

AI-powered framework for advancing 5G and 6G wireless communication

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ABSTRACT

A shift to 5G to 6G networks would provide better connectivity, transmission capacity, security, and latency, but there are still challenges such as dynamic resource allocation, energy consumption, network optimisation, and cybersecurity issues. This research presents an artificial intelligence (AI)-based approach to enhance the accuracy, efficiency and security of 5G and future 6G wireless networks. Adaptive spectrum and resource allocation is done using deep reinforcement learning (DRL), and AI traffic forecasting and dynamic beamforming helps reduce latency, boost throughput and ensure quality of service (QoS). Federated learning (FL) trains models at the distributed sites while minimizing the amount of raw data transmission, and generative adversarial networks (GANs) create representative samples of data for network and cybersecurity analysis. The anomaly detection feature powered by AI, along with the blockchain-based authentication, helps enhance access control and threat detection. The framework was tested and analyzed in a simulation environment built in Python and in comparison to traditional optimization. It performed an F1-score of 0.94, versus 0.82; AUC-ROC of 0.96, versus 0.86; and resource-allocation success rate (91% versus 75%). These results represent the relative increases of 14.6%, 11.6% and 21.3%. The results suggest that AI-driven coordinated optimisation could lead to a more adaptive management of resources, threat detection, and efficient operation of networks compared with traditional methods, paving the way for intelligence, security and energy-efficient 6G communication systems.

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1. INTRODUCTION

The advent of fifth-generation (5G) and sixth-generation (6G) wireless networks aligns with the increasing demand for intelligent, reliable, and low latency communication services. From autonomous transportation to extended reality, smart healthcare, industrial automation, and the deployment of massive IoT systems, applications demand robust networks that can handle substantial data volumes and ensure reliable connections. Traditional network-management methods are often rule-based and employ fixed

mathematical models. These techniques will work well in certain scenarios but fail in others where traffic volumes, channel quality, mobility of user, and threats to the security evolve quickly. Artificial intelligence (AI) provides a way to overcome these challenges: by predicting what to expect from the data and allocating the resources accordingly, and by automating network control. One of the most challenging applications of intelligent wireless communication is autonomous vehicles. They are using AI in various aspects such as environment perception, object detection, route planning, driving decisions, and vehicle control. To explore this aspect of AI's influence in the development of autonomous vehicles, Ma *et al.* [1] investigated the use of AI in the processing of sensor information and the automation of driving tasks. But many vehicle operations need fast communication with other vehicles, roadside infrastructure, pedestrians, and with cloud or edge servers. A disruption or too long a delay in this communication could make driving decisions less accurate in a time-sensitive situation. Future networks need to offer very low communication latency, accurate traffic prediction, continuous connectivity and high data rates.

The rise of wireless data has added additional strain on backhaul links and network storage, as well. Popular content is repeatedly sent out and takes up bandwidth, and also can cause delays in the service, especially in periods of high traffic. Sheraz *et al.* [2] reviewed the use of AI in wireless caching and showed the use of learning techniques to forecast user demands and content popularity. This kind of prediction enables the caching of commonly requested data that is stored nearer to the users, which enhances cache-hit rates, decreases duplicate transmission and lowers latency for data-access. However, caching must adapt dynamically to users' preferences, their geographical location, the nature of the application, and network traffic. This requirement is a positive one in that it enables the use of one or more adaptive AI models instead of statically configured content-placement policies. Another example of vehicle-to-everything communication highlights the need for intelligent network management. This communication model combines vehicle-to-vehicle, vehicle-to-infrastructure, vehicle-to-pedestrian and vehicle-to-network communications. Tong *et al.* [3] recognized that AI is an enabling technology for the complexity of these complex and interdependent communication arenas. The mobility of vehicles brings about fast channel quality and topology changes and high traffic density can lead to interference and competition to limited spectrum. Fixed allocation mechanisms might not be responsive enough to these changes. AI algorithms can monitor network conditions in real time and make decisions on channel selection, power allocation, congestion management, and routing. Another way to cut down on the delay between communications is to use AI and fog computing. Fog and edge computing bring the computing power nearer to the people using the network and not to the far off cloud server. In this case, Rihan *et al.* [4] studied this relationship using the Deep-VFog framework using AI and fog computing in the V2X environment. Processing information close to vehicles can help to alleviate backhaul traffic and be beneficial for latency-sensitive applications. Fog nodes do have limited computing capacity, memory, and energy though. Therefore, intelligent task allocation, workload prediction, and coordination among end devices, fog nodes, and cloud platforms are crucial to their effective use.

