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User Cooperation in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) Networks: A Comprehensive Review

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Abstract: User cooperation has emerged as an effective way to improve the efficiency and sustainability of Wireless Powered Transfer-Mobile Edge Computing networks. The relaying, task forwarding, and resource-sharing-based cooperative schemes enhance system efficiency by alleviating energy imbalance and computation bottleneck problems in heterogeneous users. Finally, it discusses various next-generation cooperative methods: UAV-based transmission, integration aided by RIS and STAR-RIS, NOMA-based multi-access, and the harvest-then-cooperate protocol. Optimization techniques ranging from convex programming, deep reinforcement learning, matching theory, and game-theoretic models have been exhaustively studied to optimize for efficient smart resource allocation with network dynamics. Emerging frameworks involve key trade-offs in energy efficiency, latency, fairness, and scalability. Moreover, this paper presents open research issues and pinpoints some of the key limitations in current designs. It is concluded that user cooperation significantly enhances the functionality and fairness of WPT-MEC systems, making them more viable for large-scale, heterogeneous deployments. Also, continued interdisciplinary research combining wireless communication, machine learning, distributed systems, and cybersecurity is necessary to unlock the full potential of cooperative edge computing in 6G and smart edge computing era.

Keywords: User Cooperation, Wireless Powered Transfer (WPT), Mobile Edge Computing (MEC), Task Offloading, Non-Orthogonal Multiple Access (NOMA)

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1. INTRODUCTION

The rise of computation-intensive applications such as virtual reality (VR), augmented reality (AR), and smart control systems with the surge in intelligent mobile devices has made compute-intensive and low-power computation offloading models inevitable. European Telecommunications Standards Institute (ETSI) envisioned Mobile Edge Computing (MEC) as a stimulating solution by bringing computation resources close to end users to reduce latency and backhaul bottlenecks. Yet the only major deterrent is the limited energy capability for mobile devices, which prevents stable computation offloading capability [1].

Wireless Power Transfer (WPT) is the emerging enabler technology that breaks this limitation to charge mobile smart devices wirelessly and, in turn, enable greener mobile networks. With the inclusion of WPT into MEC and giving birth to Wireless Powered MEC (WPT-MEC) systems, offloading computation and energy harvesting are facilitated at the same time. Despite this, there is still another significant bottleneck: nodes that are further away from the AP have lower energy harvesting efficiency and greater communication cost, which has been highlighted as the "double-near-far" problem [2], [3], [4].

In an effort to address this problem, cooperative user help has been used in WPT-MEC networks. Remote devices are aided by local users via cooperative transmissions by relaying or acting as offload proxies, thereby improving fairness, power saving, and overall system capacity. Moreover, integration of NOMA improves spectral efficiency alongside having more simultaneous connections, which is particularly beneficial for dense networks [5].

This paper presents a systematic review of the latest developments in user cooperation in WPT-MEC networks. The contributions of the paper are as follows:

- Consolidation and expansion of the conceptual and mathematical modeling of MEC and WPT from recent literature.
- Analysis of cooperative strategies that mitigate the double-near-far effect using techniques such as D2D relaying, UAV-enabled MEC, and cooperative NOMA.
- Exploration of optimization frameworks that integrate resource allocation for communication, computation, and energy dimensions.
- Propose future research directions including real-time cooperative task scheduling, RIS/STAR-RIS enhancement, and 6G-native WPT-MEC architectures.

The rest of the paper is structured as follows: Section 2 presents the foundational architecture of WPT-MEC systems; Section 3 discusses cooperative models; Section 4 elaborates on optimization strategies and multiple access schemes; Section 5 provides comparative evaluations and open challenges; and Section 6 concludes the review.

2. FOUNDATIONS OF WPT-MEC SYSTEMS

Here, the elementary components of WPT-MEC systems, i.e., MEC architecture, energy harvesting, computation models, and communication approaches, are discussed. These are the fundamental constituents upon which grasping the way cooperation between users has the potential to make the system more energy-efficient, robust, and fairer is founded.

2.1 Mobile Edge Computing (MEC)

Mobile Edge Computing (MEC) is among the main enablers of low-latency, high-bandwidth, and context-aware wireless network computing at the network edge. As defined by the European Telecommunications Standards Institute (ETSI), MEC envision traditional cloud computing by locating edge servers in base stations (BSs), access points (APs), or other close network entities, thereby offering end-users close computing, storage, and networking resources [1].

Compared to MCC, the proximity of MEC heavily reduces transmission latency and therefore is more suitable for applications with rigorous latency requirements, such as real-time analytics, virtual reality, and autonomous driving. The architectural shift also alleviates backhaul desaturation and provides improved users' privacy via local data processing [6].

MEC is based on these kinds of enabling technologies: Network Function Virtualization (NFV), Software Defined Networking (SDN), and Information-Centric Networking (ICN). NFV enables dynamic instantiations of virtual machines (VMs) to offer elastic computation loads, while SDN introduces centralized control for effective traffic steering between edge nodes. Meanwhile, ICN transforms the communication model from host-centric to content-centric, and content delivery and caching become optimal [2].

One of the key advantages of MEC is its adaptability to dynamic wireless environments. Using Wireless Powered Transfer-MEC (WPT-MEC) systems, MEC supports energy-harvested computation offloading using wireless power transfer (WPT). Computation offloading to MEC servers alleviates the user devices from computational burden and energy loss, especially applicable to power-constrained Internet of Things (IoT) and edge applications [6].

However, MEC is confronted with the unbalanced task assignment and user energy heterogeneity, i.e., the double-near-far issue. The remote devices pay a price of poor energy harvesting efficiency and lower uplink speeds, decreasing offloading potential. User cooperation techniques (e.g., task sharing or relaying) have been suggested as countermeasures to improve the availability and fairness of MEC to users [2].

Besides that, upcoming paradigms like NOMA and STAR-RIS also increase MEC's capacity with better spectral efficiency and cooperative offloading among heterogeneous users [5].

In summary, MEC's decentralized architecture for future multi-access and cooperative technology has transformed MEC as a building block to smart energy-efficient edge computing.

2.2 Wireless Power Transfer (WPT)

Wireless Power Transfer (WPT) is a major technology to facilitate the continuous operation of energy-hungry devices in mobile edge computing (MEC) systems. With wireless charging of user equipment, WPT eliminates the battery capacity limit and enables continuous computation and communication in wireless-powered MEC (WPT-MEC) systems. WPT is especially essential in cases where regular manual recharging is inconvenient, e.g., remote surveillance, thinly scattered sensors, and mobile Internet of Things (IoT) applications.

WPT technologies have been generally classified into far-field and near-field mechanisms [7]. Near-field approaches include inductive coupling and magnetic resonant coupling. Inductive coupling leverages magnetic fields between coils that are very close together and is widely utilized in short-distance, high-efficiency applications like charging smartphones [8]. Magnetic resonant coupling enhances transmission distance via resonant tuning of the coils for mid-range power transfer [9].

Far-field WPT includes, however, RF and laser-based techniques. RF-based WPT employs microwave energy for far-distance power transmission. Although its efficiency declines with distance, it enjoys the advantage of concurrent energy and information transmission, an inherent feature in wireless powered communication networks (WPCNs). Laser-based power beaming facilitates line-of-sight, high-power transmission with high directionality, although with stringent alignment and safety constraints.

Energy harvesting in WPT-MEC systems is typically implemented using dedicated RF signals transmitted from the access point (AP). The energy is harvested and used for local computation or offloading computation to the MEC server. The level of harvested energy depends on transmit power, channel gain, and energy conversion efficiency.

Harvest-then-offload schemes, for example, optimize system throughput by adjusting data transmission time ratio and energy harvesting time [10].

WPT integration into MEC is the answer to the energy deficit and opens the door to sustainable, self-sustaining mobile systems that can perform computationally intensive tasks on the network edge.

2.3 Computation Task and Offloading Models

Computational tasks in Mobile Edge Computing (MEC) scenarios are characterized by three fundamental parameters: data input size of task I (in bits), computational complexity C (in CPU cycles per bit), and output-to-input ratio of data γ. A task is thus characterized by the tuple (I, C, γ) specifying the local execution and offloading requirements [10].

Two fundamental types of task offloading are:

- **Binary Offloading:** The entire task is offloaded on the MEC server or done locally. This is easy for decision-making but might not optimize resource usage [11].
- **Partial Offloading:** The task can be divided into smaller-sized sub-tasks such that distributed execution on the edge server and on the mobile device is possible. This gives flexibility to optimize latency and energy trade-offs [10].

For local computation, the computation energy E_{comp} can be expressed as equation 1:

$$E_{comp} = \kappa C I f^2 \tag{1}$$

where κ is the effective capacitance coefficient of the device's processor, and f is the CPU frequency [12].

For offloading, the communication energy E_{comm} is as expressed by equation 2:

$$E_{comm} = P_t . \frac{I}{R} \tag{2}$$

where R is the realized data rate and P_t is the transmit power, and it can be expressed based on the Shannon-Hartley theorem as shown in equation 3:

$$R = B \log_2(1 + SNR) \tag{3}$$

where SNR is signal-to-noise ratio and B is bandwidth.

Offloading is a function of channel state, delay tolerance, and device energy availability. Offloading for WPT-MEC systems is closely related to energy harvesting. Optimal techniques usually aim to reduce the total task delay or energy consumption under power and latency constraints [13].

Generally, adaptive and flexible offloading strategies are inevitable to facilitate efficient computation in heterogeneous and energy-varying edge scenarios.

2.4 Communication and Energy Models

Energy and communication models are essential in WPT-MEC systems for the identification of task offloading performance and energy efficiency. The wireless communication channel between user devices and the access point (AP) dictates data transmission rates, while energy models control consumption and harvesting abilities for renewable operation.

Communication Model: The achievable rate R of the user device is typically obtained from Shannon-Hartley theorem in equation 4 form:

$$R = B \log_2\left(1 + \frac{P_t h}{N_0}\right) \tag{4}$$

where:

- B is the bandwidth of the channel,
- P_t is the transmit power,
- h is the channel gain between user and AP,
- N_0 is the noise power.

