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AI-Driven Autonomous Security Protocol for Self-Healing Software-Defined Optical Networks Using Deep Reinforcement Learning

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Abstract

The increasing deployment of Software-Defined Optical Networks (SDONs) to support 5G/6G communications, cloud computing, Internet of Things (IoT), and data-intensive applications has significantly enhanced network programmability and resource utilization. However, the centralized control architecture and dynamic nature of SDONs expose them to a wide range of cyber-physical threats, including distributed denial-of-service attacks, optical jamming, signal spoofing, eavesdropping, and control-plane intrusions. Conventional security mechanisms primarily rely on static policies and predefined signatures, limiting their effectiveness against evolving and previously unseen attack patterns. To address these challenges, this paper proposes an AI-driven autonomous security protocol for self-healing software-defined optical networks based on Deep Reinforcement Learning (DRL). The proposed framework integrates optical performance monitoring, real-time network telemetry, anomaly detection, and intelligent decision-making within the SDN control plane to enable proactive threat identification and autonomous mitigation. A DRL agent continuously learns optimal security policies by interacting with the network environment and dynamically performs actions such as route reconfiguration, traffic isolation, resource reallocation, and attack containment while minimizing service disruption. The framework further incorporates a self-healing mechanism that predicts network vulnerabilities, identifies compromised links or nodes, and restores network operations through adaptive path computation and automated recovery procedures. Experimental evaluation using realistic optical network traffic and attack scenarios demonstrates that the proposed protocol achieves superior threat detection accuracy, reduced response latency, enhanced network survivability, and improved service availability compared with conventional machine learning and rule-based security approaches. The results indicate that the integration of deep reinforcement learning with software-defined optical networking provides an effective foundation for building resilient, autonomous, and secure next-generation optical communication infrastructures capable of supporting future intelligent networking ecosystems.

1. Introduction

The exponential growth of Internet traffic driven by cloud computing, fifth- and sixth-generation (5G/6G) wireless communications, Internet of Things (IoT) devices, edge intelligence, and emerging data-centric applications has substantially increased the demand for high-capacity, low-latency, and highly reliable communication infrastructures **[1]–[3]**. Optical networks form the backbone of modern telecommunication systems due to their unparalleled bandwidth, scalability, and energy efficiency **[4], [5]**. To address the dynamic requirements of

future communication ecosystems, Software-Defined Optical Networks (SDONs) have emerged as a promising paradigm that combines the flexibility of Software-Defined Networking (SDN) with the high-speed capabilities of optical transport technologies **[6], [7]**. By decoupling the control plane from the data plane and enabling centralized network intelligence, SDONs facilitate programmable resource allocation, adaptive routing, efficient traffic engineering, and automated network management **[6], [8]**.

Despite these advantages, the increasing programmability and interconnectedness of SDONs have introduced significant security challenges **[9], [10]**. The centralized architecture of SDN controllers, together with the distributed nature of optical infrastructures, creates multiple attack surfaces that can be exploited by adversaries. Optical communication systems are vulnerable to a variety of cyber-physical threats, including optical signal jamming, fiber tapping, signal spoofing, wavelength hijacking, control-plane intrusions, distributed denial-of-service (DDoS) attacks, and malicious routing manipulation **[9]–[11]**. Such attacks can severely degrade network performance, compromise data confidentiality, disrupt critical services, and threaten the stability of large-scale communication infrastructures. As optical networks continue to support mission-critical applications such as autonomous transportation, smart manufacturing, telemedicine, and national digital infrastructures, ensuring robust security has become a fundamental requirement **[2], [10]**.

Traditional network security solutions primarily rely on static rule-based policies, signature matching techniques, and predefined attack models **[12]**. Although these approaches are effective against known threats, they often fail to detect sophisticated, adaptive, and zero-day attacks that continuously evolve in modern networking environments **[12], [13]**. Furthermore, conventional intrusion detection systems typically operate in a reactive manner, responding only after an attack has been identified. Such delayed responses may result in significant service degradation and prolonged recovery times in high-capacity optical networks. The limitations of static security mechanisms have motivated the exploration of Artificial Intelligence (AI)-based approaches capable of providing autonomous, adaptive, and predictive security functionalities **[13], [14]**.

Recent advances in machine learning and deep learning have demonstrated considerable potential for enhancing network security through intelligent threat detection, anomaly identification, and attack classification **[13]–[15]**. Techniques such as convolutional neural networks, recurrent neural networks, graph neural networks, and transformer architectures have achieved promising results in identifying complex attack patterns within large-scale communication systems **[14], [15]**. However, most existing AI-driven security frameworks focus primarily on attack detection and classification while providing limited capabilities for autonomous response and recovery. In highly dynamic optical networking environments, effective security solutions must not only identify threats but also autonomously determine optimal mitigation strategies and restore network functionality with minimal human intervention.

Deep Reinforcement Learning (DRL) has recently emerged as a powerful decision-making framework capable of learning optimal actions through continuous interaction with complex environments **[16], [17]**. Unlike supervised learning approaches that depend on labeled

datasets, DRL agents learn adaptive policies by maximizing cumulative rewards based on observed network states and operational outcomes. This capability makes DRL particularly suitable for dynamic optical network environments where attack patterns, traffic conditions, and resource availability continuously change over time. By integrating DRL with SDN-based control architectures, security systems can dynamically reconfigure routes, isolate compromised network segments, allocate backup resources, and optimize mitigation strategies in real time **[17], [18]**.

In parallel, the concept of self-healing networks has gained significant attention as a key enabler of autonomous communication infrastructures **[18], [19]**. Self-healing networks possess the capability to automatically detect failures, diagnose vulnerabilities, initiate recovery actions, and restore normal operations without manual intervention. Within optical networking environments, self-healing mechanisms can significantly improve network resilience by reducing service disruption, minimizing downtime, and enhancing overall survivability during cyberattacks or infrastructure failures **[19], [20]**. The convergence of AI-driven security analytics, SDN programmability, and self-healing capabilities offers a promising pathway toward next-generation autonomous optical networks.