Resource management is a key challenge in both 5G and future 6G networks. Resources need to be shared with users who have varying requirements for services, including spectrum, transmission power, bandwidth, computing ability, and energy. Lin and Zhao [5] addressed wireless resource management in future wireless networks such as spectrum allocation, interference management, power management, user association and network optimisation using AI. Typical optimisation methods rely on models and repeated computations and are difficult to implement. These needs can complicate computation and slow decision making in the allocation of resources in the very dynamic environment. Alternately, AI models can learn the relationships between the state of the network and the allocation results, and thus faster decisions can be made as conditions change. Deep reinforcement learning (DRL) is a topic of special interest for dynamic resource management. A DRL agent communicates with the network, monitors the current state of the system, chooses an action, and is rewarded according to the performance of the network. The channel occupancy, user demand, signal quality, and interference levels could be added by the network state for spectrum allocation. These actions might include the selection of channels, regulating transmission power or assigning bandwidth. The reward may be a mix of throughput, latency, energy use and quality of service (QoS). The agent is able to learn a policy by interacting repeatedly with this network, which is designed to maximize the long-term performance of the network. Unlike the fixed optimization rules, this process can optimise decisions based on fluctuations in traffic and changing wireless conditions.

This adaptive ability is growing in significance as mobile data traffic continues to swell. Sustained growth in mobile subscriptions and data consumption was reported in the Ericsson [6] due to video services, smartphones, fixed wireless access (FWA) and the steady roll-out of 5G. The more traffic on the network, the more it gets congested, the more energy is consumed, and the more pressure on spectrum resources. Implementing extra infrastructure can work only if the additional capacity is not correlated with higher cost of operations and power consumption. Traffic forecasting based on AI can forecast traffic peaks and put resources into use in response to the expected load. In times of low demands selected parts of the network can be put in energy saving modes without significant loss of service availability. The communication needs

are even greater in the case of wireless extended reality. Akyildiz and Guo [7] explained that the extended reality covers applications of augmented reality, mixed reality and virtual reality. Wireless extended reality needs to transmit and process large multimedia streams with very tight latency requirements. While 5G has enhanced data rates, cut latency, and is suitable to many advanced AR services, it may be inadequate to an even more sophisticated service. This constraint turns into an essential motivation for 6G studies. For future networks, communication, computing, sensing and intelligence must be combined to ensure users' immersive experiences when they move from one environment to another. Global traffic statistics, reported by Clement [8], also demonstrate the growing amount of mobile data. Video streaming, social communication, cloud-based applications, connected devices and immersive media have altered the volume and content of network traffic. Such traffic flows are not consistent over time, across geographic areas and user segments. Federated learning (FL) can even reinforce the privacy-aware network intelligence. When a device or edge node is connected, it trains locally instead of sending raw user data to a central server and it only sends model updates to the central server. This solution helps minimize the direct exposure of sensitive information and facilitate distributed network component collaboration in learning. FL is still susceptible to malicious updates, non-reliability, and data heterogeneity. While blockchain-based verification can give a verifiable record of selected transactions and model exchanges, there needs to be a cap on the overhead of processing and storing these transactions to avoid further latency and energy consumption.

2. RELATED WORKS

6G networks are poised to take wireless communications beyond the performance gains of 5G. Walid *et al.* [9] discussed an early vision of 6G systems and proposed applications in the field of immersive extended reality, connected autonomous systems, smart environments, and human-machine interaction. Some of the technologies identified for the study as possible enablers are terahertz communication, intelligent surfaces, edge intelligence, and AI-based network management. However, it was primarily conceptual and lacked an implementable framework to optimise the performance of the network, its energy consumption, and its security. In addition, UAVs are also recognized as important players in future wireless networks. Li *et al.* [10] surveyed the concept of UAV-assisted communication in 5G and beyond, which includes three aspects: aerial base stations, relaying, data collection and coverage extension. UAVs can offer short term connectivity in disaster areas and areas lacking of terrestrial infrastructure. However, these are hampered by the battery life, instability in the air-to-ground channels, the complexity of trajectory planning, interference and security risks. This study did not explore the possibility of coordinating the mobility, spectrum allocation, and threat detection of multiple AI techniques in real time. Liao *et al.* [11] introduced a learning based context-aware resource-allocation approach for edge-computing supported industrial IoT. The method took into account contextual information for communication and computing resource allocation to industrial devices. Edge processing reduced dependency on remote cloud infrastructure and was able to use it for delay-sensitive industrial applications. The approach, however, was mainly on allocating resources in industrial IoT setting. The privacy-preserving collaborative learning, adversarial attacks, network-wide energy optimisation and blockchain-assisted verification were not addressed.