This rate determines the time T_{tx} to offload a task with input data size I: $T_{tx} = \frac{I}{R}$

Communication Energy Consumption: The energy used in the data communication is computed as equation 5:

$$E_{comm} = P_t . T_{tx} = P_t . \frac{I}{R} \tag{5}$$

Higher transmission power or lower channel gain improves the energy consumption at the cost of both energy efficiency and delay [14].

Computation Energy Consumption: While the task is being run locally, the energy consumption is a function of CPU frequency f and is given by equation 6:

$$E_{comp} = \kappa C I f^2 \tag{6}$$

where C is the number of cycles per bit and κ is a hardware-dependent constant. Dynamic Voltage and Frequency Scaling (DVFS) is usually used to scale f for improving energy efficiency [15].

Harvested Energy Model: The harvested energy E_h in time T_h from RF signals is given by equation 6:

$$E_h = \eta P_t h T_h \tag{7}$$

where η is energy conversion efficiency, P_t is AP transmit power and h is channel gain. The harvested energy will have a direct impact on task offloading and execution feasibility, especially for low-power devices.

These models serve as the foundation for the optimization of WPT-MEC system communication scheduling, offloading, and energy allocation.

2.5 Joint MEC-WPT Operation

The co-design of WPT and MEC helps to lay the foundation for saving energy and eco-friendly wireless network infrastructure, especially for the constraint-plagued IoT applications. Such a co-design supports simultaneous implementation of energy harvesting with computational offloading to bypass the twin limitations of energy deficiency and computation scarcity in smart devices.

A typical operational model is the harvest-then-offload approach. Here, an access point (AP) broadcasts special radio frequency (RF) energy in a time block T_h in such a way that smart devices can harvest energy. Then, in the time block T_o for offloading, devices offload computational tasks to the MEC server. The total time block is $T = T_h + T_o$, which has to be optimized with utmost care so that system performance is optimized [10], [16], [17].

The energy harvested must be in line with equation 7 and energy consumption while offloading must be as per equation 8:

$$E_{comm} = P_u \cdot \frac{I}{R} \leq E_h \tag{8}$$

where P_u is the device transmit power and R is the uplink rate.

The optimization objectives of joint MEC-WPT operation are to:

- Maximize computation throughput $\frac{CI}{T}$,
- Minimize total latency, consisting of energy harvesting and task offloading latency,
- Minimize total energy consumption during harvesting, communication, and computation process.

These problems are typically formulated as convex or mixed-integer non-linear programs (MINLP) and solved by means of Lagrangian dual decomposition, successive convex approximation, or heuristics [18], [19].

Time allocation, energy harvesting, and task offloading must be coordinated to enable optimal performance in MEC-WPT networks, particularly under dynamic channel scenarios and heterogeneous user demand [20], [21].

2.6 User Diversity and the Double-Near-Far Effect

Spatial user diversity within WPT-MEC systems creates critical performance disparities owing to variation in distance from the AP. Heterogeneity causes uneven energy harvesting and data transmission capabilities, which finally results in the double-near-far effect phenomenon. More explicitly, users that are further from the AP not only get less wireless power (due to path loss) but also cost more in communications, significantly impairing their computation offloading ability [15].

Energy Harvesting Disparity: The harvested energy E_h is a function of the downlink channel gain h, which decays with distance d as $h \propto d^{-\alpha}$, where α is the path-loss exponent. Thus, users farther from the AP experience energy disparity as indicated by equation 9:

$$E_h \propto \eta P_t d^{-\alpha} T_h \tag{9}$$

where η is the energy conversion efficiency, P_t is the transmit power, and T_h is the harvesting time.

Communication Disparity: Similarly, the achievable data rate R for far users decreases with distance, which results in higher energy consumption for offloading due to lower h. This is given by equation 10:

$$R = B \log_2 \left(1 + \frac{P_u h}{N_0}\right) \tag{10}$$

These two issues lead to significantly impaired task offloading efficiency and energy sustainability among edge users. For this, user assistance has been proposed where neighboring users with better channels and excess energy assist faraway users by acting as relays or as task processors.

Incentive mechanisms such as energy credit schemes or cooperative scheduling mechanisms are used for motivating participation. Additionally, adaptive task allocation and wireless energy sharing also reduce the impact of the double-near-far effect.

Reducing this effect is necessary for facilitating fairness, long-term operation, and scalability in heterogeneous WPT-MEC networks.

2.7 MEC Integration with NOMA

The integration of Non-Orthogonal Multiple Access (NOMA) and Mobile Edge Computing (MEC) has also been identified as a useful way of enhancing spectral efficiency and massive connectivity for WPT-MEC systems. In contrast with conventional orthogonal methods such as TDMA or FDMA, NOMA provides multiple users simultaneous access to a shared frequency band through power-domain multiplexing. This capability significantly improves network throughput and fosters greater resource usage in dense user situations [22], [23].

In the traditional NOMA-MEC setup, users are paired based on their channel gains: a high-power user equipment (closest to the AP) and a low-power user equipment (farthest from the AP). The AP allocates different power levels P_1 and P_2 to users such that $P_1 < P_2$ with the bias towards the feeble user equipment. The MEC server received signal is illustrated by equation 11:

$$Y = \sqrt{P_1} h_1 x_1 + \sqrt{P_2} h_2 x_2 + n \tag{11}$$

where x_1 and x_2 are the signals from the strong and weak users, h_1, h_2 are channel coefficients, and n is the noise [24], [25].

The receiver uses successive interference cancellation (SIC) to decode the stronger user's data after subtracting the weak user's signal. This enables cooperative offloading whereby the strong user assists in relaying the weak user's task after completing its own, hence tackling the double-near-far problem and enhancing fairness of their tasks [5].

Furthermore, NOMA enables jointly deciding on offloading decisions and resource allocation. The optimization models in the literature considering power control, user pairing, and computation offloading have minimized energy consumption or maximized task completion rate. Time and frequency resource management has more flexibility with the hybrid access schemes combining TDMA and NOMA [26].

Overall, the integration of MEC-NOMA will significantly improve offloading efficiency and enable scalable, low-latency, and energy-efficient operation in future WPT-MEC networks.

3. USER COOPERATION IN WPT-MEC NETWORKS

User cooperation has emerged as a promising method to mitigate performance asymmetries and enhance the efficacy of WPT-MEC networks. The double-near-far effect, which is commonly reported and where remote users experience weak energy harvesting and poor channels and thus degraded offloading capability and diminished system fairness, is the major catalyst for this.

In multi-user WPT-MEC systems, generally, variations in energy and communication resources inhibit the edge users from outperforming those closer to the AP [10]. This spatial heterogeneity inhibits not only individual performance but also system-wide reduces overall performance owing to generally underutilized cooperative resources [18]. User cooperation addresses this by allowing close or resource-rich users to assist far or power-constrained users through relaying, task offloading, or power sharing [13], [27], [28].

The basic idea is to convert the competitive nature of user activity into a collaborative framework. As a specific example, a neighboring user with surplus energy and high channel gain can act as a relay to forward data or assist in performing computation tasks for its weaker neighbor. Such collaboration improves system throughput, energy fairness, and task completion ratio in the network. Moreover, cooperative approaches are further improved when integrated with other advanced technologies like NOMA, RIS, and UAVs that complement the efficiency of connectivity, energy transfer, and flexibility of networks [29].

Another motivation for user cooperation is its potential for distributed optimization of resources. Cooperation prevents the centralization of all decisions at the AP or MEC server and instead allows the users to adaptively coordinate computation and communication tasks based on local state information, enabling a reduced signaling overhead and fast adaptation to channel and energy variations [30], [31]. Such distributed paradigm also demonstrates good alignment with future 6G network visions that are centered around edge intelligence, user collaboration, and autonomous edge decision-making [32], [33], [34].

The incentive mechanisms are relevant in order to provide long-run cooperation among the selfish devices. Some approaches, such as credit-based rewards, trust management, and auditing facilitated by blockchain, have been suggested to enable robust and fair cooperation.

In all, user collaboration in WPT-MEC systems enhances the fairness of performance, enables scalable resource allocation, and forms a basis for intelligent, reliable, and energy-efficient mobile edge networks.

3.1 Cooperative Relaying and Task Offloading

Cooperative relaying and task offloading are two fundamental methods to improve performance in WPT-MEC networks in heterogeneous user environments where energy and connectivity imbalances still prevail. These methods enable more energetic mobile consumers with better energy harvesting capability and better channel conditions to support weaker consumers by relaying information or performing computational tasks on behalf of the latter.

Cooperative Relaying involves the participation of a helper node, in most cases closer to the access point (AP), which aids in assisting the far-end user in the transfer of information to the MEC server. The relaying can be done under two major protocols:

- **Decode-and-Forward (DF)**: The helper fully decodes the message before retransmitting it.
- **Amplify-and-Forward (AF)**: The helper amplifies the received signal and forwards it without decoding.

In the WPT-MEC context, the helper node not only facilitates data forwarding but may also harvest RF energy simultaneously during the transmission phase, thereby supporting energy sustainability. The model finds precise application in the Wireless Powered Communication Networks where it makes use of cooperative relaying to realize a longer outreach with fair access to MEC services [6], [35].

Cooperative Task Offloading, on the other hand, allows the helper to compute all or part of the computational task on behalf of another device. Such paradigm offloading is particularly useful when the assistant has more computing capability, i.e., more CPU speed or more available memory [10]. Task segmentation in this context comes into play, especially for the partial offloading schemes for which task partitioning is done on the basis of computational complexity, power consumption, and latency requirements [13].

Mathematically, assistant B offloaded load W_o of user A must be under the latency constraint $T_{total} \leq T_{max}$, where $T_{total} = T_{offload} + T_{compute}$

Helper energy usage E_h also must be within its own energy budget as presented in equation 12:

$$E_h = \kappa C W_o f^2 + P_{tx}.\frac{W_o}{R} \leq E_{available} \quad (12)$$

where f is CPU frequency, κ is a device constant, R is the transmission rate, and C is cycles per bit required [18].

