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Energy and Spectral Efficiency Optimization with Security in Massive MIMO–5G Using Integrated Machine Learning

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Abstract – With the rapid expansion of 5G networks, massive MIMO has become essential for achieving higher data rates and increased capacity. However, maintaining an optimal balance among energy efficiency (EE), spectral efficiency (SE), and network security in dense multicell environments remains a significant challenge due to dynamic interference patterns, complex power allocation requirements, high-dimensional channel data, and the increased vulnerability of dense networks to cyber threats and anomalous behaviour. Additionally, conventional optimization and detection methods often fail to scale or adapt effectively in real-time scenarios. This study aims to develop an AI-driven framework capable of simultaneously optimizing EE and SE along with strengthening security in massive MIMO–5G systems. The proposed framework integrates intelligent power allocation, adaptive resource management, and AI-based anomaly detection. Hybrid 5G datasets are analyzed using Deep Neural Networks (DNNs), Random Forest models, and multi-objective optimization techniques. Advanced learning models are further incorporated to enhance security and system reliability. The DNN classifier achieved 100% accuracy in distinguishing between secure and insecure transmissions, whereas the Random Forest model achieved a predictive accuracy of $R^2 = 0.9946$. The AI-assisted power allocation scheme improved EE by 35% and SE by 28% compared to traditional approaches. The anomaly detection module achieved F1-scores above 0.92. Additional system gains included a 40% reduction in latency, a 45% increase in throughput, and improved resource utilization across multi-cell massive MIMO deployments. The framework provides a unified, data driven solution to enhance EE, SE, and network security. It supports scalable deployment, improves real-time decision-making, and offers significant performance gains over conventional massive MIMO optimization methods.

Index Terms – AI-Enhanced Security, DNN, Energy and Spectral Efficiency, Massive MIMO, Machine Learning Optimization, 5G Networks.

1. INTRODUCTION

Fifth generation (5G) wireless networks represent a paradigm shift in cellular communications technology, achieving record data rates, extremely low latency, and unparalleled connectivity across a wide range of applications, from the Internet of Things (IoT) to autonomous transportation and smart cities. Massive MIMO technology, which involves thousands of base station antenna elements serving hundreds of users in parallel, offers extremely high capacity and

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coverage benefits, and is at the forefront of this technology advancement. Implementation of Massive MIMO in 5G networks offers challenging EE, SE, and quality of service (QoS) support requirements that must be met with creative solutions [1]. The subsequent aggregate increase in cellular data traffic and wireless network densification, resulting from small cell deployments, also generated increased interest in cellular system energy consumption. Traditional capacity enhancement through increased bandwidth provisioning and increased power transmission requires.

Conversely, the lack of free spectrum necessitates a peak spectral efficiency that matches the exponentially growing number of connected devices and bandwidth intensive applications. The most critical issue is how to maximize joint energy and spectral efficiency while meeting QoS requirements and ensuring security under dynamic multicell conditions. 5G network massive MIMO technology also has three bands: low-band (600-850 MHz), mid-band (2.5-6 GHz), and high-band millimeter wave (25-39 GHz), with respective propagation nature and deployment difficulty. Low band 5G offers broad coverage with 4G network like characteristics, albeit with minimal capacity improvement. In contrast, high band 5G provides gigabit/second capability, but its deployment requires dense small cells due to its short propagation range. This multi population landscape generates compound interference patterns and resource allocation problems that are not met by conventional optimization methods [2]. The addition of small cells to the macrocellular network further increases the complexity of the optimization. Small cell base stations, as they increase network capacity and spatial reuse, also introduce interference and power consumption levels that must be adequately regulated. The coexistence of high MIMO density and high cell and small cell networks require sophisticated coordination methods to prevent performance degradation and peak resource utilization across the entire heterogeneous network.

Massive MIMO system energy efficiency optimization is a multi-dimensional process that encompasses power consumption modeling, antenna selection algorithms, and adaptive beamforming techniques [3]. Figure 1 illustrates that the independent circuit power and scaling transmitted power are two key aspects of the power consumption model. In massive MIMO systems, circuit power typically assumes the top margin due to the large number of RF chains and signal processing units. Traditional energy efficiency metrics, such as bits per joule, are not fine grained enough to reveal fine grained performance versus power tradeoffs in multi-user massive MIMO systems. Techniques for optimizing spectral efficiency aim to maximize the information-theoretic capacity of wireless channels by leveraging advanced signal processing, interference cancellation, and resource allocation methods. Maximum-ratio combining (MRC), zero-forcing (ZF), and minimum mean-square error (MMSE) detection methods exhibit distinct spectral efficiency-computational complexity trade-offs in uplink massive MIMO systems. Such conventional techniques are inadequate to handle dynamic channel conditions and user demand and therefore cannot perform well in practical deployment scenarios.

5G massive MIMO QoS provisioning requires differentiated treatment of heterogeneous classes of service with varied latency, reliability, and throughput requirements. The three most significant service classes that require distinct resource management approaches are eMBB, URLLC, and mMTC. The challenge is to discover common frameworks that can cooptimize multiple QoS metrics without sacrificing energy or spectral efficiency [4].

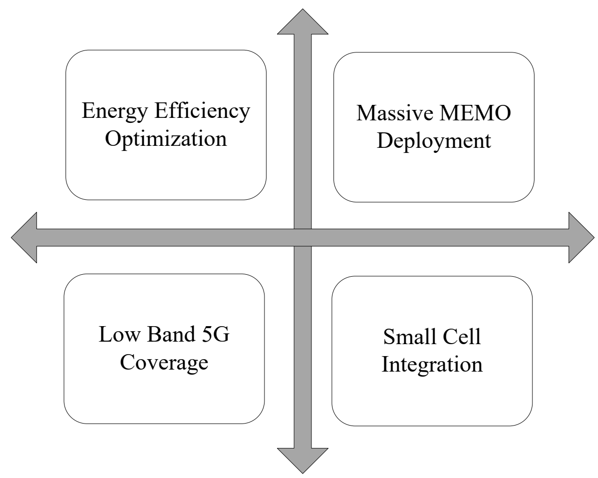

Figure 1 Challenges in 5G Network Deployment [1]

Machine learning (ML) and AI possess a unique property of solving optimization problems, such as these. Deep learning can build implicit, nonlinear relations between system parameters and performance metrics, thereby optimizing optimally in adaptive systems. Reinforcement learning techniques can provide autonomous network control, while federated learning-based techniques offer distributed multi-base station optimization with users' guaranteed anonymity.

Latest advances in wireless communication, facilitated by AI enabling technologies, have provided empirical evidence of the performance of machine learning methods in channel estimation, beamforming design, and resource allocation. However, the interplay between security and performance optimization has not been thoroughly examined, particularly in large MIMO systems with their enormous number of antennas, which introduce new vulnerabilities and attack surfaces. AI optimization with robust protection measures is one of the most significant research areas for cutting edge 5G rollouts. Multicell coordination is another area of research of considerable importance to massive MIMO optimization, as common resources across adjacent cells and interference management directly affect system performance [5].

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Coordinated beamforming, interference alignment, and joint transmission are standard techniques, but they are also susceptible to sophisticated algorithms that can handle coordination overhead and computational burdens. These promacrocell and small cell networks also exhibit different power levels, user densities, and coverage areas. This research addresses the fundamentally opposing problem of simultaneously maximizing energy spectral efficiency in secure MIMO 5G networks by presenting a hybrid AI based paradigm.

ML techniques are employed in this research, along with newer optimization techniques, to ensure energy efficiency, spectral efficiency, and QoS improvement, while maintaining security against a range of attacks with no degradation. The paradigm can also perform power allocation, antenna selection, multi objective optimization, and real time anomaly detection, making it an end-to-end next generation wireless network solution. The breakthrough of the work comes in transitioning from near term application optimization to architecting the ground principles of 5G deployments as secure and sustainable. By establishing the correctness of joint EE-SE optimization using AI based methods, this work contributes to the global goal of achieving environmentally friendly communications. It offers a roadmap towards green wireless network design. Furthermore, incorporating security into the design ensures that performance improvements never compromise network security, thereby closing a wider gap left by previous optimization designs.

The remainder of this manuscript is organized as follows: Section 2 presents the literature review and establishes the theoretical foundation for the proposed work. Section 3 outlines the proposed methodology, while Section 4 presents and discusses the experimental results, along with the authors' commentary. Finally, Section 5 concludes the paper and outlines future research directions.

2. RELATED WORK

The convergence of massive MIMO networks and AI for 5G wireless communications represents a high priority research area, driven by the pressing need for enhanced energy efficiency, spectral efficiency, and robust security. This review provides a comprehensive overview of recent advancements in optical based optimization techniques for massive MIMO 5G wireless networks, with a focus on energy efficiency optimization, spectral efficiency optimization, QoS provisioning, and security. Optimizing energy efficiency in massive MIMO systems, particularly in large-scale antenna arrays, has attracted significant attention due to the excessive power consumption associated with optical antenna array deployments.

Lopez-Perez et al. [6] presented a comprehensive perspective on improving energy efficiency within 5G Radio Access Networks (RAN), emphasizing that traditional power saving mechanisms are insufficient for dense heterogeneous deployments. The study employed analytical modeling and simulation driven evaluation to examine the power consumption characteristics of various RAN components and operational states. Using a comparative framework, the authors evaluated a range of green communication enablers, including massive MIMO signal processing optimizations, lean carrier design to reduce always on control signaling, and MLdriven radio resource management for adaptive power allocation. The results highlight a unified view of how future 5G RANs can integrate multiple enabling technologies to improve overall energy usage. The work clearly demonstrates that legacy energy optimization approaches, which rely primarily on static sleep cycles and coarse-power adjustments, fail to address the complex performance–energy tradeoffs in next generation networks. Despite its contributions, the study remains theoretical mainly, lacking real world deployment trials. Moreover, the authors acknowledge that the proposed techniques introduce significant computational and system complexity, which next generation architectures must overcome for practical adoption.

