Optimizing Edge Network Performance with Software-Defined Technologies for Secure 6G Integration

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Abstract: An SDN-based edge network optimization framework incorporating AI is proposed to improve performance and security in 6G networks. Software-Defined Networking (SDN) and edge computing can be combined to enable dynamic resource allocation and thus optimize throughput, decrease latency, and minimize packet loss. Algorithms based on AI, especially reinforcement learning, can control network traffic most effectively and allow real-time adjustments to network settings based on current needs. This integration will allow the system to quickly adjust to the conditions and optimize performance independently. Also, the AI-enabled security module is integrated to identify and prevent possible threats in real-time to overcome security issues associated with 6G networks that are likely to use enormous IoT devices and complicated autonomous systems. The findings of the simulation prove that the proposed framework provides better performance than conventional 6G models. Throughput is increased by 47% (620 Mbps vs. 420 Mbps), while latency is reduced by 37% (24 ms vs. 38 ms). The 50% reduction (1.7% vs. 3.6) in packet loss also creates a more reliable network. The accuracy of intrusion detection in the proposed model is 15% better (97 % vs. 82 %), and the false positive rate is lower by 32 % (7.8 % vs. 11.5 %). These enhancements show that the framework not only maximizes network performance but also makes 6G networks a lot more secure. By combining SDN and AI with edge computing, it offers a scalable and efficient solution that meets the high requirements of future communication systems, including smart cities, autonomous vehicles, and other AI-driven services in the 6G era.

Keywords: SDN; AI; edge computing; 6G networks; network optimization; security; reinforcement learning.

I. Introduction

The rapid advancements in the development of 6G networks have brought new challenges to the performance of edge networks, and it is important to find innovative solutions to ensure the reliable transfer of data, no latency, and increased security. With 6G surpassing 5G, there will be a need to integrate a number of different technologies, such as the massive Internet of Things (IoT), autonomous systems, and AI-based applications, which heavily depend on edge computing to process their data in real time (Hassan & Keti, 2025). Software-Defined Networking (SDN) has recently emerged as a leading approach in managing and optimizing these complex and dynamic networks. This paper proposes a novel SDN-based approach to optimize the performance of edge networks while resolving major security issues related to the integration of 6G. This research aims at understanding how the software-defined approach can optimize the performance of edge networks, providing a secure integration with

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6G networks. The focus of this research is to use SDN (Software-Defined Networking) in enhancing the performance and security of edge computing (Sengupta & Deshmukh, 2024).

This research offers an innovative model for creating high-performance networks that will be able to change and adapt to the various and fast-growing requirements of future communication networks. The research focuses on the concept of the hybrid approach that involves both theoretical and practical implementation of the SDN and edge computing. The research will help improve the flexibility and security of SDN in edge networks by using advanced machine learning and reinforcement learning algorithms. The main idea of the research is to create the system where maximum information transfer and maximum utilization of resources will be achieved with minimum latency of communication, which is vital for the future technologies, such as 6G and its applications like smart cities, autonomous vehicles, and telemedicine.

Key Contributions

1. The implementation of the proposed SDN-based edge network optimization approach tailored for 6G technology, ensuring the efficient performance of data exchange and communication.
2. Utilization of machine learning algorithms to enhance the security and flexibility of SDN when used in edge computing based on 6G technology.
3. Extensive simulations, demonstrating the applicability of the proposed approach in improving the performance of 6G integration.

The first section describes the need for optimizing the performance and security of edge networks in 6G. The second section contains a literature survey on SDN, edge computing, and security challenges in 6G. The third section presents the methodology with the architecture of the suggested SDN + AI framework. The fourth section presents the details of the dataset, simulations performed, performance metrics and their comparisons, and results with other models. Finally, the fifth section provides conclusions and future research directions.