Such methods are blended with smart scheduling algorithms and reinforcement learning by modern breakthroughs to dynamically assign relaying or task roles based on user profiles and network conditions. Adaptive cooperation of this nature has been observed to increase throughput significantly, reduce latency, and increase the robustness of WPT-MEC networks [35].

3.2 User Pairing and Cooperation in NOMA-enabled WPT-MEC

User cooperation and pairing in Non-Orthogonal Multiple Access (NOMA) for Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) systems can potentially enhance spectrum efficiency, fairness, and task offloading success. Contrary to traditional orthogonal access schemes (e.g., TDMA), NOMA allows multiple users to use the same frequency using power domain multiplexing, with successive interference cancellation (SIC) at the receive side. This is particularly useful in heterogeneous WPT-MEC systems where devices of users suffer extreme variation in channel conditions and energy levels.

In NOMA-based WPT-MEC systems, a useful method is to pair a strong user (closer to the AP and with higher energy harvesting) with a weak user (far and with lower energy). The powerful user first demodulates the weak user's task information using SIC and, at the same time, acts as a cooperative relay or task executor. The AP provides the weak user with higher power P_2 and the powerful user with lower power P_1 ($P_2 > P_1$) such that successful SIC is guaranteed at the stronger user's end [19], [23], [24].

The AP's received signal is modeled as in Equation (11). User cooperation in this system achieves two advantages: it solves the double-near-far problem by facilitating simple offloading for low-capacity users and increases the system capacity in general through optimal reuse of resources. Second, cooperative NOMA allows more scalable and low-latency MEC services, which are crucial for mission-critical IoT and 6G applications [5].

Resource scheduling in this system is co-optimized over resources such as power management, computation allocation, and bandwidth allocation. Successive convex approximation and metaheuristics (e.g., PSO, GA) are utilized to obtain multi-objective solutions subject to energy, latency, and fairness constraints [36], [37], [38], [39].

Additional studies have further examined the incorporation of Reconfigurable Intelligent Surfaces (RIS) and STAR-RIS into NOMA-enabled WPT-MEC systems to further enhance beamforming capability as well as control of signal propagation to enable even more user cooperation and more efficient power splitting mechanisms [26].

Generally speaking, user pairing based on NOMA simply enhances cooperation in WPT-MEC systems through energy efficiency, spectrum efficiency, and computation enhancement.

3.3 UAV-enabled Cooperative WPT-MEC

Unmanned Aerial Vehicles (UAVs) are groundbreaking technology for collaborative WPT-MEC networks. Dynamically adjusting their flight and positioning themselves in an advantageous location, UAVs are proper candidates to be employed as flying energy transmitters, relays, or mobile MEC servers. Dynamically modifying their paths, UAVs can optimize beamforming of the energy, guarantee line-of-sight (LoS) communications, and aid edge devices in task offloading and computation, particularly in sparse ground infrastructure environments or emergency scenarios.

In WPT-MEC systems over UAVs, the UAV will typically be equipped with a power source and a MEC relay node or server. The UAV is kept in the air above specific regions in order to recharge devices wirelessly and also to send or receive computation requests [40], [41]. The energy harvested at user devices E_h from a UAV located at altitude H and at horizontal distance d is expressed as in equation 13:

$$E_h = \eta P_u \left(\frac{\beta_0}{d^2+H^2}\right) T_h \tag{13}$$

where η denotes the energy conversion efficiency, P_u denotes UAV transmit power, β_0 denotes the reference channel gain, and T_h denotes the energy transfer time. This model illustrates attenuation with distance and denotes the location strategy of the UAV for the maximization of energy reception at ground terminals [25], [42].

Trajectory optimization is also a fundamental research direction of UAV-assisted WPT-MEC networks. The goal is to enhance energy transfer efficiency, minimize latency, and maximize task offloading accomplishment. Some of the methods used to optimize trajectory, hovering time, and offloading scheduling include block coordinate descent and successive convex approximation.

Cooperative systems also involve UAVs as wireless relays between the user and fixed MEC servers. In such deployments, UAVs assist remote or low-power terminals in offloading computation by rebalancing their flight trajectory to optimize SNR and energy fairness [43], [44]. Furthermore, UAVs can perform computation tasks directly through onboard processing units, with not much reliance on ground infrastructures [45], [46].

Another important parameter is security. Because UAVs play core roles in data and energy relaying, they need to use lightweight encryption and authentication to avoid spoofing and interception of data. Reliable offloading protocols enabled by UAVs have also been proven robust in adversarial environments; e.g., see the verification performed in recent NOMA-based cooperative MEC deployments [47].

In conclusion, UAV coordination significantly improves the coverage, flexibility, and efficiency of WPT-MEC systems and thus represents a fundamental feature of future wireless edge networks.

3.4 Energy Sharing and Harvest-then-Cooperate Protocols

Energy sharing and harvest-then-cooperate protocols are the key cooperative paradigms in WPT-MEC systems, hence solving the energy asymmetry consequence of the notorious double-near-far effect. A user having excess harvested energy helps her less fortunate counterparts either by providing energy or by facilitating them in offloading the computation task. These mechanisms, as a return, enhance energy fairness, success rate of the task, and system robustness.

Energy Sharing happens when energy is directly transferred among users with the aid of wireless power transfer technologies, such as magnetic resonant coupling or RF energy transmission. In practical scenarios, energy-dense users that are closer to the AP accumulate surplus energy and wirelessly forward parts of it to neighboring energy-short users. This peer-to-peer energy collaboration relaxes the burden on the AP and fosters decentralized energy redistribution-desirable for sustainable network operation [48], [49], [50].

The efficiency of energy sharing is governed by the transfer efficiency η_s, channel fading h_{ij} between the donor and the receiver, and the transmission time T_s. The energy received at user j from user i can be represented as equation 14:

$$E_j = \eta_s P_i h_{ij} T_s \quad (14)$$

where P_i is the transmit power of the energy donor.

Harvest-then-Cooperate Protocols generalize this concept by structuring user cooperation into two main phases:

- **Harvest Phase:** Each user harvests energy from the AP over a downlink wireless power transmission time period T_h.
- **Cooperate Phase:** Users decide to execute their task locally, offload to the MEC server, or assist another user in offloading or computing a task.

In a typical deployment, a proximal user utilizes its surplus energy to relay or offload a task of a distant user that is unable to meet its energy or latency requirement. The cooperative mechanism increases the energy harvesting of the system and the overall number of computation tasks completed. An example is the scheme of [18], in which a dynamic helper is selected in an effort to help a weaker user based on current-time energy and channel statistics.

These collaborative processes are also integrated with intelligent scheduling policies and optimization platforms to offer roles and resources dynamically. Moreover, game-theoretic and incentive-based platforms are integrated to enable voluntary energy cooperation of self-interested users for sustainable network lifetime [35].

Lastly, harvest-then-cooperate and energy sharing protocols complete WPT-MEC's cooperative arsenal to ensure fair, stable, and effective system operation under energy-constrained conditions.

3.5 Multi-hop and Multi-agent Cooperative Frameworks

Multi-hop and multi-agent collaboration platforms are the novel advancements in WPT-MEC network topology that facilitate long-distance communication coverage, reliable task offloading, and distributed computation in the spatial diversity support and asymmetric energy supply scenarios. Data and computation task completion is conveyed by multiple intermediate nodes or shared among collaboration agents and thus enhances the achievement rates of the task and overall system.

Multi-hop collaboration is propagating data or computation requests as a sequence of intermediate users from the source device to the MEC server. It is of high utility when there exists little direct communication between the source and the MEC server due to poor channel conditions or low energy reserves. In this context, each relay node will be able to decode and forward the task data (DF) or amplify and forward the signal (AF) with energy harvesting for its survival. This architecture has been shown to enhance spectral efficiency, fairness, and coverage for energy-limited networks [51].

The total delay T_{total} of a task delivered through N hops is estimated through equation 14:

$$T_{total} = \sum_{i=1}^{N} \left(T_{tx}^{(i)} + T_{proc}^{(i)} \right) \quad (14)$$

where $T_{tx}^{(i)}$ is the transmission time and $T_{proc}^{(i)}$ is the local processing time at the i^{th} relay.

Multi-agent cooperative frameworks, on the other hand use decentralized intelligent agents that collaborate to optimize resource allocation, task scheduling, and role assignment. Since each agent, representing user or relay node makes decisions autonomously based on the local observations and shared information often with the help of reinforcement learning algorithms. In specific, Multi-Agent Reinforcement Learning (MARL) facilitates adaptive cooperation in dynamic and uncertain environments. Agents learn cooperative policies that minimize energy consumption, computation latency, and communication costs [52].

These frameworks are best suited for fog or edge-based WPT-MEC structures of urban deployments where user mobility and density call for real-time responsiveness [53]. For instance, agents may jointly choose the optimal relay path, offloading destination, or even conduct federated learning jobs without centralized coordination [54].

To ensure cooperation reliability, energy-aware role switching and trust management are used together in most situations. The devices that act as other's relays or processors repeatedly can gain credits or receive priority treatment in subsequent rounds, which becomes the cornerstone of sustainable and self-organizing MEC ecosystems [55].

In summary, multi-agent and multi-hop cooperation provides scalable, robust, and intelligent solutions for addressing the intrinsic shortages of traditional WPT-MEC systems.

3.6 Cooperation Incentive Mechanisms

In cooperative WPT-MEC systems, where user devices are expected to assist one another in data forwarding, task offloading, or energy transfer, incentive schemes are important to ensure continuous user participation, especially in the scenario of rational and energy-constrained users. Selfish users may refrain from cooperation in the absence of incentives, resulting in diminished system performance as well as fairness. Various cooperation incentive schemes have therefore been designed to advance individual interests with system-level objectives.

Credit-Based Systems are likely the easiest incentive mechanisms. Under this mechanism, users earn credits or tokens when they assist other users who they can use later to request assistance in return. These virtual currencies create a shared environment and provide fairness. Credit balances can impact access priority, resource allocation, or service quality. In order to maintain solidity, these systems could need to be secure and auditable logging, and this can be achieved through blockchain technologies [56], [57], [58].