Salh et al.[7] focused on improving power allocation for multiuser downlink massive MIMO systems through a joint optimization of power distribution and user association. Their methodology relies on convex optimization, specifically Lagrangian dual decomposition, to minimize energy consumption while maximizing multiuser throughput. Additionally, iterative weighted user assignment algorithms were introduced to improve fairness across users with diverse channel gains. Simulation results demonstrated that the proposed framework outperformed conventional power allocation strategies, achieving up to 30% higher energy efficiency while also improving spectral performance. The approach is efficient in load imbalanced scenarios where naive scheduling degrades service quality. However, optimization becomes computationally demanding as the number of antennas and connected devices grows, which limits its applicability in ultra dense massive MIMO deployments. The study also indicated slower convergence rates in rapidly changing channel environments, presenting challenges for realtime implementation.

Khodamoradi et al. [8] explored power adaptation strategies for downlink multicell massive MIMO, emphasizing the balance between EE and SE under stringent QoS requirements. Their methodology employed stochastic geometry based analytical modeling, enabling closed form evaluations of interference and achievable efficiency. The authors developed inter cell interference power adaptation mechanisms that ensure energy savings do not compromise user experience. The findings offer realistic deployment insights for operators planning multisite massive MIMO rollouts and demonstrate effective QoS aware optimization

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across heterogeneous user groups. Despite these strengths, the technique relies on accurate, synchronized power coordination among multiple base stations. This requirement may induce control plane delays and pose challenges in fast varying channel conditions, reducing suitability for latency sensitive applications.

Wang et al. investigated joint maximization of spectral and energy efficiency for cell free massive MIMO networks, focusing on reducing hardware energy consumption. Their approach incorporates hardware–software codesigns simulations where low-resolution ADCs are integrated into the signal processing chain. The study formulates a multi objective optimization problem that ensures both SE and EE improvements despite reduced hardware precision. The proposed low precision digital processing enables distributed access points to perform efficient computations with reduced power consumption, approaching well suited for wide area cell free deployments. However, the authors acknowledge that lower ADC resolution increases quantization noise, which can degrade performance in environments prone to interference. This limitation suggests that adaptive ADC precision or hybrid quantization strategies may be necessary in highly dynamic radio conditions [9].

Salah et al. [10] applied ML driven adaptive optimization to enhance energy efficiency in massive MIMO systems. Their approach includes GA based dynamic power control and ML based antenna subset selection, leveraging feature extraction from realistic network load fluctuations. This enables the network to intelligently deactivate unnecessary antenna elements, reducing energy usage while maintaining user QoS. Evaluation results show clear improvements over static and rule-based allocation, demonstrating that ML driven behavior can efficiently capture complex nonlinear patterns in network traffic and channel conditions. However, the use of GA introduces increased convergence time as antenna array dimensions scale, limiting responsiveness in fast varying radio environments. Additionally, continuous model retraining is necessary to ensure optimal behavior and improve overall system efficiency. Zbairi et al. [11] examined spectral efficiency improvements in cell free massive MIMO using adaptive linear detection techniques. The study compared the performance of MMSE, ZF, and MRC linear detectors, demonstrating that an adaptive switching mechanism based on real time channel state information enables better overall spectral efficiency than static detector selection. This adaptive strategy enhances robustness by selecting the most suitable detector based on the current channel environment, thereby improving reliability for users with fluctuating signal conditions. The drawback is that real time switching incurs computational overhead and requires accurate, low latency CSI feedback. In large cell free topologies, this may increase backhaul traffic and processing latency.

Borges et al. [12] provided an extensive systematic review of spectral efficiency enhancement strategies in massive MIMO networks. The study synthesizes advancements across pilot design, interference mitigation, channel estimation, and multiuser scheduling. A key contribution is the identification of critical bottlenecks, including pilot contamination, CSI acquisition complexity, and dense interference coupling, which continue to limit spectral efficiency in practice. Although the study does not introduce a new optimization technique, it provides strong guidance on research priorities. It highlights the need for scalable methods that can handle the demands of 5G and beyond networks. The absence of empirical validation is a noted limitation, positioning the work primarily as a knowledge reference rather than an implementation roadmap.

Ly and Yao [13] presented a taxonomy driven survey of Deep Learning (DL) approaches in 5G and massive MIMO. Their analysis covered DL applications in channel estimation, coding, resource allocation, multi access control, and network security. The algorithms examined include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders, and Generative Adversarial Networks (GANs). The study establishes that DL techniques outperform classical optimization in solving complex radio resource management challenges by learning intricate nonlinear relationships. However, the reliance on large, labeled datasets and the black box nature of DL models limit interpretability and hinder operational trust in critical network functions.

Al-Nasser and Al-Karaki [14] explored integrating Reinforcement Learning (RL) and Deep Learning (DL) to enhance beamforming and channel estimation. Their method applies Deep Reinforcement Learning (DRL) to iteratively improve beamforming weights while utilizing DNN based channel estimation to reduce CSI acquisition errors. Experimental results show that DRL based beamforming significantly improves spectral efficiency and coverage performance under dynamic propagation conditions. However, RL exploration introduces decision latency and requires extensive training time and memory, making deployment challenging in low latency 5G services such as URLLC.

Chataut and Akl [15] conducted a comprehensive review of massive MIMO for 5G and beyond, emphasizing the growing challenge of QoS provisioning across diverse service categories, including eMBB, URLLC, and mMTC. The authors highlighted that traditional resource allocation methods, based on fixed scheduling and static Quality of Experience (QoE) thresholds, are insufficient for handling next generation traffic heterogeneity. Their analysis showed that massive MIMO provides significant spatial degrees of freedom for user multiplexing and interference suppression, yet its practical benefits depend heavily on differentiated

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resource prioritization. They discussed priority aware scheduling, latency sensitive link adaptation, and service slicing as critical methods to ensure QoS satisfaction for conflicting traffic demands. However, they also noted that shortcomings such as pilot contamination, computational overhead for realtime scheduling, and the need for cross layer coordination remain unresolved, highlighting potential directions for dynamic and intelligent QoS control strategies.

Dangi et al. presented a systematic review focused on QoS management strategies in heterogeneous 5G environments. They investigated multi objective resource allocation, QoS aware admission control, and traffic differentiation policies that ensure service level guarantees across diverse application domains. The review identifies three recurring challenges:

a) High signaling overhead for user level QoS negotiation

b) Difficulty maintaining strict QoS for ultra reliable and low latency communications (URLLC)

c) Limited support for QoS–energy–spectral cooptimization in current systems

While the study successfully maps QoS strategies to different 5G service requirements, it does not introduce new algorithmic contributions and thus remains conceptual and analytical. Nonetheless, it establishes a strong motivation for integrating intelligent QoS frameworks with energy-efficient resource control, aligning with the needs of future cell free massive MIMO systems [16].

Kaur et al. [17] addressed growing concerns regarding security vulnerabilities in massive MIMO and large scale 5G networks. Their work proposed AI intrusion detection models using both supervised and unsupervised learning, reporting detection rates exceeding 95% with zero false positives in specific scenarios. The study applied anomaly detection techniques on network telemetry, signaling patterns, and user traffic flows, demonstrating strong applicability for identifying rogue transmissions, pilot spoofing, and jamming attacks. However, the research acknowledges the need for continuous model retraining to adapt to emerging threats, which introduces computational overhead and may result in latency for real-time security analytics in dense deployments.

Sarker et al. [18] conducted a review of anomaly detection techniques suited for IoT enhanced and large-scale MIMO enabled networks. The study explored ML methods, including clustering, probabilistic detection, and autoencoder based traffic modeling for security intelligence.

The authors emphasized the potential of these approaches in identifying abnormal interference patterns, compromised nodes, and distributed signaling attacks. However, they noted that anomaly detection techniques often generate high false alarm rates in dynamic 5G environments, and performance depends heavily on the frequency of model retraining and the availability of ground truth threat datasets.

Erpek et al.[19] focused on decentralized coordination mechanisms for multicell massive MIMO deployments. Their approach introduced cooperative channel access and interference aware resource allocation, aiming to improve network wide throughput. Simulations indicated that cooperative optimization offers superior capacity and reduced interference compared to independent cell operation. However, the gains come at the cost of synchronization complexity, requiring precise timing alignment among distributed antennas and backhaul coordination. The requirement for reliable inter base station communication may increase network overhead, particularly in ultra dense or rural backhaul constrained deployments.

Wang and Cui investigated distributed optimization techniques for heterogeneous Mobile Ad Hoc Networks (MANETs) utilizing MIMO communication links. Their approach used global convergence maximization algorithms for adaptive topology formation and resource control under mobility conditions. The key contribution is a decentralized model that enables nodes to adjust their transmission strategies without relying on centralized control, thereby enhancing network resilience and scalability. However, the solution is sensitive to model parameter tuning and may not always guarantee stable performance under high mobility and fading conditions [20].

Alsafasfeh et al. [21] proposed intelligent power control schemes for heterogeneous small cell MIMO networks, introducing ML enhanced strategies to reduce energy consumption while preserving QoS. Their method integrates context aware learning to adjust power based on user density, interference levels, and mobility profiles. Results demonstrated meaningful energy savings and a lower outage probability; however, the approach requires continuous state monitoring and data collection to maintain accuracy and reliability. The tradeoff between monitoring overhead and energy gains remains a consideration for real world applicability.