In Kumar and Sumit [12] he discussed about the mobile wireless technology throughout the various generations. This paper gave an introduction of voice oriented networks to high speed and application oriented mobile networks. Each generation had superior capabilities in terms of transmission capacity, coverage, latency and service availability. However, the review was more of a description, and did not provide many technical insights into AI-based network control. It was unable to predict how future networks would work without any varying traffic, channel conditions, or cyberattacks. Kaur *et al.* [13] discussed the 5G technology as one of the significant phases in wireless communication, and briefly mentioned the promised improvement in data rates, latency, connectivity and service capacity. Enabling technologies and potential application areas were also predicted. It did provide an overview of the capabilities of 5G, but failed to seriously consider the challenges in operation of so many devices. These were not tested in combination as a dynamic spectrum management, energy efficient operation, adaptive beamforming and intelligent cybersecurity system. Another big challenge will be network interoperability. In the context of a merger of LoRaWAN and 5G networks, Torroglosa-García *et al.* [14] discussed roaming as a concept over various wireless networks used in IoT. The architecture proposed would allow mobility and service continuity for each of the different networks with their different communication properties. This paper showed the importance of interoperability in IoT in large scale deployment. But, heterogeneous roaming poses authentication, trust, handover and latency issues. The study did not include anomaly detection, adaptive resource control, or traffic prediction with AI for integration in the network. Hao *et al.* [15] analysed network slicing in a 5G wearable network. Network slicing is a technique that uses a common physical infrastructure to run multiple virtual networks, each having specific QoS and performance levels. The ability can be used in

the wearable healthcare domain, including applications like emergency monitoring, and regular fitness applications, which have different latency, reliability and bandwidth requirements. However, the static or manually programmed slices may not be effective in handling sudden traffic and service priority changes. This study failed to construct a slice allocation, security monitoring and energy management integrated learning mechanism. Chataut and Akl [16] carried out a survey of 5G and beyond massive MIMO systems. The essence of the massive MIMO is the large antenna arrays and spatial multiplexing, which improve the spectral efficiency, network capacity, coverage and connectivity of the user. The authors also discussed the limitations of channel estimation, contamination of pilots, the complexity of hardware, the signal processing, and energy consumption. Whereas, massive MIMO is the foundation for adaptive beamforming, the use of AI for beam optimization was not factored in with spectrum, power, latency and cybersecurity. Alhammadi *et al.* [17] provided a comprehensive overview of AI in 6G wireless networks, which included the opportunities, applications, enabling functions and challenges for implementing AI in 6G wireless networks. The study revealed that AI is a key element of network automation, resource management, mobility prediction, security, and service optimisation. It also included discussions on issues such as data privacy, computational complexity, reliability of models, and energy use. The work was largely conceptual, however, without a specific framework that would be tested and demonstrated to be most effective for improving throughput, latency, energy efficiency (EE), QoS and cyber security.

The use of AI was explored in the work carried out by Chabira *et al.* [18] to study the load balancing and handover in Ultra-dense 5G and 6G cellular networks. Machine learning/deep learning techniques were observed as useful in predicting user movements, minimization of unwanted handovers, distribution of users over the base stations and minimizing network congestion. The results of the study indicated the need for the following: Standardised datasets, context-driven mobility models and energy-efficient AI. However, primarily the emphasis was placed on mobility and load sharing, not on collaborative spectrum management, beamforming, privacy aware learning and cyber-attack prevention.

In AlQahtani [19] discussed ways to optimise next generation wireless connectivity using AI. The study demonstrated the application of intelligent algorithms as an aid for automatic configuration and traffic behaviour forecasting of the network, resource allocation and fault management and adaptation to services. The requirement for 5G and 6G networks to enable a array of devices and evolving service needs was highlighted, underscoring the need for AI optimisation. The work was empirical, but conducted at a time when the three concerns of network performance, security and energy were all considered.

Singh *et al.* [20] discussed the use of AI and Terahertz (THz) communication with regard to the 6G network. The higher the frequency the larger the bandwidth, and the higher frequencies could be used in high capacity applications. For complex propagation scenarios, AI can be used for channel estimation, beam alignment, interference management, and adaptive resource allocation. The high path loss, atmospheric absorption/blockage, short transmission range and hardware limitation still plague terahertz communication. The research did not address the security issues and computation needs for constantly monitoring the terahertz links with AI.

