A Survey on Dynamic Heterogeneous Resource Scheduling Optimization in Mobile Edge Computing

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Abstract

With the rapid development of the Internet of Things and 5G communication technology, Mobile Edge Computing, as a new computing paradigm that deploys computing, storage and network resources at the network edge, has become a key technology to address the resource constraints and low latency requirements of terminal devices. Task offloading, as the core mechanism of MEC, can significantly enhance application performance by migrating the computing tasks of terminal devices to edge nodes or the cloud. However, the dynamic and complex nature of heterogeneous resource environments poses numerous challenges to resource scheduling optimization. This paper reviews the current research status of dynamic scheduling optimization for heterogeneous resources in MEC based on task offloading. Firstly, it classifies and discusses the design ideas and key technologies of dynamic scheduling strategies from the perspectives of single-user and multi-user. Then, it analyzes the challenges faced by existing research, such as mobility management, energy efficiency, fairness, and privacy protection. Finally, it looks forward to future research directions, including AI-driven intelligent scheduling, Green and Energy-Efficient Resource Regulation Technologies, and Integrated Mechanisms for Fairness and Privacy Enhancement.

Keywords

Mobile Edge Computing, Heterogeneous Resource Scheduling, Dynamic Optimization, Resource Allocation.

1. Introduction

With the explosive growth of IoT terminals and the commercial deployment of 5G communication technology, emerging applications such as real-time video analysis, augmented reality, and autonomous driving have imposed strict requirements on computing latency, energy efficiency, and service continuity. The traditional cloud computing model, which centralizes data processing at remote data centers, has struggled to meet the demands of such applications due to long-distance transmission-induced high latency and core network congestion. Against this backdrop, mobile edge computing, as a new paradigm that deploys computing, storage, and network resources at the network edge has emerged. [1] By processing computing tasks locally, it significantly shortens response times and reduces the energy consumption of terminal devices.

In recent years, the academic and industrial communities have conducted extensive research on task offloading and heterogeneous resource scheduling. This growing focus stems from the increasing complexity of edge computing environments, where diverse resources with varying capabilities need to be coordinated to meet the demands of latency-sensitive, computation-intensive applications. [2]Heterogeneous resources, in the context of edge computing, refer to a diverse set of computing, storage, and network resources with distinct characteristics and capabilities. These include resource-constrained edge devices, edge servers, and remote cloud data centers. Edge devices typically have limited processing power, battery life, and storage, while edge servers offer moderate computing capabilities with low latency due to their proximity to end-users. Cloud data centers, on the other hand, provide massive scalable resources but suffer from longer propagation delays. The coexistence of these resources creates a heterogeneous ecosystem that requires sophisticated scheduling strategies to leverage their respective strengths.Heterogeneous resource scheduling is of paramount importance in edge computing, as it directly impacts the performance and feasibility of edge-enabled applications. First, it enhances system efficiency by dynamically matching tasks to the most suitable resources: computation-intensive tasks can be offloaded to edge servers or the cloud to reduce the burden on resource-constrained devices, while latency-critical tasks are processed locally at the edge to minimize response time. For example, offloading tasks from mobile devices to edge servers can reduce energy consumption by up to an order of magnitude. Second, it supports scalability in handling the massive influx of IoT devices ensuring that distributed resources are utilized efficiently without overload. Third, it enables the delivery of high-quality services for emerging applications such as augmented reality, autonomous driving, and real-time video analytics , which require strict latency and reliability guarantees.The topic of heterogeneous resource scheduling has emerged as a research hotspot, driven by both practical demands and technical challenges. Industrially, the proliferation of smart cities, connected vehicles, and industrial IoT has created a pressing need for seamless coordination between diverse edge and cloud resources. [3]Academically, it presents complex problems such as handling user mobility, ensuring privacy and security , and adapting to dynamic network conditions.All of which require innovative cross-disciplinary solutions integrating wireless communications, mobile computing, and artificial intelligence. As edge computing continues to evolve, heterogeneous resource scheduling will remain a core area of research, critical to unlocking the full potential of edge-enabled systems.

This study aims to solve these problems by conducting a comprehensive and in-depth review. Specifically, we first systematically collate and analyze the latest research achievements to classify dynamic scheduling strategies from the perspectives of single-user and multi-user scenarios, clarifying their design ideas, key technologies, and applicable boundaries. On this basis, we deeply dissect the core challenges faced by current research, including resource optimization in high-speed dynamic scenarios, trade-offs between energy efficiency and sustainability, and privacy protection amid resource competition supplemented by case studies to reveal the practical bottlenecks of existing solutions. Finally, we propose three frontier research directions: large model-driven adaptive scheduling, self-evolving autonomous resource allocation, and privacy-enhancing fair game mechanisms.Everyone is supported by theoretical logic and technical feasibility analysis.By constructing a systematic research framework that integrates "strategy classification-challenge dissection-future prospect", this study not only clarifies the development context of dynamic heterogeneous resource scheduling in MEC but also provides targeted theoretical references and technical paths for subsequent research, aiming to promote the practical application of MEC in complex scenarios such as smart cities and connected vehicles. Figure 1 is the overall structure diagram of the article.

