A Survey on Collaborative Optimization Technologies for Edge Computing and Cognitive Radio Convergence

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Abstract. This paper provides a systematic review of collaborative optimization technologies integrating edge computing (EC) and cognitive radio (CR), exploring their pivotal role and challenges in 6G integrated sensing, communication, and computing (ISAC). Edge computing, with its distributed computational support, significantly enhances CR's capabilities in real-time spectrum sensing and dynamic allocation. Meanwhile, CR's dynamic spectrum access technology offers flexible communication resources for edge computing task offloading, effectively alleviating spectrum scarcity while reducing communication latency and energy consumption. The study focuses on spectrum sensing and allocation, task offloading, and energy efficiency optimization, and analyzing the strengths and limitations of existing technologies. It also identifies future research directions, including key challenges such as security in dynamic resource scheduling, standardized architecture design, and lightweight AI model development. This paper aims to provide theoretical references and technical pathways for the deep integration of edge computing and cognitive radio in 6G networks, advancing the synergistic development of communication, sensing, and computing.

Keywords: Cognitive radio, edge computing, spectrum sensing and allocation, task offloading, energy efficiency optimization.

1. Introduction

The sixth-generation mobile communication system (6G) has emerged as a pivotal technology, driving the digital, mobile, networked, and intelligent transformation of society and industries. To support emerging applications such as immersive experiences, digital twins, and autonomous driving, 6G networks must simultaneously meet three critical demands: ultra-low latency and ultra-high reliability, real-time environmental sensing with ubiquitous coverage, and ultra-large bandwidth connectivity for massive devices [1]. This technological challenge is particularly urgent in the field of the Internet of Things (IoT). A study by Transforma Insights indicates that the number of global IoT connections is expected to exceed 40 billion by 2034 [2]. This staggering scale of devices places unprecedented pressure on existing wireless communication systems. Currently, almost all available communication spectrum resources have been allocated, while traditional static spectrum allocation methods cannot meet the requirements of a large number of devices. Moreover, relying solely on EC or CR cannot simultaneously address the two problems of computational efficiency and spectrum scarcity.

Against this backdrop, the deep cooperation of EC and CR has become a key point of 6G technology. By offloading computational tasks to the network edge, EC signally reduces communication delay and enhances real-time performance [3], while CR effectively alleviates spectrum scarcity through dynamic spectrum sharing mechanisms [4]. The integration of EC and CR demonstrates potential complementary benefit in 6G networks. Existing research indicates that EC's distributed computing capabilities can improve CR's real-time spectrum sensing and dynamic allocation efficiency, while CR can offer additional bandwidth for EC's task offloading, alleviating spectrum scarcity. This synergy is particularly relevant to ISAC systems. Current studies suggest that EC-CR integration is expected to overcome limitations of traditional network and have a significant impact on future wireless network architectures. However, challenges such as coordination overhead in distributed architectures and security risks in dynamic spectrum sharing remain unresolved.

Existing research has systematically explored spectrum sensing and allocation in CR [5], as well as resource management, task offloading, and energy efficiency optimization of EC in traditional wireless network environments [6]. However, there is still a deficiency of research on the combination of CR and EC, especially in the optimization of EC under dynamic spectrum environment. To address this, this paper reviews recent literature in the aera of CR and EC, with a focus on key technologies for their integration. This paper is aiming to uncover the potential and future directions of CR-EC collaborative optimization. The following structure of this paper is illustrated in Figure 1. In section II, we review fundamental theories of CR and EC. In section III, we analyze their collaborative optimization methods, and start the discussion from three core perspectives: spectrum sensing and allocation, task offloading scheduling, and energy efficiency optimization. In section IV, we provide a perspective on future research directions and technical challenges. This study aims to present the theoretical framework, technological pathways, and development trends of EC-CR convergence research through this structure. We hope to encourage greater attention from academia and industry toward such integrated innovation and providing a valuable reference for subsequent researchers exploring related fields.

