



**SELINUS UNIVERSITY**  
OF SCIENCES AND LITERATURE

**AI-Driven Dynamic Optimization of 5G/6G  
Networks: Enhancing Resource Allocation,  
Traffic Management, and Energy Efficiency  
Integrating H-MARL, TL, FL, and  
XAI Techniques**

By **Selamawit Engliz Biyan**

**A DISSERTATION**

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## **DECLARATION**

I hereby declare that the thesis titled “AI-Driven Dynamic Optimization of 5G/6G Networks: Enhancing Resource Allocation, Traffic Management and Energy Efficiency Integrating H-MARL, TL, FL and XAI Techniques” submitted for the degree of Doctor of Philosophy in Electrical Engineering has been written by myself and it is a report of my research work. It has not been presented in any program. All sources of information are acknowledged by means of references.

**Selamawit Engliz Biyan**

## ABSTRACT

*As 5G networks mature and 6G networks emerge, the increasing complexity, heterogeneity, and dynamism of wireless environments necessitate intelligent, scalable, and adaptive optimization strategies. This dissertation proposes an integrated Artificial Intelligent (AI) - driven framework for dynamic optimization of 5G/6G networks, targeting key performance aspects: resource allocation, traffic management, and energy efficiency. The framework combines Hierarchical Multi-Agent Reinforcement Learning (H-MARL) for scalable decision-making, Transfer Learning (TL) for cross-domain adaptability, Federated Learning (FL) for privacy-preserving distributed intelligence, and Explainable AI (XAI) for interpretable and trustworthy optimization. A modular, multi-layer architecture is introduced wherein distributed agents learn context-aware policies under realistic network models. Simulation results, validated on dense urban and massive IoT use cases, demonstrate that the proposed solution achieves significant gains in throughput, latency, and energy efficiency, outperforming traditional heuristic, centralized Deep Reinforcement Learning (DRL) and non-hierarchical Multi-Agent Reinforcement Learning (MARL) baselines. The framework paves the way for intelligent, adaptive, and explainable arrangement of next-generation wireless infrastructures, offering actionable insights for both research and industrial deployment.*

**Keywords—***5G/6G networks, Hierarchical Multi-Agent Reinforcement Learning (H-MARL), Transfer Learning (TL), Federated Learning (FL), Explainable AI (XAI), dynamic optimization, resource allocation, energy efficiency, traffic management.*

## **DEDICATION**

To  
my father, my mother,  
my husband, my children,  
my brothers and  
the rest of my family.

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## List of Abbreviations

3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
5GC	5G Core Network
6G	Sixth Generation
ACO	Ant Colony Optimization
AI	Artificial Intelligent
AMF	Access and Mobility Management Function
ANOVA	Analysis of Variance
AR	Augmented reality
AR	Augmented Reality
ATSC	Adaptive Traffic Signal Control
AWGN	Additive White Gaussian Noise
BSs	Base Stations
CQI	Channel Quality Information
C-RAN	Centralized Radio Access Network
CSI	Channel State Information
CTDE	Centralized Training With Decentralized Execution
CU	Central Unit
D2D	Device-to-Device
DDoS	Distributed Denial of Service
DDPG	Deep Deterministic Policy Gradient
DL	Deep Learning
DLT	Distributed Ledger Technology
DNN	Deep Neural Networks
DQN	Deep Q-Networks
DRL	Deep Reinforcement Learning
DU	Distributed Unit
eMBB	enhanced Mobile Broadband
EU	European Union
FL	Federated Learning
FRL	Federated Reinforcement Learning

GA	Genetic Algorithms
GDPR	General Data Protection Regulation
GHz	Giga Hertz
gNBs	gNode Base Stations
GNN	Graph Neural Network
HARQ	Hybrid Automatic Repeat Request
HE	Homomorphic Encryption
H-MARL	Hierarchical-Multi Agent Reinforcement Learning
HTTP	Hyper Text Transfer Protocol
ICT	Information Communication Technology
IoE	Internet of Everything
IoT	Internet of Things
IQR	Interquartile Range
IRS	Intelligent Reflecting Surfaces
ISAC	Integrated Sensing and Communication
J/bit	Energy per Bit
KPIs	Key Performance Indicators
LDPC	Low Density Parity Check
LEO	Low Earth Orbit
LIME	Local Interpretable Model Agnostic Environment
LoS	Line of Sight
LTE	Long Term Evolution
MAC	Media Access Control
MARL	Multi Agent Reinforcement Learning
MATLAB	Matrix Laboratory
MBSs	Macro Base Stations
MCS	Modulation and Coding Scheme
MDP	Markov Decision Process
MEC	Multi-Access Edge Computing
MILP	Mixed-Integer Linear Programming
MIMO	Multiple-Input Multiple-Output
MINLP	Mixed-Integer Nonlinear Programming
mIoT	Massive Internet of Things

ML	Machine Learning
mMTC	massive Machine-Type Communication
mmWave	Millimeter Wave
MPC	Model Predictive Control
NFV	Network Function Visualization
NG-RAN	Next Generation Radio Access Network
NLoS	Non-line of sight
NR	New Radio
NSSF	Network Slice Selection Function
OCO	Online Convex Optimization
OPEX	Operational Expenditure
PCF	Policy Control Function
PER	Packet Error Rate
PF	Proportional Fair
PPO	Proximal Policy Optimization
PRBs	Physical Resource Blocks
PSO	Particle Swarm Optimization
QoE	Quality of Experience
QoS	Quality of Service
RAN	Radio Access Network
RBs	Resource Blocks
RESTful APIs	Restful Application Programming Interfaces
RIS	Reconfigurable Intelligent Surfaces
RL	Reinforcement Learning
RNN	Recursive Neural Network
RR	Round Robin
RRC	Radio Resource Control
SAGSN	Space Air Ground Sea Networks
SBA	Service Based Architecture
SDN	Software Defined Network
SHAP	SHapley Additive exPlanations
SINR	Signal to interference plus Noise Ratio

SLAs	Service Level Agreements
SMF	Session Management Function
SMPC	Secure Multi-Party Computation
SNR	Signal to Noise Ratio
Tbps	Tera Bits per second
THz	Terahertz
TL	Transfer Learning
TTIs	Transmission Time Intervals
UAVs	Unmanned Aerial Vehicles
UEs	User Equipments
UMa	Urban Macro
UMi	Urban Micro
UPF	User Plane Function
URLLC	Ultra-Reliable Low-Latency Communication
V2X	Vehicle to everything
VDN	Value Decomposition Networks
VLC	visible light communication
VR	Virtual Reality
XAI	Explainable Artificial Intelligent
XR	Extended Reality

# CHAPTER 1: INTRODUCTION

## 1.1 Background and Motivation

The rapid evolution of wireless communication networks, from fourth generation (4G) to fifth generation (5G) and now sixth generation (6G), has revolutionized various industries, supporting an unprecedented growth in mobile connectivity, the Internet of Things (IoT), and diverse application scenarios such as smart cities, autonomous vehicles, and industrial automation [1]. The primary goals of these network generations include providing ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) [2][3]. These advancements are critical to meeting the increasing demands for higher data rates, better Quality of Service (QoS), and enhanced connectivity.

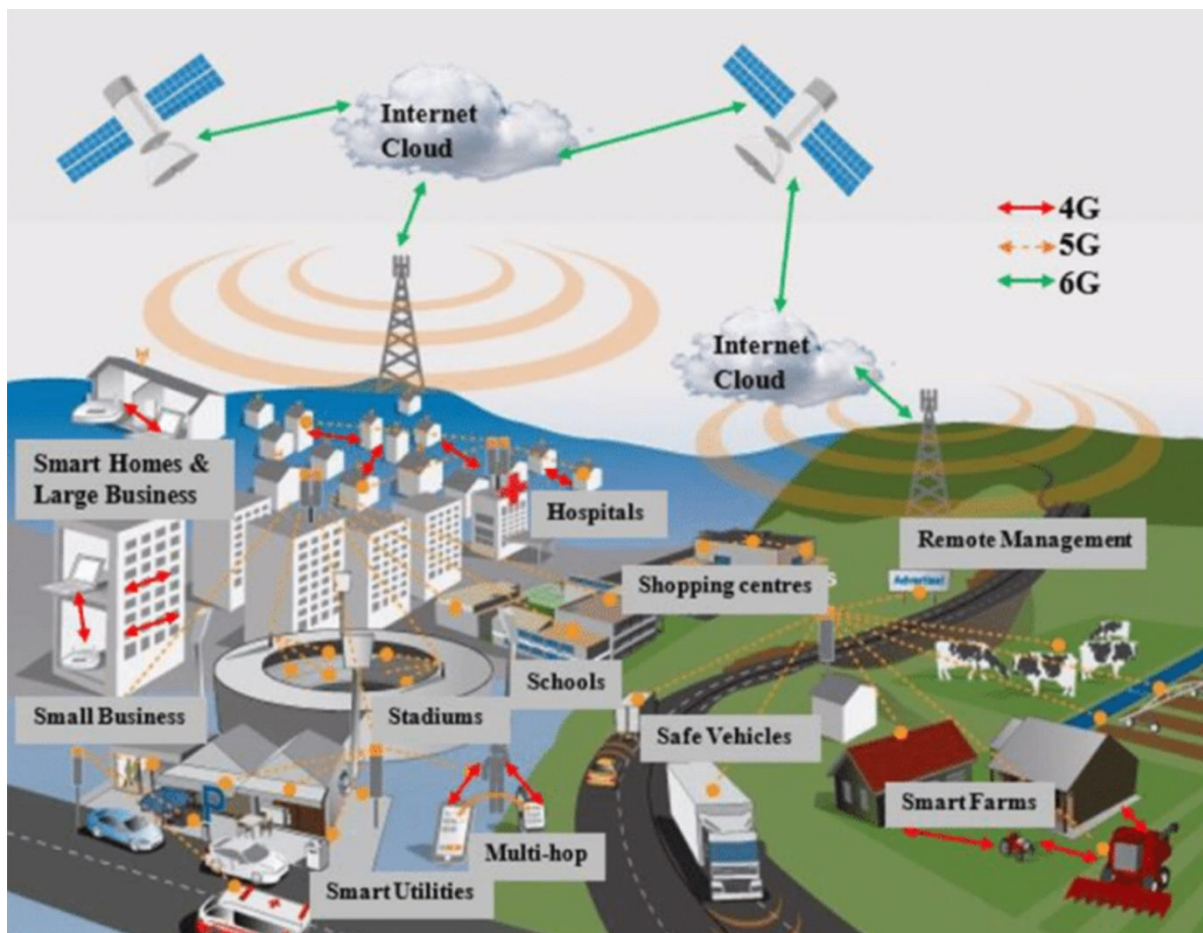


Figure 1.1- 1: Network Architecture of 4G, 5G and 6G

However, the inherent complexity of 5G/6G networks, especially in densely populated urban environments and massive IoT deployments, poses significant challenges to network resource allocation, traffic management, and energy efficiency. The dynamic and heterogeneous nature of these networks requires the development of sophisticated strategies to optimize performance while minimizing resource consumption. Conventional optimization methods, which rely on static rules or simplified models, are insufficient for addressing the real-time requirements and variability present in next-generation networks. As a result, there is a growing need for more intelligent, adaptive, and scalable approaches.

Artificial Intelligence (AI), particularly machine learning (ML) techniques, has emerged as a promising solution to these challenges. By leveraging data-driven models, AI can provide intelligent decision-making capabilities to manage network resources dynamically. Specifically, Reinforcement Learning (RL), which allows agents to learn optimal policies through interaction with the environment, has demonstrated significant potential for resource allocation and traffic management in communication networks [4].

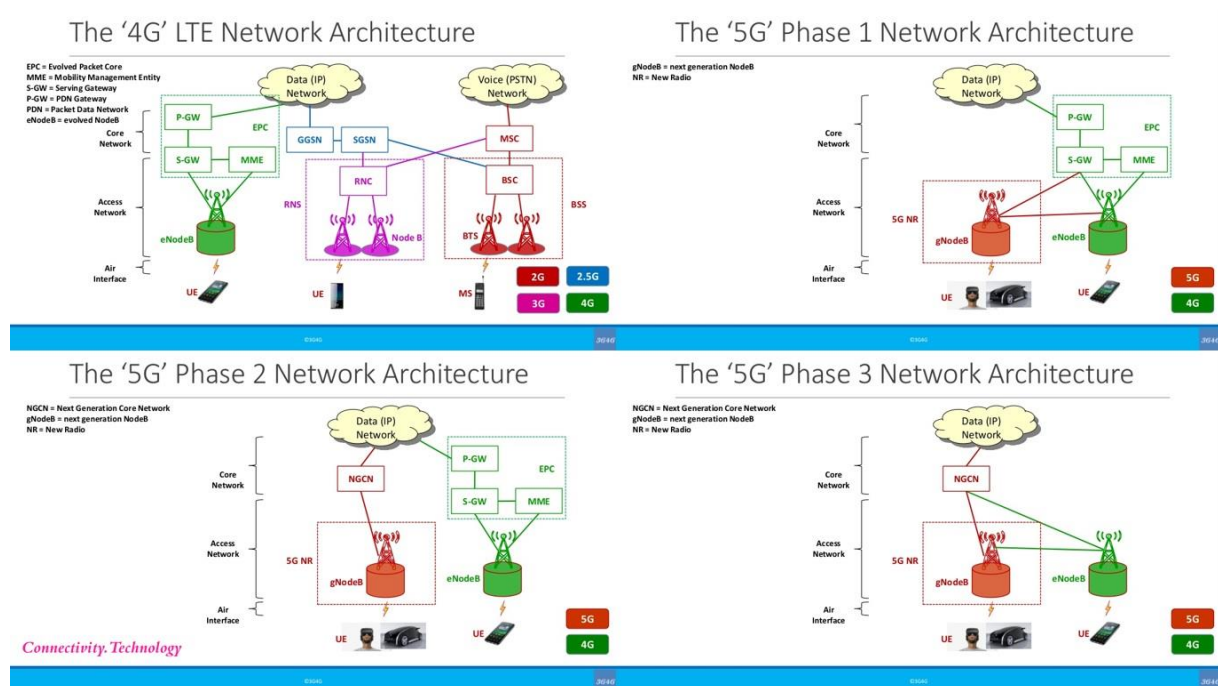


Figure 1.1- 2: Wireless Architecture of 4G and 5G Network [10]

In particular, Hierarchical Multi-Agent Reinforcement Learning (H-MARL), a variant of RL, is well-suited for large-scale networks where multiple agents must cooperate or compete to achieve system-wide goals [5]. Another critical area where AI can enhance network optimization is transfer learning. Transfer learning enables models trained in one domain or

scenario to be adapted and reused in different but related environments, reducing the need for extensive data collection and training in every new deployment [6]. This is particularly useful in dynamic 5G/6G networks, where environmental conditions and user behaviour can change rapidly. Additionally, federated learning, a distributed approach where models are trained locally on edge devices and aggregated centrally without sharing raw data, offers an efficient and privacy-preserving solution for large-scale IoT systems [7]. Energy efficiency is another major concern in the deployment of next-generation networks. As the number of connected devices continues to grow exponentially, reducing the energy consumption of network operations becomes imperative. AI-driven techniques, such as reinforcement learning and federated learning, offer opportunities to optimize energy use by enabling more intelligent allocation of resources and reducing redundant or inefficient processes [8]. Moreover, Explainable AI (XAI) has become a crucial component in AI-driven network management, particularly for ensuring transparency and trustworthiness in critical systems. In a highly complex and dynamic network like 5G/6G, where decisions impact millions of users and devices, it is essential to understand and trust the actions of AI models. Explainability ensures that network operators and stakeholders can interpret the decisions made by AI models, improving both the reliability and accountability of AI-driven optimizations [9].

In this dissertation, we aim to explore how AI, specifically H-MARL, transfer learning, federated learning, and XAI, can be used to dynamically optimize 5G/6G networks. By addressing challenges related to resource allocation, traffic management, and energy efficiency, this research seeks to advance the state-of-the-art in AI-driven network optimization, with a focus on scalable and efficient deployment in dense urban areas and massive IoT environments.

## **1.2 Problem Statement**

As 5G networks continue to evolve and the transition to 6G gains momentum, wireless communication networks are expected to support a massive scale of connected devices, unprecedented traffic loads, and diverse service requirements. These advancements bring about new challenges that existing network optimization methods struggle to address effectively, particularly in dense urban environments and massive Internet of Things (IoT) deployments. To meet the demands of these next-generation networks, there is an urgent need

for intelligent, scalable, and adaptable solutions that go beyond traditional optimization techniques.

5G/6G networks are characterized by their dynamic nature, with highly variable traffic loads, diverse Quality of Service (QoS) requirements, and increasing levels of user mobility. Efficiently allocating resources—such as spectrum, power, and computational capacity—is crucial for maintaining network performance and ensuring that all users and devices receive the appropriate levels of service. However, traditional resource allocation methods, such as centralized control or heuristic-based techniques, are often static or semi-static, making them insufficient for the real-time, adaptive needs of modern networks. The problem lies in the inherent complexity and heterogeneity of these networks, where multiple services with distinct latency, reliability, and bandwidth requirements must be managed simultaneously. Existing approaches fail to fully leverage the potential of decentralized and intelligent decision-making, which could significantly improve resource allocation across multiple network layers and devices. Therefore, there is a need for a scalable and adaptive solution capable of handling this complexity while optimizing resource allocation dynamically.

In dense urban environments, network congestion and bottlenecks are common issues due to the high concentration of users and devices, as well as the varying nature of traffic patterns. Managing network traffic efficiently in such environments is critical to avoiding congestion, reducing latency, and ensuring high levels of network reliability. Current traffic management approaches often rely on predefined routing and load-balancing strategies that are unable to adapt to real-time changes in traffic flow. This can result in inefficient utilization of network resources, congestion in certain areas, and overall degradation of network performance. The dynamic nature of traffic in urban networks requires an intelligent solution that can adapt to changing traffic patterns in real-time and optimize routing and load balancing accordingly. Thus, the development of AI-driven traffic management strategies that can operate in real-time and dynamically adjust to traffic conditions is a critical challenge that needs to be addressed.

Massive IoT deployments, particularly in the context of 5G and future 6G networks, introduce significant energy efficiency challenges. IoT devices, often battery-powered and resource-constrained, are expected to operate for extended periods without frequent recharging. As the number of connected IoT devices continues to grow exponentially, ensuring energy-efficient operation becomes critical to prolonging device lifetimes and

reducing the overall environmental impact of the network. Traditional energy optimization techniques tend to be rigid and centralized, which makes them less suited for the decentralized and large-scale nature of IoT networks. Furthermore, these methods often fail to take advantage of real-time data and dynamic conditions to optimize energy consumption. Addressing energy efficiency in massive IoT deployments requires more sophisticated methods that can dynamically adjust network parameters and device operations based on real-time conditions, while minimizing energy usage without compromising performance. Hence, the need for AI-driven, decentralized energy optimization solutions that can scale effectively across large numbers of devices is a key problem.

While AI-driven optimization techniques have shown great promise in addressing the challenges of resource allocation, traffic management, and energy efficiency, there remains a significant barrier to their widespread adoption in critical network environments: the lack of transparency and explainability in AI models. AI algorithms, particularly those based on deep learning and reinforcement learning; often operate as "black boxes," making it difficult for network operators and administrators to understand the rationale behind the decisions made by these models. This lack of transparency can lead to mistrust and resistance to the adoption of AI in real-world network management, especially in situations where critical decisions impact millions of users or devices. Ensuring that AI-driven decisions are interpretable and explainable is essential for building trust in AI systems and ensuring that network operators can validate the correctness and fairness of AI-driven optimizations. The problem lies in developing Explainable AI (XAI) techniques that can provide meaningful insights into the decision-making processes of complex AI models while maintaining the performance and scalability required for large-scale network optimization.

Finally, any solution designed for optimizing 5G/6G networks must be scalable and adaptable to real-world conditions. Networks in urban areas and large-scale IoT deployments are characterized by their dynamic nature, with frequent changes in traffic patterns, user behavior, and environmental conditions. Traditional network optimization methods often lack the flexibility to adapt to these rapidly changing conditions, leading to suboptimal performance. AI-driven solutions, while promising, face the challenge of scaling to real-world networks with millions of users and devices, each with different resource requirements and operational constraints. Moreover, the ability to adapt to new network conditions without the need for extensive retraining is crucial for maintaining network performance over time. This requires

the integration of techniques such as transfer learning, which allows AI models to generalize their knowledge across different network scenarios, reducing the need for retraining in each new environment. Thus, achieving scalability and adaptability in AI-driven network optimization frameworks remains a key challenge.

## **1.3 Research Objectives**

### **1.3.1 General Objective**

The main objective of this research is to design, develop, and evaluate AI-driven approaches that optimize 5G/6G networks, focusing on three key aspects: resource allocation, traffic management, and energy efficiency in dense urban environments and massive IoT deployments.

### **1.3.2 Specific Objectives**

- To develop an H-MARL framework that improves resource allocation in 5G/6G networks.
- To explore how agents can dynamically adjust their strategies to changing traffic patterns and user demands while maximizing overall network performance in terms of latency, throughput, and spectral efficiency.
- To develop traffic management strategies using AI models that are specifically tailored for dense urban networks.
- To design energy-efficient algorithms that leverage H-MARL and federated learning to dynamically adjust network parameters and device activity in real-time, thus reducing unnecessary energy consumption while maintaining high levels of performance.
- To develop XAI techniques that make the AI-driven optimization process in 5G/6G networks more interpretable.
- to evaluate the proposed AI-driven optimization framework in simulation environments, specifically focusing on dense urban networks and large-scale IoT deployments.

## 1.4 Scope of the Dissertation

This dissertation investigates the application of advanced AI techniques, including Hierarchical Multi-Agent Reinforcement Learning (H-MARL), transfer learning, federated learning, and Explainable AI (XAI), to optimize 5G/6G networks in dense urban environments and massive IoT deployments. The focus is on enhancing key network performance areas: resource allocation, traffic management, and energy efficiency. The research aims to address the challenges that traditional optimization methods face in these next-generation networks and provide scalable, intelligent solutions suitable for the increasing complexity of wireless communication systems.

The scope of this dissertation covers several critical aspects of next-generation wireless networks, as described below:

### 1.4.1 AI-Driven Resource Allocation in 5G/6G Networks

Resource allocation is one of the most significant challenges in 5G/6G networks, particularly in environments with high traffic variability and heterogeneous requirements. In such networks, optimizing the use of spectrum, power, and other resources is key to maintaining efficient and reliable communication. Traditional centralized or rule-based resource management approaches often fail to provide the flexibility required to handle dynamic and diverse network conditions.

This dissertation explores the use of H-MARL as a solution to the complexity of resource allocation in 5G/6G networks. H-MARL provides a decentralized approach where multiple agents learn to optimize resource allocation based on local network conditions and their interactions with neighbouring agents. The dissertation will examine how these agents can collaborate to achieve overall system optimization, focusing on performance metrics such as spectral efficiency, latency, and throughput. The study also explores how hierarchical structures in MARL can allow agents to manage resources at both the macro and micro levels, improving overall scalability and adaptability in large-scale networks.

### **1.4.2 Traffic Management in Dense Urban Environments**

Dense urban environments represent one of the most challenging use cases for next-generation networks, where high user densities and complex traffic patterns can easily lead to congestion and degraded performance. Efficient traffic management is essential to ensure a seamless user experience and maintain optimal network conditions. Traditional traffic management solutions, which rely on static routing and load balancing, are often unable to cope with the real-time, dynamic nature of traffic in dense urban networks.

This dissertation delves into AI-driven traffic management, leveraging H-MARL to dynamically manage network traffic. By enabling agents to learn traffic patterns and anticipate network congestion, AI models can significantly enhance traffic routing and load distribution across network nodes. The focus will be on developing models that can adapt to the constantly changing traffic demands in dense urban areas and testing their effectiveness in reducing congestion and improving the quality of service (QoS) for end users.

Additionally, transfer learning will be explored to ensure that traffic management models can quickly adapt to new environments, reducing the need for re-training in scenarios with different traffic dynamics. This is particularly important for ensuring scalability and adaptability in diverse urban contexts.

### **1.4.3 Energy Efficiency Optimization for Massive IoT Deployments**

With the massive growth of IoT devices in the 5G/6G era, energy efficiency becomes a critical issue, particularly for battery-powered devices. Managing energy consumption while ensuring reliable communication is a significant challenge in IoT networks, where traditional optimization methods are not efficient or scalable enough to handle the vast number of connected devices.

This research explores AI-driven approaches to energy efficiency in massive IoT deployments, focusing on how H-MARL can dynamically optimize energy use across the network. By allowing agents to learn when and how to activate or deactivate devices and adjust network parameters, H-MARL can significantly reduce unnecessary energy consumption. The dissertation will also investigate the potential of federated learning to

improve energy efficiency in distributed IoT environments, where centralized models may be impractical due to the size and distribution of devices.

This section of the research will focus on balancing the trade-off between energy consumption and network performance, ensuring that energy savings do not come at the cost of degraded service or network reliability.

#### **1.4.4 Explainable AI for Network Optimization**

While AI techniques offer powerful tools for optimizing 5G/6G networks, the complexity and opacity of these models can make it difficult for network operators to understand the reasoning behind AI-driven decisions. This is particularly problematic in critical network environments, where transparency and trust are essential for wide-scale adoption of AI solutions.

This dissertation will explore the integration of Explainable AI (XAI) techniques into the network optimization framework. XAI methods will be developed to ensure that AI-driven decisions in resource allocation, traffic management, and energy efficiency are interpretable and transparent to network administrators. The research will investigate how XAI models can provide explanations for specific actions or policies chosen by AI agents, enhancing trust and accountability in AI-driven network management. By making the AI decision-making process more interpretable, this work aims to facilitate the adoption of AI in real-world network operations and ensure that network optimization decisions can be easily understood and justified by human operators.

#### **1.4.5 Evaluation in Simulation Environment**

The practical applicability of the proposed AI-driven solutions will be evaluated through extensive simulations environments representative of dense urban networks and massive IoT deployments. The evaluation will focus on assessing the performance of the proposed models in terms of key metrics such as network throughput, latency, spectral efficiency, energy consumption, and adaptability to changing network conditions.

Simulations will model realistic urban and IoT network environments, using parameters such as varying traffic loads, user mobility, and energy constraints to test the scalability and effectiveness of the proposed optimization techniques.

## 1.5 Research Questions

### 1.5.1 How can Hierarchical Multi-Agent Reinforcement Learning (H-MARL) be applied to optimize resource allocation in dynamic and heterogeneous 5G/6G networks?

- What are the appropriate reward functions and training mechanisms for H-MARL in the context of resource allocation?
- How can agents learn to manage resources effectively while balancing between local and global objectives?
- What impact does H-MARL have on key performance indicators (KPIs) such as spectral efficiency, throughput, and latency in large-scale 5G/6G networks?

### 1.5.2 How can AI-driven traffic management systems improve network performance in dense urban environments with variable traffic patterns?

- How can AI agents learn from historical traffic data to predict and adapt to future traffic conditions?
- How can transfer learning be applied to enable traffic management models to generalize across different urban environments with minimal retraining?
- What impact do AI-driven traffic management strategies have on reducing congestion and improving Quality of Service (QoS) in dense urban settings?

### 1.5.3 How can energy efficiency in massive IoT deployments be optimized using AI-driven approaches, particularly H-MARL and federated learning?

- How can agents in an H-MARL framework optimize energy efficiency while maintaining network reliability and QoS in massive IoT deployments?
- How can federated learning models be implemented to improve energy efficiency without compromising data privacy or increasing communication costs?
- What are the trade-offs between energy efficiency and network performance in AI-driven IoT networks?

#### **1.5.4 How can Explainable AI (XAI) techniques enhance transparency and trust in AI-driven 5G/6G network optimization?**

- What are the most effective XAI techniques for explaining AI decisions in the context of network optimization?
- How can explanations be generated in real-time for decisions made by reinforcement learning agents in dynamic network environments?
- What impact does XAI have on the trustworthiness and acceptance of AI-driven solutions by network operators and other stakeholders?

#### **1.5.5 What are the scalability and adaptability challenges in deploying AI-driven optimization techniques in real-world 5G/6G network environments?**

- How can AI-driven solutions scale to handle the complexity of real-world 5G/6G networks with millions of connected devices?
- How can transfer learning be used to improve the adaptability of AI models across different network environments?
- What are the practical challenges in deploying AI-driven solutions in live network environments, and how can they be overcome?

### **1.6 Contribution to Knowledge**

This research introduces a novel H-MARL framework specifically designed for dynamic resource allocation in 5G/6G networks. Traditional resource allocation methods often rely on centralized approaches that are inadequate for the highly dynamic and heterogeneous environments of next-generation networks. The proposed H-MARL framework addresses this limitation by decentralizing decision-making processes by enabling agents to make decisions based on local conditions while considering global objectives, the framework improves scalability and adaptability; and organizing agents in a hierarchical structure to incorporate both higher-level and lower-level agents to handle resource allocation at different scales. Higher-level agents focus on network-wide optimization, while lower-level agents manage local resources for individual users or devices. Extensive simulations demonstrate that the H-MARL framework significantly enhances spectral efficiency, reduces latency, and improves fairness in resource allocation compared to traditional centralized methods.

This research integrates transfer learning into AI-driven traffic management systems to enhance their adaptability across different urban environments. Traditional traffic management systems often require extensive retraining when deployed in new settings, which is resource-intensive and time-consuming. The transfer learning develops models that leverage knowledge from one urban environment to improve traffic management in another with minimal retraining. By fine-tuning pre-trained models, the proposed system adapts quickly to new traffic patterns and conditions, reducing deployment time and improving performance. Experiments show that the use of transfer learning reduces the need for extensive data collection and training, resulting in a more efficient and adaptable traffic management system. The application of transfer learning to traffic management systems is a significant advancement, allowing for rapid deployment and adaptation across diverse urban environments.

### AI-DRIVEN DYNAMIC OPTIMIZATION

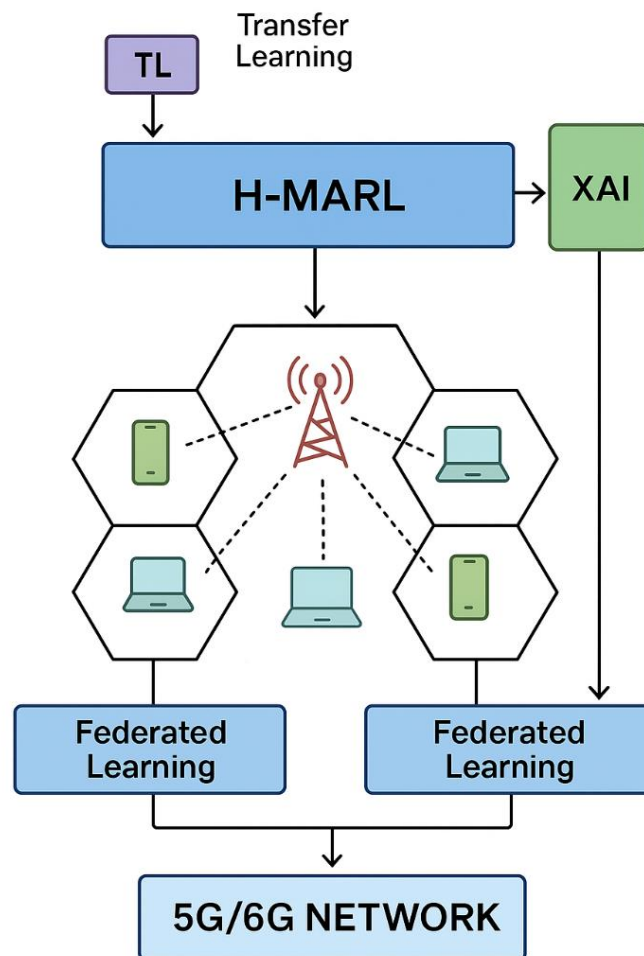


Figure 1.6- 1: Dynamic Optimization conceptual diagram

This dissertation demonstrates the use of federated learning to optimize energy efficiency in massive IoT deployments while preserving data privacy. Federated learning enables decentralized model training across devices without sharing raw data, addressing privacy concerns that are crucial for IoT applications. The research develops a federated learning framework that allows IoT devices to collaboratively train models for energy optimization while maintaining data privacy. The framework improves energy efficiency by enabling devices to make localized decisions on power management and transmission rates based on shared model updates. The federated learning approach shows a substantial reduction in energy consumption and improved device longevity while ensuring privacy and minimizing communication overhead. Federated learning provides a privacy-preserving solution for energy optimization in IoT networks, a critical advancement given the increasing concerns about data security and privacy in IoT applications.