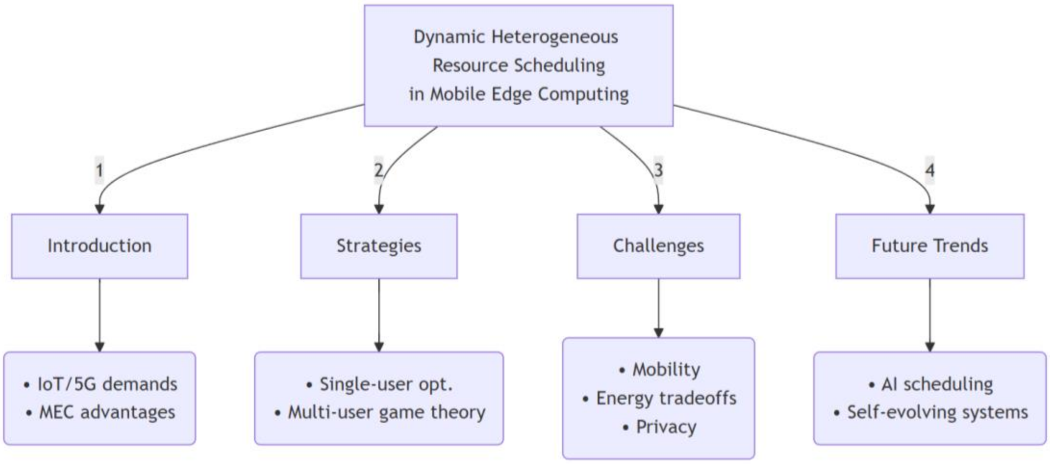

Fig.1 Flow chart

2. Dynamic Scheduling Strategies for Heterogeneous Resources

In Mobile Edge Computing, the dynamics and complexity of heterogeneous resource environments impose higher requirements on scheduling strategies. Existing studies have designed differentiated scheduling schemes for different scenarios, with the core goal of improving system performance through collaborative optimization of offloading decisions and resource allocation. The following analysis is conducted from two typical means.

2.1. Resource optimization methods for single-user scenarios

The single-user scenario focuses on the collaboration between a single terminal device and edge/cloud nodes. Its core is to achieve dynamic matching between task offloading and local processing through refined resource modeling, with emphasis on addressing the trade-off between delay and terminal energy consumption. In this scenario, dynamic changes in task characteristics and channel status are the main influencing factors, and scheduling strategies need to adapt to these changes in real time to optimize user experience.

Relevant studies have explored scheduling optimization methods for single-user scenarios from various perspectives. Literature proposes a convex optimization-driven decision-making method, which takes task offloading ratio, terminal CPU frequency, and transmission power as optimization variables to construct a convex function with the goal of delaying energy consumption. The optimal resource allocation scheme is solved by the Lagrange multiplier method to achieve dynamic balance between the two. To address the dynamics of channels and tasks, Literature [4]designs an online adaptive strategy based on Model Predictive Control, which dynamically adjusts the offloading ratio to adapt to environmental changes by periodically updating the prediction results of channel gain and task arrival rate. Literature[5], in the context of NOMA heterogeneous networks, proposes a strategy of joint wireless resource and computing resource allocation for the energy optimization problem of single-user task offloading, reducing terminal energy consumption by matching transmission power with computing resource allocation. In addition, the context-aware deep model compression method in Literature [6]also provides new ideas for single-user scenarios. By dynamically adjusting the model compression ratio of edge nodes, it reduces computing and transmission overhead while ensuring task processing accuracy. Literature [7]explores the adaptation mechanism between offloading decisions and terminal resource constraints from the basic framework of mobile edge computing, providing scheduling references for processing simple tasks and complex tasks.