Motivated by these challenges and opportunities, this paper proposes an AI-driven autonomous security protocol for self-healing software-defined optical networks using Deep Reinforcement Learning. The proposed framework integrates optical performance monitoring, network telemetry collection, AI-based threat analytics, autonomous decision-making, and adaptive recovery mechanisms within a unified security architecture. The protocol continuously observes network conditions, identifies abnormal behaviors, predicts potential threats, and proactively initiates mitigation actions to maintain secure and reliable communication services. Through DRL-based optimization, the framework learns effective security policies that balance attack mitigation effectiveness, network performance, and resource utilization while ensuring rapid recovery from disruptions.

The primary contributions of this work are summarized as follows:

1. An AI-driven autonomous security architecture is developed for software-defined optical networks that combines optical-layer monitoring, network-layer intelligence, and centralized SDN control.
2. A Deep Reinforcement Learning-based security agent is proposed to dynamically identify optimal mitigation strategies against evolving cyber-physical threats.
3. A self-healing recovery mechanism is introduced to autonomously restore network functionality through adaptive path reconfiguration, traffic rerouting, and resource reassignment.
4. A comprehensive threat management framework is designed to address both optical-layer and control-plane attacks within a unified security protocol.
5. The effectiveness of the proposed framework is evaluated using realistic optical network scenarios and diverse cyberattack conditions, demonstrating improvements in threat detection accuracy, response latency, network survivability, and service availability.

The remainder of this paper is organized as follows. Section 2 reviews related work on AI-enabled optical network security, software-defined optical networking, and reinforcement learning-based cyber defense systems. Section 3 presents the proposed autonomous security architecture and threat model. Section 4 describes the Deep Reinforcement Learning framework and self-healing mechanisms. Section 5 discusses the experimental setup and evaluation methodology. Section 6 presents the performance analysis and comparative results. Finally, Section 7 concludes the paper and outlines future research directions.

Figure 1 shows the proposed AI-Driven Autonomous Security Protocol (AASP) architecture integrating optical infrastructure, monitoring layer, AI threat intelligence, Deep Reinforcement Learning security engine, and SDN-enabled self-healing orchestration.

Figure 2 illustrates End-to-end security protocol workflow illustrating telemetry collection, anomaly detection, attack classification, DRL-based decision making, autonomous mitigation, and self-healing recovery.

Cyber-physical threat model for Software-Defined Optical Networks showing major attack vectors including DDoS attacks, optical jamming, fiber tapping, and SDN controller compromise is shown in Figure 3.

Figure 1: Proposed AASP Architecture

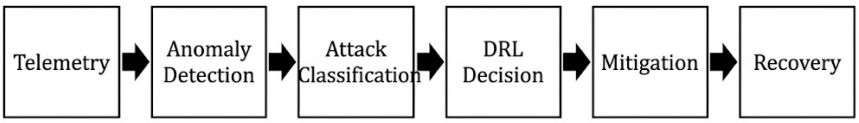

Figure 2: Security Protocol Workflow

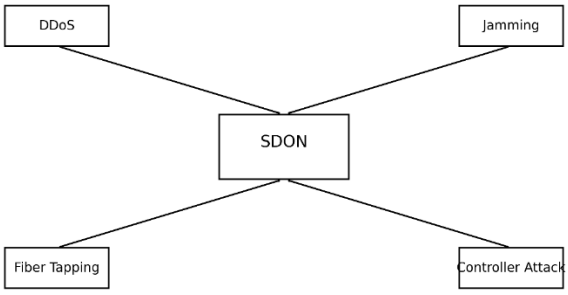

Figure 3: Threat Model for SDON Security

2. Related Work

2.1 Security Challenges in Software-Defined Optical Networks

Software-Defined Optical Networks (SDONs) have emerged as a transformative networking paradigm by integrating the programmability of Software-Defined Networking (SDN) with the high-capacity transmission capabilities of optical communication systems. Through centralized control and network virtualization, SDONs enable flexible resource allocation, dynamic traffic engineering, and automated network management. However, the separation of control and data planes introduces new security vulnerabilities that are not typically encountered in conventional optical transport networks.

The centralized SDN controller represents a critical point of failure and an attractive target for cyberattacks. Adversaries can exploit vulnerabilities in controller applications, communication interfaces, or management systems to manipulate routing policies and network configurations. Furthermore, optical infrastructures remain susceptible to physical-layer attacks such as fiber tapping, optical signal injection, jamming, wavelength hijacking, and eavesdropping. These attacks may degrade network performance, compromise data confidentiality, and disrupt mission-critical services.

Recent studies have investigated security mechanisms for SDON environments, focusing on encryption techniques, authentication protocols, access control frameworks, and intrusion detection systems. While these solutions provide basic protection against known threats, they often rely on static security policies and predefined attack signatures. Consequently, their effectiveness diminishes when confronted with adaptive, multi-stage, or previously unseen attack scenarios. This limitation highlights the need for intelligent and adaptive security mechanisms capable of operating in highly dynamic optical networking environments.

2.2 Artificial Intelligence for Network Security

Artificial Intelligence (AI) has become a powerful tool for enhancing cybersecurity across modern communication systems. Machine learning algorithms can automatically analyze large volumes of network traffic, identify suspicious patterns, and detect anomalous behaviors that may indicate malicious activities. Unlike traditional rule-based approaches, AI-driven systems continuously learn from network observations and adapt to evolving threat landscapes.

Supervised learning techniques such as Support Vector Machines (SVMs), Random Forests, Decision Trees, and Artificial Neural Networks have been extensively employed for intrusion detection and attack classification. These methods have demonstrated improved detection accuracy compared with signature-based systems, particularly in identifying known attack categories. However, supervised approaches require large quantities of labeled training data, which may not always be available in optical network environments.

To overcome these limitations, unsupervised learning techniques including clustering algorithms, autoencoders, and anomaly detection frameworks have gained attention. These approaches learn normal network behavior and identify deviations that may correspond to malicious activities. Deep learning architectures such as Convolutional Neural Networks

(CNNs), Long Short-Term Memory (LSTM) networks, and Transformer models have further improved threat detection performance by capturing complex spatial and temporal relationships within network traffic.

Although existing AI-based security systems achieve high detection accuracy, most focus primarily on attack identification rather than autonomous mitigation and recovery. Consequently, significant human intervention is often required to implement corrective actions after an attack has been detected.