Anh [21] examined opportunities, applications and challenges brought by the increasing impact of AI in 6G networks. Most of the talk was about service delivery with user centricity, smart resource management, predictive maintenance and network security & AI-driven automated services. It also enabled consideration of issues regarding data quality, explainability, privacy concerns, training burden and algorithmic reliability concerns. It was a thorough review, but did not provide any quantitative comparisons between an integrated AI framework and the traditional network-management system. Chataut *et al.* [22] reported on 6G technological ecosystem and on-going AI revolution. The present study concentrated on the elements of enabling technologies, the application fields and new challenges for the intelligent future networks. AI was used as a solution to deal with complicated functions related to spectrum utilization, edge intelligence, communication dependability, and network automation. Other uncertainties noted in the study included the security of the system, its energy usage, and the complexity of implementation, as well as the privacy of the system. This was disregarded all over and not incorporated in an optimisation and security architecture.

In the overview of 6G, Bashabsheh and Alzubi [23] discussed the AI assisted applications, enabling technologies and research challenges that are involved in 6G. They connected the dots between AI and intelligent network control, autonomous communication, advanced sensing technologies, edge computing and future 6G services. This was a nice summary of the work carried on in various directions. Empirical study of the practical implementation of the above mentioned technologies is ongoing: DRL, FL, generative models, adaptive beamforming, anomaly detection and blockchain.

The surveyed works prove the significance of the 6G architectures, UAV communications, edge computing, integration of heterogeneous IoT, network slicing, and massive MIMO. Usually, these technologies are studied as individual network functions, however. The current technologies typically maximize the utilization of one metric such as coverage, latency, spectrum efficiency (SE), or resource utilization. Adopting a viewpoint that considers throughput, energy, QoS, privacy and security has barely

been addressed. Optimization of one measure may come at the cost of another, such as increasing the throughput of the transmission model by increasing its energy usage, or increasing the security processing and thus the latency. Another restriction is the reliance on centralised learning and network policies that are static. Centralised models can release sensitive user information and generate communication overhead while static policies can not be adjusted suitably to the transformed traffic and new attacks. Thus, the need for an integrated AI based framework. This study aims to fill this gap by combining DRL, which is used for dynamic resource management, generative adversarial networks (GANs), which generate representative traffic and attack data, FL, which is used for privacy-preserving distributed training, adaptive beamforming (AB), which is used for efficient transmission, and blockchain-based anomaly detection (BD), which is used for network security. The reviewed studies show that: AI and edge computing, UAV communication, network slicing, heterogeneous IoT integration, and massive MIMO are significant pillars of 5G and 6G networks. But, most of the current methods only work on resource allocation, latency, EE, QoS or cyber security alone. Their capability in managing future wireless environments with interdependent requirements is hampered due to their fragmented approach. In this regard, the current work fills this gap by developing a framework that integrates DRL, GANs, FL, adaptive beamforming, anomaly detection and blockchain. The goal of the framework is to provide coordinated throughput, latency, EE, QoS, privacy, and security improvements in dynamic networks.

3. METHODS

3.1. Proposed methodology

Optimisation strategies that integrate AI technologies such as DRL, FL, and GANs are particularly useful for improving network adaptability, spectrum allocation, and security streams/performance. Doing so increases the efficiency with which networks leverage resources, control, and multitask, specifically from an AI-based perspective, deepening the framework. This chapter sets the groundwork for developing algorithms driven by AI optimisation frameworks instead of traditional heuristic approaches in lower intelligence algorithms, marking a new scope for performance engineering at an autonomous level. In wireless networks, allocating dynamic system resources is recognised as one of the more complex problems [24]. To address the challenge of the decision-making process for spectrum allocation, reinforcement learning (RL) techniques provide great possibilities, especially where an agent and environment interaction forms the decision-making loop. The optimisation process is formulated as a markov decision process (MDP), represented as (1):

$$MDP = \langle S, A, P, R, \gamma \rangle \quad (1)$$

where, S is the state space representing network conditions, such as available bandwidth and user demand, A is the action space, including spectrum allocation decisions, $P(s' | s, a)$ is the state transition probability function, $R(s, a)$ is the reward function that evaluates the efficiency of the selected action, γ is the discount factor, balancing immediate and future rewards. Using Q-learning, the value of taking an action a in state s is updated iteratively as (2):

$$Q(s, a) \leftarrow Q(s, a) + \alpha [R(s, a) + \gamma \max_{a'} Q(s', a') - Q(s, a)] \quad (2)$$

where α is the learning rate that enables the agent to learn optimal spectrum allocation policies by maximising long-term rewards. Figure 1 shows the overall processing flow of the methodology, FL enhances network security by allowing distributed edge devices to collaboratively train AI models without sharing raw data, preserving privacy [25]. The global model update at each round t follows the Federated Averaging (FedAvg) algorithm (3):