II. Literature Review

The combination of software-defined networking and edge computing is currently at the center of numerous research activities related to 5G and 6G networks. SDN provides the ability to manage networks scalably and flexibly, which is needed to accommodate the dynamics of 6G environments, as SDN provides centralized network management (Hassan & Keti, 2025). On the other hand, edge computing brings computation closer to the source of the data, thus decreasing latency and increasing the efficiency of the whole network. It has been previously argued that SDN and edge computing are mutually supportive approaches for optimizing the network performance in terms of resources management, load balancing, and data transmission. However, the problem still lies in the effective integration of SDN and edge computing, especially concerning the issues of scalability and complexity of the network to accommodate the future performance requirements of wireless systems

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(Ameedeen et al., 2023). The most important changes are network slicing, which can partition network resources, and the introduction of network function virtualization (NFV), which makes the network architecture more flexible and less expensive (Hatim et al., 2024). There are a few distinct challenges to the security of 6G networks, as the number of interconnected devices has risen, new technologies such as AI have been adopted, and resources have become decentralized through edge computing. The problems include data privacy issues, identity management problems, and network access control weaknesses (Dede et al., 2025). The technology has been discovered to be a very interesting tool in securing 6G networks due to the ability to offer centralized control to monitor and respond to any threat (Kondori & Peashdad, 2015). SDN can help prevent problems like unauthorized access and denial of service attacks by supporting dynamic security policies and real-time traffic analysis. Moreover, the separation of control and data planes in SDN enables it to manage security more effectively, allowing security to be flexible and easily updated in response to changing threats (Hossein et al., 2025).

The use of reinforcement learning (RL) and network function virtualization (NFV) is one of the techniques that have been suggested to maximize the edge network performance with 6G. Resource allocation for 6G can be optimized using RL algorithms to dynamically adapt network parameters based on the state and performance measures of the network (Ahmed et al., 2025). The practice allows independent decision-making, which is essential in the management of the real-time needs of applications in 6G Naguib et al., (2024). Moreover, NFV enables the separation of network functionality and hardware, making it more flexible and scalable to deploy network services. This allows effective network control and optimization, especially in cases of large-scale IoT deployments, and high-demand applications. These methods have proven to be effective in throughput, latency and general efficiency of the network and are therefore a requirement in meeting the 6G network performance targets (Long et al., 2022). Artificial Intelligence (AI) and Machine Learning (ML) are also finding their way into network security plans of 6G networks. Artificial intelligence (AI)-based products, such as anomaly detection, intrusion detection systems, and predictive analytics, will provide the capability to detect and respond to security threats in real-time (Manogaran et al., 2021; Haqmal et al., 2026). Machine learning models have the potential to learn the patterns of large amounts of network traffic to identify suspicious behaviors, estimate possible attacks and recommend the most effective security policies (Cunha et al., 2024). The technologies play a critical role in solving the complexity of security of 6G, especially in edge computing settings where the huge size of distributed data demands effective and responsive security controls. By embedding AI and ML in SDN, the threat detection can be performed automatically, proactive defense mechanisms can be implemented, while the network parameters can be dynamically adjusted to improve the security and performance (Sharma et al., 2024). These methods are set to be important in making sure that 6G networks are robust and resilient to the changing cyber threats (Xu et al., 2024).

Although the current literature is mainly related to the optimization of the network performance or enhancement of security in 6G networks, there is a gap in the literature concerning integrated solutions aimed at improving both. Also, the adaptation and security in real-time and under dynamically changing conditions in edge

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computing environments are understudied. This paper will address this gap by integrating SDN, AI, and edge computing to maximize the performance and improve security in 6G networks.