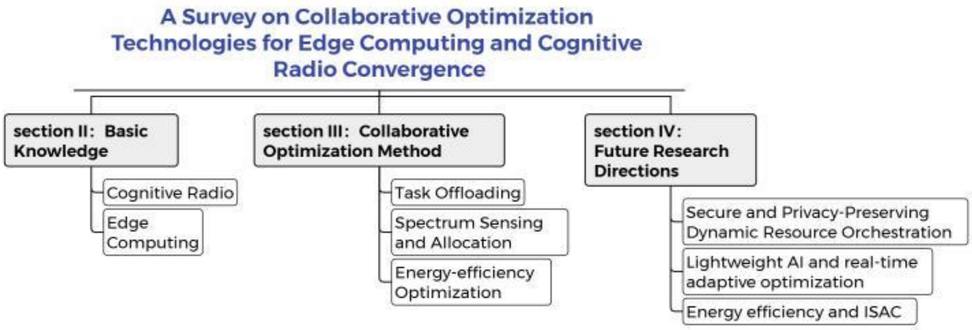

Fig.1. Organizational structure chart of this paper

2. Background

2.1. Cognitive Radio

Cognitive Radio, as an intelligent wireless communication technology with significant developmental potential, fundamentally relies on real-time spectrum sensing and dynamic spectrum access mechanisms to efficiently identify and utilize idle spectrum resources. From a network architecture perspective, CR technology categorizes users within spectrum-sharing zones into two groups: Primary Users (PUs) and Secondary Users (SUs). CR devices continuously monitor licensed frequency bands. When spectrum holes are detected, SUs can temporarily access these idle bands for communication. Once the SU senses the reactivation of the PU, it must immediately exit the frequency band to ensure priority access for licensed users [7]. The technology effectively addresses spectrum resource conflicts and shortages caused by massive IoT terminal devices access. By dynamically allocating spectrum resources, CR technology also optimizes network energy efficiency. This provides a sustainable solution for future large-scale wireless communication systems [4].

In CR-IoT systems, the spectrum sensing data continuously generated by massive terminal devices imposes a heavy communication burden. So, improving sensing efficiency/accuracy and minimizing transmission energy consumption remain critical challenges in CR networks. However, traditional schemes require raw sensing data to be transmitted back to central nodes for processing, which not only increases communication overhead but may also cause network congestion. To solve these problems, researchers are considering EC-based distributed processing architectures, which can significantly reduce transmission load while maintaining both timeliness and accuracy in spectrum sensing [8]. This distributed framework based on EC represents a hopeful paradigm shift, effectively balancing perceptual performance and system resource constraints.

2.2. Edge Computing

EC is a novel computing paradigm. It provides cloud services and IT environment services for application developers and service providers at the edge of the network. By reducing the distance between devices and users, EC ensures ultra-low latency and reduced bandwidth consumption for data transmission. Task offloading is a key technology in edge computing. It involves transferring computational tasks from resource-constrained user devices to edge servers, effectively reducing the computational burden and energy consumption of devices while optimizing the utilization of network resources.

In 6G networks, leveraging EC technology to assist spectrum sensing offers remarkable advantages. By enabling localized spectrum sensing and rapid resource allocation, EC significantly accelerates decision-making processes. This mechanism empowers EC to effortlessly handle the challenges posed by massive device connectivity and data deluge [3]. Furthermore, by utilizing additional spectrum resources provided by CR technology, EC can establish more robust communication links between edge servers and end-user devices, thereby expanding available spectrum resources for task offloading procedures [10].

3. Collaborative Optimization Method Integrating Edge Computing and Cognitive Radio

This study compiles recent research on the integration of EC and CR, as summarized in Table 1, and finds that their combined use can leverage complementary strengths to optimize computational and communication resources. Specifically, EC provides nearby computing support for CR, enabling efficient spectrum sensing, allocation, and decision-making, while CR enhances EC by offering dynamic spectrum access to mitigate spectrum scarcity. This synergy not only reduces spectrum competition but also improves task offloading efficiency and lowers energy consumption. Based on application scenarios, the existing research is categorized into three main areas: spectrum sensing and allocation, task offloading, and energy efficiency optimization.

