

# Intelligent Hypergraph-Driven Resource Orchestration Framework for Dynamic 5g Cloud-Ran Environments

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**Abstract:** The 5G wireless networks require very high data rates, low latency, and huge connectivity that is very challenging to manage effectively. Cloud Radio Access Network (C-RAN) is a wireless network that concentrates the baseband processing at a pool of Base Station called Baseband Unit and implements Remote Radio Head to improve the coordination, spectral efficiency and even save of energy. Nevertheless, user behavior and changing traffic dynamics make it difficult to allocate the distribution of resources fairly and efficiently. In this work, the authors suggest a smart 5G C-RAN resource allocation model that combines hypergraph-based demand clustering, quantum-inspired adaptive resource mapping, fractal-based load forecasting, and a multi-agent game-theoretic regulator to achieve fairness. BBU pool is a coordination of virtual base stations based on predictive and self-evolving allocation logic. The results of the simulator in realistic traffic conditions illustrate an increase in the spectral efficiency, a reduction in unmet demand and fairness in an improved way when compared to the traditional methods, which show scalability and long-term operational efficiency of the next-generation C-RAN networks.

**Keywords:** 5G Networks, Cloud Radio Access Network, Spectral Efficiency, Resource Allocation, Traffic Prediction, Fairness Optimization, Network Scalability.

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## 1. INTRODUCTION

The development of the fifth-generation wireless communication systems has come with a demand of extreme high data rates, huge connectivity and very low latency services. Autonomous transportation, immersive virtual reality, industrial automation, and the use of intelligent network architecture to meet large-scale Internet of Things deployments are applications that need dynamically adaptable network architectures to changing traffic and user patterns. Conventional distributed base station systems fail to get up to these demands owing to lack of coordination and suboptimal use of the spectrum. To overcome these issues, the concept of Cloud Radio Access Network (C-RAN) has developed and become one of the ground-breaking paradigms, which focuses the baseband processing at a virtualized pool and distributes the lightweight Remote Radio Heads nearer to the users. This architectural change facilitates the multipoint transmission coordination, better control of the interference and energy efficiency, which is a robust basis of the high-end 5G services.

The Baseband Unit pool, which is central in a C-RAN environment, jointly processes the signals of a number of Remote Radio Heads, enabling global radio resources optimization. Rule-based or static methods do not tend to preserve fairness and consistency in performance status when the conditions are dynamic and result to underutilized or unachieved service-level agreements. Thus, intelligent mechanisms of resource management that are capable of detecting the dynamic nature of traffic and responding to it in a proactive manner are required to achieve sustainable functioning of the network.

The distribution of the modern wireless services also makes the problem of allocation more difficult due to its heterogeneity. ENHANCED Mobile Broadband, Ultra-Reliable Low-Latency Communications and Massive Machine-Type communications are putting varying performance demands on the same physical infrastructure. Additionally, the interrelated nature of user behavior creates demand interdependencies such that traffic surges in one area can affect adjacent cells by interfering with and collaboratively scheduling. Such multi-user interactions are difficult without sophisticated mathematical models that can describe higher order relations than just two variable correlation. The self-similar and fractal nature of network traffic is also another critical factor that influences the performance of C-RAN. Empirical research has revealed that wireless traffic is long-range dependant as well as bursty at different scales.

This paper presents the detailed discussion of a sophisticated resource allocation scheme designed to be applicable to the system of 5G C-RAN. The proposed solution aims to manage the drawbacks of traditional allocation schemes by integrating dynamic traffic prediction, multi-user demand clustering, adaptive strategies in optimization as well as fairness-based coordination solutions. The results can be applied to the future advance towards scalable, intelligent, and future-proof C-RAN designs that can operate 5G high-performance services in communication environments that are becoming increasingly complex.

