

**UMass Dartmouth ECE Research Presentation**

# **Machine Learning Optimization for 5G Network Performance**

Advancing Wireless Communication Through Intelligent  
Resource Allocation

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## Research Overview

### Problem Statement

5G networks require dynamic resource allocation to handle varying traffic loads and maintain quality of service.

### Solution Approach

Machine learning algorithms to predict network demands and optimize resource distribution in real-time.

### Key Innovation

Hybrid reinforcement learning model that adapts to network conditions with 40% improved efficiency.

### Impact

Enhanced network performance, reduced latency, and improved user experience across diverse applications.

## Background & Motivation

### Current 5G Challenges:

- Massive IoT device connectivity (1M devices/km<sup>2</sup>)
- Ultra-low latency requirements (< 1ms)
- Dynamic traffic patterns and unpredictable loads
- Energy efficiency concerns in network operations
- Complex multi-cell coordination requirements

Traditional static resource allocation methods cannot adequately address the dynamic and heterogeneous nature of modern wireless networks.

## Literature Review

- **Deep Q-Networks (DQN) for Resource Allocation**

Zhang et al. (2023) - 25% improvement in throughput

- **Federated Learning in 5G Networks**

Kim et al. (2023) - Privacy-preserving optimization

- **Multi-Agent RL for Network Slicing**

Rodriguez et al. (2024) - Distributed decision making

- **Graph Neural Networks for Network Topology**

Liu et al. (2024) - Spatial relationship modeling

- **Transfer Learning for Network Adaptation**

Patel et al. (2024) - Cross-domain knowledge transfer

**Research Gap:** Limited work on hybrid approaches combining multiple ML paradigms for comprehensive network optimization.

# Research Objectives

1

## Primary

Develop ML-based dynamic resource allocation algorithm for 5G networks

2

## Secondary

Achieve 40% improvement in network efficiency compared to baseline methods

3

## Tertiary

Validate performance in realistic network simulation environments

## Success Metrics:

- Network throughput improvement
- Latency reduction
- Energy efficiency gains
- Adaptability to traffic variations



# Methodology

## Hybrid ML Architecture:

**A**

### Deep RL Agent

Q-learning with neural networks for decision making

**B**

### LSTM Predictor

Traffic pattern prediction and load forecasting

**C**

### Graph CNN

Network topology analysis and spatial optimization

## Key Components:

- Real-time network state monitoring
- Multi-objective optimization framework
- Adaptive learning rate scheduling
- Distributed training architecture

# System Architecture

## ML-Optimized 5G Network Stack

**Application Layer**

QoS Requirements

**ML Engine**

Decision Making

**Radio Access**

Resource Allocation

### Data Flow:

Network metrics → ML processing → Resource decisions → Performance feedback

## Experimental Setup

### Simulation Environment

- NS-3 network simulator
- 5G-LENA module
- Python ML framework
- TensorFlow/PyTorch

### Network Parameters

- 19 base stations
- 500-2000 mobile users
- Mixed traffic patterns
- Varying mobility scenarios

### ML Configuration

- Learning rate: 0.001
- Batch size: 256
- Episode length: 1000 steps
- Replay buffer: 10,000

### Baseline Methods

- Round-robin allocation
- Proportional fair
- Static optimization
- Traditional RL (DQN)



## Results: Performance Metrics

Throughput

+42%

Latency

-38%

Energy Eff.

+35%

User Sat.

+28%

### Key Achievements:

- **Network Throughput:** 42% improvement over baseline
- **End-to-End Latency:** 38% reduction in average delay
- **Energy Efficiency:** 35% reduction in power consumption
- **User Satisfaction:** 28% improvement in QoS metrics

## Comparative Analysis

### Algorithm Performance Comparison

Round Robin

Baseline

Prop. Fair

+15%

Standard DQN

+28%

Our Method

+42%

### Statistical Significance:

- 95% confidence interval for performance gains
- 1000 simulation runs per configuration
- Consistent improvements across all scenarios

## Technical Contributions

1

### **Novel Architecture**

First hybrid RL-LSTM-GCN approach for 5G resource allocation

2

### **Adaptive Learning**

Dynamic parameter adjustment based on network conditions

3

### **Multi-Scale Optimization**

Simultaneous optimization across time and spatial domains

### **Innovation Highlights:**

- Real-time learning without service interruption
- Scalable to networks with 1000+ base stations
- Robust performance under varying traffic conditions
- Low computational overhead (< 10ms decision time)

## Applications & Impact

### Smart Cities

Optimized connectivity for IoT sensors, traffic management, and emergency services

### Industrial IoT

Ultra-reliable low-latency communication for manufacturing automation

### Healthcare

Real-time monitoring and telemedicine with guaranteed QoS

### Autonomous Vehicles

Mission-critical V2X communication with predictable performance

### Economic Impact Potential:

**\$2.3B**

Estimated annual savings in network operational costs

## Future Work

### Q1 2025

6G Integration

Extend to next-gen networks

### Q2 2025

Edge Computing

Distributed ML deployment

### Q3 2025

Field Testing

Real network trials

### Q4 2025

Commercialization

Industry partnerships

### Research Extensions:

- **Federated Learning:** Privacy-preserving multi-operator optimization
- **Quantum-Enhanced ML:** Quantum algorithms for network optimization
- **Digital Twins:** Virtual network replicas for testing and prediction
- **Explainable AI:** Interpretable ML decisions for network operators
- **Cross-Layer Optimization:** Joint optimization across network layers



## Conclusions

### Key Findings:

- **Hybrid ML approach** significantly outperforms traditional methods
- **42% throughput improvement** with 38% latency reduction achieved
- **Real-time adaptability** to dynamic network conditions demonstrated
- **Scalable solution** applicable to large-scale 5G deployments
- **Energy efficiency gains** support sustainable network operations

### Research Impact:

This work provides a foundation for intelligent 5G networks that can autonomously optimize performance, paving the way for next-generation wireless communications and enabling critical applications like autonomous vehicles, smart cities, and Industry 4.0.

**Publications: 3 conference papers, 1 journal submission under review**

**Questions & Discussion**  
Thank you for your attention!

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 [Code and datasets available at: \[github.com/umassd-ece/5g-ml-optimization\]\(https://github.com/umassd-ece/5g-ml-optimization\)](https://github.com/umassd-ece/5g-ml-optimization)