MNC approaches. In these models, the black and green lines denote the traveling path of the MC and the WPT link between the MC and sensors, respectively. The red sensors are the panic sensors that have sent a charging request to the controller, while the green sensors have sufficient energy. Herein, the request queue of the MC in both SNC and MNC approaches is empty as the controller intends to serve all the pending charging requests in the current round.

In particular, the articles [69], [87], [97], [99], [100], [102], [104], [109], [113], [126], [137], [176]–[182] used the SNC approach for energy provisioning. The works [102], [104], [126] used temporal and spatial characteristics to restore the energy of the sensors. Lin *et al.* [104] devised a temporal-spatial real-time charging scheduling algorithm to minimize the number of dead sensors while maximizing the energy usage efficiency. Their algorithm finds a feasible charging tour and then optimizes it in the global view for the said objective. Besides, they proposed a node deletion algorithm and a node insertion algorithm to maximize the energy usage efficiency. The paper [126] reported a primary and passer-by scheduling algorithm. It first obtains the shortest Hamiltonian cycle through the primary sensors to be recharged and then includes some passer-by sensors in the primary charging tour using auxiliary virtual circles to maximize the survival rate. Similarly, the paper [102] proposed an optimal path planning charging algorithm to maximize the energy usage efficiency. In their

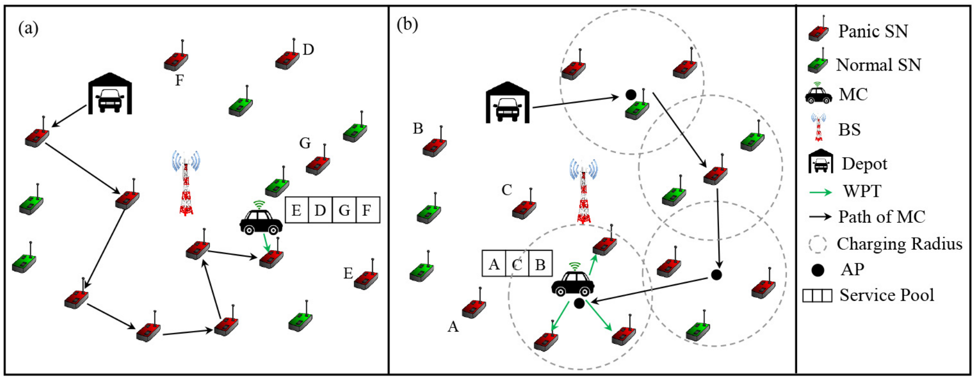

Fig. 12. Reference models of single MC-based on-demand techniques for FDA with (a) SNC and (b) MNC approaches.

scheme, when a workable charging tour is impossible, some charging requests are discarded to obtain a feasible tour.

Tsoumanis *et al.* [178] first demonstrated that the solution to the MCP depends on the network topology characteristics and traffic load. They then presented a first-come-first-based energy replenishment scheme for minimizing the total energy consumption. Lu *et al.* [183] utilized a technique for order performance by similarity to ideal solution to maximize the network lifetime. Dong *et al.* [97] grouped the sensors into several clusters and adopted a simple tree-like communication mode and a backtracking method for ensuring network connectivity within two hops. Each cluster head sends a charging request to the BS if its residual energy falls below the charging threshold. They then used ant colony optimization to determine the MC's traveling path. He *et al.* [87] dealt with the problem of recharging mobile sensors. They constructed many single-source shortest paths and selected the shortest path among them as MC's charging tour, such that the service cost is minimized and the charging deadlines of the sensors are fulfilled. Similar to [88], Zou *et al.* [179] also employed a charging vehicle carrying k portable wireless chargers. However, their scheme increases the service cost since the charging vehicle visits each demanding sensor twice per tour.

The paper [176] envisioned a multi-source energy harvesting sensor network in which sensors harvest energy from different sources such as solar, wind, and wireless power. In particular, they first obtained an optimal combination of sensors based on environmental conditions to minimize the monetary cost. Next, they partitioned the network region into many sub-regions and deployed an energy harvesting station in each sub-region. They then put forward a $4-$approximation algorithm to devise MC's charging activities. Dande *et al.* [182] used a weight function of service cost and coverage contribution to select the next-to-be-recharged sensors such that the accumulated monitoring quality is maximized. Ouyang *et al.* [177] devised a Matroid theory-based greedy algorithm to select the next recharging sensor in order to minimize the penalties under the constraint of charging deadlines. Moreover, they put forward a charging order adjustment method to reduce the service cost.

The papers [69], [87], [97], [102], [104], [126], [176]–[179], [182], [183] considered that the MC needs to recharge all the lifetime-critical sensors to their full battery capacity. However, if each sensor is fully recharged, some sensors may not be recharged before their energy depletion. Hence, the studies [99], [137], [180], [184] and [100], [109], [113], [181], [185] utilized the partial and hybrid charging policies, respectively. Feng *et al.* [137] combined periodic and on-demand charging architecture to adapt the sensor's dynamic energy consumption rates and optimize MC's traveling path to maximize the energy usage efficiency. Further, they adjusted the charging time of the sensors based on their minimum charging wait time and maximum tolerable charging delay to avoid node failure. Fu *et al.* [180] obtained a set of nested charging tours based on sensors' energy profiles and selected a suitable path for the MC to minimize the service cost. In addition, they pro-actively synchronized the sensors' request sequence with the chosen tour to lessen their charging delay. Liu *et al.* [99] proposed a reinforcement learning-based heuristic to maximize the charging reward by partially recharging mobile sensors.