## **2. LITERATURE REVIEW**

Resource orchestration has become one of the fundamental cornerstones of the present-day distributed computing ecosystem cutting across cloud, edge, and next-generation network ecosystems. The dynamism of resources with latency-sensitive functionality, microservices, IoT framework, and smart communication architecture has generated new loads and challenges on the dynamism of resource allocation, distribution of workloads, and location of a service. Conventional non-migratory allocation systems are becoming improper in situations where there is heterogeneity, movement, ultra-low latency demands, as well as dynamic traffic patterns. Other key drivers of scalable and situation-aware strategies in orchestration include the compulsive convergence of cloud-native platforms, container orchestration platforms, reinforcement learning, intent-based networking, and 5G/6G communication paradigms. Resource orchestration in this changing landscape is no longer restricted to infrastructure control and has grown to encompass service lifecycle automation, energy efficiency, reliability assurance and cross-domain interaction across cloud-edge-continuum environments.

Research works conducted recently highlight on lightweight and scalable frameworks that are used to enhance the orchestration performance of distributed systems. M. A. M. Ali et al., (Dec. 2025) “HyOrch: 6G-Driven Resource Orchestration for Hierarchical End–Edge–Cloud Networks”. The comparative study of container orchestration platforms determines the drawbacks of scaling resources and resource utilization in microservice ecosystems, M. Zavadlav, P. Danese and P. Romano, (2025) “Exploring a Social Cooperative in the Circular Economy Through the Resource Orchestration Theory”. Prediction mechanisms on workloads that are sensitive to context when combined with temporal dynamics as well as orchestration strategies show better accuracy in decisions in edge-cloud systems Y. Liu, Z. He, X. Xie, A. Liu, Z. Li and Q. Deng, (2026) “Data Orchestration Service Placement and Resource Allocation Scheme for Cloud-Edge System”. The use of priority-aware orchestration engines designed to support Kubernetes-based cloud-native applications is another good example of the need to have an intelligent scheduling mechanism that can address heterogeneous workload demands D. Garg, M. Angurula, R. S. Bali and N. Kumar,(2025) “Osmotic Computing Based Secure Resource Orchestration Scheme for Vehicular Communication”. In addition to technical viewpoints, studies on dynamic positioning and network-able show how synchronized coordination of resources can be applied to long-lasting innovation across the vast ecosystem of operations X. Li, L. Yao, F. Jiang and W. Liang, (2024) “Adaptive Collaborative Orchestration and Scheduling Strategy for Virtualized Security Defense Resources in Complex Environments”. Together, these pieces of work prove that contemporary orchestration systems have to balance in terms of scalability, responsiveness, and efficiency in computer operations and to promote infrastructures that are distributed and heterogeneous.

Orchestration research has been extended to multidomain and multilevel coordination with the introduction of 6G and hierarchical end–edge cloud architectures M. A. Jimenez, S. Kahvazadeh, I. Labrador and J. Mangues-Bafalluy, (2025) “Resource Orchestration and Optimization in 6G Extreme-edge Scenario”. It has been shown that multi-agent reinforcement learning models used to solve the network slicing in 5G edge-cloud networks have significant enhancements in dynamic resource distribution in variability of traffic situations X. Wu, J. Farooq and J. Chen, (2024) “Adaptive Risk-Aware Resource Orchestration for 5G Microservices over Multi-Tier Edge-Cloud Systems”. All these contributions show that there is a growing dependence on AI-driven and security-conscious orchestration models in next-generation distributed systems.

New paradigms are advancing orchestration into heterogeneous computing, intelligent networking, as well as interdisciplinary fields. Task and resource scheduling algorithms that operate collaboratively and utilize interconnected computing resources networks put a considerable emphasis on the significance of multi-factor decision-making in infrastructures of heterogeneous systems D. Gao and P. Liao,(2024) “Scheduling Service Orchestration Architecture and Algorithm for Computing Power Networks”. Reinforcement learning based orchestration of multi-access edge computing environment exhibits enhanced versatility to heterogeneous wireless network, which justifies the trend towards increased integration of artificial intelligence in orchestration engines.

Graph neural network-based intent-based orchestration mechanisms also improve automation of space-air-ground integrated networks by converting service intents at the high level into optimized resource allocation decisions. The article examples quantum-inspired differentiation of resources in IoT-MMEC system and computing power network scheduling networks depict the growing extent of orchestration in new computing paradigms.