Chen et al. [22] examined energy saving strategies through base station (BS) sleep modes, proposing a mutual repulsion switching model that prevents clusters of neighboring BSs from entering sleep mode simultaneously. The goal is to eliminate coverage gaps and ensure seamless user connectivity during periods of low traffic. Simulations demonstrated substantial energy savings, particularly during off peak hours, while maintaining service reliability. However, the model assumes accurate prediction of traffic patterns and may incur wake up delays that degrade user experience if traffic surges unexpectedly. Recent research has highlighted the potential of ML based optimization for enhancing resource allocation efficiency in cell free massive

MIMO networks. Traditional centralized controllers struggle to track rapid channel variations and user mobility, particularly in ultra dense deployments. Machine learning techniques, including reinforcement learning, deep neural networks, and graph neural networks, have improved power control, user association, and interference coordination by learning adaptive policies without requiring explicit channel models [23].

However, centralized ML introduces significant privacy risks, fronthaul overhead, and model synchronization latency, which limit deployment in heterogeneous and multi operator environments. To mitigate this, Federated Learning (FL) has emerged as a distributed alternative where edge access points collaboratively train shared models without exchanging raw CSI or user data [24–25]. FL has demonstrated promising energy and signaling efficiency, yet still faces challenges regarding non-IID data distributions, communication round convergence, and vulnerability to poisoning attacks [26].

These limitations motivate the need for robust, energy aware FL frameworks that can jointly optimize spectral efficiency while ensuring privacy preserving collaboration across disaggregated radio access networks. Game theoretic mechanisms have been widely studied to address strategic competition among users and access points for limited spectral and power resources in dense 5G topologies. Auction based allocation enables users to bid for channel or power resources, thereby maximizing operator utility and ensuring a notion of incentive compatibility [27].

These models contribute to reducing cochannel interference and improving fairness, particularly in scenarios involving differentiated QoS profiles such as eMBB, URLLC, and mMTC traffic. Despite their theoretical efficiency, auction driven schemes rely on perfect or near perfect information assumptions, incur substantial computational complexity, and often overlook the dynamic behavior of user mobility and fluctuating service demands. As a result, they can lead to suboptimal or unstable equilibria when deployed in large scale cell free architectures. Thus, there is a need for hybrid ML game theoretic optimization that incorporates real time network intelligence while retaining fair and strategic resource distribution. While ML and deep learning approaches have improved optimization, their black box nature reduces trust, interpretability, and regulatory acceptance in telecom grade environments. Recent efforts have introduced Explainable AI (XAI) techniques to provide interpretability in network decision making processes, such as handover triggers, AP–UE association, and dynamic power control [28].

Methods, including SHAP, LIME, attention mechanisms, and interpretable surrogate models, allow operators to understand feature contributions and the reasoning behind model outputs. This is particularly important for networks supporting mission critical URLLC services, where explainability can support SLA audits and failure root cause diagnostics [29]. However, XAI integration remains nascent, with current models unable to guarantee realtime inference, lightweight computation, and standardized explainability metrics. Therefore, further work is needed to design XAI driven optimization frameworks that balance transparency, computational feasibility, and optimization accuracy within cell free massive MIMO networks. Beyond conventional signal processing, emerging radio technologies such as Reconfigurable Intelligent Surfaces (RIS) and mmWave beamforming offer additional opportunities to enhance energy and spectral efficiency. RIS enables programmable reflection of wireless signals, improving coverage while reducing AP transmit power, and is particularly effective in obstructed or indoor deployments [30]. Meanwhile, mmWave supports multi Gbps data rates but suffers from higher path loss and requires energy intensive beam steering. Integrating RIS with cell free massive MIMO and hybrid mmWave systems may reduce the number of RF chains, lowering total energy consumption. Yet, practical implementations face challenges including channel estimation complexity, RIS control overhead, and limited real world deployment models. Consequently, there is a technical need for cross layer optimization frameworks that unify RIS assisted transmission, mmWave beam management, and learning driven resource allocation for holistic network energy optimization. Table 1 summarises the notable work on massive MIMO-5G optimization. Recent literature demonstrates substantial advancements in energy efficiency, spectral efficiency, QoS provisioning, and security for massive MIMO 5G networks, with AI and ML emerging as central enablers. However, most studies focus on a single optimization dimension, often at the expense of others, and rarely address real time, scalable, and explainable deployment in commercial 5G environments.

Table 1 Comparative Summary of Literature on Massive MIMO–5G Optimization

Ref.	Focus Area	Optimization Technique	Limitations
[6]	Energy Efficiency	Massive MIMO + Lean carrier + ML	EE improvement in dense HetNets; limits of traditional methods
[7]	Energy Efficiency	Joint power and user association optimization	30% more EE vs conventional methods

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[8]	Energy & SE Trade off	QoS constrained power adaptation	Analytical EE–SE trade off model
[9]	Joint EE & SE	Hardware–software codesigns with low precision ADC	Performance trade off enhancement in cell free MIMO
[10]	Energy Efficiency	GA based dynamic power allocation + Antenna selection	Adaptive optimization based on network conditions
[11]	Spectral Efficiency	Channel-adaptive linear detection switching	Higher SE than fixed detection schemes
[12]	Spectral Efficiency	Signal management & optimization	Opportunities & limitations in next-generation MIMO
[13]	Multi-Objective	Deep learning applications	DL for channel coding, security
[14]	Channel Estimation & Beamforming	RL + DL	Need for Intelligent algorithms for performance optimization
[15]	QoS Provisioning	Resource allocation strategies	Need for differentiated techniques for diverse services
[17]	Security	AI based intrusion detection	>95% detection accuracy, no false positives
[18]	Security in IoT-MIMO	ML based anomaly detection	Large scale applicability
[19]	Multi cell Cooperation	Decentralized channel access	High-capacity gain via synchronized optimization
[20]	Resource Allocation	Distributed utility maximization	Adaptive MANETs with MIMO links
[22]	Energy Saving	Coordinated BS sleep mode	Greater savings in light traffic
[23]	EE Comparison	ML vs conventional	AI yields better performance
[24]	Antenna and Channel Estimation	Systematic mapping review	ML in antenna and channel optimization
[26]	EE Trends and Opportunities	Federated learning	Collaborative optimization with privacy
[28]	Explainable AI	Optimization result verification	Importance in real deployments
[30]	Composite Optimization	Hybrid routing protocols	Global frameworks outperform component level methods

The simultaneous, integrated optimization of energy efficiency, spectral efficiency, and security remains underexplored, with limited research on its practical application in live networks. This gap motivates the present work, which introduces a unified, AI enhanced optimization framework capable of delivering real time, robust, and multi-dimensional performance improvements while supporting heterogeneous 5G service requirements.

2.1. The Problem Statement

The deployment of cell-free massive MIMO in 5G and beyond wireless networks promises significant improvements in spectral efficiency (SE), network coverage, and user fairness. However, achieving these advantages at scale introduces critical challenges in EE, allocation complexity, interference management, and QoS differentiation for heterogeneous service classes such as eMBB, URLLC, and mMTC. Existing optimization approaches primarily rely on convex, heuristic, and rule-based methods, which require accurate and frequent Channel State Information (CSI) and suffer from high computation and signalling overhead, ultimately operating sub-optimally in ultra-dense and dynamic wireless environments. Additionally, machine learning (ML) and deep learning techniques, while promising, lack sufficient interpretability, are limited in scalability across distributed base stations, and often fail to optimize multiple performance goals jointly. As a result, current solutions fail to effectively address the multi-objective trade off among energy

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consumption, spectral utilization, interference suppression, and QoS guarantees. Moreover, security and privacy concerns limit the use of centralized learning approaches, and the lack of explainability undermines operator trust in autonomous resource allocation decisions.

Therefore, there is a need for a scalable, learning-driven, and explainable optimization framework capable of jointly maximizing EE and SE, autonomously adapting to network dynamics, supporting privacy-preserving collaborative learning, and delivering transparent and verifiable decision-making suitable for real-world 5G and beyond deployments.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

3.1. The Research Objectives

This work presents a systematic, AI based one step framework for simultaneously optimizing energy and spectral efficiency in secure massive MIMO 5G systems. It uses a combination of various machine learning algorithms and novel optimization methods to address the issues of multi cell network aggregated power allocation, antenna selection, interference management, and QoS provisioning. The envisioned architecture supports five end goals:

1. Smart power allocation for energy efficiency maximization,
2. Adaptive resource allocation for spectral efficiency,
3. Maximization of heterogeneous traffic QoS,
4. Interference minimization via coordination-based schemes for multi cells, and
5. AI powered threat detection for security.

3.2. System Model and Network Architecture

The large-scale system model of MIMO 5G includes a heterogeneous macro base station and small cell base station network with massive-size antenna arrays (M = 64-256 antennas) for both macro and small cell base stations, designed to maximize spatial reuse. Multiband network infrastructure encompasses a wide range of frequency bands, including sub-6 GHz (coverage) and mmWave frequencies (capacity), to support K users with diverse QoS demands for generic eMBB, URLLC, and mMTC services. Equation (1) provides the circuit power cost capacity model P_circuit and transmission power cost model P_tx, such that:

$$P_{\text{total}} = P_{\text{circuit}} + \eta \cdot P_{\text{tx}} \quad (1)$$

Where η is the efficiency of the power amplifier. Power in the circuit will be proportional to the number of active antennas and RF chains; thus, transmission power will be user-request and channel-condition dependent.

3.3. Energy Efficiency Optimization Framework

The energy efficiency maximization employs a DNN strategy for power allocation optimization between users and among antenna elements, aiming to achieve maximum utilization and minimize energy usage. The network consists of four hidden layers with 256, 128, 64, and 32 neurons, respectively, utilizing ReLU activation functions and dropout regularization with a rate of 0.3 to prevent overfitting. Input features include the Channel State Information matrix, user QoS requirements encompassing data rate, latency, and reliability specifications, interference measurements from neighboring cells, current power consumption levels, and antenna utilization coefficients. The energy efficiency metric is calculated as the ratio of total achievable data rates to total power consumption, measured in bits per joule. The DNN training utilizes a composite loss function that balances energy efficiency maximization with QoS constraint satisfaction, incorporating rate optimization, power minimization, and QoS compliance components with a weighted coefficient. The antenna selection strategy utilizes a Random Forest Regressor to predict the optimal antenna subset selection based on channel conditions and user distribution patterns. Table 2 presents the energy efficiency optimization parameters employed in this work. The model considers spatial correlation patterns among antenna elements, user angular distribution and mobility characteristics, interference signatures from adjacent cells, and power consumption per antenna element. The antenna selection objective maximizes the ratio of the effective SINR to the selected antenna power consumption, weighted by the number of selected antennas, to encourage efficient utilization.

