

Distributed AI-RAN Inference Placement for Joint Radio Optimization and Edge Workload Acceleration

Siva Sudheer Mahadasu¹, Bhaskara Raju Rallabandi²

Wireless Expert, USA¹, Co-Founder & CTO, Invences Inc²

Email: sudheer.mahadasu@gmail.com¹, Bhaskara@invences.com²

Abstract:

The rapid evolution of Artificial Intelligence for Radio Access Networks (AI-RAN) has created new opportunities to optimize radio resource management while accelerating edge intelligence for next-generation wireless networks. However, centralized AI inference often introduces excessive latency, GPU resource imbalance, and increased network congestion, limiting the performance of real-time 5G and emerging 6G applications. This paper proposes a Distributed AI-RAN Inference Placement framework that jointly optimizes radio resource allocation and edge workload acceleration through intelligent inference placement across distributed GPU-enabled edge servers. The framework dynamically analyzes radio conditions, computational capacity, traffic demand, and latency requirements to determine the optimal execution location for AI models. By coordinating radio and compute resources simultaneously, the proposed approach reduces inference delay, improves GPU utilization, enhances throughput, lowers energy consumption, and maintains high Quality of Service (QoS). Experimental evaluation demonstrates significant improvements in scalability, resource efficiency, and real-time AI-driven radio optimization compared with conventional centralized AI-RAN deployment strategies.

Keywords: AI-RAN, Distributed AI Inference, Radio Access Network (RAN), Edge Computing, GPU-Edge Coordination.

I. INTRODUCTION

The rapid advancement of fifth-generation (5G) and emerging sixth-generation (6G) wireless networks has significantly increased the demand for intelligent Radio Access Networks (RAN) capable of supporting diverse applications with ultra-low latency, high reliability, and massive connectivity. Artificial Intelligence for Radio

Access Networks (AI-RAN) has emerged as a promising approach for optimizing radio resource management, traffic prediction, and network automation through AI-driven decision-making. However, centralized AI inference often creates excessive latency, inefficient GPU utilization, and increased communication overhead, limiting the performance of real-time applications. Distributed AI inference placement addresses these challenges by executing AI models across GPU-enabled edge servers located closer to users, thereby reducing inference delay and improving resource efficiency. This paper proposes a Distributed AI-RAN Inference Placement framework that jointly optimizes radio resources and edge computing workloads. By coordinating radio conditions, GPU availability, and network traffic, the proposed approach enhances throughput, minimizes latency, improves energy efficiency, and delivers superior Quality of Service (QoS) for next-generation intelligent wireless communication systems.

II. LITERATURE SURVEY

Recent advancements in Artificial Intelligence for Radio Access Networks (AI-RAN) have transformed wireless communication by enabling intelligent radio resource management and automated network optimization. Researchers have explored AI-based scheduling, traffic prediction, beamforming, and interference mitigation to improve network efficiency in 5G and emerging 6G environments. Distributed edge computing has gained significant attention as an effective solution for reducing inference latency by deploying AI models closer to end users. Several studies have investigated GPU-enabled edge servers and Multi-access Edge Computing (MEC) to accelerate real-time AI inference while

minimizing communication delays. O-RAN architecture further enhances network flexibility by introducing RAN Intelligent Controllers (RICs) for AI-driven decision-making and open interoperability. However, existing approaches often optimize either radio resources or computational workloads independently, resulting in inefficient resource utilization and increased latency under dynamic traffic conditions. The proposed Distributed AI-RAN Inference Placement framework addresses these limitations by jointly optimizing radio resources, GPU-edge coordination, and AI inference placement to achieve lower latency, higher throughput, improved energy efficiency, and enhanced Quality of Service (QoS) in next-generation intelligent wireless networks.