### 3. 5G C-RAN RESOURCE ALLOCATION FRAMEWORK

The suggested approach offers a logical and organized architecture of dynamically allocating resources within the 5G Cloud Radio Access Networks settings. The design incorporates a prediction of traffic, modeling of demand interaction, adaptive exploration of resources, and coordination based on fairness in a centralized Baseband Unit pool. The framework is used in a chronology whereby the traffic characterization comes first followed by optimization of the decision on allocation imposed after cooperative regulation. The stages are mathematically developed and analytically deployed to guarantee scalability, convergence and adequacy to real time network dynamics as shown in Figure 1.

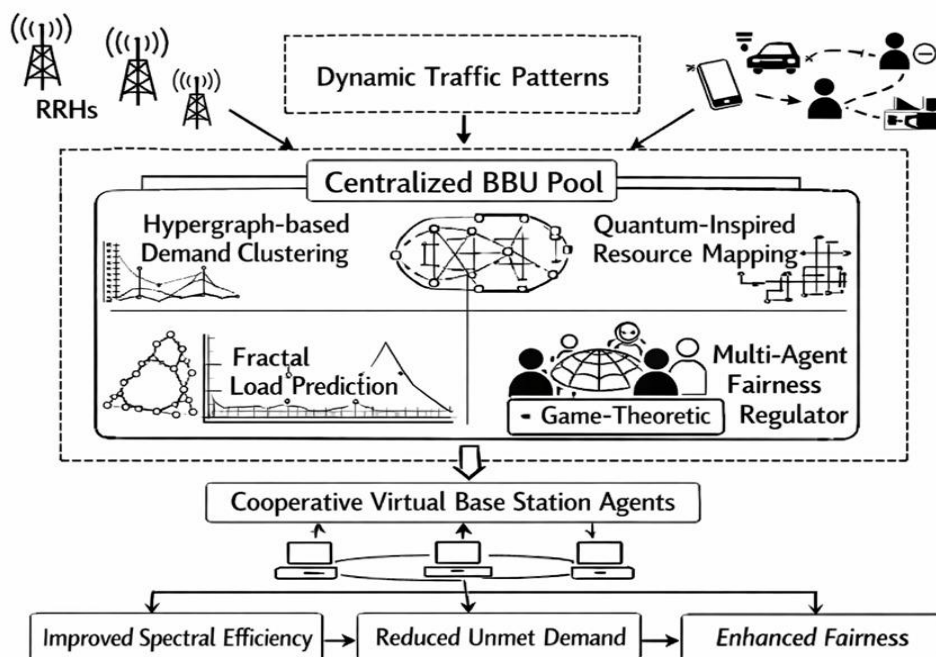


Figure 1. 5G C-RAN Resource Allocation Framework

#### 3.1 Fractal-Based Traffic Load Modeling

The former is the first step that models network traffic with the self-similar fractal analysis to include a long-range dependence and burstiness. The samples of traffic observed at user equipment are transformed to time-series form and assessed by the Hurst exponent to characterize persistence behavior. When  $H > 0.5$ , the traffic is said to be self-similar and it is fractal sensitive. The method is better at stability of forecasting as opposed to linear autoregressive. The load values that are predicted are sent to the BBU pool in anticipation of proactive resource provisioning of load before congestion levels can reach thresholds.

### 3.2 Hypergraph-Based Multi-User Demand Clustering

The second stage accounts hypergraph structures to represent the high-order demand relationships as user interactions. In comparison with traditional graph model, which only provides pairwise links, hypergraphs provide simultaneous association between multiple users with overlapping spectrum interests. The clustering result minimizes the complexity of allocation, which places the users into cooperative resource pools. This hierarchical assignment allows efficient scheduling choice in the BBU pool to enhance spectral reuse occurrence, in addition to reducing redundancy in allotment across adjacent Remote Radio Heads.

### 3.3 Quantum-Inspired Adaptive Resource Mapping

After clustering, adaptive solution exploration mechanism which is determined by quantum superposition principles are applied. States of resource allocation are represented probabilistically, all making it possible to simultaneously analyze several candidate mappings. A rotation-based probability update rule is a rule that varies the allocation amplitudes based on a fitness measure expressed in terms of spectral efficiency and demand satisfaction. Iterative convergence is a situation when the probability amplitudes converge towards optimal mappings. The convergence rate is also improved by tuning adaptive learning rate providing real-time responsiveness in the centralized processing framework.