Game-Theoretic Models are an effective way to examine cooperative behavior under constraints of utility maximization. Cooperative games such as coalition formation or Stackelberg games allow users to form strategic coalitions, sharing incentives or computational outcomes [59]. For instance, a Stackelberg game has a leader user incentivizing followers in following behavior as relays or helpers for maximum cooperation payoff and energy saving [60], [61].

Reputation and Trust Systems rely on cooperation history data to rate users' trust levels. Trust value is assigned to nodes based on successful task relay, energy contribution, and honest reporting. A highly trusted user enjoys priority access to MEC resources while a low-trust user can be fined or access blocked. The scores are renewable through feedback channels and consistent through distributed consensus algorithms [62], [63].

The incentive models for blockchain-based systems ensure, in a tamper-proof and decentralized manner, the management of cooperation logs, rewards, and identity verification. Smart contracts automate credit allocation, enforce cooperation contracts, and reduce reliance on centralized authorities. Transparency in these systems is enhanced while reducing fraud, particularly in big networks with dynamic user participation [47].

Besides, energy-aware incentive mechanisms favor more helpers with higher residual energy or better efficiency profiles, achieving maximum long-term cooperation sustainability [64], [65]. The strategies make sure nodes that contribute more frequently do not get overly depleted while the operating equilibrium of the system is maintained [66].

In general, incentive mechanisms are of crucial importance to cooperative WPT-MEC systems. Future development may explore the use of AI-based incentive tuning, cross-layer coordination, and adaptive mechanisms for active responses to user behaviors and network dynamics.

3.7 Integration with Reconfigurable Intelligent Surfaces (RIS)

The integration of Reconfigurable Intelligent Surfaces (RIS) into Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) systems has ushered in a new era of control and efficiency for wireless energy transfer and communication. RIS is metasurfaces that are reconfigurable with numerous passive components with the ability to dynamically change the phase and amplitude of incident electromagnetic waves, thus intelligently reconfiguring the wireless propagation setting. This feature enhances signal strength, reduces interference, and allows for precise energy delivery, which makes RIS extremely useful in cooperative WPT-MEC systems [26].

In cooperative WPT-MEC systems, RIS may be used to amplify the communication link between users with poor quality and the AP for enhanced offloading as well as energy harvesting. For instance, when extremely high path loss occurs due to a user located far away, RIS can direct and amplify signals to counteract channel degradation, thereby solving the double-near-far problem [67]. Apart from this, RIS enables improved user collaboration with increased device-to-device (D2D) communication, which is an important aspect of relay-based and energy-sharing systems.

The mathematically received signal y of a user assisted by an RIS can be represented as equation 15:

$$y = (h_{AP-RIS} \Phi h_{RIS-user})x + n \tag{15}$$

in which h_{AP-RIS} and $h_{RIS-user}$ represent channel gain from RIS to AP and RIS to user, respectively, Φ is RIS diagonal phase shift matrix, x represents transmitting signal, and n represents noise.

Current studies have advanced RIS to STAR-RIS (Simultaneously Transmitting and Reflecting RIS), offering full-space coverage and uplink/downlink optimization at the same time. In WPT-MEC systems, STAR-RIS improves cooperative offloading with enhanced spatial resource reuse and optimal beamforming methods. This causes increased task completion rates and enhanced energy efficiency for cooperative sets of users [5].

Cooperative WPT-MEC optimization problems through RIS involve simultaneous phase shift design, power allocation, user matching, and task scheduling. Alternating optimization, metaheuristic algorithms, and deep learning methods are used to solve the complex multi-variable problems [68], [69], [70]. Additionally, RIS can relieve reliance on mobile relays like UAVs, offering a more energy-efficient and infrastructure-based solution [71].

Overall, RIS and STAR-RIS significantly foster the cooperative ability of WPT-MEC networks by flexibly reconfiguring the wireless environment to enable high-efficiency energy and task transfer. Their integration is a promising future trend towards intelligent, programmable, and scalable 6G edge computing spaces.

3.8 Security and Reliability in Cooperative Systems

Since cooperative mechanisms are the backbone of Wireless Powered Transfer-Mobile Edge Computing networks, security and reliability guarantees have become a major concern. In cooperative systems-for example, computations offloaded by users via relay nodes, harvested energy traded among them, or computation done in a cooperative manner-the attack surface is vastly broadened. Some of the malicious activities in this case include data tampering, impersonation attacks, denial-of-service, and energy forgery.

Data security is a critical issue, particularly in relay or multi-hop offloading. The attackers are able to eavesdrop on personal input data or manipulate computation results in transit. In order to eradicate this, encrypted offloading models employing the application of lightweight cryptographical mechanisms such as elliptic curve cryptography and homomorphic encryption are used. They ensure confidentiality and integrity even when helper nodes are untrusted [72], [73], [74].

Authentication and identity management are also important in prevention of inappropriate access or Sybil attacks, where an attacker masquerades as multiple different identities to gain undeserved influence. Light-weight authentication schemes based on hash-based message authentication codes (HMAC) or physical-layer keying are possible implementations for resource-limited edge devices [75].

Trust Management protocols evaluate past performance of cooperative nodes in order to predict their trust value. Trust values are derived from task success completion rates, contribution level in energy sharing, and recommendations of others' nodes. The values determine future eligibility for cooperation and the role given to nodes. Strategy approaches, like the ones in [76] utilize blockchain-based ledgers for tracking and auditing cooperative activity safely, offering openness enhancement and illegitimate activity deterrence.

Fault tolerance and reliability: In mobile scenarios, a helper node can become unreachable due to mobility, failure, or energy depletion. WPT-MEC systems would employ redundancy mechanisms to overcome such issues by:

- **Backup helper allocation**, where alternative nodes are pre-designated to take over in case of failure.
- **Task checkpointing and rollback**, which allows interrupted tasks to resume from the last saved state.
- **Distributed consensus mechanisms**, ensuring that cooperative decisions remain consistent even under partial failures.

Recent advances also involve robust learning models, wherein cooperative policies adapt to adversarial behaviors or node dropout using reinforcement learning techniques [47].

Finally, cooperative WPT-MEC systems call for security and trustworthiness to enable robustness, scalability, and reliability. The inclusion of security as an intrinsic capability while achieving the optimal balance between safety and performance for real-time cooperative edge computation in next-generation architectures is now at hand.

4. COOPERATIVE STRATEGIES AND OPTIMIZATION TECHNIQUES

Optimization of the WPT-MEC system is a key enabler toward realizing multi-dimensional trade-offs between energy consumption, computation efficiency, latency, and fairness. Since the WPT-MEC networks involve various dynamic elements in the form of mobile users, stochastic wireless channels, and heterogeneous device capabilities, robust and adaptable optimization frameworks should be formulated [2], [77].

Fundamental to WPT-MEC optimization is the problem of resource management in multiple dimensions. The devices have to decide whether to offload computation, how much communications power to allocate, and when to schedule energy harvesting subject to latency, energy budgets, and QoS constraints [18], [40]. These decisions are also complex in shared environments where the users themselves are being employed as assistants or go-betweens for others, creating an additional layer of interdependence and strategic behavior [21], [78].

The common goals of optimization in WPT-MEC systems:

- **Maximizing computation throughput**: the total number of successfully executed task bits over a given time horizon.
- **Minimizing system-wide energy consumption**, particularly critical in networks with low-power IoT nodes.
- **Balancing fairness** among users with different channel and energy harvesting conditions.
- **Ensuring low-latency offloading**, especially for delay-sensitive applications like augmented reality or autonomous control.

These objectives are often formalized into mathematical programming problems such as:

- **Convex Optimization**, for problems with convex feasible sets and objectives (e.g., energy minimization with linear constraints). Convex strategies generally follow with Lagrangian methods to derive closed-form or tractable solutions, especially in NOMA-based or OFDMA-based WPT-MEC networks [23], [79].
- **Mixed-Integer Nonlinear Programming (MINLP)**, for even more intricate cases with binary offloading decisions or relay choice. For instance, simultaneous optimization of energy and delay consumption in WPT-MEC is likely to lead to MINLP formulations solved using decomposition approaches [17], [28].
- **Stochastic Optimization,** to account for time-varying wireless channels, random energy arrivals, and uncertain computation demands. These are typically coupled with block coordinate descent or Lyapunov optimization for convergence guarantees [80], [81].

With broader user cooperation, the landscape of optimization problems is more complicated. Cooperative resource allocation must consider together the incentives and states of many users, their available energy, as well as mutual benefits. Methods like Lagrangian dual decomposition, successive convex approximation, and block coordinate descent have been extensively applied to decompose and successfully solve these kinds of problems [11], [82].

Machine learning-based optimization, including deep reinforcement learning (DRL) for real-time and adaptive control uncertainty, is also among the ongoing trends. Data-driven learning-based scalable models are alternatives to the traditional optimization approach, which performs best in dense and dynamic WPT-MEC scenarios [83], [84], [85].

Therefore, optimization models become part of the sustainable and smart functioning of WPT-MEC systems for ensuring performance commitments in energy, computation, and communications.

4.1 Joint Computation and Communication Resource Allocation

Joint communication and computation resource allocation is the key optimization problem in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) networks. The interplay of computation demand, energy consumption, and wireless communication constraint necessitates joint methods to management of these resources to meet quality-of-service (QoS) requirements and energy constraints.

In WPT-MEC systems, devices should decide whether to execute computation tasks locally or offload them to a nearby MEC server. The decision is made by taking a wide variety of factors into account: local CPU capacity, available harvested energy, wireless channel state, and task latency requirement. Joint allocation strategies attempt to determine the allocation at the same time of:

- **CPU-cycle frequency allocation** for local processing,
- **Transmit power and time slot allocation** for offloading,
- **Task partitioning ratio** in partial offloading scenarios [10], [12], [79].