In single-user scenarios, scheduling strategies demonstrate significant advantages through refined resource management. Single-user scenarios can focus on the task requirements and device status of a single entity. Through specific technical means such as constructing dynamic priority-based task queue models and transmission power adaptive algorithms combined with channel state information, precise resource scheduling is achieved. For example, when a terminal runs multiple computing tasks simultaneously, it can dynamically allocate CPU core resources through integer programming models based on the task deadlines and computational complexity, reducing the processing delay of high-priority tasks to the millisecond level. In the wireless transmission process, the modulation and demodulation methods and transmission power are adjusted in real-time with the help of channel fading prediction models, thereby reducing the energy consumption per unit of data transmission.However, existing studies still have two obvious limitations: First, there are limitations in the assumptions about channel and task characteristics. Most schemes only optimize for channel fluctuations in stable states and periodic tasks. When encountering sudden tasks or extreme channel environments, the adaptability of scheduling algorithms drops sharply, and even task blocking occurs. Second, the consideration of coupling with terminal hardware characteristics is insufficient. Existing models often regard terminals as ideal computing/communication nodes, ignoring the impact of different hardware architectures and hardware resource constraints on scheduling strategies, which makes it difficult to achieve optimal performance on resource-constrained edge terminals. Future research can make breakthroughs in the following directions: First, construct a dynamic scheduling framework that integrates extreme channel characteristics and sudden task characteristics, and introduce reinforcement learning algorithms to realize real-time perception and adaptive decision-making in non-stationary environments. Second, deepen the collaborative design of terminal hardware characteristics and scheduling strategies, establish a mapping model of hardware resources-task requirements-scheduling goals, and customize lightweight scheduling algorithms for different hardware architectures.

2.2. Resource optimization methods for multi-user scenarios

In multi-user scenarios, multiple terminal devices share limited edge resources. The core challenge is to balance system efficiency and user fairness in a resource-competitive environment, ensuring that the Quality of Service requirements of different users are met. In this scenario, resource competition among users and differences in task types are key issues that scheduling strategies need to address.

Existing studies tackle the challenges of multi-user scenarios through game theory, priority scheduling, load balancing, and other methods. Literature [8]models multi-user offloading decisions as a non-cooperative game, with resource occupation fee and transmission energy consumption as the utility function. Through users' bidding behavior for edge CPU cores and wireless subcarriers, the base station allocates resources according to the resource consumption ratio, improving system efficiency while ensuring fairness. To address differences in task priorities, Literature [9] proposes a scheduling algorithm based on Weighted Fair Queuing, which allocates higher weights to high-priority tasks to reduce latency, and limits the resource occupation ratio of high-priority tasks through the fairness criterion to avoid starvation of low-priority tasks. In terms of load balancing, Literature [10] designs a multi-cell collaborative strategy that monitors the CPU utilization of edge nodes in real time. When the load of a node exceeds the threshold, new tasks are automatically offloaded to adjacent nodes with low loads to alleviate resource competition. In addition, Literature [11] designs a task scheduling scheme for multi-core processors based on game theory, realizing collaborative optimization of performance and energy consumption by modeling the resource allocation game among users; Literature [12] proposes an improved

NSGAII algorithm for the Internet of Vehicles scenario, dynamically scheduling computing resources to adapt to the real-time task requirements of multi-user vehicles.

In multi-user scenarios, scheduling strategies have achieved substantial breakthroughs in resolving resource competition and ensuring fairness in allocation through technological innovations such as hierarchical resource pooling and distributed conflict negotiation. Unlike the independent optimization logic in single-user scenarios, multi-user scheduling must balance differences in individual needs with overall resource efficiency. For instance, power-domain resource allocation schemes based on NOMA superimpose signals from multiple users on the same time-frequency resource while dynamically adjusting power weights, thereby improving spectrum utilization. Wireless scheduling mechanisms adopting proportional fair algorithms, on the other hand, can update scheduling priorities in real-time according to channel quality under the premise of ensuring each user's minimum rate requirements, significantly reducing the waiting delay for high-priority users. These technologies have transformed resource competition among users into quantifiable optimization objectives, realizing a shift.However, the limitations of existing schemes remain prominent: First, the assumption of users' complete rationality in game theory-based methods is difficult to hold in practice. When there is information asymmetry among users,such as some users concealing the urgency of their tasks or exaggerating resource demands,so the game equilibrium point deviates from the optimal state. Taking multi-user power scheduling in smart grids as an example, some users may illegally obtain electrical resources exceeding their reasonable share by falsifying electricity load data, seriously affecting the stable operation of the power grid. Second, the weight setting for priority scheduling mostly adopts static configurations, which cannot respond to dynamic changes in task types. For example, in the industrial Internet of Things, when a user's periodic monitoring task suddenly switches to an urgent fault report, the fixed weight mechanism will lead to an increase in the transmission delay of critical information.Future research can deepen breakthroughs in two directions: First, establish a game model based on bounded rationality, introduce cognitive bias theories from psychology to correct users' decision-making behaviors, and simultaneously integrate blockchain technology to achieve credible sharing and immutability of user information, thereby enhancing the stability of scheduling strategies in scenarios with information asymmetry. For example, record users' historical behavior data through smart contracts and impose penalties on users who engage in information fraud to increase their cost of fraud. Second, develop an adaptive weight dynamic adjustment mechanism, extract task features through deep learning, and establish a mapping relationship between weights and task types. For instance, allocate higher CPU resource weights to computation-intensive tasks and grant priority communication rights to delay-sensitive tasks.