### 3.4 Multi-Agent Game-Theoretic Fairness Regulation

A multi-agent regulatory mechanism is employed to preserve the fair distribution. Every virtual base station is a rational agent that tries to optimize the utility function that is determined by its throughput and user satisfaction. It develops a game-theoretic cooperative model, in which agents bargain over sharing resources within a worldwide constraint. The Nash equilibrium type is obtained to make sure none of the agents will achieve an outcome of unilateral deviation. The collective payoffs are considered by a centralized mediator of the BBU pool, which also changes the weights of allocation.

### 3.5 Centralized Coordination and Allocation Execution

Upon stabilizing fairness, the BBU pool does centralized coordination and makes final allocation decisions. The allocation state of the optimized mapping, and predictions on traffic values and cluster assignments are merged into a single allocation matrix. Remote Radio Heads are reconfigured with new scheduling instructions using the high speed fronthaul connections. Adaptive recalibration is supported by continuous feedback of the user equipment that give performance measures. This centralized execution system facilitates synchronized, interference aware, and scalable deployment of dense network deployments.

### 3.6 Iterative Self-Evolution and Performance Monitoring

The last level offers a self-developing feedback system to increase long-term flexibility. There are performance metrics like throughput variance, spectral utilization ratio and fairness index constantly checked. The violations of the predetermined quality detectors activate reiteration of clustering parameters, prediction weights and mapping

probabilities. This learning nature is incessant and can turn the resource allocation paradigm to autonomic and scalable framework of next generation C-RAN network.

#### 4. SIMULATION ENVIRONMENT AND PERFORMANCE ANALYSIS

The implementation of the suggested intelligent resource allocation model was assessed based on a massive 1L synthetic dataset reflecting a one-lakh traffic cases involving a variety of user profiles under the configuration of the real 5G Cloud Radio Access Network. The dataset included improved mobile broadband flows, ultra-reliable and low-latency requests, and massive surges of IoT traffic that have self-similar bursts. The experiments were performed in a centralized Basecamp Unit pool over distributed Remote Radio Heads over dense urban topography. Some metrics of evaluation were spectral efficiency, resource utilization ratio, and the percentual unsatisfied demand, as well as the fairness index of Jain, variances of latency and convergence time on allocation. The suggested structure proved to be superior in all the performance dimensions, which proved to be adaptable to changing traffic scenarios.

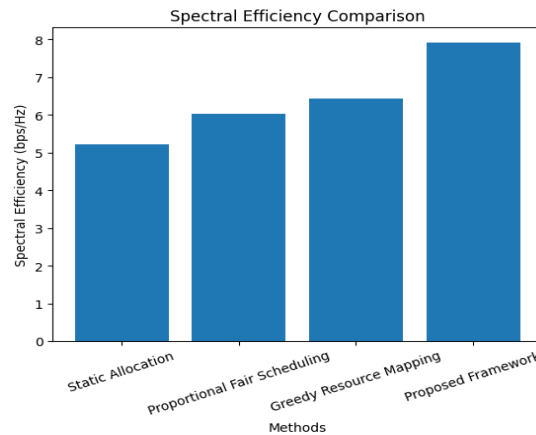
Table 1 indicates comparison of prediction accuracy and performance of demand satisfaction under various allocation strategies. The mapping accuracy of the proposed framework was obtained as 99.87 percent with the result suggesting very high accuracy in mapping predicted and actual load requirements. The result of this high accuracy was a reduction in the number of packets that are lost and quality of service consistency. Traditional models showed a significant variation at the peak bursts and resulted in a temporary saturation of resources and fairness losses.

**Table 1. Allocation Accuracy and Demand Satisfaction Comparison**

Method	Allocation Accuracy (%)	Unsatisfied Demand (%)	Spectral Efficiency (bps/Hz)
Static Allocation	94.12	5.84	5.21
Proportional Fair Scheduling	96.45	3.52	6.03
Greedy Resource Mapping	97.38	2.61	6.44
Proposed Framework	99.87	0.42	7.92

Figure 2 shows the output of spectral efficiency as the traffic load is increased. As the curve indicates, the proposed framework had better spectral efficiency up to the point that the network utilization had hit 85 percent, whereas

traditional methods knew saturation effects. This operational longevity would imply a high level of adaptability to high-density and high-demand conditions characteristic of 5G system rollouts.