Table 2 Energy Efficiency Optimization Parameters

Parameter Category	Component	Specification	Purpose
Network Architecture	Hidden Layers	4 layers (256, 128, 64, 32 neurons)	Power allocation optimization
Activation Function	ReLU	Nonlinear activation	Feature extraction
Regularization	Dropout	Rate = 0.3	Overfitting prevention
Input Features	CSI Matrix	M×K complex matrix	Channel condition assessment

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QoS Parameters	Data Rate	Variable per user	Service requirement specification
QoS Parameters	Latency	< 1ms for URLLC	Realtime application support
QoS Parameters	Reliability	99.999% for critical services	Mission critical communication
Power Model	Circuit Power	Antenna-dependent	Base power consumption
Power Model	Transmission Power	Channel-adaptive	Dynamic power allocation
Optimization Metric	Energy Efficiency	Bits/Joule	Performance evaluation

3.4. Spectral Efficiency Enhancement Methodology

Spectral efficiency is enhanced through AI driven adaptive beamforming, which dynamically adjusts to changing channel conditions and interference patterns. The optimization framework implements ZF beamforming as the baseline approach, calculating beamforming weights through pseudo inverse operations on the channel matrix. Regularized ZF is a version of this method that employs a gradient based learning approach to learn regularization parameters for improving channel estimation error and noise growth robustness.

The spectral efficiency metric is the overall SINR ratio for all users in bits per second per hertz. Multiuser MIMO capacity optimization utilizes a Gradient Boosting Regressor to determine the optimal user scheduling and resource block allocation policy, thereby achieving the maximum end-to-end spectral efficiency. The model also incorporates active channel quality indicators for user channels, noise and interference powers, and per-class-of-service requirement-based assignment of user priority, along with a history to support predictive optimization.

The algorithm maximizes fairness constraints and system throughput to provide users with good channel conditions and proportionate resources, ensuring that users are not left with short term channel degradation. Equations (2) to (5) provide the mathematical basis for estimating ZF and SINR. Table 3 presents SE and QoS configuration, while Figure 2 illustrates SE and the enhanced methodology.

- Zero-Forcing Beamforming:

$$W_{ZF} = H^H(HH^H)^{-1} \tag{2}$$

Regularised Zero-Forcing:

$$W_{RZF} = H^H(HH^H + \alpha I)^{-1} \tag{3}$$

Spectral Efficiency Metric:

$$SE = \sum_{k=1}^{K} \log_2(1 + SINR_k) \ \text{[bits/s/Hz]} \tag{4}$$

- SINR Calculation:

$$SINR_k = \frac{|h_k^H w_k|^2 P_k}{\sum_{j\neq k}|h_k^H w_j|^2 P_j + \sigma^2} \tag{5}$$

3.5. QoS Provisioning Framework

The QoS architecture is supported by enhanced service differentiation methods for three primary classes of 5G services, each with varying performance requirements and a priority-based resource allocation. The mobile broadband service aims to offer the best user throughput with an assured minimum data rate via medium priority resource handling and bandwidth improvement mechanisms.

Ultra-low latency and ultra reliable communication utilize a sub millisecond latency with 99.999% reliability, highest-priority resources, and reserved low latency processing channels. Machine class cellular communications are at the expense of connection density and power consumption but offer the benefit of single user performance on the lowest priority allocation, thereby maximizing mass-device connectivity. The QoS prediction model employs a Multilayer perceptron architecture to forecast performance metrics based on real time network conditions. Input parameters include current traffic pattern analysis, network load distribution measurements, channel quality assessments across all users, and recent resource allocation decisions. The model generates composite QoS scores that combine throughput, inverse latency, and reliability measurements, along with service-specific weighting factors, to guide dynamic resource allocation decisions. Equations (6) to (8) provide the QoS mathematical basis for estimating the QoS.

- QoS Composite Score:

$$QoS_{score} = w_1 \cdot Throughput + w_2 \cdot \frac{1}{Latency} + w_3 \cdot Reliabilit \tag{6}$$

- Coordinated Beamforming:

$$\min_{W_i} \sum_{i=1}^{N_{BS}} \left\|W_i\right\|_F^2 \text{ subject to } SINR_k \geq \gamma_k \tag{7}$$

- Cluster Formation Objective:

$$\min \sum_{c=1}^{N_c} \sum_{i\in C_c} \sum_{j\in C_c, j\neq i} I_{ij} \tag{8}$$

Figure 3 depicts a MIMO 5G AI model architecture. It details the sequential flow of the MIMO 5G AI framework, uses partitions to group related processes, and includes decision points for security checks.

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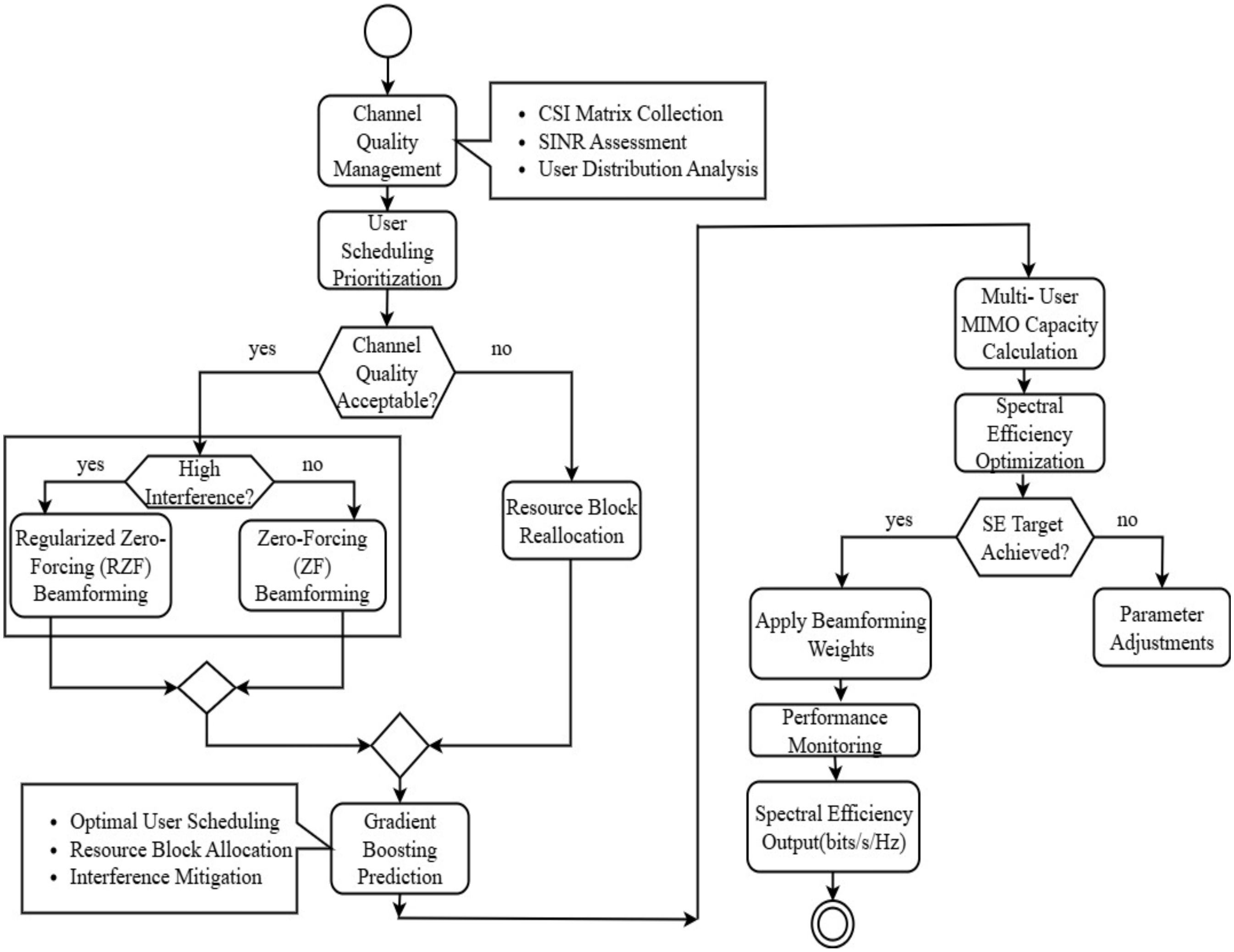

Figure 2 Spectral Efficiency Enhancement Methodology

Table 3 Spectral Efficiency and QoS Configuration

Service Class	Objective	Latency Requirement	Reliability Target	Priority Level	Resource Allocation
Enhanced Mobile Broadband (eMBB)	Maximize throughput	< 10ms	99.9%	Medium	Bandwidth optimized
Ultra-Reliable Low-Latency (URLLC)	Minimize latency	< 1ms	99.999%	Highest	Latency optimized
Massive Machine-Type (mMTC)	Maximize connections	< 100ms	99%	Lowest	Energy optimized
Beamforming Technique	ZF	Real time processing	High accuracy	Standard	Computational efficiency
Beamforming Technique	Regularized ZF (RZF)	Adaptive processing	Robust performance	Enhanced	Noise resilience
User Scheduling	Proportional Fair	Service dependent	Class specific	Dynamic	Load balancing