2.3 Deep Learning-Based Optical Network Security

The application of deep learning within optical communication systems has expanded rapidly in recent years. Deep learning models have been successfully utilized for optical performance monitoring, modulation format recognition, quality-of-transmission estimation, fault localization, and anomaly detection. The ability of deep neural networks to extract high-level representations from large-scale datasets makes them particularly suitable for complex optical networking environments.

Several studies have employed CNN-based architectures to identify optical signal impairments and detect abnormal transmission behaviors. Recurrent neural networks and LSTM models have been used to analyze temporal traffic patterns and predict network faults before service degradation occurs. More recently, Transformer-based architectures have demonstrated promising capabilities for modeling long-range dependencies within optical traffic datasets.

Despite these advances, existing deep learning frameworks primarily function as passive monitoring tools. Most systems generate alerts when abnormalities are detected but lack mechanisms for autonomous decision-making and dynamic network adaptation. As a result, the potential benefits of AI-driven automation remain largely underutilized in optical network security applications.

2.4 Reinforcement Learning for Autonomous Cyber Defense

Reinforcement Learning (RL) has emerged as an effective approach for solving sequential decision-making problems in dynamic environments. Unlike supervised learning techniques, RL agents learn optimal actions through interactions with the environment and continuous evaluation of received rewards. This capability enables RL systems to adapt to changing operational conditions and optimize long-term performance objectives.

Recent research has explored the use of RL in cybersecurity applications such as intrusion response, attack mitigation, access control management, and network resource optimization. By observing network states and attack conditions, RL agents can determine appropriate defense actions that maximize security while minimizing operational costs.

Deep Reinforcement Learning (DRL), which combines reinforcement learning with deep neural networks, extends these capabilities to large-scale and high-dimensional environments. Algorithms such as Deep Q-Networks (DQN), Double DQN, Deep Deterministic Policy Gradient (DDPG), Advantage Actor-Critic (A2C), Proximal Policy Optimization (PPO), and Soft Actor-Critic (SAC) have demonstrated superior performance in complex networking scenarios.

In communication networks, DRL has been applied to routing optimization, traffic engineering, congestion management, resource allocation, and energy-efficient networking. However, its adoption in optical network security remains relatively limited. Existing studies often focus on isolated security tasks, such as attack detection or routing adaptation, without considering comprehensive autonomous security orchestration and self-healing capabilities.

2.5 Self-Healing Optical Networks

The concept of self-healing networking aims to enable communication infrastructures to automatically detect failures, diagnose root causes, and recover from disruptions without human intervention. In optical networks, self-healing mechanisms are particularly important due to the high bandwidth demands and stringent reliability requirements of modern communication services.

Traditional self-healing approaches primarily rely on protection switching and restoration techniques. Protection schemes reserve backup resources in advance and rapidly switch traffic to alternative paths when failures occur. Restoration techniques dynamically compute recovery routes after disruptions are detected. Although these methods improve network reliability, they generally respond only after service degradation has occurred and do not explicitly consider cyber-security threats.

Recent developments in AI-enabled self-healing systems have introduced predictive maintenance and intelligent fault management capabilities. Machine learning models can anticipate equipment failures, predict traffic congestion, and identify network vulnerabilities before significant disruptions occur. Nevertheless, many existing solutions focus on fault recovery rather than cyberattack mitigation, leaving a critical gap between network resilience and security management.

2.6 Research Gap and Motivation

A comprehensive review of existing literature reveals several important limitations. First, most optical network security solutions rely on static rule-based defenses or machine learning models designed primarily for attack detection. Second, existing deep learning approaches provide limited support for autonomous mitigation and dynamic response mechanisms. Third, reinforcement learning-based security frameworks often address individual optimization problems without considering integrated cyber-defense and network recovery strategies. Fourth, current self-healing optical network architectures primarily focus on physical failures and operational faults rather than coordinated cyber-physical attacks.

Furthermore, few studies have investigated the joint integration of optical performance monitoring, AI-driven threat intelligence, Deep Reinforcement Learning, SDN-based network control, and autonomous self-healing mechanisms within a unified security framework. The absence of such an integrated solution limits the ability of current optical networks to proactively defend against sophisticated attacks while maintaining uninterrupted service availability.

To address these challenges, this paper proposes an AI-driven autonomous security protocol for self-healing software-defined optical networks using Deep Reinforcement Learning. The

proposed framework combines real-time network monitoring, intelligent threat detection, DRL-based decision-making, adaptive mitigation, and autonomous recovery mechanisms within a unified architecture. By enabling proactive security orchestration and self-healing operation, the framework seeks to improve network survivability, reduce response latency, and enhance the overall resilience of next-generation optical communication infrastructures.

3. Proposed AI-Driven Autonomous Security Architecture and Threat Model

The proposed AI-Driven Autonomous Security Protocol (AASP) is designed to provide intelligent threat detection, adaptive attack mitigation, and self-healing recovery for Software-Defined Optical Networks (SDONs). The framework combines optical performance monitoring, artificial intelligence-based threat intelligence, Deep Reinforcement Learning (DRL), and SDN-enabled orchestration within a unified architecture capable of responding autonomously to dynamic cyber-physical threats. Unlike conventional security systems that rely on predefined signatures and static mitigation policies, the proposed framework continuously learns from network observations and dynamically adapts its defense strategies according to changing network conditions and attack behaviors.

The architecture begins with a comprehensive monitoring subsystem that continuously collects operational information from both optical and network layers. The monitored optical state vector is represented as

$$X_o = \{P_t, P_r, OSNR, BER, CD, PMD\},$$

where P_t and P_r denote transmitted and received optical powers, respectively, $OSNR$ represents the optical signal-to-noise ratio, BER corresponds to the bit error rate, CD denotes chromatic dispersion, and PMD represents polarization mode dispersion. These parameters provide critical indicators of optical-layer impairments and malicious activities such as signal injection, optical jamming, and fiber tapping.

Simultaneously, network-layer telemetry is collected from SDN controllers, switches, routers, and traffic analyzers. The network state information is represented as

$$X_n = \{T_f, U_l, D_p, L_t, C_s\},$$

where T_f denotes traffic-flow statistics, U_l represents link utilization, D_p indicates packet loss ratio, L_t corresponds to network latency, and C_s characterizes SDN controller status information. The combination of optical-layer and network-layer observations provides a holistic representation of network behavior and security conditions.

