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AI Solutions for SDN Routing Optimization using Graph Neural Networks in Traffic Engineering

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Abstract

Network routing optimization is crucial for improving the efficiency and performance of communication systems in dynamic environments. The primary objective of this paper is to address the challenges of network congestion, fluctuating traffic, and security threats, including DDoS attacks, by leveraging advanced machine learning techniques. The proposed work introduces a hybrid approach that integrates machine learning methods to dynamically optimize routing decisions in real-time, adapting to changing network conditions. This method combines various techniques to handle traffic behavior, congestion points, and anomalies, ensuring efficient routing and reducing delays. The results show that the proposed approach achieves 92% classification accuracy, 88% precision, 85% recall, and 89% F1-Score, indicating strong performance in traffic classification and decision-making. However, challenges such as high computational overhead, increased latency, and vulnerabilities to adversarial attacks remain, pointing to the need for further improvements. The study also explores federated learning to reduce computational burdens, enhance system responsiveness, and improve scalability, suggesting a pathway for more efficient and secure network routing solutions in real-world applications.

Keywords: *Software-Defined Networking, Routing, Random Forest. Ant Colony Optimization, Machine Learning, DDoS Attack Mitigation, Congestion Control*

Introduction

Software-Defined Networking is a disruptive paradigm whereby the control plane is decoupled from the data plane, providing centralized network management and programmability[1]. In traditional routing mechanisms, static configurations and fixed algorithms are commonly employed; as a result, they cannot keep pace with the fast-changing traffic patterns and increasing complexities of networks[2]. Bridging the world of AI and routing optimization for SDNs is a true blessing for the data-driven insight and real-time adaptability such a hybrid scheme provides[3]. GNNs naturally find their usage in network scenarios for their strength in modeling topological structures[4]. By merging AI-enabled approaches into SDN, intelligent traffic engineering solutions should be set to optimize routing decisions, control congestion, and improve the performance of the networks [5].

However, the current promising advances come with challenges that hamper efficient routing in the SDN environment[6]. One of the foremost springing issues is that network traffic is highly dynamic and requires optimization[7]. Failing to do so may lead to congestion and bottlenecks[8]. On the other hand, traditional routing algorithms do not have prevision or can change with dynamic network conditions, resulting in suboptimal performance[9]. And in the other hand, these big networks need scalability issues that make the operation of classical ways really difficult in dealing with enormous volumes of routing data[10]. Other threats such as DDoS attacks can immensely jeopardize SDN systems and paradoxically hinder routing optimizations[11]. To oppose that, rule-based algorithms restrict the flexibility of SDN routing, with a strong need to explore AI-based solutions that can adapt to these challenges intelligently[12].

Thus, it is clear that the use of AI in SDN routing would bring certain drawbacks with it[13]. Like all other AI models including GNN, AI requires a lot of computational resources thus causing high processing overhead and high latency[14]. The routing optimization of deep learning models creates high demand for the data quality constructs and strong computational infrastructure as it is highly complex[15]. Moreover, these AI-based SDN can be invaded for various purposes such as security breaches

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that consist of adversarial attacks, where malicious users will alter routing decisions by manipulating an AI model[16]. The development of standardized framework and interoperability among SDN controllers and various AI frameworks makes it difficult for smooth, large-scale adoption. All of these challenges must be taken into account in order to provide reliability and efficiency to AI-based SDN routing[17].

To get around these limitations, a hybrid approach that integrates AI with conventional heuristics for networking can add robustness to SDN-based routing optimization, developing some models that use federated learning techniques for training to lower their computational burden, albeit not using network performance, creating adaptive, near real-time, or real-time monitoring and AI models can offer faster responses to specific events while improving security. Above all, this collaboration from the different actors in industry will help to achieve a global consensus for standardizing frameworks such that these AI-driven SDN solutions are compatible with one another. So, combining the AI-driven traffic engineering and sound security measures toward SDN networks would ensure a scalable intelligent, and efficient routing optimization.