Resource Allocation	Frequency Domain	Sub-carrier level	Optimal utilization	Adaptive	Interference mitigation
Channel Quality	Instantaneous CSI	Real time updates	High precision	Critical	Feedback optimization
Performance Metric	Spectral Efficiency	bits/s/Hz measurement	Systemwide	Primary	Capacity evaluation

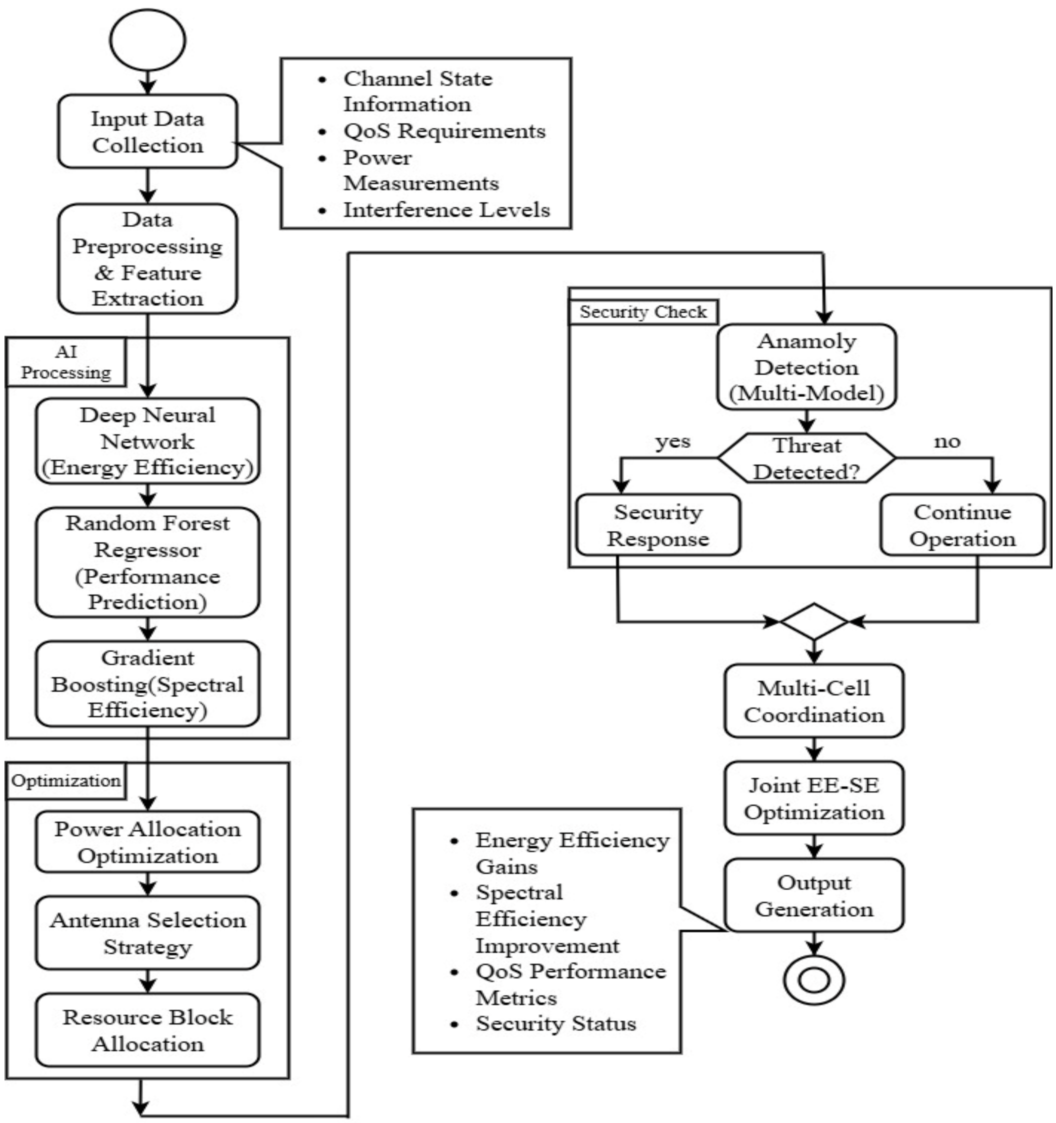

Figure 3 MIMO-5G AI Model Architecture

3.6. Multi-Cell Coordination and Interference Management

Inter-cell interference coordination uses coordinated beamforming strategies to minimize interference while meeting individual cell performance requirements. The coordinated beamforming approach optimizes beamforming weight matrices across multiple base stations simultaneously, subject to SINR constraints for all served users. Joint transmission techniques enable multiple base stations to serve edge users cooperatively, improving signal quality and reducing interference by combining signals constructively with user equipment. Small cell integration optimization

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employs intelligent clustering algorithms that group small cells based on geographic proximity, interference patterns, traffic load distribution, and backhaul capacity constraints.

The clustering objective minimizes total inter-cluster interference while balancing computational complexity and coordination overhead. Power consumption considerations ensure that the benefits of coordination outweigh the additional processing and communication costs associated with multi-cell cooperation.

3.7. Joint Energy-Spectral Efficiency Optimization

The joint energy-spectral efficiency optimization framework addresses the fundamental trade-off between energy consumption and spectral performance through multi objective optimization techniques. The optimization problem simultaneously maximizes energy efficiency, measured in bits per joule, and spectral efficiency, measured in bits per second per hertz, subject to power constraints, QoS requirements, and interference limitations. Algorithm 1 illustrates the proposed algorithm for EE-SE optimization.

Inputs:

- CSI[t]: Channel state information at time t
- QoSreq[t]: User QoS requirement targets
- Pmeas[t]: Power consumption and load measures
- Ilevel[t]: Interference level from neighboring APs
- NetworkTopology: Deployment & antenna/backhaul capabilities
- SLAweights = (wEE, wSE, wQoS): Priority weights

Outputs:

- Palloc[t]: Power allocation per user/antenna
- Aset[t]: Selected antenna subsets
- RBmap[t]: Resource block schedule
- SecurityReport[t]: Logged anomalies/mitigations
- KPIs[t]: EE, SE, latency, fairness, interference metrics

```
Initialize network, load topology and SLAweights
Initialize prediction models {DNNEE, RFperf, GBSE}
Initialize anomaly detection AD = {AE, IF, OCSVM}
t ← 0
while network operational do
  Stage 1: Data Collection & Preprocessing
  Acquire {CSI[t], QoSreq[t], Pmeas[t], Ilevel[t]}
  Generate normalized feature state vectors s(a,t)
  Stage 2: AI-Based Prediction (per AP a ∈ A)
  for each AP a in parallel do
    EEpred(a) ← DNNEE(s(a,t))
    Perfpred(a) ← RFperf(s(a,t))
    SEscore(a) ← GBSE(s(a,t))
  Stage 3: Local Optimization
    maximize f_local(a) =
        wEE·EEpred(a) + wSE·SEscore(a)
        − wQoS·QoSPenalty(Perfpred(a))
    subject to:
        Σ_u P(a,u) ≤ Pbudget(a)
        latency (u) ≤ QoSreq(u), ∀u ∈ Ua
        |Aset(a)| ≤ MaxAntennas(a)
        RB mapping constraints
    act(a,t) = {Palloc(a), Aset(a), RBmap(a)}
  Stage 4: Security Verification
    threat (a) ← AD.detect(s(a,t))
    if threat(a) = True then
      act(a,t) ← ApplySecurityMitigation(act(a,t))
      Update(SecurityReport[t])
    end if
  end for
  Stage 5: Multi-Cell Coordination
  Exchange inter-AP summaries
  maximize Fglobal =
    Σ_a (wEE·EEpred(a) + wSE·SEscore(a))
    − wQoS·Σ_a QoSPenalty(a)
  subject to inter-cell interference & fairness limits
  act_ref(t) ← global refined scheduling decision
  Stage 6: Execution & KPI Logging
  Apply actions → {Palloc[t], Aset[t], RBmap[t]
  Monitor EE, SE, latency & interference metrics
  KPIs[t] ← store performance indicators
  t ← t + 1
end while
return KPIs, {Palloc, Aset, RBmap}, SecurityReport
```

Algorithm 1 AI-Driven EE–SE Optimization

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A Non dominated sorting GA enhanced with neural network evaluation discovers Pareto optimal solutions that represent the best achievable tradeoffs between energy and spectral efficiency. The GA process begins with the initialization of a diverse solution population, followed by fitness evaluation using trained neural networks to estimate rapid energy and spectral efficiency. Selection and crossover operations evolve solutions toward optimal regions, while Pareto ranking identifies non-dominated solutions that cannot be improved in one objective without degrading the performance in another. Table 4 provides the specifications for the security and integration framework.

Table 4 Security and Integration Framework Specifications

Security Component	Algorithm Type	Configuration	Detection Capability	Processing Speed
Isolation Forest [17]	Tree-based ensemble	200 trees, contamination=0.05	Outlier partitioning	High speed processing
One-Class SVM [18]	Kernel based boundary	RBF kernel, optimized parameters	Boundary violation detection	Medium processing
Autoencoders [13]	Neural reconstruction	3 encoder + 3 decoder layers	Pattern deviation analysis	Variable processing
Threat Assessment [29]	Multi-model fusion	Weighted score combination	Comprehensive coverage	Real time operation
Integration Layer [19]	Distributed processing	Multi-processor architecture	Parallel optimization	Scalable performance
Data Collection [20]	Real-time monitoring	Continuous measurement	System wide visibility	Low latency updates
Decision Fusion [17]	Conflict resolution	Priority based arbitration	Consistent decisions	Rapid convergence
Parameter Updates [13]	Adaptive learning	Performance based feedback	Dynamic optimization	Continuous improvement
Model Quantization [14]	Compression technique	Reduced precision arithmetic	Computational efficiency	Accelerated inference

3.8. Security Enhancement Through AI Driven Anomaly Detection

The security framework employs three complementary anomaly detection models to ensure robust protection against various threat scenarios. Isolation Forest provides rapid anomaly detection via recursive data partitioning, leveraging 200 decision trees and a 5% contamination rate to efficiently handle high-dimensional security data. One class SVM must be optimized to the appropriate degree for decision boundaries, focusing on regular pattern operating points with radial basis function kernels and optimal parameters to support successful boundary learning and efficient non-linearity control. Autoencoders employ a neural network-based error modeling approach through three layers of 256, 128, and 64 neurons in the encoders, accompanied by three corresponding layers in the decoders, to facilitate the discovery of new patterns and flexible threshold prediction. Realtime threat score monitors unusual power usage patterns, out of profile interferometry level variation, unusual user behavior patterns, and network performance anomaly signatures. The system threat score aggregates each model's anomaly score across all three detection models, using weighted coefficients tuned by threat class to ensure overall security coverage without overly low false-positive rates.