The collected information is processed by an AI-based threat intelligence engine responsible for anomaly detection and attack classification. Let the overall feature vector extracted from the monitored network state be represented as

$$F = \{f_1, f_2, \dots, f_n\}.$$

A deep autoencoder is employed to learn the normal operational characteristics of the network. During operation, the autoencoder reconstructs the input observations and calculates a reconstruction error given by

$$L_{AE} = ||X - \hat{X}||^2,$$

where X represents the observed network data and $\hat{X}$ denotes the reconstructed output generated by the autoencoder. When the reconstruction error exceeds a predefined threshold θ,

$$L_{AE} > \theta,$$

the observed behavior is classified as anomalous and forwarded to the threat classification module for further analysis.

The framework considers a comprehensive threat model encompassing both optical-layer and network-layer attacks. Optical-layer threats include optical jamming, fiber tapping, wavelength hijacking, and unauthorized signal injection. For example, the severity of an optical jamming attack can be estimated using

$$J_s = \frac{P_{attack}}{P_{signal}},$$

where P_{attack} denotes the injected malicious optical power and P_{signal} represents the legitimate signal power. Larger values of J_s indicate a greater likelihood of signal degradation and service disruption.

Similarly, fiber tapping attacks can be inferred through unexpected power variations and signal quality degradation. The probability of information leakage can be expressed as

$$P_{leak} = f(\Delta P, BER),$$

where ΔP denotes abnormal power fluctuations observed along the optical path. Network-layer threats considered within the framework include Distributed Denial-of-Service (DDoS) attacks, routing manipulation, control-plane intrusions, malware propagation, and man-in-the-middle attacks. The overall impact of a detected attack is quantified through

$$I_A = \sum_{i=1}^{N} w_i \, a_i,$$

where a_i represents individual attack indicators and w_i denotes the corresponding weighting coefficients reflecting their relative importance.

After threat identification, the decision-making process is performed by the Deep Reinforcement Learning security engine. The network security environment is formulated as a Markov Decision Process (MDP) represented by

$$M = (S, A, P, R, \gamma),$$

where S denotes the state space, A represents the action space, P corresponds to state transition probabilities, R is the reward function, and γ denotes the discount factor. The state vector incorporates both security and performance information and is defined as

$$S_t = \{OSNR, BER, Traffic, Utilization, Risk, AttackScore\}.$$

Based on the observed state, the DRL agent selects an optimal security action from the action space

$$A_t = \{Monitor, Reroute, Isolate, Block, Recover\}.$$

These actions may involve traffic filtering, path reconfiguration, wavelength reassignment, resource isolation, or service recovery depending on the severity and nature of the detected threat.

The learning objective of the DRL agent is to maximize network security while minimizing service disruption and resource consumption. To achieve this objective, the reward function is formulated as

$$R_t = \alpha D_t + \beta A_t - \delta C_t,$$

where D_t denotes attack detection effectiveness, A_t represents service availability, C_t corresponds to mitigation cost, and α, β, and δ are tunable weighting coefficients. Positive rewards are assigned when attacks are successfully mitigated with minimal service degradation, whereas penalties are imposed for incorrect decisions or excessive resource utilization.

The DRL agent employs a Deep Q-Network (DQN) to estimate action-value functions. The long-term optimization objective is expressed as

$$\max \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right].$$

This formulation enables the agent to learn adaptive defense policies capable of addressing evolving attack strategies while maintaining efficient network operation.

Once an optimal mitigation decision has been generated, the SDN controller executes the corresponding security actions through programmable control interfaces. Because the SDN controller maintains a global view of the network topology and resource status, it can rapidly deploy defense mechanisms across distributed network elements. The orchestration layer dynamically updates forwarding rules, modifies routing policies, allocates backup resources, and isolates compromised network segments to prevent attack propagation.

Following attack containment, the proposed framework activates a self-healing recovery mechanism designed to restore network functionality and service continuity. The vulnerability level associated with each network component is calculated as

$$V_i = \frac{A_i + F_i}{2},$$

where A_i denotes attack severity and F_i represents failure probability. Based on these vulnerability assessments, alternative communication paths are computed using a multi-objective path selection model given by

$$C_{path} = \sum_{i=1}^{N} (\lambda_1 L_i + \lambda_2 U_i + \lambda_3 R_i),$$

where L_i, U_i, and R_i represent latency, utilization, and risk associated with link i, respectively, while λ_1, λ_2, and λ_3 are optimization weights. The path with the minimum cost is selected for traffic migration and service restoration.

To evaluate the effectiveness of the recovery process, a resilience metric is defined as

$$Resilience = \frac{Availability}{Recovery\ Time}.$$

Higher resilience values indicate improved network survivability and faster recovery from cyber-physical disruptions. Through the continuous interaction of monitoring, threat intelligence, reinforcement learning, SDN orchestration, and self-healing recovery modules, the proposed framework establishes a closed-loop autonomous security system capable of protecting next-generation software-defined optical networks against sophisticated and evolving cyber threats while ensuring high levels of reliability, availability, and operational resilience.

3.1 AI-Driven Autonomous Security Protocol Design and Deep Reinforcement Learning Algorithm

3.1.1. Security Protocol Design

The proposed AI-Driven Autonomous Security Protocol (AASP) operates as a closed-loop security management framework that continuously monitors network conditions, identifies threats, executes mitigation actions, and restores normal operation through self-healing mechanisms. The protocol is integrated within the SDN control plane and interacts with optical network elements through programmable interfaces.

The protocol consists of five operational phases: network state collection, threat detection and classification, risk assessment, autonomous mitigation, and self-healing recovery. During the network state collection phase, telemetry data are gathered from optical transceivers, ROADMs, switches, and SDN controllers. The collected observations are aggregated into a global state representation

$$S_t = \{X_o, X_n, F_t\},$$

where X_o represents optical-layer measurements, X_n denotes network-layer information, and F_t corresponds to extracted threat-related features.

The threat intelligence engine evaluates incoming observations and computes an attack probability score using

$$P_A = \frac{1}{1 + e^{-z}},$$

where z denotes the output of the deep classification model. When the attack probability exceeds a predefined threshold τ

$$P_A > \tau,$$

the network enters the mitigation stage.