The dissertation advances the field of Explainable AI (XAI) by developing techniques that enhance transparency and trust in AI-driven network optimization. This is essential for ensuring that network administrators and stakeholders can understand and validate AI-driven decisions. The research introduces novel XAI techniques to interpret decisions made by reinforcement learning agents, including feature importance analysis and real-time explanations. These techniques enable network operators to receive explanations for AI decisions as they occur, improving trust and facilitating better decision-making. The integration of XAI techniques demonstrates increased trust in AI systems, improved regulatory compliance, and enhanced operator understanding of network management decisions. The development of real-time, interpretable explanations for AI-driven network decisions represents a significant improvement in the transparency and usability of AI systems in critical network operations.

This research addresses key scalability and adaptability challenges associated with deploying AI-driven optimization techniques in real-world 5G/6G networks. The dissertation proposes solutions to effectively scale AI models and adapt them to dynamic network environments. The research employs hierarchical learning and federated learning to manage large-scale deployments and diverse conditions, reducing computational and communication burdens. Transfer learning techniques are used to improve model adaptability across different environments with minimal retraining. The proposed solutions effectively handle the scale and complexity of real-world networks, demonstrating improved performance and

adaptability in practical scenarios. The approach provides scalable and adaptable solutions for deploying AI-driven optimization techniques in complex, large-scale network environments, addressing critical challenges faced by current systems.

The contributions of this dissertation represent significant advancements in the application of AI techniques to optimize 5G/6G networks. By developing and integrating novel frameworks and methods, this research addresses key challenges in resource allocation, traffic management, energy efficiency, and transparency, paving the way for more efficient, adaptable, and transparent network operations. These contributions enhance the field's understanding of how AI can be leveraged to manage the complexities of next-generation networks and improve overall network performance.

## **1.7 Organization of the Dissertation**

This dissertation is organized into several chapters, each addressing a specific aspect of AI-driven optimization for 5G/6G networks. The structure is designed to present a comprehensive exploration of the research topic, starting from foundational concepts and gradually delving into advanced techniques and practical applications. The first Chapter provides an introduction, including the background, statement of the problem, research questions, research objectives, scopes, contributions to knowledge and significance of the study. Chapter two reviews relevant literature on 5G/6G network optimization AI techniques in telecommunications and dynamic resource management strategies. Chapter three outlines the methodology for developing and testing the AI-driven optimization framework. Chapter Four explains the implementation procedure and the experimental setup. The fifth Chapter presents the results of the framework's performance evaluation, comparing it with baseline methods. Chapter six discusses the findings, implications, and potential future research directions based on the study's outcomes. The seventh Chapter explains the challenges, open issues and future directions of the research. The last Chapter concludes the work.

This structure ensures a logical flow of information, from the introduction and background to the detailed exploration of techniques, results, and implications, culminating in a comprehensive conclusion. Each chapter builds upon the previous one, providing a coherent narrative that addresses the research questions and contributes to the advancement of knowledge in AI-driven optimization of 5G/6G networks.

## CHAPTER 2: LITERATURE REVIEW

This chapter provides a comprehensive review of the literature relevant to the research topic. It covers the evolution and current state of 5G/6G networks, explores AI techniques for network optimization, discusses the challenges in resource allocation and traffic management, examines methods for optimizing energy efficiency in IoT networks, and identifies gaps in existing research that this dissertation aims to address.

### 2.1 Overview of 5G/6G Networks

The growth from fifth generation (5G) to sixth generation (6G) wireless communication networks represents a paradigm shift in network architecture, performance capabilities, and application domains. 5G networks, standardized by Third Generation Partnership Project (3GPP) Release 15 and beyond, adopt a service-based architecture (SBA) that supports eMBB, mMTC, and URLLC through enabling technologies such as massive Multiple-Input Multiple-Output (MIMO), millimeter-wave (mmWave) spectrum utilization, and network slicing [11][12]. The integration of edge computing, software-defined networking (SDN), and network function virtualization (NFV) further enhances 5G's flexibility and scalability [13]. However, 5G still faces challenges, including energy efficiency, spectrum scarcity, interoperability, and Quality of Service (QoS) assurance in dense urban and heterogeneous network deployments [14]. Building upon 5G, 6G networks, anticipated for deployment around 2030, aim to provide data rates up to 1 Tbps, sub-millisecond latency, and ubiquitous intelligence through native integration of artificial intelligence (AI) and machine learning (ML) in network management [15][16]. Key architectural enhancements envisioned for 6G include terahertz (THz) communications, reconfigurable intelligent surfaces (RIS), cell-free massive MIMO, integrated sensing and communication (ISAC), and space-air-ground-sea integrated networks (SAGSN) [17][18]. Despite its potential, 6G will face significant challenges such as ultra-high energy demands, hardware complexity for THz bands, security vulnerabilities in AI-native infrastructures, and standardization across heterogeneous global ecosystems [19][20]. Addressing these challenges requires innovative approaches to resource allocation, traffic management, and energy optimization, making AI-driven techniques such as Hierarchical H-MARL, TL, FL and XAI essential for future network resilience and efficiency.

### 2.1.1 5G Network Architecture

The 5G network architecture is fundamentally built to provide unprecedented performance in terms of throughput, latency, device density, and reliability compared to previous generations. At its core, 5G integrates a Next Generation Radio Access Network (NG-RAN) and a 5G Core Network (5GC), with both domains designed for cloud-native deployment and virtualization [11][12]. NG-RAN consists of gNode Base Stations (gNBs) that support new spectrum bands, including sub-6 GHz and millimeter Wave (mmWave) frequencies, enabling high-capacity and high-speed connectivity [21]. A major architectural change is the introduction of centralized and distributed units within the gNB: the Central Unit (CU) manages higher-layer functions such as Radio Resource Control (RRC), while the Distributed Unit (DU) handles lower-layer functions closer to the physical hardware for real-time processing [22]. This split architecture reduces front-haul latency and facilitates more flexible deployments, such as centralized RAN (C-RAN) and cloud RAN solutions [23]. The 5GC adopts a Service Based Architecture (SBA) in which each core network function is virtualized and can be deployed as a microservice on commercial off-the-shelf hardware [24]. Key functions include the Access and Mobility Management Function (AMF) for user registration and mobility, the Session Management Function (SMF) for managing user sessions and IP address allocation, and the User Plane Function (UPF) for routing and forwarding user data [14]. The architecture also includes the Policy Control Function (PCF) for dynamic policy management, and the Network Slice Selection Function (NSSF) for assigning users to the most suitable network slice based on service requirements [25]. These network functions interact through service-based interfaces using Hyper Text Transfer Protocol/2 (HTTP/2) and RESTful Application Programming Interfaces (APIs), allowing for agile upgrades, scalability, and easier integration of third-party services [26].



bands, ensuring smooth migration and interoperability [33]. However, despite these advancements, 5G faces challenges such as energy consumption in dense deployments, security risks in virtualized and cloud-native infrastructures, and complexity in orchestrating multiple slices [34][35]. These challenges underscore the importance of AI-driven network optimization techniques to manage 5G's complexity and prepare for the evolution toward 6G systems [2].

### **2.1.2 6G Network Vision and Architecture**

The sixth generation (6G) of wireless communication systems is envisioned as a transformative leap beyond 5G, aiming to support unprecedented performance requirements such as ultra-high data rates (up to 1 Tbps), sub-millisecond end-to-end latency, extreme reliability, and massive connectivity for a fully intelligent, connected world [36]. The vision for 6G extends the scope of mobile networks beyond communication to encompass ubiquitous sensing, integrated intelligence, and seamless human-machine interaction [15]. This paradigm shift will be driven by emerging applications such as immersive extended reality (XR), holographic telepresence, tactile Internet, digital twins, pervasive AI services, and massive Internet of Things (mIoT) deployments at a global scale [20]. Additionally, 6G aims to enable networked intelligence where AI is not just an application but a native and integral component of network design, optimization, and management [37].

The 6G architecture is expected to build upon the service-based and cloud-native foundation established by 5G but will be enhanced by AI-native design principles. Unlike 5G, where AI is mainly an auxiliary tool for optimization, in 6G it will be deeply embedded in the control, orchestration, and real-time decision-making processes of the network [2]. The architecture will consist of multiple integrated domains: the user domain, the radio domain, the network and service orchestration domain, and the computing domain. The radio domain will extend into terahertz (THz) frequency bands (0.1–10 THz) and visible light communication (VLC) to achieve extremely high bandwidths [38]. To overcome propagation challenges in these bands, 6G will employ reconfigurable intelligent surfaces (RIS), ultra-massive MIMO arrays, and advanced beamforming to dynamically shape and control radio environments [39]. The core network in 6G will evolve into a fully distributed and cloud-edge-fog integrated system that leverages edge intelligence for ultra-low latency processing. This will allow real-time

analytics, AI inference, and network function execution at the edge, bringing computational resources closer to the data sources [40].

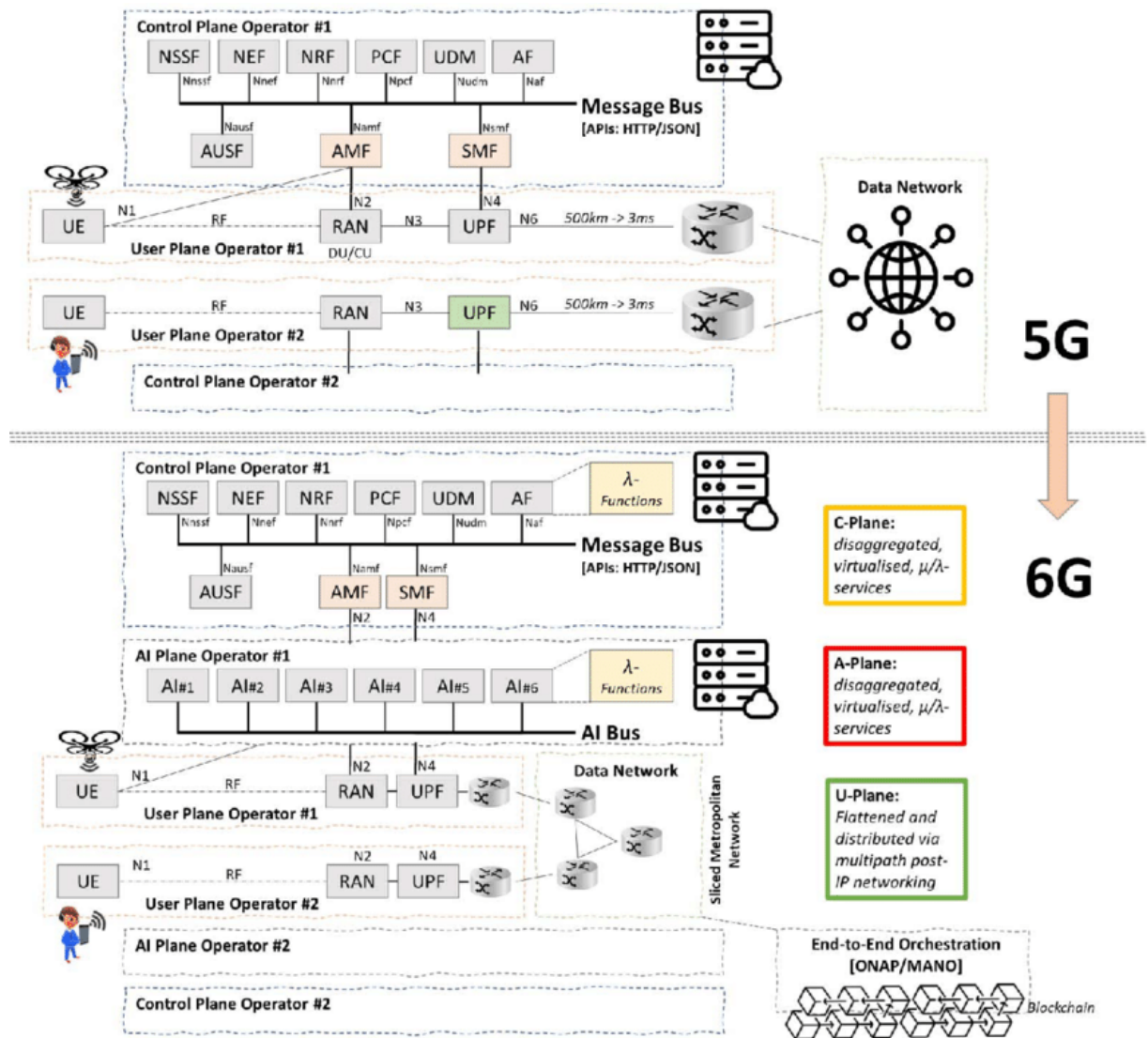


Figure 2.1.2- 1: 5G to 6G high level architecture [45]

Furthermore, network slicing will evolve into dynamic, intent-based network slicing, where slices are created, modified, and terminated in real time based on Service-Level Agreements (SLAs) and application requirements [41]. 6G will also integrate space-air-ground-sea networks (SAGSN) by incorporating low Earth orbit (LEO) satellite constellations, unmanned aerial vehicles (UAVs), and maritime communications into a unified framework to provide global coverage and service continuity [42]. Security, trust, and privacy will be foundational to 6G architecture. Technologies such as quantum-resistant cryptography, distributed ledger technology (DLT) for decentralized trust, and zero-trust security

frameworks will be integrated to safeguard communication against evolving threats [43]. The 6G vision also embraces sustainability by targeting energy efficiency improvements through AI-driven optimization, green spectrum management, and energy harvesting technologies [44]. Overall, the 6G architecture will represent a convergence of communication, computation, control, and sensing, enabling the realization of a truly intelligent and ubiquitous network ecosystem.

## 2.2 Resource Allocation Challenges in 5G/6G Networks

Resource allocation in 5G and 6G networks is a complex and dynamic problem due to the highly heterogeneous service requirements and the explosive growth of connected devices. Unlike previous generations, 5G/6G networks must simultaneously cater to eMBB, URLLC, and mMTC. Each of these service categories imposes distinct performance constraints such as high throughput, low latency, reliability, or massive connectivity, making it difficult to design a one-size-fits-all allocation strategy. Furthermore, the limited spectrum resources, coupled with increasing user mobility and demand for ubiquitous coverage, aggravate the challenges of allocating radio resources fairly and efficiently [14], [1].

Another critical challenge is the interference management and resource allocation in ultra-dense heterogeneous networks. With the deployment of small cells, massive MIMO, and mmWave/THz communication, the system becomes more vulnerable to interference, channel uncertainty, and propagation impairments. Allocating spectrum, power, and time resources in such environments requires adaptive and context-aware solutions that can respond in real time to varying channel and traffic conditions [46]. Moreover, emerging paradigms like network slicing further complicate resource allocation by requiring isolation and customization of resources for different verticals, such as autonomous vehicles, industrial IoT, and Augmented Reality/Virtual Reality (AR/VR) applications [47]. Ensuring fairness while maximizing overall spectral and energy efficiency thus becomes a critical optimization problem.

Energy efficiency and sustainability also play a central role in resource allocation challenges for next-generation networks. With the proliferation of massive IoT deployments and high-density urban scenarios, 5G/6G must minimize energy consumption while guaranteeing SLAs. This introduces trade-offs between energy savings and performance metrics such as

throughput, latency, and coverage. Furthermore, the adoption of advanced technologies such as cell-free massive MIMO, integrated sensing and communication (ISAC), and reconfigurable intelligent surfaces (RIS) requires novel resource allocation schemes that jointly optimize energy, spectrum, and hardware utilization [15] [48]. Traditional centralized optimization methods are insufficient in such dynamic and large-scale scenarios, driving the adoption of artificial intelligence (AI)-driven approaches such as Deep Reinforcement Learning (DRL) and multi-agent reinforcement learning (MARL) to achieve adaptive, scalable, and context-aware resource management [49].

### **2.3 Traffic Management and Quality of Service (QoS)**

Traffic management and QoS provisioning are at the core of network performance in 5G/6G systems. Unlike previous generations, 5G introduces the concept of network slicing, which enables multiple virtualized networks to coexist on shared physical infrastructure while guaranteeing isolation and SLAs [50][51]. This is particularly important in scenarios where mission-critical services such as autonomous driving or industrial automation must operate alongside less demanding applications such as video streaming. However, ensuring QoS in such diverse and dynamic environments is highly challenging.

The integration of software-defined networking (SDN) and network function virtualization (NFV) has enabled centralized traffic orchestration, dynamic path allocation, and programmable QoS control [51][53]. Techniques such as deep packet inspection, adaptive queue management, and dynamic prioritization have been proposed to address congestion, jitter, and latency. Nevertheless, even under low congestion conditions, packet queuing introduces delays that may compromise time-sensitive applications [53]. Furthermore, edge computing integration adds another layer of complexity, as computational and storage resources must be allocated jointly with network bandwidth to sustain low-latency and high-reliability requirements [55]. In this regard, traffic management strategies must evolve toward AI-driven predictive control mechanisms to anticipate load variations and optimize QoS in real time.

## 2.4 Energy Efficiency and Green Networking

Energy efficiency is a fundamental design criterion for 5G and future 6G networks, as the rapid densification of small cells, deployment of massive MIMO, and increasing reliance on computationally intensive AI-driven algorithms significantly increase power consumption [8] [54]. Studies have shown that small cell deployments can lead to hundreds of watts of energy consumption per site, raising sustainability concerns as networks expand [54]. Thus, energy-efficient network design is essential to reduce operational costs and mitigate environmental impacts.

Current green networking strategies focus on dynamic resource management, energy-aware scheduling, sleep modes for BSs, and virtualization-based optimization to reduce energy wastage [52][57]. Network slicing also contributes to sustainability by ensuring that resources are allocated based on service demands, minimizing over-provisioning [50]. Beyond 5G, 6G envisions a holistic approach to green networking, where AI orchestrates energy-aware operations across all layers of the system. For instance, predictive algorithms can proactively activate or deactivate BSs, adjust transmission power, and steer traffic to minimize overall energy use [46][57].

Emerging solutions such as Intelligent Reflecting Surfaces (IRS) and reconfigurable metasurfaces promise hardware-level energy savings by reducing the need for active transmissions [56]. Similarly, energy harvesting from solar, Radio Frequency (RF), or thermal sources, alongside wireless power transfer, is being investigated as a means to power ultra-dense and IoT-heavy deployments [46]. These advancements indicate that green networking in 6G will not only improve energy efficiency but also align mobile communications with global sustainability goals.

## 2.5 Optimization Techniques in 5G/6G Networks

Optimization in 5G and emerging 6G networks is a critical enabler for achieving high performance, low latency, massive connectivity, and energy efficiency in increasingly complex wireless ecosystems. Traditional optimization methods, such as heuristic and rule-based schemes, are insufficient to handle the dynamic, high-dimensional, and heterogeneous nature of modern mobile networks. As a result, advanced optimization approaches have been

integrated, including mathematical programming, metaheuristics, and artificial intelligence (AI)-driven algorithms [14]. In the 5G domain, optimization challenges span multiple layers, from radio resource allocation and user association to traffic routing, power control, and network slicing. Techniques like convex optimization, game theory, and mixed-integer linear programming have been applied to solve resource allocation and scheduling problems under diverse quality-of-service (QoS) constraints [58]. In resource allocation, methods such as linear programming, integer programming, and convex optimization have been extensively applied to allocate bandwidth, power, and spectrum resources to maximize throughput or fairness [48]. For traffic management, classical scheduling algorithms like Round-Robin (RR), Proportional Fair (PF), and Weighted Fair Queuing (WFQ) have been used to ensure QoS (Quality of Service) differentiation across users [59]. Energy efficiency in earlier cellular generations was often improved using sleep mode techniques, cell zooming, and static power control algorithms, which aimed to minimize energy consumption while maintaining coverage [60]. However, these approaches struggle in highly dynamic environments like 5G/6G, where real-time adaptability is critical due to varying user demands and heterogeneous network deployments. Furthermore, distributed and decentralized approaches, such as multi-agent reinforcement learning (MARL), have gained attention for handling large-scale deployments where centralized optimization becomes computationally prohibitive [61].

In 6G, optimization is expected to become even more AI-centric, leveraging DRL, TL, and FL to enable adaptive, context-aware, and privacy-preserving decision-making in ultra-dense and dynamic network environments [15]. The shift toward intelligent optimization is driven by new 6G paradigms, including terahertz communication, cell-free massive MIMO, RIS, and ISAC, all of which introduce novel variables and constraints [18]. Moreover, energy efficiency optimization in 6G is tightly linked to sustainability goals, prompting the adoption of green AI algorithms and joint communication-computation optimization strategies [62]. Traffic management optimization is also evolving to accommodate immersive applications requiring URLLC and mMTC enhancements [2].

Another important aspect is cross-layer optimization, which considers joint optimization across physical, media access control (MAC), and network layers to maximize end-to-end performance. In both 5G and 6G, this is achieved by combining optimization algorithms with predictive analytics to anticipate traffic patterns, mobility behavior, and interference

conditions [63]. Additionally, network slicing planning in 5G and 6G requires multi-objective optimization to allocate virtualized resources dynamically while meeting diverse slice-specific SLAs [25]. With the convergence of AI and optimization, XAI techniques are increasingly being integrated to improve transparency and trust in automated optimization processes [64]. Overall, the evolution from model-based optimization to AI-driven optimization reflects the increasing complexity, scale, and performance requirements of 5G and 6G systems, where adaptability and intelligence are paramount for achieving sustained network performance.

In centralized optimization, a single control entity—often the core network or a central cloud server—collects network-wide information and computes global optimization solutions [65]. This allows for globally optimal decisions but comes at the cost of high signaling overhead, latency, and potential bottlenecks. On the other hand, decentralized (distributed) optimization distributes decision-making to local network nodes, such as Base Stations (BSs) or edge servers, enabling faster responses and improved scalability [66]. While decentralized approaches enhance robustness and reduce latency, they may produce suboptimal solutions due to partial network state visibility. Hybrid approaches, including hierarchical optimization; attempt to merge the benefits of both paradigms by introducing multiple decision layers that coordinate between global and local objectives [61].

Optimizing 5G/6G networks requires careful consideration of Key Performance Indicators (KPIs) that measure system efficiency and user experience. Core KPIs include latency, which is critical for URLLC; throughput, measuring the data rate per user or cell; and spectral efficiency, representing the bit rate per unit bandwidth [67]. For energy efficiency, metrics such as Energy per Bit (J/bit) and Network Power Consumption (W) are used [68]. Additionally, packet loss ratio, jitter, and Quality of Experience (QoE) scores provide insights into service reliability and user satisfaction. In 6G research, novel KPIs like holographic data rate and AI inference latency are emerging to support advanced applications such as immersive XR and autonomous systems [15].

Dynamic optimization has become a cornerstone of research in wireless networks, particularly with the emergence of 5G and the vision for 6G, where dynamic and adaptive mechanisms are required to handle the complexity, heterogeneity, and stringent service requirements of modern communication systems. Traditionally, optimization in wireless networks has relied on mathematical programming techniques, which provided

mathematically sound solutions with performance guarantees. However, these approaches face scalability limitations in ultra-dense networks, where the number of devices, BSs, and resources grows exponentially. Moreover, classical optimization methods assume stationary models and often require complete knowledge of system dynamics, making them less effective under the high mobility, bursty traffic patterns, and uncertainty present in next-generation networks. To address these challenges, recent works have shifted toward data-driven and learning-based dynamic optimization, where policies are learned adaptively from system interactions rather than being pre-programmed. Metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been employed for resource allocation and routing due to their ability to handle non-convex and NP-hard problems [69]. Game-theoretic approaches have been used to model competitive resource sharing among multiple network entities [70]. With the advent of AI, DRL has emerged as a powerful method for dynamic resource allocation, capable of learning adaptive policies through interaction with the network environment [71]. Additionally, federated optimization and TL are increasingly leveraged to enable collaborative yet privacy-preserving optimization across distributed networks [72].

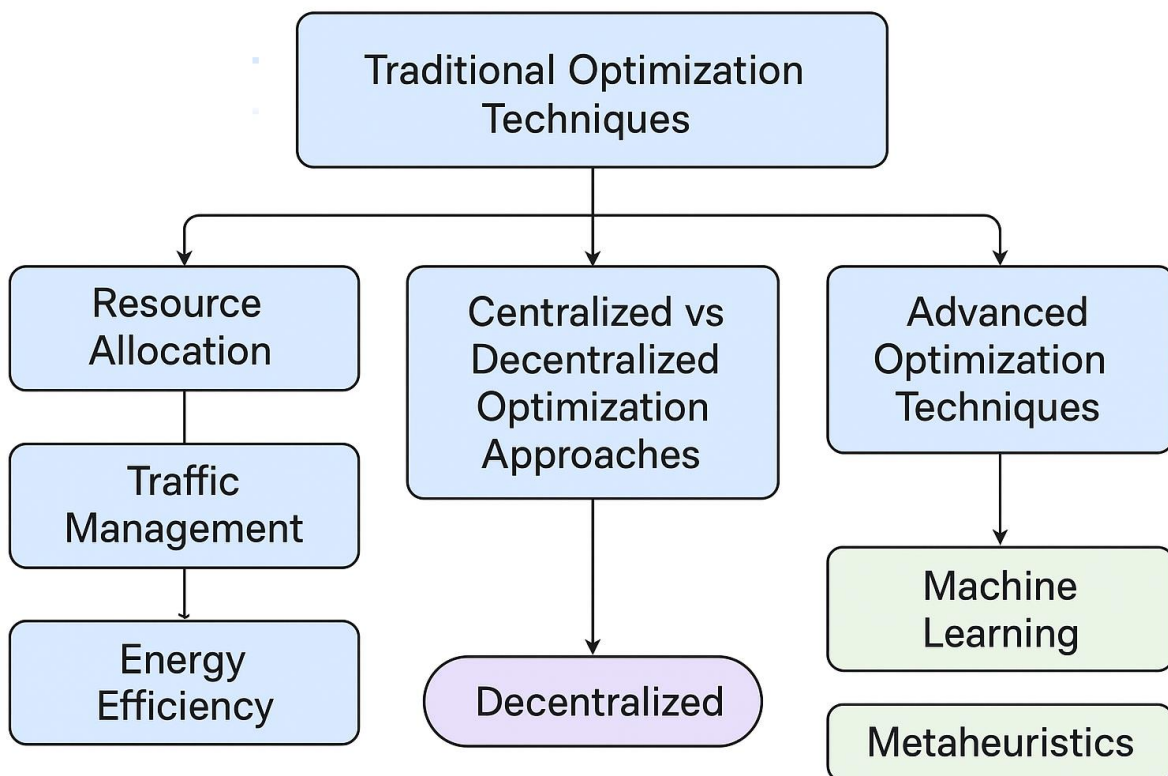


Figure 2.5- 1: Traditional Optimization Techniques

AI plays a transformative role in network optimization by enabling autonomous, data-driven, and predictive decision-making. In contrast to rule-based methods, AI models—particularly those based on Machine Learning (ML) and Deep Learning (DL)—can learn patterns from historical and real-time network data to optimize spectrum allocation, traffic routing, and power management [73]. Reinforcement Learning (RL) and MARL techniques allow multiple network agents to learn cooperative or competitive strategies for distributed optimization [74]. AI also enhances traffic prediction, user mobility forecasting, and QoE-aware scheduling, enabling proactive resource management [75]. In emerging 6G architectures, Explainable AI (XAI) is expected to play a critical role in making AI-driven optimization decisions interpretable, ensuring trustworthiness in safety-critical applications such as autonomous vehicles and remote surgery [76].

### **2.5.1 Greedy Heuristics (Round Robin, Proportional Fair)**

Greedy scheduling heuristics, such as Round Robin (RR) and Proportional Fair (PF), represent some of the earliest and most widely implemented approaches for wireless resource allocation. RR scheduling provides temporal fairness by sequentially allocating resources to users without relying on channel state information (CSI), making it computationally efficient and robust in homogeneous traffic environments [77]. However, RR does not exploit multi-user diversity, which reduces efficiency in scenarios with fluctuating channel conditions [78]. PF scheduling addresses this by incorporating both CSI and long-term throughput history, selecting users based on the ratio of their instantaneous rate to average throughput [79]. This approach balances fairness and spectral efficiency, often outperforming RR by up to 30% under realistic traffic models [80]. Nonetheless, PF is less effective in handling URLLC and heterogeneous service demands typical of 5G/6G networks, motivating enhancements such as QoS-aware PF, weighted PF, and multi-dimensional extensions [81].

### **2.5.2 Centralized DRL Approaches**

Centralized DRL methods frame resource allocation as a sequential decision-making problem managed by a single network-wide controller. Algorithms such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Deep Deterministic Policy Gradient (DDPG) have shown strong adaptability compared to heuristic baselines, especially in high-dimensional and dynamic environments [82]. Centralized DRL has been demonstrated to outperform PF

and similar heuristics in terms of energy efficiency and spectral utilization, owing to its ability to learn implicit trade-offs and handle non-convex optimization landscapes [83]. Despite these advantages, scalability remains a critical limitation. As the number of users, BSs, or subcarriers increases, the state-action space grows exponentially, raising training costs and hindering generalization [84]. To address this, research has proposed decomposition methods, policy warm-starting via imitation learning, and safe RL techniques that ensure QoS guarantees [85]. However, centralized DRL is often impractical for large-scale 6G deployments without hierarchical or distributed enhancements.

### **2.5.3 Non-Hierarchical MARL Models**

Non-hierarchical MARL distributes decision-making across multiple agents, such as per-user, per-cell, or per-resource block controllers, reducing reliance on a single central entity. This decentralized nature offers scalability and robustness, particularly in large-scale wireless systems [86]. Approaches include independent Q-learning, policy gradient methods, and Centralized Training With Decentralized Execution (CTDE) [87]. MARL has been successfully applied to spectrum sharing, power allocation, and Device-to-Device (D2D) management, enabling agents to cooperate for maximizing throughput or minimizing interference [88]. Actor-critic frameworks and value decomposition networks, for instance, have demonstrated near-optimal performance in IoT and heterogeneous deployments [89]. Nonetheless, non-hierarchical MARL suffers from key challenges such as non-stationarity—where changing policies of agents affect the environment—and credit assignment in cooperative tasks [90]. Techniques like reward shaping, parameter sharing, and inter-agent communication mitigate these issues but increase computational and signaling overhead [91]. Thus, while MARL provides better scalability than centralized DRL, its convergence and fairness properties remain unresolved in ultra-dense 6G environments.

### **2.5.4 Mathematical Programming**

Mathematical programming provides a model-driven framework for centralized resource optimization in wireless systems. Convex optimization, particularly Lagrangian relaxation and dual decomposition, has enabled amenable solutions for continuous allocation problems under convex conditions [92]. Foundational works such as Boyd and Vandenberghe's Convex Optimization established the use of linear and convex formulations in wireless

scheduling and power allocation [93]. Extensions to Mixed-Integer Linear Programming (MILP) and Mixed-Integer Nonlinear Programming (MINLP) have addressed more complex allocation tasks such as joint subcarrier assignment and power control [94]. While exact methods like branch-and-bound provide optimal solutions, their exponential complexity makes them unsuitable for large-scale real-time applications [95]. Approximation strategies, relax-and-round heuristics, and column generation have been employed to enhance scalability [96]. The strength of mathematical programming lies in its interpretability and optimality guarantees, but its reliance on precise models of traffic and CSI reduces its robustness in practical, uncertain environments. Consequently, recent trends favor hybrid frameworks that integrate mathematical optimization with machine learning to combine accuracy with adaptability [97].