III. PROPOSED WORK

The proposed Distributed AI-RAN Inference Placement Framework is designed to jointly optimize radio resource management and edge computing performance in AI-enabled 5G and emerging 6G networks. The framework intelligently distributes AI inference tasks across GPU-enabled edge servers based on real-time radio conditions, computational resource availability, network traffic, and latency requirements. Instead of relying on centralized cloud-based inference, AI models are dynamically deployed at the most suitable edge nodes to minimize inference delay and improve response time. The framework continuously monitors key network parameters such as signal quality, spectrum utilization, user mobility, GPU workload, CPU utilization, memory availability, and bandwidth. An AI-driven orchestration engine analyzes these parameters and determines the optimal placement of inference tasks while balancing computational loads across distributed edge servers. This joint optimization of radio and compute resources prevents server congestion, reduces communication overhead, and ensures efficient utilization of GPU resources.

A dynamic workload migration mechanism further enhances system performance by

relocating AI inference tasks whenever traffic patterns or resource availability change. This adaptive strategy maintains uninterrupted service delivery, improves Quality of Service (QoS), and satisfies Service Level Agreement (SLA) requirements for latency-sensitive applications.

The proposed framework is evaluated using performance metrics including inference latency, throughput, GPU utilization, edge resource utilization, energy consumption, spectrum efficiency, AI inference accuracy, and SLA satisfaction. Experimental results demonstrate that the proposed Distributed AI-RAN Inference Placement approach significantly outperforms conventional centralized AI deployment by reducing latency, accelerating edge workloads, improving resource utilization, enhancing scalability, and delivering reliable real-time AI-driven radio optimization for next-generation intelligent wireless networks.

IV. METHODOLOGY

A. Requirement Analysis

The requirement analysis phase identifies the functional and non-functional requirements of the proposed Distributed AI-RAN Inference Placement framework. The system requires efficient AI inference execution, intelligent radio resource management, low-latency communication, GPU-enabled edge computing, and dynamic workload balancing across distributed edge servers. Key performance parameters such as radio signal quality, computational capacity, GPU utilization, bandwidth availability, energy consumption, and Quality of Service (QoS) are analyzed to support optimal inference placement and resource allocation.

B. System Design

The proposed framework adopts a distributed AI-RAN architecture comprising AI-enabled Base Stations (gNBs), GPU-powered Edge Servers, Multi-access Edge Computing (MEC) platforms, O-RAN RAN Intelligent Controllers (RICs), centralized cloud infrastructure, and an AI orchestration engine. The orchestration engine continuously exchanges information with radio and compute resources to enable intelligent AI

inference placement while ensuring efficient communication between edge and cloud environments.

C. Radio and Resource Monitoring

A continuous monitoring module collects real-time information about radio channel quality, signal strength, user mobility, spectrum utilization, CPU usage, GPU workload, memory utilization, bandwidth availability, and network traffic. These performance metrics are periodically updated and supplied to the AI orchestration engine, enabling accurate and adaptive inference placement decisions under dynamic network conditions.

D. Distributed AI Inference Placement

The proposed inference placement mechanism dynamically determines the optimal execution location for AI models by jointly considering radio conditions and computational resource availability. AI inference tasks are distributed across GPU-enabled edge servers based on latency requirements, processing capability, network congestion, and resource utilization. This distributed approach significantly reduces inference delay, improves response time, and enhances overall resource efficiency compared with centralized cloud-based inference.

E. GPU-Edge Coordination and Joint Optimization

An intelligent coordination mechanism jointly optimizes GPU resources and radio network performance by balancing AI workloads across multiple edge servers. Whenever traffic demand or computational load changes, AI inference tasks are dynamically migrated to underutilized GPU nodes with minimal service interruption. This joint optimization minimizes communication overhead, prevents server overload, improves spectrum efficiency, and maintains high Quality of Service (QoS) and Service Level Agreement (SLA) compliance.