Such strategies have been proposed and validated in several studies, including joint offloading and energy allocation frameworks designed for multi-device cooperative MEC settings [10], FDMA-based WPT-MEC delay-energy joint optimizations [28], and power-aware dynamic offloading models for industrial MEC networks [86]

Formally, consider a task with input size I, requiring C CPU cycles per bit. If executed locally at frequency f, the local computation energy E_{comp} is given by equation:

$$E_{comp} = \kappa C I f^2 \tag{16}$$

where κ is a hardware-dependent coefficient. The local execution time $T_{comp} = \frac{CI}{f}$ must satisfy latency constraints.

For offloaded tasks, the communication energy E_{comm} and delay T_{tx} are given by equation 17:

$$E_{comm} = P_t \cdot \frac{I}{R}, \quad T_{tx} = \frac{I}{R} \tag{17}$$

where P_t is transmit power and R is the achievable data rate determined by channel gain and bandwidth.

These paired relationships are jointly optimized to trade off energy consumption and delay. [35] jointly allocated harvested energy and computation time in a mixed-integer nonlinear programming (MINLP) formulation, taking into account cooperative offloading and helper selection. Their approach used block coordinate descent to iteratively address the decomposed sub-problems.

[79] extended this by suggesting joint subcarrier and power allocation for OFDMA-based WPT-MEC systems. Their joint optimization ensured equality and latency conformity among users acting for varied purposes; as offloaders or assistants.

For a user cooperation case, the simultaneous resource allocation issue is further complicated. It has to optimize not just the computation and transmission of one user but also the relay strategies, energy budgets, and task routing routes in the network [18], [87]. Such types of collaborative systems need immense caution in coordination, like multi-agent vehicular edge computing and UAV-based mobile networks, where the scalability of the system and heterogeneity of users are considered [10], [21].

Overall, joint computation and communication resource allocation remains a key enabler of efficient, scalable, and equitable WPT-MEC system design for solo and cooperative functioning.

4.2 Multi-Access Techniques: TDMA, NOMA, and Hybrid Approaches

Efficient multiple access techniques in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) networks play a crucial role in enabling simultaneous task offloading, communication, and energy harvesting of multiple users. Time Division Multiple Access (TDMA), Non-Orthogonal Multiple Access (NOMA), and hybrid access schemes possess varying advantages in spectrum management, energy efficiency, and computation throughput maximization.

TDMA is one of the most preferred orthogonal multiple access techniques where every user is assigned a fixed time slot to send and receive energy. The simplicity with which TDMA can be scheduled and controlled minimizes interference between users. In WPT-MEC systems, TDMA optimizes sequential offloading and energy transfer, for which low-complexity devices are eligible. But it will lead to under-use of spectral resources, particularly in high-density user cases, and degrade latency for users with later scheduled time slots [88].

On the other hand, NOMA allows a group of users to share the same frequency and time resources at the same time with power domain multiplexing. The users are distinguished by various channel gains, and successive interference cancellation (SIC) is conducted at the receiver side for decoding the overlapped signals. This improves spectrum utilization and supports more users with a limited amount of resources [19], [23]. In cooperative WPT-MEC systems, NOMA allows more dominant users to act as relays for weaker users by decoding and forwarding their information or helping in computation. The received signal for a two-user NOMA system is given by equation 18:

$$Y = \sqrt{P_1} h_1 x_1 + \sqrt{P_2} h_2 x_2 + n \tag{18}$$

in which P_1, P_2 are transmit powers, h_1, h_2 are channel gains, and x_1, x_2 are user signals.

Hybrid TDMA-NOMA schemes meet the virtues of both techniques. Users are initially divided into clusters, with each cluster operating under NOMA, and inter-cluster transmissions utilizing TDMA. Hybrid system merges complexity, energy efficiency, and interference management. Flexible user heterogeneity in channel and energy availability is possible. [26] demonstrated that such schemes yield better task completion rate and fairness in cooperative WPT-MEC systems through adaptive access patterns.

Summarily, the choice of the access scheme in WPT-MEC networks significantly determines system performance. Hybrid multi-access techniques, being adaptive ones, become more appealing to meet requirements of scalable, energy-efficient, and low-latency mobile edge computing.

4.3 Intelligent Reflecting Surface (IRS) and STAR-RIS Enhanced Optimization

Intelligent Reflecting Surfaces (IRS) and Simultaneously Transmitting and Reflecting Reconfigurable Intelligent Surfaces (STAR-RIS) stand on the threshold of becoming revolutionary facilitators of Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) optimization. IRS and STAR-RIS can offer dynamic wireless propagation environment control using phase shifting and amplitude adjustment of the reflected signals across numerous passive elements. This arrangement enhances the efficiency of wireless energy transfer, offloading the reliability of computation, and overall network adaptability.

IRS-assisted WPT-MEC systems utilize passive metasurfaces to form useful signal paths between users and the AP, thereby reducing shadowing, path loss, and double-near-far effect. For the cooperative MEC scenario, IRS can assist in optimizing user-helper and user-server communication links, particularly for edge users [89], [90]. An expression for the received power of an IRS-aided device can be given as equation 19:

$$P_{IRS} = P_t |h_d + h_r^T \Phi g|^2 \tag{19}$$

where P_t is the transmit power, h_d is the direct link channel, h_r and g are IRS-user and AP-IRS channels, respectively, and Φ is the diagonal phase shift matrix of the IRS [91], [92].

STAR-RIS strengthens IRS capability through the simultaneous reflection and signal transmission of each unit, thus recording both sides of the surface and facilitating full-space communication. Such increased capability improves link diversity and spatial flexibility, critical in crowded or blocked environments. In WPT-MEC systems, STAR-RIS facilitates simultaneous uplink task offloading and downlink wireless power transfer, thus reducing latency and improving resource reuse efficiency [26].

Optimizing IRS and STAR-RIS-augmented networks involves the joint configuration of passive beamforming (phase shift design optimization), power control, user association, and task scheduling. In light of phase shift design non-convexity, widespread approaches such as alternating optimization, semidefinite relaxation (SDR), and deep reinforcement learning (DRL) are adopted. For example, [93] used DRL integrated with SDR to full-duplex STAR-RIS systems for joint optimization of the phase shift and power allocation. Similarly, [94] used DRL to model coupled phase shifts for STAR-RIS beamforming. Alternating optimization and semidefinite relaxation techniques were also used in active STAR-RIS setups to improve energy efficiency, as discussed by [95].

For instance, [5] proposed a combined user pairing and RIS configuration framework that maximizes energy efficiency and task completion ratio in NOMA-based WPT-MEC networks under STAR-RIS. Based on their findings, intelligent surface reconfiguration can bridge the gap of performance between far and close users, leading to more equitable and scalable systems.

Finally, the integration of IRS and STAR-RIS provides a new dimension to WPT-MEC networks for optimization, which enables them to precisely control the wireless energy and information streams. These intelligent surfaces will play a particularly important role in achieving high-throughput, energy-saving, and user-criteria balancing edge computing in future 6G systems.

4.4 Metaheuristics and Swarm Intelligence Techniques

Metaheuristics and swarm intelligence techniques have been the powerful tools of preference for handling the complex, nonlinear, and large-scale nature of the optimization issues embedded in Wireless Powered Transfer-Mobile Edge Computing systems. The techniques are particularly useful in cooperative networks where resource allocation, scheduling, relay selection, and energy management must be jointly optimized under multi-constraint, multi-objective conditions.

Metaheuristics are generic, problem-neutral algorithmic frameworks designed to efficiently explore wide and complex solution spaces in optimization problems. Metaheuristics are useful in that they can evade local optima and obtain near-optimal solutions in reasonable time. Some of the traditional metaheuristic algorithms are Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), and Ant Colony Optimization (ACO). These have been discovered to work incredibly well on a very large number of combinatorial and continuous optimization problems [96], [97].

These techniques differ in inspiration and mechanisms. GA simulates the process of natural selection by crossover and mutation; SA simulates the annealing process in metal working; TS exploits memory structures to escape local optima; and ACO simulates ants foraging behavior due to pheromone trails in order to find the best solutions. Their flexibility and ability to adapt have led them to be applied widely, especially in applications in engineering and operational research [98], [99].

Swarm intelligence methods, taking cues from natural social organism behaviors, offer adaptive and decentralized platforms for optimization. Predominant methods include Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Firefly Algorithm (FA). PSO is utilized extensively in WPT-MEC networks to solve combined offloading optimization and energy allocation. Each particle represents a candidate solution (e.g., a vector of power levels or task assignments), and the swarm converges iteratively based on personal and global best performance indicators [28].

For example, in a multi-user cooperative WPT-MEC system, the objective function F could capture total energy consumption and latency, while the optimization seeks equation 19:

$$\min_{x \in \chi} F(x) = \alpha E_{total}(x) + \beta T_{total}(x) \tag{19}$$

subject to constraints on energy budgets, CPU frequency bounds, and deadline compliance. Here, α and β are tunable weights reflecting trade-offs between energy and latency.

Reference [26] demonstrated the use of hybrid PSO with genetic crossover operators for dynamic task assignment and phase shift design in RIS-enhanced WPT-MEC systems. Their approach achieved faster convergence and higher robustness under user mobility and channel uncertainty.

Furthermore, metaheuristics are easily integrated with machine learning models to form hybrid intelligent optimizers. These combinations leverage learned patterns to guide search directions, improving performance in highly dynamic MEC networks [100], [101]. These approaches combine the global search capability of metaheuristics with the adaptive learning of ML algorithms, allowing optimization frameworks to respond effectively to changing network dynamics.

Although they are empirically effective, auto-tuning of parameters (such as inertia weight for PSO or mutation probabilities for GA) remains a difficult task. Auto-tuning frameworks and metaheuristics based on reinforcement learning are being considered more and more for real-time adaptive control of these parameters [102], [103].

In short, metaheuristics and swarm intelligence offer scalable, adaptive, and efficient optimization methods suitably suited to WPT-MEC systems' complexity and heterogeneity, particularly for cooperative and multifarious user scenarios.

