Wireless Powered Mobile Edge Computing Networks: A Survey

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Wireless Powered Mobile Edge Computing (WPMEC) is an integration of **Mobile Edge Computing (MEC)** and **Wireless Power Transfer (WPT)** technologies, to both improve computing capabilities of mobile devices and energy compensation for their limited battery capabilities. Generally, energy transmitters, mobile devices, and edge servers form a WPMEC system that realizes a closed loop of sending and collecting energy as well as offloading and receiving task data. Due to constraints of time-varying network environments, time-coupled battery levels, and the half-duplex character of mobile devices, the joint design of computation offloading and resource allocation solutions in WPMEC systems has become extremely challenging, and a great number of studies have been devoted to it in recent years. In this article, we first introduce the basic model of the WPMEC system. Then, we present key issues and techniques related to WPMEC. In addition, we summarize solutions for computation offloading and resource allocation to solve critical issues in WPMEC networks. Finally, we discuss some research challenges and open issues.

CCS Concepts: • **Networks** → **Network management**; • **General and reference** → **Surveys and overviews**; • **Computer systems organization** → *Distributed architectures.*

Additional Key Words and Phrases: Energy harvesting, mobile networks, edge computing, wireless power transfer, resource management

1 INTRODUCTION

With the explosive increase in the number of mobile devices and the volume of network traffic, great challenges have been posed on the mobile wireless network, to satisfy the requirements of bandwidth consumption, latency, and energy consumption [1, 71]. Although **Mobile Edge Computing (MEC)** can improve the performance of computing-intensive and latency-sensitive applications. The limited battery capacity of mobile devices has

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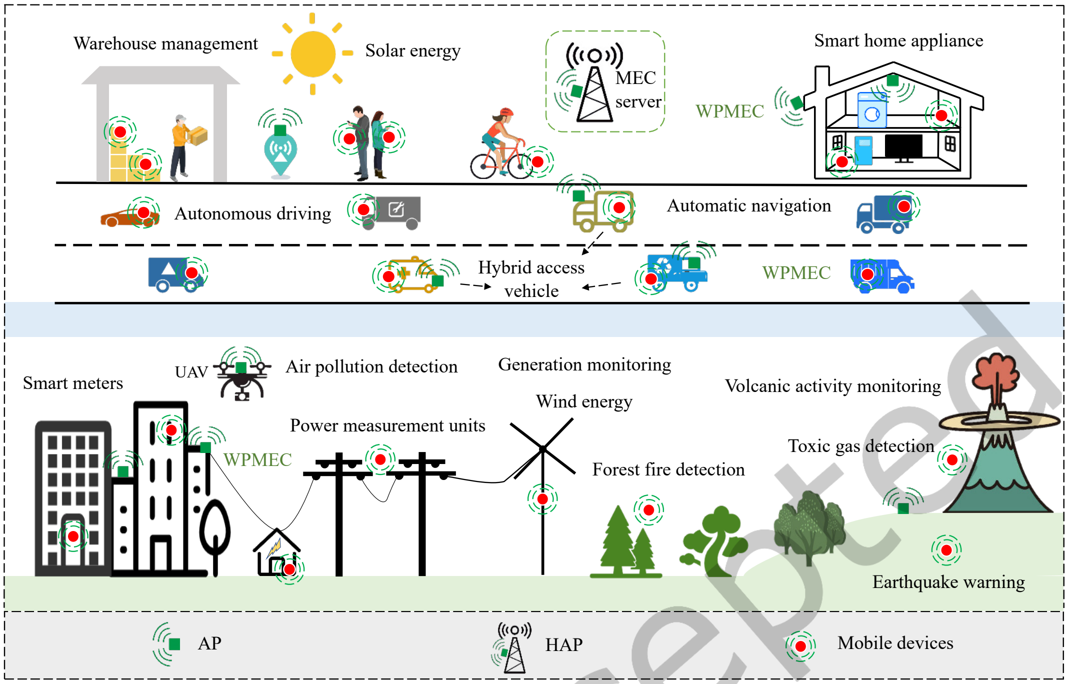

Fig. 1. Illustrative applications of WPMEC, where **Access Points (APs)** can emit energy signals, and mobile devices keep normal operation by harvesting energy. In addition, **Hybrid Access Points (HAPs)** has the ability to both send RF signals and process offloaded tasks [5].

become an energy bottleneck that affects network performance [141]. This is because high data rates, ultra-low latency communications, and strong data processing abilities are required for the upcoming 6G networks, leading to the high energy consumption of network devices [46]. However, it is not practical to expand the battery capacities of mobile devices to infinity. In addition, in remote areas and emergency circumstances, it is impossible to always recharge mobile devices by grid power.

The above challenge can be alleviated with the recent development of wireless **Energy Harvesting (EH)** technologies, such as renewable EH and **Wireless Power Transfer (WPT)** [47]. Renewable EH depends on solar, wind, ocean, as well as other renewable energy sources, and is excessively affected by natural conditions (e.g., weather, and climate) [53]. WPT realizes wireless charging of mobile devices by utilizing wireless APs to send **Radio Frequency (RF)** signals. Compared with renewable EH, it can provide stable and reliable energy supplies for mobile devices while prolonging their battery life [5].

1.1 Overview of WPEMC

Wireless Powered Mobile Edge Computing (WPMEC) is a new network paradigm, which combines WPT and MEC, and has the advantages of the above two technologies, i.e., boosting computing capabilities of mobile devices while relieving their energy shortage. Mobile devices can collect RF energy signals or other renewable energy signals to sustain their operations, such as local task processing or computation task offloading. In the upcoming 6G networks, WPMEC technology can alleviate energy limitations of **Internet of Things (IoT)** nodes, and ensure quick responses and real-time experiences for network applications [99]. It is worth mentioning that IoT requires satisfying performance at a controlled expense [74], while IoT with traditional MEC applications requires frequent device battery replacement [5]. Applying WPMEC to IoT scenarios extends the life of the device and reduces operations and maintenance costs used to replace batteries [4].

As shown in Fig. 1, application scenarios empowered by WPMEC mainly includes three categories [5]. The first contains applications in the IoT [5], such as autonomous driving [110], automatic navigation [31], smart home appliance [33], and warehouse management [120]. The second consists of applications in wireless sensor networks [51], such as air quality monitoring [61], water quality monitoring [135], forest fire detection [21], toxic gas detection [127], earthquake warning [15], and volcanic activity monitoring [143]. The last inlcudes applications in smart grids [13], e.g., smart meters [79] and generation monitoring [32]. In these scenarios, energy transmitters, mobile devices, and edge servers form a WPMEC network, where a closed loop of energy emission, energy receiving as well as task offloading and processing is realized. One typical use case enabled by WPMEC in IoT is warehouse management. In this application scenario, heterogeneous IoT devices are deployed around the warehouse. Those IoT devices are powered by APs and process application tasks with the assistance of MEC servers based on the collected environmental data.

Although the investigation of MEC and WPT techniques has been conducted in recent years, the latest technology of WPMEC has not been thoroughly reviewed so far, to the best of our knowledge.

1.2 Comparison and Contributions

Although the investigation of MEC and WPT techniques has been conducted in recent years, ***the latest technology of WPMEC has not been thoroughly reviewed so far, to the best of our knowledge*** Currently, some surveys focus on WPT technology. Authors in [42, 94] focus on EH technology to collect ambient energy for energy-constraint terminals. Authors in [2, 5, 7, 59, 101] investigate the RF-enabled WPT technology for wireless communications, where a **Wireless Powered Communication Network (WPCN)** can be built. Specifically, authors in [5] describe the design of **Simultaneous Wireless Information and Power Transfer (SWIPT)** as well as research challenges of WPCNs, and authors in [101] summarize some research results of WPCNs in terms of resource allocation and transmission scheduling strategies. Focusing on the RF signal fading problem, authors in [59] summarize the progress of WPCNs in improving EH efficiency. Authors in [7] overview network structures and performance enhancement techniques for WPCNs. Authors in [2] focus on the investigation of using beamforming technology to cope with the energy signal fading sensitivity of WPCNs. Authors in [2, 5, 7, 59, 101] combine WPT and wireless communications, conducting a process of collecting energy and then communicating. Compared with WPMEC, WPT solves the energy limitation problem of mobile devices, but does not take into account the limited computing resources of mobile devices.

In addition, some surveys focus on MEC, and can be roughly classified into four categories. The first category is about resource management, for example, authors in [43, 52, 85, 93] focus on resource management and computation offloading of MEC systems. The second category is related to application scenarios, for example, authors in [78, 81, 92] summarize the research progress of using MEC technology in IoT, industrial IoT, and mobile augmented reality applications, respectively. The third category is about related technologies, for example, authors in [18, 62, 87] summarize research applying **Machine Learning (ML)** , deep learning, and game theory techniques to MEC system, respectively. The last category is about security, i.e., authors in [83, 84] analyze security vulnerabilities and countermeasures of the MEC system. However, the limited battery capacities of mobile devices in MEC systems has a heavy impact on the system performance and the quality of user experience.

In Table 1, we provide comparisons among related surveys. we can conclude that most of exsiting surveys related to WPT technologies focus on applications, key technologies, and resource allocation of WPCNs. In addition, the investigation related to MEC involves aspects of resource allocation, computation offloading, application scenarios, related technologies, and security issues. However, there is a lack of systematic review articles that provide a comprehensive and specific discussion of research results on the deep integration of MEC and WPT.

Table 1. Comparisons among related surveys on MEC and WPT.

Network	Focuses	Ref.	Contributions
WPT	Renewable EH	[42]	Investigate RF energy harvesting networks
		[94]	Investigate architectures of EH-enabled sensor networks
	RF-enabled WPT	[5]	Summarize applications and challenges of WPCN
		[101]	Summarize applications of EH communication networks
		[2]	Survey energy beamforming techniques in WPCNs
		[7]	Investigate related techniques for WPCNs
		[59]	Summarize techniques for RF wireless networks
MEC	Security	[84]	Analyze security and privacy of the MEC system
		[83]	Reveal security vulnerabilities in MEC systems
	Application scenarios	[78]	Survey IoT applications and synergies with MEC
		[81]	Summarize architectures of MEC-related Industrial IoT
		[92]	Survey mobile augmented reality based on MEC and 5G
	Resource management	[93]	Discuss the smart resource deployment for MEC
		[85]	Survey service migration and resource allocation in MEC systems
		[52]	Investigate resource management of MEC systems
		[43]	Investigate resource allocation in MEC systems
	Related technologies	[87]	Survey the use of ML technology in MEC systems
		[62]	Summarize the use of game theory in MEC systems
		[18]	Summarize the use of deep learning in MEC systems
WPMEC	Resource allocation, related technologies, and solutions	This article	Summarize basic models, key issues, techniques, solutions, challenges and open issues for computation offloading and resource allocation in WPMEC systems

This has given impetus to this study, prompting us to conduct a comprehensive survey on basic models, key issues, techniques, and solutions of computation offloading and resource allocation in WPMEC systems. Our main contributions can be summarized as follows:

- We first survey related techologies of WPT and MEC, and then summarize system models, key issues and common techniques of WPMEC. It is promising to extend application scenarios from traditional static scenarios to dynamic scenarios with real-time responses, and reduce system energy consumption by reducing energy transfer attenuation and improving computation offloading efficiency.
- We summarize various approaches for computation offloading and resource allocation to solve key issues in WPMEC systems, present a generic model of each approach and provide the corresponding learned lessons. Side-by-side comparisons are provided for the state-of-the-art of WPMEC.
- We discuss several open issues and future research directions for WPMEC, including improved technologies for WPMEC, UAV-assisted WPMEC, time allocation for WPMEC, energy harvesting and transmission for WPMEC, and security issues in WPMEC.