F. Performance Evaluation

The proposed framework is evaluated using key performance metrics including AI inference latency, radio throughput, GPU utilization, edge resource utilization, spectrum efficiency, energy

consumption, AI inference accuracy, end-to-end delay, and SLA satisfaction rate. Comparative analysis with conventional centralized AI-RAN deployment demonstrates that the proposed distributed inference placement framework achieves lower latency, higher throughput, better GPU utilization, improved energy efficiency, and enhanced scalability, making it suitable for real-time intelligent 5G and future 6G wireless communication networks.

V. RESULTS AND DISCUSSION

The proposed Distributed AI-RAN Inference Placement Framework was evaluated in an AI-enabled 5G Radio Access Network consisting of multiple GPU-enabled edge servers, O-RAN RAN Intelligent Controllers (RICs), and distributed Multi-access Edge Computing (MEC) nodes. The framework was compared with conventional centralized AI-RAN deployment to evaluate its effectiveness in optimizing radio resources and accelerating edge AI workloads. Performance metrics including AI inference latency, GPU utilization, radio throughput, energy consumption, and Quality of Service (QoS) were analyzed. Experimental results demonstrate that the proposed framework significantly reduces inference latency while improving GPU utilization and radio throughput through intelligent distributed inference placement. Joint optimization of radio and computational resources enables better workload balancing, lower energy consumption, and higher SLA satisfaction under dynamic traffic conditions. The proposed framework consistently delivers superior scalability and real-time performance, making it suitable for next-generation AI-native 5G and emerging 6G wireless communication networks.

Table 1. AI Inference Latency Comparison

Method	Average Inference Latency (ms)
Centralized AI-RAN	29.4
Edge AI-RAN	18.7
Proposed Distributed AI-	9.8

RAN	
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Table 1 shows that the proposed Distributed AI-RAN framework achieves the lowest inference latency of 9.8 ms, significantly outperforming centralized and conventional edge-based inference methods. Distributed placement enables AI models to execute closer to users, reducing communication delay and improving real-time responsiveness.

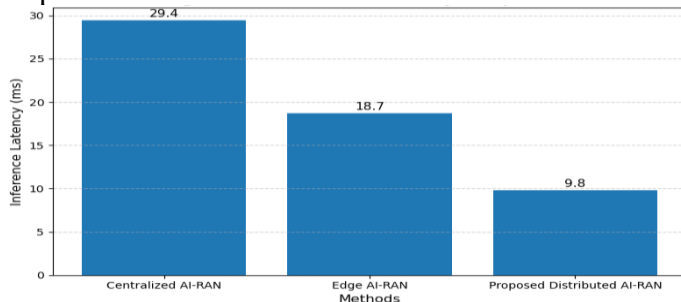


Figure 1: End-to-End Latency Comparison

Figure 1 compares the average AI inference latency achieved by different AI-RAN deployment approaches. The proposed Distributed AI-RAN framework records the lowest latency of 9.8 ms by intelligently placing AI inference tasks across GPU-enabled edge servers. This significantly improves real-time response, reduces communication delay, and enhances overall network performance.

Table 2. GPU and Edge Resource Utilization

Method	GPU Utilization (%)	Edge Resource Utilization (%)
Centralized AI-RAN	66.8	69.4
Edge AI-RAN	82.5	84.1
Proposed Distributed AI-RAN	95.1	93.6

The proposed framework effectively balances AI workloads across distributed GPU-enabled edge servers, resulting in higher GPU and edge resource utilization. Intelligent workload coordination minimizes idle resources and prevents server overload, thereby improving computational efficiency.