Table 1. Technology direction table

Key Technologies	Issue	Advantages	Disadvantages	Ref
Spectrum sensing and allocation	Optimize the collaborative perception capability of distributed nodes	High-performance detection, Strong generalization	Data dependency	[11]
	Optimize the utilization of time slots in the spectrum allocation process	Intelligent allocation	Implementation complexity, 6G dependency	[12]
	Improve the spectrum resource utilization and quality of service (QoS) of autonomous vehicle networks (AV)	Efficient resource allocation	High computational complexity, Limited experimental scenarios	[13]
	Optimize the spectrum sharing of cognitive radio Internet of Things devices	Efficient spectrum utilization, Low-latency performance	Implementation complexity	[14]
	Optimize the spectrum sensing and allocation performance of multi-terminal and multi-channel complex networks	Enhanced spectrum efficiency, Lower latency	Implementation complexity, Energy consumption trade-offs	[15]
Task offloading	Resource allocation in multi-user and multi-channel scenarios	Optimal energy efficiency, Flexible spectrum sharing	High complexity, Dynamic channel challenges	[16]
	Task offloading under mixed traffic in 5G multi-user edge computing	Multi-service integration, Energy efficiency optimization	High computational complexity, Stringent assumptions	[17]
	Under the conditions of limited spectrum resources and energy in MEC, improve the efficiency of task offloading	Novel framework, Joint optimization	High computational complexity, Ideal assumptions	[18]
	Minimize energy consumption and maximize the transmission rate of the subsystem	Efficient cooperation, Enhanced security	High computational complexity, Ideal assumptions	[19]
Optimize energy efficiency	Solve the problem of occupied channels and high computational overhead in single-band sensing repeated detection	High Energy-efficient, Multiband cooperative	Limited mobility support	[20]
	Reduce the energy consumption of multi-access edge computing systems that support CRN	Energy efficiency improvement, Dynamic resource optimization	Limited mobility support	[21]
	Improve the energy efficiency (EE) of wireless devices (WD) and optimize the computing offloading performance	Novel framework, Efficient optimization	High complexity, Ideal assumptions	[10]
	Improve the processing efficiency of computing tasks in industrial wireless networks	Low-latency processing	Static topology limitation, High computational complexity	[22]
	Long-term energy efficiency optimization of task offloading in EC-CRN	Dynamic optimization efficiency, Energy-latency tradeoff	High training complexity, Limited real-time performance	[23]

2.3. Spectrum Sensing and Allocation

Spectrum sensing is a key technology in CR networks, designed to detect idle frequency bands not occupied by PUs, known as spectrum holes. Its core function is to identify available spectrum resources by monitoring the spectral usage in the environment. Spectrum allocation refers to the process of dynamically assigning these available frequency bands to SUs based on specific criteria (such as interference, power, fairness, etc.), aiming to optimize resource utilization and meet users' QoS requirements [7]. Given the increasing complexity of heterogeneous networks, multi-user collaborative detection is often required to enhance sensing performance. Previous research has categorized cooperative spectrum sensing into two architectures: centralized and distributed. The centralized architecture relies on a fusion center to aggregate local detection results, while the distributed architecture achieves cooperation through direct interaction among users [4].

In the field of EC and CR integration, distributed collaborative architectures have become critical to optimizing spectrum management. Regarding distributed collaborative architectures, in [14], researchers proposed a distributed spectrum management method supported by Mobile Edge Computing (MEC), aiming to optimize spectrum utilization in cooperative environments. In [15], researchers further introduced a distributed edge node cooperative sensing framework. They combined the framework with energy detection algorithms to improve spectrum detection accuracy, effectively reducing the missed detection rate. On the other hand, deploying deep learning models at the edge enhances spectrum sensing capabilities significantly. For instance, the deep learning-based signal detector in [11] achieves superior detection performance without prior information, substantially improving spectrum utilization while reducing interference with PUs. In [12], the DeepBlocks scheme uses EC's real-time decision-making. It combines Deep Q-Networks (DQN) to improve spectrum allocation. This boosts time-slot use and cuts service delays. The integration of MEC and spectrum sensing technologies in complex situations expands application boundaries. In [13], researchers focused on CR in Autonomous Vehicle Networks (AVNETs) and proposed an MEC-driven dynamic spectrum management framework. This framework employs SDN/NFV (Software-Defined Networking/Network Function Virtualization) to achieve dynamic spectrum slicing allocation between base stations and vehicles.

The combination of EC and CR in spectrum sensing and allocation exhibits potential advantages such as efficient sensing and real-time performance, better utilization of available spectrum, improved adaptation capacity. However, certain problems remain unaddressed. Firstly, some researchers have failed to pay attention to communication security issues caused by resource competition when realizing resource sharing. When it is applied to actual deployment, this can cause serious security risks. Secondly, although the proposed advanced algorithms enhance the precision of sensed information with the development of deep learning techniques, a large amount of computational burden may also arise due to extremely high requirements for processing. Most research works assume ideal situations in the theoretical deployment scheme, but they did not consider practical complications that would appear during heterogeneity, including dynamic topology structure changes and different state conditions. Therefore, we need further work addressing these challenges.