1.3 Structure

The rest of this article is organized as follows. Section 2 first introduces the WPMEC model, and then discusses key issues and promising techniques in WPMEC systems. Section 3 overviews relevant solutions in WPMEC, and Section 4 discusses challenges and future research directions in WPMEC. A summary of this article is given in Section 5. For ease of reference, we provide definitions of commonly used acronyms in Table 2 (details in Appendix A of Supplemental File).

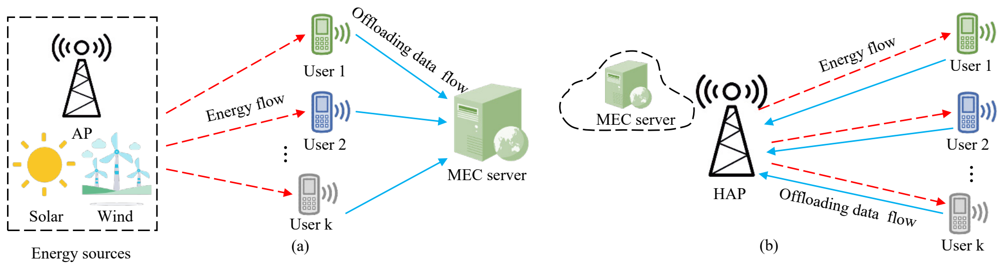

Fig. 2. System models of WPMEC: a) distributed deployment of energy transmitters and MEC servers; b) centralized deployment of energy transmitters and MEC servers.

2 WIRELESS POWERED MEC NETWORKS

Applying WPT technology to MEC networks alleviates the long-standing tug-of-war between satisfing system performance and tolerable energy consumption. This section first presents architectures, computation offloading models of WPMEC networks, and focuses on performance metrics from both user and operator perspectives. Then, we discuss corresponding key issues in detail. Finally, we focus on related techniques commonly used to solve key issues in WPMEC networks, i.e., convex optimization, and ML techniques.

2.1 System Models of WPMEC

WPMEC combines the benefits of WPT and MEC to provide controllable energy supply and low-latency edge services for mobile devices. The key technologies of WPT as well as MEC and the related architectures are detailed in Appendix B of Supplemental File.

The traditional WPMEC architecture mainly consists of edge servers, mobile devices and energy sources (including the solar, the wind, and APs with RF energy transmitters). Energy sources fulfill the charging needs of mobile devices to extend their runtime, while edge servers provide computing resources for them to improve their peformance [89]. In some studies, edge servers and APs are inetgrated, called HAP, which is capable of both transmitting RF signals and processing computation tasks offloaded by mobile devices.

2.1.1 Architectures. There are two major architectures for multi-user WPMEC networks, and their essential difference is whether the RF transmitter is deployed in the same place as the MEC server. The distributed deployment architecture in Fig. 2a consists of energy sources, k mobile devices, and an MEC server. The centralized deployment architecture in Fig. 2b consists of a HAP and k mobile devices. Since the RF transmitter and the MEC server are integrated at the HAP, the energy source of a HAP is the AP. Without loss of generality, both APs and MEC servers have long-term stable wired-power supplies. It is generally assumed that all mobile devices, RF transmitters, and MEC servers are equipped with a single antenna, and the wireless downlink is used for WPT and the uplink is used for computation offloading. It is always presumed that the sub-channel between the MEC server and mobile devices is a block fading channel, i.e., the channel power gain is constant in a time block.

2.1.2 Computation Offloading Models. Generally, there are two models adopted for computation offloading, i.e., binary and partial offloading. Binary offloading allows the computation task to be either processed locally or offloaded to the MEC server, taking into account factors including latency constraints and computation intensities of offloaded tasks [68, 90]. Some researchers have found that different parts of one task may have different latency and computational requirements, and thus offloading the whole task to the MEC server increases the latency and wastes resources [44]. Therefore, the partial offloading model is proposed, which divides the task into two parts based on factors such as latency and the amount of computation, with one part used for local computing and the other for server processing [70, 73].

In the multi-user WPMEC network, many users offload tasks simultaneously. To support multi-user offloading, some researchers adopt **Time Division Multiple Access (TDMA)** technology, dividing the offloading phase into multiple time slots and performing computation offloading for different users in different time slots [67]. TDMA mechanism enables the joint optimization of task offloading and energy collection, allowing for flexible time allocation schemes. By applying **Orthogonal Frequency Division Multiple Access (OFDMA)** technology, each user delivers computation tasks to the MEC server through mutually orthogonal subchannels . Theoretically, OFDMA technology can improve the spectrum utilization of multi-user WPMEC networks [103]. In addition, **Non-Orthogonal Multiple Access (NOMA)** technology enables spectrum sharing among multiple users and power allocation to different users. The NOMA collaborative offloading model can be applied to alleviate doubly near-far effects in WPMEC networks [35, 139].

2.1.3 Major Metrics. In WPMEC networks, operators are responsible for deploying APs with RF transmitters and installing energy receivers on commercial mobile devices, while the corresponding users pay operators for the convenience of no repeated charging. One of the major advantages of WPMEC over traditional MEC is that it alleviates the contradiction between the small capacity of device batteries and high-performance requirements. To evaluate the system performance of WPMEC, some metrics are introduced from both operator and user perspectives. Operators generally concern about the following metrics:

- Energy consumption: It refers to the energy consumed by the AP, users or the entire system in a time slot [76]. Although WPT and renewable EH technologies alleviate the energy limitations of the device, energy acquisition still has a cost. For example, the energy transmitted in the WPT phase originates from the grid, and a high upfront capital investment is also required for equipment deployment and energy conversion of renewable EHs.
- Energy efficiency: It is defined as bit-per-joule, i.e., the number of computation bits that can be implemented per unit joule in the system [63]. Energy efficiency has become an increasingly important metric because it trade-offs the conflict between computation performance and energy consumption. In addition, computation efficiency is defined by the inverse of energy efficiency and refers to the ratio of the energy consumed by the system to the number of bits computed.
- Computing completion rate: It is defined as the ratio between the data processed by the system and the total generated data [142]. In the case of poor wireless channel quality, insufficient device energy, and inadequate transmission time, some computation tasks may be dropped or stored in the buffer to wait for transmission in the next time slot.

Users commonly pay attention to the following metrics:

- Latency: It refers to the average completion time of tasks in the system within the task life cycle [39]. In recent years, delay-sensitive applications such as augmented reality and autonomous driving have received a great deal of attention, and the real-time delivery of processing results is critical to the network.
- Compututation bits: It refers to the total number of computed bits for all users in the system [51]. MEC brings computational resources down to the network edge, empowering mobile devices with powerful computing capabilities. Both of resource allocation and offloading decisions affect the computation rate.
- Throughput: It refers to the number of data bits that are successfully transmitted per time unit [88]. The time-varying wireless channels, the choice of edge servers, the formulation of user offloading modes, and the allocation of system resources all influence system throughput. In scenarios such as IoT, where a large amount of sensor information needs to be collected, the throughput is an important metric to measure system efficiency.

2.2 Issues of WPMEC

Although WPMEC technology compensates for the shortcomings of mobile devices with limited computational and energy resources, the performance of WPMEC systems is still affected by a set of challenges including half-duplex hardware constraints, doubly far-near effects, attenuation of signal transmission, high intermittency of renewable energy, the randomness of task arrivals, the order of task processing, the imperfect CSI, nonlinear EH models, and the selection of MEC servers. In this section, we discuss those key issues in detail.

2.2.1 Half-Duplex Hardware Constraints. In recent studies on WPMEC systems that rely on WPT technology to charge mobile devices, the collecting of RF energy and the offloading of task data are separated in the time domain by considering half-duplex hardware constraints [49]. Therefore, reasonable resource allocation and time division for RF energy collection and task offloading are required. However, there are conflicts between time division and resource allocation, since WPT determines task offloading, which in turn impacts the next phase of WPT. Therefore, the solution for resource allocation and computation offloading in WPMEC systems becomes extremely challenging.

2.2.2 Doubly Far-Near Effects. The doubly far-near effect is often generated in multi-user scenarios, where both energy emitters and MEC servers are deployed at the HAP. Specifically, users far away from the HAP collect less energy compared with those near the HAP in the same duration, and face a longer transmission distance for computation offloading [9]. This leads to inequities in EH and computation offloading among users, and performance for users farther away from the HAP cannot be guaranteed.

The optimization of key metrics such as energy consumption, energy efficiency, and computation rates in WPMEC systems is based on a compromise due to doubly far-near effects. In some way, the system metrics are always optimized to benefit mobile devices closer to the HAP at the expense of the performance of devices further away [98]. However, it is important to ensure fairness among mobile devices in the WPMEC system. Instead of concentrating on the overall performance of the system, some researchers focus on the performance of each mobile device [38, 49]. That is to say, a competition exists among mobile devices, and a Nash equilibrium should be achieved, and even the fairness among devices needs to be guaranteed. In addition, mobile devices can also work in a cooperative manner for mutual assistance to solve the doubly far-near effect.

2.2.3 Attenuation of Signal Transmission. The signal transmission attenuation refers to the energy attenuation of RF signal caused by the increasing transmission distance along with the task data blockage caused by the poor channel state. The attenuation of RF energy transmission needs to be considered when WPT technology is applied in practical scenarios. To solve the above challenge, researchers leverage multi-antenna techniques such as EB and **Multi-Iput Multi-Output (MIMO)** to improve energy efficiency and information transmission from point to point [12, 14]. Due to the high attenuation of WPT and the limitation of offloading duration, improving EH and offloading efficiency is urgent. **Backscatter Communications (BC)** and **Intelligent Reflecting Surface (IRS)** technologies are applied to WPMEC systems due to its ability to reflect wireless signals so as to assist in WPT and task transmission phases. In addition, a robust communication link can be established when the UAV is close to the mobile user. Therefore, **Unmanned Aerial Vehicles (UAVs)** acting as HAPs are also promising to improve the channel conditions between mobile devices and HAPs.

2.2.4 The High Intermittency of Renewable Energy. Although renewable energy sources such as solar, wind, and ocean in the nature are free of charge, they have disadvantages such as high environmental impacts and intermittency. Therefore, computation offloading and resource allocation strategies originally used for battery-powered MEC systems are not suitable for WPMEC systems powered by renewable energy [41]. Due to the high unpredictability of ambient EH, the energy collected in the current time slot is always assumed to be available for use in the next time slot [60].

To simulate the stochastic and high intermittency of renewable EH process, EH process can be modeled as an **Independent Identically Distributed (IID)** stochastic process [58, 112]. Then, the energy consumed by the current time slot for local computation and task offloading cannot exceed the sum of the energy collected by the current time slot and the remaining energy in the battery of the previous time slot. When making resource allocation decisions, compared to WPMEC systems based on WPT technology, those based on renewable EH need to consider energy state information along with CSI. Moreover, the time-dependent battery energy level couples computation offloading and resource allocation decisions across different time slots, requiring a good balance between system performance in current and future time slots. Such optimization problems with mutual coupling among time slots can generally resort to Lyapunov optimization and ML methods. The specific details are described in subsection 2.3.