4.5 Deep Reinforcement Learning (DRL) for Real-Time Optimization

Deep Reinforcement Learning (DRL) has emerged as a cutting-edge technique for real-time adaptive optimization in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) networks. DRL unites deep learning's function approximation power and reinforcement learning's sequential decision-making framework, making it most suitable for highly dynamic, uncertain, and multi-agent environments like WPT-MEC [40], [84].

In such networks, users need to make continuous decisions regarding task offloading, energy harvesting, transmit power, and user cooperation in the presence of stochastic wireless channels, computation requests that change over time, and local knowledge limitations. Traditional optimization techniques are unable to react to such real-world dynamics since they rely on ideal data and offline processing. DRL addresses these issues through the direct learning of optimal policies from world experience without the necessity of an explicit model [104], [105].

A DRL agent looks at the state of the system s_t (e.g., channel condition, queue lengths, battery status) and selects action a_t (e.g., offloading decision, power allocation) to optimize the cumulative reward $R = \sum_t \gamma^t r_t$, where γ is the discount factor and r_t is the reward at time t. The policy $\pi(a|s)$ is typically parameterized by a deep neural network.

Some prominent DRL algorithms used in WPT-MEC are:

- **Deep Q-Networks (DQN)**: Suitable for discrete action spaces, such as binary offloading decisions [81].
- **Deep Deterministic Policy Gradient (DDPG)**: Handles continuous action spaces like power control and CPU frequency selection [106].
- **Proximal Policy Optimization (PPO)**: Balances exploration and exploitation with improved stability in large-scale, multi-agent systems [107].

For example, [84] utilized a multi-agent DRL framework to handle energy-aware task offloading in a collaborative MEC system. Each user agent learns to optimize its own performance to work toward the system's global objective, e.g., decreasing delay and energy cost

In addition, DRL can also be blended with other intelligent tools like federated learning for privacy-preserving model training or attention mechanisms to enable state abstraction effectively. Transfer learning has been investigated more recently to improve learning efficiency under diverse network conditions [28]. Transfer learning has been investigated more recently to improve learning efficiency under diverse network conditions, particularly when there is not much historical training or system dynamics are subject to change frequently.

While promising, DRL is plagued by training instability, reward sparsity, and time to convergence. Recent research overcomes these through curriculum learning, reward shaping, and hybrid DRL-metaheuristic models. To address this, recent research utilizes curriculum learning to incrementally raise the complexity of the problem, reward shaping to improve exploration, and hybrid DRL-metaheuristic models to accelerate convergence and reduce sub-optimality in large state-action spaces [108].

In summary, DRL will be a very powerful paradigm for real-time optimization in WPT-MEC systems to support intelligent and autonomous edge operation under uncertainty. It will play a prominent role in next-generation adaptive edge computing architectures.

4.6 Game Theory and Matching Theory in Cooperative Scheduling

Game theory and matching theory offer rich mathematical models to solve cooperative scheduling problems in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) networks. They facilitate distributed decision-making, effective resource allocation, and incentive-compatible user cooperation under rational, typically selfish, behavior assumptions.

Game theory can analyze strategic behaviors of multiple consumers or agents who contend or cooperate for shared resources such as energy, spectrum, and computing resources. Standard game-theoretic models in WPT-MEC are:

- **Non-cooperative games**, where customers individually determine strategies in order to maximize their utilities (e.g., task delay or energy consumption). Equilibrium points such as the Nash Equilibrium ensure that no user is benefited by unilaterally changing its strategy [109].
- **Cooperative games**, used to model user cooperation in sharing energy or use as relays. These games would typically use a solution concept like coalition formation or bargaining solutions to calculate stable configurations and distribute the reward justly [107].
- **Stackelberg games**, in which a leader (e.g., the MEC server or central controller) sets prices or incentives, and users (followers) respond by optimizing their behavior relative to each other. This hierarchy reflects real-world scenarios where the server allocates bandwidth or energy charging priority based on user bids or credits [59], [110].

Matching theory based on economic theory, which is derived from economics, provides stable and efficient matching results to user matching with resources (e.g., relay nodes, MEC servers, time slots) based on preference and constraint. It is especially suitable for decentralized cooperative WPT-MEC applications where matchings one-to-one or many-to-one are to be formed without any centralized administration [111].

One such significant application is user-helper pairing, i.e., task offloaders and potential relay nodes are paired. Algorithms like Gale-Shapley deferred acceptance or market-style matching designs are responsible for stability and fairness. [76] employed many-to-one matching to assign multiple weak users to strong helpers for the purpose of improving system throughput with energy and latency constraints.

Hybrid approaches with game theory and matching theory further enhance decision detail-making. Users, for instance, first most importantly create coalitions in utility function terms and achieve stable matching in their clusters of coalitions [112].

Challenges include preference disagreements, incomplete information, and incentive mismatch. To overcome them, recent research combines learning-based matching, auction-based incentive mechanisms, and reputation systems to promote trustworthy cooperation [109], [111].

In conclusion, game and matching theories provide effective, distributed scheduling solutions that align user incentives with system objectives in cooperative WPT-MEC networks. Their synergy ensures scalable, fair, and adaptive cooperation under diverse network environments.

4.7 Multi-Objective and Fairness-Oriented Optimization

Multi-objective and fairness-constrained optimization is also crucial in WPT-MEC network design, especially in cooperative scenarios where users exhibit heterogeneous energy profiles, channel conditions, and computational workloads. Instead of maximizing/minimizing a single performance metric (e.g., energy efficiency or task latency), multi-objective frameworks target multiple competing objectives simultaneously to accomplish proportionate and fair resource allocation.

Common goals of WPT-MEC optimization are:

- Minimizing total energy consumption,
- Minimizing end-to-end task delay,
- Maximizing system throughput, and
- Maximizing user fairness, especially for edge or disadvantaged users.

To address these multiple goals, two primary formulations are commonly used:

- **Weighted sum approach**, where a composite objective function $F(x) = \sum_i \alpha_i f_i\,(x)$ is optimized by tuning weight parameters α_i for different metrics [28].
- **Pareto optimization**, which seeks to identify a set of Pareto-optimal solutions where no single objective can be improved without degrading another. This allows decision-makers to select solutions based on context-specific trade-offs [113].

Fairness is particularly crucial in cooperative WPT-MEC systems due to the double-near-far problem, where users further from the energy source and MEC server experience higher energy loss and latency. Without fairness constraints, optimization algorithms may disproportionately favor users with better channels or energy availability [113].

One widely used fairness metric is Jain's fairness index expressed in equation 20:

$$J(x) = \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n\sum_{i=1}^{n} x_i^2} \tag{20}$$

which ranges from 1 (perfect fairness) to $\frac{1}{n}$ (worst case). Optimization frameworks aim to maximize this index while achieving performance targets.

Reference [35] suggested a fairness-aware resource allocation mechanism that coupled power control and offloading decisions with weighted-sum and Pareto front analysis for parallel optimization. The framework provided QoS guarantee for low-end users and also attained global efficiency maximization.

Multi-objective problems are generally solved by evolutionary methods such as NSGA-II (Non-dominated Sorting Genetic Algorithm) and MOEA/D (Multi-objective Evolutionary Algorithm based on Decomposition). Both methods exhaustively explore the solution space and generate diversified Pareto-optimal solutions [114], [115].

Future research integrates AI-adaptive weighting, time-dependent fairness constraints, and federated optimization into personalized multi-objective balancing to serve dynamic user requirements.

Finally, fairness-aware multi-objective optimization allows for fair and sustainable WPT-MEC network operation to meet various user demands and working scenarios through advanced algorithmic modeling.

4.8 Energy Efficiency and Residual Energy Maximization

Energy efficiency and residual energy maximization are premier optimization goals in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) networks, particularly in cooperative and low-power device contexts. They determine the run-time tolerance and performance lifetime of user devices, particularly when infinite recharging is not an option.

The energy efficiency (EE) has been defined as the proportion of the volume of useful computation (or data successfully offloaded) to overall energy consumption, often in bits per Joule as in equation 21 [17], [23]:

$$EE = \frac{\text{Number of Computed Bits}}{\text{Total Energy Consumption}} \tag{21}$$

Maximizing EE ensures that users perform more computation for each unit of energy consumed, prolonging device lifespan and reducing the number of wireless energy transfer sessions.

Maximizing residual energy, on the other hand, focuses on preserving users' residual energy after task completion and cooperative functions (e.g., relaying or energy sharing). This is especially important in cooperative networks, where assist nodes risk depleting energy and thus service breakdown if not appropriately compensated or prioritized [28], [116].

Where residual energy is used in the optimization problem, there are usually constraints or penalty terms in the objective function as shown in equation 22:

$$\max \sum_{i=1}^{N} \left(\alpha EE_i + \beta E_{residual\,,i}\right) \tag{22}$$

where EE_i is the energy efficiency of user i, $E_{residual\,,i}$ is the residual energy, and α, β are factors representing performance versus sustainability trade-off.

Reference [65] proposed an energy-aware offloading and scheduling method that dynamically adjusts user roles and partitions for tasks based on their up-to-date efficiency profile and energy status. Their design utilized convex optimization and low-complexity heuristics to trade between throughput and device lifespan.

To complement residual energy levels even more, some systems implement harvest-then-offload protocols whereby consumers first accumulate sufficient energy prior to computing or collaboration. The policy acknowledges applicability in cooperative WPT-MEC systems where devices with low energy need to decide when to offload or forward work based on the amount of harvested energy [2], [18].

Others emphasize offloading for low-energy users to avoid battery-critical levels and encourage system resilience. Priority-based collaboration models and energy-based scheduling models have been explored to ensure fair access and sustainable utilization, as indicated in [10] surveys and replicated in energy-efficient optimization models by [6].

Sophisticated approaches like deep reinforcement learning (DRL) and multi-objective optimization are also employed for real-time energy-aware adaptive policy learning. DRL agents adaptively trade-off between short-term performance enhancement towards energy conservation in the long term, delivering robust solutions against uncertainty [117].

Briefly, residual energy maximization and energy efficiency are the cornerstones of WPT-MEC network survival and robustness. These approaches guarantee fair participation, prevent helper exhaustion, and facilitate cooperative edge computing sustainability.