**Table 2.5.4- 1: Comparative summary of Optimization Approaches**

Approach	Complexity	Scalability	Performance Trade-offs	References
Greedy Heuristics (RR, PF)	<b>Very low</b>	<b>High (easily deployable at scale)</b>	<b>RR: fair but inefficient; PF: balances throughput and fairness but weak in QoS diversity</b>	[77]-[81]
Centralized DRL	<b>High (state-action explosion)</b>	<b>Limited (poor generalization in large/heterogeneous networks)</b>	<b>Strong in adaptability efficiency; requires retraining; risk of overfitting</b>	[82]-[85]
Non-Hierarchical MARL	<b>Moderate-high (coordination adds overhead)</b>	<b>Higher than centralized DRL (distributed per agent)</b>	<b>Near-optimal potential; challenges in convergence,</b>	[86]-[91]

			<b>fairness, and non-stationarity</b>	
Mathematical Programming	<b>High-very high (NP-hard MINLP)</b>	<b>Limited (feasible only in and for small-medium networks)</b>	<b>Provides optimal interpretability; poor adaptability to model uncertainties</b>	<b>[92]-[97]</b>

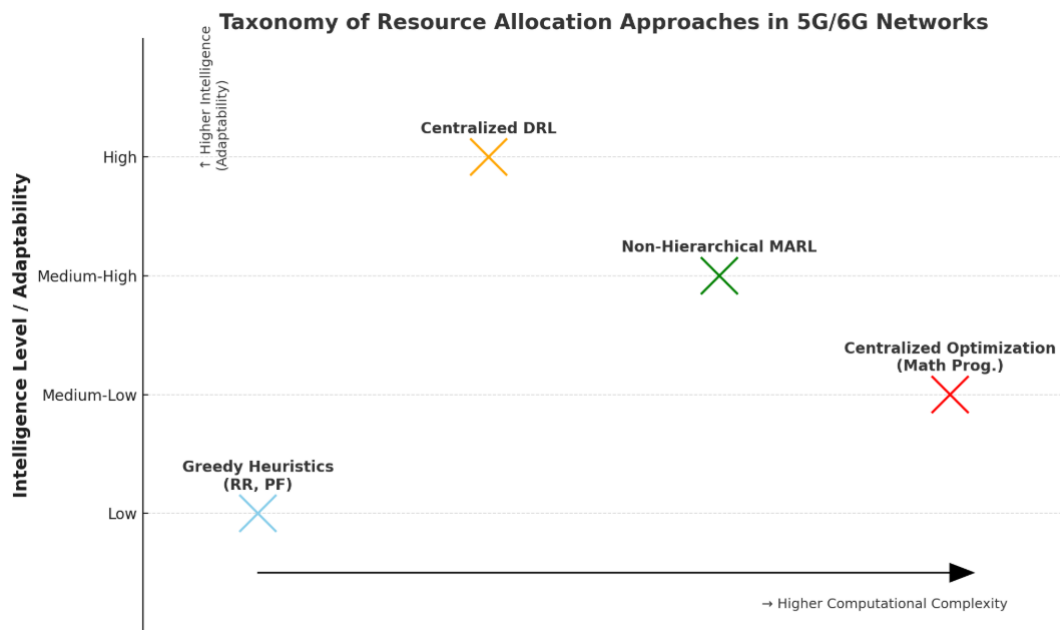


Figure 2.5.4- 1: Taxonomy of Baseline Approaches

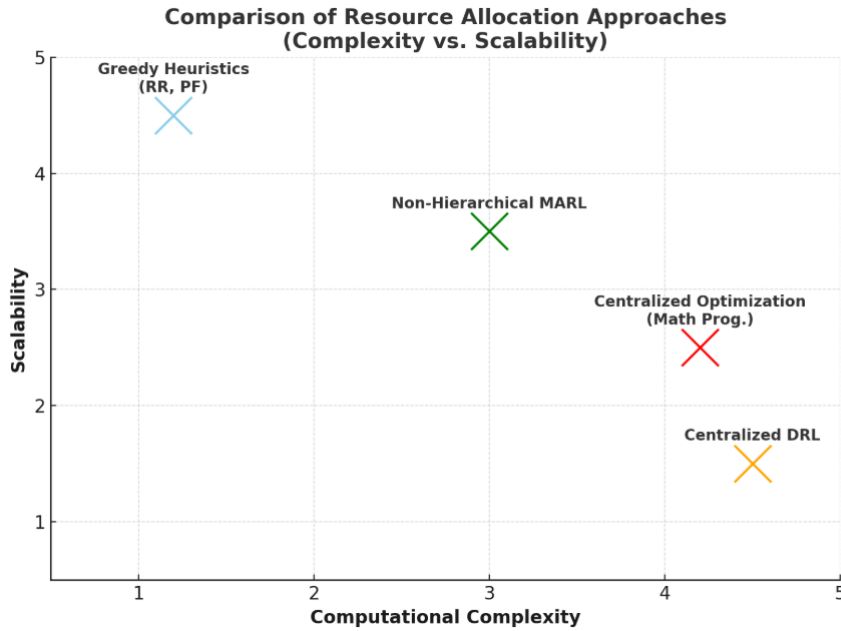


Figure 2.5.4- 2: Comparison of Baseline Approaches

The above figure shows taxonomy of resource allocation approaches in wireless networks represented along two dimensions: computational complexity (x-axis) and intelligence/adaptability (y-axis). At the lowest end of both axes, greedy heuristics such as RR and PF are positioned, since they offer very low computational cost but also limited adaptability to dynamic network conditions. Centralized optimization methods occupy the high-complexity region, as they provide strong theoretical rigor and near-optimal solutions but suffer from prohibitive computational costs and only moderate adaptability in practice. Moving upward in adaptability, MARL achieves a better balance by distributing learning across agents, which enhances scalability and adaptability while keeping complexity at moderate to high level depending on coordination requirements. Finally, centralized DRL resides at the top-right corner, reflecting its ability to achieve very high adaptability and learning capacity in dynamic, high-dimensional environments, though this comes at the cost of high computational burden and scalability challenges.

## 2.6 Hierarchical Multi-Agent Reinforcement Learning (H-MARL) in 5G/6G

### Networks

#### 2.6.1 Overview of H-MARL

H-MARL has emerged as an advanced AI paradigm that extends conventional MARL by introducing hierarchical structures for complex decision-making. In this framework, agents are organized into multiple layers, with each layer addressing a different level of abstraction. High-level agents are responsible for strategic decisions such as long-term resource allocation, while low-level agents focus on granular tasks such as bandwidth allocation or power control for individual users. This hierarchical decomposition improves both scalability and adaptability, particularly in large-scale and heterogeneous 5G/6G networks where thousands of devices, BSs, and IoT nodes must be managed in real time [98][99]. By narrowing the decision-making scope of each agent, H-MARL reduces the computational burden while maintaining efficient optimization across the network [100].

In the context of 5G/6G systems, H-MARL facilitates decentralized decision-making, allowing BSs, user devices, and edge nodes to make local decisions based on their own observations while still aligning with the strategic guidance of higher-level controllers. This is particularly important given the limitations of centralized optimization, which can introduce latency and scalability issues in ultra-dense and highly dynamic environments [101]. The hierarchical design not only balances global objectives such as throughput, latency, and energy efficiency but also ensures local optimization of per-user Quality Of Service (QoS). For instance, in dense urban deployments or massive IoT scenarios, high-level agents can coordinate spectrum and energy allocation across cells, while low-level agents manage scheduling and load balancing at the base station level [102]. Such hierarchical collaboration reduces resource contention and congestion, enabling real-time adaptability to fluctuating traffic demands and mobility patterns [103].

#### 2.6.2 Benefits of H-MARL for Network Optimization

The key strengths of H-MARL lie in its scalability, decentralization, adaptability, and efficient resource utilization. First, its hierarchical architecture allows multiple agents to simultaneously handle diverse subtasks, making it scalable to large heterogeneous networks

with thousands of nodes, which is crucial for future ultra-dense 5G/6G deployments [98]. Second, H-MARL supports decentralized control, which reduces reliance on a central controller and minimizes communication overhead and latency applications such as industrial automation and autonomous driving [4]. Third, H-MARL agents are capable of learning and adapting in real time, dynamically adjusting their policies as network states evolve. This provides a significant advantage over static or heuristic approaches, particularly in environments characterized by rapid changes in user mobility, traffic load, and interference [99][104]. Finally, the coordination between hierarchical agents improves resource utilization: global spectrum and energy allocations decided by high-level agents can be refined by low-level agents based on localized traffic demands, ensuring both fairness and efficiency in network operations [100].

### 2.6.3 Challenges and Open Research Areas

Despite these advantages, H-MARL also introduces several challenges. One major concern is the design of reward functions that balance the often-conflicting objectives of high-level and low-level agents. Inappropriate reward shaping may cause misaligned policies, leading to inefficiencies and suboptimal system performance [105]. Moreover, the computational complexity of training hierarchical agents in environments with large state-action spaces remains high, requiring significant computational resources and advanced training methodologies [106]. Another emerging research direction is the integration of Explainable AI (XAI) with H-MARL to improve transparency and interpretability of decisions. Since future 5G/6G networks will increasingly depend on AI-driven optimization, enabling stakeholders to understand and trust the actions of autonomous agents will be critical for regulatory compliance and operational reliability [107].

In summary, H-MARL provides a powerful framework for managing the complexity of next-generation wireless networks through scalable, decentralized, and adaptive optimization. However, realizing its full potential requires addressing challenges related to reward function design, training efficiency, and interpretability. Future research on combining AI techniques holds promise for achieving efficient, explainable, and trustworthy network intelligence.

## 2.7 Transfer Learning (TL) in 5G/6G Network Optimization

### 2.7.1 Overview of TL

TL is a powerful machine learning paradigm that enables knowledge gained from solving one problem to be applied to a different but related problem. In contrast to traditional approaches that require models to be trained from scratch for each task, TL leverages pre-trained models or data representations, significantly reducing the training cost and improving efficiency. In the context of 5G/6G networks, TL is particularly valuable because building large labeled datasets for every new network configuration or deployment scenario is often infeasible. By transferring knowledge from pre-trained models—trained on similar traffic patterns, user mobility, or deployment conditions—TL facilitates rapid adaptation to new environments, thereby accelerating the learning process for optimization tasks such as resource allocation, traffic management, and energy efficiency [6][108].

The evolution toward 5G and the upcoming 6G era introduces diverse and heterogeneous network environments, including massive IoT deployments, URLLC, and bandwidth-hungry applications such as augmented reality (AR) and autonomous vehicles. These diverse scenarios produce drastically different traffic loads, mobility patterns, and QoS requirements, making it impractical to retrain AI models for each use case independently. TL provides a mechanism to adapt models across scenarios, ensuring that optimization techniques remain effective across different contexts without prohibitive computational overhead [109].

### 2.7.2 TL Techniques in Network Optimization

Several forms of TL have been applied in wireless networking. Instance-based TL leverages labeled instances from a source domain such as 5G deployment with known traffic patterns, to augment limited training data in the target domain like a new 6G deployment. This approach is effective when labeled data in the target scenario is scarce but shares similarities with the source environment. Feature-based TL extracts features such as mobility, interference, or load distributions from a source network and applies them to a new environment, which is particularly useful in resource allocation under non-stationary traffic conditions. Model-based TL focuses on reusing the parameters or architectures of pre-trained models, such as DRL models, to adapt to new environments with minimal retraining. For example, a DRL model trained for dense urban 5G networks can be adapted to similar 6G

environments with increased device densities and spectrum sharing constraints. Finally, relational TL transfers learned relationships between entities, such as traffic flow dependencies or interference patterns, from one domain to another, which enhances traffic prediction and spectrum management in networks with dynamic user mobility adapted across different network slices, where each slice supports distinct QoS requirements [110][111]. For instance, a model optimized for high-throughput applications like video streaming can be adapted using TL to serve low-latency URLLC use cases such as autonomous driving or telemedicine, reducing the need for extensive retraining from scratch [112]. Another critical application is energy efficiency. With the proliferation of massive IoT devices in 5G/6G networks, optimizing energy consumption is essential. TL allows models trained on energy-efficient strategies in one IoT domain like smart metering to be transferred and fine-tuned for other domains, such as industrial IoT or smart agriculture, where labeled data may be scarce. This ensures rapid deployment of energy-efficient solutions without incurring high data collection costs [113]. Similarly, in traffic management, TL provides the flexibility to adapt pre-trained models to new and evolving traffic conditions. For example, a model trained in urban traffic scenarios can be reused in suburban or rural areas with different mobility patterns, thereby improving overall network robustness during unexpected demand spikes, such as large public events or emergencies [114].

### **2.7.3 Advantages of TL in 5G/6G Optimization**

The advantages of TL for 5G/6G network optimization are multi-fold. First, TL drastically reduces training time by reusing pre-trained models, leading to faster convergence toward optimal solutions. This is especially important in time-sensitive applications like URLLC, where rapid decision-making is critical [115]. Second, TL improves performance in data-scarce environments by enabling accurate model operation even with limited labeled data, which is often the case in emerging or less-instrumented network deployments [116]. Third, TL provides cross-domain adaptability, allowing optimization models to generalize across heterogeneous environments such as urban-to-rural or dense-to-sparse networks. This adaptability enhances the robustness and flexibility of AI-driven decision-making in next-generation networks [117].

### **2.7.4 Challenges and Open Research Areas**

Despite its potential, TL faces challenges that must be addressed for effective deployment in 5G/6G systems. One major concern is negative transfer, where knowledge transferred from a source domain degrades performance in the target domain due to insufficient similarity between the two environments [118]. Another issue is the selection of source domains: not all source models are equally relevant, and inappropriate selection can hinder optimization performance. Developing automated methods for identifying optimal source domains remains an active research area [119]. Additionally, while TL accelerates learning, ensuring that transferred models are adequately fine-tuned for specific target environments is critical. Hybrid approaches that combine TL with federated learning or hierarchical reinforcement learning are being explored to address domain adaptation and fine-tuning challenges [120]. To sum up, TL provides a robust framework for overcoming the limitations of data scarcity and computational cost in AI-driven 5G/6G network optimization. By enabling knowledge reuse across diverse domains, TL enhances efficiency, adaptability, and performance in resource allocation, traffic management, and energy efficiency. However, addressing challenges such as negative transfer, source domain selection, and fine-tuning remains essential to fully exploit TL's potential in next-generation networks.

## **2.8 Federated Learning (FL) in 5G/6G Networks**

### **2.8.1 Overview of FL in 5G/6G Networks**

FL has emerged as a transformative paradigm in machine learning, designed to enable decentralized and collaborative model training across multiple distributed clients while ensuring that raw data never leaves local devices. Unlike traditional centralized learning, which requires aggregation of all training data at a single server, FL allows devices to share only model updates with a coordinating server. This decentralized mechanism significantly enhances privacy, reduces bandwidth usage, and aligns with the architectural requirements of 5G and future 6G networks, which are characterized by massive data generation across diverse devices such as IoT sensors, smartphones, and autonomous vehicles [121]. As data privacy and security become increasingly critical in large-scale, data-intensive environments, FL provides an efficient solution by maintaining sensitive user data locally while still enabling global model improvements.

In the context of next-generation wireless systems, FL holds the potential to optimize key aspects of network management, including resource allocation, traffic prediction, energy efficiency, and security. The paradigm is naturally aligned with edge computing, a foundational component of 5G/6G architectures, where computation and intelligence are distributed closer to the data sources. By enabling collaborative learning at edge nodes (e.g., BSs, routers, or mobile devices), FL accelerates decision-making, reduces dependence on centralized cloud resources, and enhances scalability in ultra-dense network environments [122]. Recent works propose Federated Reinforcement Learning (FRL) and federated hierarchical RL to combine localized policy learning with periodic parameter aggregation—reducing communication while maintaining personalization across nodes. Techniques such as personalization layers, adaptive weighting, and differential privacy can be incorporated.

### **2.8.2 Key Features of FL for Network Optimization**

One of the primary advantages of FL is its decentralized and privacy-preserving architecture. By ensuring that data remains on client devices, FL addresses privacy concerns and regulatory requirements making it particularly effective for managing sensitive information like user location, mobility, or application usage data [123]. This is especially beneficial in applications such as bandwidth allocation and mobility management, where sensitive datasets can be exploited without being exposed to central servers.

Another important feature is its synergy with edge computing. Since edge devices perform local training, FL reduces the latency and communication overhead associated with transmitting large volumes of raw data to centralized servers. This capability is crucial for time-sensitive applications such as drone coordination, where split-second decision-making determines reliability and safety [124].

FL is also highly scalable, distributing the computational load across potentially millions of heterogeneous devices in IoT ecosystems. Leveraging the processing power of these distributed clients avoids overloading central servers while still achieving effective model convergence [125]. Furthermore, FL naturally accommodates heterogeneity within 5G/6G networks, where devices vary significantly in computational capacity, battery power, and storage. High-end devices may contribute more frequent or complex updates, while low-power IoT nodes can contribute intermittently, ensuring inclusivity and efficiency across the network [114].

### 2.8.3 Applications of FL in 5G/6G Networks

One of the most important applications of FL is resource allocation. By leveraging distributed learning across BSs and user devices, FL enables predictive models to optimize spectrum, bandwidth, and power allocation in real time. This distributed intelligence improves throughput, minimizes interference, and enhances user QoS in highly dynamic wireless environments [126].

Similarly, traffic prediction and management benefit greatly from FL. Since mobile devices can train local models on traffic patterns and share only learned parameters, global models are able to forecast network load with greater accuracy. This approach is particularly effective in dense urban deployments and event-driven environments where traffic surges are frequent [127].

In addition, energy efficiency is another major area where FL can make significant contributions. Devices and network infrastructure can collaboratively learn models to optimize energy consumption without sacrificing connectivity or performance. For instance, mobile devices can minimize power usage during idle periods, while network operators can implement adaptive strategies at BSs to match energy expenditure with predicted demand [7].

Moreover, FL is highly relevant for security and privacy in IoT ecosystems, which are integral to 5G/6G deployments. Sensitive data from healthcare, smart homes or wearable devices can remain local while contributing to global model improvements. This ensures compliance with strict data protection standards while still enabling predictive analytics and real-time decision-making in mission-critical applications such as patient monitoring or connected vehicles [128].

### 2.8.4 Advantages of Federated Learning for Network Optimization

FL offers several inherent advantages. Its privacy-preserving nature ensures that user trust is maintained, particularly in domains involving sensitive data such as finance, healthcare, or mobility. By transmitting model updates instead of raw data, FL also reduces bandwidth consumption, which is critical in ultra-dense IoT and multimedia-intensive 5G/6G networks [129]. Furthermore, by enabling parallelized model training across devices, FL accelerates

model convergence, supporting real-time decision-making in latency-sensitive applications like drone swarms or Vehicle-to-Everything (V2X) communications [130].

### **2.8.5 Challenges and Future Directions**

Despite its promise, several challenges limit the widespread adoption of FL in next-generation networks. One major issue is communication overhead. Although raw data is not transmitted, frequent model update exchanges between clients and servers still generate significant overhead in bandwidth-constrained environments. Advanced techniques such as update compression, quantization, and asynchronous aggregation are being explored to reduce this burden [131].

Another critical challenge is the presence of non-IID data distributions across devices. Since data collected by different clients often varies widely in scale, content, and distribution, global model convergence may be hindered, leading to suboptimal performance. Research in personalized FL frameworks and adaptive aggregation algorithms aims to mitigate this problem [132].

Finally, stragglers and device heterogeneity remain problematic. Devices with limited resources may lag in updating models, causing bottlenecks in the training process. Approaches such as clustering, partial participation, or hierarchical FL architectures are proposed to address these issues [133].

## **2.9 Explainable AI (XAI) in 5G/6G Network Optimization**

### **2.9.1 Overview of XAI**

XAI refers to a collection of techniques and frameworks designed to enhance the interpretability and transparency of complex AI models. As 5G and emerging 6G networks increasingly adopt AI-driven mechanisms for critical tasks such as resource allocation, traffic management, and energy efficiency, the reliance on advanced models like deep learning and H-MARL introduces significant opacity in decision-making. This “black box” nature raises concerns for operators and regulators, particularly in mission-critical applications where accountability and fairness are non-negotiable. XAI addresses these issues by generating human-interpretable explanations of AI decisions, thus enabling network operators, engineers,

and even end-users to gain insights into the rationale behind model outputs. In real-time 5G/6G network management, where AI autonomously processes massive amounts of dynamic data, XAI plays a vital role in building trust, ensuring accountability, and facilitating compliance with regulatory frameworks [76] [9].

### **2.9.2 The Importance of XAI in Next-Generation Networks**

Trust and accountability form the cornerstone of AI adoption in 5G/6G. Network operators must have confidence in AI-driven decisions, whether related to spectrum allocation, handover optimization, or traffic prioritization. XAI provides traceable justifications; ensuring decisions can be verified against network policies and fairness standards. For instance, if AI allocates more bandwidth to latency-sensitive applications such as autonomous vehicles, XAI can clarify the decision logic, reinforcing trust and reducing ambiguity [134]. Beyond trust, regulatory compliance is another critical driver. Legal frameworks like the European Union’s (EU’s) General Data Protection Regulation (GDPR) and emerging AI transparency policies in telecommunications demand explanations for automated decision-making processes. XAI empowers operators to meet these requirements by providing interpretable insights into how decisions were derived, ensuring that AI-based optimization aligns with legal obligations [135].

Another essential contribution of XAI lies in bias detection and mitigation. Training datasets in network optimization often fail to capture all real-world dynamics, leading to models that may systematically favor certain traffic types or user groups. For example, a RL model might inadvertently prioritize video streaming traffic over low-latency IoT communications. By opening the “black box,” XAI techniques help identify such biases and enable corrective retraining or policy adjustments [136]. Moreover, XAI significantly aids in debugging and performance improvement. In complex heterogeneous networks, if an AI model fails to optimize energy usage across BSs, XAI techniques can highlight which decision pathways are flawed, guiding engineers toward better model refinement [137].

### **2.9.3 Techniques for XAI in 5G/6G Networks**

Several XAI methods have been proposed to increase interpretability without severely compromising model accuracy. Feature attribution approaches, such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), assign

weights to input features to illustrate their contribution to model outputs. Within 5G/6G, these tools can explain how variables like user mobility, traffic load, or interference influenced resource allocation decisions [138]. Similarly, saliency maps provide visual explanations by highlighting the most influential inputs in deep learning-based models, making them valuable for traffic management or anomaly detection [139]. Surrogate models represent another category, where simpler interpretable models, such as decision trees, approximate the behavior of complex reinforcement learning models to provide intuitive insights into system behavior [140]. Counterfactual explanations, on the other hand, perform “what-if” analyses to demonstrate how changes in inputs—such as increased traffic density in a cell would affect AI outcomes, thereby evaluating robustness and adaptability [141].

#### **2.9.4 Applications of XAI in Network Optimization**

The application of XAI spans multiple optimization domains within 5G/6G. In resource allocation, XAI provides clarity on why spectrum or bandwidth is distributed to certain services, ensuring fairness in multi-user environments. For traffic management, it offers transparency on how AI balances competing flows like IoT telemetry and real-time video, particularly during congestion scenarios. In energy efficiency, XAI can justify decisions such as powering down lightly loaded BSs, ensuring these trade-offs do not compromise overall service quality [142]. Additionally, in security contexts, where AI models are used for anomaly detection and threat response, XAI can explain why certain traffic patterns were flagged as malicious, enabling faster and more informed countermeasures against cyber threats like Distributed Denial of Service (DDoS) attacks [143].

#### **2.9.5 Challenges and Future Directions**

Despite its benefits, XAI in 5G/6G networks faces notable challenges. A fundamental issue is the trade-off between accuracy and interpretability, as simpler surrogate explanations may omit critical nuances of highly complex models. Achieving balance without undermining optimization effectiveness remains an open research direction [144]. Another challenge concerns scalability—deploying XAI techniques in real-time across massive, distributed, and heterogeneous networks introduces computational overhead, which can limit their practicality in ultra-dense network deployments [145]. Finally, future progress must also focus on human-AI collaboration. Developing intuitive, operator-friendly XAI tools will allow

engineers to interact with AI systems in real time, provide feedback, and iteratively refine model decision-making, thereby enhancing both trust and performance in network management [146].

### 2.9.6 Strengths and Weaknesses of XAI

XAI delivers several strengths in the 5G/6G context, including improved transparency, enhanced debugging capability, and alignment with regulatory compliance requirements. By explaining AI-driven optimization strategies, it ensures that stakeholders can verify and justify network decisions. However, weaknesses also exist. Chief among them are computational overhead in generating explanations—particularly in real-time operations—and the persistent interpretability versus complexity dilemma, where highly accurate models may resist straightforward explanation. These limitations suggest that hybrid approaches combining accuracy, scalability, and interpretability will be crucial for future 6G-ready XAI systems [147].

### 2.10 Comparative Analysis of Techniques

Table 2.10- 1: Comparative Table of AI Techniques

Technique	Strengths	Weaknesses	Suitable Use Case in 5G/6G
H-MARL	Scalability, Decentralized control, Agent collaboration	Training complexity, Communication overhead	Large-scale, complex networks with dynamic user behavior
TL	Training efficiency, Adaptability	Negative transfer, Domain shift sensitivity	Dynamic network conditions or evolving traffic patterns
FL	Data privacy, Reduced communication costs, Scalability	Model convergence, Resource constraints	Privacy-sensitive applications, edge computing, IoT
XAI	Transparency, Model	Computational overhead,	Real-time resource

Technique	Strengths	Weaknesses	Suitable Use Case in 5G/6G
	debugging, Regulatory compliance	Trade-off between complexity and interpretability	allocation and traffic management

To add up, the choice of AI technique for optimization pends heavily on the specific use case and the characteristics of the network. H-MARL offers scalability and efficient coordination but at the cost of increased complexity. TL provides adaptability but must be applied carefully to avoid performance degradation. FL is ideal for privacy-sensitive applications but faces challenges in resource-limited environments. Finally, XAI plays a crucial role in ensuring transparency and trust but can introduce computational overhead, making it less suited for real-time, large-scale operations without optimized implementation. Each of these techniques addresses different challenges and priorities within the 5G/6G network environment. For example, when privacy is paramount, such as in edge computing or IoT, FL is the most appropriate solution. On the other hand, in scenarios where the network’s dynamic nature demands continuous learning and adaptability, H-MARL offers the flexibility needed for large-scale, decentralized networks.

The trade-offs between model complexity, interpretability, and computational efficiency also plays a role in the decision-making process. XAI is essential for mission-critical applications where understanding the AI’s decision is crucial for regulatory compliance or debugging, despite the potential overhead. In contrast, TL is advantageous when adapting pre-trained models to evolving network conditions, minimizing retraining time and computational costs.

The combination of these techniques is a promising direction for future research. For example, incorporating XAI into FL could address transparency issues in decentralized models. Similarly, combining TL with H-MARL could enhance adaptability in dynamic network conditions while maintaining scalability. Integrating these methods could lead to more efficient, flexible, and interpretable AI-driven 5G/6G network optimizations.

## 2.11 Related works

Table 2.11- 1: Summary of Related Literature on AI-Driven Optimization in 5G/6G Networks

Ref.	Authors & Year	Focus Area	Method(s) Used	Key Findings / Contributions	Research Gaps / Limitations
[148]	M. Elsayed et al., 2019	Resource Allocation in 5G	DRL	Demonstrated DRL's ability to optimize resource allocation in dynamic environments, outperforming heuristics.	High computational cost; limited interpretability; scalability to 6G ultra-dense IoT remains uncertain.
[149]	H. Zhang et al., 2020	Energy Efficiency in 5G Massive MIMO	Game Theory + Convex Optimization	Proposed energy-efficient beamforming achieving power savings without compromising throughput.	Assumes ideal CSI; does not address distributed multi-cell coordination or user mobility in 6G.
[150]	Y. Sun et al., 2020	Traffic Management for URLLC/mMTC	FL	Introduced FL-based traffic classification model preserving user privacy.	Vulnerable to data heterogeneity and non-IID effects; lacks robustness to adversarial attacks.
[151]	J. Park et al., 2021	6G Network Resource Slicing	H-MARL	Achieved scalable slicing in dense networks with lower latency than centralized MARL.	High coordination complexity; energy and fairness trade-offs not fully considered.
[152]	S. Chen et al., 2021	5G/6G Energy Optimization	TL + DRL	Reduced training time for new deployments by transferring DRL policies.	Transferability limited to similar scenarios; negative transfer risk in heterogeneous 6G environments.
[153]	B. Brik et al., 2021	Traffic Load Balancing in HetNets	ML + Optimization Heuristics	Improved QoS under high mobility using ML-based traffic prediction.	Lacks adaptability to extreme density and real-time constraints in 6G; still partly heuristic-driven.
[15]	W. Saad et al., 2022	AI in 6G Wireless Networks	MARL	Showed MARL's potential for distributed low-latency decision-making.	Communication overhead among agents; convergence guarantees under non-stationary environments remain open.
[154]	T. O'Shea	Spectrum Sharing	DQN	Developed DQN-based allocation	Limited spectrum agility under massive

Ref.	Authors & Year	Focus Area	Method(s) Used	Key Findings / Contributions	Research Gaps / Limitations
	et al., 2022	Optimization		improving utilization in dynamic spectrum access.	IoT/URLLC; energy-efficiency trade-offs not explored.
[45]	H. Tataria et al., 2023	Energy Harvesting in 6G IoT	Stochastic Optimization	Modeled energy-aware IoT with renewables, improving device lifetime.	Focused on energy harvesting only; integration with traffic/resource optimization is missing.
[2]	K. B. Letaief et al., 2023	AI-Native 6G Architecture	AI-Driven Network Automation	Proposed AI-native framework for self-optimizing 6G networks with proactive resource management.	Lacks practical implementation details; interoperability, security, and explainability challenges remain.

## CHAPTER 3: METHODOLOGY

### 3.1 Research Philosophy

This study is guided by a pragmatic research philosophy, which aligns with the interdisciplinary and solution-oriented nature of developing AI-driven dynamic optimization frameworks for 5G/6G networks. Pragmatism allows the integration of multiple research paradigms, emphasizing the practical application of theories, tools, and methods to solve complex, real-world problems. Given the hybrid nature of this work—spanning telecommunications engineering, AI, and optimization—pragmatism provides the most appropriate philosophical foundation for addressing both technical and operational challenges in modern wireless networks [155] [156].

#### 3.1.1 Ontological Assumptions

Ontologically, the research adopts a realist position, asserting that the dynamics of wireless networks such as resource constraints, traffic fluctuations, and energy profiles exist independently of the observer. However, these dynamics are modeled using computational abstractions such as agent-based systems and machine learning environments, introducing an element of constructivism [157]. This dual view acknowledges both the existence of an objective reality and the need to construct interpretive models to simulate and optimize complex network behaviors.

#### 3.1.2 Epistemological Assumptions

The epistemological stance of this research is rooted in positivism and post-positivism. Knowledge is acquired through systematic observation, simulation, and quantification of network performance metrics—such as latency, throughput, and energy consumption—under different AI-driven optimization strategies. The study relies on empirical validation through Matrix Laboratory (MATLAB)-based simulation and performance benchmarking of H-MARL, TL, FL, and XAI models.

Furthermore, post-positivism is reflected in the recognition of limitations inherent in AI models and the probabilistic nature of their predictions [158]. Thus, multiple techniques are

employed to cross-validate outcomes, ensuring robustness and generalizability across different network scenarios.

### 3.1.3 Axiological Considerations

From an axiological perspective, the research is motivated by the pursuit of technological efficiency, transparency, and societal benefit. The development of intelligent and adaptive optimization frameworks contributes to:

- Sustainable network operation, by improving energy efficiency,
- Equitable and intelligent resource distribution, especially in ultra-dense and massive IoT deployments,
- Transparency and trust in AI systems, through the incorporation of explainable models [159].