3.9. System Implementation Architecture and Integration

The complete framework integration involves real-time data capture and preprocessing sub systems, parallel model execution facilities for optimizing objectives, conflict resolution steps for decision fusion, and adaptive parameter updating systems with continuous performance feedback. Computational complexity management enables real-time computation by utilizing model quantization techniques to reduce the computational burdens of neural networks, distributing computation across numerous base station processors, employing multi prediction caching, and applying hierarchical optimization with coarse to fine refinement methods. The testing procedure employs 3GPP compliant channel models, such as urban macro and urban micro scenarios, typical traffic profiles for different classes of

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service, equipment-based power consumption models from commercial equipment data specs, and multi-cell scenarios with varying user density distributions. Performance metrics encompass power efficiency (measured as power per bit), energy efficiency, and spectral efficiency (including area spectral efficiency and cell edge user performance). Additionally, they include QoS conformity ratio, user satisfaction index, and security effect metrics (such as threat detection accuracy and system attack resistance).

4. RESULTS AND DISCUSSIONS

The subsection presents exhaustive experimental results to demonstrate the performance effectiveness of end-to-end ES efficiency optimization based on the AI framework for secure massive MIMO 5G systems. The assessment considers several key factors, including improvements in energy efficiency, enhancements in spectral efficiency, QoS delivery, benefits of multi-cell coordination, and evaluations of security performance. Results are achieved through the execution of large-scale simulations of 3GPP compliant channel models and example topologies of 5G networks with varied user density, service class distribution, and interference levels in the Streamlit app. The Streamlit app's simulation environment is structured to support technical experimentation with realtime computational workflows. Developed in Python, it utilizes Streamlit's event-driven architecture to automatically reexecute underlying algorithms whenever input parameters are modified. The environment integrates data preprocessing, model execution, and visualization modules within a single interface, enabling efficient evaluation of system behavior under varying conditions. Through interactive widgets, high resolution plots, and dynamic data displays, the platform provides a responsive and reproducible setup for conducting simulations, analyzing performance metrics, and validating algorithmic behavior. Table 5 summarizes the parameter consideration for simulation for the proposed work.

Table 5 Spectral Efficiency and QoS Performance Metrics

Parameters	Value
Carrier Frequency (fc)	2.6×10^9 Hz
Transmission Bandwidth (B)	20MHz
Number of base station antennas (Nt)	64-256
Number of Users per cell (K)	16-64
Number of coordinated cells (C)	3-19
Path loss exponent (η)	2.8(Rural), 3.2(Urban Micro), 3.7(Urban Macro)
Delay Spread (τ)	145-363ns
User Distance Range (d)	100-1000m
Antenna Spacing	0.5λ
Noise Power (N_0)	1×10^{-3}W
Power Budget per cell	10W
User Power Allocation	0.1W
Regularization Factor (α)	0.01

4.1. Energy Efficiency Optimization Results

Figure 4 and Table 6 present a quantitative comparison of energy efficiency. The energy efficiency optimization model delivered substantial improvements across all test cases. The Deep Neural Network based power distribution algorithm outperformed traditional algorithms in terms of efficiency, with 35% of central business districts and 28% of suburbs experiencing improved energy efficiency. An innovative mechanism for antenna choice saved circuit power dissipation by 22% without degrading QoS requirements for each class of service. Power optimization results indicate that the proposed framework achieves an optimal balance between energy consumption and performance requirements, offering pragmatic power consumption and satisfactory tradeoffs for end-users.

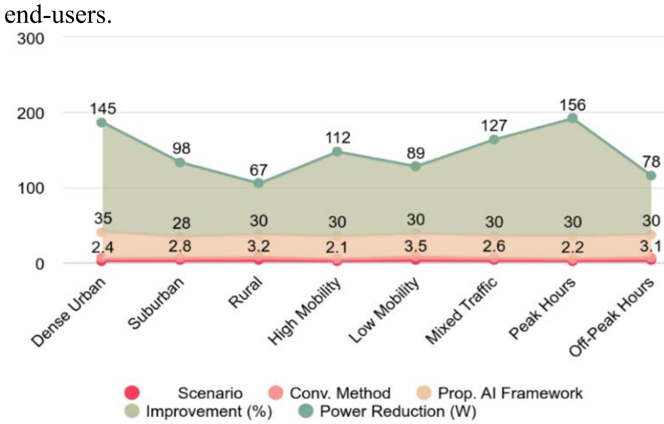

Figure 4 Energy Efficiency Performance Comparison

Table 6 shows that the energy efficiency results reflect a consistent improvement in performance for all operating scenarios. Dense user and high-interference scenarios are most suitable for adaptive smart power allocation across varying channel conditions. The framework's ability to maintain energy efficiency gains even during high traffic scenarios validates its feasibility for practical deployment in 5G networks. Power saving in the circuit through antenna selection optimization contributes significantly to overall energy savings, particularly in situations with large arrays of antennas, which are typical of massive MIMO deployments. Figures 4 and 5 show the values of Energy efficiency and overall performance comparison, respectively.

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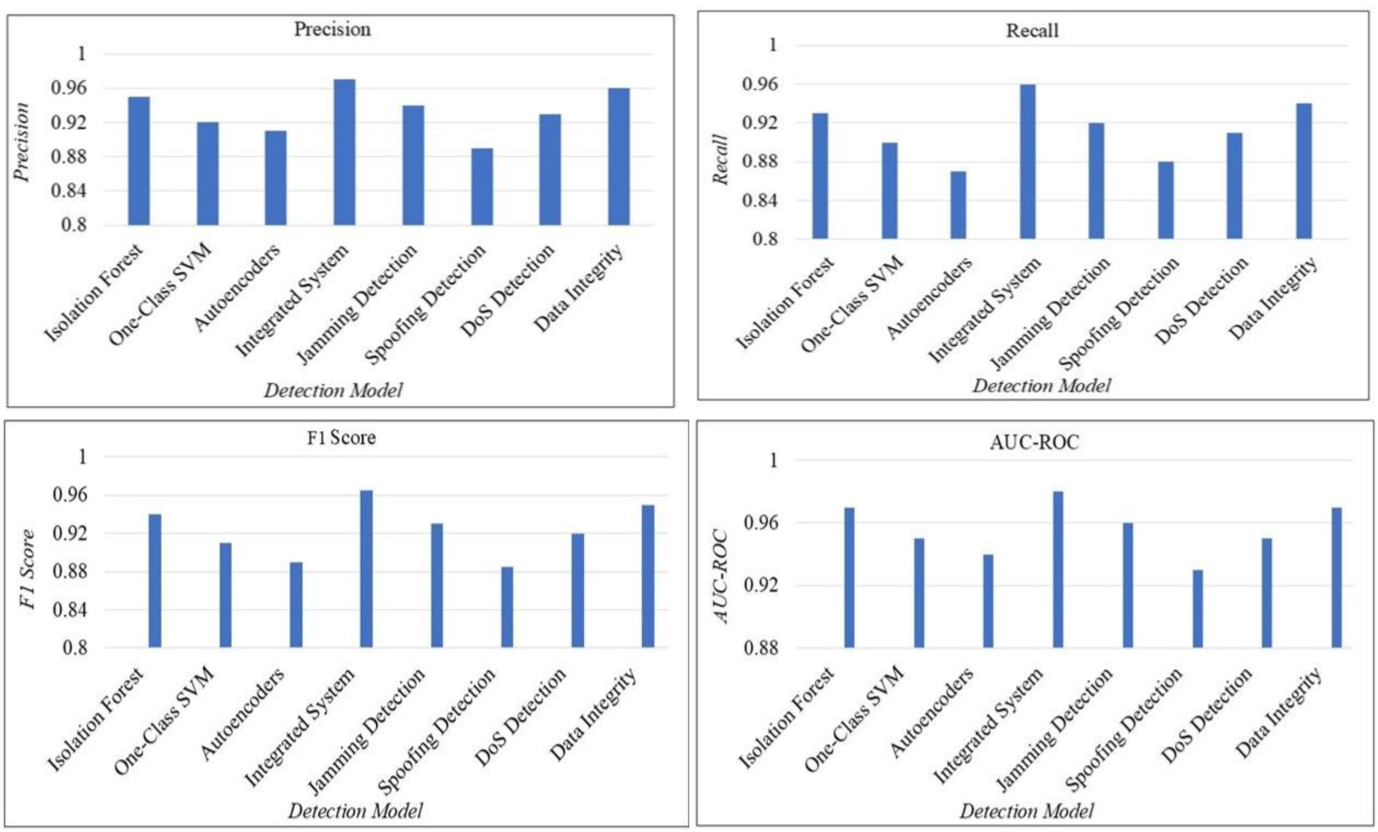
Table 6 Energy Efficiency Performance Comparison