2.2.5 The Randomness of Task Arrivals. Currently, many researchers provide a strong assumption for the processing of a single computation task in WPMEC systems, i.e., the task reaches each mobile device uniformly at the beginning of the time slot and can be resolved within that time slot [47]. The short-term performance optimization of latency-strict tasks simplifies the computation offloading process but faces challenges in real-world applications. When there are latency-tolerant application tasks (e.g., file backup), the random task arrival model needs to be considered to stabilize the long-term system performance [104].

To simulate the data arrival in practical scenarios, some researchers have designed random task arrival models [102, 104, 131]. The task arrivals of each mobile device are independent among time slots and can be modeled as an IID uniform distribution. Furthermore, mobile devices are generally considered to have a task arrival queue that satisfies the first-in-first-out processing order [47, 114]. Keep the above task arrival queue stable, and then all tasks arriving at mobile devices can be processed in a limited amount of time. Overall, WPMEC systems based on random task arrival models have to consider the stability of time-coupled task queues, and thus Lyapunov optimization methods applicable to solving classical queueing problems can be considered.

2.2.6 The Order of Task Processing. To better simulate the practical scenario, it is assumed that the computational resources of the MEC server is not infinite [17]. Therefore, the MEC server with a task buffer is leveraged for the mobile device to store its tasks that have not yet been processed. Then, the amount of unprocessed tasks in the current time slot is equal to the amount of offloaded tasks in the current time slot plus the amount of unprocessed tasks in the previous time slots minus the amount of processed tasks in the current time slot. We consider the constraint of data availability, i.e., a mobile device cannot offload more bits of data than the amount of data stored in its task buffer.

2.2.7 The Imperfect CSI. Typically, researchers assume perfect CSI or **Network State Information (NSI)** in WPMEC systems when developing task offloading and radio resource allocation policies [115]. However, CSI/NSI estimations are all derived from the real-time feedback of the pilot signal between the mobile device and the HAP [105]. In practical scenarios, there are signaling overheads, feedback delays, and prediction errors regarding all the CSI/NSI predictions. Therefore, it can be considered that only the past CSI/NSI is known. In some cases, when a mobile device needs to capture CSI/NSI estimations, the AP allocates a specific period to send the feedback information. The feedback is collected every τ time slot, where $\tau \in \{1, \dots, m\}$, and m is the maximum feedback interval. Based on their asymptotic nature, stochastic optimization methods such as standard Lyapunov optimization and stochastic gradient descent can be leveraged to improve the system performance even when outdated CSI/NSI is used.

2.2.8 Nonlinear EH Models. There are two major types of EH models, i.e., linear and nonlinear EH ones. The former considers that the conversion from RF energy to direct current power is a straightforward linear transformation, which is an idealized model [8, 38]. Whereas, in practical applications, the collected energy power varies nonlinearly with the input, because the collected energy tends to saturate in the high input power range

[75, 139]. The nonlinear model is more complex than the linear one, but it is also more accurate in portraying the EH process. Regarding the energy saturation problem in the nonlinear model, multiple EH rectifiers can be developed [75].

2.2.9 The Selection of MEC Servers. For the mobile device, how to select a target MEC server within the wireless communication coverage is a key research point for computation offloading [3]. Since different MEC servers have different workloads, radio channel fading and interference, the selection of the target MEC server is important for performance improvement. In particular, in WPMEC systems, the dynamic arrival of energy and tasks complicates computation offloading decisions in WPMEC systems [97]. Compared to traditional mathematical approaches, such as convex optimization, **Deep Reinforcement Learning (DRL)**, which is highly adaptive to environmental changes, is more efficent.

2.3 Technologies of WPMEC

To allocate system resources and develop computation offloading strategies, researchers typically formulate an optimization problem with a key metric as the goal, and use convex optimization or ML learning techniques to solve it. This subsection describe concepts and details related to convex optimization and ML techniques that are often used in the latest WPMEC-related research.

2.3.1 Convex Optimization. It can provide low-complexity solutions for large-scale optimization problems. The convex optimization methods commonly used in WPMEC systems include the Lagrangian dual method, **Alternate Directional Multiplier Method (ADMM)**, coordinate descent method, generalized Benders decomposition method, **Successive Convex Approximation (SCA)** method, Dinkelbach method, and Lyapunov optimization method.

When the optimization equation and the feasible set are convex, the Lagrangian dual method can be used to solve this kind of optimization problems. The Lagrangian dual method belongs to one of classical convex optimization methods, which converts the original optimization problem with constraints into an unconstrained problem by Lagrange functions. Since WPMEC systems require joint computation offloading and resource allocation decisions, the optimization problems are usually relatively complex. Therefore, under the conditions of Karush-Kuhn-Tucker pairwise complementarity, the dual problem of the original optimization problem is solved by the Lagrangian dual method [10]. ADMM is mainly used for solving convex optimization problems with a divisible structure. It decomposes the combinatorial optimization problem into N smaller parallel integer programming problems (N denotes the number of mobile devices), and obtains a global solution by solving N subproblems in parallel and coordinating their solutions [8].

Coordinate descent is a linear search algorithm based on one dimension, which can find the minimum value along the coordinate axis direction at each iteration. However, the coordinate descent method cannot solve high-dimensional problems. Instead, the **Block Coordinate Descent (BCD)** method is suitable to handle problems in high dimensions. It can be used to separate and alternately optimize variables related to resource allocation and computation offloading decisions until the algorithm converges. Since the optimization problem can be split into several subproblems, the BCD method is often used to solve WPMEC-related problems with a large number of optimization variables [48]. The generalized Benders decomposition method is a mathematical tool to decouple complex optimization problems into small-scale subproblems. It is known that integer and nonlinear constraints make the optimization problems of WPMEC-related systems difficult to solve. By using the generalized Benders decomposition method, the original optimization problem can be decomposed into a master problem and a subproblem. The master problem only has complex integer constraints and nonlinear constraint variables, and the subproblem is only with linear constraint variables. It is worth noting that the lower and upper bounds of the performance can be obtained by solving the master problem and the subproblem, respectively [38].

In particular, there are also some optimization problems in the WPMEC system with non-convex objective functions that are difficult to solve. SCA method finds a stable point as a local suboptimal solution for the original non-convex optimization problem by iteratively solving some convex optimization problems similar to the original non-convex problem [4]. When energy efficiency, computational efficiency, and other metrics are optimized in the WPMEC system, the objective function usually appears as a fractional expression. Dinkelbach's algorithm can be widely used for solving fractional programming problems by converting the original optimization problem into an optimization problem in the form of parametric subtraction, which can be solved by the convex optimization method [31]. Since Lyapunov optimization theory is a classical approach used to solve queueing problems, it can be specifically used to solve stochastic optimization problems with random arrival of tasks and time-coupled battery energy in the WPMEC system. Lyapunov optimization method decouples the original problem into a series of deterministic subproblems with independent time slots, which can be solved by convex optimization methods as mentioned before [131].

2.3.2 ML. ML is usually classified into the following three types, i.e., supervised learning, unsupervised learning, and **Reinforcement Learning (RL)**. Due to its adaptability to dynamic environments, ability to handle big data, and effectiveness in problem solving, ML has been applied in WPMEC networks to improve system performance.

Compared to traditional mathematical methods, algorithms developed based on ML techniques for resource management, computation offloading, and mobility management of WPMEC systems have two major advantages. First, with the development and maturity of related technologies, the network topology of the WPMEC system becomes increasingly large, and a huge amount of information need to be processed in each time slot. ML can learn useful information from a large amount of input data. For example, convolutional neural networks in deep learning can achieve the function of extracting sequence and spatial features from time-varying received information [20]. Second, in practical scenarios, the network conditions of WPMEC are unknown or highly dynamic. RL can enable real-time resource allocation and computation offloading decision making based on trained policies. Deep neural networks, also known as function approximators, can approximate traditional high-complexity mathematical algorithms infinitely. It is a low-complexity approach to achieve similar functions with traditional high-complexity mathematical algorithms, thus enabling fast responses to time-varying environmental states [109].

Generally, ML algorithms used for WPMEC systems include Q-learning and actor-critic, which maximizes the long-term performance through continuous learning [121, 132]. Due to its model-free property, RL is often used to train computation offloading policies for low-complexity systems, in the presence of time-varying channels and partial system observations. In the face of large and complex WPMEC networks with a large number of potential states, the performance of traditional RL methods may become unstable or even fail to converge [58]. Since **Deep Neural Network (DNN)** can be used as function approximators for RL strategies, DRL algorithms integrating DNNs and RL can achieve dimensionality reduction in the state-action space and avoid dimensional catastrophes. The two DRL algorithms commonly used for WPMEC systems are **Deep Q Networks (DQN)** and **Deep Deterministic Policy Gradients (DDPG)** [34].

3 SOLUTIONS ON WPMEC

WPMEC requires a trade-off among computing, communication, and EH. Although WPT charges mobile devices wirelessly through RF signals, the energy collected within a limited period is necessarily finite, and the energy consumed by computation and communication needs to be reasonably allocated. Therefore, researchers need to develop computation offloading strategies and jointly manage the allocation of energy, time, and computation resources. In the face of various issues mentioned in subsection 2.2, several approaches can be implemented to solve them in developing reasonable resource allocation schemes and computation offloading strategies. These methods include time allocation strategies, user cooperation frameworks, BC approaches, IRS approaches,

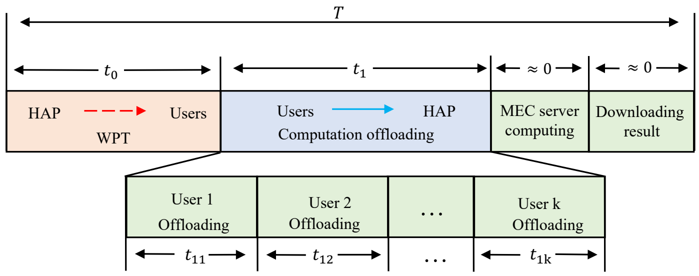

Fig. 3. An illustrative time division structure.

UAV-assisted frameworks, EB approaches, NOMA approaches, SWIPT approaches, queueing based solutions, and learning based solutions. Subsequently, we summarize the latest relevant research on these solutions and give learned lessons.

3.1 Time allocation strategies

Due to the half-duplex hardware limitation of devices, the process of collecting energy and that of offloading task data cannot be performed simultaneously. Therefore, many researchers have focused on how to reasonably schedule EH and computation offloading processes in the time domain.

Typically, the time division of the system considering half-duplex hardware constraints is shown in Fig. 3. A time block with length T can be further divided into four phases, i.e., WPT phase t_0, computation offloading phase t_1, the MEC server computing phase, and the result downloading phase. The computation capability of the MEC server is much higher compared to that of mobile devices [110]. Therefore, some researchers assume that the processing delay caused by the MEC server is negligible compared to that taken for offloading and transmitting [8, 48]. Moreover, the size of the computation result is much smaller than that of the original task, and thus the duration of the downloading stage is negligible [30, 116, 142]. Thereby, the time block can be regarded to include merely WPT phase t_0 and computation offloading phase t_1.