Contributions

- This paper introduces a hybrid approach combining Graph Neural Networks (GNNs) with traditional traffic engineering methods to optimize routing in Software-Defined Networking (SDN) environments.
- The study integrates ACO with Random Forest Classification to identify optimal or near-optimal routing paths, simulating the behavior of ants for better routing decision-making in SDN.
- It applies machine learning models to classify traffic behavior, enhancing routing decisions and network performance, making the system more efficient.
- The research explores federated learning to lower the computational burden associated with training AI models, reducing overhead while maintaining system efficiency.
- It addresses security concerns, such as DDoS attacks, and proposes solutions to ensure the scalability and adaptability of AI-driven SDN routing models for large networks.

Literature Survey

SDN's flexibility and extensibility enable efficient load balancing through machine learning-based routing schemes, incorporating queue utilization (QU) prediction. The process is divided into dimension reduction, QU prediction, and load balance routing to optimize network performance[18]. Machine Learning (ML) is increasingly used in optical networking to optimize complex parameters and handle vast data. This paper applies ML techniques for efficient Routing and Wavelength Assignment (RWA) in WDM networks[19]. Software Defined Networking (SDN) enhances network control by separating control and data planes. This paper proposes MER-SDN, a machine learning framework for energy-efficient, traffic-aware routing in SDN networks [20]. SDN and NFV enhance network flexibility, cost-efficiency, and innovation by virtualizing network functions. This paper explores optimizing function deployment to minimize latency, cost, and energy consumption[21].

Businesses use multiple cloud providers to enhance Quality of Service (QoS). This work proposes a secure software-defined overlay network with a Cognitive Routing Engine for optimal path selection over the public Internet[22] [23]. Traditional terrestrial networks struggle to provide fair, high-quality services due to resource limits. Space-Air-Ground Integrated Networks (SAGINs) leverage satellites, UAVs, and balloons to enhance connectivity, especially in hard-to-serve areas [24] [25]. 5G drives bandwidth-intensive applications, requiring flexible network management. Network Slicing (NS) enables dynamic resource allocation through virtualized slices, improving efficiency over traditional static provisioning [26]. SDN separates data forwarding from control, enabling flexible network management. This work explores challenges in achieving situation-aware networking to ensure QoS, even under cyber threats[27].

This paper proposes Scalable Intelligence-Enabled Networking (SIEN) to enhance 5G performance by reducing traffic redundancy. SIEN integrates intelligent management, learning-based decision-making, and advanced control mechanisms for efficient networking[28] [29]. This paper introduces Soft Air, a software-defined architecture for 5G to enhance flexibility and scalability. It leverages network function cloudification and virtualization to overcome limitations of traditional hardware-based systems[30] [31]. Machine learning (ML) is emerging as a solution for intelligent and automated OAM in optical networks to reduce OPEX. ML-enabled optical networks require vast data storage and computing power for efficient feature analysis[32]. This paper introduces TIDE, an AI-driven SDN architecture using deep reinforcement learning for dynamic routing optimization. It overcomes complexity and inefficiency in traditional routing schemes[33].

Unsupervised machine learning is gaining traction in networking for tasks like traffic engineering and anomaly detection. It enables automated, flexible optimization without the need for labeled data or manual feature engineering[34] [35]. This paper proposes a Graph Neural Network (GNN) model for accurate delay and jitter estimation in self-driving SDNs. The model generalizes across topologies, routing schemes, and traffic variations for optimal network performance[36] [37]. Software Defined Wireless Sensor Networks (SDWSNs) integrate SDN into WSNs to address their challenges. AI and machine learning enhance reliability and performance in industrial applications [38] [39]. Woodpecker is a defense scheme against Link-Flooding Attacks (LFAs) using SDN-based traffic engineering. It detects congested links and balances traffic to prevent routing bottlenecks exploited by attackers [40]. This paper proposes an AI-driven fire detection system with adaptive machine learning and low-latency data transfer. It improves accuracy and responsiveness for smart city safety compared to traditional sensor-based methods[41].