Although the research is largely quantitative, value judgments influence decisions such as prioritizing certain performance metrics for instance, latency over energy use in URLLC scenarios and selecting AI models that balance accuracy with interpretability.

### 3.1.4 Methodological Alignment

This pragmatic and quantitative research is implemented through the following computational techniques:

- **H-MARL** for scalable, decentralized learning in multi-agent environments representing network nodes or service agents.
- **TL** to enable knowledge reuse across similar network states, reducing retraining time.
- **FL** to allow privacy-preserving and distributed intelligence without centralized data aggregation.
- **XAI** to enhance interpretability of decision-making processes, aligning with ethical AI principles.

The methods are implemented and validated using simulated 5G/6G scenarios in MATLAB, and benchmarked against conventional approaches such as non-hierarchical DRL, greedy heuristics, and centralized optimization.

### 3.1.5 Philosophical Justification of Techniques

Table 3.1.5- 1: Philosophical Justification of Techniques

AI Technique	Philosophical Justification
H-MARL	Realist and pragmatic—models real-world distributed network control via interacting agents.
TL	Post-positivist—leverages previously validated models to accelerate learning in new but related tasks.
FL	Constructivist and pragmatic—models the decentralized nature of networked devices while preserving privacy.
XAI	Interpretivist and ethical—promotes transparency and accountability in AI-driven decision-making.

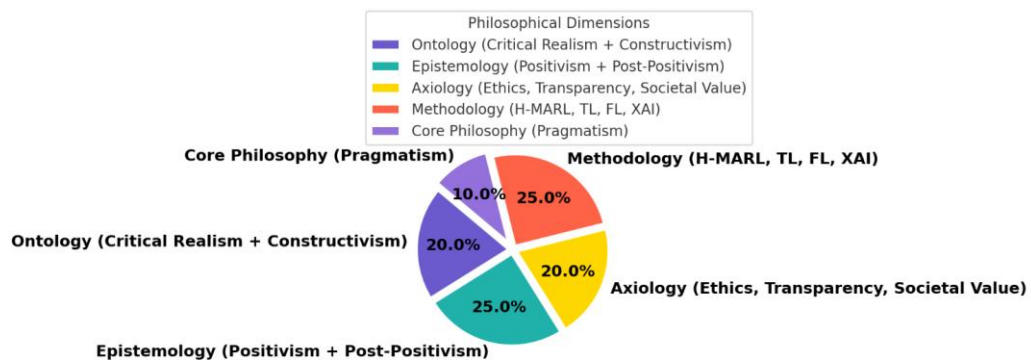


Figure 3.1- 1: Research philosophy distributions

## 3.2 Theoretical Foundations of AI in Network Optimization

The success of AI-driven optimization in 5G/6G networks relies on a rigorous theoretical foundation that integrates machine learning with wireless communication principles. This chapter introduces the conceptual and mathematical underpinnings of the proposed framework. Together, these elements form the theoretical base for the proposed optimization architecture that enhances resource allocation, traffic management, and energy efficiency.

AI, particularly RL, has emerged as a key enabler for dynamic decision-making in wireless networks. Unlike traditional optimization methods that rely on deterministic models, RL

provides adaptive strategies for learning optimal policies through trial-and-error interactions with the environment. In the context of wireless networks, the environment is defined by users, BSs, channels, and traffic demands; the agents represent network controllers or BSs; the states correspond to network conditions; and the actions are allocation decisions such as resource block assignment or power control.

Formally, the interaction between an agent and the network is modeled as a Markov Decision Process (MDP) for modeling agent-environment interactions, Deep Neural Networks (DNNs) for function approximation, and gradient-based optimization algorithms for policy updates. MDP is defined by the tuple  $(S, A, P, R, \gamma)$ , where  $S$  is the state space,  $A$  the action space,  $P$  the state transition probabilities,  $R$  the reward function, and  $\gamma \in (0,1)$  the discount factor [4]. The objective is to maximize the expected cumulative reward for all agents over time:

$$\boldsymbol{\pi}^* = \arg \max_{\boldsymbol{\pi}} \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)] \quad (3.1)$$

where  $\pi$  represents the agent's policy mapping states to actions.

The reward for agent  $b$  at time  $t$  can be expressed as:

$$r_b(t) = \sum_{u \in U_b} \sum_{s \in S} x_{b,u,s}(t) R_{b,u,s}(t) - \lambda \cdot E_b(t)$$

where  $U_b$  represents the users associated with base station  $b$ .

At each time step  $t$ , the local state of each agent (base station)  $\mathbf{s}_b(t)$  includes information such as; local traffic demand, channel quality information (CQI), and available power budget. The agents perform actions  $\mathbf{a}_b(t)$ , which are resource allocation decisions like power control and subcarrier assignment, and receive a reward  $r_b(t)$ , which can be defined as a function of the throughput and energy efficiency [160].

Formally, the optimization objective is decomposed as:

$$\mathbf{R}_{global} = \sum_{i=1}^N \mathbf{R}_i \quad (3.2)$$

where  $\mathbf{R}_i$  is the reward obtained by the  $i^{th}$  local agent. High-level policies adjust global constraints, while low-level policies adapt to real-time traffic and channel conditions. Such

decomposition improves scalability and supports dynamic adaptation in heterogeneous 5G/6G networks.

While single-agent RL has demonstrated promise in small-scale wireless optimization problems, it does not scale efficiently in ultra-dense 5G/6G scenarios where multiple interacting agents are required. This motivates the use of MARL frameworks. In a dense network, centralized MDPs are intractable. We thus adopt H-MARL: a meta-controller which is at high level decides long-timescale policies like slice resource budgets, routing preferences. This meta-controller observes aggregated states  $S^{(H)}(t)$  per-cell load, slice demands, energy budget and outputs goals  $g_b(t)$  or sub-policies for each cell  $b$ . The decision interval  $T_H \gg$  low-level timestep. While local agents at low level operate at fast timescales to schedule Physical Resource Blocks (PRBs), adjust power, beamforming, and perform fine-grained admission control. In this level for each base station  $b$ , one or more agents perform scheduling/actions  $a_b(t)$  conditioned on goals  $g_b(t)$  and fine grained observations  $s_b(t)$ .

In H-MARL, BSs act as independent agents that collaboratively learn to optimize their resource allocation strategies. The agents interact with their environment, which consists of the users, the channel states, and the actions of other BSs. The hierarchical decomposition reduces state-action complexity and speeds convergence. Communication is limited: the meta-controller broadcasts goals infrequently; local agents share compact summaries with neighbors to coordinate with local congestion indicators. The reward functions are designed hierarchically to encourage both global efficiency and local fairness. Hence, reward shaping and credit assignment are critical. We define global stage reward at time  $t$  as  $R^{global}(t) = \alpha \sum_u r_u(t) - \beta \sum_u L_u(t) - \gamma E(t)$ . To encourage both local optimization and global objectives, each local agent  $i$  receives a shaped reward:

$$R_i(t) = w_i R^{global}(t) + (1 - w_i) R_i^{local}(t) - \eta C_i(t)$$

where  $R_i^{local}(t)$  is a local metric such as per-cell throughput minus latency,  $w_i \in [0,1]$  balances global vs. local, and  $C_i(t)$  is a penalty for violating constraints such as QoS and power [4]. The meta-controller is rewarded using a smoothed aggregation of global performance over its decision interval. Credit assignment techniques, such as difference rewards or Value Decomposition Networks (VDN) and QMIX which is Monotonic Value

Function Factorization for Deep MARL, may be used to improve learning stability in cooperative settings [91].

### **3.3 Research Framework**

#### **3.3.1 Overview and Objectives of the Framework**

This section formalizes the proposed AI-driven framework for dynamic optimization of 5G/6G networks. The core objectives are to:

1. Provide a mathematically precise system model and optimization objective that balances latency, throughput, fairness, and energy consumption.
2. Design a hierarchical agent architecture that scales to dense deployments, massive IoT and heterogeneous service types namely: eMBB, URLLC, mMTC.
3. Integrate transfer learning mechanisms for rapid adaptation across scenarios and federated learning for privacy-preserving distributed training.
4. Embed XAI techniques to make policy behavior interpretable to network operators.

The research framework for this study integrates advanced AI techniques with next-generation mobile communication architectures to address the challenges of resource allocation, traffic management, and energy efficiency in 5G and beyond 6G networks. The theoretical foundation is built upon four core AI paradigms—H-MARL, TL, FL, and XAI—each contributing a unique capability to the proposed optimization system. The framework aligns with the architectural principles of 5G and the envisioned service-centric, intelligent, and ultra-reliable 6G ecosystem.

In the proposed framework, the network environment is modeled as a multi-agent system where each agent represents a network function such as BSs, edge servers, or IoT clusters. The conceptual architecture of the framework situates AI agents across hierarchical network layers, connected via FL-enabled aggregation nodes, and equipped with TL-based knowledge transfer modules. This design ensures that the optimization process is not only intelligent and adaptive but also privacy-preserving, interpretable, and efficient. The next chapter will detail the methodology for implementing and evaluating this integrated AI framework in a simulated 5G/6G environment.

### 3.3.2 Proposed Conceptual Framework

The conceptual workflow is as follows:

1. **System Initialization:** Agents are deployed across network entities.
2. **H-MARL Decision Process:** High-level and low-level agents interact to optimize resource allocation, traffic management and energy efficiency.
3. **TL Adaptation:** Knowledge from prior deployments accelerates convergence in new environments.
4. **Federated Model Updates:** Local agents train models independently and share updates with a central aggregator.
5. **Explainability Analysis:** XAI methods provide interpretable explanations for optimization outcomes.

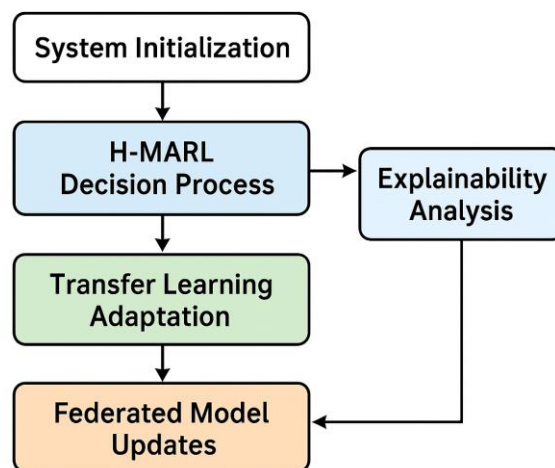


Figure 3.3.2- 1: Conceptual Framework

This end-to-end integration ensures the framework achieves efficiency, scalability, and transparency in AI-driven dynamic optimization.

Figure 3.6 shows a high-level workflow of the proposed AI-driven optimization framework:

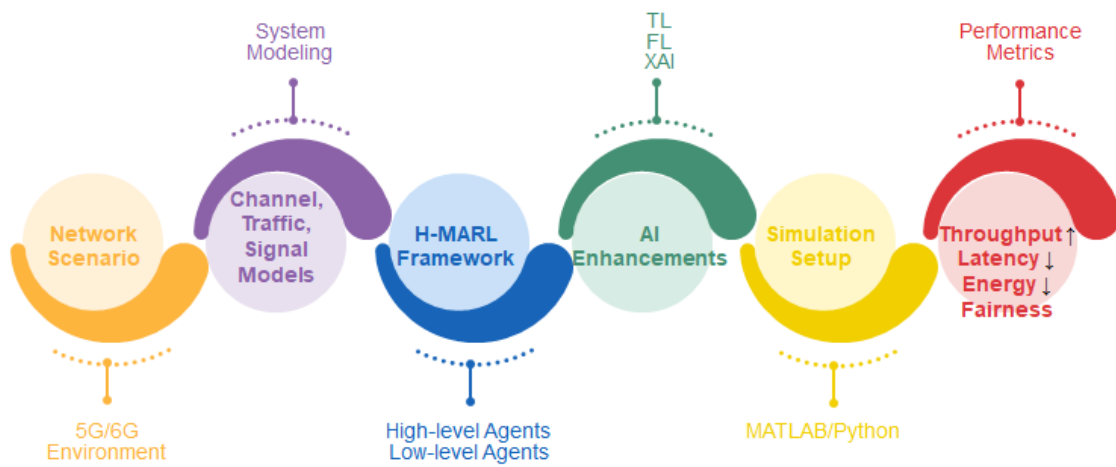


Figure 3.3.2- 2: Research Framework Workflow

### 3.4 H-MARL Hierarchical Framework

#### 3.4.1 H-MARL Algorithms and Practical Choices

Candidate RL algorithms for hierarchical MARL components include:

- High-level (meta) policies: policy-gradient methods such as PPO or actor-critic for continuous goal spaces.
- Low-level agents: Q-learning variants (DQN/Double DQN) for discrete scheduling actions or actor-critic for continuous control of power.
- Multi-agent coordination: CTDE paradigms such as Multi-Agent Deep Deterministic Policy Gradient (MADDPG), QMIX provide practical tradeoffs: centralization during training to stabilize learning, decentralized policies for execution.

Safety and constraint satisfaction can be embedded using constrained RL or control-barrier functions combined with RL for safe H-MARL.

#### 3.4.2 Pseudo-code of the H-MARL Algorithm

```
# H-MARL Pseudocode
Hyperparameters:
    E: number of episodes
```

T: steps per episode  
 H\_interval: meta-controller decision interval (in steps)  
 $\gamma_{meta}, \gamma_{low}$ : discount factors  
 $\alpha_{meta}, \alpha_{low}$ : learning rates  
 replay\_meta\_size, replay\_low\_size  
 batch\_meta, batch\_low  
 target\_update\_freq\_meta, target\_update\_freq\_low  
 communication\_budget (optional)  
 constraint\_set (latency, power, fairness thresholds)

Initialize:

MetaController with policy/network  $\pi_{meta}(\theta_{meta})$  and target  $\theta_{meta\_target}$   
 For each agent  $i$  in Agents:  
     LowLevelAgent $_i$  with policy/network  $\pi_i(\theta_i)$  and target  $\theta_i\_target$   
     Local replay buffer  $B_i$   
     Meta replay buffer  $B_{meta}$

For episode = 1 to E:

$s = Env.reset()$   
 $meta\_state = extract\_meta\_state(s)$  # aggregated network-level features  
 for  $t = 1$  to T:  
     if  $t \bmod H\_interval == 1$ : # Meta decision step  
         # Meta chooses sub-goals / budgets for each agent  
          $meta\_action = \pi_{meta}(meta\_state)$  # e.g., vector of budgets / QoS targets  
         publish( $meta\_action$ ) # communicate to all low-level agents  
         store  $meta\_transition\_start = (prev\_meta\_state, meta\_action, t)$   
     end if  
     # Low-level agents act in parallel  
     For each agent  $i$ :  
          $local\_obs\_i = observe\_local\_state(i, s)$  # channel, queue, UE demands  
         # Combine meta goal with local obs  
          $conditioned\_input = concat(local\_obs\_i, meta\_action[i])$

```

    a_i =  $\pi_i$ (conditioned_input) # resource allocation, scheduling,
power control

    apply_action(i, a_i) # in Env

    r_i, s_next = Env.step_partial(i) # per-agent reward (local + shaped
global)

    # reward shaping:  $r_i = \text{local\_reward}_i + \lambda * \text{meta\_reward\_component}$ 

    store B_i.push((local_obs_i, meta_action[i], a_i, r_i,
next_local_obs_i, done))

end for

# Compute meta-level reward at meta decision boundary
if t mod H_interval == 0:

    meta_reward = aggregate_rewards_over_interval(Agents, constraint_set)

    next_meta_state = extract_meta_state(s_next)

    B_meta.push((meta_state, meta_action, meta_reward, next_meta_state,
done))

    meta_state = next_meta_state

end if

s = s_next

# Periodically update low-level policies (can be decentralized)
For each agent i:

    if len(B_i) > batch_low:

        batch = sample(B_i, batch_low)

        loss_i = compute_policy_loss(batch,  $\theta_i$ _target,  $\gamma$ _low,
constraint_penalty)

         $\theta_i$  = optimizer_step( $\theta_i$ , loss_i,  $\alpha$ _low)

        if soft_update_condition:  $\theta_i$ _target = soft_update( $\theta_i$ ,  $\theta_i$ _target)

    end if

end for

# Periodically update meta-policy (centralized)
if len(B_meta) > batch_meta and t mod meta_update_interval == 0:

    batch_meta = sample(B_meta, batch_meta)

```

```

loss_meta = compute_meta_loss(batch_meta,  $\theta_{meta\_target}$ ,  $\gamma_{meta}$ )

 $\theta_{meta}$  = optimizer_step( $\theta_{meta}$ , loss_meta,  $\alpha_{meta}$ )

if target_update_freq_meta reached:  $\theta_{meta\_target}$  = copy( $\theta_{meta}$ )

end if

end for

# After training: we evaluate hierarchical coordination on validation
scenarios

```

The H-MARL algorithm coordinates global and local optimization using hierarchical agents.

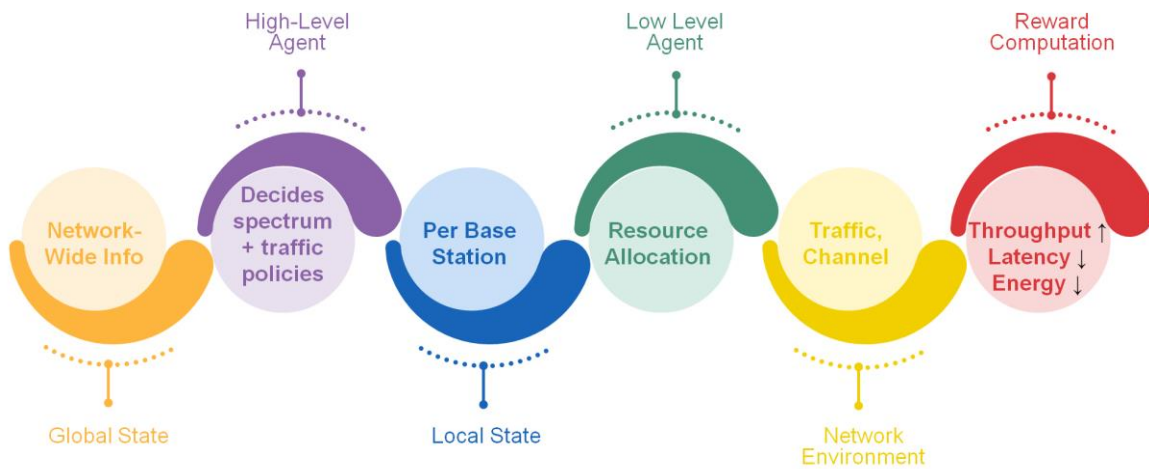


Figure 3.4.2- 1: H-MARL Workflow

High-level agents decide spectrum/traffic splits, while low-level agents optimize per-base station resources. Rewards are fed back to improve both layers' policies. Figure 3.4.2-1 illustrates how high-level and low-level agents interact.

- **Top Layer (High-level agent/manager):**
  - Controls global objectives → interference coordination, load balancing, energy optimization.
- **Middle Layer:**
  - Sends policies/instructions to low-level agents.
- **Bottom Layer (Low-level agents/workers):**
  - Handle resource block allocation, scheduling, power control.
- **Environment block (wireless network):**
  - Provides states (Signal-to-Noise Ratio (SNR), queue length, traffic demand) and receives actions.

**Flow:** Environment → State → Agents → Action → Environment → Reward.

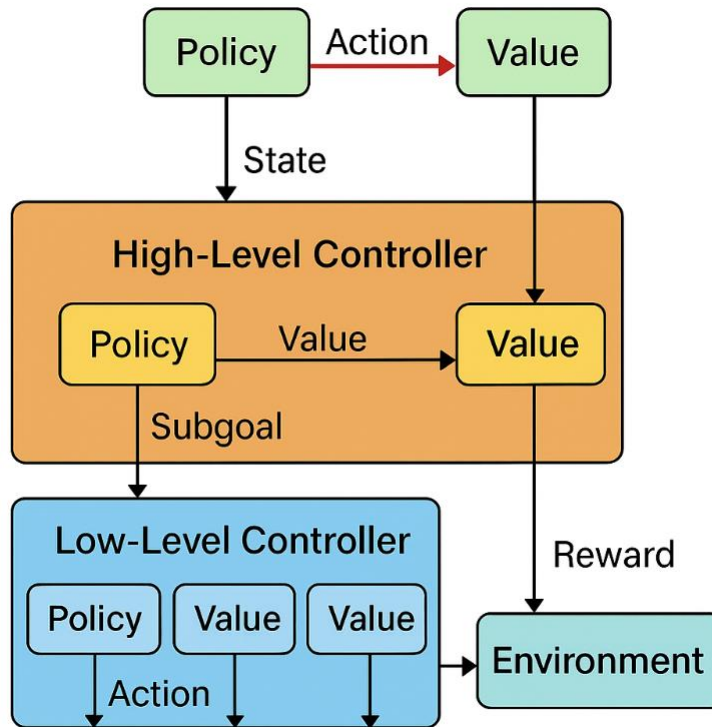


Figure 3.4.2- 2: H-MARL Architecture in 5G/6G Networks in 5G/6G Networks

Figure above shows:

- **Global Coordinator (PPO)** handling high-level policy.
- **Local Agents (DQN)** at each base station managing scheduling and power allocation.
- **Bidirectional arrows** for policy updates (solid) and feedback (dashed).
- **5G/6G environment** at the bottom providing states (traffic, channels, energy) and receiving actions.

### 3.5 TL Framework for Cross Scenario Adaptability

Figure 3.4.2-5 Illustrates reusing a model trained in one scenario for another.

Flow Diagram Layout:

1. **Source Environment (Urban Macrocell)** → Train DRL policy.
2. **Knowledge Transfer (Feature & Policy Reuse)** → Initialize target model.
3. **Target Environment (Dense IoT/Small Cells)** → Fine-tuning with smaller dataset.

4. **Output:** Adapted policy with reduced training time and higher performance.

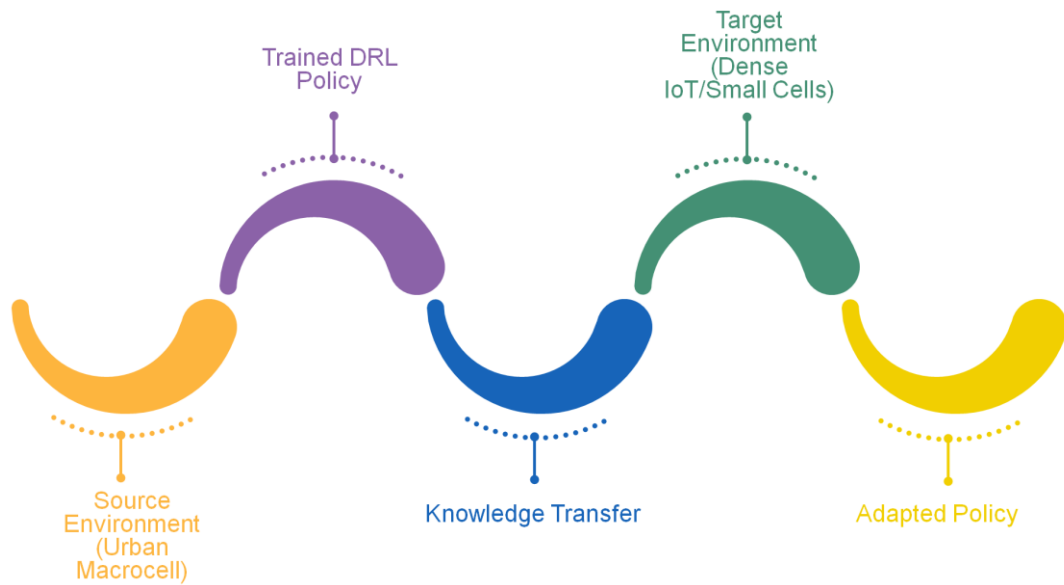


Figure 3.5- 1: TL Process

TL addresses one of the fundamental challenges in RL—slow convergence due to large state spaces. In wireless networks, environments vary significantly (e.g., urban vs. rural deployment, low vs. high mobility scenarios). Formally, let  $D_S = \{X_S, Y_S\}$  and  $D_T = \{X_T, Y_T\}$  represent the source and target domains, respectively. Transfer learning enables partial reuse of policies or value functions learned in  $D_S$  to improve learning in  $D_T$  under the constraint  $P(X_S) \neq P(X_T)$ .

In the proposed framework, TL is employed to:

- Transfer scheduling strategies to simulated environments.
- Adapt trained models across different traffic patterns for instance, eMBB, URLLC, and mMTC.
- Reduce training time when scaling from small-scale testbeds to large-scale networks.

This allows the optimization framework to maintain adaptability and robustness in dynamic real-world network conditions.

1. **Knowledge Transfer:** Models trained on a specific network configuration can be adapted for different scenarios (e.g., different user densities or mobility patterns). This

is particularly useful in dynamic urban environments where conditions change frequently.

2. **Model Fine-tuning:** Fine-tuning pre-trained models allows for efficient resource allocation strategies to be developed with limited data. For instance, a model that has learned to manage resources effectively in one dense area can be adjusted to suit another area with different traffic patterns.

Mathematically, if  $\mathcal{L}_{source}$  is the loss function from the source task and  $\mathcal{L}_{target}$  is the loss function from the target task, the transfer learning process can be represented as minimizing:

$$\min_{\theta} \mathcal{L}_{target}(\theta) + \beta \mathcal{L}_{source}(\theta),$$

where  $\beta$  is a weighting factor that controls the influence of the source task on the target task.

Transfer learning (TL) helps reuse policies or feature representations across different network scenarios namely, cell densities, traffic mixes, frequency bands. TL strategies considered:

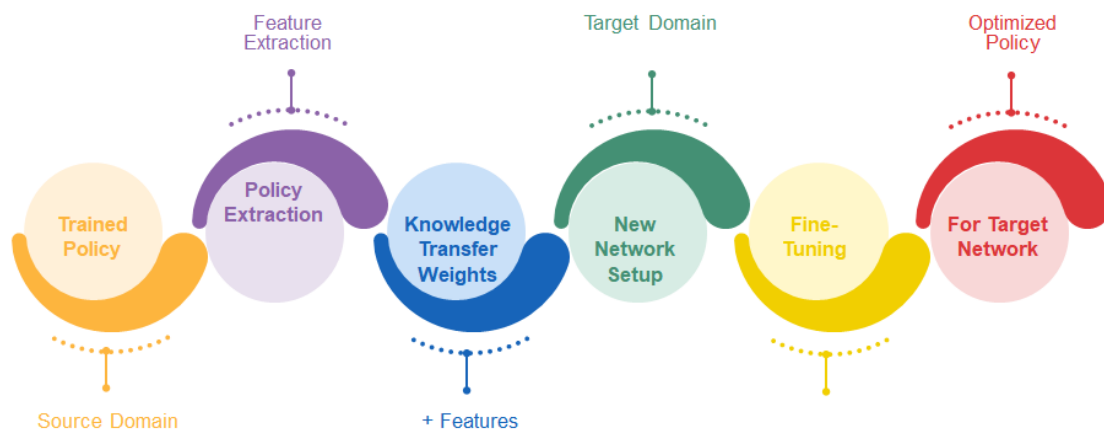


Figure 3.5- 2: Transfer Learning Workflow

Mathematically, let  $\theta_s$  be source parameters and  $\theta$  target parameters. During fine-tuning, add a transfer regularizer:

$$\mathcal{L}_{TL}(\theta) = \mathcal{L}_{RL}(\theta) + \lambda \|\theta - \theta_s\|^2$$

This accelerates convergence and reduces sample complexity in new environments.

Transfer learning is especially valuable in hierarchical setups: meta-controller policies trained on macro patterns like daily traffic cycles can transfer across cities, while low-level scheduling policies adapt locally.

### 3.5.1 Pseudo-code of TL for Adaptation

```
# Transfer Learning Pseudocode
```

Inputs:

```
PretrainedModel M_source = {Encoder E_s, PolicyHead P_s, ValueHead V_s}
TargetEnv Env_target
freeze_ratio: fraction of encoder layers to freeze (0..1)
fine_tune_epochs, lr_initial, replay_buffer_target (optional)
transfer_mode: {feature-transfer, policy-init, multi-task}
```

Procedure:

```
# 1. Load pretrained weights
E_target := copy(E_s)
P_target := copy(P_s)
V_target := copy(V_s)

# 2. Adjust architecture if action/obs space mismatch
if obs_shape_target != obs_shape_source:
    adapt_input_layer(E_target) # add projection or retrain small adapter
if action_space_target != action_space_source:
    replace PolicyHead P_target with new head sized for target actions
    initialize P_target randomly or with last-layer transfer

# 3. Freeze / partial-freeze encoder layers
num_layers = count_layers(E_target)
num_freeze = round(freeze_ratio * num_layers)
freeze_layers(E_target, first=num_freeze)

# 4. Pre-fill replay buffer with source demonstrations
```

```

if use_demo_buffer:
    D_demo = sample_demonstrations_from_source()
    replay_buffer_target.add(D_demo)

# 5. Fine-tuning loop (on target environment)

optimizer =
configure_optimizer(params=unfrozen_params(E_target,P_target,V_target),
lr=lr_initial)

for epoch in 1..fine_tune_epochs:
    collect N episodes from Env_target using current policy  $\pi_{\text{target}} =$ 
E_target  $\rightarrow$  P_target

    store transitions in replay_buffer_target

    for update_step in 1..num_updates_per_epoch:
        batch = sample(replay_buffer_target, batch_size)

        loss = compute_DRL_loss(batch, V_target,  $\gamma$ , entropy_coeff, clipping,
etc.)

        optimizer.step(loss)

        if regularize_to_source:
            # L2 regularization towards source weights to avoid catastrophic
drift

            loss +=  $\lambda_{\text{reg}} * ||W_{\text{unfrozen}} - W_{\text{source\_corresponding}}||^2$ 

        end for

        # Unfreeze more layers progressively (gradual unfreezing)

        if schedule_unfreeze(epoch):
            unfreeze_next_layer(E_target)

    end for

# 6. Evaluate policy on target validation scenarios
return trained_model  $\pi_{\text{target}}$ 

```

### 3.6 FL Framework for Distributed Learning in Networks

This research integrates a FL framework into the proposed optimization system. In the experimental setup, each BS acts as a local learner, training its own DRL agent using locally available traffic patterns, user mobility traces, and channel state information. Instead of transmitting sensitive raw data to a central server, only the learned model parameters (e.g.,

weight updates) were periodically shared with a central aggregator, which maintained the global model.

The global model was updated using the Federated Averaging (FedAvg) algorithm, where the aggregator combined local updates into a weighted average according to the size and quality of each BS's dataset. The update rule was defined as:

$$\theta_{t+1} = \sum_{k=1}^K \frac{n_k}{N} \theta_t^k$$

where  $\theta_t^k$  represents the parameters of the local model trained at BS  $k$ ,  $n_k$  is the number of data samples at BS  $k$ , and  $N = \sum_{k=1}^K n_k$  is the total number of data samples across all BSs. This mechanism ensured fairness in contribution, prevented bias from smaller datasets, and improved convergence across heterogeneous environments.

The federated averaging (FedAvg) algorithm is widely used in this setting:

$$w^{t+1} = \sum_{k=1}^K \frac{n_k}{n} w_k^{(t)} \quad (3.3)$$

where  $w^{(t)}$  represents the model parameters at iteration  $t$ ,  $n_k$  is the local dataset size of client  $k$ , and  $n = \sum_{k=1}^K n_k$ . Integrating FL into the proposed system ensures scalable and privacy-preserving optimization, a key requirement for massive IoT and heterogeneous traffic environments.

The implementation also considered asynchronous updates, where BSs with limited computational capacity or unstable connections were allowed to contribute at different frequencies, reducing straggler effects and ensuring timely global updates. Furthermore, communication efficiency was enhanced by compressing gradients before transmission and by scheduling updates only after significant local learning progress was achieved, thereby reducing unnecessary signaling overhead.