In the WPMEC system, researchers consider applying time allocation strategies to solve the half-duplex hardware constraint. For example, authors in [48] perform time allocation and computation offloading decision making by solving the max-min energy efficiency optimization problem. By considering the half-duplex hardware of the mobile device, the HAP is assumed to equipped with two antennas to achieve spatial separation of WPT and receive computation task streams, i.e., mobile devices are in half-duplex operation mode while the HAP is in full-duplex operation mode. In terms of time allocation, the antenna used by the HAP for WPT works for a full-time slot, while the offloading process of mobile devices is in TDMA mode and each mobile device can collect RF signals during the rest of the time when offloading is not performed.

Different from the study in [48], which assumes a full-duplex mode of operation for HAPs, authors in [8] investigate the problem of offloading mode selection and time allocation when both HAPs and mobile devices are in half-duplex modes. The time allocation is first obtained by Dichotomous search method, and then the coordinate descent method is used to optimize the offloading mode selection. Similar to [8], authors in [38] also investigate the joint time allocation and task offloading problem under half-duplex constraints. However, Different from the study in [8, 48], authors in [38] take both of the processing time of the MEC server and the downloading time of the task results into consideration. The formulated optimization problem is a mixed-integer combinatorial nonconvex optimization problem, and can be decomposed into two subproblems of computational mode selection and communication as well as computational resource allocation, where GBD method is leveraged to solve them.

Unlike the previously mentioned studies dedicated to systems with one edge server, authors in [142] design algorithms that address time allocation and computational resource scheduling in multi-server scenarios. By considering that different load and channel conditions may result in different energy and time consumption for task offloading, the selection of MEC servers is also modeled as an optimization problem to maximize the computation completion rate. When time allocation is fixed, the optimization problem can be decoupled into a generalized allocation problem and a computational scheduling algorithm, where the generalized allocation algorithm is designed to solve them. Different from studies in [8, 38, 48, 142] based on linear EH models, authors in [116] investigate time and energy optimization problems based on non-linear EH models. By considering the diversity of tasks in wireless networks, a hybrid offloading paradigm with both partial and binary offloading is proposed. The formulated optimization problem is transformed into two subproblems, i.e., offloading decision making and resource allocation, which are solved by a greedy algorithm and a convex optimization method, respectively.

Considering the advantages of ML methods in solving high-dimensional complex problems, some researchers utilize them for time allocation and offloading decision making in WPMEC systems. DROO [30] is a DRL-based task offloading and time allocation algorithm by considering dynamic wireless channels. Since DROO can learn from past offloading experience and is applicable for continuous state spaces, it can solve complex mixed-integer programming problems and does not require discretization of the channel gain. To reduce the computational complexity of the high-dimensional action space, DROO considers an order-preserving action generation method. Different from the research dedicated to centralized resource management in [30], OLD-COP [110] provides distributed time allocation and offloading decisions in scenarios with multiple edge servers. By considering task deadlines and energy constraints, the optimization problem is formulated to minimize the total task delay. It takes into account the consensus of multiple edge servers for the WPT period, and each edge server performs offloading decisions independently using its trained policy. The edge server learns and decides the processing order of collected tasks, processes them in order, and sends them back to the target mobile device.

Lesson 1: Time allocation policies are widely used for resource allocation and computation offloading decision making in WPMEC systems, to achieve time-domain separation of WPT and task offloading processes for solving the half-duplex problem of devices. However, mobile devices can only perform local computing and EH during WPT time slots. This time allocation strategy is reasonable but still has room for improvement in its time utilization. For example, mobile devices can be divided into two types, and time utilization can be improved by alternating WPT and task offloading between the two types of devices.

3.2 SWIPT Approaches

The half-duplex hardware constraint of the WPMEC system makes WPT and computation offloading processes separated. SWIPT technology is introduced to improve the efficiency of spectrum utilization [24, 75, 102, 134], which transmits energy and information data in parallel. We have briefly described the corresponding receiver architecture for SWIPT techniques in Appendix B of Supplemental File.

Different from WPMEC systems that leverage traditional post-collection communication protocols, authors in [134] consider the SWIPT approach, which allows for the simultaneous transmission of information and energy. The EH and ID modules are integrated into the mobile device, which collects energy from the SWIPT signal sent by the HAP and decodes the information. A user scheduling framework is designed, where a time frame is divided into multiple time blocks and only one mobile device is served in one time block. The user offloading order is first fixed to optimize the PS value, offloading policy, and time allocation, and then the order is selected by fixing the PS value, offloading policy, and time allocation. However, for time-sensitive tasks, this model is not efficient because a block of time serves only one mobile device. Different from the study in [134], which considers a traditional WPMEC system, authors in [24] design a satellite IoT system that combines SWIPT approach and MEC technology. APs operate in the full-duplex mode and are powered by a mix of grid and renewable energy sources. The non-convex nonlinear optimization problem with the throughput of mobile devices as the optimization metric can be decomposed into two subproblems: i) **Central Processing Unit (CPU)** frequency selection of mobile devices and task allocation, and ii) the offloading power determination.

Different from the study in [24, 134] where linear EH models are considered, authors in [75] study WPMEC systems using non-linear EH models and SWIPT methods. The idea of having multiple nonlinear EH rectifiers in mobile devices is proposed to avoid EH entering the saturation zone. When the mobile device receives the SWIPT signal, a portion of the signal power is used for ID, while the remaining portion is distributed to multiple EH rectifiers for energy harvesting. The optimization problem with task delay as the optimization metric can be solved by the Lagrangian dual method. Different from the study in [75], authors in [102] not only consider the nonlinear EH model and SWIPT method, but also address the random task arrival problem. Due to the time-varying channel and the dynamic task arrival, MDP is used to describe the optimization problem to minimize system energy consumption. An intelligent computation offloading algorithm based on DDPG is designed to solve the control problem with the coexistence of discrete and continuous states.

Lesson 2: The design of optimization problems using the SWIPT method is focused on the formulation of computation offloading decisions without considering the allocation of limited time resources for mobile devices. Therefore, while optimizing the power distribution ratio of SWIPT, the conflict between WPT and offloading duration should be relieved.

3.3 User Cooperation Frameworks

With the deployment of HAPs, WPMEC networks are susceptible to the doubly far-near effect, which directly leads to inequities in both EH and computation offloading among users. The introduction of user cooperation schemes can improve network efficiency and achieve good network performance for the WPMEC network. Fig. 4a shows an example of user cooperation in WPMEC networks, consisting of two users and a HAP. The user far from the HAP is set by the **Far User (FU)** and that near to the HAP is the **Near User (NU)** [50]. Distances from the FU and the NU to the HAP are d_1 and d_2 respectively (obviously, $d_1 > d_2$), and the distance between the FU and the NU is d_{12} ($d_{12} < d_1$). Since this system is affected by the doubly far-near effect, the NU is considered to cooperate with the FU for computation offloading to ensure system fairness [10, 31, 36, 45]. Due to the lower offloading cost of the NU than that of the FU, the cooperative computation offloading phase can be divided into phases t_{11} and t_{12} [28, 35]. In t_{11} phase, the FU offloads tasks to the NU and the HAP, respectively. In t_{12} phase, the NU forwards computation tasks from the FU and its own tasks to APs. Cooperative offloading is not limited to the use of cellular links. Authors in [95] leverage **Device-to-Device (D2D)** communications among mobile devices to assist cooperative offloading in WPMEC networks. D2D communication-assisted offloading mode is convenient and energy-efficient, since it can facilitate relaying and performing computation tasks among neighboring devices.

To fully utilize available resources and ensure fairness among users, many researchers focus on user cooperation-assisted WPMEC systems. In this system, computational and communication resources of users can be shared to some degree. Existing related studies can be classified into two categories: dual-user cooperation and multi-user cooperation. RT-EEM [31] is a dual-user cooperative resource allocation algorithm with energy efficiency as the optimization metric, and a collaborative offloading mechanism is designed to mitigate the doubly far-near effect. The original optimization problem is a concave fractional programming problem, which is transformed into a convex optimization problem in the form of parameter subtraction with the Dinkelbach algorithm and solved by the Newton iteration, Lagrangian, and subgradient algorithms. Different from the study in [31], which only optimizes time allocation, UC-JOPT [28] is a user cooperative resource allocation algorithm that jointly optimizes energy and time. The optimization problem aiming to minimize energy consumption of APs is first converted

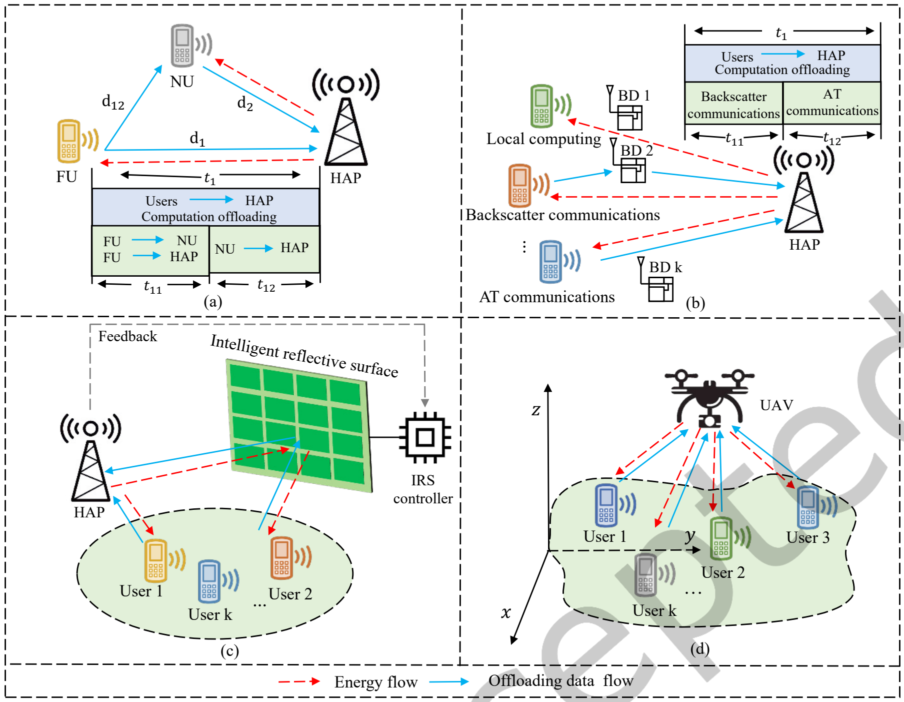

Fig. 4. Schematics of different solutions in the WPMEC network: a) user cooperation frameworks; b) BC approaches; c) IRS approaches; d) UAV-assisted frameworks.

into a minimum-maximum energy consumption problem and then solved by Lagrangian dual method. A user cooperation scheme with joint computation and time resource allocation is proposed in [35]. The introduction of NOMA technology can lower user energy consumption, and far and near users can offload their tasks at the same time by using NOMA in the offloading phase [28, 31].

In contrast to studies in [28, 31, 35], which consider dual-user cooperation in WPMEC systems, MRACO [36] is a multi-user cooperative computation offloading algorithm. Tasks can be offloaded to the MEC server with the help of neighboring nodes. The MRACO algorithm aims to determine the optimal relay device, task assignment, and offloading power for the user. Since a mobile device selects multiple relay-assisted offloading nodes, this, in turn, optimizes the task splitting rate. By taking the task execution time and the number of dropped tasks as penalties, the optimization problem is a high-dimensional **Markov Decision Process (MDP)** problem. The objective function is converted into two unrelated functions and solved separately by Lyapunov optimization method.