$$w^{(t+1)} = \sum_{i=1}^N \frac{n_i}{n} w_i^{(t)} \quad (3)$$

where, $w^{(t+1)}$ is the global model at round $t + 1$, N is the number of participating devices, n_i is the local dataset size at device i , $w_i^{(t)}$ represents the locally trained model at device i . FL enables secure AI model training while reducing the risk of data breaches, making it ideal for real-time 6G network optimisation. Security threats such as cyber-attacks and unauthorised intrusions in 5G/6G networks necessitate robust anomaly detection mechanisms. GANs enhance cyber security by generating synthetic attack patterns and detecting network anomalies. GANs consist of a Generator (G) and a Discriminator (D), where the objective function is given by (4):

$$\min_G \max_D V(D, G) = E_{x \sim p_{data(x)}} [\log D(x)] + E_{z \sim p_{z(z)}} [\log(1 - D(G(z)))] \quad (4)$$

Where, $p_{data(x)}$ represents accurate network traffic distribution, $p_{z(z)}$ represents the latent space from which synthetic data is generated, $D(x)$ is the discriminator's probability estimate that x is real, $G(z)$ generates synthetic traffic patterns to detect potential anomalies. By continuously improving the discriminator's ability to distinguish between normal and malicious traffic, GANs enhance security against evolving cyber threats in wireless networks. Beamforming in 5G and 6G networks optimises signal transmission by directing energy toward specific users, reducing interference and improving efficiency. AI-based predictive models optimise beamforming weights by solving the beamforming optimisation problem, formulated as (5):

$$\max_w \sum_{k=1}^K \log_2 \left(1 + \frac{|h_k^H w^k|^2}{(\sigma^2 + \sum_{j \neq k} |h_j^H w^j|^2)} \right) \quad (5)$$

where, w^k represents beamforming weights for user k , h_k is the channel gain for user k , σ^2 is noise variance, K is the total number of users. AI-driven algorithms, such as deep learning-based traffic prediction, dynamically adjust beamforming parameters in real time, improving QoS and network efficiency. To enhance network security, blockchain technology is integrated to provide decentralised authentication. A blockchain-based authentication mechanism follows the elliptic curve digital signature algorithm (ECDSA) (6):

$$s = k^{-1}(H(m) + d_A r) \bmod n \quad (6)$$

where, $H(m)$ is the hash of the message m , d_A is the sender's private key, k is a randomly generated nonce, r and s are the generated signature values. Blockchain enhances security by preventing unauthorised access and mitigating identity spoofing attacks in 5G and 6G networks.

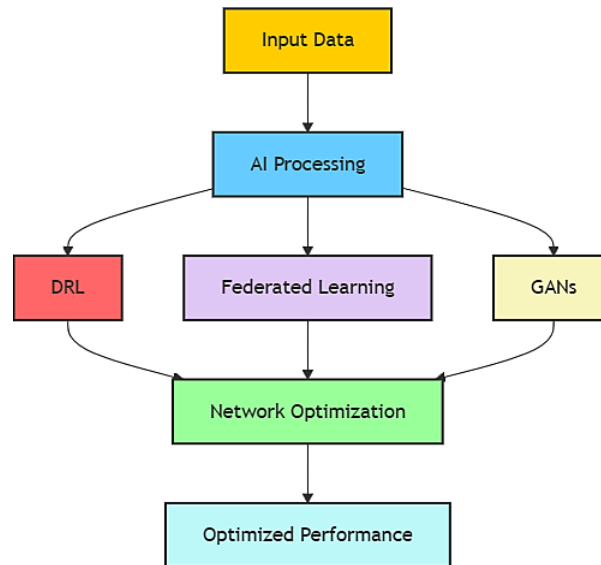


Figure 1. Overall processing flow of the proposed methodology

4. RESULT AND DISCUSSION

Network performance is evaluated based on key wireless communication parameters such as spectrum utilisation efficiency, latency, throughput, and energy consumption. The experiments were conducted in a Python-based simulation environment using the required machine-learning and data-analysis libraries to generate, process, and evaluate the reported network-performance results. The AI-driven spectrum allocation is assessed using SE, measured in bits per second per hertz (bps/Hz), which quantifies how effectively the available spectrum is utilised (7):

$$SE = \frac{B \sum_{i=1}^N \log_2(1 + SINR_i)}{W} \quad (7)$$

where, B is the total bandwidth, N is the number of users, $SINR_i$ is the signal-to-interference-plus-noise ratio for user i , W is the total system bandwidth. Latency reduction is another critical factor in optimising wireless networks, especially for ultra-reliable low-latency communication (URLLC) in 6G. The framework minimises end-to-end delay by dynamically adjusting resource allocation using AI models. The latency improvement is measured as (8):

