REVIEW ARTICLE

A Review of Dynamic Resource Allocation Techniques for Integrated Sensing, Communication, and Computing Networks Based on Deep Reinforcement Learning

Tao Guo[1], **Rongxin Wu**[1], **Hui Yi**[1] and **Huilin Jiang**[1,*]

[1] School of Electromechanical Engineering, Nanjing Xiaozhuang University, Nanjing 211171, China

Abstract

The integrated sensing, communication, and computing (ISCC) network, as a core direction of the sixth-generation mobile communication system, provides a key enabling technology for efficient collaboration in future intelligent networks by deeply integrating communication, sensing, and computing capabilities. However, the dynamic management and joint optimization of multi-dimensional heterogeneous resources in ISCC networks face severe challenges such as high-dimensional state spaces, tightly coupled constraints, and time-varying environments. Traditional optimization methods struggle to achieve both real-time performance and optimality. Deep reinforcement learning (DRL), with its end-to-end learning capability for complex sequential decision-making problems, offers a novel solution to this dilemma. This paper systematically reviews the current research status of dynamic resource allocation in ISCC networks. It analyzes the fundamental background and resource management challenges of ISCC networks, reviews representative domestic and international research advances in DRL-based resource allocation covering both single-agent and multi-agent approaches, and provides a critical discussion of existing limitations and future research directions.

Keywords: integrated sensing, communication, and computing (ISCC), deep reinforcement learning, dynamic resource allocation, multi-agent reinforcement learning, 6G network.

1 Research Background and Significance

1.1 Research Background

The sixth-generation mobile communication system is evolving from a simple information transmission pipeline into a comprehensive information service platform that deeply integrates multiple functions, including communication, sensing, computing, and intelligence [1]. Integrated sensing and communication (ISAC) has been widely recognized as one of the defining application scenarios for 6G networks, as reflected in dedicated special issues and standardization discussions within the research community [2]. Integrated sensing, communication, and computing (ISCC) further introduces the computing dimension on this basis, enabling joint optimization of communication links, sensing

Submitted: 16 May 2026
Accepted: 22 June 2026
Published: 27 June 2026

Vol. 1, **No.** 2, 2026.
10.62762/TICPS.2026.591816

***Corresponding author:**
Huilin Jiang
huilin.jiang@njxzc.edu.cn

Citation
Guo, T., Wu, R., Yi, H., & Jiang, H. (2026). A Review of Dynamic Resource Allocation Techniques for Integrated Sensing, Communication, and Computing Networks Based on Deep Reinforcement Learning. *ICCK Transactions on Intelligent Cyber-Physical Systems*, 1(2), 76–82.

© 2026 ICCK (Institute of Central Computation and Knowledge)

functions, and distributed computing tasks. In an ISCC network, base stations and terminal devices not only undertake traditional communication tasks but also actively sense the environment and use edge computing resources to process sensing data in real time, with all three sharing the same set of spectrum, hardware, and computing infrastructure.

This technological paradigm shift has given rise to a series of new resource management challenges [21]. In the ISCC network, the resources that need to be scheduled and allocated include not only traditional communication resources such as spectrum, bandwidth, and power, but also perception resources such as detection wave forms, observation time and beam directions, as well as computational resources, including CPU/GPU cycles and storage capacity [3]. Complex coupling and trade-offs exist among different dimensions of resources: power allocation must simultaneously satisfy the signal-to-noise ratio requirement for communication and the detection probability requirement for sensing; bandwidth allocation requires balancing data transmission rate against sensing resolution; the timing of computing resource allocation and offloading decisions directly affects the end-to-end latency and energy consumption of tasks, a challenge that manifests across diverse multi-stream and multi-task edge computing deployments [4]. Faced with these mutually constraining multi-dimensional resource constraints, traditional isolated optimization methods are no longer adequate. Traditional approaches such as convex optimization and game-theoretic methods, while effective in static or simplified settings, cannot efficiently handle the high-dimensional, time-varying, and tightly coupled nature of ISCC resource management.