The previously mentioned user cooperation models assume that the NU as a relay node is willing to help the FU transmit task data, but this assumption is too ideal. Generally, the NU consumes its energy and storage resources by receiving the task data offloaded by the FU and forwarding it to the HAP. Therefore, it is worth considering how to motivate the NU to relay the task data for the FU. Authors in [45] discuss the above issues in detail, and design EH-based incentives that stimulate NUs to act as relay nodes by collecting energy from FUs. The study in [10] is conducted on the scenario with a single relay and multiple mobile devices, where the relay node can help users forward and process computation tasks. To motivate mobile devices to serve as relays, an EH-based incentive mechanism is proposed, i.e., it uses SWIPT technique and allows the relay device to receive offloading data while also collecting energy. By considering that simultaneous transmission of SWIPT signals by multiple users is susceptible to interference, the NOMA technique is used in the offloading phase. This method not only mitigates the dual far-near effect by using the relay cooperation model but also motivates mobile devices to participate in task offloading based on SWIPT technique.

Since EH-based incentives increase the hardware cost of mobile devices (due to the need to send SWIPT signals), other incentive mechanism can be considered to apply in the WPMEC system, such as monetary-based incentives [54], social relationship-based incentives [96], reputation-based incentives [129], bandwidth exchange-based incentives [117], and hybrid incentives [86].

Lesson 3: Most of existing studies assume that relay devices are willing to participate in the cooperative offloading process, which is ideal. Fortunately, the SWIPT technique and EH-based incentives can be utilized for cooperation. In addition, in user cooperation mode, it causes delays when the mobile device forwards task information to other mobile devices. Therefore, the issue of choosing the appropriate relay device while ensuring the completion of computation tasks is worthy of investigation.

3.4 BC Approaches

Active Transport (AT) refers to the process of offloading computation tasks to the MEC server via traditional radio architectures. Since AT contains components such as power amplifiers and carrier oscillators that consume most of the collected energy, it is difficult to reduce energy consumption of AT without affecting transmission performance. BC refers to the process of scattering electromagnetic waves in different directions when electromagnetic waves and antennas interact. The **Backscatter Device (BD)** in the BC process can modulate and help reflect the input signal from the transmitter to the receiver at low energy. Therefore, BC is often used to assist the communication process and reduce communication energy consumption. Since energy-free components are used, the energy consumed by the transmission process using BC is several orders of magnitude less compared to AT [144].

Due to the half-duplex limitation of the hardware, WPT duration and computation offloading duration should be counterbalanced. When the collected energy is utilized for energy-consuming operations (e.g., computing offloading), the mismatch exists between the collected energy and that required by mobile devices. To solve the above challenge, authors in [66, 91, 122, 144] apply BC to the WPMEC system. Passive transmission applied with BC consumes less energy, but is relatively dependent on a positive channel environment. AT achieves more stable and reliable transmission by sacrificing power consumption. Thus, mobile devices can use passive transmission and AT to jointly deal with dynamic channel scenarios. Fig. 4b shows a multi-user WPMEC system integrated with BC, where BDs are deployed on mobile devices and can assist in the computation task offloading process. The offloading phase is then divided into a passive offloading phase using BC and an active offloading phase based on AT. The user can adjust load impedance to achieve flexible switching between BC offloading mode and AT offloading mode, according to channel conditions and task delay tolerance [144].

Authors in [108] consider resource allocation of mobile devices in WPMEC networks when accessing WiFi and cellular networks. Mobile devices connected to WiFi can transmit data to the access point with the assistance of BC technology. Due to the limited communication range of BC, mobile devices connected to the cellular network can only collect ambient energy and then transmit data. The formulated resource allocation problem is solved by the Lagrangian dual method. FEA [66] is a fast and efficient resource allocation algorithm for IoT devices based on BC and OFDMA technologies. It considers a scenario with single-user and single-BD, without paying attention to the energy consumption of BD components. Since the complexity of this optimization problem is high, authors optimize time division and offloading decisions under the condition of maximizing the transmit power and the backscattering coefficient.

Authors in [122] design a resource allocation scheme with multiple BDs and multiple users. In contrast to the FEA method [66], which solves the original optimization problem by fixing the optimal transmit power and the backscattering coefficient, authors in [122] optimize the transmit power and the backscattering coefficient by the alternating optimization method. The original optimization problem is divided into two subproblems: i) the first subproblem is to optimize user offloading duration and offloading decisions with fixed backscattering coefficient and transmit power; and ii) the second subproblem is to optimize backscattering coefficient and transmit power with fixed user offloading duration and offloading decisions. Similar to [122], Hybrid-DOS [145] is a computation offloading algorithm that takes into account energy consumption of BDs. In particular, it is assumed that both wireless devices and BDs are powered wirelessly by the AP. In the case of sufficient energy, users can choose the active offloading mode, i.e., offloading computation tasks directly to the MEC server. Whereas, in the case of mobile devices with insufficient energy, BC-assisted offloading is adopted. The BC-assisted offloading mode is characterized by low rates, low power consumption, and susceptibility to channel changes, and thus the hybrid offloading scheme adopted by Hybrid-DOS is expected to balance the conflict between the transmission rate and energy consumption during the computation offloading phase.

Lesson 4: Although BDs are devices with a low energy level, the total energy consumption needs to be minimized when massive BDs are deployed. Besides collecting RF signals from APs similar with mobile devices, BDs can also collect ambient energy to maintain operations.

3.5 IRS Approaches

IRS is an artificial surface manufactured from electromagnetic materials and is regarded as a new technology capable of reconfiguring the WPMEC environment to improve the efficiency of energy and information transfer [4, 51, 56]. IRS can be constructed by an integrated panel, consisting of a controller circuit and some passive reflective elements with low costs. The IRS gain refers to the combination of the virtual array gain and the reflected beamforming gain, and can be achieved by adjusting the amplitude and the phase of the incident signal with each reflective element [25]. Similar to BC technology, IRS technology can also assist WPMEC systems by reflecting RF signals and offloading data. Unlike BC, IRS can establish an additional real-time communication link intelligently through the IRS controller. Based on the feedback provided by the HAP, the IRS controller can adjust the reflection coefficient of the reflective element in real-time to improve the reflection efficiency. Fig. 4c shows a WPMEC system deployed with IRS containing N reflective elements, and the coefficients of each reflective element are adjusted in real-time by the IRS controller through the optimization feedback provided by the HAP. Reflection-based beamforming is performed by modifying the uplink and downlink phases to boost the efficiency of energy transmission and computation offloading.

Authors in [4] combine IRS techniques to jointly optimize energy, time and computational resource allocation. An IRS containing N reflective elements is deployed near the device, and a portion of the RF signal and offloading data is reflected by the IRS and reaches the target side. It also applies OFDMA technology in the offloading phase to improve the transmission efficiency. The original optimization problem is decomposed into two subproblems: i) WPT; and ii) time division and computational resource allocation. Subproblems are solved by SCA and interior point methods. Different from [4], authors in [51] design a joint time, energy, and computation resource allocation strategy, to both minimize the IRS energy consumption and maximize the number of computation bits. The original optimization problem is a non-convex nonlinear problem that is not easy to solve due to the coupling among optimization variables. It is decomposed into four subproblems by using the BCD method, i.e., offloading power and time allocation, CPU frequency selection of mobile devices, designs of downlink EB and uplink beamforming.

Lesson 5: First, since the number of IRS is proportional to the transmission efficiency, IRS energy consumption is not negligible in scenarios where numerous IRS components are deployed. Second, due to IRS energy consumption and fixed deployment locations, some IRS reflection dead spots exist. It is promising to combine UAVs with IRS, which can provide a full range of charging and computing services for mobile devices [133].

3.6 UAV-assisted Frameworks

Based on microwave **Line-of-Sight (LoS)** transmission, the practical scenario of ground-based wireless RF signal transmission and data offloading is bound to have a high path loss, caused by a variety of static or dynamic object occlusion. A robust communication link can be established when the UAV is close to the mobile device, its transmit power is greatly reduced and the energy utilization of the transmission link is higher than that of conventional WPT. Owing to their advantages including high flexibility and controlled mobility, UAVs are often used as mobile relays and airborne base stations to assist infrastructure for communications [69, 72, 111, 128]. As shown in Fig. 4d, the UAV plays the role of an MEC server, which wirelessly charges k mobile devices and provides computing services for them. Mobile devices are fixed on the ground, and the UAV flies at a fixed altitude of H meters (H>0).

In the majority of studies on WPMEC, mobile devices charge through a fixed AP and the provision of additional computing resources is considered. However, the coverage of the fixed AP is limited and the mobility of devices is not negligible. Authors in [40, 138] integrate UAV communications with a WPMEC network to compensate for the lack of fixed APs. Equipped with both high-capacity batteries and computing processors, the UAV can provide controlled energy for ground-based mobile devices and expand their computing capabilities [40]. By communicating over a low-path-loss link between the UAV and the mobile device, both offloading and transmission energy consumption can be reduced.

Authors in [138] investigate the UAV cooperative approach for jointly optimizing UAV movement trajectory, energy, and computational resource allocation under partial offloading and binary offloading modes in WPMEC networks, respectively. In this case, the UAV charges mobile devices and provides computing services. It is assumed that the UAV is in the full-duplex mode, i.e., WPT and computation offloading are performed simultaneously, while the mobile device is in the half-duplex mode and uses TDMA for offloading time allocation. Since the optimization problem is nonconvex and variables are nonlinearly coupled, it is decomposed into two subproblems: i) the design of UAV trajectory; and ii) the selection of offloading power, time allocation, and CPU of mobile devices. They are solved separately with subgradient and SCA methods.

Unlike the study in [138] where energy consumption of UAVs is not considered, authors in [40] investigate trajectory design, resource allocation, and computation offloading decisions for UAV cooperation to minimize energy consumption of UAVs in the WPMEC system. Considering the randomness of tasks, mobile devices within a time slot can be divided into active ones with computation tasks and negative ones without computation tasks. The user cooperation model is also considered to solve the doubly far-near problem, i.e., negative devices help with task processing and offloading. The optimization problem with UAV energy consumption as the optimization metric is nonconvex and has highly coupled variables. SCA and alternating iterations methods are used to solve the formulated optimization problem.

Different from studies in [40, 138], which utilize UAVs to act as HAPs, authors in [19] consider an IoT scenario where both ground-based HAPs and UAVs provide charging and computing services for mobile devices. An energy-aware resource scheduling scheme with on-demand sensing and WPT is proposed to minimize energy consumption of IoT nodes, where IoT nodes with service requirements and the HAPs providing services are first identified, and then task offloading is performed. The above studies of UAV-assisted communication and offloading do not consider the issue of energy sources for UAVs, authors in [39] introduce the concept of UAV laser charging. Both the UAV and the macro base station can provide computing services to ground users, with the UAV sustained by the collection of laser energy from the macro base station. The formulated optimization problem with UAV service time and task completion time as optimization metrics is a mixed integer nonlinear problem, which can be decomposed into two subproblems of UAV placement, computational resources and bandwidth allocation, that are solved separately by convex optimization methods.

Similar to [39], authors in [29] consider laser-charged UAV-assisted WPMEC systems. The UAV serves as a relay, assisting in task offloading and energy transmission. On one hand, the AP charges the UAV via laser, while the UAV sends RF signals to mobile devices. On the other hand, mobile devices offload tasks to the UAV, and the UAV considers processing these tasks or offloading them to the AP. Thus, the UAV acts as an information and energy relay, mitigating doubly far-near effect and signal transmission fading problems. Since the optimization problem with task completion bits as the optimization metric is non-convex and variables are highly coupled, the formulated problem is decomposed into three subproblems, i.e., WPT power selection, time allocation, and UAV trajectory plan, and solved by Lagrangian dual, SCA, and subgradient methods, respectively.