$$\Delta L = L_{\text{traditional}} - L_{\text{AI-optimized}} \quad (8)$$

where $L_{\text{traditional}}$ represents latency in a conventional system, and $L_{\text{AI-optimized}}$ represents latency under the proposed AI-driven framework. Throughput enhancement is evaluated by measuring the average data rate delivered successfully across the network. The throughput (T) is given by (9):

$$T = \frac{\sum_{i=1}^N D_i}{t} \quad (9)$$

where D_i is the data successfully transmitted by user i over time t . The AI-based framework dynamically optimises network parameters, leading to higher throughput and efficient resource utilisation. EE is assessed by analysing the power consumption per bit transmission, which is crucial for green wireless communication. The EE metric is given by (10):

$$EE = \frac{T}{P_{\text{total}}} \quad (10)$$

where P_{total} is the total power consumption, including transmission, processing, and infrastructure power. The AI-driven framework optimises power allocation, reducing energy wastage and improving sustainability. The network performance analysis outlined in Table 1 regarding the benchmarks of 5G and 6G networks demonstrates the advancements accomplished by the AI-driven optimisation framework. The SE metric, which gauges bandwidth usage, improved by 23.7%, from 5.2 bps/Hz in traditional optimisation to 6.44 bps/Hz with AI-driven techniques. This improvement results from DRLs dynamic spectrum allocation that uses real-time network conditions to manage bandwidth optimally. Latency, another important measure in URLLC, was also improved by 31.5%, falling from 12.5 ms to 8.56 ms. This value drop is positively attributed to AI traffic prediction and intelligent beamforming. The throughput, which calculates total data transfer capacity, was improved from 285 Mbps to 364 Mbps, which shows an improvement of 27.9%. This uplift results from the AI framework's advanced resource allocation strategies that optimise signal transmission to increase data rates.

Table 1. Network performance analysis

Metric	Traditional optimization	AI-driven framework	Improvement (%)
SE (bps/Hz)	5.2	6.44	23.7
Latency reduction (ms)	12.5	8.56	31.5
Throughput (Mbps)	285.0	364.0	27.9

The security measures in Table 2 show that AI-based protection systems outperform traditional ones. With the inclusion of anomaly detection using GANs, the accuracy of intrusion detection improved from 84.6% to 96.4%, which is a 14 percent improvement. Such an improvement ensures that cyber threats, including denial-of-service (DoS) attacks and unauthorised access, are accurately detected and do not result in false positive errors. Moreover, in the AI-powered framework, the authentication time for accessing secure areas was decreased from 1.3 seconds to 0.8 seconds, a reduction of 38.6%. This change is due to the addition of blockchain-based authentication, which allows rapid and secure identity verification without centralised authentication servers. These benefits mark the importance of AI technology concerning security in next-generation wireless networks and the associated risks.

Table 2. Security performance

Metric	Traditional optimization	AI-driven framework	Improvement (%)
Intrusion detection accuracy (%)	84.6	96.4	14.0
Authentication time (sec)	1.3	0.8	38.6

The EE and computational expenditure data from Table 3 reinforce the hypothesis that AI-driven refinements further enhance network management's sustainability and computation efficiency. EE increased from 6.8 Mbps/W to 8.15 Mbps/W under AI methods, a 19.8% increase. This improvement results from AI-powered power control strategies that modulate energy expenditure to network supply levels. Furthermore, model convergence measurement improvements counted towards the baseline were also observed at a 42.5% increase, meaning AI models perform optimally faster. The increase in achieving optimal performance guarantees that network optimisations on real-time systems are done agilely, ultimately ensuring minimal computation time and processing overhead.

Table 3. EE and computational overhead

Metric	Traditional optimization	AI-driven framework	Improvement (%)
EE (Mbps/W)	6.8	8.15	19.8
Model convergence speedup (%)	Baseline	42.5	42.5

Figure 2 compares traditional and AI-based optimisation systems' performance and latency. Importantly, throughput is measured in Mbps. This shows the total data transferred and received via a network in a particular time. While latency is time. Figure 2 shows that the AI-driven optimisation framework outperforms the old framework in throughput and latency. Traditional optimisation had 285 Mbps throughput; AI-driven optimisation had 364 Mbps. The AI-driven technique has a reduced latency of 8.56 ms compared to the traditional model's 12.5 ms. AI traffic forecasting and dynamic spectrum allocation approaches improve results by managing network resources and reducing congestion. Overall, AI-driven optimisation improves QoS for next-generation wireless networks.