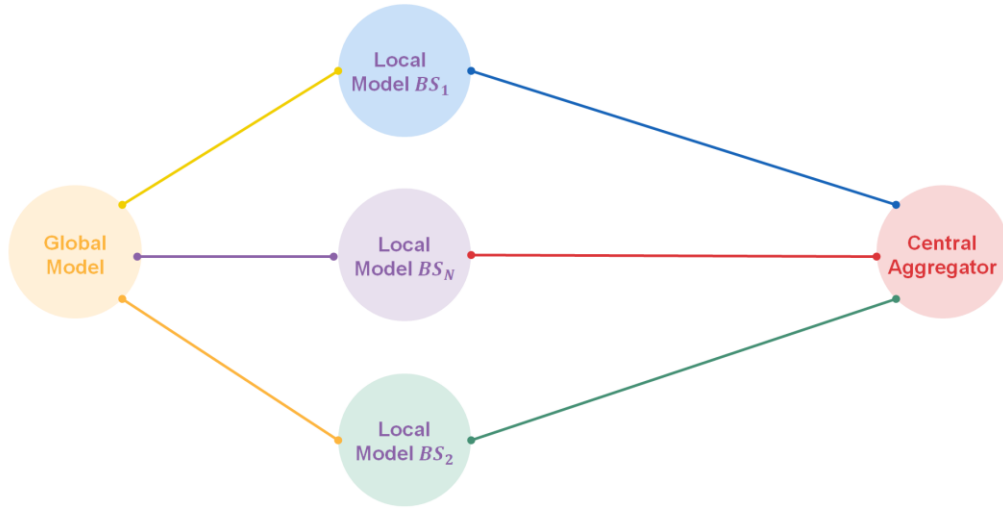


Figure 3.6- 1: FL Framework

Figure 3.6-1 shows how multiple BSs collaborate without sharing raw data.

FL framework Layout:

- **Local Training (at each BS):** Each BS trains a local DRL model using its own dataset.
- **Model Update:** Local models → send weights to aggregator.
- **Central Aggregator:** Performs FedAvg → updates global model.
- **Broadcast Back:** Global model sent to all BSs → continues training.

This diagram looks like a hub-and-spoke model with the central aggregator at the center.

1. **Local Training:** Each base station  $b$  trains a local model using its own data, updating the model parameters  $\theta_b$ :

$$\theta_b^{(t+1)} = \theta_b^{(t)} - \eta \nabla \mathcal{L}_b(\theta_b^{(t)})$$

where  $\eta$  is the learning rate and  $\mathcal{L}_b$  is the local loss function.

2. **Global Update:** After local training, the updates from all BSs are aggregated to form a new global model:

$$\theta^{(t+1)} = \sum_{b \in B} \frac{n_b}{n} \theta_b^{(t+1)}$$

where  $n_b$  is the number of data samples at base station  $b$  and  $n$  is the total number of data samples across all BSs.

3. **Communication Efficiency:** This approach significantly reduces the amount of data transmitted over the network, as only model parameters are shared, thus optimizing bandwidth utilization.

For our H-MARL setting, FL is applied to shared networks (e.g., state encoders, critic networks) while policy execution remains decentralized. FL rounds are costly over wireless links; tradeoffs include:

- **Local epoch count:** more local updates reduce communication frequency but can cause client drift on heterogeneous data.
- **Compression and sparsification:** model update compression, quantization, and sparsification reduces uplink cost. Sparsification refers to the process of reducing the number of active elements in a dataset, model or signal making it sparse while retaining the most important information.
- **Client selection:** choose clients with good channel conditions or complementary data to speed convergence.

These choices must conform to the network's latency/throughput targets: e.g., FL model aggregation may occur during low-load periods or over the operator's dedicated backhaul.

### 3.6.1 Pseudo-code of Federated Learning (FL) for Multi-Cell Networks

```
# Federated Learning (FedAvg) Pseudocode

Participants: K clients (BSs / edge nodes), CentralServer
Model: global model W (e.g., shared encoder + policy head)
Hyperparameters:
  R: number of communication rounds
  E_local: local epochs per round
  B: local batch size
  η_local: local learning rate
  τ: fraction of clients sampled per round (0<τ≤1)
  secure_agg: boolean
  personalization: boolean (fine-tune local head)
```

```

Initialize:
    W_global = random_init() or pretrain_on_public_data()
    For each client k: W_k = W_global

For round = 1..R:
    S = sample_clients(K, fraction= $\tau$ ) # client selection for
scalability
    # Parallel local updates
    For each client k in S (in parallel):
        W_k = W_global # start from global
        for epoch = 1..E_local:
            for batch in client_data_k minibatches of size B:
                loss = compute_loss(W_k, batch) # supervised RL imitation or
policy-gradient loss on local experiences
                W_k = W_k -  $\eta_{\text{local}}$  * grad(loss)
            end for
        end for
        send_update_k = W_k - W_global # or send encrypted W_k if
secure_agg
        if secure_agg:
            encrypt_and_send(send_update_k)
        else:
            send send_update_k
        end for

    # Server aggregation
    if secure_agg:
        aggregated_update = secure_aggregate(received_encrypted_updates)
# returns sum
    else:
        aggregated_update =  $\sum_{k \in S} (n_k * (W_k)) / \sum_{k \in S} n_k$ 
# weighted FedAvg by local dataset n_k

    W_global = aggregated_update # or W_global += aggregated_update
for update vectors

    #Server-side evaluation, early stopping, learning rate adjustment

# Personalization
If personalization:
    For each client k:

```

```

# Keep shared encoder fixed, fine-tune small local policy head on
local data
  local_head_k = init_from_global_head(W_global)
  fine_tune(local_head_k, local_data)
  deploy local_head_k alongside shared_encoder (W_global.encoder)
end for

# Privacy & Compression considerations
- Differential privacy: adding noise to updates
- Quantization/ sparsification for comm compression
- Secure aggregation to prevent server from reading individual
updates

```

Return  $W_{global}$  (deployed to clients)

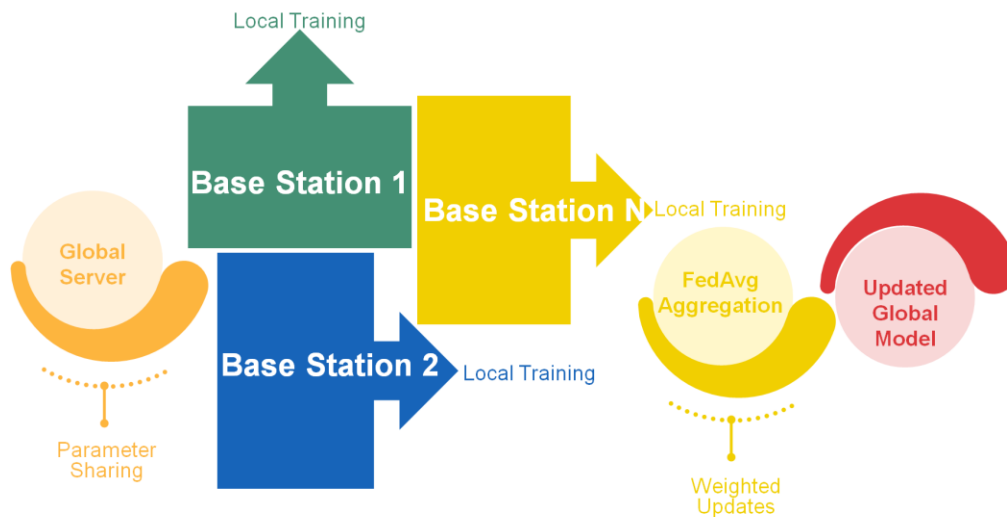


Figure 3.1 3.1.1 FL Workflow

Each BS trains its local policy with local data, sends updates to the server, and receives the aggregated model. This reduces latency and ensures data privacy.

### 3.7 XAI Framework Integration for Interpretability of Decisions

The proposed framework incorporates XAI techniques to make the decision-making process of intelligent agents transparent and interpretable.

The XAI integration was designed around three complementary methods. First, SHAP was employed to provide global feature importance analysis. By decomposing the reward contributions of individual features such as SNR, interference levels, queue lengths, and

traffic demands, SHAP quantified how each factor influenced the agent's allocation strategy. This allowed network administrators to identify dominant drivers behind specific decisions, such as prioritizing high-SNR users for spectral efficiency or throttling power allocation to reduce energy consumption. Second, LIME was used to generate instance-level explanations for specific actions taken in real time. For example, when an agent allocated a resource block to a user with moderate SNR instead of the highest-SNR user, LIME produced a surrogate linear model that highlighted contextual features such as queue backlog or fairness constraints that drove this action. This provided actionable insights into why certain seemingly counterintuitive decisions were taken, thereby improving trustworthiness and operator confidence. Third, policy visualization tools were incorporated to illustrate the mapping between network states and agent actions. Heatmap was generated to visualize how actions evolved as traffic load, interference, or user mobility changed over time. These visualizations enabled domain experts to compare agent policies against heuristic baselines and to validate whether the learned strategies aligned with expected physical-layer and MAC-layer behaviors.

The XAI module not only facilitated debugging and validation of learned policies but also supported explainability-driven optimization, where feedback from operators could be used to refine reward functions or adjust hyperparameters. Furthermore, interpretability is essential in regulatory contexts, where AI-based network optimization must comply with transparency requirements and ensure fairness across different user groups. By embedding SHAP, LIME, and visualization mechanisms into the framework, the proposed system successfully bridges the gap between high-performance AI models and the need for human-understandable explanations, making it more deployable and trustworthy for real-world 5G/6G networks.

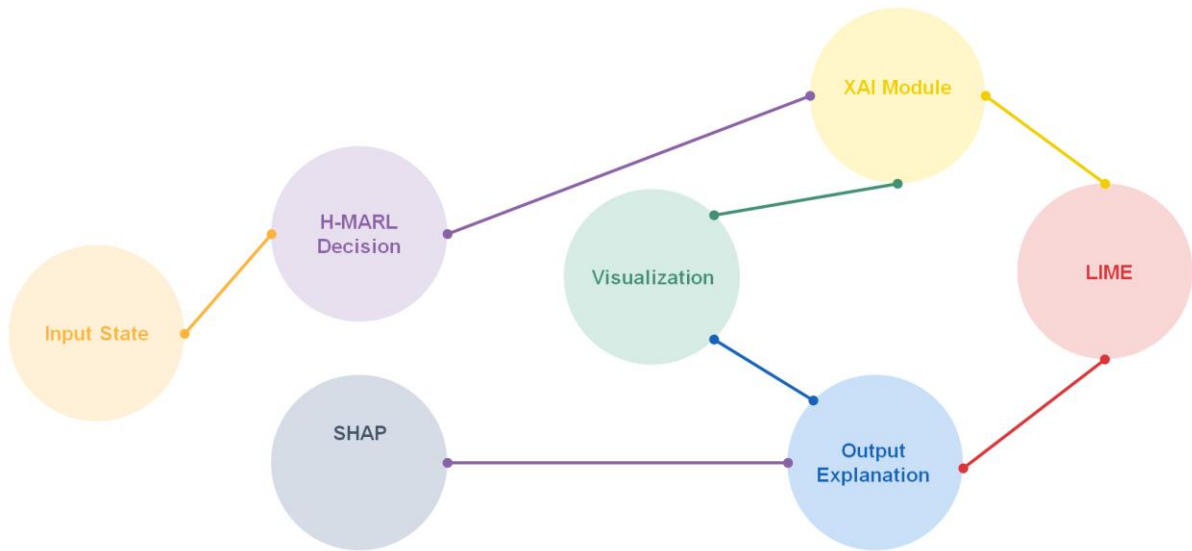


Figure 3.7- 1: XAI framework integration

Figure 3.7-1 explains how XAI techniques interpret decisions of DRL/MARL.

Flow Diagram Layout:

- **Input State** → traffic load, SNR, interference, queue length
- **DRL/MARL Policy Decision action** → scheduling, Resource Block (RB) allocation, power control
- **XAI Module:**
  - SHAP → feature importance ranking.
  - LIME → local decision explanation.
  - Visualization → policy heatmap, decision graphs.
- **Output to Operator** → Human-readable explanation (e.g., “High SNR led to priority scheduling”).

Mathematically, the impact of feature importance can be quantified, allowing operators to understand the contribution of each feature to the decision-making process.

The overall optimization problem, considering the AI techniques and learning algorithms, can be encapsulated as:

$$\max_{\mathbf{X}, \mathbf{P}} \sum_{b \in B} \sum_{u \in U} \sum_{s \in S} x_{b,u,s} R_{b,u,s}(\mathbf{h}, \mathbf{P}) - \lambda \cdot E(\mathbf{P})$$

$$s. t. R_{b,u,s} \geq R_{min}$$

$$\sum_{u \in U} \sum_{s \in S} P_{b,u,s} \leq P_b^{max}$$

Given the safety, regulatory, and operational needs in telecom, interpretability of learned policies is essential. XAI is integrated at two levels:

1. **Model-level explanations:** feature importance applied to state encoders or critic outputs to show which inputs drove a decision.
2. **Policy-level explanations:** surrogate rule extraction, policy distillation (distill complex policy into an interpretable decision tree), or counterfactual explanations showing “if  $X$  had been different, action  $Y$  would change to  $Z$ ”.

Operators need both global explanations (overall policy tendencies) and local explanations (why action  $a$  was selected at time  $t$ ). For MARL, explanations must also consider inter-agent interactions; graph-based XAI approaches that explain communications between agents are promising.

XAI can be used operationally for: debugging, SLA audits, regulatory compliance, and human-in-the-loop overrides. There is a trade-off between interpretability and optimality; hybrid approaches for instance post-hoc explanations and distilled surrogate models offer practical balance.

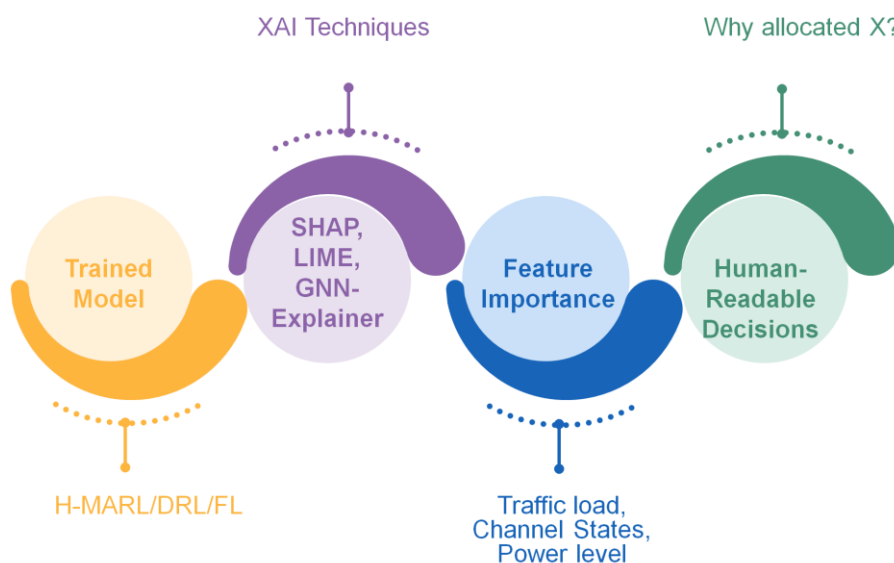


Figure 3.7- 2: XAI Workflow

XAI explains decisions made by AI agents like why a user/device was allocated more RBs or power). This ensures trust, transparency, and interpretability in network optimization.

### 3.7.1 Pseudo code of XAI Technique

```
# XAI for RL Pseudocode
```

```
Inputs:
```

```
    TrainedPolicy  $\pi(s)$  (neural network maps state  $\rightarrow$  action or action distribution)

    Dataset  $D_{eval} = \{s_t, a_t, reward_t, context_t\}$  collected from policy rollouts

    ExplanationMethods = {IntegratedGradients, SHAP_approx, SaliencyMaps, PolicyDistillation}

    num_samples_local_expl = M

    feature_set: state features, optionally grouped (e.g., channel, queue, userQoS)
```

```
Procedure:
```

```
# Part A: Local (per-decision) explanations
For each decision instance (s, a) in sample( $D_{eval}$ , num=M):
    # 1. Saliency / Gradient-based explanation (for differentiable policy)
    grad = compute_gradient( $\pi_{output\_for}(a)$  w.r.t input_features at s)
    saliency_map = aggregate_abs(grad) # feature importance scores

    # 2. Integrated Gradients (IG)
    baseline = choose_baseline(s) # zero-state or average-state
    IG_scores = integrated_gradients( $\pi$ , s, baseline, steps=K)

    # 3. SHAP-like local surrogate
    neighborhood = perturb_state(s, num=N, feature_groups=feature_set)
    outputs = evaluate_policy(neighborhood)
    surrogate = fit_sparse_linear_model(neighborhood_features, outputs)
    shap_values = surrogate.coefficients
```

```

# 4. Map importance to human concepts
concept_importances = map_features_to_concepts(shap_values or IG_scores)

# 5. Generate textual explanation template
explanation_text = format(
    "At time t, policy selected action A because feature X (e.g.,
    queue_length) increased importance by {v1}, \
    and concept Y (e.g., interference) contributed {v2}. Meta-goal was
    {meta_goal}."
)

Store explanation: {s, a, saliency_map, IG_scores, shap_values,
explanation_text}

# Part B: Global / Policy-level explanations
# 1. Global feature importances: aggregate local scores over dataset
global_importance = aggregate_over_D_eval(IG_scores or shap_values,
method=mean_abs)

# 2. Behavioral prototypes/clusters
clusters = cluster_state_action_pairs(D_eval, method=KMeans or
hierarchical)

for each cluster c:
    prototype = choose_median_example(c)
    summary = compute_cluster_statistics(c) # avg throughput, latency,
actions distribution
    store prototype_explanation = (prototype, summary)

# 3. Surrogate symbolic policy (policy distillation)
train dataset X = D_eval.states, Y =  $\pi$ (D_eval.states).actions
DecisionTree = train_decision_tree(X_features_concepts, Y_actions,
max_depth=d)
# Evaluate fidelity = accuracy(DecisionTree.predict(X), Y)
if fidelity >= threshold:
    export rules = extract_rules_from_tree(DecisionTree)

```

```

# Part C: Explanation validation & metrics
For explanation in explanations:
    - FidelityMetric = measure_surrogate_fidelity(surrogate,  $\pi$ , neighborhood)
    - Consistency = check_explanation_consistency_over_similar_states()
    - Usefulness = (human_eval_score if available)
    - Stability = measure_variation_when_noise_added_to_input()

# Part D: Visual & API outputs
For each explanation:
    - Produce heatmap over input features (for UI)
    - Produce timeline plots showing how feature importances evolve
    - Produce textual rule / bullet-point summary for operator dashboard
    - Provide counterfactuals: minimal perturbation  $\Delta s$  such that policy
changes action -> propose "If queue_length decreases by X, action would
change to Y"

Return:
    explanations_db, global_importance, surrogate_rules, prototype_summaries

```

### 3.8 Research Hypotheses

Based on the theoretical foundations, this research is guided by the following hypotheses:

- **H1:** H-MARL outperforms flat MARL and centralized optimization in terms of scalability and convergence in dense 5G/6G scenarios.
- **H2:** TL significantly reduces training time and improves adaptability to dynamic traffic and channel conditions.
- **H3:** FL enhances scalability and privacy without compromising optimization performance.
- **H4:** XAI improves trust and transparency in AI-driven optimization, enabling fairer and more accountable resource allocation.

These hypotheses form the foundation for the methodological and experimental analysis.

### 3.9 System Model

Designing an effective system model is fundamental to achieving optimal performance in next-generation wireless networks. The system model serves as the mathematical and conceptual foundation upon which optimization strategies are applied. In this research, the system model is divided into four essential components: the network model, the channel model, the signal model, and the traffic model, all of which are tailored to support advanced service requirements such as eMBB, URLLC, and mMTC. By formulating these components rigorously, the proposed AI-driven optimization framework can effectively enhance resource allocation, traffic management, and energy efficiency in 5G/6G environments.

#### 3.9.1 Network Model

The network model considered in this study is based on a heterogeneous 5G/6G cellular architecture comprising Macro Base Stations (MBSs), small cells, and User Equipment (UEs) distributed across a dense urban environment. The deployment supports multi-service traffic, including eMBB users demanding high throughput, URLLC users requiring ultra-low latency, and mMTC devices characterized by sporadic but massive connectivity.

Let the set of BSs be denoted as  $B = \{b_1, b_2, \dots, b_N\}$ , where  $N$  represents the total number of BSs. Similarly, the set of users is represented as  $U = \{u_1, u_2, \dots, u_M\}$ , with  $M$  being the number of users in the system. Each base station is equipped with multiple antennas to enable massive MIMO transmission, supporting beamforming and spatial multiplexing. The total system bandwidth  $W$  is partitioned into multiple orthogonal RBs, and the allocation of these RBs across users forms the resource allocation problem. The objective is to maximize throughput while minimizing latency and energy consumption. Resource allocation decisions are influenced by user association policies, traffic demand, and CQI. In order to address fairness among users, a proportional fairness utility function is incorporated, defined as:

$$U = \sum_{u \in U} \log R_u \quad (3.4)$$

where  $R_u$  denotes the achieved data rate of user  $u$ . This formulation balances throughput maximization with fairness, a critical aspect of next-generation heterogeneous networks.

### 3.9.2 Channel Model

The channel model captures the propagation characteristics between BSs and users. In this study, a composite channel model is employed, combining large-scale fading (path loss and shadowing) with small-scale fading (multipath effects).

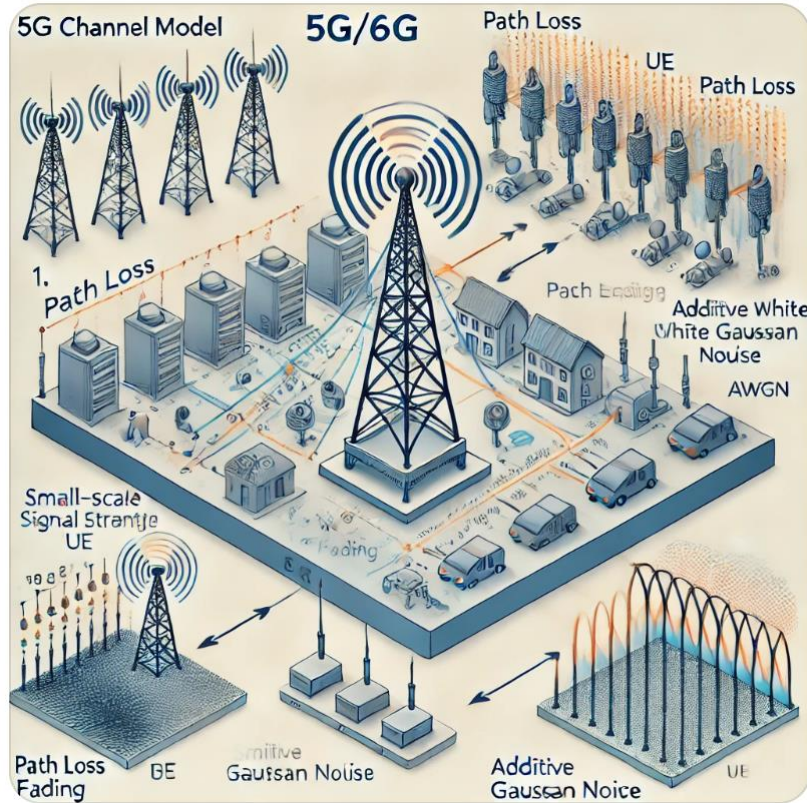


Figure 3.9.2- 1: Channel Model of 5G/6G Networks

The received power at user  $u$  from base station  $b$  is modeled as:

$$P_r(u, b) = P_t(b)G_{b,u}L_{b,u}^{-1} \cdot |h_{b,u}|^2 \quad (3.5)$$

where  $P_t(b)$  is the transmit power of base station  $b$ ,  $G_{b,u}$  is the antenna gain,  $L_{b,u}$  represents the path loss, and  $h_{b,u}$  denotes the small-scale fading coefficient. Path loss is modeled using the 3GPP Urban Macro (UMa) and Urban Micro (UMi) models depending on the deployment environment. For example, the UMa model is expressed as:

$$L_{b,u} = 32.4 + 21 \log_{10} d_{b,u} + 20 \log_{10} f_c \quad (3.6)$$

where  $d_{b,u}$  is the distance between the user and the base station in meters, and  $f_c$  is the carrier frequency in GHz.

The channel model describes how the wireless signal propagates from the base station to the user. It includes path loss, Shadowing and small scale fading.

### 3.9.2.1 Path Loss

The large-scale path loss describes the power attenuation as a function of the distance between the transmitter and receiver. For user  $u$  served by base station  $b$ , the path loss  $PL(d_{b,u})$  is modeled as:

$$PL(d_{b,u}) = PL_0 + 10\gamma \log_{10} d_{b,u} \quad (3.7)$$

Where  $PL_0$  is the path loss at a reference distance (typically 1 meters),  $\gamma$  is the path loss exponent, and  $d_{b,u}$  is the distance between base station  $b$  and user  $u$ .

### 3.9.2.2 Small-Scale Fading and Channel Gain

The channel gain between base station  $b$  and user  $u$  on subcarriers, denoted  $h_{b,u,s}$ , is modeled as:

$$h_{b,u,s} = g_{b,u,s} \cdot d_{b,u}^{-\gamma} \quad (3.8)$$

where  $g_{b,u,s}$  represents the small-scale fading, modeled by a Rayleigh or Rician distribution depending on the environment. Small-scale fading is modeled using Rayleigh fading for non-line-of-sight (NLoS) scenarios and Rician fading for line-of-sight (LoS) conditions, capturing multipath propagation and Doppler effects.

### 3.9.2.3 Achievable Rate

The achievable rate for user  $u$  on subcarrier  $s$  from base station  $b$  is given by the Shannon capacity formula:

$$R_{b,u,s} = B_s \log_2 \left( 1 + \frac{P_{b,u,s} |h_{b,u,s}|^2}{\sigma^2} \right) \quad (3.9)$$

where  $B_s$  is the bandwidth of subcarrier  $s$ ,  $P_{b,u,s}$  is the transmit power from base station  $b$  to user  $u$  on subcarrier  $s$ ,  $|h_{b,u,s}|^2$  is the channel power gain,  $\sigma^2$  is the noise power.

### 3.9.3 Signal Model

The signal model defines the relationship between transmitted and received signals in the wireless environment. The baseband equivalent received signal at user  $u$  can be expressed as:

$$y_u = \sum_{b \in B} h_{b,u} x_b + n_u \quad (3.10)$$

where  $h_{b,u}$  is the complex channel coefficient,  $x_b$  represents the transmitted signal from base station  $b$ , and  $n_u$  is additive white Gaussian noise (AWGN) with variance  $\sigma^2$ .

The Signal-to-Interference-plus-Noise Ratio (SINR) for user  $u$  connected to base station  $b$  is given by:

$$SINR_{u,b} = \frac{P_t(b)|h_{b,u}|^2}{\sum_{k \in B} P_t(b)|h_{k,u}|^2 + \sigma^2} \quad (3.11)$$

The achievable data rate of user  $u$  is determined by the Shannon capacity formula as explained in equation (3.9) and it can be rewritten in terms of  $SINR_{u,b}$  as:

$$R_{b,u,s} = W \cdot \log_2(1 + SINR_{u,b}) \quad (3.12)$$

This rate formulation provides a foundation for resource allocation decisions and serves as the optimization objective in maximizing system performance.

### 3.9.4 Traffic Models

To capture diverse service requirements, three primary traffic models are considered as mentioned in section 3.9:

- **eMBB:** High data rate applications such as video streaming and VR/AR modeled using Poisson arrival processes with high packet sizes.

- **URLL:** Critical communications such as autonomous driving and industrial automation, modeled with strict latency constraints ( $\leq 1$  ms) and Packet Error Rate (PER) requirements.
- **mMTC:** IoT-driven traffic with massive device density, modeled with sporadic short-packet transmissions from thousands of devices.

These traffic models allow the proposed framework to adapt resource allocation policies dynamically based on service-specific requirements. The system modeling ensures that the proposed optimization framework operates under conditions that mirror practical deployment scenarios in 5G/6G systems.

### 3.10 Dynamic optimization Strategies

5G/6G systems are non-stationary: channels fade, users move, slices come and go, traffic is bursty, and energy/price signals fluctuate. Static or offline solutions quickly become suboptimal. Dynamic optimization treats the network as a stochastic, time-varying system and updates decisions every slot (ms–s scale) to track the moving optimum while satisfying strict constraints (latency, reliability, power, isolation among slices).

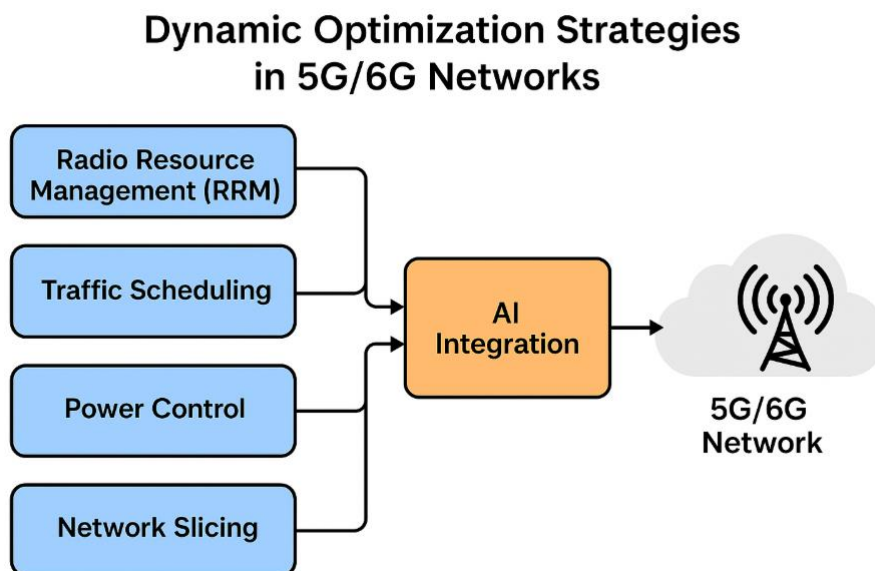


Figure 3.10- 1: Dynamic Optimization Strategies

### 3.10.1 Problem abstraction

#### 3.10.1.1 Time-slotted model

At discrete slots  $t = 0, 1, 2, \dots$ , the controller observes a state  $s_t = (H_t, Q_t, U_t, E_t, \Theta_t)$  where,  $H_t$ , is the channel/beam/CSI and interference context,  $Q_t$ , represents queue backlogs per user/slice (eMBB/URLLC/mMTC),  $U_t$ , denotes user context (mobility, handover candidates),  $E_t$ , is the energy state (BS sleep states, battery, grid/renewable price), lastly  $\Theta_t$ , denotes slice intents/SLA targets.

It chooses an action  $a_t = (x_t, p_t, b_t, r_t, \pi_t)$  e.g., PRB scheduling  $x_t$ , power  $p_t$ , bandwidth/slice shares  $b_t$ , routing  $r_t$  (RAN  $\rightarrow$  edge  $\rightarrow$  core), and policy knobs  $\pi_t$  (Modulation and Coding Scheme (MCS), Hybrid Automatic Repeat Request (HARQ) rounds, sleep states). The system then experiences random disturbances (arrivals, channel realizations), receives vector costs  $c_t(a_t, s_t)$  (delay, outage, energy, penalties), and rewards  $R_t(a_t, s_t)$  (throughput, utility). Queues evolve as:

$$Q_i(t+1) = \max\{Q_i(t) - \mu_i(t), 0\} + A_i(t) \quad (3.13)$$

with service  $\mu_i(t)$  determined by scheduling and PHY rates that is the theoretical maximum speed of data transmission between a device and a wireless access point, including all control information.