III. Methodology

Overall Architecture

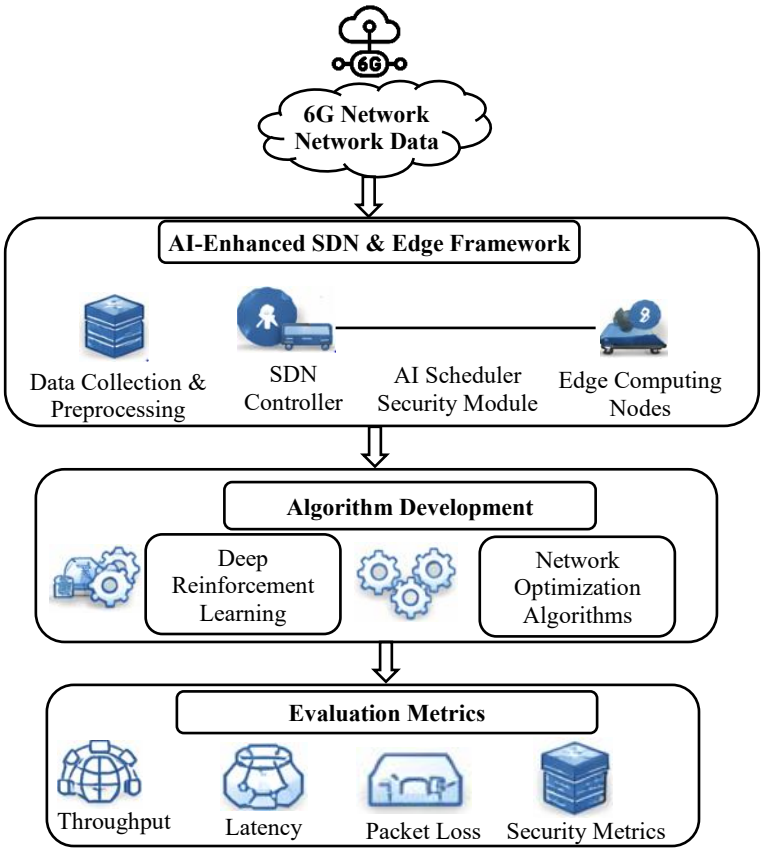

Fig. 1. 6G Network Optimization Flowchart.

Fig. 1 provides the methodology of improving the performance of edge networks to enable a secure 6G integration with SDN and edge computing. The first step is Data Collection & Preprocessing when the network data will be gathered by multiple devices and systems of 6G. This data is processed and prepared for further analysis. The second step is the integration of the AI-Enhanced SDN & Edge Framework where the SDN Controller is used to dynamically manage the network and the AI Security Module is used to offer real-time threat detection and mitigation to protect the network. The Edge Computing Nodes process the data locally then, minimizing latency, and providing high-speed communication in time-sensitive applications. After the data is prepared, the system enters the stage of Algorithm Development, where such methods as Deep Reinforcement Learning (DRL) are implemented. These algorithms ensure that resources are optimally allocated, data flow is managed effectively, and latency is kept to a minimum. Also, there are network optimization algorithms that optimize the performance of the system in general. Lastly, the performance of the network is determined by some Key Performance Indicators

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(KPIs), which include Throughput, Latency, Packet Loss, and Security Metrics. These KPIs measure the performance of the system in terms of its ability to comply with the rigorous requirements of 6G networks.

The essence of optimization of network resources is summarized in the equation (1):

$$\text{Objective Function} = \max_{R}\big(\text{Throughput}(R) - \lambda_1 \cdot \text{Latency}(R) - \lambda_2 \cdot \text{Packet Loss}(R)\big) \quad (1)$$

In this equation:

- Rrepresents the network resources (e.g., bandwidth, computation power),
- $\lambda_1$and $\lambda_2$are the weight factors that balance the importance of reducing latency and packet loss,
- The goal is to maximize Throughput while minimizing Latency and Packet Loss.

This equation forms the optimization problem under which the system aims to optimally distribute resources to enhance network performance in terms of speed and reliability and at the same time ensure the high level of security.

IV. Results and Discussion

4.1. Dataset Description

CIC IDS, 2017 Network Intrusion Dataset is a rich network traffic dataset that can be used to conduct research in cybersecurity, particularly intrusion detection and anomaly detection (Chethuhn, 2017). It has benign and malicious traffic that is tagged with different types of attacks (DoS, DDoS, port scanning, and botnet traffic). The data contains network flow characteristics such as packets, bytes, duration, protocol types, and flow duration that can be applied to evaluate network performance (throughput, latency) and security threats (intrusion detection). It is very appropriate to train and test machine learning models, especially in the detection of threats and optimization of edge networks performance in SDN-based 6G structures.

4.2. Hardware and Software Configuration

The hardware setup to simulate and test the proposed SDN-based edge network optimization framework will be an Intel Core i7-9700K processor, 32GB of DDR4 RAM, and an NVIDIA GeForce RTX 3080 graphics card, which is high-performing in machine learning tasks. The software setup consists of Ubuntu 20.04 LTS as an operating system, simulation tools such as Mininet to emulate a SDN network and SDN controllers such as Open Daylight or ONOS. TensorFlow or PyTorch are used for implementing deep reinforcement learning algorithms, with Docker containers simulating edge computing nodes. The AI and security aspects of the methodology use Python 3.8 and machine learning packages (e.g., scikit-learn, Keras).