The papers [100], [181] assumed that a sensor could be revived partially multiple times in a charging tour to restore its energy level completely. Xu *et al.* [100] introduced a new partial-charging model and addressed two optimization problems. The first problem aims to maximize the sum of the normalized lifetime of sensors, whereas the second one intends to minimize the service cost while maximizing the sum of the sensor's lifetime. Liang *et al.* [181] proposed two approximation algorithms with provably performance guarantees to solve the charging reward maximization problems under full and partial charging settings, respectively.

The authors in [109], [113] proposed two-phase MCTs. The first phase selects a set of to-be-recharged sensors based on their criticality and determines the charging tour of the MC through these sensors for full charging. The second phase adjusts this tour when it is not schedulable. In particular, Lin *et al.* [113] suggested three modules called evaluation, adjustment, and selection to finalize the tour. Wang *et al.* [109] first selected an appropriate number of sensors for partial charging and obtained their charging time to adjust the tour. They then utilized an exhaustive search method to form a new charging tour of the MC. If the obtained tour is still not schedulable, they removed some sensors from the tour to make it feasible. Wu *et al.* [185] proposed a task-driven and collaborated recharging scheme that jointly solves the charging tour scheduling and energy allocation problems.

TABLE V
COMPARISON OF DIFFERENT SINGLE MC-BASED TECHNIQUES FOR ON-DEMAND CHARGING ARCHITECTURE, WHERE "CHARGING POLICY (CP)," "TYPE OF CHARGING (ToC)," "DESIGN ISSUES (DI)," "PERFORMANCE METRICS (PM)," "EVALUATION METHODS (EVM)," "THEORETICAL ANALYSIS (TA)," "NUMERICAL SIMULATIONS (NS)," AND "FIELD EXPERIMENTS (FE)"