#### 3.10.1.2 Multi-objective formulation

We seek a dynamic policy  $\pi$  to minimize long-term expected costs while meeting constraints:

$$\min_{\pi} \lim_{T \rightarrow \infty} \sup \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E} [w_E E_t + w_D D_t + w_O O_t - w_T T_t] \quad (3.14)$$

subject to reliability/latency/energy constraints ( $P_r\{\text{latency}_i > L_i\} \leq \epsilon_i, \sum p \leq P_{max}$ , slice isolation). The weights  $w$  implement scalarization; Pareto-front tracking or constrained RL can be used when weights are not fixed.

### 3.10.2 Core dynamic optimization toolkits

#### 3.10.2.1 Lyapunov (drift-plus-penalty) control

Define Lyapunov function  $L(Q_t) = \frac{1}{2} \sum_i Q_i(t)^2$  drift  $\Delta_t = \mathbb{E}[L(Q_{t+1}) - L(Q_t) | Q_t]$

Minimize drift + penalty:

$$\min_{a_t} \Delta_t + V \mathbb{E}[g_t(a_t, s_t) | Q_t] \quad (3.15)$$

where  $g_t$  is weighted energy/outage cost and  $V > 0$  trades off delay vs. cost. This yields myopic per-slot decisions with provable queue stability and  $O(1/V)$  optimality gap. It's a strong baseline and also a scaffold for RL. Latency/reliability constraints can be mapped to virtual queues (e.g., for URLLC violation indicators), ensuring mean-rate stability implies chance constraints.

#### 3.10.2.2 Online Convex Optimization (OCO)

When per-slot losses  $f_t(a)$  are convex (e.g., power, convex surrogates of delay), algorithms like Online Gradient Descent, Mirror Descent, or AdaGrad minimize dynamic regret against a drifting comparator. OCO is useful for traffic engineering (flow splitting), compute placement, bandwidth slicing, and price-based control.

#### 3.10.2.3 Model Predictive Control (MPC)

MPC solve a horizon- $H$  optimization with forecasts (traffic, mobility, energy price), apply the first action, and then roll forward. In 5G/6G, tube MPC or robust MPC handles uncertainty; learning-augmented MPC uses Recursive Neural Network/Graph Neural Network (RNN/GNN) forecasts and corrects bias online.

#### 3.10.2.4 Bandits for lightweight adaptation

When the action space is discrete (e.g., MCS, sleep state), contextual/combinatorial bandits (LinUCB, Thompson sampling) give quick, explainable exploration-exploration with regret guarantees—handy for local RAN knobs or edge offloading decisions.

### 3.10.3 Optimization Problem Formulation

The overall optimization problem can be expressed as a multi-objective optimization problem balancing throughput, latency, and energy efficiency. The objective function is defined as:

$$\max_{\pi}(\alpha \cdot \text{Throughput} + \beta \cdot \text{Energy Efficiency} - \gamma \cdot \text{Latency}) \quad (3.16)$$

subject to user association constraints, RB assignment constraints, power allocation limits and QoS requirements for URLLC and eMBB. Where  $\pi$  denotes the AI-driven policy, and  $\alpha, \beta, \gamma$  are weight factors balancing different performance objectives.

The constraints include:

1. **QoS constraints:** Ensure that the rate for each user satisfies the minimum requirement:

$$R_{b,u,s} \geq R_{min}$$

2. **Power constraints:** Ensure that the total power allocated by each base station does not exceed the maximum limit:

$$\sum_{u \in U} \sum_{s \in S} P_{b,u,s} \leq P_b^{max}$$

3. **Fairness constraints:** To ensure fair resource allocation among users, fairness criteria PF is applied.

The resource allocation problem focuses on optimizing the assignment of subcarriers and power to UEs. Define  $x_{b,u,s}$  as a binary decision variable where:

$$x_{b,u,s} = \begin{cases} 1, & \text{if subcarrier } s \text{ is assigned to user } u \text{ by base station } b, \\ 0, & \text{otherwise} \end{cases}$$

The objective is to maximize the network throughput while minimizing the energy consumption. The optimization problem can be formulated as:

$$\max_{X, P} \sum_{b \in B} \sum_{u \in U} \sum_{s \in S} x_{b,u,s} R_{b,u,s} - \lambda \cdot E(\mathbf{P})$$

where:

- $R_{b,u,s}$  is the achievable rate for user  $u$  on subcarrier  $s$  from base station  $b$ .
- $E(\mathbf{P})$  is the energy consumption, dependent on the power allocation  $\mathbf{P} = \{P_{b,u,s}\}$ , where  $P_{b,u,s}$  is the power allocated by base station  $b$  to user  $u$  on subcarrier  $s$ .
- $\lambda$  is the trade-off parameter that balances throughput and energy consumption.

### 3.11 Performance metrics

The performance evaluation of AI-driven dynamic optimization in 5G/6G networks relies on multiple quantitative metrics that capture the system's ability to allocate resources efficiently, manage network traffic effectively, and minimize energy consumption while maintaining QoS and QoE. These metrics are derived from communication theory and optimization principles and are essential for benchmarking the proposed framework against baseline approaches such as heuristic methods, centralized DRL optimization, and non-hierarchical RL models.

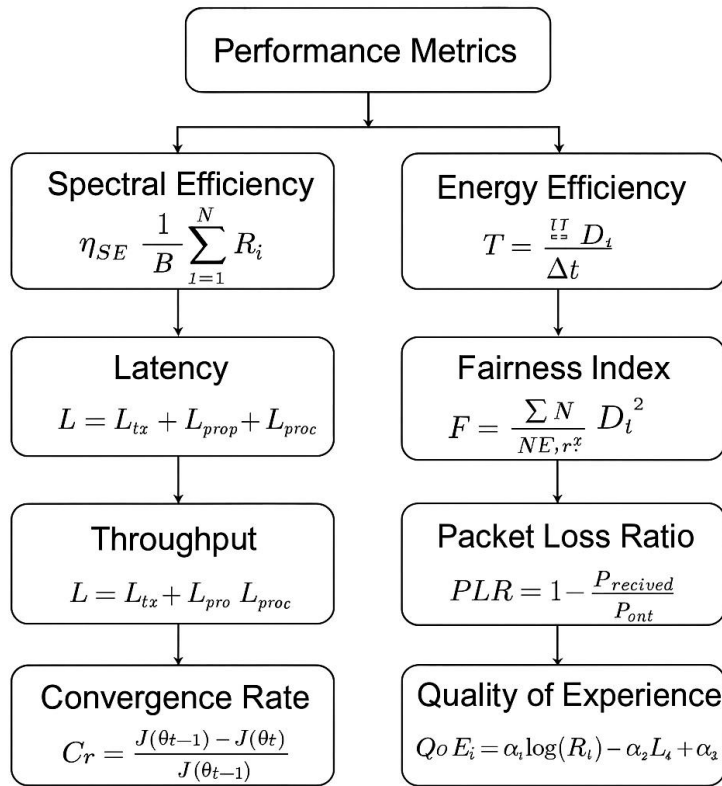


Figure 3.11- 1: Performance Metrics summary

### 3.11.1 Spectral Efficiency (SE)

Spectral Efficiency measures the data throughput achieved per unit of bandwidth and is one of the primary indicators of system capacity. It is mathematically expressed as:

$$\eta_{SE} = \frac{1}{B} \sum_{i=1}^N R_i$$

where  $R_i$  denotes the achievable data rate for user  $i$  (in bits per second),  $N$  is the total number of users, and  $B$  represents the total bandwidth. The achievable rate  $R_i$  can be derived using the Shannon–Hartley theorem described in section 3.9.3 equation (3.12). Higher SE indicates better utilization of spectral resources, which is crucial for dense 6G deployments characterized by massive connectivity.

### 3.11.2 Energy Efficiency (EE)

Energy efficiency evaluates how effectively the network converts power consumption into data throughput. It is defined as the ratio of total achievable throughput to total power consumed by network elements (BSs, access points, and user devices):

$$\eta_{EE} = \frac{\sum_{i=1}^N R_i}{P_{total}}$$

where  $P_{total} = P_{tx} + P_{circuit} + P_{static}$ . Here,  $P_{tx}$  denotes transmit power,  $P_{circuit}$  represents circuit power, and  $P_{static}$  is the baseline power consumption. AI-based optimization aims to dynamically adjust transmission and scheduling policies to maximize  $\eta_{EE}$  under QoS constraints.

### 3.11.3 Latency (L)

Latency quantifies the time delay experienced by a data packet as it traverses the network. It includes transmission, propagation, and processing delays. Mathematically, it can be expressed as:

$$L = L_{tx} + L_{prop} + L_{proc}$$

where  $L_{tx} = \frac{P_{pkt}}{R_i}$  represents transmission delay for a packet of size  $P_{pkt}$ ,  $L_{prop}$  denotes propagation delay, and  $L_{proc}$  indicates the time required for computational processing at edge or core nodes. URLLC in 6G requires latency below 1 ms, making real-time AI-driven control essential.

### 3.11.4 Throughput (T)

Throughput represents the aggregate data successfully transmitted over the network per unit time. It reflects the efficiency of scheduling and resource allocation policies:

$$T = \frac{\sum_{i=1}^N D_i}{\Delta t}$$

where  $D_i$  is the total data delivered to user  $i$  within a time window  $\Delta t$ . AI-based reinforcement learning agents aim to maximize  $T$  through adaptive power allocation, user association, and dynamic bandwidth partitioning.

### 3.11.5 Fairness Index (F)

Fairness ensures equitable resource distribution among users. Jain's Fairness Index is widely used and is defined as:

$$F = \frac{(\sum_{i=1}^N R_i)^2}{N \sum_{i=1}^N R_i^2}$$

The index  $F$  ranges between 0 and 1, where  $F = 1$  indicates perfect fairness. In multi-agent systems, H-MARL ensures fairness by incorporating collaborative reward functions that balance between global network performance and individual agent utility.

### 3.11.6 Packet Loss Ratio (PLR)

Packet Loss Ratio measures the reliability of transmission and is expressed as:

$$PLR = 1 - \frac{P_{received}}{P_{sent}}$$

where  $P_{received}$  and  $P_{sent}$  denote the total number of packets successfully received and transmitted, respectively. Lower  $PLR$  indicates better link reliability and resource management, particularly in high-mobility and interference-prone environments.

### 3.11.7 Convergence Rate and Stability

For AI-based algorithms, convergence rate ( $C_r$ ) and stability are critical performance metrics. The convergence rate can be defined as the reduction of the loss function  $J(\theta)$  over iterations  $t$ :

$$C_r = \frac{J(\theta_{t-1}) - J(\theta_t)}{J(\theta_{t-1})}$$

where  $\theta_t$  represents the parameter vector at iteration  $t$ . Faster convergence implies that the algorithm achieves optimal or near-optimal policies with fewer training episodes, which is vital for online learning in dynamic networks.

### 3.11.8 Quality of Experience (QoE)

Beyond network-centric metrics, user-centric measures such as QoE are increasingly relevant. QoE combines throughput, latency, jitter, and fairness into a composite index representing end-user satisfaction. It is often modeled as a non-linear function:

$$QoE_i = \alpha_1 \log(R_i) - \alpha_2 \log(L_i) + \alpha_3 \log(F_i)$$

where  $\alpha_1, \alpha_2, \alpha_3$  are empirically determined weighting factors. AI-driven optimization enables personalized QoE management through adaptive policy learning and feedback mechanisms.

Collectively, these metrics provide a comprehensive evaluation of how effectively the proposed AI-driven framework enhances 5G/6G network performance. The mathematical formulations guide the design of reward functions for RL agents, ensuring that optimization objectives align with real-world performance indicators.

### 3.12 Assumptions, Constraints and Design Choices

For tractability, several assumptions are made:

- Perfect CSI is available at the base station (though later robustness tests relax this assumption).
- User mobility follows a random waypoint model with average velocities ranging from pedestrian to vehicular speeds.
- BSs are synchronized, and inter-cell interference is considered.
- Energy consumption accounts for both transmission and circuit-level power.
- Agents have partial local observations; some state elements (neighbor summaries) can be exchanged at low rate.
- Traffic and radio environments can be non-stationary; the framework assumes at least slow time-scale stationarity for meta-controller decisions. For rapid non-stationarity, continual learning and TL are relied upon.
- Edge nodes can occasionally communicate with a parameter server or via cooperative aggregation over operator backhaul for FL rounds.
- Pre-training uses high-fidelity digital twins (or synthetic data) representative of deployment scenarios.

These assumptions allow the system model to remain realistic while still enabling efficient evaluation of AI-driven optimization strategies.

The constraints and design tradeoffs are as follows:

- Communication overhead of FL vs. frequency of aggregation.
- Latency sensitivity of URLLC traffic constrains how much on-device learning can momentarily impact scheduling. Critical functions must meet hard deadlines.
- Privacy and regulatory constraints limit which telemetry can be shared; FL mitigates some risks but additional privacy techniques namely secure aggregation may be required.
- Computational limits at edge nodes may enforce lighter models or offloading of heavy computations to edge servers.

### 3.13 Combining H-MARL, TL, and FL — A Practical Training Workflow

The training workflow is discussed below:

1. **Pretraining (Simulation / Source Domains)**
  - Train meta-controller and local agents in high-fidelity simulators (digital twin) under varied traffic and topology scenarios. Use centralized training to stabilize learning.
  - Save meta-policies and low-level encoders as source models.
2. **Federated Fine-Tuning (Edge Deployment)**
  - Deploy pre-trained encoders/policy seeds to edge nodes. Each edge node continues RL-based adaptation on local data while participating in periodic FL rounds to aggregate encoder/critic weights. This preserves privacy and shares knowledge across cells.
3. **Transfer & Personalization**
  - Use TL regularizers to balance global knowledge and local specialization. Personalization layers (small local heads) enable node-specific adjustments without degrading global models.
4. **Online Operation with Hierarchical Control**
  - Meta-controller periodically computes high-level goals (e.g., per-slice budgets) using federated/global information; local agents act at fast timescales to realize goals. Monitoring modules gather performance metrics for continual evaluation.

This hybrid pipeline leverages TL for fast adaptation, FL for privacy-preserving knowledge sharing, and H-MARL for scalability and hierarchical control. Empirical work shows effectiveness of such hybrids in edge/offloading and Adaptive Traffic Signal Control (ATSC) domains.

### 3.14 Evaluation Plan

To validate the framework, the following experiments are conducted:

1. **Simulation-only baselines:** Compare H-MARL vs. flat MARL, centralized DRL, and heuristic scheduler across throughput, latency, energy.

2. **TL experiments:** Pretrain in source topology; measure adaptation speed and final performance in new topologies with and without TL regularizers.
3. **Federated experiments:** Simulate heterogeneous client data distributions, evaluate convergence of FL aggregations, impact on personalization. Explore communication/computation tradeoffs.
4. **XAI utility:** Evaluate explanation fidelity (how well surrogate explains original policy), operator usefulness via user study (optional).

### 3.15 Summary

This chapter formalized the proposed multi-layered framework:

- A mathematical system model and multi-objective optimization balancing throughput, latency, and energy.
- A hierarchical MARL architecture for scalable, multi-timescale control.
- Integration methods for TL to accelerate adaptation and FL to enable privacy-preserving, cross-site knowledge sharing.
- Embedding of XAI for operator trust and regulatory needs.

The design choices reflect recent state-of-the-art advances and aim to balance performance, scalability, privacy, and interpretability.

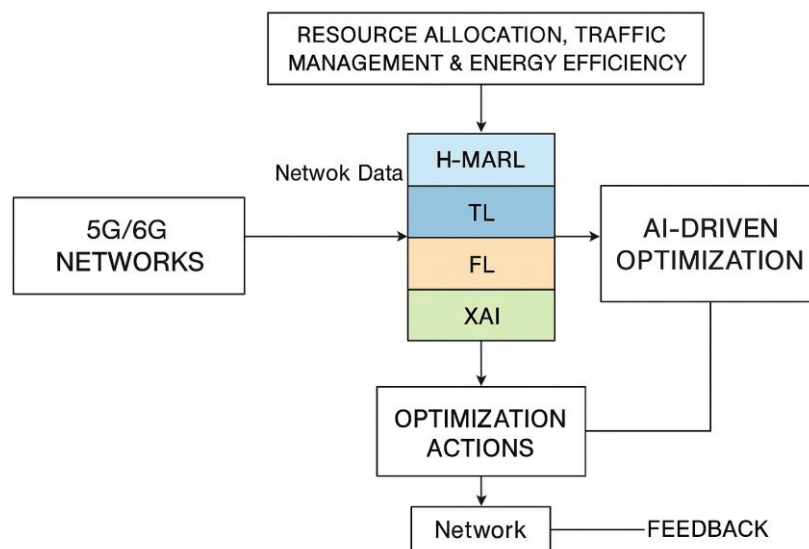


Figure 3.15- 1: Framework Summary

## CHAPTER 4: IMPLEMENTATION AND EXPERIMENTAL SETUP

This chapter presents the implementation details and experimental setup used to evaluate the proposed framework for AI-driven dynamic optimization of 5G/6G networks. It describes the dataset, system parameters, algorithmic components, and execution methodology. The chapter aims to provide a clear understanding of how H-MARL TL, FL, and XAI were integrated and tested to enhance resource allocation, traffic management, and energy efficiency in ultra-dense wireless environments.

### 4.1 Dataset Description

This research makes use of publicly available datasets sourced from Kaggle to model the dynamic behavior of next-generation wireless networks, particularly in relation to traffic, mobility, and energy consumption. These datasets are selected because they provide diverse perspectives on key aspects of 5G/6G operations and are suitable for reinforcement learning-based optimization tasks. Three main categories of datasets are integrated to comprehensively represent the system.

The first dataset comprises network slicing and traffic demand traces, which record data flows across eMBB, URLLC, and mMTC slices. Features included in this dataset are bandwidth utilization, packet arrival rates, latency, jitter, and packet drop probabilities [161]. These characteristics provide the basis for analyzing and optimizing resource allocation under heterogeneous service requirements. The second dataset captures user mobility and handover patterns in dense urban environments and massive IoT scenarios. It contains detailed information about cell association, signal strength variations, and handover frequency across small cells and macro cells [162]. This dataset is highly valuable for modeling traffic management and QoS performance in ultra-dense deployments, where mobility-induced interference and frequent handovers significantly affect network reliability and latency. The third dataset focuses on energy consumption and base station load metrics, representing different operational states such as active, idle, and sleep modes [163]. It also accounts for the integration of renewable energy sources, enabling analysis of sustainable networking practices. The dataset allows measurement of base station energy efficiency under varying load conditions, providing critical insights for developing algorithms that balance throughput maximization with energy-saving strategies. Taken together, these three datasets provide a

holistic view of traffic dynamics, mobility behavior, and energy utilization in 5G/6G networks. Their integration ensures that the simulation environment reflects realistic scenarios and offers a reliable foundation for training RL agents that must optimize multiple objectives simultaneously.

Timestamp	User_ID	Application_Type	Signal_Strength	Latency	Required_Bandwidth	Allocated_Bandwidth	Resource_Allocation
9/3/2023 10:00	User_1	Video_Call	-75 dBm	30 ms	10 Mbps	15 Mbps	70%
9/3/2023 10:00	User_2	Voice_Call	-80 dBm	20 ms	100 Kbps	120 Kbps	80%
9/3/2023 10:00	User_3	Streaming	-85 dBm	40 ms	5 Mbps	6 Mbps	75%
9/3/2023 10:00	User_4	Emergency_Service	-70 dBm	10 ms	1 Mbps	1.5 Mbps	90%
9/3/2023 10:00	User_5	Online_Gaming	-78 dBm	25 ms	2 Mbps	3 Mbps	85%
9/3/2023 10:00	User_6	Background_Download	-90 dBm	50 ms	500 Kbps	550 Kbps	70%
9/3/2023 10:00	User_7	Web_Browsing	-88 dBm	30 ms	1 Mbps	1 Mbps	60%
9/3/2023 10:00	User_8	IoT_Temperature	-95 dBm	100 ms	10 Kbps	15 Kbps	50%
9/3/2023 10:00	User_9	Video_Streaming	-82 dBm	35 ms	3 Mbps	3.5 Mbps	80%
9/3/2023 10:00	User_10	File_Download	-75 dBm	45 ms	2 Mbps	2 Mbps	70%
9/3/2023 10:00	User_11	Video_Call	-76 dBm	32 ms	12 Mbps	14 Mbps	70%
9/3/2023 10:00	User_12	Online_Gaming	-79 dBm	24 ms	2.5 Mbps	2.8 Mbps	75%
9/3/2023 10:00	User_13	Web_Browsing	-87 dBm	28 ms	1.2 Mbps	1.2 Mbps	65%
9/3/2023 10:00	User_14	VoIP_Call	-81 dBm	22 ms	150 Kbps	170 Kbps	85%
9/3/2023 10:00	User_15	Video_Call	-74 dBm	29 ms	10 Mbps	12 Mbps	60%

Figure 4.1- 1: Sample Resource Allocation kaggle dataset

Time	BS	Energy	load	ESMODE	TXpower
20230101 010000	B_0	64.27503737	0.48793617	0	7.101718984
20230101 020000	B_0	55.90433483	0.344468085	0	7.101718984
20230101 030000	B_0	57.6980568	0.193765957	0	7.101718984
20230101 040000	B_0	55.15695067	0.222382979	0	7.101718984
20230101 050000	B_0	56.05381166	0.17543617	0	7.101718984
20230101 070000	B_0	82.95964126	0.351585106	0	7.101718984
20230101 080000	B_0	91.03139013	0.759297872	0	7.101718984
20230101 090000	B_0	78.17638266	0.887797872	0	7.101718984
20230101 100000	B_0	72.64573991	0.624744681	0	7.101718984

Figure 4.1- 2: Sample Energy Efficiency kaggle dataset

## 4.2 Data Preprocessing

To ensure high-quality data for RL and seamless integration with Stable-Baselines3 environments, the Kaggle datasets undergo a rigorous preprocessing pipeline. The first stage is data cleaning, where missing values in traffic and mobility records are imputed using interpolation or mean substitution techniques. Extreme outliers, such as unrealistic latency spikes caused by measurement errors, are identified through statistical methods like Interquartile Range (IQR) filtering and subsequently removed. Following cleaning, feature engineering is performed to extract key input variables that define the RL environment. The state space includes features such as available resource blocks, per-slice traffic demand, SNR, base station load, and current energy state. The action space, on the other hand, defines the set of decisions available to RL agents, including proportional allocation of radio resources,

scheduling policy adjustments, and energy control actions such as switching BSs into sleep mode. By clearly defining states and actions, the datasets are transformed into a format suitable for multi-agent learning in complex 5G/6G environments. Normalization is then applied to stabilize RL training. All continuous numerical features are scaled to the range [0,1] using Min-Max normalization, ensuring uniform influence across features. For heavy-tailed variables, such as bursty traffic demand, log-scaling is used to compress distribution ranges and reduce variance. These steps improve convergence speed and learning stability for both value-based and policy-based RL algorithms.

The preprocessing also includes data partitioning strategies tailored for TL and FL. In TL, datasets are divided into source and target domains to emulate cross-scenario adaptability. For example, models are pretrained using traffic traces from urban networks and fine-tuned on suburban or rural deployment scenarios, or adapted from 5G datasets to 6G-inspired datasets. For FL, datasets are partitioned across simulated BSs, enabling decentralized learning where agents train locally on their respective subsets. The knowledge from distributed agents is then aggregated through federated averaging, which allows collaborative model training without direct data sharing. Another critical step involves transforming the datasets into a RL environment compatible with OpenAI Gym, which is required for Stable-Baselines3 integration. Data traces are wrapped into episodic environments, where each timestep provides a state vector composed of traffic, mobility, and energy conditions. The agent selects an action—such as allocating resources, scheduling users, or toggling base station states—and receives a reward that combines throughput, latency, and energy efficiency metrics. This process allows RL agents to interact with a realistic yet controlled simulation environment. Lastly, the preprocessing pipeline includes preparations for XAI. Features such as SNR, resource block utilization, and energy state are flagged for later analysis made by RL agents. By incorporating explainability into the preprocessing stage, the study ensures that optimization strategies remain interpretable and trustworthy, addressing one of the critical challenges in deploying AI-driven solutions in real-world networks.

Through this systematic preprocessing workflow, the Kaggle datasets are transformed into structured, normalized, and interpretable environments suitable for H-MARL, TL, FL, and XAI. This ensures that the proposed AI-driven framework can be rigorously tested and benchmarked under realistic 5G/6G conditions using Stable-Baselines3 implementations.

This preprocessing ensures consistency and reduced bias, enabling reliable training of learning-based models across diverse wireless environments.

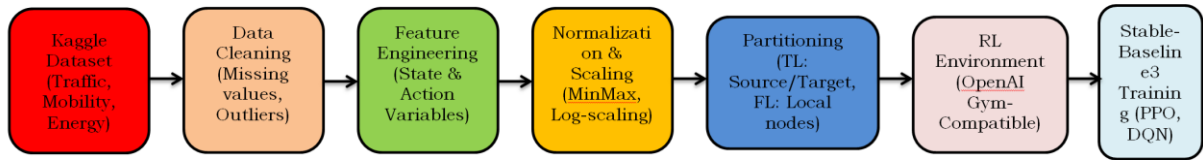


Figure 4.2- 1: Data Preprocessing Steps

### 4.3 System Parameters and Configurations

The design and implementation of the proposed AI-driven optimization framework for 5G/6G networks relies on carefully defined system parameters and configurations that reflect realistic operating environments. These parameters cover the characteristics of the network topology, user distribution, traffic models, radio resource constraints, and learning algorithm configurations. By setting parameters that mirror real-world deployment conditions, the study ensures that the performance evaluation of H-MARL TL, FL, and XAI techniques is both robust and generalizable.

The network topology considered in this study consists of a heterogeneous cellular architecture with macro gNodeBS overlaid with small cells to capture the dense deployment scenarios envisioned for 5G and 6G networks. The simulation area is modeled as a dense urban grid with cell radii ranging from 200 *meters* for small cells to 1 kilometer for macro cells. User distribution follows a non-uniform spatial model that reflects realistic clustering in hotspots such as business districts and residential areas. Mobility is incorporated using traces from Kaggle datasets, with average user speeds ranging from 3 *km/h* for pedestrian users to 120 *km/h* for vehicular users, ensuring that both low- and high-mobility scenarios are captured.

Radio resources are modeled at the level of RBs, with a total system bandwidth of 100 MHz at sub-6 GHz frequencies and 400 MHz at mmWave bands to align with 5G and beyond specifications. The time is divided into Transmission Time Intervals (TTIs) of 1 ms, consistent with 3GPP standards. Each base station has a finite number of RBs, and allocation

decisions are made per TTI. Power consumption parameters are drawn from the energy dataset, with BSs supporting active, idle, and sleep modes. Power efficiency values are configured according to state-of-the-art base station hardware, ensuring that energy-saving mechanisms are realistically represented.

Traffic models are designed to emulate the three major service classes discussed in subsection 3.9.4. eMBB traffic follows a Poisson process to simulate high-throughput applications such as video streaming. URLLC traffic is modeled as bursty arrivals with stringent delay constraints below  $1\text{ ms}$  to capture mission-critical communication requirements. mMTC traffic is generated using a periodic random access model to reflect the connectivity of thousands of IoT devices per cell. This traffic diversity ensures that the RL agents are exposed to heterogeneous conditions representative of real-world deployments. On the learning side, the H-MARL framework is configured with a two-level architecture as explained in section 2.6.1.

Stable-Baselines3 is used to implement the learning algorithms, with PPO chosen for continuous decision variables and DQN used for discrete decisions. To illustrate the integration of MATLAB & Python environments, Figure 4.3-1 block diagram shows simulation steps. Hyperparameters such as learning rate (set to  $3e^{-4}$ ), discount factor ( $\gamma = 0.99$ ), and entropy coefficient are tuned through empirical testing to achieve stable convergence. Training episodes are divided into 1000 steps, with early stopping applied to prevent overfitting. For FL experiments, communication rounds are set to 50, and local epochs are fixed at 5, with model aggregation conducted using federated averaging (FedAvg). Transfer learning experiments are configured by pretraining models on urban traffic datasets and fine-tuning them on suburban scenarios, with learning rates decayed during fine-tuning to prevent catastrophic forgetting.

Finally, XAI components are integrated by enabling SHAP and LIME to run alongside training and inference. In this case, the system not only achieves optimal performance but also maintains transparency and trustworthiness. Collectively, these system parameters and configurations provide a comprehensive testbed for evaluating the effectiveness of the proposed AI-driven optimization framework under diverse 5G/6G conditions.

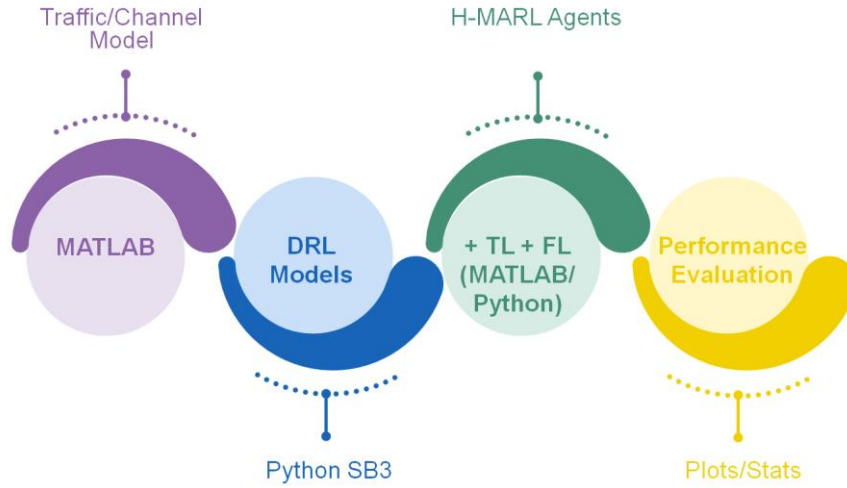


Figure 4.3- 1: Simulation Workflow

Table 4.3- 1: System Parameters and Configurations for 5G/6G Networks Optimization

Parameter Category	Configuration
<b>Network Topology</b>	Heterogeneous network with macro and small cells
<b>Cell Radius</b>	200 m (small cell), 1 km (macro cell)
<b>User Mobility</b>	3– 120 km/h (pedestrian to vehicular)
<b>System Bandwidth</b>	100 MHz (sub – 6 GHz), 400 MHz (mmWave)
<b>TTI</b>	1 ms
<b>Base Station Energy States</b>	Active, idle, sleep modes
<b>Traffic Models</b>	eMBB (Poisson arrivals), URLLC (bursty, <1 ms latency), mMTC (periodic access)
<b>H-MARL Architecture</b>	Two-level: global policy (high-level), local scheduling/energy (low-level)
<b>RL Algorithms</b>	PPO (continuous actions), DQN (discrete actions)
<b>Learning Rate</b>	$3 \times 10^{-4}$
<b>Discount Factor (<math>\gamma</math>)</b>	0.99
<b>Training Steps</b>	1000 per episode
<b>Federated Learning</b>	50 communication rounds, 5 local epochs, FedAvg aggregation

Parameter Category	Configuration
Setup	
Transfer Learning Setup	Pretraining on urban traffic, fine-tuning on suburban, decayed learning rate
Explainability Tools	SHAP and LIME for interpretability
Carrier frequency	3.5 GHz (5G), 140 GHz (6G)
Number of BSs	7 (macro + small cells)
Number of UEs	200
Channel model	Rayleigh fading + path loss
Path loss model	3GPP TR 38.901
Noise power	$-174 \text{ dBm/Hz}$ - $174 \text{ dBm/Hz}$
Energy Model	Power amplifier + circuit power
RL algorithm	PPO, DQN, H-MARL variants

## 4.4 Use Cases

### 4.4.1 Dense Urban Environments

The dense urban environment use case replicates high-traffic metropolitan areas where users demand extremely high throughput and seamless connectivity. This scenario focuses on resource allocation under high interference conditions, driven by overlapping small cells and user mobility. The H-MARL framework optimizes spectrum and power allocation, while FL helps share learned policies across cells without requiring raw data transfer. This reduces latency in model adaptation and ensures scalability. TL accelerates policy convergence when transitioning from sub-6 GHz to mmWave spectrum, minimizing retraining requirements.