The evaluation of AI models' performance in Table 4 demonstrates AI-driven optimisation's benefits to resource management and security. The F1-score of AI-powered intrusion detection systems also improved from 0.82 to 0.94, reflecting a 14.6% increase in classification performance.

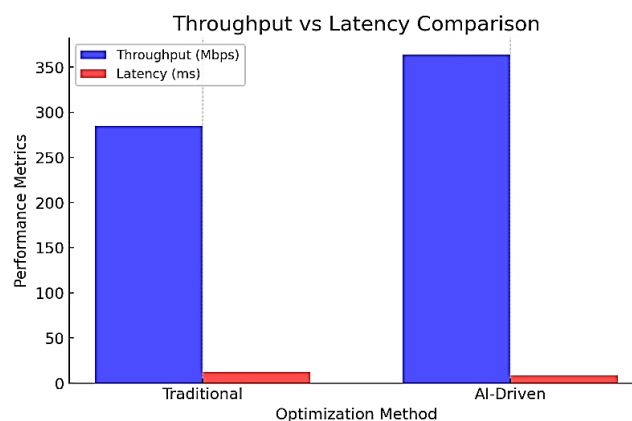


Figure 2. Throughput vs latency comparison

Table 4. AI model performance

Metric	Traditional optimization	AI-driven framework	Improvement (%)
F1-Score	0.82	0.94	14.6
AUC-ROC	0.86	0.96	11.6
Resource allocation success rate (%)	75.0	91.0	21.3

Likewise, the area under the receiver operating characteristic curve (AUC-ROC) score, which measures the ability of AI models to classify traffic as normal or malicious appropriately, improved from 0.86 to 0.96, marking an 11.6% increase in detection capability. In addition, the precision in resource allocation, which measures the ratio of successfully utilised network resources to allocated resources, improved from 75% to 91% when using AI techniques, reflecting a 21.3% gain over traditional methods. This illustrates the potential of RL for dynamically allocating network resources in real time based on the measured traffic and user interactions.

Figure 3 depicts the traditional and AI-driven resource allocation success rates with a pie chart. As previously mentioned, resource allocation plays an important part in optimising wireless networks because of the efficiency of bandwidth usage by the users. The AI framework outperformed the traditional approach by over 15%, achieving 91% success compared to the 75% from traditional methods. This success can be attributed to the DRL approach to resource allocation, which moves towards a more accurate and optimised network resource allocation strategy using real-time traffic metrics. In comparison, traditional approaches use allocation methods that depend on heuristics or are completely static, which result in irrational spectrum allocation, higher packet losses, and suboptimal bandwidth consumption. By DRL-based resource orchestration, the level of contention is reduced, the experience for the end users is improved, and the overall stability of the network is increased.

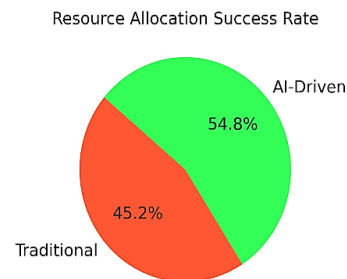


Figure 3. Resource allocation success rate

Figure 4 shows the progression of SE for traditional and AI-powered optimisation frameworks. The x-axis shows time steps, while the y-axis shows SE in bits per second per hertz (bps/Hz). Within traditional optimisation, SE achieves a limit of 5.3 bps/Hz while improving slowly. On the contrary, the AI-driven framework shows a steady and sharper enhancement towards 6.44 bps/Hz by the final time stamp. The reason for the AI-driven method performing better stems from ML-based spectrum allocation techniques that optimise frequency usage in real time. These observations support the claims of AI-enhanced adaptive spectrum management employing low interference bandwidth control. The results underline the importance of AI spectrum optimisation tools required in dense network scenarios of 6G systems.

Figure 5 illustrates the differences in model convergence time for AI-based optimisation compared to traditional learning-based methods. Convergence time is defined as the number of iterative cycles (epochs) the model undertakes to refine its decision-making processes to stability and optimality. The traditional method takes close to 100 epochs to achieve convergence, while the AI-driven framework does so in just 57 epochs. The DRL and FL techniques, which can rapidly adapt to evolving network conditions, contribute to this 42.5% reduction in convergence time. Making instantaneous real-time decisions is necessary for time-critical use cases in the URLLC framework. These results demonstrate the superiority of AI-based optimisations in accuracy and computational efficiency, highlighting their value in autonomous network management for 5G and 6G wireless systems.