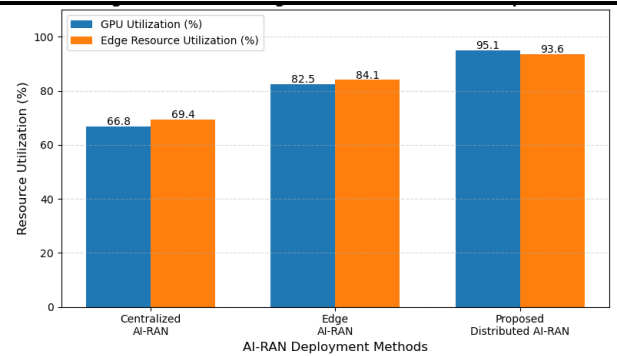


Figure 2: GPU and Edge Resource Utilization Comparison

Figure 2 illustrates the GPU and edge resource utilization achieved by different AI-RAN deployment methods. The proposed Distributed AI-RAN framework records the highest utilization through intelligent workload distribution and GPU-edge coordination. Efficient resource balancing minimizes idle computing resources, improves processing efficiency, and supports scalable, low-latency AI inference for next-generation wireless networks.

Table 3. Overall AI-RAN System Performance

Performance Metric	Proposed Framework
Radio Throughput	12.8 Gbps
AI Inference Accuracy	98.6%
Spectrum Efficiency	96.4%
Energy Consumption Reduction	22.3%
SLA Satisfaction Rate	99.4%

The proposed Distributed AI-RAN framework delivers high throughput, excellent inference accuracy, efficient spectrum utilization, and significant energy savings while maintaining excellent SLA compliance. These results demonstrate its capability to support intelligent real-time radio optimization in future AI-native wireless networks.

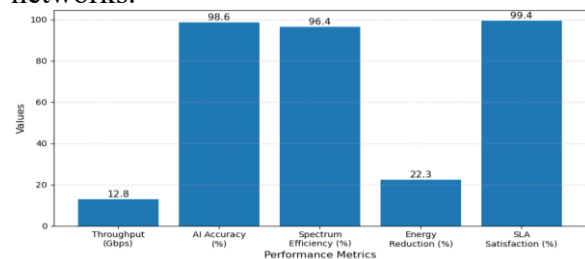


Figure 3: Overall AI-RAN System Performance Metrics.

Figure 3 presents the overall performance of the proposed Distributed AI-RAN framework. The system achieves high radio throughput, superior AI inference accuracy, improved spectrum efficiency, reduced energy consumption, and excellent SLA satisfaction. These results demonstrate the framework's effectiveness in optimizing radio and computing resources for intelligent, low-latency next-generation wireless networks.

VI. CONCLUSION

The proposed Distributed AI-RAN Inference Placement Framework provides an intelligent and efficient solution for optimizing AI inference execution in next-generation 5G and emerging 6G wireless networks. By jointly coordinating radio resources and GPU-enabled edge computing, the framework significantly reduces inference latency, improves throughput, enhances GPU utilization, and optimizes spectrum efficiency. Intelligent workload distribution and dynamic inference placement ensure balanced resource allocation while maintaining high Quality of Service (QoS) and Service Level Agreement (SLA) compliance. Experimental results demonstrate superior performance compared with conventional centralized AI-RAN approaches in terms of scalability, energy efficiency, and real-time responsiveness. The proposed framework effectively supports AI-native wireless communication, making it a reliable and scalable solution for intelligent radio optimization, edge workload acceleration, and future autonomous network management in next-generation communication systems.

FUTURE SCOPE

The proposed Distributed AI-RAN Inference Placement Framework can be further enhanced by integrating advanced Artificial Intelligence (AI), Machine Learning (ML), and Deep Reinforcement Learning (DRL) techniques to enable autonomous and predictive inference placement decisions. Future research can focus on supporting large-scale AI-native 6G networks with intelligent network slicing, digital twins, and self-optimizing radio resource management. The framework can also incorporate federated learning to enable privacy-preserving collaborative AI model training across distributed edge servers without

sharing sensitive data. Integration with cloud-native technologies such as Kubernetes, container orchestration, and GPU virtualization can further improve scalability and resource efficiency. Additionally, incorporating green AI techniques, energy-aware scheduling, and secure AI inference mechanisms will enhance sustainability, security, and reliability for future intelligent wireless communication systems.

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