Lesson 6: For UAV cooperation in the WPMEC system, it is assumed that WPT and task offloading are performed simultaneously, without considering the half-duplex constraints of mobile devices. However, this assumption is too ideal. To better simulate the mutual impacts among energy, time, and computational resources in real-world scenarios, researchers need to design more reasonable resource allocation schemes for UAV cooperation.

3.7 NOMA Approaches

To improve the computation offloading efficiency in the multi-user WPMEC system, the researchers introduce the NOMA technique. Unlike traditional multiple access technologies such as FDMA, TDMA, and OFDMA, NOMA technology enables multiple users to share the same spectrum resources. Since NOMA technology can flexibly allocate user communication power ratio and has a minimum transmission rate, it can even guarantee user fairness and relieve the doubly far-near effect [23, 107, 126, 136].

Fig. 5a shows a basic two-user WPEMC system, where time and spectrum allocation among users can be realized based on NOMA technology. Similar to subsection 3.3, it is assumed that mobile devices closer to the MEC server and with strong channel gain are NUs, and those relatively far away from the MEC server and with weak channel gain are FUs. During the data transmission process, the signals from the NU and the FU are superimposed on each other with different power. Due to the difference in channel gain amplitudes, the system tends to assign a larger power to the FU compared to the NU. When the MEC server receives the superimposed signals of the NU and the FU, it performs successive interference cancellation to decode signals.

Authors in [126] introduce NOMA technology into multi-user WPMEC networks to improve offloading efficiency in multi-user scenarios. It is assumed that both the mobile device and the HAP have full duplex characteristics, i.e., mobile devices can offload computation tasks to the HAP and collect energy sent by the HAP. Mobile devices are divided into multiple groups, with each group sharing a system subcarrier. The computation offloading is performed sequentially among groups in a TDMA mode, and mobile devices within a group offload computation tasks simultaneously on the same subcarrier via the NOMA approach.

Different from the study in [126] which assumes a full-duplex mode for HAPs and mobile devices, authors in [107] consider a time allocation strategy to cope with half-duplex hardware constraints, and develop dynamic offloading and resource allocation strategies to minimize task completion latency. The spectrum is divided into multiple subcarriers, and the mobile device collects ambient energy to charge itself. Similar to [107], authors in [136] leverage NOMA technology for resource allocation and offloading decisions in WPMEC systems. Meanwhile, the nonlinear EH model is also considered. The optimization problem to maximize the computation efficiency is solved based on both partial and binary offloading modes with TDMA and NOMA technologies, respectively. The results indicate that the partial offloading mode and the NOMA approach are superior to the binary offloading mode and the TDMA approach in improving the computational efficiency of the system.

The above solutions all consider APs with fixed locations, while authors in [23] apply NOMA and hybrid beamforming techniques to maximize the computation efficiency in the UAV-assisted WPMEC system. It is

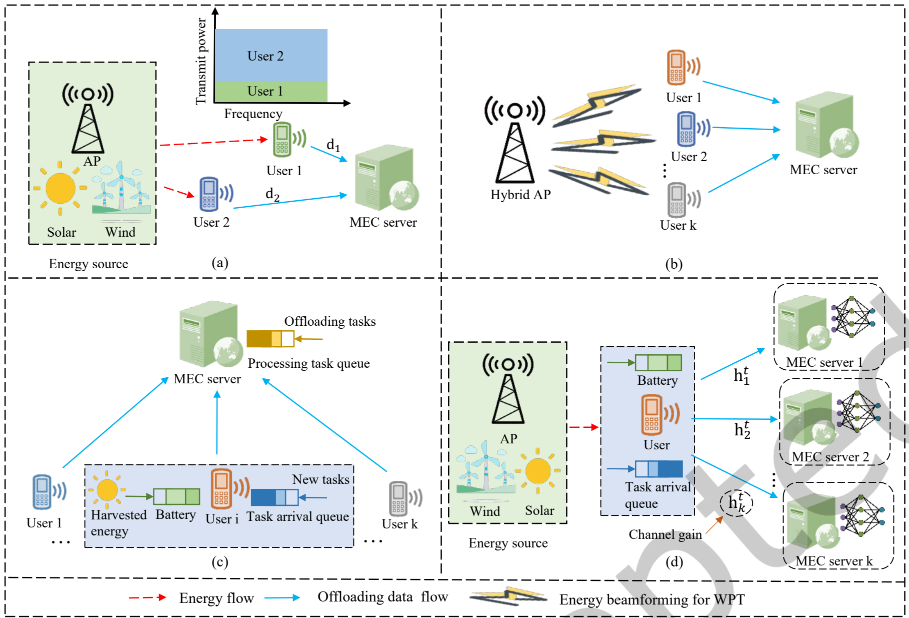

Fig. 5. Schematics of different solutions in the WPMEC network: a) NOMA approaches; b) EB approaches; c) queueing based solutions; d) learning based solutions.

assumed that the UAV operates on the millimeter wave band, and uses a hybrid beamforming structure consisting of an analog beamformer and a digital beamformer. The formulated optimization problem is decoupled into two subproblems, i.e., the design of UAV 3D layout, WPT and hybrid beamforming optimization. Polyhedral annexation procedure and semi-definite relaxation can be used to solve the above subproblems.

Lesson 7: The above-mentioned studies based on NOMA assume perfect continuous interference cancellation, while in reality there is co-channel interference among mobile devices, and errors may occur during the implementation of continuous interference cancellation. To simulate realistic application scenarios, it is necessary to consider the corresponding NOMA-assisted WPMEC solutions in the presence of continuous interference cancellation scenarios with errors.

3.8 EB Approaches

Different from data transmission, the sensitivity of the energy transmission process in WPMEC systems is extremely low[106]. Therefore, the increasing demand for high-powered energy signals has prompted some researchers to use multi-antenna techniques such as EB to improve energy efficiency [104, 105, 140]. Since beamforming technology has strict directionality, the interference caused by omnidirectional antennas radiating in all directions is almost non-existent in EB technology. Fig. 5b shows a WPMEC system that uses the EB approach in the WPT phase, where the AP can send multiple energy beams to charge the mobile device.

To reduce the energy transmission attenuation in the WPT phase, authors in [106] design a framework for the WPMEC system based on the EB method. Instead of using a time allocation strategy, it is assumed that WPT and computation offloading are performed simultaneously in the orthogonal bands. EB, CPU frequency, and the number of offloaded bits are jointly optimized to minimize energy consumption of the AP. Different from the static environment considered in [106], authors in [104] investigate the WPMEC system aided by EB methods and with dynamic task arrivals. Specifically, it is assumed that the perfect CSI/TSI is unknown in advance, and WPT and computation offloading are performed simultaneously on mutually orthogonal frequency bands. Authors first obtain the offline solution with known perfect CSI/TSI, and then investigate the sliding window-based online resource allocation scheme with known past CSI/TSI. Similar to [104], authors in [105] also consider the system energy consumption when CSI and TSI are only causally known. The difference is that it investigates system resource allocation and task offloading in terms of time-varying channels or static channels and fully known CSI/TSI or only causally known CSI/TSI, respectively. The offline solution based on completely known CSI/TSI is obtained by convex optimization techniques, and a heuristic online algorithm is developed when CSI/TSI is only causally known. Similar to [104, 105], DCO [140] is an offloading strategy that considers harvesting ambient energy and uses MIMO technology to improve offloading efficiency in WPMEC networks. The issue of high intermittency of renewable energy and the task discard cost is taken into account, and the time averaging and queueing problem to minimize the system cost is solved by the Lyapunov optimization method.

Lesson 8: In a WPMEC system using the EB method, the microwave signal in the designated interval used to transfer energy is stronger than the normal RF signal and may be harmful to human health. A distributed antenna system can be considered to improve information transmission efficiency, in which each antenna uses relatively weak omnidirectional radiation. The radiation angle of multiple antennas can be adjusted to make their combined effects in a specifics direction. In addition, when combined with sensor technology, distributed antenna system can detect human blocking and dynamically adjust the antenna combination.

3.9 Queueing Based Solutions

As described in subsection 2.2, there are challenges of high intermittent EH, dynamic task arrival, and task processing order in the WPMEC system. The above problem can be quantified by modeling the battery energy, arrival tasks, and processing tasks as queueing models in the system. The formulated optimization problem can be simplified and solved by Lyapunov optimization [17, 47, 53, 95, 114, 115, 119, 125, 130, 131]. Fig. 5c shows a WPMEC system based on queueing models, where each mobile device is equipped with a task queue and a battery, and the MEC server is equipped with a task queue. All queues are based on the first-in-first-out principle. Specifically, it is necessary to maintain the stability of the aforementioned queues for computation offloading and resource allocation optimization.

LYP-CEMA [130] is a resource allocation algorithm based on Lyapunov optimization. It defines the task queue backlog at the MEC server as the amount of unprocessed tasks at the end of each time slot, by considering the randomness of task arrivals and the execution order of tasks. The quality of service is quantified as ρ, which is the ratio of the amount of data not processed in time to the total amount of data. LYP-CEMA assumes that each device can tolerate certain delay, varying from device to device. By introducing battery virtual queues and quality of service virtual queues as well as decoupled process of EH and task transmission, the time coupling and offloading decisions can be made in each time slot by Lyapunov optimization. Similar to [130], authors in [95] design a dynamic offloading algorithm in IoT. By considering the difference in computing resources and loads among mobile devices, they can help each other transmit or process tasks to solve the doubly far-near problem through D2D technology. The original fractional programming problem is transformed into a stochastic optimization problem in the parametric subtractive form by the Dinkelbach method, and further transformed into a deterministic subproblem based on Lyapunov optimization. The deterministic problem can be solved by three steps: i) selection of CPU frequency and transimt power for task offloading; ii) selection of WPT transmit power; and iii) D2D link transmit power allocation.

Different from studies in [95, 130] where only the task queue of the MEC server is considered, authors in [131] also pay attention to the stability of the task arrival queue and the result returning queue. The offloaded tasks are first stored in the task arrival queue to wait for assignment. After the edge server executes the assigned task, the mobile device gets the result from the result returning queue. The optimization problem with energy consumption and latency as optimization metrics involves time-coupled energy queue, task arrival queue, and download result queue. The average weighted sum of energy consumption and execution delay is used as a penalty, and the EH along with the optimization of task assignment is achieved by the ODLOO algorithm based on Lyapunov optimization.

The previously mentioned studies in [53, 95, 130, 131] all consider the resource allocation problem in a single MEC server scenario. Different from them, authors in [17] consider the scenario with multiple servers and mobile devices, in which high intermittency of renewable energy, random arrival of tasks, and the task processing order should be addressed. DTM algorithm based on perturbed Lyapunov optimization is used to optimize the system throughput under task queue and energy queue stabilization, transforming the complex stochastic optimization problem into a deterministic subproblem. Similar to [17], authors in [119] investigate the problem of distributed computation offloading and resource allocation in the WPMEC system with multi-HAPs and multi-users. To allocate computing resources, suitable MEC servers should be assigned to users with different offloading requirements. To stabilize the battery energy level and task queues, a game theory-based mechanism for edge cloud resource allocation is first developed. Since the game theory-based solution is computationally complex and requires a large number of storage resources, it is not suitable for resource-limited mobile devices. Then, it further designs an online distributed algorithm based on Lyapunov optimization to perform resource scheduling. Similar with the DTM algorithm in [17], the above solution in [119] also address the selection of the target MEC server.