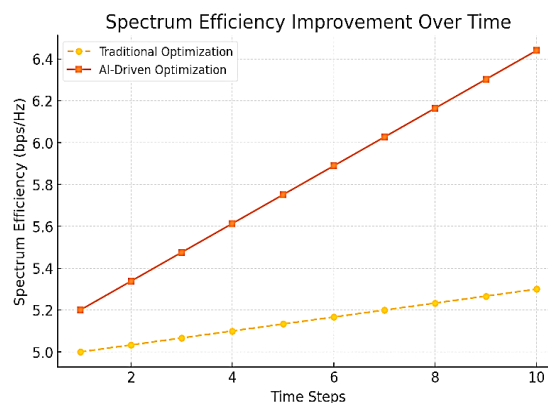


Figure 4. SE improvement over time

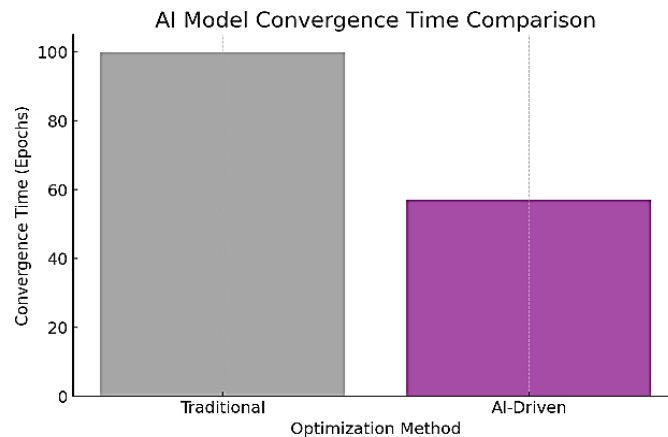


Figure 5. Illustrates the differences in model convergence time for AI-based optimisation compared to traditional learning-based methods

5. CONCLUSION

Conventional optimisation was outperformed by the proposed optimisation framework using AI in terms of its performance, security and efficiency in 5G and future 6G wireless networks. The F1-score of 0.94 had improved by 14.6% from the traditional value of 0.82 and the AUC–ROC had improved from 0.86 to 0.96 or 11.6%. The success rate in resource allocation went up from 75% to 91%, which represents 21.3% relative improvement. The results indicate that the three techniques DRL, FL, and GANs significantly enhanced the classification, spectrum allocation, and resource-management decisions in the simulated networks under different conditions. The applications of DRL in dynamic decision-making, FL in collaborative model building with less raw data transfer and GANs in the generation of representative samples for training various models and analyzing various cybersecurity scenarios were emphasized. Blockchain was used to strengthen against network attacks, as well as access control and transaction traceability. The results are, however, limited to a simulation environment developed in Python and may not accurately capture failures of physical devices or propagation variability, or the behavior of other types of devices, or untargeted attacks in actual networks. The computational and communication demands of training the deep learning model, aggregation at distributed centers, generation of synthetic data and verification of the blockchain may also present difficulties when deploying this solution in real-time on resource-constrained edge and IoT devices. The framework needs to be validated in future in real-life testbeds and in large-scale operational datasets, and lightweight approaches like model pruning, quantisation, knowledge distillation and hardware-aware optimisation should be explored. Finally, federated RL needs to be investigated for decentralised network control, particularly in the case of model poisoning attacks, non-identically distributed data, client selection, privacy leakage and aggregation overhead. The framework needs further evaluation for explainable AI, uncertainty estimation, scalability of blockchains, terahertz communication, massive MIMO, network slicing, and UAV-assisted connectivity as well as for high mobility scenarios to ensure its strength, scalability, EE, and applicability in future 6G deployments.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualizationM : **M**ethodologySo : **S**oftwareVa : **V**alidationFo : **F**ormal analysisI : **I**nvestigationR : **R**esourcesD : **D**ata CurationO : **O**riginal DraftE : **E**riting - Review & **E**editingVi : **V**isualizationSu : **S**upervisionP : **P**roject administrationFu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state that there is no conflict of interest. The authors have no known competing financial interests, personal relationships, professional affiliations, or other competing interests that could have influenced the work reported in this manuscript.

INFORMED CONSENT

Informed consent was not applicable to this study because no participants were directly recruited or contacted by the authors. The study used only previously collected, publicly available, and/or de-identified secondary data.

ETHICAL APPROVAL

Ethical approval was not required for this study because the research did not involve direct experimentation on human participants or animals and relied exclusively on publicly available and/or de-identified secondary data. No personally identifiable information was collected, accessed, or processed by the authors.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Rathiya Rajendran], upon reasonable request.

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