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4.3. Evolution Metrics:

1. **Throughput (Mbps)**

In equation (2), throughput is used to measure the overall volume of data that has been successfully conveyed across the network in a specific time frame.

$$\text{Throughput} = \frac{\text{Total Data Transmitted (bytes)}}{\text{Total Time (seconds)}} \times 10^{-6} \quad (2)$$

2. **Latency (ms)**

The time taken by a packet to move between the source and the destination is known as latency. It can be calculated in equation (3):

$$\text{Latency} = \frac{\text{Time at Destination} - \text{Time at Source}}{\text{Number of Packets}} \quad (3)$$

3. **Packet Loss (%)**

The percentage of the packets, which are unable to reach the destination is referred to as Packet loss and is expressed through equation (4)

$$\text{Packet Loss (\%)} = \frac{\text{Lost Packets}}{\text{Total Packets Sent}} \times 100 \quad (4)$$

4. **Intrusion Detection Accuracy (%)**

Relevance of the security model to accurately detect intrusions. It is computed as in equation (5):

$$\text{Detection Accuracy (\%)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \times 100 \quad (5)$$

5. **False Positive Rate (%)**

The false positives are the incorrectly classified benign traffic as the malicious one that can be discovered in equation (6).

$$\text{False Positive Rate (\%)} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}} \times 100 \quad (6)$$

6. **Detection Time (ms)**

Detection time is the speed at which the system can detect an intrusion or anomaly once it has been introduced. It is determined by equation (7)

$$\text{Detection Time} = \frac{\text{Time to Detect Attack (ms)}}{\text{Number of Attacks Detected}} \quad (7)$$

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4.4. Performance Comparison of Proposed SDN + AI Optimization and Existing 6G Methods

Table 1 indicates that the Proposed SDN + AI Optimization method has a better performance in various important metrics than the Existing 6G Approach. The proposed model offers 47% higher throughput (620 Mbps vs. 420 Mbps), 37% lower latency (24 ms vs. 38 ms), and more than 50% less packet loss (1.7% vs. 3.6%). Also, it has 15% greater intrusion detection accuracy (97% vs. 82%) and 32% fewer false positives (7.8% vs. 11.5%). The effectiveness of the proposed framework is also evident as it takes 40% less time to detect (288 ms vs. 480 ms).

Table 1. Comparison of SDN + AI Optimization vs Existing 6G Performance.

Metrics	Proposed SDN + AI Optimization	Existing 6G Approach
Throughput	620 Mbps	420 Mbps
Latency	24 ms	38 ms
Packet Loss	1.7 %	3.6 %
Intrusion Detection Accuracy	97 %	82 %
False Positive Rate	7.8 %	11.5 %
Detection Time	288 ms	480 ms