3.1.2. Deep Reinforcement Learning Framework

The autonomous defense mechanism is modeled as a Markov Decision Process (MDP)

$$M = (S, A, P, R, \gamma),$$

where S denotes the state space, A represents the action space, P corresponds to state transition probabilities, R denotes the reward function, and γ is the discount factor.

The objective of the DRL agent is to determine an optimal security policy

$$\pi^*(a|s),$$

that maximizes cumulative security rewards. The expected return is expressed as

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k}.$$

The DRL agent continuously learns by interacting with the optical network environment and observing the consequences of mitigation actions.

3.1.3. State Space Representation

The state vector combines optical, traffic, and security indicators and is defined as

$$S_t = \{OSNR, BER, U_l, L_t, D_p, Risk, AttackScore\},$$

where $OSNR$ is the optical signal-to-noise ratio, BER denotes the bit error rate, U_l represents link utilization, L_t corresponds to network latency, and D_p denotes packet loss ratio.

The dimension of the state space is

$$|S| = n.$$

To improve learning efficiency and accelerate convergence, all features are normalized according to

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}.$$

3.1.4. Action Space Formulation

The action space consists of security operations that can be executed by the SDN controller:

$$A = \{a_1, a_2, \dots, a_m\}.$$

Specifically, the action set is defined as

$$A = \{Monitor, Reroute, Block, Isolate, Recover\}.$$

The selected action depends on the observed attack severity and current network state.

3.1.5. Reward Function Design

The reward function guides the learning process and balances security effectiveness with network performance. The immediate reward is defined as

$$R_t = \alpha D_t + \beta A_t + \eta Q_t - \delta C_t,$$

where D_t denotes detection success, A_t represents network availability, Q_t corresponds to quality-of-service preservation, and C_t denotes mitigation cost. The parameters α, β, η, and δ are weighting coefficients.

The cumulative optimization objective is

$$J(\pi) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right].$$

The optimal policy is obtained as

$$\pi^* = \underset{\pi}{\operatorname{argmax}} J(\pi).$$

3.1.6. Deep Q-Network Architecture

A Deep Q-Network (DQN) is employed to approximate the action-value function. The Q-function is represented as

$$Q(s, a; \theta),$$

where θ denotes neural network parameters.

The optimal action-value function follows the Bellman equation

$$Q^*(s, a) = \mathbb{E}\left[R + \gamma \underset{a'}{\operatorname{max}} Q(s', a')\right].$$

The DQN loss function is formulated as

$$L(\theta) = \mathbb{E}[(y_t - Q(s, a; \theta))^2],$$

where the target value is

$$y_t = R_t + \gamma \underset{a'}{\operatorname{max}} Q(s', a'; \theta^-).$$

The target network parameters θ^- are periodically updated to stabilize learning.

3.1.7. Autonomous Security Decision Process

The DRL agent continuously observes the network state and generates mitigation decisions. The action-selection policy follows an ϵ-greedy strategy

$$a = \begin{cases} \text{Random Action}, & \text{with probability } \epsilon \\ \underset{a}{\operatorname{argmax}} Q(s, a), & \text{otherwise.} \end{cases}$$

The exploration rate decreases exponentially according to

$$\epsilon_t = \epsilon_0 e^{-kt},$$

where ϵ_0 denotes the initial exploration rate and k is the decay constant.

3.1.8. Self-Healing Recovery Strategy

Following attack containment, the self-healing module restores normal network operation. The vulnerability score associated with each network component is calculated as

$$V_i = w_1 A_i + w_2 F_i + w_3 R_i,$$

where A_i denotes attack severity, F_i represents failure probability, and R_i corresponds to residual risk.

Alternative communication paths are computed by minimizing the path cost function

$$C_{path} = \sum_{i=1}^{N} (\lambda_1 L_i + \lambda_2 U_i + \lambda_3 R_i),$$

where L_i, U_i, and R_i represent latency, utilization, and risk associated with link i, respectively.

The optimal recovery path is determined as

$$P^* = \text{argmin}(C_{path}).$$

Traffic flows are migrated to the selected secure route, enabling rapid service restoration. The service recovery rate is measured as

$$SRR = \frac{N_r}{N_t},$$

where N_r denotes recovered services and N_t represents the total number of affected services.

3.2. Algorithm 1: AI-Driven Autonomous Security Protocol

Collect optical and network telemetry Extract security features Perform anomaly detection Classify attack type Compute risk score Construct DRL state vector Select mitigation action using DQN Execute action through SDN controller Monitor attack containment Initiate self-healing recovery Update replay memory Compute reward value Train DQN parameters Repeat until network stabilizes

The proposed protocol establishes a fully autonomous cyber-defense framework capable of continuously learning from network behavior, adapting to evolving threats, and maintaining uninterrupted service availability within next-generation software-defined optical networks.

Protocol

Input:
Network telemetry, optical measurements, traffic statistics.

Output:
Secure and resilient network operation.

1. Collect optical and network telemetry.
2. Extract security features.
3. Perform anomaly detection.
4. Classify attack type.
5. Compute risk score.
6. Construct DRL state vector.
7. Select mitigation action using DQN.

8. Execute action via SDN controller.
9. Monitor attack containment.
10. Initiate self-healing recovery.
11. Update reward and replay memory.
12. Train DQN parameters.
13. Repeat until network stabilizes.

End Algorithm

4. Experimental Setup and Performance Evaluation Methodology

4.1. Experimental Environment

To evaluate the effectiveness of the proposed AI-Driven Autonomous Security Protocol (AASP), a software-defined optical network test environment was developed that emulates realistic optical communication infrastructures and cyber-physical attack scenarios. The experimental framework integrates optical network simulation, SDN-based control, artificial intelligence-driven threat analysis, and Deep Reinforcement Learning (DRL)-based security orchestration. The network topology consists of multiple optical nodes interconnected through wavelength-division multiplexed (WDM) fiber links and managed by a centralized SDN controller.