1.2 Research Significance

Deep reinforcement learning, by deeply integrating the perceptual representation capability of deep learning with the decision optimization capability of reinforcement learning, opens a new path for solving resource allocation problems in complex dynamic environments [5]. Compared with traditional optimization methods, DRL does not rely on an accurate mathematical model of the environment, can learn optimal strategies autonomously from historical interaction data, and achieves millisecond-level response speed for online decision-making. These characteristics are particularly advantageous in ISAC and ISCC systems, where the tightly coupled communication and sensing functions demand adaptive, low-latency resource control [6]. These characteristics make DRL particularly suitable for highly dynamic, difficult-to-model scenarios such as ISCC networks.

From the perspective of technological evolution, DRL-based dynamic resource allocation strategy generation can break through the bottlenecks of traditional centralized scheduling algorithms in dynamic environments, such as prediction errors of resource demands and dynamic game of task priorities—a capability demonstrated across multi-layer wireless network architectures that share structural similarities with ISCC deployments [7]. This not only helps improve network resource utilization and energy efficiency but also provides a feasible technical path for realizing endogenous network intelligence. Therefore, systematically reviewing the research progress in this field and identifying key challenges and development directions has significant academic value and practical relevance for advancing ISCC networks from theory to practice.

1.3 Literature Search Methodology

To ensure a systematic and reproducible synthesis, the literature reviewed in this paper was identified through structured searches conducted in April–May 2026 across IEEE Xplore, ACM Digital Library, Web of Science, and Google Scholar. The primary Boolean search query was: `("integrated sensing" OR "ISAC" OR "ISCC") AND ("deep reinforcement learning" OR "DRL" OR "multi-agent reinforcement learning") AND ("resource allocation" OR "resource management")`. Supplementary searches were conducted using terms such as `"6G resource scheduling"`, `"ISCC edge computing"`, and `"MADRL wireless network"`.

Inclusion criteria: peer-reviewed journal articles, conference papers, and arXiv preprints (2019–2026) directly addressing DRL-based resource allocation in ISAC or ISCC systems, with quantitative performance results. Exclusion criteria: works focused solely on physical-layer waveform design without resource allocation components, non-English publications, and works without accessible full text. Two preprints ([8, 9]) were included due to their direct relevance and active citation within the community, and are explicitly identified as such in the text. A total of 47 candidate papers were initially retrieved; after screening against the above criteria, 21 representative studies were selected for detailed analysis and discussion.

2 Current Research Status in China and Abroad

2.1 International Research Status and Development Trends

International academic research on dynamic resource allocation for ISCC started relatively early, and exploration around DRL methods has been particularly active. At the theoretical framework level, Merluzzi et al. [8] proposed the concept of a "three-function network," advocating that the availability of computing resources and AI models be explicitly considered in resource allocation decisions. Although this work is currently available as a preprint, its theoretical contributions have been actively referenced in the research community. Their theoretical analysis revealed the natural coupling relationships among the service performance boundaries of sensing, communication, and computing. This work laid a theoretical foundation for resource management in ISCC, demonstrating that introducing the computing dimension is not merely a simple overlay on communication and sensing problems but requires a fundamental restructuring of the resource allocation framework.

Regarding dynamic beamforming and power allocation, the DRL method developed by Dao et al. [9] achieved an order-of-magnitude improvement in operational performance—achieving approximately 80% of the spectral efficiency of the SDR benchmark (results from a preprint pending peer review), highlighting DRL's real-time advantages in practical deployments. Furthermore, in radar-service-driven ISAC systems, Smeenk et al. [10] pioneered the application of DRL for joint resource scheduling in vehicle-mounted radar sensing and communication, laying foundational groundwork for subsequent research.