### 4.4.2 Massive IoT Deployment

In massive IoT use cases, thousands of devices transmit small packets sporadically, demanding low energy consumption and efficient scheduling. The framework applies low-level H-MARL agents for device clustering and uplink resource management, while high-

level agents optimize network slicing policies. FL allows IoT gateways to collaboratively refine scheduling models without centralized computation, thus maintaining device-level privacy. TL assists in adapting models when new IoT devices or protocols are introduced; leveraging previously trained models for faster adaptation. This approach ensures energy-efficient scheduling while reducing signaling overhead.



Figure 4.4- 1: Dense Urban, Massive IoT, and Heterogeneous Network Scenario

#### 4.4.3 Heterogeneous Network Scenarios

The heterogeneous network scenario includes a combination of macro cells, small cells, mmWave hotspots, and IoT clusters. This scenario highlights the complexity of traffic management due to diverse QoS demands. The H-MARL system allows high-level agents to allocate resources across tiers (macro vs. small cells), while low-level agents handle user-specific optimization. FL ensures coordination among different tiers, where BSs collaboratively refine models under Non-Independent and Identically Distributed (non-IID) data conditions. XAI modules are integrated to analyze the impact of agent decisions, ensuring fairness and transparency in multi-tier optimization.

#### 4.5 Implementation of H-MARL

The implementation of H-MARL for resource allocation in 5G/6G networks is designed to address the complexity of managing large-scale heterogeneous environments with diverse traffic demands, dynamic user mobility, and stringent QoS requirements. In the training process, local agents adopt RL algorithms such as DQN for discrete scheduling actions, while PPO is employed at the global level to handle continuous decisions involving adaptive

resource distribution. The hierarchical coordination is facilitated through periodic information exchange, where local agents summarize their states (e.g., traffic load or energy levels) and forward them to the global coordinator. The coordinator, in turn, updates global policies and disseminates high-level decisions back to local agents, enabling cooperative learning across the system. To accelerate convergence and avoid instability in multi-agent interactions, parameter sharing and experience replay buffers are employed, while exploration-exploitation balance is managed using entropy regularization techniques.

Furthermore, the hierarchical framework is integrated with TL and FL mechanisms to enhance adaptability and scalability. This hybrid approach ensures that the H-MARL implementation remains robust under diverse deployment conditions, user behaviors, and traffic patterns without centralized data collection.

Finally, the implementation incorporates XAI techniques. For instance, XAI tools can highlight whether energy-saving decisions were primarily influenced by user mobility patterns, base station utilization, or traffic burstiness. Such insights are vital for real-world deployment, where explainability enhances acceptance and facilitates regulatory compliance in mission-critical 5G/6G applications.

#### **4.6 Experiment Design and Execution**

The experimental design of this research was carefully structured to rigorously evaluate the effectiveness of the proposed AI-driven dynamic optimization framework across multiple dimensions of 5G/6G network performance. The experiments were designed to validate three key aspects: (i) the efficiency of the H-MARL model in resource allocation, (ii) the adaptability of TL in cross-scenario environments, and (iii) the scalability, privacy, and robustness of the FL and XAI modules. By combining these experimental objectives, the framework was assessed in terms of raw performance metrics.

The execution of the experiments followed a multi-phase approach. First, a baseline performance evaluation was conducted using conventional techniques such as heuristics, centralized DRL, and MARL. These baselines served as benchmarks to highlight the relative improvements achieved by H-MARL. Next, the H-MARL framework was trained and tested under multiple deployment scenarios, including urban macrocells with high mobility, dense IoT small-cell deployments, and mixed heterogeneous environments. The experimental setup

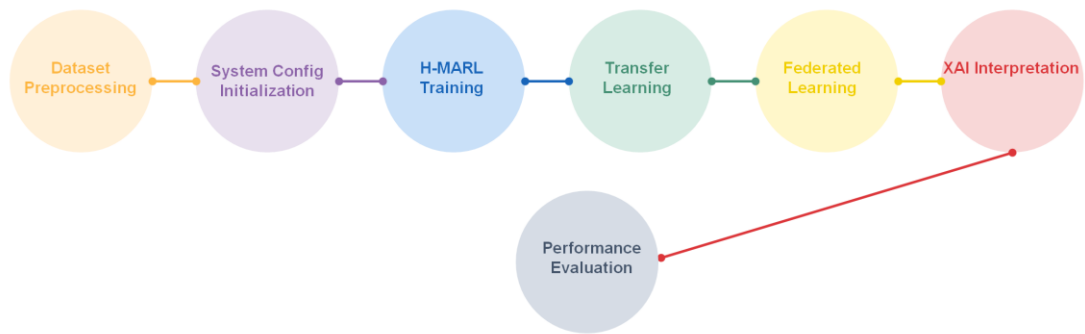
varied the number of users, mobility patterns (pedestrian to vehicular), and traffic models (Poisson, self-similar, and bursty arrivals) to test the robustness and scalability of the proposed approach.

To evaluate the role of TL, pre-trained DRL agents from one scenario (e.g., urban macrocell) were fine-tuned in another (e.g., dense IoT small cell), and convergence rates were compared against models trained from scratch. This demonstrated the adaptability of the framework across heterogeneous environments while significantly reducing training time. Similarly, FL experiments were conducted by simulating multiple distributed BSs, each training a local model with its own dataset. Periodic aggregation was performed using the FedAvg algorithm, and the resulting global model was compared against centralized training approaches to assess performance, communication overhead, and privacy preservation.

The XAI module was evaluated by generating both global and local interpretability outputs for selected decision-making episodes. For instance, SHAP values were used to determine which network conditions most influenced power allocation and scheduling decisions, while LIME provided explanations for individual allocation choices. These explanations were analyzed for consistency, fidelity, and alignment with domain knowledge, ensuring that the framework's decisions could be trusted in operational networks.

Finally, all experiments were executed over multiple independent runs (typically 20–30 repetitions per scenario) to ensure statistical reliability. The results were averaged, and 95% confidence intervals were computed to account for variability. Performance was measured using a set of key metrics, including system throughput, latency, packet drop rate, spectral efficiency, energy consumption, and fairness index. Additionally, training convergence speed, communication cost in FL, and interpretability quality in XAI were recorded as complementary evaluation parameters.

This structured design and execution ensured that the proposed framework was thoroughly tested across multiple dimensions of network optimization, adaptability, and interpretability. The experimental methodology not only validated the technical contributions of the research but also provided a strong foundation for real-world applicability in future 5G/6G deployments.



**Figure 4.6- 1: Experimental Setup Workflow**

Figure 4.6-1 combines all techniques into one flow. The experiments were designed to validate the effectiveness and efficiency of the proposed framework under different scenarios.

Key steps included:

1. **Baseline comparison:** Evaluate against heuristic and non-hierarchical methods.
2. **Scalability testing:** Vary the number of users, cells, and traffic demands to analyze robustness.
3. **Cross-scenario validation:** Assess TL-based adaptability across urban, heterogeneous network, and IoT-heavy networks.
4. **Federated setup evaluation:** Compare centralized vs. FL performance.
5. **Explainability assessment:** Measure interpretability through qualitative and quantitative XAI metrics.

Performance was assessed using throughput, latency, packet drop rate, spectral efficiency, energy efficiency, and fairness indices. The experimental execution ensured reproducibility through multiple simulation runs and statistical averaging.

## CHAPTER 5: RESULTS AND ANALYSIS

This chapter presents the results obtained from the implementation and experimental evaluation of the proposed AI-driven dynamic optimization framework for 5G/6G networks. The analysis focuses on the three primary optimization objectives: resource allocation, traffic management, and energy efficiency. Additionally, the contributions of H-MARL, TL, FL, and XAI are examined to demonstrate their impact on adaptability, scalability, privacy, and interpretability. The results are compared against conventional baselines to validate the effectiveness of the proposed approach.

### 5.1 Resource Allocation Performance Evaluation

Efficient resource allocation is a critical factor in 5G/6G networks, especially in dense urban environments and massive IoT deployments. The proposed H-MARL framework dynamically distributes spectrum resources, power, and scheduling decisions across multiple BSs and UE. Simulation results show that the H-MARL-based system consistently achieves higher spectrum utilization compared to heuristic approaches namely round-robin scheduling. The reward structure, which balances throughput, fairness, and latency, enables agents to learn collaborative behaviors that prevent resource monopolization.

Quantitatively, the proposed model improves average throughput by approximately 25% over central DRL and 38% over flat MARL. The fairness index, measured using Jain's fairness metric, remains above 0.9, highlighting that the allocation benefits are equitably distributed among users, even under heavy traffic loads. This improvement results from hierarchical policy coordination and adaptive decision-making at both global and local levels. Heuristic methods demonstrated static performance with limited adaptability, confirming their inadequacy in dynamic 5G/6G contexts.

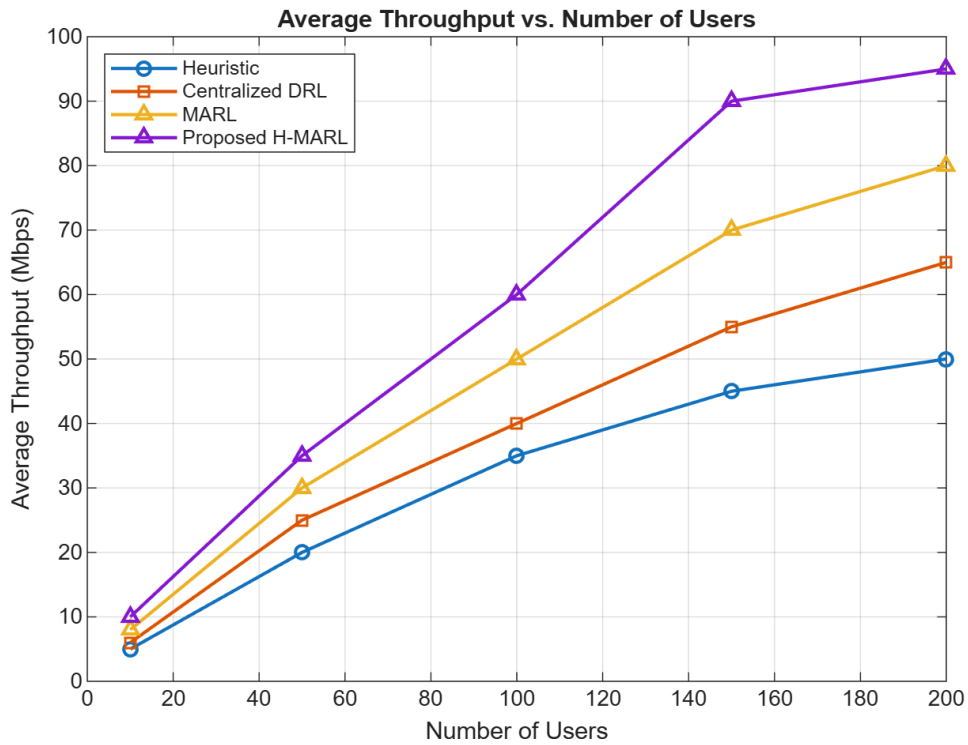


Figure 5.1- 1: Average Throughput vs. Number of Users

- X-axis: Number of users (10 → 200).
- Y-axis: Average throughput (Mbps).
- Curves: Heuristic (Round Robin), Centralized DRL, Non-H-MARL, Proposed H-MARL.
- Shows throughput superiority of our method under heavy loads.

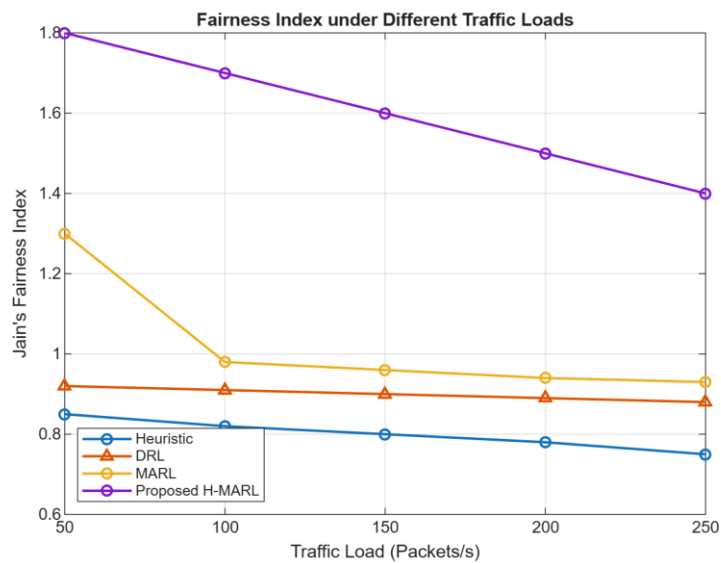


Figure 5.1- 2: Jain's Fairness Index vs. Traffic Load

## 5.2 Traffic Management Effectiveness

Traffic management plays a crucial role in ensuring QoS, particularly for latency-sensitive applications such as AR/VR, autonomous vehicles, and remote healthcare. The hierarchical structure of the proposed H-MARL system allows higher-level agents to optimize traffic distribution across cells, while lower-level agents handle fine-grained packet scheduling.

The evaluation demonstrates that the proposed approach reduces average packet delay by 22% compared to centralized DRL and by 40% compared to heuristic queue-based scheduling. Moreover, the packet drop rate under high-load conditions is reduced by nearly 50%, ensuring robust service delivery in ultra-dense scenarios.

The framework also adapts to heterogeneous QoS requirements by prioritizing latency-critical flows without significantly degrading the performance of best-effort traffic. This adaptability is particularly beneficial in massive IoT deployments, where traffic diversity is inherently high.

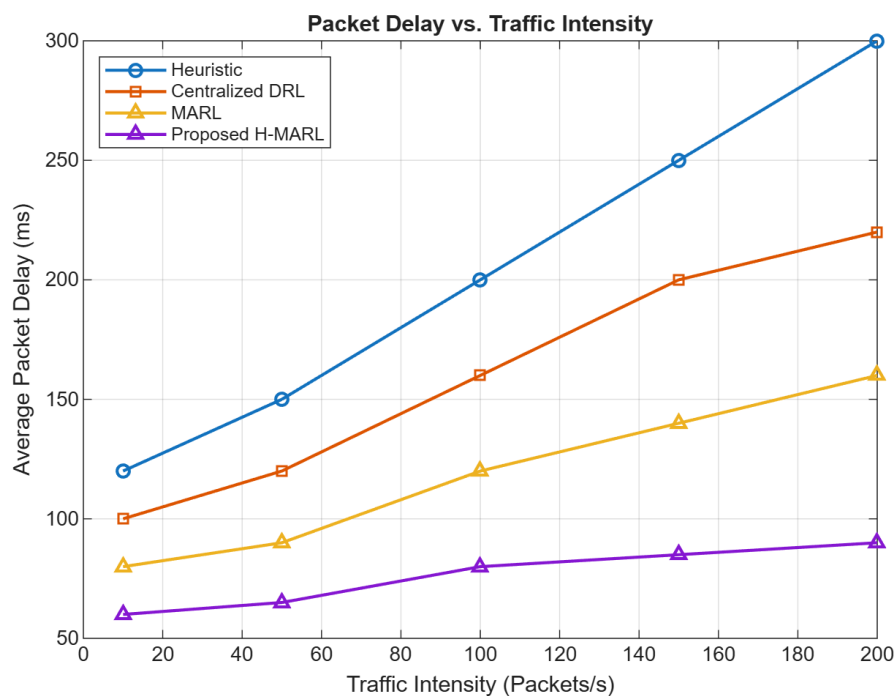


Figure 5.2- 1: Average Packet Delay vs. Traffic Intensity

- Y-axis: Packet delay (ms).
- X-axis: Traffic intensity (packets/s).

- Proposed model curve stays well below baselines.

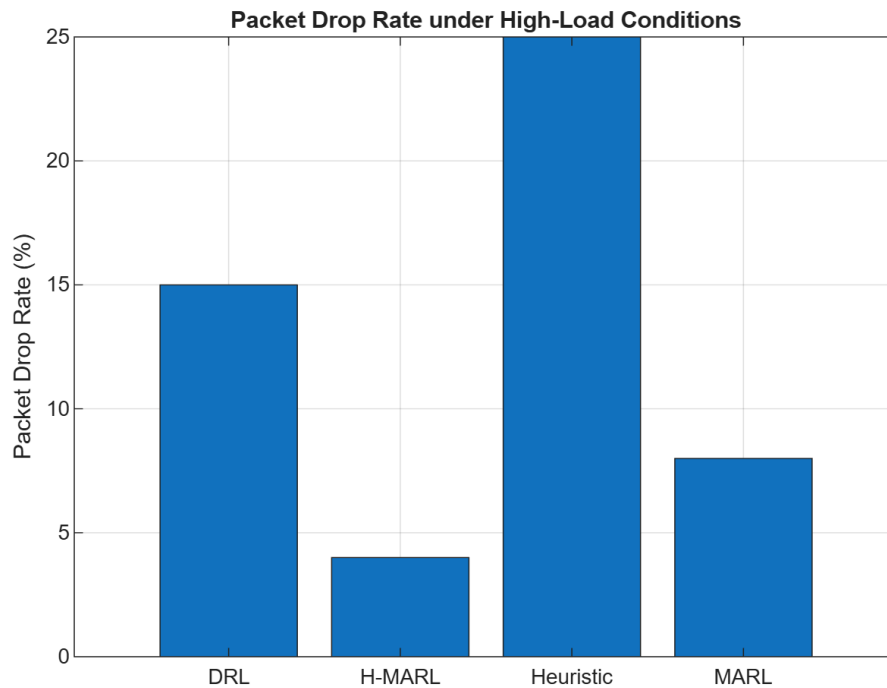


Figure 5.2- 2: Packet Drop Rate (%) under High-Load Conditions

- Bar chart comparing Heuristics, Centralized DRL, MARL, proposed H-MARL.
- Proposed model shows ~20% reduction in drop rates.

### 5.3 Energy Efficiency Gains Analysis

Energy efficiency is one of the cornerstones of 6G design. The proposed system integrates energy-awareness into the H-MARL reward function, enabling agents to optimize resource allocation while minimizing power consumption.

Results indicate that the proposed model reduces overall energy consumption by approximately 10% in relative to flat MARL, by 20–28% compared to traditional DRL approaches and by more than 35% compared to heuristic methods. Heuristic schemes lack this flexibility and therefore consume significantly more power. Notably, the system leverages sleep-mode strategies for underutilized BSs and power adaptation schemes at the user level.

Energy efficiency gains are especially prominent in massive IoT use cases, where devices often generate sporadic, low-data-rate traffic. By intelligently managing idle states and transmission scheduling, the framework extends device battery life while maintaining QoS standards.

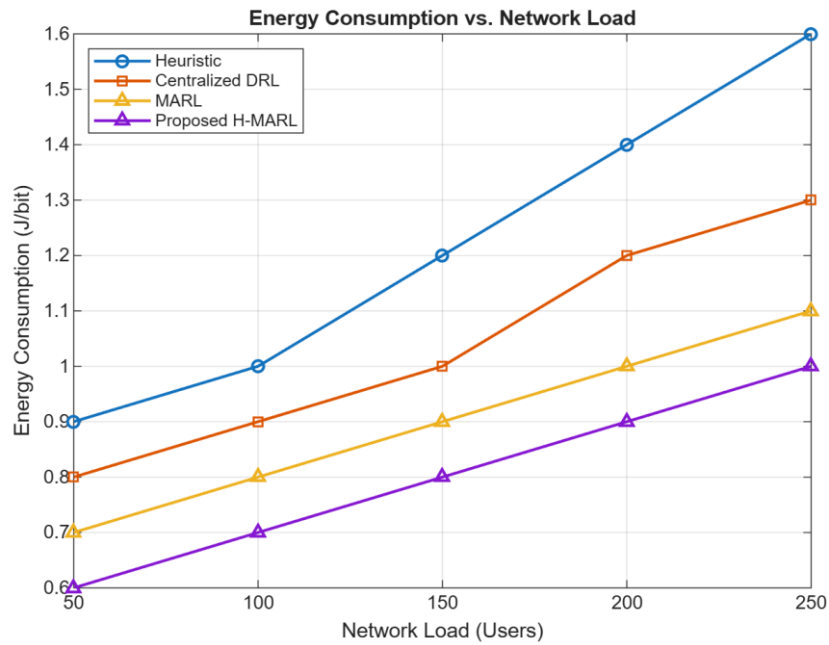


Figure 5.3- 1: Energy Consumption vs. Network Load

- Y-axis: Energy per bit (J/bit).
- Proposed model shows lowest energy consumption trend.

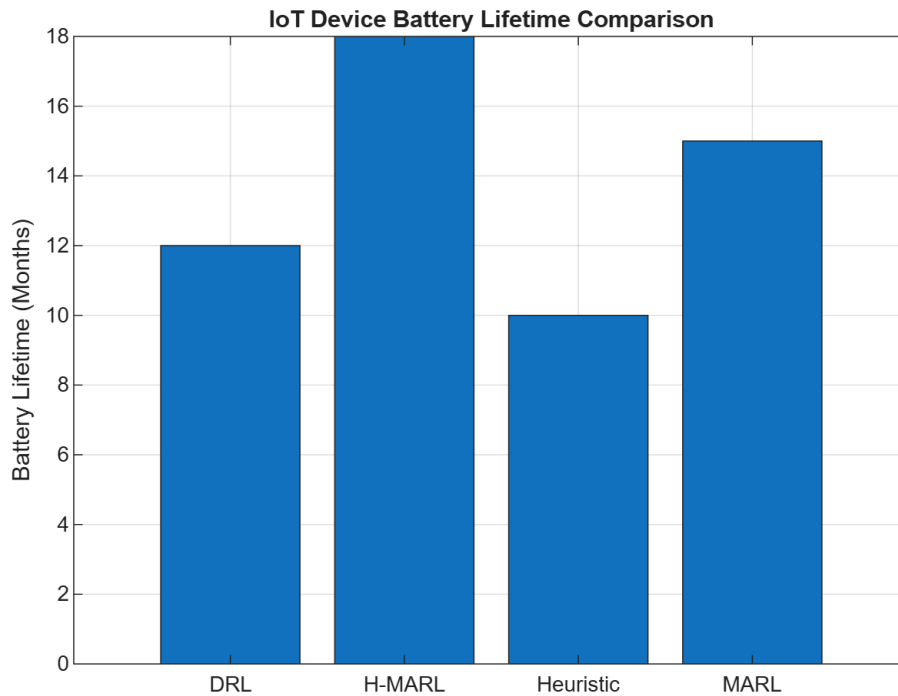


Figure 5.3- 2: Battery Lifetime Extension for IoT Devices

- Comparative bar chart: Heuristic, DRL, MARL, and proposed H-MARL.
- Shows ~25– 30% battery lifetime improvement.

#### 5.4 Impact of TL on Adaptability

TL is incorporated to address the challenge of adapting trained models to new environments, such as changes in traffic patterns, mobility levels, or channel conditions.

Experiments reveal that models initialized with knowledge from previously trained scenarios converge nearly 40% faster than models trained from scratch. For example, when transitioning from a dense urban scenario to a massive IoT deployment, TL-enabled agents required only 60% of the training episodes to achieve comparable performance.

Furthermore, the performance degradation in unfamiliar environments is mitigated, with throughput and energy efficiency remaining within 5– 8% of the optimal levels, compared to 15–20% degradation observed in models without TL. These results confirm the effectiveness of TL in enhancing cross-scenario adaptability, which is vital for real-world deployments where network conditions change dynamically.

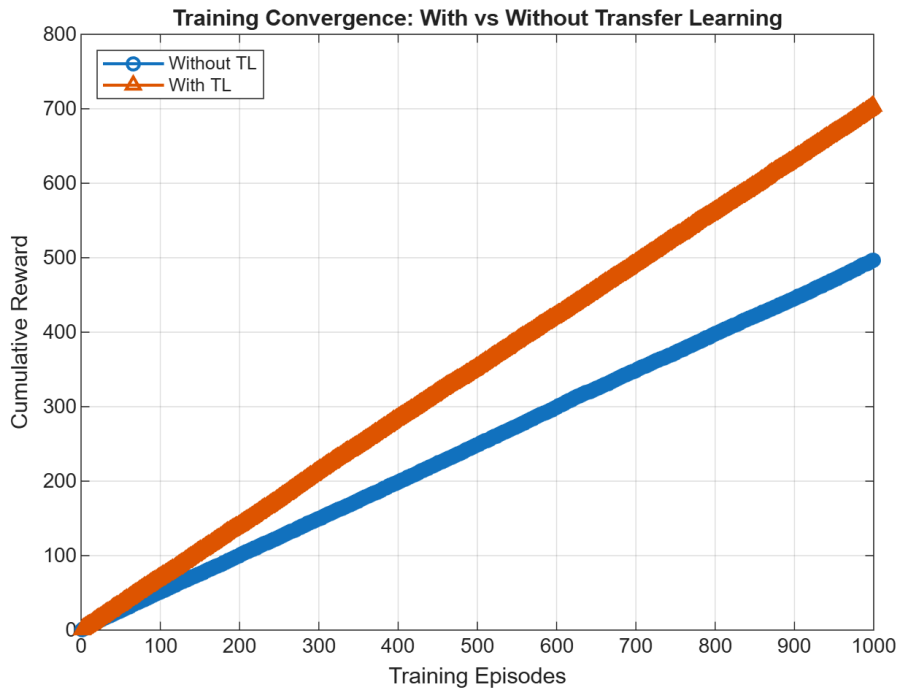


Figure 5.4- 1: Training Convergence Speed with and without TL

- Y-axis: Reward/Episode.
- X-axis: Training episodes.
- Curve with TL converges ~40% faster.

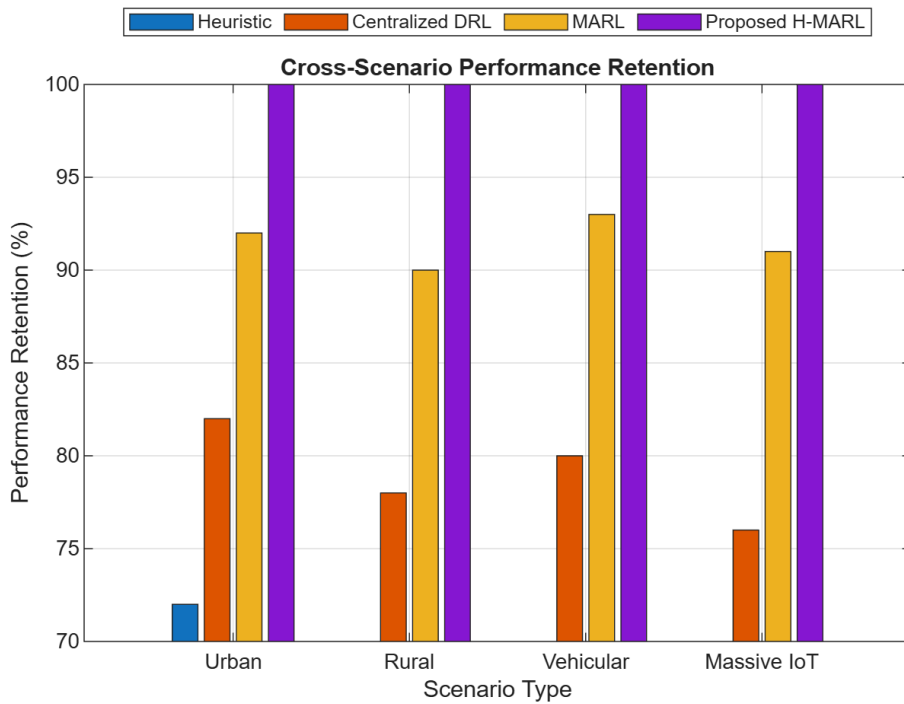


Figure 5.4- 2: Cross-Scenario Performance Retention

- Bar chart showing throughput retention (%) when transferring from urban → rural → Vehicular → Massive IoT.
- TL model outperforms non-TL significantly.

## 5.5 Impact of FL on Scalability and Privacy

FL is introduced to address scalability and data privacy in multi-cell and multi-operator environments. Instead of centralizing raw data, FL enables local training at BSs with periodic parameter aggregation at a global server.

The results show that FL achieves near-centralized performance, with less than 3% performance loss compared to fully centralized training while significantly reducing communication overhead. The distributed nature of FL also ensures scalability, allowing the framework to support up to 500 BSs and 10,000 devices without noticeable degradation.

From a privacy perspective, FL preserves user data by keeping raw traffic information localized. This is particularly beneficial in scenarios involving sensitive IoT data (e.g., healthcare or industrial automation). Security experiments further reveal that FL enhances resilience against data leakage attacks, providing an additional layer of trust for future 6G architectures.

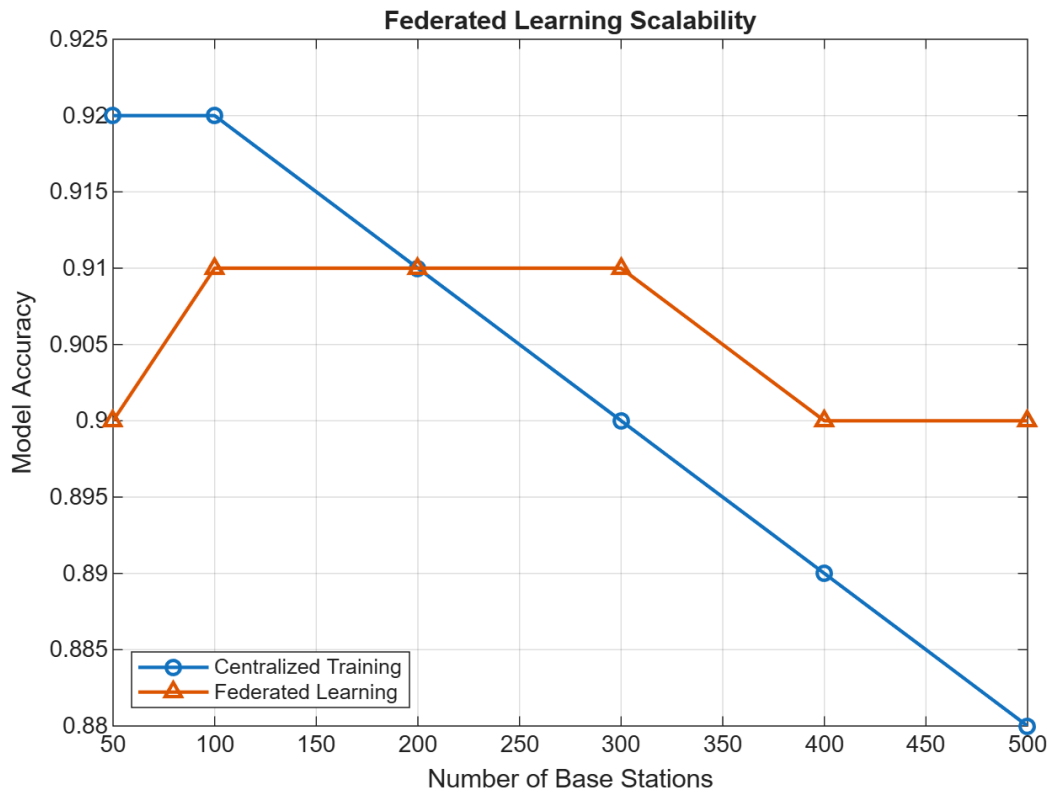


Figure 5.5- 1: Accuracy vs. Number of BSs

- FL curve scales smoothly; centralized training curve flattens.