	Paper	Objectives	Constraints	Approaches	CP	ToC	DI	PM	EVM	Limitations
On-Demand SMT for QDA	[179]	**O1:** Minimization of SRC **O2:** Minimization of TEC	Energy capacity of the MC	Centralized, Heuristic	Full	SNC	TP	TEC	TA, NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[104]	**O1:** Minimization of number dead sensors **O2:** Maximization of EUE	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Heuristic, Approximation	Full	SNC	TP	DCD, EUE	NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[126]	Maximization of NL	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Approximation	Full	SNC	TP	SR, CHT	NS	**L1:** Fixed energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[102]	Maximization of EUE	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Heuristic	Full	SNC	TP	FR, SRC, EUE	NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[180]	Maximization of number of charged sensors	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Distributed, Clustering, Heuristic	Full	SNC	TP	SRC, Coverage ratio	TA, NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[98]	**O1:** Maximization of CU/CR **O2:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Maximum SRC	Centralized, Heuristic, Approximation	Full	MNC	TP	CU/CR, SRC	TA, NS	Perpetual NL is not guaranteed
	[188]	Maximization of number of charged sensors	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Clustering, Clique Partitioning	Full	MNC	TP	TEC	TA, NS	Perpetual NL is not guaranteed
	[187]	Minimization of TEC	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Clustering	Full	MNC	TP	CD, TEC	NS	Perpetual NL is not guaranteed
	[178]	**O1:** Minimization of penalty **O2:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Greedy, Matroid Model	Full	SNC	TP, CT	Total penalty, FR	TA, NS	Perpetual NL is not guaranteed
	[101]	Maximization of CU/CR	**C1:** Maximum SRC **C2:** Charging deadline	Centralized, Approximation	Full	MNC	TP, CT	CU/CR	FE, TA, NS	**L1:** No constraint of MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[181]	Minimization of SRC	Energy synchronization constraints	Centralized, Clustering	Partial	SNC	TP, CT	SRC, CD	FE, TA, NS	**L1:** No constraint of MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[137]	**O1:** Maximization of EUE **O2:** Minimization of number of dead sensors	Minimum recharging threshold	Centralized, Heuristic	Partial	SNC	TP, CT	Number of charged sensors	TA	**L1:** No constraint on MC's energy capacity **L2:** Same energy consumption rate of sensors **L3:** Perpetual NL is not guaranteed
	[99]	Maximization of CU/CR	Energy capacity of the MC	Centralized, Markov Model, Heuristic, Approximation	Partial	SNC	TP, CT	CU/CR	TA, NS	**L1:** Fixed energy consumption rate of sensors **L2:** Fixed trajectory of mobile sensors **L3:** Perpetual NL is not guaranteed
	[185]	**O1:** Maximization of EUE **O2:** Minimization of number of dead sensors	Energy capacity of the MC	Centralized, Iterative, Approximation	Partial	MNC	TP, CT	Number of dead sensors, EUE, SRC	TA, NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[100]	**O1:** Maximization of sum of sensor's lifetime **O2:** Minimization of SRC	Energy capacity of the MC	Centralized, Heuristic, Approximation	Hybrid	SNC	TP, CT	Dead duration, SRC	TA, NS, FE	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[182]	Maximization of CU/CR	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Approximation	Hybrid	SNC	TP, CT	CU/CR, TEC	TA, NS	Perpetual NL is not guaranteed
	[113]	Maximization of EUE	**C1:** Energy capacity of the MC **C2:** Minimum recharging threshold	Centralized, Heuristic	Hybrid	SNC	TP, CT	SR, SRC, CHT, EUE	FE, TA, NS	Perpetual NL is not guaranteed
	[109]	Maximization of total dead time	**C1:** Energy capacity of the MC **C2:** Minimum recharging threshold	Centralized, Heuristic	Hybrid	SNC	TP, CT	SR, CHT, ST, RT	NS	Perpetual NL is not guaranteed
	[186]	Minimization of SRC	Energy capacity of the MC	Centralized, Heuristic, Approximation	Hybrid	MNC	TP, CT	Overall task utility, EUE	TA, NS	Perpetual NL is not guaranteed
	[183]	Maximization of accumulated monitoring quality	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Heuristic	Full	SNC	TP, CC, CT, FLR	SRC, Total dead time	NS	Perpetual NL is not guaranteed
	[189]	Minimization of total dead time	FLR constraints	Centralized, Heuristic	Full	MNC	TP, CC, CT, FLR	Total dead time, Collected data	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[69]	Maximization of number of charged sensors	Energy capacity of the MC	Centralized, Clustering, Approximation	Full	SNC	TP, CC, SS	Network coverage, SRC	FE, NS	**L1:** MC's traveling time is not considered **L2:** Perpetual NL is not guaranteed
	[177]	**O1**: Minimization of manufacturing cost **O2:** Maximization of payload energy **O3:** Maximization of sensor coverage **O4:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Approximation	Full	SNC	TP, CT, CC, SS	Network coverage, NL, Payload energy, Cost	TA, NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[97]	Maximization of EUE	FLR constraints	Centralized, Heuristic	Full	SNC	TP, CC, CT, FLR	SRC	TA, NS	**L1:** No constraint of MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[87]	Minimization of SRC	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Approximation	Full	SNC	TP, VC	SRC	TA, NS	**L1:** Fixed trajectory of mobile sensors **L2:** Perpetual NL is not guaranteed
On-Demand SMT for FDA	[116]	**O1:** Maximization of CHT **O2:** Minimization of CD	Energy capacity of the MC	Centralized, Greedy Heuristic	Full	SNC	TP	CHT, CD	FE, TA, NS	Perpetual NL is not guaranteed
	[106]	Maximization of NL	Charging deadline	Centralized, Greedy Heuristic	Full	SNC	TP	CHT, RT, WT	NS	**L1:** Same energy consumption rate of sensors **L2:** Charging time is not considered **L3:** Perpetual NL is not guaranteed
	[17]	Minimization of CD	Charging deadline	Centralized, Metaheuristic	Full	SNC	TP	CD	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[190]	Maximization of EUE	Energy capacity of the MC	Semi-Distributed, Heuristic	Hybrid	SNC	TP	SRC, Residual energy of sensors	NS	Perpetual NL is not guaranteed
	[142]	Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Charging window constraints	Centralized, Reinforcement Learning	Full	SNC	TP	SRC	TA, NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[134]	Minimization of FR	Energy capacity of the MC	Centralized, Greedy Heuristic	Full	SNC	TP, CT	FR, CD, SRC	TA, NS	Perpetual NL is not guaranteed
	[75]	**O1:** Maximization of payload energy **O2:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** Charging window constraints	Centralized, Greedy Heuristic	Partial	SNC	TP, CT	Payload energy, EUE, FR, SRC	TA, NS	Perpetual NL is not guaranteed
	[191]	Minimization of number of dead sensors	Energy capacity of the MC	Centralized, Heuristic, Reinforcement learning	Partial	MNC	TP, CT	NL	NS	Perpetual NL is not guaranteed
	[192]	Maximization of network coverage	Sensor state transition constraints	Centralized, Greedy Heuristic	Full	SNC	TP, SS, CC, CT	CD, Network coverage	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[184]	Maximization of NL	**C1:** **C2:** FLR constraints	Centralized, Heuristic	Full	MNC	TP, FLR	NL, TEC, Packet loss	TA, NS	**L1:** Charging time is not considered **L2:** Perpetual NL is not guaranteed

The studies [98], [101], [184]–[188] adopted the MNC approach for recharging the sensors. Ma *et al.* [98] solved two problems. The first problem aims to maximize the charging utility under MC's limited energy capacity constraint. The second one intends to minimize the service cost assuming that the MC has an adequate energy supply to recharge all the requesting sensors. Khellandi *et al.* [187] transformed the MCP into a clique partition problem and devised an on-demand multi-node charging algorithm to obtain MC's charging tour with minimum APs. Na *et al.* [186] divided the panic sensors into some clusters using the Welzl algorithm and devised the best charging efficiency algorithm to determine MC's traveling path. They also devised a branching second-best efficiency algorithm as an improvement over the first algorithm. Tian *et al.* [188] devised a greedy algorithm to obtain MC's traveling path for the JDCEP. In addition, they also utilized a UAV as an assistant data collector to the MC.