3. Key Challenges

3.1. Resource Optimization Challenges in High-Speed Dynamic Scenarios

High-speed mobility of terminal devices presents significant challenges to resource optimization. Firstly, the Doppler effect from rapid movement causes abrupt channel quality fluctuations, with signal-to-noise ratio dropping in milliseconds, making traditional resource allocation algorithms unable to track real-time changes, thus disrupting task offloading accuracy and potentially leading to execution failures or delays. Secondly, the ultra-dynamic network topology due to high mobility exacerbates resource coordination issues; frequent handovers between edge nodes demand real-time resource status synchronization across nodes, but current inter-node communication latency lags behind topology change speed, resulting in resource perception lag, which can assign critical tasks to overloaded nodes and increase delays, especially problematic for time-sensitive applications like autonomous driving. Thirdly, diverse mobility patterns hinder effective resource pre-allocation models; traditional prediction-based reservation methods depend on stable trajectories, but in complex dynamic scenarios, trajectory prediction errors are often excessive, causing either idle reserved resources or insufficient supply and reducing resource utilization efficiency.

3.2. Challenges in Dynamic Trade-offs Between Energy Efficiency and Sustainability in Heterogeneous Resource Scenarios

In current edge computing, the coupling of heterogeneous resources and conflicting multi-objective optimization hinder energy efficiency and sustainability. Edge nodes integrate computing, communication, and storage, while terminals are limited by battery and computing power, with inherent conflicts in their energy consumption characteristics. Existing multi-objective optimization frameworks mostly use static weight allocation, failing to adapt to dynamic edge environments. As edge node scales expand, the conflict between carbon neutrality and local energy efficiency optimization grows: single-node energy-saving measures may cause adjacent nodes' energy consumption to surge via load transfer, creating an energy-saving island"effect, yet research lacks exploration of multi-node collaborative low-carbon scheduling to minimize overall carbon footprints. Additionally, insufficient intelligent drive restricts sustainability improvements: traditional game theory models assume complete rationality, deviating from reality; deep reinforcement learning struggles with state space explosion in heterogeneous resources and sparse long-term rewards, leading to local optima; large model-empowered intelligent decision-making has potential but faces edge-side computing power and data volume constraints, making achieving a dynamic balance between global energy efficiency and sustainability via lightweight models a core issue.

3.3. Challenges of Privacy Protection Amid Heterogeneous Resource Competition

In scenarios where multiple users share edge resources, performance disparities and allocation imbalances of heterogeneous resources intensify resource competition and pose multi-layered privacy protection challenges. High-priority or computing-intensive users often occupy high-quality resources, forcing resource-constrained terminals to compromise,such as lowering data encryption levels or exposing redundant identity information to secure necessary support, increasing privacy leakage risks. Existing fairness optimization mechanisms, relying on static weight allocation, struggle to dynamically balance efficiency and privacy needs in heterogeneous resource competition. With highly sensitive tasks, fixed allocation strategies may push high-privacy tasks to use unsafe offloading paths due to insufficient resources, or induce low-priority users to over-share privacy data as a bargaining chip, causing privacy devaluation. Moreover, distributed heterogeneous resource deployment scatters a task's computing, storage, and communication across nodes with varying security capabilities, leading to a barrel effect where a single protection vulnerability triggers full-link leakage. A deeper issue is the poor dynamic adaptability between privacy technologies and resource competition: homomorphic encryption's high computing overhead strains edge resources, worsening competition, while federated learning-based distributed training in heterogeneous environments faces node computing power differences, causing parameter upload delays exploitable by attackers for timing attacks. Establishing a privacy-efficiency-fairness balance amid dynamic resource competition is thus a critical bottleneck for large-scale edge computing applications.