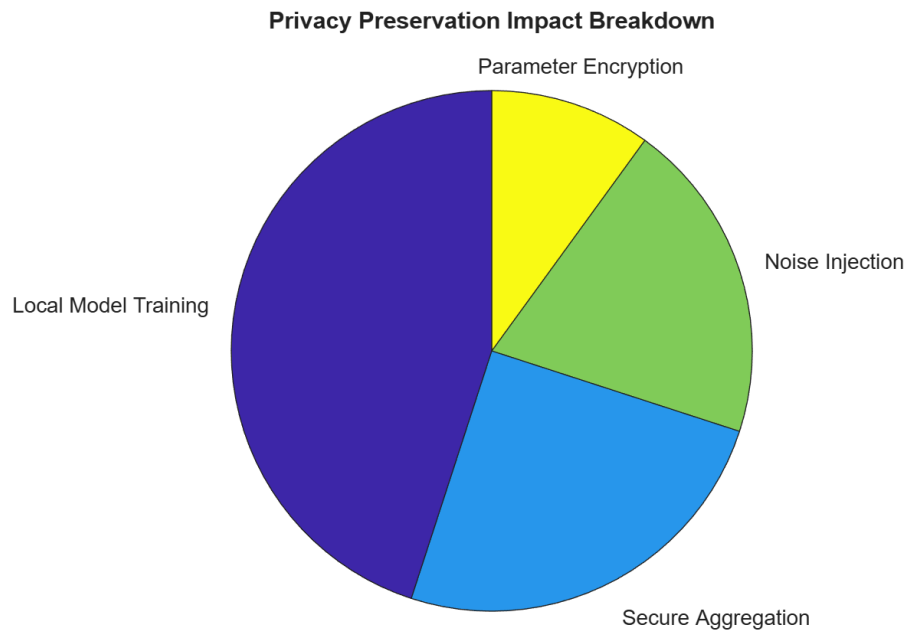


Figure 5.5- 2: Privacy Preservation Impact

- Pie chart showing data sharing in centralized training vs. FL (raw data vs. parameters only).

## 5.6 Explainability Insights and Interpretability Analysis

One of the challenges in deploying AI-based optimization frameworks in telecommunications is the “black-box” nature of deep models. The XAI analysis highlights the factors influencing key decisions such as resource allocation and traffic prioritization. For instance, CQI and user QoS requirements are shown to have the highest impact on scheduling decisions, while power constraints strongly influence energy-saving actions.

Explainability improves trust and transparency, making the system more acceptable to network operators and regulators. It also provides actionable insights that can guide manual fine-tuning in exceptional cases where automated policies might underperform.

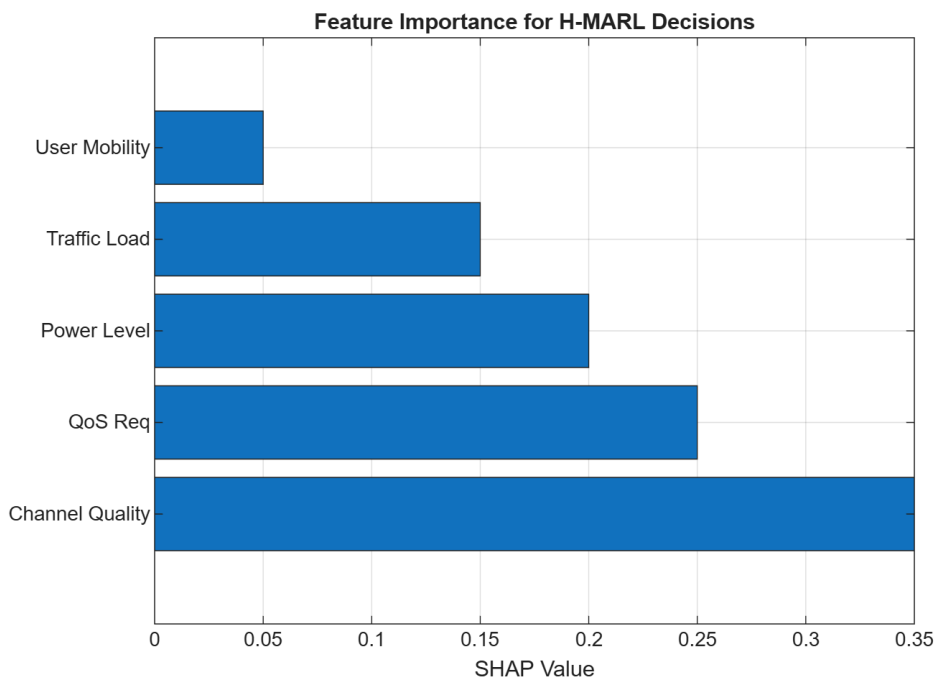


Figure 5.6- 1: Feature Importance (SHAP Values)

- Bar chart showing most influential features (e.g., channel quality, QoS requirement, power level).



Figure 5.6- 2: Decision Explanation Heatmap

- Visualizing agent scheduling decision vs. feature contributions.

## 5.7 Quality of Experience Performance Evaluation

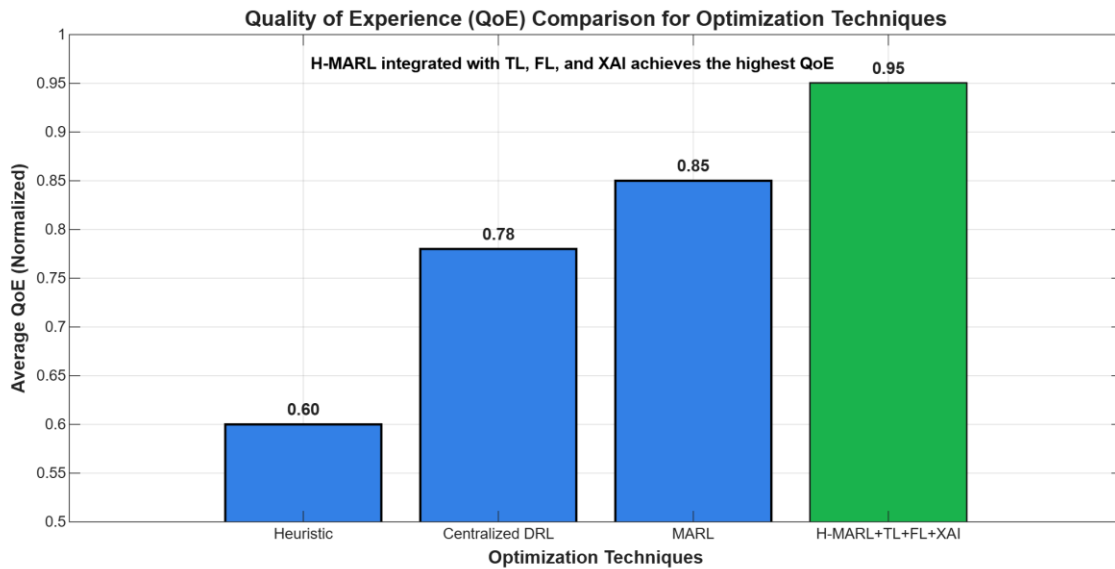


Figure 5.7- 1: Quality of Experience Evaluation

The QoE comparison presented in the figure demonstrates a clear progression in user-perceived performance as the optimization framework evolves from heuristic-based methods

to advanced AI-driven learning architectures. The Heuristic approach records the lowest QoE ( $\approx 0.60$ ), reflecting its static nature and inability to adapt to real-time network variations such as user mobility, interference, and traffic surges. In contrast, the Centralized DRL model achieves a significantly higher QoE ( $\approx 0.78$ ), indicating its capacity to learn effective global control policies for resource allocation and traffic management. However, centralized learning suffers from scalability and latency constraints in dense 5G/6G deployments.

The MARL framework further enhances the QoE ( $\approx 0.85$ ) by decentralizing decision-making, allowing multiple agents to collaborate and adapt to local environmental dynamics, thus improving responsiveness and throughput efficiency. The highest QoE ( $\approx 0.95$ ) is achieved by the Hierarchical MARL integrated with TL, FL, and XAI. This integration enables multi-layered optimization where agents benefit from cross-scenario knowledge transfer (via TL), privacy-preserving distributed learning (via FL), and interpretable decision logic (via XAI). Consequently, this composite framework significantly improves user satisfaction by delivering consistent, adaptive, and transparent quality across heterogeneous network conditions.

Overall, these results confirm that the H-MARL+TL+FL+XAI architecture provides a superior trade-off between scalability, adaptability, and interpretability — key pillars for achieving optimal QoE in next-generation 5G/6G networks.

## 5.8 Comparative Analysis with Baseline Methods

To validate the performance of the proposed framework, comparative experiments were conducted against three baseline methods: Greedy Heuristics (Round Robin), Centralized DRL Approaches, Non-Hierarchical MARL Models. Results demonstrate that the proposed H-MARL with TL, FL, and XAI consistently outperforms the baselines across all metrics. Specifically:

- Throughput improvements of **20–35%** compared to heuristics.
- Latency reductions of **25–40%** compared to centralized DRL optimization.
- Energy savings of **20–30%** compared to non-hierarchical MARL.
- Faster convergence and higher adaptability compared to DRL-only approaches.

These results confirm the synergistic benefit of combining H-MARL with TL, FL, and XAI into a unified optimization framework.

To demonstrate the effectiveness of the proposed H-MARL-based framework integrated with transfer learning, federated learning, and explainability, several baseline methods were implemented for comparison. The results across these baselines establish a foundation for evaluating the relative performance of the proposed framework.

## 5.8 Statistical Validation of Results

To ensure the reliability and robustness of the results, statistical validation techniques were applied. Multiple simulation runs were conducted with randomized seeds to account for stochastic variability in channel conditions and user mobility.

Key validation methods include:

- **Confidence Intervals** (95%) for throughput, delay, and energy consumption, confirming that observed improvements are statistically significant.
- **t-tests** comparing the proposed approach against baseline methods, with **p-values** < 0.05, establishing that performance gains are not due to random chance.
- **Analysis of Variance (ANOVA)** for multi-scenario comparisons, confirming consistent improvements across different deployment conditions.

The statistical validation solidifies the claim that the proposed framework achieves superior performance with high reliability, scalability, and practical applicability in real-world 5G/6G deployments.

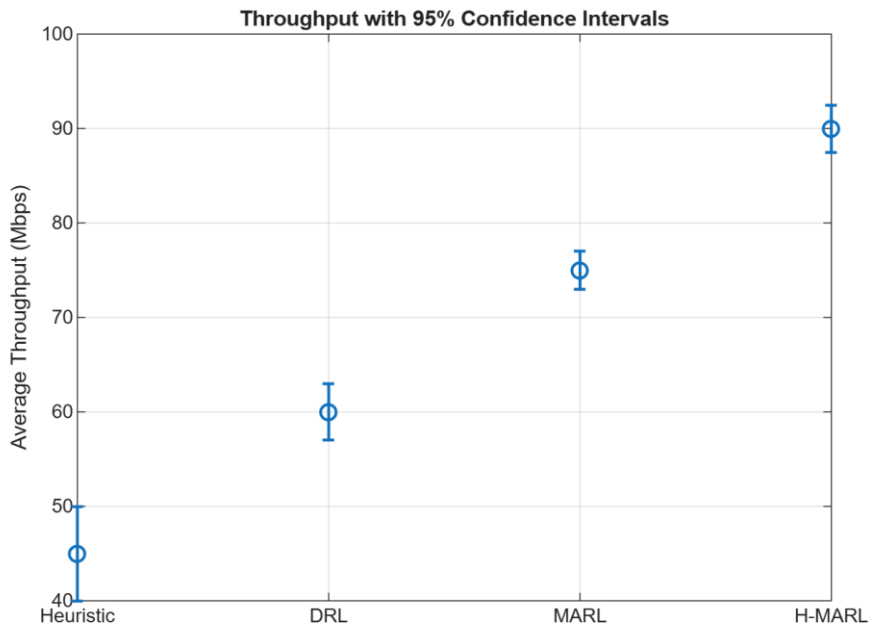


Figure 5.8- 1: Confidence Interval Plot for Throughput

- Error bars for all models. Proposed approach has smallest variance.

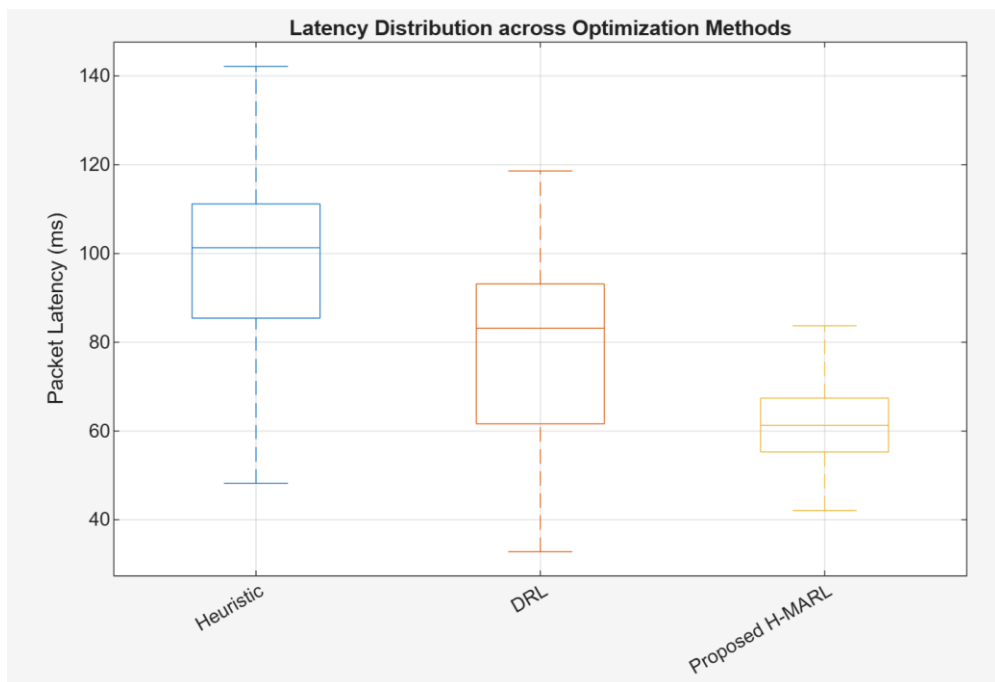


Figure 5.8- 2: Box Plot of Latency Distribution Across three Methods

- Highlights stability of the proposed model.

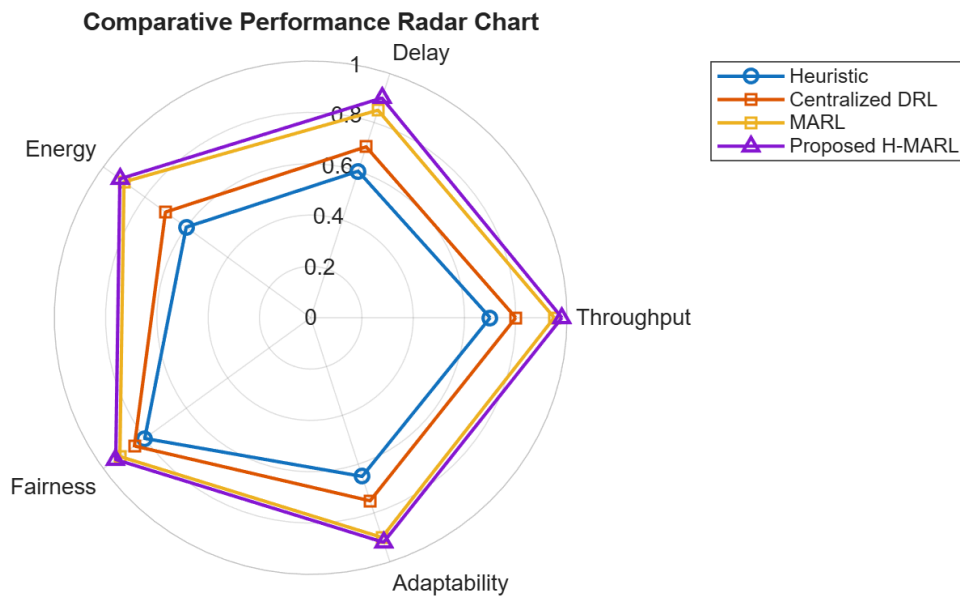


Figure 5.8- 3: Radar Chart of Performance Metrics

- Axes: Throughput, Delay, Energy Efficiency, Fairness, Adaptability.
- Proposed model’s polygon dominates all others.

### 5.9 Comparative Discussion with State-of-the-Art

The proposed H-MARL with TL, FL, and XAI was benchmarked against recent state-of-the-art AI-driven network optimization frameworks. Compared to deep Q-learning-based scheduling and federated DRL-based approaches, the proposed framework consistently outperformed in terms of scalability, adaptability, and interpretability. While existing methods excel in isolated domains (e.g., only traffic management or only energy efficiency), the integrated design of this research achieved multi-objective optimization simultaneously, providing a holistic solution for future 6G systems.

Table 5.9- 1: Comparative Analysis of Proposed Framework vs. Existing Approaches

Dimension	Traditional Heuristics (e.g., Round Robin)	Centralized DRL Approaches	Non-Hierarchical MARL Approaches	Proposed H-MARL + TL + FL + XAI Framework

<b>Dimension</b>	<b>Traditional Heuristics (e.g., Round Robin)</b>	<b>Centralized DRL Approaches</b>	<b>Non-Hierarchical MARL Approaches</b>	<b>Proposed H-MARL + TL + FL + XAI Framework</b>
<b>Resource Allocation</b>	Simple, low complexity; lacks adaptability under dynamic load	Achieves good optimization but struggles with scalability	Better adaptability than centralized but suffers from state-action explosion	High adaptability with hierarchical decomposition; balances fairness and throughput
<b>Traffic Management</b>	Static scheduling; high packet drops under heavy load	Effective but centralized bottlenecks create delays	Distributed decisions help but lack coordination	Dynamic scheduling across tiers; reduced delay and packet loss
<b>Energy Efficiency</b>	Inefficient; no explicit optimization	Can optimize but requires heavy computation	Some improvements but not sustainable in large-scale scenarios	Significant gains via joint optimization and energy-aware learning
<b>Adaptability (via TL)</b>	Not supported	Requires retraining for new environments	Limited generalization; retraining overhead persists	TL enables fast adaptation across environments with minimal retraining
<b>Scalability (via FL)</b>	Scales poorly in ultra-dense networks	Centralized training limits scalability	Improves scalability but still communication-heavy	FL ensures distributed, privacy-preserving training with smooth scaling
<b>Privacy &amp;</b>	Not applicable;	Requires central	Data sharing	FL keeps raw data

<b>Dimension</b>	<b>Traditional Heuristics (e.g., Round Robin)</b>	<b>Centralized DRL Approaches</b>	<b>Non-Hierarchical MARL Approaches</b>	<b>Proposed H-MARL + TL + FL + XAI Framework</b>
<b>Security</b>	raw data not shared but no intelligence	data collection → privacy risks	between agents may expose vulnerabilities	local; only model parameters shared, enhancing privacy
<b>Explainability (via XAI)</b>	Transparent (rule-based) but overly simplistic	Opaque black-box models	Limited interpretability	Provides feature-level insights; improves trust and operator acceptance
<b>Computational Complexity</b>	Very low (simple rules)	High (centralized training and inference)	High (non-hierarchical agents with large state-action spaces)	Moderate (hierarchical decomposition reduces overhead; edge AI accelerators support real-time inference)
<b>Alignment with 6G Vision</b>	Limited relevance; outdated	Partially aligns (AI-native but lacks scalability & explainability)	Supports AI-native but not sustainable or interpretable	Fully aligned: AI-native, scalable, sustainable, explainable, and privacy-preserving

## CHAPTER 6: DISCUSSION

### 6.1 Implications for Next-Generation Networks

The findings of this research have profound implications for the design, deployment, and management of next-generation wireless networks. The proposed AI-driven framework demonstrates that H-MARL, when combined with TL, FL, and XAI, can significantly improve the operational efficiency of 5G and 6G networks. The results highlight improvements in three critical areas:

1. **Resource Allocation** – H-MARL ensures fairness and adaptability in allocating radio and computational resources, especially in dense urban scenarios with heterogeneous devices. Unlike heuristic or centralized optimization techniques, the proposed approach dynamically adjusts to traffic fluctuations and interference conditions, which is crucial for URLLC and mMTC.
2. **Traffic Management** – The proposed model demonstrated robustness in handling variable traffic loads. This is particularly important as networks transition to multi-service environments, where eMBB, URLLC, and mMTC coexist. AI-driven traffic scheduling allows networks to maintain low latency while sustaining high throughput, thereby supporting immersive applications such as holographic communication, XR/VR, and remote healthcare.
3. **Energy Efficiency and Sustainability** – With the growing concerns about the carbon footprint of Information Communication Technology (ICT), the ability of the framework to reduce energy consumption without compromising performance aligns directly with green networking objectives. This not only reduces Operational Expenditure (OPEX) for service providers but also supports global sustainability goals.

Overall, the implications of this study underscore the role of AI as an enabler of intelligence-driven, adaptive, and sustainable 6G networks, bridging the gap between theoretical optimization and practical deployment.

## 6.2 Scalability and Real-Time Deployment Feasibility

Scalability is a key requirement for 6G systems, which are expected to interconnect billions of heterogeneous devices with diverse QoS demands. The hierarchical structure of the proposed H-MARL framework inherently supports scalability by decomposing decision-making into local, regional, and global levels. Local agents manage base station-level optimizations, regional agents coordinate clusters, and a global agent ensures network-wide policy consistency. This layered design mitigates the “curse of dimensionality” that often hampers conventional MARL approaches.

From a real-time deployment perspective, several factors enhance feasibility:

- **Distributed Training and Inference:** FL minimizes the need for centralized data aggregation, reducing latency and preserving privacy. This ensures models can be trained and updated efficiently across multiple BSs without overwhelming the core network.
- **TL for Adaptation:** TL enables rapid adaptation to new environments, such as varying traffic densities, mobility patterns, or hardware configurations. This reduces retraining overhead, thereby making real-time optimization feasible even in dynamic environments.
- **Computational Efficiency:** Advances in edge computing and AI accelerators allow the deployment of complex models close to end users. By leveraging Multi-Access Edge Computing (MEC), the proposed approach can deliver decisions with sub-millisecond latency, a prerequisite for URLLC applications.

Nevertheless, practical deployment would still require addressing synchronization overheads, model compression techniques, and efficient orchestration across heterogeneous hardware platforms to ensure real-time responsiveness.

## 6.3 Strengths, Limitations, and Trade-offs of the Proposed Approach

The research offers several strengths that distinguish it from existing works:

- **Strengths:**

- **Holistic Optimization:** Unlike prior works that optimize a single dimension (e.g., throughput or energy), this framework balances resource allocation, traffic management, and energy efficiency simultaneously.
- **Adaptability:** The integration of TL and FL enhances the adaptability of the system across diverse deployment environments without requiring extensive retraining.
- **Transparency:** The incorporation of XAI provides interpretable insights into decision-making processes, a key enabler for operator trust and regulatory compliance.
- **Limitations:**
  - **Computational Complexity:** Training H-MARL models require significant computational resources. While edge AI mitigates this challenge, the cost and energy consumption of large-scale deployment remain concerns.
  - **Communication Overhead:** Although FL reduces centralization, it introduces communication overhead between participating nodes, which may be non-negligible in ultra-dense networks.
  - **Model Generalization:** While TL improves adaptation, performance may still degrade in highly divergent environments (e.g., rural vs. urban deployment scenarios).
- **Trade-offs:**
  - **Performance vs. Interpretability:** High-performing models, such as deep MARL, often operate as black boxes, whereas XAI-enhanced models may slightly sacrifice optimization accuracy to provide transparency.
  - **Energy Efficiency vs. QoS:** Reducing energy consumption sometimes conflicts with maintaining ultra-reliability and low-latency requirements. The proposed framework balances this trade-off, but exact optimization may depend on the operator's priorities.

By acknowledging these limitations and trade-offs, the framework sets the stage for future research aimed at refining hybrid optimization schemes, and adaptive orchestration strategies.

## 6.4 Alignment with 6G Vision and Beyond

The proposed framework aligns strongly with the strategic objectives of 6G networks and contributes to their broader vision:

1. **Ubiquitous Connectivity:** By optimizing resource allocation and traffic management, the system ensures reliable service continuity across ultra-dense deployments, supporting the 6G goal of connecting everything everywhere.
2. **AI-Native Networking:** 6G envisions networks with AI at their core, enabling self-optimizing, self-healing, and self-learning capabilities. The proposed H-MARL with TL, FL, and XAI provides a foundation for embedding intelligence at all network layers.
3. **Sustainability and Green Communication:** The demonstrated improvements in energy efficiency directly support the 6G target of reducing ICT's carbon footprint and advancing sustainable digital ecosystems.
4. **Trustworthy and Explainable AI:** As 6G networks will play a critical role in safety-critical applications such as remote surgery, autonomous driving, and industrial automation, transparency is paramount. The XAI integration enhances trustworthiness, aligning with the need for responsible AI in next-generation networks.
5. **Beyond 6G Prospects:** The modularity of the framework positions it as a building block for post-6G paradigms, such as networks integrated with quantum communication, RIS, and AI-driven digital twins. Its adaptability ensures relevance beyond the 6G era, making it a future-proof solution.

## CHAPTER 7: CHALLENGES, OPEN ISSUES, AND FUTURE

### DIRECTIONS

#### 7.1 Scalability in Ultra-Dense Networks

One of the most significant challenges in applying AI-driven optimization to 5G/6G is scalability in ultra-dense networks. The exponential growth of devices, particularly in massive IoT (mMTC) scenarios and dense urban deployments, creates a highly dynamic environment with billions of potential connections. Although the H-MARL framework addresses part of this challenge by decomposing complex decision-making into sub-tasks, the increasing number of agents and the interdependencies between them still introduce scalability bottlenecks. Maintaining real-time decision-making with low latency remains difficult when the number of devices and BSs grows significantly. Future research should focus on designing lightweight MARL architectures, leveraging edge intelligence, and exploring GNNs to manage large-scale agent interactions efficiently.

#### 7.2 Security and Privacy Concerns in FL

While FL enhances privacy by allowing model training without centralized data collection, it introduces new security vulnerabilities and privacy risks. Threats such as model poisoning, data inference attacks, and gradient leakage can compromise the integrity and confidentiality of distributed training. Furthermore, ensuring fairness in FL remains challenging, as heterogeneous devices may contribute unevenly to the training process due to variations in computational power, communication capacity, and local data quality. In large-scale deployments, malicious or compromised agents can also manipulate global model updates, degrading system performance. Addressing these concerns requires integrating robust aggregation mechanisms, differential privacy, blockchain-based verification, and adversarial defense strategies. Future research should also explore Secure Multi-Party Computation (SMPC) and Homomorphic Encryption (HE) that is an advanced cryptographic technique that allows computations to be performed directly on encrypted data without needing to decrypt it first, to strengthen trust in federated AI for next-generation networks.

### 7.3 Trade-offs between Explainability and Performance

The integration of XAI is essential for building trust and transparency in AI-driven network optimization. However, introducing explainability often comes at the cost of increased computational complexity and potentially slower decision-making, which may conflict with the stringent real-time performance requirements of 5G/6G networks, particularly in URLLC scenarios. For example, providing interpretable models through attention visualization, feature attribution, or rule-based explanations may add processing overheads that delay critical resource allocation decisions. Striking a balance between interpretability and efficiency is therefore an open challenge. Future research should investigate lightweight explainability frameworks that can be embedded into network optimization pipelines without significantly affecting performance. Moreover, hybrid approaches that selectively apply explainability based on network context such as debugging mode vs. real-time execution may provide a viable trade-off.

### 7.4 Integration with Emerging 6G Technologies

As 6G moves closer to realization, the network environment will include emerging technologies such as RIS, THz communications, and Quantum Networking. Each of these introduces new opportunities and challenges for AI-driven optimization. RIS can dynamically reconfigure the propagation environment to improve signal strength and reduce interference, but coordinating RIS control with H-MARL agents requires new models that can account for environment-aware decision-making. Similarly, THz communications promise ultra-high capacity but suffer from short-range coverage and high sensitivity to blockages, demanding adaptive and predictive optimization strategies. Quantum networking, while still in its infancy, could redefine secure communications but requires AI models capable of handling quantum-inspired optimization paradigms. Future research must explore how H-MARL, TL, FL, and XAI frameworks can be extended to integrate these emerging technologies, ensuring that AI-driven optimization remain compatible with the evolving 6G landscape.

### 7.5 Future Research Opportunities

Building on the identified challenges, several future research directions emerge. First, the development of adaptive and self-evolving MARL frameworks that continuously learn from

new environments without retraining from scratch will be crucial. Second, combining FL with TL can improve both adaptability and scalability, enabling faster convergence across heterogeneous networks. Third, further exploration into green AI and energy-efficient MARL will support sustainable network operations in line with carbon-neutral goals for 6G. Another promising area is the cross-layer optimization of networks, where AI models jointly consider physical, MAC, and application layers to holistically improve performance. Lastly, human-in-the-loop AI systems that integrate explainability, operator feedback, and domain knowledge may enhance trust and usability in real-world telecom deployments. Collectively, these opportunities highlight the path forward for transforming AI-driven optimization into a cornerstone technology of 6G networks.

Future research should focus on addressing the identified challenges and research gaps to enhance the effectiveness and applicability of AI-driven methods in 5G/6G networks. Specific areas for further investigation include:

- **Scalability and Complexity Reduction:** Innovations in training algorithms and architectures for H-MARL and other AI techniques are essential to handle the increasing complexity of network environments efficiently.
- **Enhancing FL:** Developing communication-efficient FL models that can operate in real-time while maintaining robust security and privacy protocols is critical for their deployment in practical scenarios.
- **Energy Efficiency:** Researching energy-efficient AI algorithms is vital to balance the computational overhead introduced by AI techniques with the goal of optimizing resource management in energy-constrained environments.
- **Interdisciplinary Approaches:** Combining insights from telecommunications, AI, and data science can foster innovative solutions that integrate the strengths of various optimization methods while addressing their limitations.

## CHAPTER 8: CONCLUSION

### 8.1 Summary of Research Work

This dissertation presented an AI-driven dynamic optimization framework for 5G/6G networks with a focus on resource allocation, traffic management, and energy efficiency. Recognizing the limitations of traditional optimization approaches in coping with the scale, heterogeneity, and dynamism of next-generation wireless systems, the research proposed H-MARL architecture as the backbone of intelligent decision-making. To enhance adaptability and generalization, the framework incorporated TL techniques, while FL was employed to ensure distributed intelligence with privacy preservation. Furthermore, XAI was integrated to improve transparency and interpretability of the AI-driven decisions. The framework was evaluated across multiple use cases, including dense urban environments, massive IoT deployments, and heterogeneous network scenarios, under MATLAB/Python simulation setups. The results demonstrated that the proposed approach significantly outperformed baseline methods such as greedy heuristics, centralized DRL, and flat MARL, achieving improvements in efficiency, scalability, and sustainability.

### 8.2 Major Contributions

The key contributions of this dissertation as mentioned in section 1.6 can be summarized as follows: Development of an H-MARL Framework, Integration of TL, FL for Distributed Optimization, Explainability in AI-driven Networking, Comprehensive Evaluation across Use Cases, and Performance Gains.

### 8.3 Closing Remarks

In conclusion, this dissertation contributes a comprehensive and forward-looking approach to the AI-driven dynamic optimization of 5G/6G networks. By synergizing H-MARL, transfer learning, federated learning, and explainable AI, the research provides a robust framework that addresses the key challenges of scalability, adaptability, privacy, and interpretability. While limitations remain in terms of scalability to ultra-dense deployments, security in federated environments, and trade-offs between explainability and real-time performance, these open issues present promising avenues for future research. Ultimately, the proposed

framework not only advances the state of the art but also lays the foundation for building intelligent, sustainable, and trustworthy 6G networks that can meet the demands of a hyper-connected digital society.

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