Similar to [109], [113], Liu *et al.* [184] proposed a charging path planning algorithm to form a primary traveling path for the MC via the sensors with urgent charging requests. Their algorithm then adjusts the charging time of some sensors if the full charging is not feasible for all the sensors in the primary path. Next, they devised a charging path optimization algorithm to further enhance the energy usage

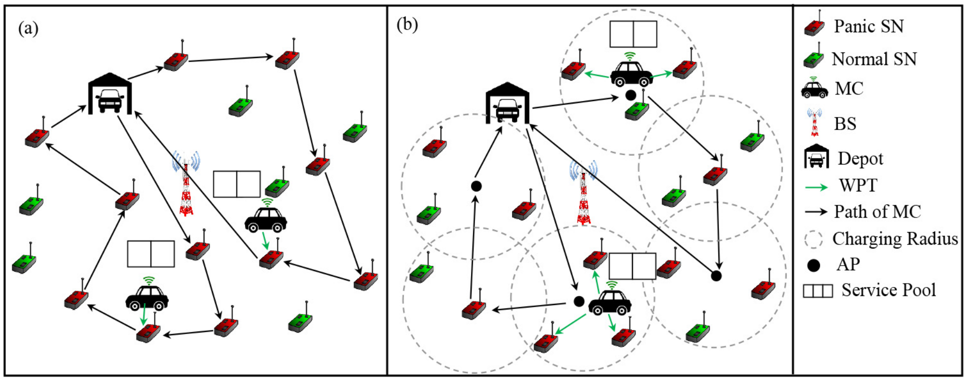

Fig. 13. Reference models of multiple MCs-based on-demand techniques for QDA with (a) SNC and (b) MNC approaches.

efficiency by reordering the charging sequence of the sensors. Yang *et al.* [101] jointly optimized the AP selection and charging tour determination to maximize the charging utility.

2) Fully-Dynamic Approach (FDA): In contrast to QDA, the MC in FDA approach serves one (or a few) charging request(s) at a time to accommodate urgent energy demands from the sensors. In other words, the controller updates MC's charging plan after completing each charging task in the FDA. Fig. 12 shows the reference models of single MC-based on-demand FDA techniques with SNC and MNC approaches. Notice that the MC in Fig. 12a still has sensors E, D, G, and F in its request queue as the MC serves only a single sensor at a time. Likewise, the MC in Fig 12b also has sensors A, C, and B in its queue as the MC fulfills only a few requests at a time in the MNC approach.

The works [17], [106], [116], [189] considered both temporal and spatial constraints for selecting the next-to-be-served request. He *et al.* [116] devised a nearest-job-next with preemption algorithm in which the MC can replace the next to-be-recharged sensor with a spatially nearest sensor. However, when the preemption occurs repeatedly, a significant portion of MC's energy is wasted for traveling. Moreover, the far-away sensors may face starvation as sensors located close to the MC can frequently preempt the charging activity of the former. To bridge this gap, the work [106] selected the next-to-be-recharged sensors based on a mixed priority of the temporal and spatial characteristics. Kaswan *et al.* [17] used the gravitational search algorithm with a new agent representation scheme to minimize the charging delay. Gharaei *et al.* [189] partitioned the network region into different zones and deployed a static power bank in each zone, which acts as a broker between sensors and the MC. In particular, the MC first recharges the power banks and then the power banks restore the energy of sensors within their zones.

Yu *et al.* [191] devised two algorithms to fulfill the energy demands of sensors in a manner that maximizes the network coverage, defined as the ratio of the area covered by the active sensors to the area of the network. Zhao *et al.* [75] solved traveling path planning and charging time allocation problems to maximize the payload energy while minimizing the service cost. A few papers [142], [190] utilized reinforcement learning to choose the next-to-be-recharged sensors. Cao *et al.* [142] selected the next recharging sensors using a reinforcement learning-based charging algorithm to minimize the service cost. Similarly, Nguyen *et al.* [190] first divided the network into square grids and proposed a heuristic to determine the appropriate charging time of the sensors and the candidate locations for the APs to recharge sensors. They then employed q-learning to select one of the MC's candidate APs as the next AP. Zhu *et al.* [134] estimated the energy consumption rates of the sensors using their current and previous residual energy. They then proposed two next node selection algorithms that utilize the sensors' charging probability, and minimum waiting time and maximum tolerable charging delay, respectively. Table V summarizes and compares various single MC-based on-demand MCTs using the attributes of the proposed taxonomy.

B. Multiple MCs-Based Techniques (MMT)

As stated earlier, a single MC cannot recharge all the energy-deficient sensors before their energy exhaustion in a large-scale network. It is because the MC carries only a limited amount of energy and takes significant time to recharge a sensor. However, multiple MCs can speed up the charging process and cover more sensors in time. In this section, we present different multiple MCs-based QDA and FDA techniques.

1) Quasi-Dynamic Approach (QDA): Fig. 13 demonstrates the reference models of multiple MCs-based QDA techniques with SNC and MNC approaches, which should be interpreted as described in Section VI-A1, with the exception that here multiple MCs are used instead of a single MC.