4. Future Development Trends

4.1. Large Model-Driven Adaptive Scheduling Optimization Framework

To address dynamic scheduling challenges from terminal mobility, future efforts will focus on building an adaptive scheduling system centered on large models, overcoming limitations of traditional AI methods. [13]Leveraging large models' massive parameters and cross-domain knowledge transfer, this framework enables in-depth perception and global optimization of heterogeneous resource scenarios, with three technical paths: first, a scheduling decision model via domain knowledge fine-tuning, which uses edge computing historical data to let the model capture spatio-temporal correlations of mobile terminals, fuse multi-dimensional states quickly, and generate optimal pre-allocation strategies; second, a collaborative mechanism for lightweight deployment and real-time reasoning, compressing and distilling the large model into edge-suitable lightweight sub-models to retain core decision-making capabilities, supporting real-time local calls during high-speed movement and rapid response to sudden needs with minimal delay; third, continuous evolution in dynamic environments, using the large model's online learning and federated learning to aggregate scheduling feedback from edge nodes, incrementally updating parameters for strategy adaptation to new scenarios. Compared to traditional AI, this large model-driven framework breaks single-task or static scenario limits, achieving "perception-decision-evolution" closed-loop optimization in heterogeneous resource competition and dynamic topology changes, and supporting service continuity in high-mobility scenarios.

4.2. Self - evolving and self - adaptive autonomous resource allocation method

To address energy efficiency and sustainability challenges in edge computing, future efforts will focus on low-power scheduling algorithms, energy recovery technologies, and self-evolving, adaptive autonomous resource allocation methods. Refined energy consumption models for edge node resources will be combined with renewable energy supply characteristics to dynamically adjust task offloading and resource allocation, optimizing "energy consumption-performance" coordination. Radio frequency energy harvesting and adaptive multi-energy integrated management systems by using machine learning to predict renewable energy supply and terminal energy demands for autonomous charging/discharging and energy source switching which will reduce reliance on traditional grids. [14]

The core lies in a self-organizing resource regulation framework with closed-loop feedback: it establishes multi-dimensional energy consumption models integrating edge hardware's dynamic power curves and renewable energy patterns, monitors real-time task attributes and resource loads to trigger autonomous reconfiguration, and incorporates game theory to coordinate multi-resource energy efficiency goals amid competition for limited energy. This approach enables edge systems to dynamically balance energy efficiency, service performance, and sustainability in complex environments, laying a key foundation for green edge computing development. [15]

4.3. Privacy-Enhancing Resource Allocation Mechanism Based on Trusted Computing and Adaptive Fairness Game

To address the challenge of synergistic optimization between fairness and privacy protection in multi-user scenarios, future research will focus on an integrated mechanism grounded in trusted computing technology and centered on dynamic game models, achieving deep coupling of "privacy protection-resource allocation-fairness perception" through specific technical paths. Firstly, a privacy protection foundation will be built using hardware-level trusted execution environments and secure multi-party computation: TEE on edge nodes creates isolated encrypted spaces for highly sensitive tasks, ensuring "usable but invisible" data processing, while SMPC via secret sharing allows multiple users to negotiate resource demands and verify fairness indices without exposing raw data. [16] Secondly, an adaptive fairness optimization algorithm based on dynamic games will be designed, moving beyond static weight allocation to construct a multi-user non-cooperative fairness game model.Convert users' resource demands, task priorities, and privacy sensitivity into quantifiable utility functions, with real-time strategy adjustments via reinforcement learning. This model dynamically increases allocation weights for high-priority users' urgent requests while enhancing privacy protection, and balances fairness for low-priority users through a privacy compensation mechanism. [17] Thirdly, closed-loop optimization of resource allocation under privacy constraints will be realized by incorporating privacy protection overhead into allocation constraints and establishing a tripartite objective function of privacy security level-fairness threshold-resource utilization.Combining trusted computing with dynamic game theory, this mechanism resolves the separation of privacy protection and fairness in traditional schemes, improves feasibility via quantifiable indicators, and offers a technically sound and practical path for fairness and privacy protection in multi-user edge scenarios. [18]

5. Conclusion

Based on the reviewed literature, this paper conducts a systematic analysis of dynamic scheduling optimization for heterogeneous resources in mobile edge computing (MEC). Firstly, focusing on the core mechanism of task offloading, existing studies are classified into two scenarios: single-user and multi-user. The design ideas and technical characteristics of scheduling strategies in each scenario are elaborated in detail, demonstrating the differentiated paths of resource collaborative optimization in different scenarios. On this basis, the key challenges faced by MEC are deeply analyzed. In response to these challenges, future development trends are further proposed to achieve dual guarantees. By systematically sorting out existing research, analyzing challenges, and looking forward to trends, this paper provides researchers in the MEC field with a clear research context and reference directions, which is conducive to promoting the in-depth development of heterogeneous resource dynamic scheduling technologies and facilitating the large-scale application of MEC in practical scenarios.

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