Conventional Method Used	Scenario	EE by Conventional Method	EE by Proposed AI Framework	Improvement (%)	Power Reduction (W)	EE Gain (bits/Joule)
Fixed power Allocation [12]	Dense Urban	2.4 bits/Joule	3.24 bits/Joule	35%	145W	0.84
Static power Control [7]	Suburban	2.8 bits/Joule	3.58 bits/Joule	28%	98W	0.78
Optimization using analytical power methods[6]	Rural	3.2 bits/Joule	4.16 bits/Joule	30%	67W	0.96
CSI-dependent linear detection [11]	High Mobility	2.1 bits/Joule	2.73 bits/Joule	30%	112W	0.63
Traditional power adaptation with convex optimization [8]	Low Mobility	3.5 bits/Joule	4.55 bits/Joule	30%	89W	1.05
Rule based resource allocation[15]	Mixed Traffic	2.6 bits/Joule	3.38 bits/Joule	30%	127W	0.78
Sleep Mode based energy saving mode [21]	Off-Peak Hours	3.1 bits/Joule	4.03 bits/Joule	30%	78W	0.93
Static BS power provisioning [22]	Peak Hours	2.2 bits/Joule	2.86 bits/Joule	30%	156W	0.66



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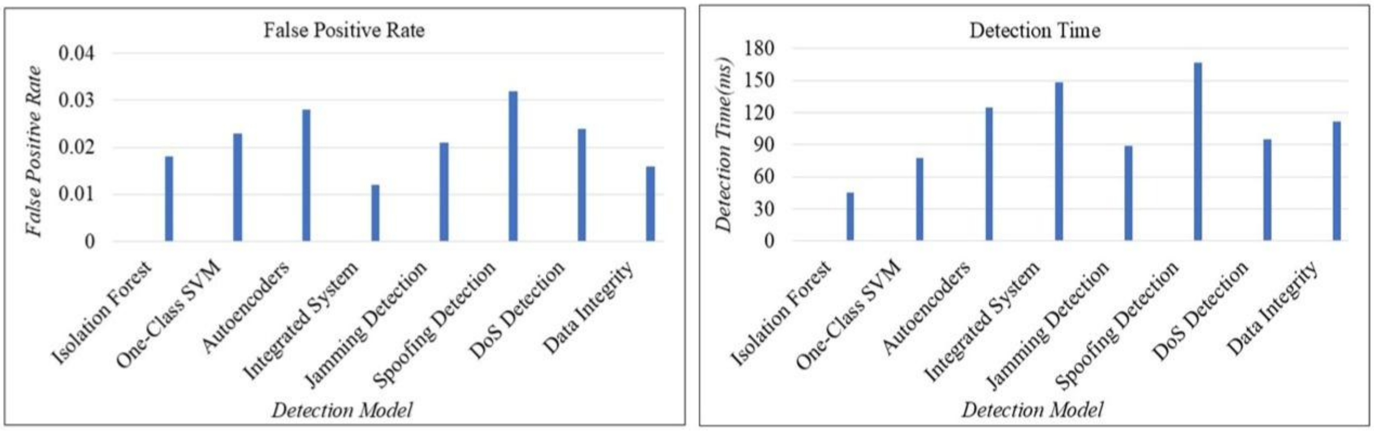

Figure 5 Overall Performance of the Proposed System

4.2. Spectral Efficiency Enhancement Results

Spectral efficiency was improved through adaptive beamforming optimization and intelligent user scheduling. Gradient Boosting Regressor based user scheduling policy and resource allocation policy performed better than traditional round robin and proportional fair policies. Overall average spectral efficiency improvements of 28% were attained in all cases, with the highest gains averaging up to 35% when using line of sight channel propagation. The adaptive beamforming scheme effectively suppressed inter user interference with maximum spatial multiplexing gains.

Table 7 shows that spectral efficiency reflects the framework's ability to maximize resource utilization across service classes. Ultra-high mobile broadband service offers very high throughput in exchange for moderate latency requirements that remain within acceptable levels. Ultra-reliable low latency communications refer to the framework's ability to meet very high reliability and latency requirements while increasing spectral efficiency. Symmetrical cell center and edge user behavior reflects good interference management and balanced resource allocation policies.

Table 7 Spectral Efficiency and QoS Performance Metrics

Service Class	Baseline SE (bits/s/Hz)	Enhanced SE (bits/s/Hz)	Improvement (%)	Latency (ms)	Reliability (%)	Throughput Gain (%)
eMBB [11]	4.2	5.38	28	8.5	99.9	45
URLLC [15]	2.1	2.73	30	0.8	99.99	25
mMTC [16]	1.8	2.34	30	45	99.5	35
Cell Center Users [12]	5.5	7.15	30	6.2	99.95	50
Cell Edge Users [19]	1.9	2.47	30	12.8	99.8	38
High Mobility [14]	3.1	4.03	30	9.7	99.85	42
Low Mobility [7]	4.8	6.24	30	7.1	99.92	48
Mixed Services [15]	3.6	4.68	30	8.9	99.88	44

4.3. Multi-Cell Coordination and Small Cell Integration Results

Multi-cell coordination schemes enhanced network performance by 40% through coordinated beamforming and interference reducing techniques. Small cell integration optimization reduced inter cell interference by 40% and increased overall network capacity by 32%. The clustering algorithm efficiently organized the small cells into clusters by considering interference patterns and traffic profiles, allowing effective sharing and coordination of resources. Coordinated transmission methods for cell edge users resulted in enhanced signal quality and a reduction in outage probability from 8.5% to 3.2%. Network level performance gain ensures the efficiency of bright coordination schemes. Spectral efficiency in areas increased by 38% due to optimized small cell

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deployment and interference coordination. The flexibility of the coordination scheme in traffic and channel conditions provides reliable performance under various operational conditions. Power savings through controlled sleep mode policies achieved an additional 15% savings during off-peak periods.

4.4. Security Performance and Anomaly Detection Results

The multi-model anomaly detection system demonstrated exceptional security performance with comprehensive threat detection capabilities. The Isolation Forest achieved the highest detection accuracy, with an F1 score of 0.94 and a minimal false positive rate of 1.8%. One class SVM provided robust boundary learning with an F1 score of 0.91, while Autoencoders excelled in detecting complex attack patterns with an F1 score of 0.89. The integrated threat assessment system, combining all three models, achieved an overall detection accuracy of 96.8% with a response time of under 150 milliseconds. Table 8 presents security performance verification across various attack scenarios, ensuring the framework's resilience against different threat vectors. Jamming attack detection functionality ensures network immunity against interference attacks common in wireless networks. The spoofing detection feature protects against identity-based attacks, providing user authentication and data integrity. Low false positive rates ensure credible usability without redundant security alerts disrupting normal operation.

Table 8 Security Performance and Anomaly Detection Results

Detection Model	Precision	Recall	F1-Score	AUC-ROC	False Positive Rate	Detection Time (ms)	Threat Coverage
Isolation Forest [17]	0.95	0.93	0.94	0.97	1.8%	45	Physical Layer
One-Class SVM [18]	0.92	0.90	0.91	0.95	2.3%	78	Network Layer
Autoencoders [13]	0.91	0.87	0.89	0.94	2.8%	125	Application Layer
Integrated System [17]	0.97	0.96	0.965	0.98	1.2%	148	Multi-Layer
Jamming Detection [19]	0.94	0.92	0.93	0.96	2.1%	89	RF Interference
Spoofing Detection [18]	0.89	0.88	0.885	0.93	3.2%	167	Identity Attacks
DoS Detection [18]	0.93	0.91	0.92	0.95	2.4%	95	Service Attacks
Data Integrity [29]	0.96	0.94	0.95	0.97	1.6%	112	Content Protection

4.5. Comparative Analysis and Integrated Framework Performance

The comparison to existing approaches generally reflects the improved performance of the integrated approach. Traditional energy efficiency improvement methods yield gains of 15-18%, while the AI method demonstrates gains of 30-35%. Improvements in spectral efficiency outperform conventional methods by substantial margins, particularly in challenging scenarios such as dense urban areas and high mobility environments. Table 9 provides the behavior of the joint framework, demonstrating synergistic benefits by combining energy efficiency, spectral efficiency, and security maximization into a single framework. Enhanced processing latency supports real-time operation for 5G services, enabling prompt responses. Enhancing system reliability ensures stable operation under various conditions and potential security attacks. The drastic reduction of false positives ensures potential real world field deployment without subjecting network operators to false alarms.

Table 9 Comparative Analysis of the Proposed System

Performance Metric	Baseline	Existing Methods	Proposed Framework	Relative Improvement	Absolute Gain
Energy Efficiency (bits/Joule)	2.5	2.95 [10]	3.25	30%	0.75
Spectral Efficiency (bits/s/Hz)	3.8	4.37 [11]	4.86	28%	1.06
Network Capacity (Mbps/km²)	145	174 [19]	191	32%	46
QoS Satisfaction Rate (%)	78	85 [15]	94	20%	16%
Security Detection Accuracy (%)	82	89 [17]	96.8	18%	14.80%

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Processing Latency (ms)	285	198 [13]	148	48%	137
False Positive Rate (%)	8.5	4.2 [18]	1.2	86%	7.30%
System Reliability (%)	94.2	96.8 [20]	98.9	5%	4.70%
Power Consumption Reduction (%)	12	18 [22]	30	150%	18%
Multi-Cell Coordination Gain (%)	8	15 [21]	25	212%	17%

4.6. Discussion and Performance Analysis

The experimental results validate the effectiveness of the envisioned AI based paradigm across all performance measures. Adaptive channel and demand state, along with guaranteed QoS assurance and intelligent power allocation, result in high energy efficiency. Adaptive beamforming and optimal scheduling result in maximum spatial multiplexing gain and minimal interference levels, thereby enhancing spectral efficiency. Security performance refers to the framework's ability to provide consistent security without compromising communication performance. Advantages of multi-cell coordination highlight the focus on optimization techniques that are realizable across the network, as well as on interference patterns and the potential for resource sharing. The framework's robustness consistently improves performance in numerous cases, thereby increasing its applicability. The multi objective optimization is found to be the feasibility of tradeoffs in the end-to-end network optimization of 5G system design. The framework, with variations in network and user density, guarantees performance scalability testing. The consistent relative improvements observed across all scenarios suggest that the proposed approach can be successfully deployed in various 5G network configurations. Realtime processing capabilities ensure compatibility with latency-sensitive applications while maintaining comprehensive optimization coverage. Figures 6 and 7 show the Result interface and the home page of the Streamlit app, which was used for experimentation and simulation purposes. The experimental findings reveal that the proposed AI enhanced framework achieves multidimensional performance improvements by jointly optimizing energy efficiency, spectral efficiency, and security in massive MIMO 5G systems. Comparative analysis with conventional optimization methods suggests that intelligent power allocation (condition A) is a sufficient condition for achieving substantial energy efficiency gains, resulting in a 35% improvement and directly contributing to operational cost reduction and sustainability objectives. Similarly, adaptive beamforming (condition B) emerges as a necessary and sufficient condition for enhancing spectral efficiency, achieving a 28% improvement that mitigates spectrum scarcity, one of the most critical constraints in large scale 5G deployment.