The studies [62], [128], [135], [139], [192]–[194] employed the SNC approach to recharge the sensors. Liang [193] dealt with the problem of finding the minimum number of MCs and their charging tours under the constraint of MC's energy capacity and charging deadlines. They devised an approximation algorithm to solve the said problem when the energy consumption of sensors is negligible during a charging round. Otherwise, they suggested a heuristic solution by adjusting the approximation algorithm to address the same problem. Wang *et al.* [135] first devised a hybrid data gathering scheme. In this scheme, the sensors transmit their delay-sensitive data to the BS in real-time, whereas an MS periodically collects their delay-insensitive data and uploads it to the BS. They then formed the shortest Hamiltonian cycle via some APs

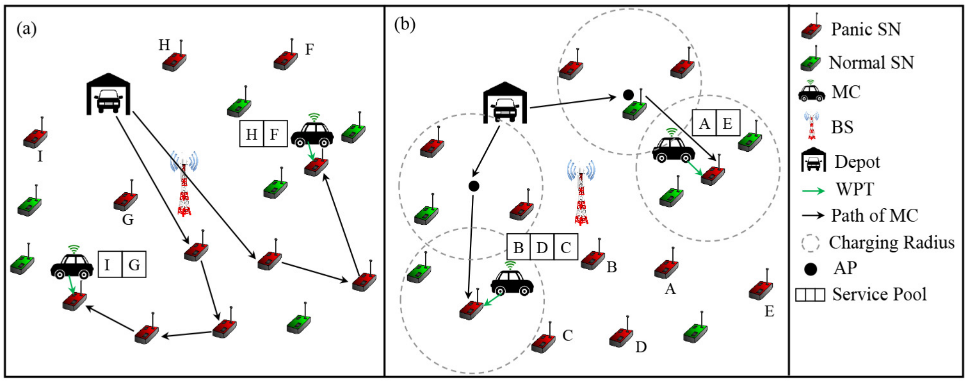

Fig. 14. Reference models of multiple MCs-based on-demand techniques for FDA with (a) SNC and (b) MNC approaches.

and assigned traveling paths to various MCs by splitting the original circuit. Haung *et al.* [128] presented a heuristic to maximize the max flow at sinks and minimize the service cost.

The articles [62], [139], [192], [194] presented various JDCEP techniques. The work [139] employed both MSs and MCs, whereas the papers [62], [192], [194] utilized only MCs. Wang *et al.* [139] first proposed a greedy algorithm that selects a sensor with minimum remaining energy as the next recharging sensor at each step. In contrast, they offered another algorithm that uses a capacitated minimum spanning tree to select the next sensors under the MC's charging capacity constraint. Han *et al.* [192] employed a mother MC carrying three sub-MCs to traverse the network for data gathering and recharging using a weight function of energy and distance. In particular, the mother MC unloads the sub MCs at predetermined APs when a cluster has more than one sensor to be recharged.

Wang *et al.* [62] suggested a three-level network architecture. First, they proposed a distributed approximation algorithm to install solar-powered cluster heads in a discrete space. After that, they presented an iterative solution for a continuous space using the Weiszfeld algorithm. Next, they devised a distributed head re-selection algorithm to attain energy balance in the network. This algorithm selects some wireless-powered sensors as cluster heads if solar energy is inadequate. At last, they proposed a linear-time algorithm for minimizing the length of traveling paths of the MCs. Similarly, Wang *et al.* [194] used clustering and a weight function to propose a combined recharging and data collection model.

Unlike the studies [62], [110], [139], [192], [193], the papers [89], [110], [123], [144], [195] utilized the MNC approach. These studies determined the MCs' APs by organizing the sensors into clusters and finalized their charging plans. The works [123], [144] divided the APs into some groups and assigned each group to an MC to revive energy-critical sensors. The authors then determined the charging tours with an approximation algorithm in [123] and an iterative algorithm in [144] such that there is no aggregated electromagnetic radiation (EMR) in the network. The work [89] utilized a non-dominated sorting genetic algorithm II and multi-criteria decision-making to recharge the sensors partially. Feng *et al.* [110] put forward a newborn particle swarm optimization algorithm to solve the MCP. It first finds an initial charging plan for half of the energy-critical sensors based on their charging time window. It then generates new particles for the leftover sensors and inserts them at appropriate positions in the initial path. Han *et al.* [195] suggested a new framework to facilitate multi-hop energy transfer by equipping sensors with low-cost resonant repeaters. Herein, the sensors act as relays and transmit excessive energy to their neighboring sensors. In particular, they used uneven clustering to obtain the MCs' charging tours based on average residual lifetime and inter-cluster distances.

2) Fully-Dynamic Approach (FDA): We show the reference models of multiple MCs-based FDA techniques with SNC and MNC approaches in Fig. 14. As mentioned before, the existing MCTs adhere to a non-partition-based approach [93], [105], [140], [196] or partition-based approach [85], [96], [107], [108], [111], [129], [197] to select the next recharging entity for the MCs. The former approach allows an MC to recharge any sensors (or MCs) in the network, whereas the MC can recharge sensors belonging to a specific area or group in the latter approach. The partition-based strategies adopt area partitioning [85], [96], [111], [197] or clustering [107], [108], [129] methods.

Lin *et al.* [105] utilized two charging request thresholds to combine the temporal and spatial importance of the energy-deficit sensors. They first presented a double warning threshold with a double preemption algorithm to select the subsequent recharging sensor for a single MC and then extended it for multiple MCs. The studies [93], [196] proposed game-theoretical collaborative scheduling in which the MCs play repeated games and find the next sensors (or MCs) to recharge based on Nash equilibrium. However, the work [196] results in reduced energy usage efficiency as more than one MC can decide to charge the same sensors. In contrast, the algorithm proposed in [93] dealt with such charging conflicts among the MCs by intelligently preparing the payoff function. Chen *et al.* [140] put forward a multi-agent reinforcement learning framework to schedule multiple MCs for maximizing the network lifetime and energy usage efficiency.