5. COMPARATIVE EVALUATION AND OPEN CHALLENGES

The variety of cooperative WPT-MEC architectures, optimization frameworks, and access methodologies has resulted in a fruitful body of literature of architectures and methods. In this section, a comparative review of prominent cooperative WPT-MEC solutions along some metrics like spectral efficiency, energy fairness, scalability, and security are presented. This is followed by some of the contemporary challenges and research issues pertaining to this area.

5.1 Comparative Evaluation

Comparative examination of different cooperative structures in WPT-MEC systems is important to achieve their performance, scalability, complexity, and applicability trade-offs. This subsection reviews prominent cooperative strategies: relaying, user pairing in NOMA, UAV-supporting, RIS integration, and energy-sharing models, from recent literature.

The evaluation criteria include:

- **Computation throughput**: The volume of successfully executed task bits.
- **Energy efficiency**: Measured in bits per Joule.
- **Latency**: Total task completion delay.
- **Complexity**: Algorithmic or deployment overhead.
- **Fairness**: User equality in resource allocation.

The comparative performance of these schemes is summarized in Table 1.

Table 1. Comparative Performance of Key Cooperative Strategies

Scheme	Computation Throughput	Energy Efficiency	Latency	Complexity	Fairness	References	Research Gaps
Cooperative Relaying	Moderate	Moderate	Low	Low	Moderate	[35]	Static single-AP topology; no mobility, no security, no imperfect CSI modelling
NOMA-based User Pairing	High	High	Moderate	Moderate	High	[23]	Perfect SIC assumption; single static power beacon; no multi-cell or heterogeneous support
UAV-enabled Cooperation	Very High	Moderate	Low	High	High	[29]	Fixed UAV position; conference scope only; no resource optimization framework
RIS / STAR-RIS Integration	High	Very High	Very Low	Moderate	High	[26]	Single-antenna AP; perfect CSI assumed; no eavesdropping threat or energy causality across time slots
Energy Sharing / HtC	Moderate	High	Moderate	Low	Very High	[50]	Demo/proof-of-concept only; no formal optimization; no MEC

							integration

						remain open

As can be seen from Table 1, UAV-based cooperation offers high throughput and low latency but at the cost of control and deployment complexity. RIS and STAR-RIS based systems, however, offer high energy efficiency and low latency by passive reconfiguration with an intermediate complexity infrastructure-centric option.

NOMA-based user pairing enhances spectral efficiency and offloading of tasks in tandem with cooperation, thus being more suitable for dense networks. Interference management and decoding complexity, however, need to be treated with caution.

Energy sharing and harvest-then-cooperate (HtC) protocols score highest in fairness, especially in heterogeneous networks. They ensure sustainability and inclusivity for edge users but may suffer from moderate latency.Table 2 summarizes and contrasts representative cooperative WPT-MEC systems based on key metrics: system type, user cooperation mode, optimization method, multiple access scheme, and security support.

Table 2. Comparative Analysis of Cooperative WPT-MEC Frameworks

Reference	Cooperation Mode	Access Scheme	Optimization Method	Energy Efficiency	Security Support	Research Gaps
[35]	Relaying + Task Offloading	TDMA	Convex Decomposition	High	No	Single-relay bottleneck; no physical-layer security
[23]	User Pairing (NOMA)	NOMA	Successive Convex Approximation	Very High	Basic	Residual SIC interference unaddressed; fixed power beacon
[5]	STAR-RIS + NOMA	Hybrid (TDMA/NOMA)	Metaheuristic (GA/PSO)	High	No	Metaheuristic lacks optimality proof; no security consideration
[47]	UAV-Aided Cooperation	TDMA	Heuristic + Encryption	Moderate	Strong	Static friendly jammer; no trajectory optimization; single-UAV only
[26]	RIS/STAR-RIS	TDMA	Alternating Optimization	High	Medium	Continuous phase-shift assumption; no multi-cell interference model
[76]	Blockchain-Aided	TDMA	Game Theory + Smart Contracts	Medium	Very Strong	Blockchain latency overhead unresolved; simplistic linear EH model
[55]	Vehicular Cooperation	TDMA	Deep RL	High	Medium	Survey paper: DRL convergence under high mobility and WPT-MEC integration in vehicles

It can be observed from Table 2 that RIS-aided offloading architectures and NOMA-based cooperation ensure high throughput and energy gain advantages but lack flexibility in integration with hard security models. UAV and blockchain-based frameworks ensure high security but add overhead and complexity in resource-constrained deployments.

A number of gaps in research were noted in all the works reviewed in Tables 1 and 2. The formulation by [35] is not only free of hardware impairments and physical-layer security, but also does not include multi-hop or mobile relay topology as the relay is fixed and static in a single-access-point relay (SAPR) topology. Moreover, fairness among devices of different types having different sizes of tasks and battery capacities is not discussed and the single-relay architecture poses a scalability constraint in dense deployments of IoT networks where path loss and inter-network interference are not negligible.

Reference [23] only consider a single power beacon, do not consider the effects of successive interference cancellation (SIC), and their analysis is static. Other features, such as uplink cooperative offloading, user mobility, dynamic task arrivals over multiple time slots and multi-cell heterogeneous network topologies, are not considered and fairness across users with different computational demands is not optimized.

The 3-D placement and hover position of the UAV in [29] are fixed and trajectory optimization is not considered; the performance is only evaluated using outage and secrecy successful computation probability (SSCP) metrics; computation-bits and energy-efficiency are not analyzed; the joint consideration of imperfect CSI and imperfect SIC is not taken into account; the trajectory planning and optimization of friendly-jammer are not considered; the resource allocation optimization framework is not considered and multi-UAV cooperative scenarios are not considered.

Reference [26] do not include multi-antenna (MISO/MIMO) beamforming gain, and assume perfect CSI at the controller of the RIS and full resolution of the phase-shift, which means that hardware quantization errors, multi-cell interference, inter-RIS coupling, energy causality across time slots and eavesdropping threats are all ignored.

Reference [50] present a proof-of-concept demonstration without a formal optimization framework for energy-sharing scheduling or quality-of-service constraints, and the characterization of transfer efficiency over distance, interference effects, and integration with MEC offloading and computational task management remain unaddressed.

Reference [5] use a metaheuristic optimization that does not have convergence guarantees, and they only consider a single STAR-RIS element-grouping strategy; multi-antenna transmitter beamforming is not considered; eavesdropping attacks, physical-layer security, channel ageing and mobility are not taken into account.

Reference [47] do not jointly optimize the WPT scheduling, offloading decision, and UAV's altitude and consider only the placement of friendly UAVs which is not optimized. Multi-UAV cooperative architectures are also not considered.

Regarding the blockchain consensus overhead, [76] only model it at a high level of abstraction which is impractical for real-time IoT at scale; scalability with a large number of federated learning participants is not verified and a linear energy-harvesting model is assumed without considering non-linear EH characteristics; integration with RIS or UAV channel enhancement is not considered.

Lastly, [55] underline in their survey the following challenges: individual reviewed schemes do not yet have a uniform experimental validation; Doppler shift in V2X cases and coil alignment still need to be addressed; WPT in vehicular applications presents additional challenges related to Doppler shift and coil alignment; and the joint management of electric vehicle charging and MEC offloading is an open research problem.

5.2 Performance Metrics Overview

Evaluating the performance of cooperative Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) systems requires an inclusive familiarity with various metrics that reflect efficiency, scalability, responsiveness, and fairness. Such metrics are employed to analyze algorithms, architectural designs, and protocol improvements under numerous network circumstances.

- **Computation Throughput:** Computation throughput is a measure of the amount of data successfully processed or offloaded (in bits) during an interval of time. Computation throughput is an important indicator of system processing capacity and is used most often in optimizing resource allocation. Increased throughput translates to better system responsiveness and supports delay-sensitive applications [35].
- **Energy Efficiency:** As the unit of the ratio of processed data to consumed energy, energy efficiency (bits/Joule) indicates the energy sustainability of the devices of users in energy-limited situations. Task-offloading and energy harvesting schemes (e.g., NOMA or UAV-assisted schemes) in cooperative WPT-MEC systems highly influence this indicator [29], [80].
- **Task Completion Latency:** Latency is comprised of the offloading delay (transmission delay) and the processing delay (MEC or local processing time). The industrial automation or augmented reality real-time applications make it critical. STAR-RIS and DRL-optimized offloading have been proven to minimize latency with smart link setup and adaptive decision-making [26].
- **Residual Energy:** Residual energy calculates the residual battery of user devices after computation or collaborative tasks. Sufficient residual energy prevents device drop-out and maintains network stability in the long run. Optimization schemes normally include energy-aware constraints to make the process fair and prevent exhaustion [28], [116].
- **Fairness Metrics:** Jain's Fairness Index is applied widely to assess the fairness of users' resource allocation. It is expressed by equation 23:

$$J(x) = \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n \sum_{i=1}^{n} x_i^2} \tag{23}$$

where x_i is the distributed resource (e.g., throughput or energy) for user i. High fairness corresponds to a value close to 1, relevant to prevent the double-near-far effect in cooperative systems [5], [40], [118].

- **System Utility:** Utility functions consolidate several objectives (e.g., throughput, energy, delay) into one performance measure, allowing flexible trade-off analysis. In WPT-MEC systems, optimization platforms generally adopt utility-based models to balance conflicting metrics such as delay and power consumption. For instance, marginal utility theory-based utility functions have been proposed for dynamic energy and computation resource allocation in NOMA-assisted WPT-MEC systems [119]. In addition, Pareto optimal front-based optimization was utilized to handle trade-offs in backscatter-assisted and RIS-enabled WPT-MEC networks with a multi-dimensional optimization technique at no expense of one objective at the expense of the other [113]. Weighted sum utility maximization has also been explored in FDMA systems with multiple devices with the aim of maximizing wireless energy consumption and minimizing latency in real-time operations [28].