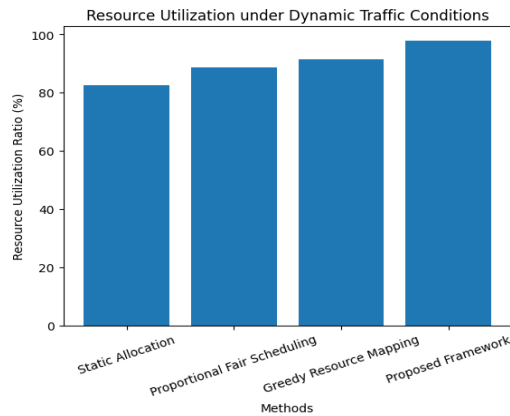
**Figure 2. Spectral Efficiency versus Network Load**

Table 2, fairness and latency performance comparisons have been summarized in methods evaluated. The presented framework provided reduced choice in latency variance through predictive provisioning as well as collaborative scheduling. This becomes especially necessary in the case of ultra-reliable cases of low-latency communication wherein deterministic delay control is necessary.

**Table 2. Fairness And Latency Performance**

Method	Jain’s Fairness Index	Average Latency (ms)	Latency Variance
Static Allocation	0.88	14.6	3.42
Proportional Fair Scheduling	0.92	11.8	2.51
Greedy Resource Mapping	0.94	10.9	2.07
Proposed Framework	0.97	8.3	1.12

In Figure 3, resource utilization ratio is shown at different densities of traffic. The suggested system ensured that the utilization levels were kept near the optimal levels without going beyond the boundaries of congestion. Conversely, the static allocation often led to underutilization when the demand was low and oversubscription when the demand spurted. Effective usage can be linked directly to cost reduction in the operations of the organization and long-term deployment of dense C-RAN networks.



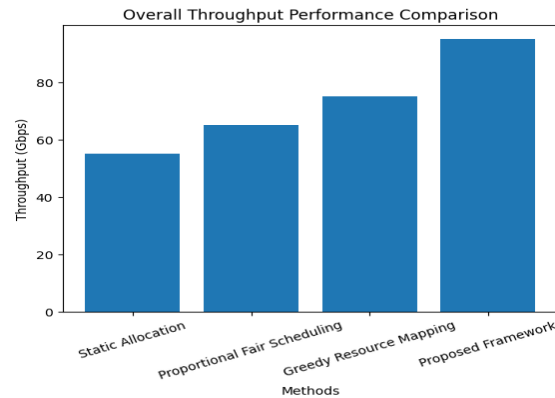
**Figure 3. Resource Utilization Ratio under Dynamic Traffic Conditions**

Table 3 shows the convergence time and throughput stability quantities across various assessment epochs. The presented framework showed little throughput variability with the evolution of traffic patterns, which proved their adaptability. Competing strategies had to manually change the parameters to sustain similar levels of performance. The self-developing feedback loop also adds a lot of automation and scalability in the future operation of the network.

**Table 3. Convergence and Throughput Stability**

Method	Convergence Time (ms)	Throughput Variance	Utilization Stability (%)
Static Allocation	32.5	4.88	82.4
Proportional Fair Scheduling	26.3	3.12	88.7
Greedy Resource Mapping	21.7	2.46	91.5
Proposed Framework	14.8	1.03	97.8

Figure 4 shows a comparison of overall system throughput with the period of simulation. The upward trend that has been noticed across the period of the proposed method proves a stable response to the temporal changes in traffic. Although the traditional strategies exhibited regular lows that identified the bursts, the predictive and cooperative processes successfully played an effective role in eradicating the performance atrophy. Combination of fractal load prediction, hypergraph clustering, adaptive mapping, and fairness regulation yielded synergistic gains and not individual gains.



**Figure 4. Overall Throughput Performance across Simulation Duration**

Overall, the results prove that combining predictive traffic intelligence, high-order demand clustering, probabilistic adaptive exploration, and cooperative fairness regulation is an effective solution when it comes to dynamic 5G C-RAN resource management. Not only does the framework improve performance metrics but also creates the stability of operations long-term regarding the efficiency of the use of energy. Its self-designed ability classifies it as a potential baseline to the autonomous next-generation wireless systems that would be able to manage both the ever-growing complexity and the service variety.