Multi-agent deep reinforcement learning (MADRL) is another important direction in recent international research. In a drone-assisted integrated perception-and-action network, Du et al. [11] proposed a resource allocation algorithm based on MADDPG that leverages multi-drone collaboration to jointly optimize access control, task offloading, and transmission power. Simulation results demonstrate a 73% reduction in latency and a 44% decrease in total costs. For more complex multi-agent collaborative scenarios, Huroon et al. [12] developed a three-agent joint optimization framework—optimizing drone trajectories (DDPG), RIS phase shifts (TD3), and beamforming matrices (PPO)—achieving a synergistic improvement of 22% in perception SNR and 20% in communication rate.

In the realm of new technology integration, transfer learning and federated learning have emerged as pivotal approaches for enhancing the generalization capabilities and privacy protection of DRL algorithms. Saikia et al. [13] introduced a transfer-learning-enhanced DDPG method into a hybrid RIS-enabled drone-assisted ISAC system, leveraging pre-training knowledge to accelerate policy convergence in target domains and address the low sample efficiency issue in DRL within dynamic environments. The introduced F-DDPG algorithm [13] outperforms both traditional centralized DDPG and distributed DQN methods in multi-agent systems.

In summary, international research trends in this domain can be characterized along four dimensions: (1) theoretical frameworks have expanded from the two-dimensional communication–sensing paradigm to a three-dimensional sensing–communication–computing integration, yielding a more rigorous theoretical basis for resource coupling; (2) DRL methods have substantially improved real-time decision-making and facilitated engineering implementation; (3) multi-agent DRL has emerged as the dominant approach for multi-objective joint optimization in collaborative scenarios; and (4) the incorporation of transfer learning and federated learning has enhanced algorithm generalization, sample efficiency, and privacy protection, driving rapid progress toward intelligent, real-time, and collaborative network management.

2.2 Domestic Research Status and Development Trends

Domestic scholars have also made fruitful and distinctive research achievements in the field of ISCC integrated network resource allocation based on deep reinforcement learning. Domestic research has made significant contributions across multiple application domains.

At the basic algorithm and architecture design level, Qi et al. [14] proposed a joint waveform and beamforming design scheme for uplink ISCC based on deep learning on IEEE Transactions on wireless communications, and solved the nonconvex optimization problem of maximizing weighted normalized sensing rate and communication rate by unsupervised learning through deep neural network (ISACNN). Theoretical analysis and simulation verified the effectiveness and robustness of the deep learning scheme in complex mutual interference environment. In the more dynamic scenario of UAV ISCC, Qin et al. [15] systematically studied the resource allocation and trajectory planning of multiple UAVs based on deep reinforcement learning, respectively using the centralized soft actor critic (SAC) algorithm and decentralized multi-agent SAC (MASAC) algorithm, and innovatively introducing the adaptive data enhancement mechanism based on permutation group equivalence to design the experience playback buffer. Experiments show that this scheme is significantly superior to the traditional centralized solution method in terms of training speed and weighted spectral efficiency, and the adaptive SAC algorithm achieves an average weighted spectral efficiency improvement of 14.3% compared with the benchmark SAC.

In the hot field of the integration of communication, sensing and computing in the vehicular network, Yang et al. [16] proposed an integrated system of communication, sensing and computing in the vehicular network based on the over-the-air federated learning (AirFL) architecture, which uses the deep deterministic policy gradient (DDPG) algorithm to jointly optimize the transmit beamforming and power resource allocation, and maximizes the communication data rate under the premise of ensuring the sensing and computing performance. This research applies DDPG algorithms to the resource optimization of the integrated auxiliary system of communication, sensing and computing for the first time. Liu et al. [17] proposed a more in-depth solution on IEEE Transactions on vehicular technology, and built a multi-agent DRL framework to jointly optimize the channel, power and bandwidth allocation. DDPG algorithm was used to dynamically allocate the channel and power, and then the deep Q-network (DQN) algorithm was used to flexibly allocate the frequency bandwidth. Simulation results show that the proposed algorithm is significantly superior to the benchmark scheme in terms of spectral efficiency and communication rate. In addition, Wang et al. [18] innovatively proposed a reward function integrating mutual information and communication rate for the ISCC of UAV group, and compared various reinforcement learning methods such as Q-learning, SARSA, DQN, and Dueling DQN to verify the performance advantages and low time complexity of deep reinforcement learning in resource allocation.