2.4. Task Offloading

Task offloading moves computing jobs from limited servers to edge devices. Its efficiency relies on how well spectrum resources are allocated between devices and edge servers in changing wireless conditions. Traditional static spectrum allocation methods struggle to meet the ever-increasing communication demands, resulting in intense competition for spectrum resources. In device-dense 6G scenarios, limited spectrum availability may compromise the feasibility of task offloading. CR technology holds promise for alleviating spectrum scarcity, thereby optimizing the latency and energy efficiency of EC.

Existing research has significantly enhanced the efficiency and stability of task offloading across multiple dimensions by leveraging CR's dynamic spectrum management capabilities. Firstly, CR technology creates additional transmission channels for MEC task offloading through real-time spectrum sensing. For instance, study [16] introduced continuous spectrum sharing technology, breaking the conventional limitation of exclusive channel access in traditional spectrum allocation. This approach enables multiple users to share and collaboratively offload tasks on the same channel, demonstrating superior performance in spectrum utilization, energy efficiency, and global optimality compared to existing benchmarks. The method provides novel insights for CR-enabled MEC task offloading. Moreover, in dynamic spectrum environments, CR ensures offloading stability through PU activity prediction and adaptive power control. Research [17] proposed a joint task offloading and resource allocation method combining CR with stochastic optimization. By integrating extreme value theory with Lyapunov optimization, this approach guarantees statistical queue stability for eMBB services while minimizing interference to PUs. The synergy between CR and MEC also manifests remarkable advantages in joint spectrum-energy allocation. Study [18] developed an MEC framework integrating CR with wireless power transfer (WPT) under imperfect spectrum sensing conditions. Through dynamic adjustment of spectrum sensing duration, energy harvesting time, and offloading power, the scheme maximizes computational bits while effectively reducing PU interference and enhancing EC performance. Further advancing this field, research [19] proposed a MEC-assisted cooperative NOMA scheme featuring phased resource allocation for CR systems. This strategy creates transmission opportunities for SUs while ensuring PU communication security, significantly improving spectrum efficiency and system throughput. The work provides crucial references for the co-optimization of computing and communication resources in future intelligent networks.

The collaborative offloading optimization between EC and CR has tremendous benefits but also requires addressing some urgent challenges. With the dynamic spectrum access, CR offers flexible radio transmission links for edge computing task offloading, which can mitigate competing issues caused by limited spectrum resources. In addition, the emerging technologies of NOMA improves system throughput and energy-efficiency performance. However, there is a huge gap in people's understanding about task offloading. Ideally speaking, many researches presume that enough spectrums are available, while this assumption does not exist in reality. Moreover, existing works ignore most multi-device spectra competition situations, so it will result in considerable latency and excessive energy consumption overheads when implemented in large-scale networks. What's more, current validations fail to analyze deeply about security attacks or data privacy leakage across cross-domain transmissions. We expect future research efforts could design a few lightweight algorithms and standard structure with security building blocks so as to enable practical implementation of related techniques.

2.5. Energy-efficiency optimization

When combining with EC and CR, the optimization of energy efficiency has multidimensional challenges. For dynamic spectrum sharing scenarios, besides considering computational load, latency constraint, and MEC server resource status [9], the spectrum sensing overheads as well as the randomness of spectrum access should also be considered - which makes the problem of optimizing energy efficiency even more complicated. Moreover, the heterogeneity of MEC servers and their dynamic load variations further exacerbate the difficulty of resource allocation and load balancing. Meanwhile, continuous spectrum sensing and dynamic switching may introduce additional communication energy consumption during computational migration [20]. However, CR technology conversely enables substantial energy savings: dynamically identifying and utilizing idle spectrum resources reduces wireless transmission energy consumption, while EC nodes' proximity processing decreases long-distance data transfer energy costs. This intricate interplay of energy efficiency trade-offs across multiple dimensions constitutes the core challenge in optimizing the integrated system's energy performance.