Different from [93], [105], [196], the studies [85], [96], [107], [108], [111], [129], [197] divided sensors into several groups and employed an MC in each group to recharge the sensors based on their energy demands. Han *et al.* [197] partitioned the network into three concentric square regions, i.e., inner, middle, and outer. The square regions are further

TABLE VI
COMPARISON OF DIFFERENT MULTIPLE MCS-BASED TECHNIQUES FOR ON-DEMAND CHARGING ARCHITECTURE, WHERE "CHARGING POLICY (CP)," "TYPE OF CHARGING (ToC)," "DESIGN ISSUES (DI)," "PERFORMANCE METRICS (PM)," "EVALUATION METHODS (EVM)," "THEORETICAL ANALYSIS (TA)," "NUMERICAL SIMULATIONS (NS)," AND "FIELD EXPERIMENTS (FE)"

	Paper	Objectives	Constraints	Approaches	CP	ToC	DI	PM	EVM	Limitations
On-Demand MMT for QDA	[196]	Minimization of number of dead sensors	Energy capacity of the MC	Semi-Distributed, Clustering, Heuristic	Full	MNC	TP	TEC, Number of dead sensors	TA, NS	Perpetual NL is not guaranteed
	[144]	Minimization of SRC	Maximum EMR level	Centralized, Approximation	Full	MNC	TP, CT	WT, TT	TA, NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[89]	**O1:** Minimization of SRC **O2:** Maximization of NL	Energy capacity of the MC	Centralized, Metaheuristic	Partial	MNC	TP, CT	SRC, NL, FR	NS	Perpetual NL is not guaranteed
	[128]	**O1:** Maximization of max flow **O2:** Minimization of SRC	**C1:** Energy capacity of the MC **C2:** FLR constraints	Centralized, Heuristic	Full	SNC	TP, CS, FLR	Max flow	NS	Perpetual NL is not guaranteed
	[110]	Maximization of NL	Charging deadline	Centralized, Metaheuristic	Full	MNC	TP, FLR, CC, MNoM	NoM, EUE	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[135]	Minimization of TEC	Connectivity constraints	Semi-Distributed, Approximation	Full	SNC	TP, FLR, CC	TEC	NS	**L1:** Uniform sensor deployment **L2:** No constraint on MC's energy capacity
	[139]	Maximization of difference of payload and traveling energy	**C1:** Energy capacity of the MC **C2:** FLR constraints **C3:** Charging deadline	Centralized, Greedy, Approximation, Heuristic	Full	SNC	TP, FLR, CC, MNoM	FR , Fairness index	TA, NS	Perpetual NL is not guaranteed
	[193]	Minimization of CYT	**C1:** Energy capacity of the MC **C2:** Charging deadline	Centralized, Clustering	Full	SNC	TP, FLR	Number of dead sensors, CD	NS	Perpetual NL is not guaranteed
	[62]	**O1:** Maximization of CT **O2:** Minimization of SRC	Energy capacity of the MC	Semi-Distributed, Approximation	Hybrid	SNC	TP, CC, CS, CT	TEC, SRC	NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[123]	Minimization of CD	**C1:** Maximum CYT **C2:** Energy capacity of the MC	Centralized, Approximation	Full	MNC	TP, CC, CS, CT	CD, SRC, Dead duration	TA, NS	**L1:** Energy loss in WPT is not considered **L2:** Perpetual NL is not guaranteed
	[194]	Minimization of NoM	Energy capacity of the MC	Centralized, Approximation	Full	SNC	TP, CC, CS, CT, MNoM	NoM, SRC	NS	**L1:** Fixed energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[195]	Maximization of NL	FLR constraints	Centralized, Heuristic, Approximation	Full	SNC	TP, CT, FLR, CC, CS, MNoM	NL	TA, NS	**L1:** No constraint of MC's energy capacity **L2:** Perpetual NL is not guaranteed
On-Demand MMT for FDA	[129]	**O1:** Maximization of number of alive sensors **O2:** Minimization of traveling energy	Energy capacity of the MC	Centralized, Clustering, Heuristic	Full	SNC	TP	SR, Traveling energy, TT	TA, NS	Perpetual NL is not guaranteed
	[85]	Maximization of NL	Energy capacity of the MC	Semi-Distributed, Heuristic, Fuzzy-Logic	Full	MNC	TP	SR, CD, EUE	NS	Perpetual NL is not guaranteed
	[105]	Maximization of EUE	Minimum recharging threshold	Centralized, Approximation	Full	SNC	TP, CS	EUE	FE, NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[140]	**O1:** Maximization of NL **O2:** Maximization of EUE	Minimum SINR requirement	Centralized, Reinforcement Learning	Full	SNC	TP, CS	NL, EUE	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed
	[108]	**O1:** Minimization of number of dead sensors **O2:** Maximization of EUE	Energy capacity of the MC	Centralized, Heuristic	Full	SNC	TP, CS	CHT, SR, FR, WT	NS	Perpetual NL is not guaranteed
	[198]	Maximization of NL	Energy capacity of the MC	Centralized, Heuristic	Full	SNC	TP, CS	Number of dead sensors	NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[93]	Maximization of EUE	Energy capacity of the MC	Semi-Distributed, Game Theory	Full	SNC	TP, CS	Number of deployed sensors	TA, NS, FE	Perpetual NL is not guaranteed
	[107]	Maximization of EUE	Energy capacity of the MC	Semi-Distributed, Game Theory	Full	SNC	TP, CS	EUE, Number of dead sensors	NS	**L1:** Same energy consumption rate of sensors **L2:** Perpetual NL is not guaranteed
	[111]	**O1:** Maximization of EUE **O2:** Minimization of number of dead sensors	**C1:** Energy capacity of the MC **C2:** FLR constraints	Semi-Distributed, Clustering, Heuristic	Full	SNC	TP, FLR	FR, EUE	NS	**L1:** Uniform sensor deployment **L2:** Perpetual NL is not guaranteed
	[96]	Minimization of TEC	FLR constraints	Semi-Distributed, Metaheuristic	Partial	SNC	TP, CT, FLR	TEC	NS	**L1:** No constraint on MC's energy capacity **L2:** Perpetual NL is not guaranteed