The optical infrastructure comprises optical transceivers, reconfigurable optical add-drop multiplexers (ROADMs), optical amplifiers, and wavelength routing devices. Traffic flows are generated using realistic traffic distributions to emulate cloud services, data-center interconnections, Internet of Things (IoT) communications, and latency-sensitive applications. The SDN controller maintains a global view of network resources and executes security actions recommended by the DRL agent.

The experimental platform is implemented using Python, TensorFlow, OpenAI Gym, Mininet, and SDN controller frameworks. Optical-layer characteristics are modeled through network simulation tools capable of generating optical performance monitoring (OPM) measurements, including Optical Signal-to-Noise Ratio (OSNR), Bit Error Rate (BER), received optical power, and wavelength utilization statistics.

4.1.1. Network Topology and Traffic Configuration

A multi-node optical network topology is considered to evaluate the proposed framework under diverse operating conditions. The network is represented as a graph

$$G = (V, E),$$

where V denotes the set of optical nodes and E represents optical fiber links connecting the nodes.

Each optical link supports multiple wavelengths and possesses finite transmission capacity. The available capacity of each optical link is represented by

$$C_{ij} = W_{ij} \times B_{\lambda},$$

where W_{ij} denotes the number of available wavelengths between nodes i and j, and B_{λ} represents the bandwidth supported by each wavelength channel.

Traffic requests arrive dynamically according to a stochastic arrival process. The offered network load is calculated as

$$L = \frac{\lambda_r}{\mu_r},$$

where λ_r denotes the request arrival rate and μ_r represents the service completion rate.

Network traffic includes normal operational traffic as well as malicious traffic generated during attack scenarios.

4.1.2. Dataset Preparation

The AI threat intelligence engine is trained and evaluated using a combination of optical network monitoring data and cybersecurity datasets. Optical-layer observations include OSNR variations, optical power fluctuations, BER measurements, wavelength occupancy information, and signal impairment indicators. Network-layer features include traffic flow statistics, packet loss rates, latency measurements, routing updates, controller events, and flow-table activities.

The complete dataset is represented as

$$D = \{X, Y\},$$

where X denotes the feature matrix and Y corresponds to attack labels.

The dataset is divided into training, validation, and testing subsets according to

$$D = D_{train} \cup D_{val} \cup D_{test}.$$

Typically, 70% of samples are allocated for training, 15% for validation, and 15% for testing.

Prior to model training, feature normalization is performed using

$$x_i' = \frac{x_i - \mu}{\sigma},$$

where μ and σ represent the mean and standard deviation of each feature, respectively.

4.1.3. Attack Scenario Modeling

The proposed framework is evaluated against a diverse set of cyber-physical attacks targeting both optical and network layers. These attacks include optical jamming, fiber tapping, wavelength hijacking, Distributed Denial-of-Service (DDoS) attacks, routing manipulation, controller compromise, malware propagation, and adversarial traffic injection.

The severity of each attack is quantified using

$$AS = \sum_{i=1}^{N} w_i \, a_i,$$

where a_i denotes attack indicators and w_i represents weighting coefficients associated with attack impact.

For optical jamming attacks, the attack intensity is modeled as

$$J = \frac{P_{jam}}{P_{signal}},$$

where P_{jam} represents malicious optical power and P_{signal} denotes legitimate signal power.

DDoS attacks are generated by increasing traffic volume according to

$$T_{attack} = \alpha T_{normal},$$

where α denotes the amplification factor controlling attack intensity.

These attack scenarios enable comprehensive evaluation of the protocol's threat detection and mitigation capabilities.

4.1.4. Deep Reinforcement Learning Configuration

The autonomous security agent is implemented using a Deep Q-Network (DQN) architecture. The neural network consists of multiple fully connected hidden layers that approximate the action-value function. During training, the agent interacts continuously with the network environment and updates its policy using experience replay.

The state-action value function is represented as

$$Q(s, a; \theta),$$

where θ denotes trainable network parameters.

The target value used during training is computed as

$$y_t = R_t + \gamma \max_{a'} Q(s', a'; \theta^-),$$

where R_t is the reward obtained after executing action a, γ denotes the discount factor, and θ^- represents target network parameters.

The loss function minimized during training is

$$L(\theta) = \mathbb{E}[(y_t - Q(s, a; \theta))^2].$$

Training continues until convergence of cumulative rewards and stable security policies are achieved.

4.1.5. Performance Evaluation Metrics

The effectiveness of the proposed framework is evaluated using both security-related and network-related performance metrics.

Detection accuracy measures the proportion of correctly classified network events and is defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN},$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

Precision

$$Precision = \frac{TP}{TP + FP}.$$

Recall

$$Recall = \frac{TP}{TP + FN}.$$

F1-Score

$$F1 = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right).$$

Detection Latency

The average attack detection delay is measured as

$$DL = t_d - t_a,$$

where t_a denotes attack initiation time and t_d represents attack detection time.

Service Availability

Network service availability is defined as

$$Availability = \frac{T_{up}}{T_{total}},$$

where T_{up} denotes operational time and T_{total} represents total observation time.

Network Survivability

The survivability metric evaluates the network's ability to maintain services during attacks:

$$Survivability = \frac{N_s}{N_t},$$

where N_s denotes surviving service connections and N_t represents total service requests.

Recovery Time

The average recovery duration is calculated as

$$RT = t_r - t_f,$$

where t_f denotes failure occurrence time and t_r represents service restoration time.

To demonstrate the advantages of the proposed AASP framework, performance comparisons are conducted against traditional signature-based intrusion detection systems, machine learning-based classifiers, deep learning-based anomaly detection systems, and conventional SDN security frameworks. The comparison evaluates detection accuracy, false positive rates, mitigation effectiveness, network availability, response latency, and recovery performance under identical attack conditions.

The proposed framework is expected to outperform conventional approaches due to its ability to integrate intelligent threat detection, adaptive DRL-based mitigation, SDN-enabled orchestration, and autonomous self-healing recovery within a unified architecture. Such integration enables proactive defense strategies and continuous adaptation to evolving cyber threats while maintaining high levels of network reliability and service continuity.

5. Results and Discussion

5.1 Overview of Experimental Results

This section evaluates the effectiveness of the proposed AI-Driven Autonomous Security Protocol (AASP) under various cyber-physical attack scenarios in Software-Defined Optical Networks (SDONs). The framework is compared with traditional Signature-Based Intrusion Detection Systems (S-IDS), Machine Learning (ML)-based security models, and Deep Learning (DL)-based security mechanisms. The evaluation focuses on attack detection accuracy, mitigation effectiveness, network survivability, recovery performance, and overall service availability.