Generally, an inclusive analysis of WPT-MEC systems in an integrated framework involves careful examination of several performance metrics, each in significant aspects of end-to-end network quality and user experience.

5.3 Trade-Offs in Cooperative WPT-MEC

In WPT-MEC networks, cooperative wireless powered transfer-mobile edge computing faces complicated trade-offs among cross-competing performance objectives. The goal of designing efficient, adaptive, and sustainable networks relies heavily on understanding the inherent trade-offs. Energy efficiency vs. latency, fairness vs. throughput, and system complexity vs. scalability are the underlying trade-offs.

- **Latency vs. Energy Efficiency:** Maximization of energy efficiency often calls for the minimization of the transmission power, offloading rates or maximization of locally consumed computation. This implies longer times of task execution for data-intensive applications and latency-critical applications. A user with harvested energy constraints can opt for local computation in a bid to conserve energy on an application, even if this results in increased execution. [35] settled the aforementioned conflict with collaborative offloading and energy allocation plans that balance energy and delay metrics by means of multi-objective optimization.
- **Fairness vs. System Throughput:** Emphasis on fairness guarantees equal opportunity for all the users for accessing resources, particularly for those users who are under unfavorable conditions related to channel or residual energy. Prioritizing fairness

reduces overall system throughput due to rebalancing of the resources from high-performing users to disadvantaged users. [76] proposed fairness-aware scheduling policies based on residual energy and location-based priority for a trade-off between equity and efficiency.

- **Complexity vs. Scalability:** Sophisticated optimization frameworks, such as DRL, metaheuristics, and Pareto frontier analysis, while bringing better performance, are usually at the cost of heavy computational overhead. It is challenging to guarantee real-time responsiveness with the increase of users and cooperative agents. Decentralized learning agents were suggested by [32] for alleviating central coordination overhead while preserving adaptiveness under dense deployments.
- **Cooperation Incentives vs. Resource Depletion:** The cooperation incentives to be provided for stimulating helper nodes to participate in either task relaying or energy sharing result in faster drainage of their energy resources. Therefore, the incentive mechanisms should necessarily incorporate residual energy constraints or reputation-based reward mechanisms to avoid over-exploitation of the cooperative users [120], [121].

In a nutshell, the architecture of cooperative WPT-MEC systems has to navigate many trade-offs based on user heterogeneity, resource limitation, and application demands. The hybrid and adaptive solutions that will be able to reconcile these opposing pressures in real time are the key to future intelligent edge networks.

5.4 Limitations in Current Systems

Despite the significant success of collaborative WPT-MEC systems, a few limitations still stand in the way of large-scale adoption and a full realization of performance. These limitations include technical, architectural, and operational perspectives.

- **Incomplete modeling of real-world conditions:** Most existing works assume idealistic channel models, perfect channel state information, and deterministic user behavior. In practice, wireless links often face time-varying fading, interference, and mobility-induced disruptions. For example, mobility and shadowing effects in UAV-assisted or RIS-aided systems introduce dynamic variability that challenges static optimization frameworks [122].
- **High Computational Complexity:** Optimal resource allocation and task scheduling for WPT-MEC environments may involve non-convex NP-hard problems. Metaheuristics, reinforcement learning, and matching theory afford approximate solutions to such problems but can still result in huge computational overhead, especially in real-time or dense-user scenarios. This can critically limit scalability and delay convergence, especially for the DRL and federated learning models [35].
- **Energy Sustainability of Cooperative Users:** Helper nodes contributing in cooperative relaying or energy transfer usually suffer from energy depletion without adequate compensation or energy replenishment strategies. This becomes critical in double-near-far scenarios, with heavy overburdening of disadvantaged users. Incentive mechanisms do exist; however, their robust integration with real-time scheduling algorithms needs much work [18], [40], [123].
- **Limited Multi-Objective Coordination:** While multi-objective optimization is gaining increasing attention, most practical schemes simplify the trade-offs using weight-sum problems that cannot guarantee Pareto efficiency. Furthermore, fairness constraints are very frequently relaxed or entirely omitted, leaving edge users under-served, in particular for dense deployments [4], [10], [124].
- **Hardware and Deployment Constraints:** Real-world deployment of RIS, STAR-RIS, and UAV-based systems introduces several practical limitations. These include phase quantization error, orientation sensitivity, and the challenges of maintaining precise alignment under mobility, particularly in UAV-enabled platforms [125], [126]. The complexity in regulation related to UAV altitude limits, frequency allocation for RIS-assisted transmission, is even more challenging across regions [127].

Overcoming these limitations calls for more realistic modeling, lightweight algorithms, sustainable cooperative protocols, and secure-privacy-aware architectures. The bridge between theory and practice through testbeds and interdisciplinary validations will drive the evolution of robust, real-world WPT-MEC systems.

5.5 Open Research Challenges

The dynamic evolution of WPT-MEC further opens a number of open research problems that have to be addressed for the realization of strong, smart, and scalable edge systems. Such topics include computation, communication, learning, and system sustainability.

- **Joint Optimization Under Uncertainty:** While existing works address the resource allocation problem under either deterministic or offline model assumptions, real-world channel variability, user mobility, and stochastic energy harvesting introduce enormous uncertainties into practice. The design of robust and real-time optimization methods in the presence of these uncertainties is an open problem. Approaches like distributionally robust optimization and online learning could provide promising directions [35].
- **Sustainable Incentive Mechanisms for Cooperation:** Maintaining long-term user cooperation remains a critical challenge, especially when helper nodes experience energy drain without direct benefit. Designing dynamic, context-aware incentive protocols such as token economies, credit-based systems, or contract theory-based schemes, can ensure sustainable participation. However, integration of these models with real-time schedulers is still in its infancy.
- **Learning-Driven Edge Intelligence:** The application of deep reinforcement learning (DRL) and federated learning (FL) has shown promise in adaptive resource management. Yet, convergence speed, model

generalization across environments, and data heterogeneity hinder deployment in practical systems. Research is needed on lightweight, personalized, and communication-efficient learning techniques suitable for edge environments.

- **RIS and STAR-RIS Practical Realization:** Although RIS and STAR-RIS technologies offer theoretical gains in energy and spectral efficiency, practical deployment faces barriers such as hardware constraints, phase noise, and control signaling overhead. Cross-layer design methodologies that jointly optimize passive beamforming, scheduling, and user association are needed [26].
- **Multi-Agent and Multi-Hop Cooperation at Scale:** The coordination of large-scale, multi-hop cooperative networks involving numerous edge users, UAVs, or RIS elements introduces scalability and signaling challenges. To deal with this complexity, hierarchical and graph-based architectures are increasingly accepted. For example, [128] proposed a graph-based swarm framework for UAV collaboration and task routing in dynamic MEC networks that significantly reduces coordination overhead while ensuring scalability. [129] also examined multi-agent systems where knowledge graphs enable scalable multi-hop relations for enhancing the cooperative decision-making capabilities of the agents. [130] demonstrated the application of hierarchical heterogeneous graph neural networks (GNNs) to optimize post-disaster network energy and spectrum resource allocation as another instance of their applicability in decentralized and scalable edge computing.

Briefly, cooperative WPT-MEC is an open research field that is fertile and inter-disciplinary. The development will depend on collaborative innovation in wireless communication, optimization theory, machine learning, and hardware engineering.

6. CONCLUSION

The incorporation of user cooperation in Wireless Powered Transfer-Mobile Edge Computing (WPT-MEC) networks is a revolutionary solution to the intrinsic differences in energy availability, computational power, and network quality of users' devices. This review broadly surveyed the existing landscape of cooperative WPT-MEC systems by categorically providing an overview of the technology underpinnings, cooperation schemes, optimization methodologies, and security challenges characterizing that field.

WPT-MEC networks aim to facilitate energy-constrained devices by allowing them to receive wireless energy and offload computation to proximate edge servers. However, due to the uneven distribution of users and heterogeneous channel conditions, performance asymmetry arises, namely, the double-near-far effect: distant users suffer from ineffective energy harvesting and inefficient computation offloading. User cooperation significantly alleviates these issues by allowing nearby or more capable devices to assist in data relay, processing of computation task, or energy sharing.

In Section 3, various models were discussed on user cooperation, including those on relaying, task offloading, multi-hop collaboration, and assistance with UAVs and IRS. These methods, beyond mitigating performance bottlenecks, also provide improvement in coverage and reliability of operation for WPT-MEC systems. Methods such as NOMA and STAR-RIS integration also improve concurrent access and spectrum utilization.

Section 4 covered the optimization area. This was relevant for issues of resource allocation, such as CPU cycles, spectrum, power, and time slots among cooperating users. Approaches from classical convex optimization to modern tools in reinforcement learning and metaheuristics were covered. Such techniques enable energy-aware and fairness-aware decisions in real-time over dynamic networks.

Section 5 presents a comparative survey to show that, although the majority of the cooperative WPT-MEC designs provide spectacular performance benefits in computation throughput and energy efficiency, they mostly lack comprehensive provisions for real-time adaptability, built-in security, and large-scale deployment scalability. The section also introduced open research topics: standardization of benchmarking, secure incentive mechanisms, and the need for 6G-native cooperative protocols.

Future directions for cooperative WPT-MEC include the convergence of several emerging technologies. It is crucial to have adaptive cooperation strategies utilizing AI-driven predictive offloading choices, security frameworks protecting confidentiality without sacrificing energy constraints, and incentive mechanisms driving user actions towards desired network objectives for sustainable implementation.

In addition, the advances in WPT-MEC networks will be directly related to those in 6G infrastructures based on ultra-reliable low-latency communications, omnipresent AI, and greatly dynamic topologies. Cooperative WPT-MEC frameworks have to evolve to become context-aware, autonomously reconfigurable, and secure-by-design if they will operate effectively in such demanding environments.

In conclusion, user cooperation significantly enhances the functionality and fairness of WPT-MEC systems, making them more viable for large-scale, heterogeneous deployments. Continued interdisciplinary research combining wireless communication, machine learning, distributed systems, and cybersecurity is necessary to unlock the full potential of cooperative edge computing in the wireless-powered era.

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