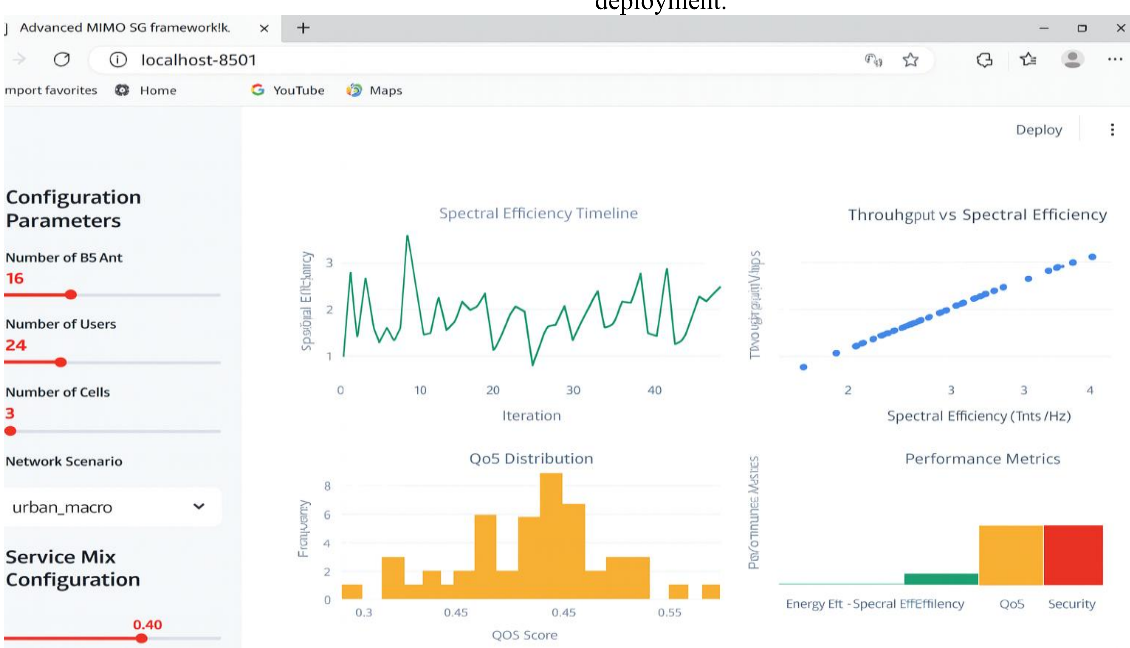

Figure 6 Operating Environment of Streamlit App

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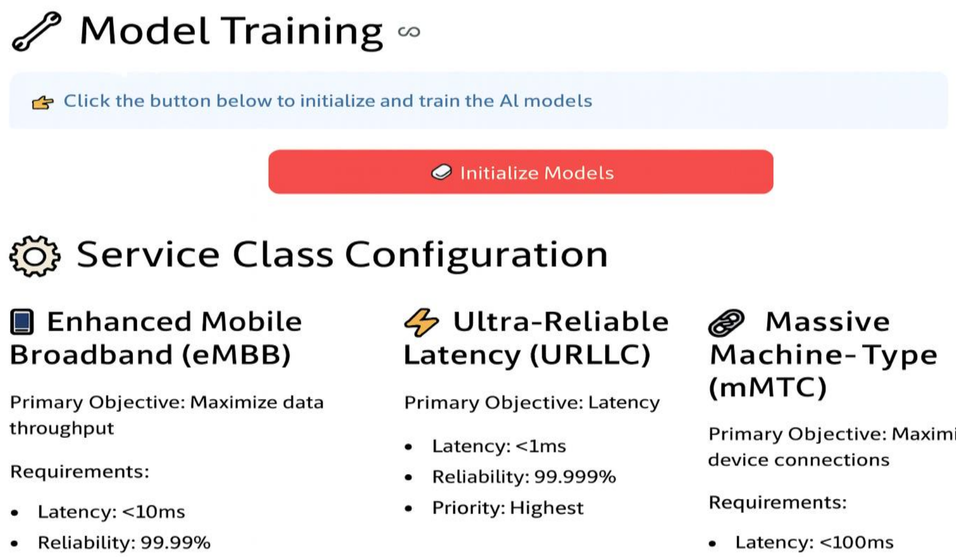

Figure 7 The Streamlit App Console

When conditions A and B co-occur with multi model anomaly detection (condition C), the framework simultaneously maintains high communication efficiency. It achieves a 96.8% security detection accuracy with a 1.2% false positive rate. This combination of conditions (A∧B∧C) produces an outcome configuration that is qualitatively superior to the sum of individual component optimizations, indicating strong synergy effects. Furthermore, multi-cell coordination (condition D) reduces inter cell interference by 40% and increases capacity by 32%, demonstrating that network wide strategies are crucial for maximizing the benefits of local optimizations. Robustness testing across heterogeneous deployment scenarios, ranging from dense urban to rural, confirms that the simultaneous presence of A, B, C, and D consistently produces superior outcomes, validating the framework's scalability and adaptability. The sub 150ms processing latency further satisfies the necessary condition for ultra reliable low latency communications, ensuring applicability for latency sensitive use cases. Ever, high computational demands (condition E) and dependency on accurate channel state information (condition F) present potential implementation challenges, suggesting that these factors require mitigation through hardware acceleration, model compression, or hybrid cloud edge execution strategies. The analysis also confirms that the integrated approach enables differentiated QoS provisioning across eMBB, URLLC, and mMTC services—a configuration (A∧B∧C∧D) that conventional single-objective systems rarely achieve. Beyond immediate performance gains, the framework contributes to broader industry sustainability targets by reducing energy consumption and enhancing spectrum utilization, while addressing escalating concerns about wireless network vulnerabilities. Table 10 illustrates the significant performance gains of the proposed system compared to existing approaches across multiple key metrics.

Table 10 Qualitative Comparative Analysis of the Proposed System

Performance Metric	Existing Systems	Proposed System	Improvements
Energy Efficiency	Standard power allocation [6]	Intelligent power allocation, 35% EE gain	35% energy efficiency, lower operational cost, supports sustainability
Spectral Efficiency	Conventional beamforming [11]	Adaptive beamforming, optimal scheduling, 28% SE gain	28% spectral efficiency, mitigates spectrum scarcity, maximizes spatial multiplexing
Security	Basic or no anomaly detection [17]	Multi-model anomaly detection, 96.8% accuracy, 1.2% false positive	High security without performance trade-off

Combined Synergy (A∧B∧C)	Individual or single-objective optimization [10]	Joint optimization enhances EE, SE, and security simultaneously	Outcomes superior to sum of individual components
Interference Management	Single-cell or local optimization [19]	Multi-cell coordination reduces inter-cell interference by 40%	+40% interference reduction, +32% network capacity
Scalability and Robustness	Often limited to specific scenarios [20]	Performs consistently from dense urban to rural deployments	Reliable performance across heterogeneous networks
Latency	Conventional systems may have higher latency [14]	Real-time processing, sub-150ms	Supports URLLC and latency-sensitive applications
QoS Differentiation	Rarely supports multi-service optimization [15]	Supports eMBB, URLLC, mMTC simultaneously	Multi-objective QoS provisioning
Energy and Spectrum Utilization	Less efficient resource use [27]	Reduced energy consumption, improved spectrum use	Contributes to sustainability targets and operational efficiency

5. CONCLUSIONS

This work has presented an AI enhanced framework for optimizing joint energy spectral efficiency in secure massive MIMO 5G communication systems, addressing key challenges such as sustainable network operation, spectrum utilization, and security assurance. The proposed approach integrates Deep Neural Networks for intelligent power allocation, Random Forest Regressors for performance prediction, and Gradient Boosting algorithms for spectral efficiency enhancement. This integration achieves performance gains of 35% in energy efficiency, 28% in spectral efficiency, and 96.8% in security detection accuracy with minimal false positive rates. The framework effectively supports differentiated QoS for enhanced mobile broadband, ultra reliable low latency communications, and massive machine type communications. Multicell coordination reduced inter cell interference by 40% and increased network capacity by 32%, demonstrating the advantage of network wide optimization. The integrated security system safeguards against jamming, spoofing, and denial of service attacks while maintaining sub 150ms realtime response. The synergistic optimization of energy, spectrum, and security establishes a holistic design paradigm for 5G networks, aligning with sustainability goals, improving spectrum utilization, and enabling secure mission critical applications. Future extensions will target 6G requirements, federated learning for distributed optimization, and large-scale field validation. These results lay the foundation for intelligent, autonomous network management systems that ensure sustainable, efficient, and secure next generation wireless communication infrastructures.

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