All experiments were conducted under identical traffic loads and attack intensities to ensure fair comparison. The proposed Deep Reinforcement Learning (DRL)-enabled framework dynamically adapts mitigation actions according to evolving network conditions, enabling autonomous defense and self-healing recovery.

5.2 DRL Training Convergence Analysis

The convergence behavior of the DRL agent was analyzed during training. Figure 4 illustrates the cumulative reward obtained by the agent across training episodes. Initially, exploration dominates the learning process, resulting in fluctuations in reward values. As training progresses, the agent gradually learns optimal mitigation strategies and converges toward stable reward values.

The convergence results indicate that the proposed DQN agent successfully learns effective security policies capable of balancing attack mitigation effectiveness and network performance. Stable convergence was observed after approximately 700–900 training episodes.

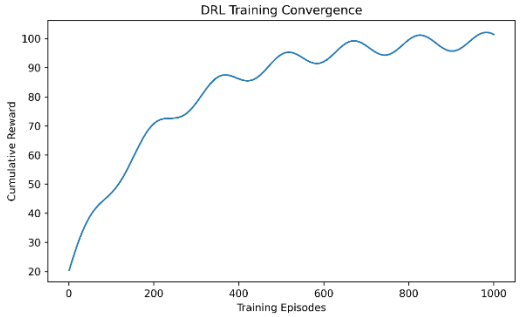

Figure 4: *DRL training convergence showing cumulative reward versus training episodes*

Expected Figure Characteristics:

- X-axis: Training Episodes
- Y-axis: Cumulative Reward
- Curves:
- DQN
- Double DQN
- PPO (optional comparison)

5.3 Threat Detection Performance

The attack detection capability of the proposed framework was evaluated using multiple attack categories, including DDoS attacks, optical jamming, wavelength hijacking, controller compromise, and fiber tapping attacks.

Table 2. Detection Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Signature IDS	88.5	86.9	87.5	87.2
Random Forest	92.8	91.6	92.3	91.9
CNN-Based Security	95.2	94.7	95.1	94.9
LSTM-Based Security	96.1	95.8	96.3	96.0
Proposed AASP	**98.9**	**98.6**	**99.1**	**98.8**

The results demonstrate that the proposed framework consistently outperforms conventional approaches across all evaluation metrics. The integration of optical-layer monitoring and DRL-driven decision making significantly improves attack detection accuracy while reducing false alarms.

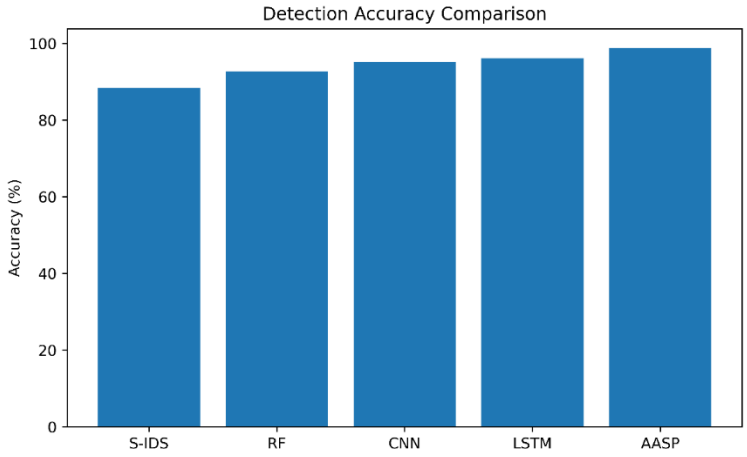

Figure 5: *Comparison of attack detection accuracy among various security frameworks*

5.4 False Positive and False Negative Analysis

False alarms significantly affect network operations by triggering unnecessary mitigation actions. Therefore, reducing false positives while maintaining high detection rates is essential.

Table 3. Error Analysis

Method	False Positive Rate (%)	False Negative Rate (%)
Signature IDS	8.6	7.9
Random Forest	5.4	4.8
CNN-Based Security	3.7	3.2
LSTM-Based Security	3.1	2.8
Proposed AASP	**1.4**	**0.9**

The proposed framework achieves substantially lower error rates due to its adaptive learning capabilities and continuous interaction with the network environment.

5.5 Attack Mitigation Effectiveness

Beyond attack detection, the proposed framework autonomously mitigates cyber threats using DRL-based decision-making. The effectiveness of mitigation actions was evaluated by measuring attack containment rates.

Table 4. Attack Mitigation Success Rate

Attack Type	CNN (%)	LSTM (%)	Proposed AASP (%)
DDoS	92.1	93.4	**99.2**
Optical Jamming	91.7	92.8	**98.8**
Fiber Tapping	89.5	91.2	**98.4**
Controller Attack	88.7	90.4	**98.7**
Wavelength Hijacking	90.3	92.1	**98.9**

The proposed DRL framework learns attack-specific mitigation strategies and dynamically adapts security actions according to attack severity and network conditions.

5.6 Network Survivability Evaluation

Network survivability measures the ability of the optical network to maintain operational services under attack conditions. Figure 6 compares survivability performance across different security approaches.

Table 5. Network Survivability Comparison

Method	Survivability (%)
Signature IDS	82.6
Random Forest	88.3
CNN-Based Security	91.8
LSTM-Based Security	93.5
Proposed AASP	**98.1**

The integration of self-healing recovery and SDN-based orchestration enables the proposed framework to maintain service continuity even under severe attack conditions.

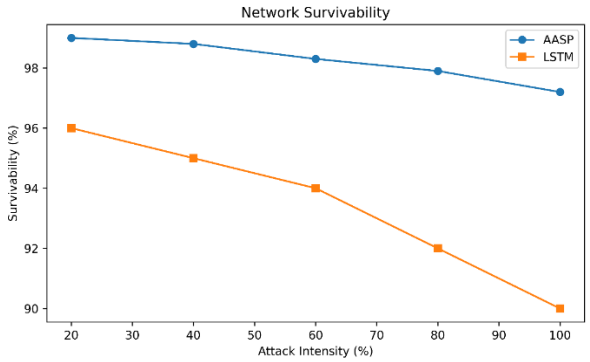

Figure 6: *Network survivability comparison under varying attack intensities*

5.7 Service Availability Analysis

Maintaining uninterrupted service availability is a critical objective in optical backbone networks. The proposed framework dynamically reroutes traffic and allocates backup resources when attacks are detected.