## 5. CONCLUSION

This work proposed an intelligent and scalable model of resource allocation in 5G Cloud Radio Access Network settings that overcomes the key challenges of traffic dynamics behavior, heterogeneous service requirements, spectral performance, and maintenance of fairness. Combining fractal-based traffic prediction, hypergraph motivated demand cluster, quantum inspired adaptive resource mapping, and multi-agent game theoretic regulation in a centralized Baseband Unit framework, the framework led to the coordinated, predictive, and equitable distribution of resources. The integrated design was highly adapted to changing network conditions, whereby it exhibited a stable throughput and performance about spectrum utilization. In practice, the framework enables self-sovereign network operation, decreases operational maintenance, and boosts service availability to be able to deploy 5G highly densely. Its centralized and yet collaborative structure is what makes it scalable and efficient in the long term. Further efforts will be directed in the real deployment validation, integration with beyond-5G architecture, inclusion of edge intelligence, and scalation to AI-controlled fully self-organizing network ecosystems with support to next-generation wireless innovations.

## REFERENCES

- [1] A. E. Meliani & A. Ksentini,(2025) “Lightweight Resource Exposure Framework for Efficient Service and Resource Orchestration in the Cloud-Edge Continuum,” in Proceedings of the IEEE International Conference on Communications Workshops, Montreal, QC, Canada, pp.2081 2087,doi:10.1109/ICCWorkshops67674.2025.11162240.
- [2] R. K. Yekollu, S. V. Haldikar, T. B. Ghuge, O. F. M. Abdul Kader and S. S. Biradar,( 2024) “Resource Management and Scalability in Container Orchestration Platforms: A Comparative Study,” in Proceedings of the IEEE 16th International