Similar to [17, 119, 131], authors in [47] consider task offloading and energy transfer strategies under both task arrival and task offloading buffers. Although the mobile device is powered by RF energy signals sent by the AP, the mobile device battery level is considered and a time allocation strategy is used to solve the half-duplex problem. A stochastic optimization problem for resource allocation with energy consumption and task completion delay as optimization metrics is solved by the designed offloading schemes based on TDMA and FDMA, respectively. The optimization problem is further decoupled by the Lyapunov optimization method, and then solved by the BCD method in alternating iterations. Similar to [17, 47, 119, 131], considering the randomness of energy and task arrivals, authors in [125] investigate the resource allocation problem for minimizing UAV energy consumption with energy and data queue stability constraints. This optimization problem can be decoupled into a deterministic problem for each time slot by Lyapunov optimization, and then solved by convex optimization methods.

Unlike the above papers, which assume a perfect CSI/NSI, authors in [114] design resource allocation strategies in the case where only the past CSI/NSI is known. It also addresses key issues such as half-duplex constraints, random arrival of tasks, and the order of task processing in WPMEC systems. An online decision algorithm based on Lyapunov optimization is studied to solve stochastic optimization problems with the throughput as the optimization metric. Similar to [114], a resource allocation strategy based on outdated network information in Industrial IoT is proposed in [115]. A data age-aware scheduling mechanism is designed, and the spectrum is shared in a TDMA mode during WPT and computation offloading phases. The data age-aware virtual queue is introduced to transform the original problem into a stochastic optimization problem and it is decoupled by the Lyapunov optimization method.

Lesson 9: The above approaches for queue-based stabilization in WPMEC focus on dynamic scenarios with dynamic battery levels and random task arrivals. However, both WPT and computation offloading are affected by time-varying wireless channels. Therefore, computation offloading and resource allocation in dynamic wireless channel scenarios should be studied. In addition, since queue stabilization is mainly solved by the online algorithm based on Lyapunov optimization theory without considering a priori information such as CSI and TSI, it is only applicable to low-complexity WPMEC systems. Therefore, queueing-based solutions for large dynamic scenarios should be investigated.

In Tables 2 and 3, we summarize optimization metrics considered in the above resource management and computation offloading strategies for the WPMEC system based on traditional optimization methods.

Table 2. Summary of traditional optimization for WPMEC

Ref.	Description	Solutions	Optimization metrics: WPT duration	WPT transmit power	Local CPU frequency	Task allocation	Offloading power	Beamforming	Offloading order	Task arrival rate	Battery levels
[142]	Computation completion ratio maximization for computation scheduling	Time allocation strategies	√	×	√	√	×	×	√	×	×
[48]	Max-min energy efficiency optimization for resource allocation	Time allocation strategies	√	√	×	×	√	×	√	×	×
[8]	Computation rate maximization for binary computation offloading	Time allocation strategies	√	×	√	√	×	×	√	×	×
[134]	Energy minimization for fog-assisted SWIPT networks	Time allocation strategies	√	×	×	√	√	×	√	×	×
[116]	Residual energy maximization with hybrid offloading	Time allocation strategies	√	√	×	√	√	×	√	×	×
[10]	Energy-efficient optimization for relay networks	SWIPT approaches	√	×	×	√	√	×	×	×	×
[75]	Latency minimization for SWIPT networks	SWIPT approaches	×	×	√	√	√	×	√	×	×
[24]	Achievable rate optimization for SWIPT systems	SWIPT approaches	×	×	√	√	√	×	√	×	×
[28]	Energy minimization for user cooperation networks	User cooperation frameworks	√	√	×	×	√	×	√	×	×
[36]	Multi-relay assisted computation offloading framework	User cooperation frameworks	×	×	√	√	√	×	×	×	√
[31]	Energy-efficient optimization for relay networks	User cooperation frameworks	√	×	×	×	×	×	√	×	×
[122]	Energy minimization for BC-assisted networks	BC approaches	√	×	√	√	√	×	×	×	×
[145]	Energy minimization with BC-aided hybrid offloading	BC approaches	×	×	×	√	×	√	√	×	×
[51]	Computation rate maximization for resource allocation	IRS approaches	√	×	√	×	√	√	√	×	×
[4]	Energy minimization for IRS-assisted networks	IRS approaches	√	×	√	√	√	×	×	×	×
[23]	Computation rate maximization for NOMA networks	UAV-assisted frameworks	√	×	√	√	√	√	×	×	×
[39]	Task completion time minimization for UAV networks	UAV-assisted frameworks	×	×	√	√	×	×	×	×	×

(“√” if the soultion satisfies the property, “×” if not)

Table 3. Summary of traditional optimization for WPMEC (cont.)

Ref.	**Description**	**Solutions**	**Optimization metrics**									
			WPT duration	**WPT transmit power**	**Local CPU frequency**	**Task allocation**	**Offloading power**	**Beamforming**	**Offloading order**	**Task arrival rate**	**Battery levels**	**Dynamic channel**
[29]	Computation completion bits maximization with cooperative UAVs	UAV-assisted frameworks	×	√	×	√	×	×	√	×	×	×
[40]	Energy minimization for UAV-assisted networks	UAV-assisted frameworks	×	×	√	√	√	×	√	×	×	×
[138]	Computation rate maximization in UAV networks	UAV-assisted frameworks	×	×	√	×	√	×	√	×	×	×
[125]	Energy minimization for EH networks	UAV-assisted frameworks	×	×	√	√	×	×	√	√	√	×
[104]	Energy minimization for task causality resource allocation	EB approaches	×	×	√	√	√	√	×	√	√	×
[105]	Energy minimization for online resource allocation	EB approaches	×	√	×	√	×	√	×	√	×	√
[35]	Energy minimization for NOMA-assisted networks	NOMA approaches	√	×	√	√	√	×	×	×	×	×
[137]	Computation efficiency maximization scheduling	NOMA approaches	√	√	√	×	√	×	×	×	×	×
[107]	Latency minimization for NOMA-assisted networks	NOMA approaches	√	×	√	√	√	×	×	×	×	×
[140]	Latency minimization for MIMO-assisted networks	NOMA approaches	×	×	√	√	×	√	×	×	√	×
[53]	Latency minimization for online computation offloading	Queue based solutions	×	×	√	√	√	×	×	×	√	×
[114]	Throughput maximization for industrial IoT networks	Queue based solutions	√	×	×	√	√	×	√	×	√	√
[17]	Throughput maximization for online resource allocation	Queue based solutions	×	×	√	√	√	×	×	√	√	√
[115]	Throughput maximization for IoT resource scheduling	Queue based solutions	√	×	×	√	×	×	√	√	×	×
[47]	Computation offloading and resource allocation	Queue based solutions	√	×	√	×	√	×	×	√	√	√
[131]	Energy efficiency and delay tradeoff for dynamic offloading	Queue based solutions	×	×	√	√	√	×	×	×	√	×
[95]	Energy efficiency optimization in D2D networks	Queue based solutions	×	√	√	×	√	×	×	×	√	×
[130]	Energy minimization for resource allocation	Queue based solutions	×	×	√	√	×	×	×	√	√	×
[119]	Energy consumption and latency tradeoff	Queue based solutions	×	×	√	√	×	×	×	√	√	×
[37]	Throughput maximization for cognitive data sensing	Queue based solutions	×	×	√	√	√	×	×	×	√	√

(“√” if the soultion satisfies the property, “×” if not)

3.10 Learning Based Solutions

The existing issues such as the unpredictability of EH, the randomness of computation task arrivals, rapidly changing channel states, and the selection of target MEC servers in distributed WPMEC systems make resource allocation and computation offloading problems challenging to solve. Considering that the ML method is more responsive to the time-varying system in real-time than the traditional method because of its adaptability to the dynamic environment and low complexity of the algorithm. Therefore, researchers consider using RL and DRL methods to solve computation offloading and resource allocation problems for WPMEC [11, 58, 97, 113, 121, 132]. Fig. 5d shows a WPMEC system based on the learning method. In this scenario, mobile devices harvest energy from the environment and obtain computing sevices from multiple MEC servers. MEC servers deploy intelligent agents that can learn from past experiences to make intelligent decisions. Due to issues such as the high intermittency of renewable energy, random arrival of tasks, and selection of edge servers, intelligent resource allocation and offloading decision making is important for mobile devices to adapt to such dynamic environments.

To cope with the randomness of channel states, energy and task arrivals, authors in [113] investigate Q-learning-based resource allocation and computation offloading algorithms in IoT. Task prioritization and energy limitation of the mobile device are considered. The ambient EH model for the mobile device is modeled as an IID random process, and the offloading process is modeled as a continuous MDP. Since the state space of continuous MDPs contains too many elements, this computation offloading scheme focuses on post-state decisions, and defines the corresponding post-states with smaller spaces according to the state-action pairs.

Instead of considering a single mobile device similar with [113], DRLCCDCO [132] is an offloading and computational resource allocation algorithm for multiple mobile devices. Each mobile device is equipped with a queue of computation tasks, and the tasks for the current time slot may contain the remaining tasks from the previous time slot. By modeling the arrival of tasks within a time slot as IID poisson processes, mobile devices can dynamically adjust the local CPU frequency to control time and energy consumption. The continuous control problem is designed with the system execution time and energy consumption as optimization metrics, which is then formulated as a multi-intelligent continuous decision process due to the mutual influence of decisions among mobile devices. The DDPG-based DRLCCDCO algorithm is designed to learn centralized policies by coordinating among mobile devices and executing in a distributed manner. Similar to [132], GCN-DDPG [11] is also a DDPG-based computation offloading and resource allocation algorithm for dynamic environments. Unlike traditional DDPG methods, GCN-DDPG combines graph convolutional networks and DDPG, and has the ability of graph-based relational derivation and the self-evolutionary ability of empirical training.

Different from the study in [11, 132], which considers a centralized MEC server in the system, authors in [121] investigate resource allocation and offloading decision making in the WPMEC system with multiple MEC servers. It is assumed that both MEC servers and mobile devices are powered by environmental energy harvesting, and MEC servers are also constrained by dynamic battery energy levels. Compution tasks can be processed through the collaboration of multiple MEC servers. Dynamic offloading and edge server provisioning decisions can be formulated in real time based on the battery level of the mobile device, the state of wireless channels, and the number of computation tasks. To overcome the high-dimensional problem caused by the increase of the state space, the post-decision state is used in the design of the RL-based algorithm.

Similar to [121], RLO [58] is RL-based computation offloading algorithm for single-user, and multi-edge server scenarios. The RLO scheme develops rewards in terms of latency, energy consumption, and task failure, and selects the current target MEC server and the offloading rate in real-time based on the learning model. Since the performance of the RLO scheme degrades severely as the dimensionality of the action state space increases, authors in [58] design a DRL-based offloading scheme, named DRLO, to improve system performance. The DRLO uses a deep neural network to downscale the action state space, improving the offloading performance in large action space scenarios.