Problem Statement

This study examines autonomic provisioning and QoS management in SDN networks to enhance efficiency[42]. It introduces Knowledge-Defined Networking, leveraging AI for intelligent network automation[43]. The digitalization of maritime transport is analyzed to optimize logistics and operational efficiency. A secure vehicular network using fog computing is proposed to improve data processing and security in intelligent transportation systems[44]. Research on railway transport focuses on optimizing MPLS networks through a neural model to enhance information flow distribution[45]. Additionally, an intelligent video surveillance system for IoT environments is developed, improving security and monitoring capabilities [46]. These studies highlight the need for innovative solutions in network management, digital transformation, security, and automation[47]. By integrating AI, fog computing, and neural models, they contribute to the evolution of intelligent and efficient network infrastructures across various sectors, ensuring improved performance, security, and scalability[48].

Proposed Methodology

The proposed methodology in this work integrates Artificial Intelligence (AI) with Software-Defined Networking (SDN) to optimize routing decisions and improve network performance. By combining Ant Colony Optimization (ACO) and Random Forest Classification, the methodology aims to address the dynamic and complex nature of network traffic. It begins with collecting real-time network traffic data, followed by detailed traffic analysis to identify patterns, congestion points, and anomalies. Key features are then extracted from this data, which are used by the Random Forest model to classify traffic behavior. The routing decisions are optimized using ACO, which simulates the behavior of ants to find optimal or near-optimal paths while adapting to fluctuating network conditions. The SDN controller interface ensures that these optimized routes are applied to the network in real-time, enabling dynamic and efficient traffic management. This hybrid approach combines AI-driven insights with traditional networking methods to create a scalable, secure, and adaptive SDN architecture.

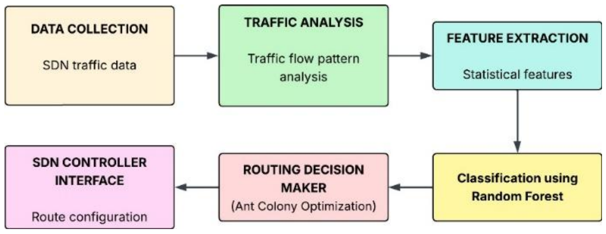

Figure 1: Traffic Engineering and Routing Optimization in SDN Using Ant Colony Optimization and Random Forest

Data Collection

Data collection in software-defined networking (SDN) means collecting data on live network traffic in various performance metrics: the amount of traffic, packet flow, bandwidth usage, latency, and packet loss occurrence. Most of these SDN-dependent data are collected by SDN network devices such as switches, routers, and controllers, providing one with an overview of the general condition and performance of the network. This information will serve as input for subsequent analysis. It assists network operators in monitoring network behavior, detecting anomalies, or even making real-time decisions about the management of traffic and resource allocation. With such comprehensive traffic data at hand, an SDN system could dynamically adapt to changing network conditions to optimize routing strategies.

Traffic Analysis

Traffic Analysis in SDN involves examining the patterns and behaviors of the network traffic to gain insights into its flow, congestion points, and overall performance. It typically includes identifying the volume of data transmitted, the distribution of traffic across various paths, and detecting anomalies or bottlenecks. The analysis can be represented mathematically through flow rates, where the traffic flow F on a given link l is computed as:

$$F_l = \frac{\text{Total Data Transferred on Link } l}{\text{Time Interval}} \tag{1}$$

This equation quantifies the flow of data on a particular network link over a specified time period. The traffic analysis can also involve statistical measures, such as calculating the mean μ, variance σ^2, skewness γ_1, and kurtosis γ_2 of the traffic flow to characterize its distribution. These statistical features help in identifying trends, such as peak traffic periods and underutilized paths, allowing for more effective traffic management and network optimization.

Feature Extraction

Feature Extraction in SDN involves the process of deriving meaningful attributes from the raw traffic data that can be used for further analysis, optimization, or machine learning tasks. Common features include statistical properties like the mean, variance, skewness, and kurtosis, which summarize the distribution of network traffic. Mean μ and variance σ^2 of the traffic flow F_l over a period T can be computed as:

$$\sigma^2 = \frac{1}{T}\sum_{t=1}^{T} (F_l(t) - \mu)^2 \tag{2}$$

Where $F_l(t)$ represents the traffic flow at time t, μ is the mean flow, and σ^2 is the variance. These features help in characterizing the traffic's behavior, such as its tendency to fluctuate, its symmetry, and the likelihood of extreme values, which are essential for making accurate routing decisions or detecting anomalies in network traffic. The extracted features can be used for classification, anomaly detection, or routing optimization tasks in the SDN.