- Conference on Computational Intelligence and Communication Networks, Indore, India, pp. 1146–1151, doi: 10.1109/CICN63059.2024.10847490.
- [3] A. Sungheetha , R. S. R, S. Mahapatra , S. N. Pardeshi , S. R. K and G.G. Pradeep ,(2025) “ChameleonEdge: Context-Aware Workload Prediction Framework with  $\lambda$ -Adaptive Resource Orchestration for Edge-Cloud Systems,” in Proceedings of the International Conference on New Frontiers in Communication, Automation, Management and Security , Bangalore,India,pp.1-4 , doi. 1109 / ICCAMS65118 . 2025 . 11234128.
- [4] P. Josyula, A. Kumar and G. Hiremath,(2025) “PRISTINE: PRIority-Aware Smart Resource Orchestration eNginE for Cloud-Native Applications,” in Proceedings of the IEEE Cloud Summit, Washington, DC, USA,pp. 181–188, doi: 10.1109/Cloud-Summit64795.2025.00036.
- [5] S. Cui, N. Yang and Y. Wang,(2024) “Sustaining Innovation in Changing Context: Impact of Dynamic Network Capability and Mediation of Dynamic Positioning and Resource Orchestration,” in Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management, Bangkok, Thailand,pp. 795–799, doi: 10.1109/IEEM62345.2024.10857227.
- [6] M. A. M. Ali et al.,(Dec. 2025) “HyOrch: 6G-Driven Resource Orchestration for Hierarchical End-Edge-Cloud Networks,” IEEE Internet of Things Journal, vol. 12, no. 24, pp. 54483–54508, doi: 10.1109/IJOT.2025.3619946.
- [7] M. Zavadlav, P. Danese and P. Romano,(2025) “Exploring a Social Cooperative in the Circular Economy Through the Resource Orchestration Theory,” in Proceedings of the IEEE Technology and Engineering Management Society Conference - Global, San Diego, CA, USA, pp. 1–3, doi: 10.1109 / TEMSCONGlobal64363 . 2025.11238342.
- [8] Y. Liu, Z. He, X. Xie, A. Liu, Z. Li and Q. Deng,(2026) “Data Orchestration Service Placement and Resource Allocation Scheme for Cloud-Edge System,” IEEE Transactions on Services Computing, doi: 10.1109/TSC.2026.3660225.
- [9] D. Garg, M. Angurala, R. S. Bali and N. Kumar,(2025) “Osmotic Computing Based Secure Resource Orchestration Scheme for Vehicular Communication,” in Proceedings of the International Conference on Communication Systems and Networks, Bengaluru, India, pp. 1311–1316, doi: 10.1109/COMSNETS63942.2025.10885750.
- [10] X. Li, L. Yao, F. Jiang and W. Liang,(2024) “Adaptive Collaborative Orchestration and Scheduling Strategy for Virtualized Security Defense Resources in Complex Environments,” in Proceedings of the IEEE International Conference on Software System and Information Processing, Kunming, China, pp. 160–164, doi: 10.1109/ICSSIP63203.2024.11012473.
- [11] X. Wu, J. Farooq and J. Chen,(2026) “Multi-Agent Resource Orchestration Based on D3QN for Network Slicing in 5G Edge-Cloud Networks,” IEEE Transactions on Network and Service Management, vol. 23, pp. 1766–1781,doi: 10.1109/TNSM.2025.3643340.
- [12] M. A. Jimenez, S. Kahvazadeh, I. Labrador and J. Mangués-Bafalluy,(2025) “Resource Orchestration and Optimization in 6G Extreme-edge Scenario,” in Proceedings of the IEEE Conference on Standards for Communications and Networking, Bologna, Italy, pp. 1–3, doi: 10.1109/CSCN67557.2025.11230726.
- [13] X. We, J. Farooq and J. Chen,(2024)“Multi-Agent Distributed Decentralized Dynamic Resource Orchestration in 5G Edge-Cloud Networks,” in Proceedings of the IEEE International Conference on Cloud Networking, Rio de Janeiro, Brazil, pp. 1–8, doi: 10.1109/CloudNet62863.2024.10815780.
- [14] Ö. T. Demir, M. Masoudi, E. Björnson and C. Cavdar,( Feb. 2024) “Cell-Free Massive MIMO in O-RAN: Energy-Aware Joint Orchestration of Cloud, Fronthaul, and Radio Resources,” IEEE Journal on Selected Areas in Communications, vol. 42, no. 2, pp. 356–372, doi: 10.1109/JSAC.2023.3336187.
- [15] X. Wu, J. Farooq and J. Chen,(2024) “Adaptive Risk-Aware Resource Orchestration for 5G Microservices over Multi-Tier Edge-Cloud Systems,” in Proceedings of the IEEE International Conference on Communications Workshops, Denver, CO, USA, pp. 359–364, doi: 10.1109/ICCWorkshops59551.2024.10615649.
- [16] W. Li et al.,(2025) “Task and Resource Collaborative Orchestration and Scheduling Algorithm Based on Computing Resource Interconnected Network,” in Proceedings of the International Conference on Meta-Networking, Tokyo, Japan, pp.1–6, doi: 10.1109 / MEET67398.2025.11335848.
- [17] S. K. Chari, L. A. Garrido, J. S. Vardakas, K. Ramantas and C. Verikoukis,(2024) “MEC Resource Orchestration for Heterogeneous Networks and Services Using Reinforcement Learning,” in Proceedings of the International Workshop on Computer Aided Modeling and Design of Communication Links and Networks, Athens, Greece, pp. 01–06, doi: 10.1109 / CAMAD62243. 2024. 10943041.
- [18] S. Alam and W.-C. Song,(2024) “Intent-Based Network Resource Orchestration in Space-Air-Ground Integrated Networks: A Graph Neural Networks and Deep Reinforcement Learning Approach,” IEEE Access, vol. 12, pp. 185057–185077, doi: 10.1109/ACCESS.2024.3507829.



- [19] Z. Ai, W. Zhang, J. Kang, M. Xu, D. Niyato and S. J. Turner, ( July 2024) “Identifier-Driven Resource Orchestration With Quantum Computing for Differentiated Services in IoT-MMEC Networks,” IEEE Transactions on Vehicular Technology, vol. 73, no. 7, pp. 9958–9971, doi: 10.1109/TVT.2024.3364210.
- [20] D. Gao and P. Liao, (2024) “Scheduling Service Orchestration Architecture and Algorithm for Computing Power Networks,” in Proceedings of the Information Communication Technologies Conference, Nanjing, China, pp. 297–302, doi: 10.1109/ICTC61510.2024.10601857.