In the field of energy efficiency optimization for EC-CR integrated systems, technological evolution has shifted from single-algorithm optimization to multi-technology collaborative innovation. Current research primarily focuses on three directions: dynamic resource management, cross-layer optimization, and intelligent algorithm integration. Study [21] proposed a CR-based dynamic resource allocation method using a UAV-GBS (ground base station) collaborative MEC architecture, achieving efficient management of computing, communication, and spectrum resources. Notably, it introduced an innovative concept where MEC systems can dynamically adjust battery sleep modes and output voltage based on CR technology to optimize energy efficiency. Research [22] formulated CR`s spectrum allocation and EC`s computing resource management as a stochastic optimization problem, subsequently implementing dynamic resource scheduling through a lightweight online algorithm. Meanwhile, study [10] advanced a tri-technique framework combining CR, WPT, and MEC. By jointly optimizing multiple parameters to solve non-convex optimization problems, the framework maximizes CR-EC system`s energy efficiency in both partial offloading and local computing scenarios. Intelligent algorithms have also demonstrated unique potential in this domain. Work [23] transformed CR-EC system`s long-term energy efficiency constraints into single-slot optimization problems using Lyapunov optimization theory, combined with a Proximal Policy Optimization (PPO) based deep reinforcement learning algorithm (LRATS) to dynamically adjust task partitioning ratios, transmission power, and computing frequencies. The EC-CR integration is especially valuable for industrial internet. As demonstrated in [22], this approach boosts energy efficiency while maintaining low latency, offering new solutions for industrial IoT performance optimization.

The EC-CR integrated system demonstrates remarkable complementary advantages in energy efficiency optimization. EC helps CR with distributed computing for faster spectrum sensing, while CR gives EC flexible spectrum access for smarter task offloading. Deep reinforcement learning-based resource allocation outperforms conventional local computing and full offloading strategies in experimental validation. However, current research still faces several challenges, including oversimplified models, lack of a unified architecture, high algorithmic complexity, and insufficient security evaluation. Most existing studies rely on simplified network models that consider only a limited set of variables. They ignore some factors like interference patterns, dynamically changing channel conditions, and multi-user competition scenarios. More critically, the absence of a unified computing-communication co-design architecture makes it difficult to effectively balance the trade-offs between spectrum sensing costs, dynamic spectrum access overhead, and computational offloading benefits when evaluating system energy consumption.

4. Future Research Directions

2.6. Secure and Privacy-Preserving Dynamic Resource Orchestration

Future research should focus on security enhancement technologies in dynamic spectrum sharing environments, including lightweight encryption algorithms, spectrum sensing attack detection mechanisms, and cross-domain privacy protection schemes. Specific directions include: developing distributed trust management frameworks to ensure traceability and tamper resistance in spectrum allocation; investigating the application of differential privacy techniques in edge node data aggregation to prevent user behavior leakage; and designing adversarial machine learning models to improve the robustness of spectrum sensing systems against malicious interference. Additionally, it is essential to explore zero-trust security architectures in dynamic resource scheduling to achieve fine-grained access control and real-time threat response.

2.7. Lightweight AI and real-time adaptive optimization

Future research should focus on reducing the computational complexity of AI models for deployment on resource-constrained edge devices, with key directions including: employing knowledge distillation and quantization-aware training to compress deep learning models and reduce inference latency; leveraging federated learning for distributed collaborative optimization to avoid privacy risks from centralized data collection; utilizing online reinforcement learning, like PPO and DQN, to dynamically adjust resource allocation strategies in rapidly changing spectrum environments;

and exploring edge-side neural architecture search (NAS) techniques to automatically generate hardware-adaptive lightweight models for further real-time performance optimization.

2.8. Energy efficiency and ISAC

Future research should focus on energy efficiency optimization in ISAC scenarios by exploring collaborative management of sensing, communication, and computing resources, with key directions including: designing joint optimization algorithms to balance spectrum sensing overhead, task offloading energy consumption, and computational efficiency; investigating integrated solutions combining WPT and dynamic spectrum access to enhance energy sustainability of edge devices; developing edge computing-based real-time ISAC processing frameworks for joint encoding and resource sharing of environmental sensing data and communication signals; and exploring intelligent reflecting surface assisted energy efficiency optimization through dynamic channel environment modulation to reduce transmission power consumption and further improve overall system energy efficiency.

5. Conclusion

This paper provides a systematic review of collaborative optimization techniques for the integration of EC and CR. By analyzing existing literature, it explores key technologies and challenges in EC-CR synergy, focusing on spectrum sensing and allocation, task offloading, and energy efficiency optimization. The collaboration between EC and CR significantly enhances spectrum utilization, task offloading efficiency, and energy performance. The study offers a comprehensive analysis and classification of the current research landscape, paving the way for deeper integration of EC and CR in 6G networks. Future research should further investigate lightweight AI models, standardized architecture design, and security optimization in dynamic environments to address the complexities of real-world deployment.

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