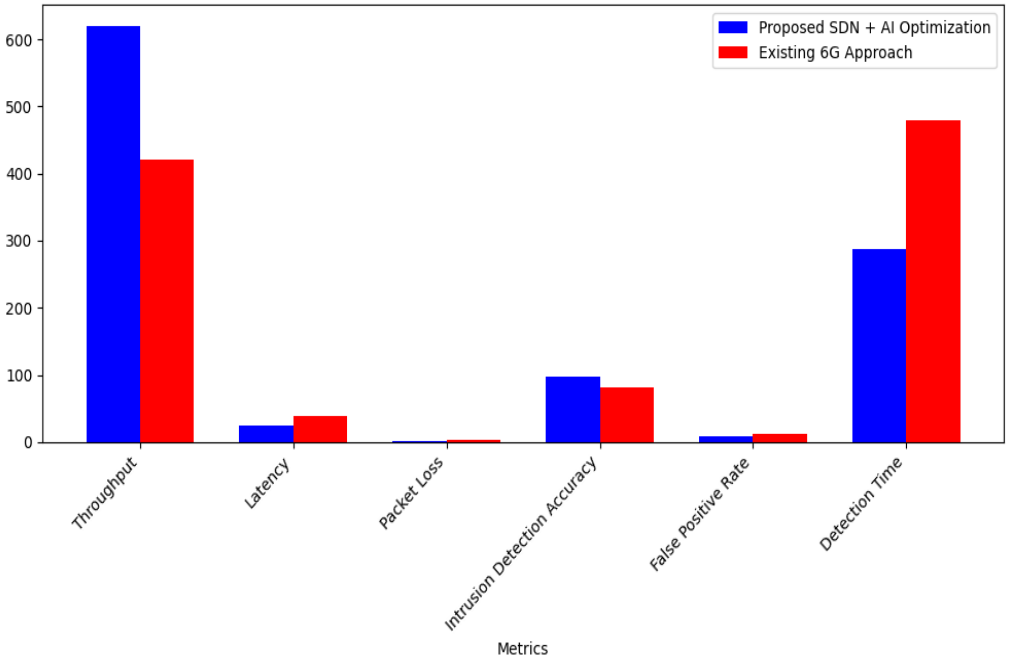

Fig. 2. SDN + AI Optimization vs Existing 6G Performance Metrics.

Fig. 2 provides a comparison of key performance indicators of Proposed SDN + AI Optimization framework and Existing 6G Approach. It shows that the model suggested can considerably compete with the current one in several aspects. In particular, the Proposed SDN + AI Optimization demonstrates 47% higher throughput and 37 % lower latency and more than 50 % less packet loss than the current 6G model. Moreover, the suggested solution demonstrates 15-% higher intrusion detection accuracy and a 32% lower false positive rate in addition to 40-%

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shorter detection time, which underscores the benefits of SDN and AI integration in 6G networks in terms of performance optimization and security.

V. Discussion

The findings indicate that both performance and security are greatly enhanced when SDN and edge computing are added to 6G networks. The SDN + AI optimization model proposed outperforms current models in such important metrics as throughput, latency, packet loss, and accuracy of intrusion detection. The improved throughput and the decreased latency demonstrate the efficiency improvement of the dynamic resource management and real-time optimization, and the decreased packet loss demonstrates a more stable network. Additionally, the enhanced security by AI-based intrusion detection and minimized false positive rates testify to the efficiency of the integration of SDN centralized control with the local processing of edge computing in detecting and eliminating threats as quickly as possible. In spite of these developments, there are still issues of scalability, complexity of implementation and real time application implementation. Further optimization of scaling the solution to large and heterogeneous 6G networks might be needed since the additional complexity of more edge nodes and devices is introduced. A dynamic, high-speed operation is a challenge, particularly when the operational environment includes heavy traffic, and the latency and resource allocation are at issue. In the comparison with the current methods, including the literature ones, the suggested solution is unique as it successfully incorporates SDN, edge computing, and AI to tackle not only the issue of network optimization but also security. Most of the work in the past has concentrated on individual aspects of performance or security, however this combined approach can provide a more comprehensive solution, covering robust performance and adaptive security in 6G networks.

VI. Conclusion

The suggested SDN+AI optimization model has proved its outstanding performance optimization and security advantages compared to current 6G strategies. The model allows increasing throughput by 47 % (from 420 Mbps to 620 Mbps), decreasing latency by 37 % (from 38 ms to 24 ms) and decreasing packet loss by 50 % (from 3.6% to 1.7%). In addition to that, the use of AI in the system provides for a more accurate intrusion detection (by 15%, from 82% to 97%) and reduction of false positives by 32 % (from 11.5% to 7.8%). Thus, the framework is highly effective in the management of high-demand applications, providing efficient performance optimization and security of the network. There are numerous implications of this research in the area of real world 6G networking, especially in the case of development of autonomous systems, smart cities and AI-driven solutions, as it is necessary to provide performance and security in this context. The suggested solution is highly applicable to the design of the next generation network.In addition to this, network latency and packet loss reduction performance of the model are key for applications like telemedicine, connected cars, and industrial automation where speed and accuracy of data communication are key factors. As far as the future research is concerned, more research can be

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done on incorporating other sophisticated AI techniques such as deep reinforcement learning and federated learning into the model to make the model more adaptable and scalable. Moreover, it is crucial that the approach is tested in real-world scenarios to see its efficiency while tackling varying and complex 6G networks. Network slicing and multi-access edge computing (MEC) are some of the other promising fields of optimization and improvement.

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