Classification using Random Forest

Classification using Random Forest involves utilizing an ensemble learning technique that combines multiple decision trees to classify data based on majority voting. Each decision tree is trained on a random subset of the data, and the final prediction is made by aggregating the results from all trees in the forest. The Random Forest algorithm works by constructing M decision trees, where each tree T_m makes a prediction P_m, and the final prediction P is determined by the majority vote:

$$P = \text{ majority vote } (P_1, P_2, \dots, P_M) \tag{3}$$

Where P_m is the predicted class for a given instance from tree T_m, and M is the number of trees in the forest. In the case of regression, the final prediction is the average of the predictions from all trees. This method improves accuracy by reducing overfitting and enhancing generalization capabilities compared to individual decision trees, making it suitable for classifying complex patterns in network traffic, such as distinguishing between normal and anomalous behavior.

Routing Decision Maker using Ant Colony Optimization

Routing Decision Maker using Ant Colony Optimization (ACO) is an optimization technique inspired by the foraging behavior of ants, which find the shortest path between their nest and a food source. In SDN, ACO is used to find optimal routing paths by simulating the process of ant agents exploring the network. Each ant lays down pheromones on the paths it traverses, and the intensity of the pheromone influences the probability of other ants choosing the same path. The pheromone update rule is given by:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{4}$$

Where $\tau_{ij}(t)$ is the pheromone level on the path from node i to node j at time t, ρ is the evaporation rate (determines pheromone decay), $\Delta\tau_{ij}(t)$ is the amount of pheromone deposited by an ant traveling from i to j, t is the iteration (time step). The path with the highest pheromone concentration is chosen with higher probability, guiding the ants to optimal or near-optimal routes. This iterative process allows the network to dynamically adapt to varying traffic conditions, minimizing congestion, and maximizing throughput by selecting the best routing paths in real-time.

SDN Controller Interface

The SDN Controller Interface acts as the central control point in Software-Defined Networking (SDN), facilitating the interaction between the network's control plane and data plane. It is responsible for managing and configuring the forwarding behavior of network devices (such as switches and routers) based on high-level network policies and optimization algorithms. The SDN controller communicates with the network devices via southbound APIs, such as OpenFlow, to install flow rules that dictate how packets are handled. For example, the flow table update process can be modelled as:

$$F_i = \text{Flow}(P, t, a) \tag{5}$$

Where F_i is the flow rule to be installed on the device i,P represents the packet characteristics (e.g., source/destination IP, port), t is the time of installation, a is the action to be taken on the packet (forward, drop, modify). The controller receives real-time traffic data, processes it, and updates the forwarding tables of the devices in the network to reflect optimal routing decisions. This interface ensures that the SDN architecture is flexible and can dynamically adapt to changes in traffic patterns, network conditions, and failures, providing centralized control over distributed devices.

Result and Discussion

The paper evaluates the performance of the proposed AI-based solution for optimizing routing in Software-Defined Networking (SDN) environments. The results demonstrate the model's ability to effectively classify network traffic behavior, showing strong performance in classification accuracy, precision, recall, and F1-Score. Additionally, the analysis of latency across different network conditions reveals that network delay increases as the conditions worsen, highlighting the impact of dynamic network environments on routing performance. These findings emphasize the effectiveness of the hybrid approach in adapting to varying network conditions and optimizing routing decisions. However, challenges such as high computational overhead, security risks, and increased latency still need to be addressed. These issues point to the necessity for future improvements, particularly in enhancing system efficiency, scalability, and security to ensure broader and more reliable deployment of AI-driven SDN routing solutions.