In terms of the deep integration of edge computing and integrated sensing, Shen et al. [19] proposed a robust offload and resource allocation scheme based on the proximal policy optimization (PPO) algorithm in the sensors Journal for the computational uncertainty in the edge computing assisted ISCC, which jointly optimized the transmit beamforming, offload ratio and computational resource allocation, and constructed a Markov decision process (MDP) model considering the perceptual constraints and delay constraints. Chen et al. [20] further introduced the rate-splitting multiple access (RSMA) technology into the ISCC network of multi-user edge computing, and proposed a joint optimization scheme based on soft actor critic (SAC). By optimizing power allocation, beamforming and computing data rate, the total computing throughput of the system was maximized. Simulation results show that the RSMA auxiliary scheme can improve the spectral efficiency by more than 40% compared with the traditional NOMA scheme.

From the perspective of development trends, domestic research exhibits three clear directions. First, the field is evolving from single-agent to multi-agent collaborative decision-making to address resource coupling in distributed scenarios such as multi-UAV and vehicular networks. Second, the focus is shifting from single-resource optimization to joint multi-dimensional resource management spanning communication, sensing, and computing, with research objectives extending beyond spectral efficiency to encompass multi-objective trade-offs among computational energy efficiency, sensing accuracy, and latency. Third, algorithm design is deepening from deterministic problem formulations toward robust optimization under uncertainty, with practical constraints such as channel estimation errors and computational task variability becoming central considerations. In the future, for complex scenarios such as 6G space to ground integration and ultra reliable low delay communication, the ISCC resource allocation scheme integrating transfer learning, federated learning and hierarchical reinforcement learning will become the key breakthrough direction of domestic research.

3 Literature Review and Discussion

Looking at the current research status both domestically and internationally, significant progress has been made in the dynamic resource allocation technology of integrated sensing and computing networks based on deep reinforcement learning. However, there are still several key challenges and research bottlenecks that need to be overcome.

The advantages of existing research are mainly reflected in the following aspects: the theoretical framework is becoming increasingly systematic, and international research has expanded from the traditional “communication perception” two-dimensional architecture to a “perception communication computing” three-dimensional fusion system, providing a clear theoretical basis for resource coupling relationships; In China, innovative solutions have been proposed in areas such as joint waveform design and multi-objective non convex optimization; Deep reinforcement learning methods have significantly improved real-time decision-making capabilities and greatly promoted the potential for engineering implementation; The introduction of multi-agent and transfer/federated learning effectively addresses collaboration and generalization issues: MADRL achieves significant reductions in latency and cost in multi drone and multi vehicle collaboration; Transfer learning and federated learning alleviate the low sample efficiency and privacy protection requirements in dynamic environments.

However, existing research still has certain limitations and challenges. Insufficient robustness in dynamic environments - existing algorithms often assume perfect channel state information (CSI) and ideal computational task conditions, but uncertainty factors such as channel estimation errors and computation request bursts have not been fully modeled and validated in practice; The scalability and convergence challenges in multi-agent collaboration - as the number of agents increases, the joint action space grows exponentially, and existing algorithms such as MADDPG and MASAC have high training complexity and are prone to falling into local optima; The non convex optimization challenge brought by the strong coupling of multi-dimensional resources in communication, sensing, and computing - existing solutions often adopt heuristic or hierarchical optimization, lack a unified online joint optimization framework, and the Pareto boundary between perception accuracy, communication rate, and computational energy consumption is not yet clear; The gap between simulation and actual deployment - most verifications are based on idealized simulation environments, with insufficient consideration of factors such as real hardware latency, limited computing power, and distributed execution; The balance between privacy and communication overhead - Despite the introduction of federated learning, further trade-offs are still needed between the communication load caused by multiple rounds of interaction and the strength of privacy protection.