divided into smaller regions with diagonal lines. They then proposed three algorithms to select the next recharging sensors based on their energy profiles and locations. Tomar *et al.* [85] used the sensor's angular distance from a base axis line to divide them into different groups. In each group, the MC then uses Mamdani fuzzy interface system to find the recharging sequence of the sensors. Sha *et al.* [111] proposed a cost-balanced data uploading scheme using annulus-based partitioning and deterministic deployment. In each annulus, the MC selects the sensors to be recharged based on requesting sensors' survival probability and maximum tolerable recharging delay. In addition, an adaptive model to compute the recharging request threshold of the sensors is also proposed in [85], [111]. Zhong *et al.* [96] first partitioned the network based on a minimum spanning tree and selected some APs in each sub-region. After that, in each sub-region, they formed MC's traveling path under the sensor's buffer size, data collection delay, and energy constraints.

The studies [107], [108], [129] first exploited k-means algorithm to cluster the sensors and assign an MC to each cluster for energy replenishment. After that, Lin *et al.* [108] proposed three algorithms to address the MCP. First, they presented a shortest-path charging algorithm to minimize the service cost. Second, they proposed an emergency charging algorithm to prioritize the requesting sensors based on their residual lifetime. Third, they devised a hybrid optimal charging algorithm to combine the temporal and spatial constraints of the sensors. The paper [107] proposed a mixed temporal and spatial collaborative charging algorithm to maximize the energy usage efficiency. Likewise, Kumar and Mukherjee [129] devised algorithms for maximizing the number of alive sensors while minimizing the energy consumed by the MCs for traveling. Table VI briefly summarizes different multiple MCs-based on-demand charging techniques.

VII. FUTURE RESEARCH DIRECTIONS

The research on energy provisioning in WRSNs with MCs lasts for more than a decade and still attracts significant attention from industry and academia. Fig. 15 shows the year-wise distribution of research papers covered in this survey. Although enormous studies have been conducted, a few vital issues and methodologies remain underexplored and could emerge as new research hot spots.

A. Impact of Electromagnetic Radiation (EMR)

The existing works on mobile energy replenishment primarily optimize various performance metrics as described in Section IV. However, the WPT technology introduces a new source of electromagnetic radiation. It has been observed that exposure to high EMR levels leads to tissue impairment, brain tumors, miscarriage, and mental diseases [198]. EMR safety implies that the aggregated EMR level, i.e., the sum of EMR emitted by all the nearby MCs (and wireless devices) at any location in the network, should be less than a threshold value beyond which it is hazardous to human health. However, none of the existing papers on MCTs (except [144]) has focused on EMR safety during wireless charging of the sensors. Indeed, EMR from WPT adds to the radiation emitted from other existing wireless communication technologies

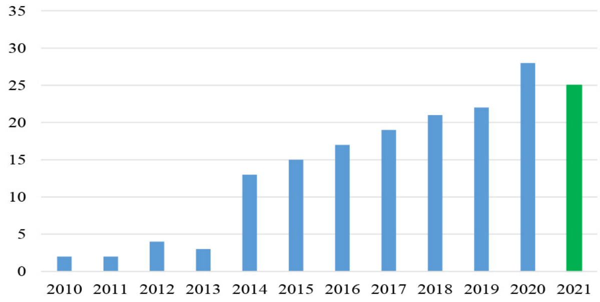

Fig. 15. Year-wise distribution of number of papers surveyed.

such as Zigbee, Bluetooth, Wi-Fi, etc. Due to strong assumptions, the existing MCTs cannot be adjusted to deal with EMR exposure. Nevertheless, maintaining EMR level within the safety threshold without impacting the quality of sensing and WPT efficiency is a critical issue in WRSNs. Therefore, future MCTs work should align with EMR safety standards.

B. Usage of Multiple Depots

In large-scale networks, a single depot is usually considered insufficient to guarantee uninterrupted network operation. The reason is that the MCs can carry a limited amount of energy, necessitating frequent travel back to the depot for their own energy replenishment. Hence, they spend a significant portion of their energy traveling back and forth, and a small amount is left to recharge critical sensors located very far from the depot. Hence, many sensors may suffer from starvation and become dead. Recently, some works [83], [118], [131] deployed multiple depots to deal with the limitation described above and ensure uninterrupted network operation. Nonetheless, the works [118], [131] assumed that the minimum number of depots and their locations to ensure the perpetual network lifetime are already known. In contrast, Jiang *et al.* [83] demonstrated that the requisite number of MCs and their service cost could be significantly reduced when multiple depots are used. However, the study [83] is applicable to deterministic networks and is unsuitable for dynamic networks. In fact, the problem of depot positioning has several technical challenges. First, finding the minimum number of depots required to ensure trade-offs among various objectives is very hard. Second, the number of potential sites where we can deploy the depots is infinite. Third, the two problems of finding the minimum number of depots and their locations are tightly coupled. Therefore, new techniques should be devised to solve the depot positioning problem in the future efficiently.