Table 4. Summary of ML for WPMEC

Ref.	Description	Solutions	Optimization metrics									
			WPT duration	Local CPU frequency	Task allocation	Offloading power	Beamforming	Offloading order	MEC server selection	Task arrival rate	Dynamic battery	Dynamic channel
[110]	Latency minimization for distributed computation offloading	Learning based solutions	√	×	√	×	×	×	√	×	×	√
[22]	Computation rate maximization for UAV networks	Learning based solutions	×	√	√	√	√	×	×	×	×	√
[97]	Energy consumption and delay tradeoff for computation offloading	Learning based solutions	×	×	√	×	×	×	√	×	√	×
[121]	Latency minimization for dynamic resource management	Learning based solutions	×	×	√	×	×	×	√	√	√	√
[132]	Energy consumption and delay tradeoff for computation offloading	Learning based solutions	×	√	√	√	×	×	×	√	√	√
[58]	Energy minimization for IoT networks	Learning based solutions	×	×	√	×	×	×	√	×	√	√
[30]	Computation rate maximization for resource allocation	Learning based solutions	√	×	√	×	×	√	×	×	×	√
[113]	Latency minimization for computation offloading	Learning based solutions	×	×	√	×	×	×	×	√	√	×
[11]	Energy consumption and delay tradeoff for computation offloading	Learning based solutions	×	√	√	√	×	×	×	×	√	√

("√" if the soultion satisfies the property, "×" if not)

Similar to [58], DQNN [97] is a DRL-based computation offloading algorithm that determines offloading rates of mobile devices and the selection of edge servers. Specifically, the optimization problem is treated as an online sequential decision making problem, and the DQNN algorithm is developed by combining the RL approach and noisy neural networks. Since noise is added to each linear layer of the neural network, DQNN can learn perturbations in network weights to automatically adjust the noise level explored by the agent. The above studies in [58, 97, 121] address the issues of random arrival of channel state information, highly intermittent renewable energy, and the selection of MEC servers. We summarize resource management and computation offloading policies based on ML for the WPMEC system in Table 4.

Lesson 10: Studies based on ML in WPMEC systems try to resolve issues such as time-varying wireless channels, dynamic battery levels, and the selection of target MEC servers. The ML-based solution can develop optimized network policies by learning past information, i.e., the selection of edge servers, offloading rates, and the allocation of computational resources. Due to its model-free property, RL is often used to train computation offloading policies for low-complexity systems, in the presence of time-varying channels and obtained partial system information. In the face of large network scenarios with the high-dimensional state-action space, the DRL method is promising to realize the dimensionality reduction of the state-action space and avoid the dimensional disaster. However, DRL has the drawback of over-adaptation and is not suitable for the environment with rapidly changing wireless channels.

Comparisons among the above approaches can be found in Appendix C of Supplemental File. It is worth noting that the above approaches are not completely independent, and their combination can bring broader application scenarios and better system performance.

4 RESEARCH CHALLENGES AND OPEN ISSUES

In previous sections, we have summarized recent research on resource allocation and offloading strategies in WPMEC. However, there are still some unresolved issues and research challenges. In the following, we elaborate on them subsequently.

4.1 Improved Technologies for WPMEC

Traditional optimization methods tend to solve problems in WPMEC systems with a static environment, approximating the optimal solution through a complex mathematical process. However, in realistic scenarios, time-varying channel conditions, dynamic task arrival and battery energy levels need to be considered. Although Lyapunov optimization can be used to solve the resource allocation problem by modeling task arrivals and processing as queueing models, merely an approximate optimal solution can be obtained [112]. By considering that the RL method can continuously update the strategy through experience replay during the training process until the network achieves the desired performance, it is possible to use the RL method to compensate for the shortcomings of Lyapunov optimization in solving the problem. Consequently, researchers can consider combining Lyapunov optimization and RL to make optimal choices in real-time while ensuring system stability [6].

Furthermore, the dynamic battery energy level causes optimization variables coupled with each other. Using traditional optimization methods to decouple optimization variables may increase the complexity of the solution. Multiple neural networks can be used to simulate complex and coupled mathematical formulations and achieve a low-complexity solution compared to traditional optimization methods [100]. In addition, constant channel states are always assumed to exist in WPMEC networks when traditional optimization methods are appied [144]. Therefore, it is worthwhile to investigate how to improve traditional optimization methods to deal with time-varying channel conditions in WPMEC systems.

Compared with traditional optimization methods, the ML-based approach is more suitable for intelligent resource management in large-scale WPMEC systems. However, existing ML algorithms still deserve improvement for WPMEC systems. First, classical learning algorithms (e.g. random forest, k-nearest neighbor and kd-tree) usually have a high time complexity which does not satisfy the real-time requirements in practical scenarios [77, 80]. Thus, how to reduce their time complexity for the application in WPMEC systems deserves further study. Second, due to high-dimensional action sets in the WPMEC system, sometimes both discrete and continuous actions are included. In this case, it is possible to consider designing ML-based algorithms that can handle both discrete and continuous actions. Finally, the classical empirical replay technique uses randomly extracted memory samples to update the model parameters, which leads to a situation where many valuable samples are not effectively utilized. Consequently, some prioritized experience replay techniques (e.g., SumTree structures) can be considered to improve algorithm performance in WPMEC systems [123].

4.2 UAV-assisted WPMEC

The UAV-assisted WPMEC system has attracted a lot of attention, since it can leverage UAVs with controlled mobility to provide ubiquitous charging and computation offloading services for mobile devices. However, there are still some challenges in UAV-assisted WPMEC. Many studies leverage UAVs for wireless charging of mobile devices. But so far, how to extend the operating time of UAVs is still an issue that needs to be considered. Although some studies consider integrating the laser charging technique with UAVs [26], the use of high-energy lasers may produce gases and noises that can harm the environment and the human body. Consequently, laser-based wireless charging must be performed in a relatively airtight environment and is not suitable for open space scenarios.

In addition, there are some challenges in the trajectory and scheduling optimization of UAVs. For example, although many papers have studied the UAV trajectory optimization problem, they generally assume that the UAV flies at a fixed altitude and do not consider its response strategy when encounters obstacles. Therefore, it is necessary to develop intelligent 3D trajectory optimization algorithms for UAVs. In large WPMEC networks, multiple UAVs are required to cooperate to serve mobile devices. However, there is a lack of incentive algorithms to make UAVs cooperate in an efficient way [118].

4.3 Time Allocation for WPMEC

Time division and allocation has been widely noticed by the WPMEC research community. On-demand energy and computing service provisioning can be achieved by allocating limited time resources to WPT and computation offloading. Although the time allocation scheme under static wireless channels is valid, there are still some challenges for that under dynamic wireless channel conditions. The current studies on UAV-based WPMEC systems assume that WPT and computation offloading can all be performed simultaneously and without interference on orthogonal frequency bands, which is too ideal. By considering time allocation under the half-duplex hardware constraint, the joint design of WPT and offloading time can better simulate the relationship among energy, time, and computational resources in actual UAV-based WPMEC systems.

In addition, time-coupled variables, such as dynamic battery levels and random task arrivals, are considered in the dynamic wireless channel scenario. On one hand, most relevant studies consider the use of renewable energy sources for charge supply and assume simultaneous ambient EH and computation offloading. On the other hand, a few relevant studies are dedicated to systems using RF energy. However, these studies either fix the WPT period in advance or do not consider the allocation of WPT time. Therefore, it is a challenge to design time allocation schemes for dynamic wireless channel scenarios.

4.4 Energy Harvesting and Transmission for WPMEC

Although energy harvesting and transmission in WPMEC systems can be improved by BC, IRS, EB, and UAV cooperation approaches, there are still some open issues in practical applications.

4.4.1 *Selection of Energy Source.*

Although renewable energy sources such as solar, wind and ocean are freely available from the nature, the equipment for energy harvesting has the disadvantages of significant environmental impacts and high deployment costs. The WPT technology provides stable and reliable energy supplies, but the energy signal attenuation is high and the energy transmitter needs to be powered by the grid energy. Therefore, how to integrate renewable EH technology with WPT technology to design the hybrid energy supply mechanism deserves to be investigated. However, resource allocation and computation offloading strategies with hybrid energy supply becomes more complex. In addition, in most scenarios with renewable EH, the long-term cost of harvesting ambient energy, i.e., the expense of EH equipment and the energy consumption of the EH process, is not considered.

4.4.2 *Multi-Antenna Technologies.*

There are challenges in mitigating energy degradation in the WPT phase. Although some studies have considered EB and MIMO techniques in WPMEC systems [140], almost all of them consider perfect CSI by default. However, in fact, the CSI estimation accuracy is proportional to the consumed resources. The trade-off between resource consumption for the estimated CSI and the EB gain needs to be considered in WPMEC systems. In addition, since EB technology concentrates energy in a specific orientation, it needs to take account of fairness issues in multi-user scenarios [57]. The MIMO technology requires the deployment of multiple antennas on the mobile device side, and the size of the energy receiver at the mobile device side needs to be taken into account within the constraints of manageable costs and system performance [16].

4.4.3 Impact of Mobility. In practical scenarios, the mobility of users is not negligible [124]. The frequent movement of users may lead to rapid changes in the channel state between the mobile device and the AP. Then, it is necessary to design dynamic and adaptive resource allocation algorithms. By regarding the doubly far-near problem in WPMEC networks caused by fixed HAPs, it is possible to consider deploying APs with mobility. Authors in [42] investigate the impact of APs on user energy gain with both of the edge mobility model and center-to-center mobility model. In addition, to ensure the fairness of gain for all users, the signal transmitting power and the distance between APs and users need to be balanced. What's more, researchers can also consider vehicles with mobility as HAPs [27].

4.5 Security Issues in WPMEC

At present, there are merely a few studies focusing on the security of WPMEC systems, and two kinds of security issues are important in WPMEC systems, i.e., privacy and radiation security. We elaborate them as follows.

4.5.1 Privacy. In WPMEC networks, privacy issues are important, but always ignored. On one hand, to avoid privacy leakage, some sensitive tasks (e.g., online healthcare) cannot be completely offloaded to the edge server. When selecting the target edge server, it is necessary to verify its identity, because a malicious MEC server can take the opportunity to steal information. On the other hand, mobile devices generally use weak encryption schemes to keep the cost controllable, and are vulnerable to information cloning and tampering. Consequently, in a user-cooperative WPMEC scenario, it is important to verify the trustworthiness of mobile devices. In addition, intervening attacks (relay manipulation or misuse of information) can destroy the information integrity during the task offloading process [82]. Quantum resistance authentication is suitable for resource-constrained mobile devices in WPMEC systems because of its low cryptographic primitive overhead [55].

4.5.2 Radiation Security. The intense RF exposure may heat materials of limited electrical conductivity (including biological tissue) [64]. Studies in [65] indicate that RF exposure in radio communications is safe, but there are genetic effects when RF reaches the upper international safe level. Therefore, there is a lack of research on the safety of deploying high-powered dedicated RF energy emitters.

5 CONCLUSIONS

In this article, we provide a comprehensive and specific review of research on WPMEC, which is a deep integration of MEC and WPT. Specifically, we review basic models, existing issues and key technologies of WPMEC. Next, we summarize the latest research related to resource allocation and computation offloading in WPMEC systems. Finally, we point out some research challenges and future research directions. We believe that this article will facilitate the further development of WPMEC because it will be an important building block for future wireless networks to achieve energy self-sufficiency and intelligent operation of devices.

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