Therefore, potential research directions in the future can be explored through the following paths: designing a sensing computing resource allocation scheme that integrates transfer learning, federated learning, and hierarchical reinforcement learning for 6G space ground integration and ultra reliable low latency communication scenarios, in order to enhance the algorithm’s adaptive and generalization capabilities in dynamic and heterogeneous networks; Develop a deep reinforcement learning framework with strong robustness and interpretability, modeling channel uncertainty and computational task randomness as partially observable Markov decision processes, and combining Bayesian DRL or meta learning to enhance anti-interference capabilities; Explore lightweight DRL models and edge cloud collaborative architectures to reduce model inference latency and storage overhead, and promote real-time deployment of algorithms on resource constrained edge nodes; Build a unified performance evaluation benchmark for sensory computing, covering multiple scenarios (vehicle networking, drone swarms, industrial Internet of Things), multiple objectives (spectrum efficiency, energy efficiency, perception accuracy, latency), and real hardware in the loop testing to bridge the gap between simulation and reality.

Data Availability Statement

Not applicable.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Wang, X., Han, Z., Jin, J., Xi, R., Wang, Y., Han, L., ... & Liu, G. (2024). Multistatic integrated sensing and communication system based on macro–micro cooperation. *Sensors, 24*(8), 2498. [CrossRef]

[2] Mi, D., Zhou, Z., Liu, F., Fei, Z., Ai, B., Ng, D. W. K., & Zhao, Y. (2024). Special issue on integrated sensing and communications (ISAC). *Journal of Communications and Networks, 26*(5), 472-476. [CrossRef]

[3] Cheng, Q., Wu, W., & Zhou, Y. (2026). D3PG-Light: A Lightweight and Stable Resource Scheduling Framework for UAV-Integrated Sensing, Communication, and Computation Systems. *Sensors, 26*(6), 1829. [CrossRef]

[4] Yuan, S. (2025). Multi video stream collaborative adaptive offloading scheme based on equilibrium game theory. *Scientific Reports, 15*(1), 30129. [CrossRef]

[5] Luong, N. C., Hoang, D. T., Gong, S., Niyato, D., Wang, P., Liang, Y. C., & Kim, D. I. (2019). Applications of deep reinforcement learning in communications and networking: A survey. *IEEE communications surveys & tutorials, 21*(4), 3133-3174. [CrossRef]

[6] Liu, F., Cui, Y., Masouros, C., Xu, J., Han, T. X., Eldar, Y. C., & Buzzi, S. (2022). Integrated sensing and communications: Toward dual-functional wireless networks for 6G and beyond. *IEEE journal on selected areas in communications, 40*(6), 1728-1767. [CrossRef]

[7] Xu, L., Han, S., Fu, W., Zhu, Z., Wu, J., & Zhu, X. (2026). GNN-DRL-based intelligent routing and resource allocation algorithms for multi-layer wireless mesh network. *Sensors, 26*(4), 1170. [CrossRef]

[8] Merluzzi, M., Filippou, M. C., Di Lorenzo, P., & Alexandropoulos, G. C. (2026). Toward Integrated Sensing, Communications, and Edge Intelligence Networks. *arXiv preprint arXiv:2603.22958*. [CrossRef]

[9] Dao, D. N., Kokkeler, A. B., Zhang, H., & Miao, Y. (2025). Dynamic Beamforming and Power Allocation in ISAC via Deep Reinforcement Learning. *arXiv preprint arXiv:2510.25496*. [CrossRef]

[10] Smeenk, C., Zhao, Z., Schneider, C., Robert, J., & Del Galdo, G. (2024, September). Optimizing radio resources for radar services in ISAC systems by deep reinforcement learning. In *2024 IEEE 35th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)* (pp. 1-6). IEEE. [CrossRef]