C. Recharging of Mobile WRSNs

Majority of the existing MCTs assume that all the sensors remain stationary once deployed. However, many real-life applications of WRSNs such as battlefield surveillance, forest fire detection, and wildlife and pollution monitoring require both stationary and mobile sensors. Sensor mobility causes frequent changes in network topology due to changes in the sensor's location, resulting in dynamic energy consumption rates of the sensors. Only a few works, such as [87], [99], [143], [168] studied the MCP with a network scenario having mobile sensors in which the sensors move along fixed trajectories. However, the sensors may not always follow a fixed mobility pattern due to the critical application requirements. The existing solutions may not perform well in such situations because additional constraints and variables must be incorporated to handle the sensor's unpredictable motion. The main issue with dynamic mobility is that WPT and data collection performances become time-varying, and resource allocation needs to be adaptive. Hence, future research should explore various mobility patterns to design stable and resilient energy replenishment schemes for both stationary and mobile sensors.

D. Multi-Source Energy Harvesting and Recycling

The rapid advancement in energy harvesting technologies enables realizing the perpetual operation of WRSNs. Most of the existing energy replenishment methods mainly focused on energy harvesting from ambient sources [10] such as solar, wind or wireless charging sources [13] such as RF radiation or magnetic coupling. Ambient energy sources offer a higher power density and energy generation if multiple sources are combined. However, the amount of harvested energy from ambient sources may still be insufficient to attain perpetual network operation due to various spatial-temporal factors, such as sunlight angle, humidity, temperature, and building obstructions. In contrast, WPT using one or more MCs has been proven a stable and promising technique to recharge hundreds of sensors reliably. However, a significant portion of MC's energy is wasted during traveling and wireless charging. Realizing the pros and cons of both methods, a few papers [15], [62], [128], [136], [176] used hybrid network composition in which different network components can harvest and recycle energy from multiple sources to achieve sustainability. The naive idea is to equip all the sensors, MCs, depots and the BS with all kinds of harvesting devices. Nevertheless, this approach would increase the system cost and complexity drastically. Hence, there is a scope to explore trade-offs among the system cost, complexity, and energy harvesting and recycling capabilities.

E. Usage of Artificial Intelligence Techniques

In recent years, artificial intelligence (AI) techniques, such as reinforcement learning, machine learning, artificial neural networks, and deep learning have been widely used to solve various problems in traditional WSNs [199]. These problems are routing, localization, congestion control, mobile sink scheduling, synchronization, target tracking, and fault tolerance issues. In contrast, a few researchers [99], [140], [142], [143] have used reinforcement learning to solve the MCP. However, AI techniques, including machine learning, artificial neural networks, and deep learning remain underexplored. AI would yield new possibilities for mobile charging in WRSNs by making various network components intelligent with self-adaption capabilities to deal with dynamic networks. In fact, these techniques can be used to predict the sensors' data generation rates, energy consumption rates, and energy demands. Predicted values can then be utilized to determine the minimum number of MCs and depots with their energy capacities and locations and plan efficient space-time scheduling of the MCs to attain perpetual network lifetime. However, implementing AI-based solutions

in resource-constrained WRSNs is a challenging task due to requirement of high computation power and memory than the traditional methods. In the future, the research community should revisit the MCP from a deeper AI perspective.

F. Usage of Mobile Edge Computing

Mobile edge computing (MEC) [200] has emerged as an efficient computing paradigm. Usually, the MEC is a three-layer architecture: cloud servers at the top layer, mobile and static edge devices at the middle layer, and end-user devices at the bottom layer. We can adapt the MEC architecture to design well-planned MCTs. In general, the top layer can still consist of cloud servers. Nonetheless, the middle layer can comprise MCs as mobile edge devices, and depots and the BS as static edge devices. The bottom layer can include stationary and mobile sensors. In such an arrangement, the middle layer would connect the bottom layer to the powerful cloud servers of the top layer to execute complex AI-based solutions for mobile charging in WRSNs. Besides, this type of architecture would aid in implementing AI-based distributed solutions, which require less computational power and memory footprint than the centralized ones. In addition to this, distributed solutions would allow network components to adapt their behaviors with the change in network dynamics quickly. Therefore, there is a great potential to design new MCTs based on MEC to solve the MCP efficiently.

VIII. CONCLUSION

In this paper, we have conferred a comprehensive survey on the MCTs in WRSNs. To begin with, we briefly summarized and compared the related survey papers to clarify the positioning of this paper. Then we presented the basic architectures of various network components and the quantitative models of the sensor's flow routing and energy consumption, MC's charging behavior and WPT techniques. We next described various fundamental design issues dealt by the MCTs and defined several vital metrics to quantify their performance. We then introduced a complete taxonomy of the MCTs based on various design attributes and surveyed the state-of-the-art literature by categorizing them into periodic and on-demand charging techniques. In addition, we compared and contrasted various MCTs in terms of objectives, constraints, solution approaches, charging options, design issues, performance metrics, evaluation methods, and limitations. Finally, we provided some possible future research directions.

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