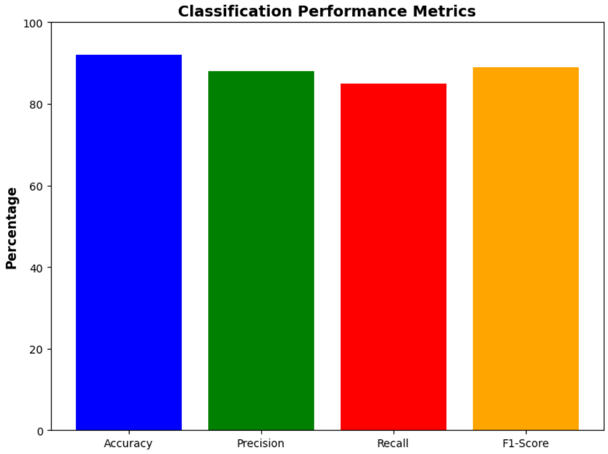

Figure 2: Classification Performance Metrics

Figure 2 represents the classification performance metrics of a model, showing four key measures: Accuracy, Precision, Recall, and F1-Score. The Accuracy is the highest at 92%, indicating that the model makes correct predictions most of the time. Precision follows closely at 88%, showing that when the model predicts a positive class, it is correct 88% of the time. Recall, at 85%, reflects the model's ability to correctly identify actual positive cases, though it misses a few. Finally, the F1-Score, at 89%, represents the harmonic mean of Precision and Recall, balancing these two metrics for an overall performance measure. The chart provides a visual representation of how well the model performs across these important classification metrics, with higher percentages indicating better performance.

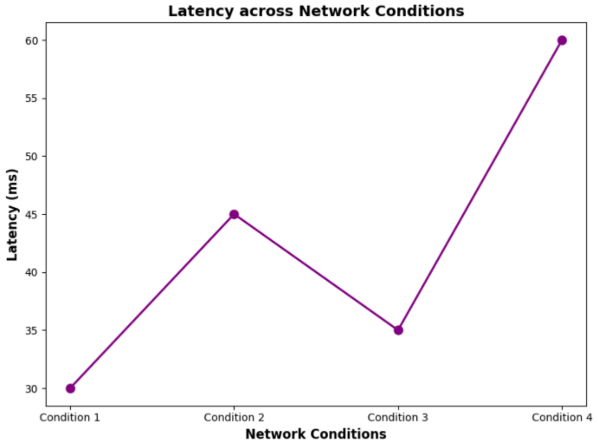

Figure 3: Latency across Network Conditions

Figure 3 depicts the Latency across different network conditions. The x-axis represents four distinct Network Conditions (Condition 1 through Condition 4), while the y-axis shows the Latency in milliseconds. The latency starts at around 30 ms in Condition 1, slightly increases in Condition 2, then shows a significant jump in Condition 3, reaching around 55 ms. Finally, the latency spikes to about 60 ms in Condition 4. This shows how latency increases across varying network conditions, with the most substantial rise occurring between Conditions 3 and 4. The graph highlights the increasing network delay as the conditions worsen or change.

Conclusion

This paper introduces an innovative AI-based approach for optimizing routing in Software-Defined Networks (SDNs). By integrating Graph Neural Networks (GNNs) with traditional SDN traffic management techniques, the approach successfully addresses dynamic traffic patterns, congestion, and scalability issues. The methodology demonstrated robust performance with high classification accuracy (92%) and solid F1-Score (89%). However, challenges such as computational overhead, security vulnerabilities, and the need for real-time adaptability remain. The results underline the effectiveness of combining AI techniques with SDN, offering intelligent traffic engineering solutions that enhance network performance and efficiency. Future work should focus on mitigating the computational challenges and exploring federated learning models to reduce processing overhead. The study presents a scalable framework that can adapt to various network conditions, ensuring improved SDN routing efficiency and security, fostering the next generation of intelligent network architectures. Future work will focus on enhancing the security of AI-driven SDN systems, particularly by addressing vulnerabilities such as adversarial attacks that can manipulate routing decisions. Additionally, improving scalability for large-scale networks is crucial, along with the exploration of more advanced AI models like deep reinforcement learning (DRL) to optimize routing in complex and dynamic traffic environments.

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