[11] Du, P., Xiao, T., Cao, H., Qing, C., & Mumtaz, S. (2025). MADDPG-Based Resource Allocation for Integrated Communication, Sensing and Computing in UAV-Assisted IoV Networks. *IEEE Transactions on Vehicular Technology, 75*(6), 11159-11172. [CrossRef]

[12] Huroon, A. M., Tarekegn, G. B., Abdo, A. M. A., Amjad, A., Tai, L. C., & Wang, L. C. (2025). Multiagent Deep Reinforcement Learning for AAV-RIS-Assisted Integrated Sensing and Communication. *IEEE Internet of Things Journal, 12*(19), 40083-40097. [CrossRef]

[13] Saikia, P., Jee, A., Singh, K., Huang, W. J., Boulogeorgos, A. A. A., & Tsiftsis, T. A. (2025). Hybrid-RIS Empowered UAV-Assisted ISAC Systems: Transfer Learning-Based DRL. *IEEE Transactions on Communications, 73*(9), 8314-8329. [CrossRef]

[14] Qi, Q., Chen, X., Zhong, C., Yuen, C., & Zhang, Z. (2024). Deep learning-based design of uplink integrated sensing and communication. *IEEE Transactions on Wireless Communications, 23*(9), 10639-10652. [CrossRef]

[15] Qin, Y., Zhang, Z., Li, X., Huangfu, W., & Zhang, H. (2023). Deep reinforcement learning based resource allocation and trajectory planning in integrated sensing and communications UAV network. *IEEE Transactions on Wireless Communications, 22*(11), 8158-8169. [CrossRef]

[16] Yang, L., Wei, Y., Feng, Z., Zhang, Q., & Han, Z. (2024). Deep reinforcement learning-based resource allocation for integrated sensing, communication, and computation in vehicular network. *IEEE Transactions on Wireless Communications, 23*(12), 18608-18622. [CrossRef]

[17] Liu, C., Xia, M., Zhao, J., Li, H., & Gong, Y. (2024). Optimal resource allocation for integrated sensing and communications in internet of vehicles: A deep reinforcement learning approach. *IEEE Transactions on Vehicular Technology, 74*(2), 3028-3038. [CrossRef]

[18] Wang, M., Chen, P., Cao, Z., & Chen, Y. (2022). Reinforcement learning-based UAVs resource allocation for integrated sensing and communication (ISAC) system. *Electronics, 11*(3), 441. [CrossRef]

[19] Shen, L., Li, B., & Zhu, X. (2024). Robust offloading for edge computing-assisted sensing and communication systems: A deep reinforcement learning approach. *Sensors, 24*(8), 2489. [CrossRef]

[20] Chen, C., He, L., Fan, L., Lei, X., & Nallanathan, A. (2025). Towards Integrated Sensing in Multi-Tier Multi-User MEC: A DRL-Driven RSMA-Assisted Approach. *IEEE Transactions on Vehicular Technology, 75*(1), 824-833. [CrossRef]

[21] Wen, D., Zhou, Y., Li, X., Shi, Y., Huang, K., & Letaief, K. B. (2025). A Survey on Integrated Sensing, Communication, and Computation. *IEEE Communications Surveys & Tutorials, 27*(5), 3058-3098. [CrossRef]

Tao Guo , male. Currently pursuing the Master's degree in New Generation Electronic Information Technology at Nanjing Xiaozhuang University. (Email: guotao031230@163.com)

Rongxin Wu , male. Currently pursuing the Bachelor's degree with the School of Electronic Engineering, Nanjing Xiaozhuang University. (Email: wrx050308@163.com)

Hui Yi , female. Currently pursuing the Bachelor's degree with the School of Electronic Engineering, Nanjing Xiaozhuang University. (Email: 19279735500@163.com)

Huilin Jiang , female. Currently an associate professor with the School of Electronic Engineering, Nanjing Xiaozhuang University. (Email: huilin.jiang@njxzc.edu.cn)