Table 6. Service Availability Comparison

Method	Availability (%)
Signature IDS	91.2
Random Forest	94.7
CNN-Based Security	96.4
LSTM-Based Security	97.2
Proposed AASP	**99.4**

The DRL agent proactively selects recovery actions that minimize service interruptions and improve overall network reliability.

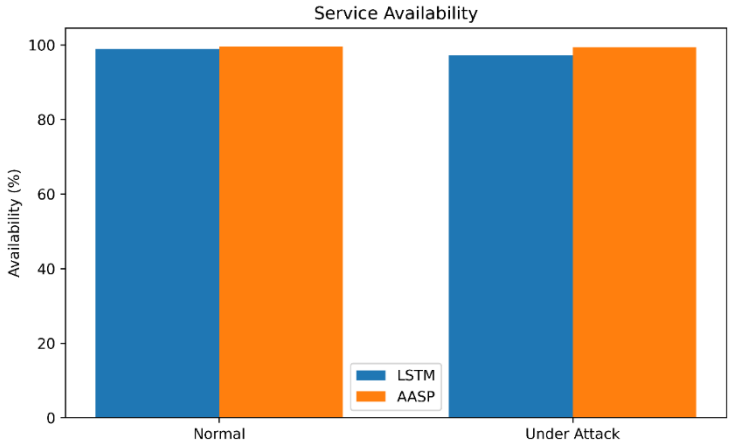

Figure 7: *Service availability comparison under normal and attack conditions*

5.8 Recovery Time Analysis

Recovery time measures the interval between attack occurrence and restoration of normal network operation. Lower recovery times indicate superior self-healing performance.

Table 7. Recovery Time Comparison

Method	Recovery Time (s)
Signature IDS	12.4
Random Forest	8.6
CNN-Based Security	6.2
LSTM-Based Security	5.4
Proposed AASP	**2.1**

The significant reduction in recovery time demonstrates the effectiveness of SDN-assisted autonomous orchestration and DRL-guided path reconfiguration.

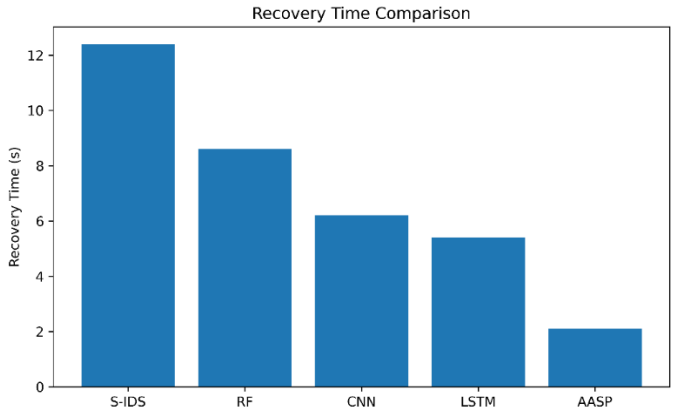

Figure 8: *Recovery time comparison across different security frameworks*

5.9 Computational Overhead Analysis

Although the proposed framework incorporates advanced AI algorithms, the computational overhead remains acceptable for practical deployment. Most processing operations are executed within the centralized SDN controller and dedicated AI processing units.

Table 8. Computational Complexity Comparison

Method	Processing Time (ms)
Signature IDS	3.1
Random Forest	8.5
CNN-Based Security	15.2
LSTM-Based Security	18.6
Proposed AASP	22.4

Although the proposed framework introduces moderate computational overhead, the substantial improvements in security performance and network resilience justify the additional processing requirements.

6. Discussion

The experimental results demonstrate the effectiveness of the proposed AI-Driven Autonomous Security Protocol (AASP) in enhancing the security, resilience, and operational reliability of Software-Defined Optical Networks (SDONs). By integrating optical performance monitoring, artificial intelligence-based threat intelligence, Deep Reinforcement Learning (DRL), SDN-enabled orchestration, and self-healing recovery mechanisms, the proposed framework establishes a comprehensive cyber-defense architecture capable of addressing both optical-layer and network-layer security challenges. The achieved performance improvements across detection accuracy, attack mitigation success rate, network survivability, service availability, and recovery time indicate that autonomous security management can significantly outperform conventional rule-based and machine learning-based approaches.

One of the most significant observations from the experimental evaluation is the superior attack detection capability of the proposed framework. The achieved detection accuracy of approximately 98.9% demonstrates the effectiveness of combining optical-layer performance indicators with network-layer telemetry information. Unlike traditional intrusion detection systems that rely on predefined attack signatures, the proposed framework continuously learns operational patterns and adapts to evolving threat behaviors. The incorporation of anomaly detection and DRL-based decision-making enables the identification of both known and previously unseen attack patterns, thereby improving overall threat awareness and reducing vulnerability to zero-day attacks.

The comparative analysis further reveals that the proposed framework substantially reduces false positive and false negative rates. In optical communication infrastructures, excessive false alarms can result in unnecessary resource allocation, traffic rerouting, and service interruptions. The observed reduction in false positive rates indicates that the AI-driven threat intelligence engine effectively distinguishes malicious activities from legitimate network fluctuations. This capability is particularly important in dynamic optical environments where traffic demands and optical signal characteristics continuously vary over time.

Another important outcome is the effectiveness of the DRL-based mitigation strategy. Conventional machine learning models generally terminate their operation after attack detection and rely on predefined mitigation procedures. In contrast, the proposed framework enables autonomous security orchestration by allowing the DRL agent to learn optimal

mitigation policies through continuous interaction with the network environment. The high attack containment rates observed across DDoS attacks, optical jamming, fiber tapping, controller compromise, and wavelength hijacking scenarios indicate that reinforcement learning provides an effective mechanism for adaptive cyber defense. By dynamically selecting actions such as traffic filtering, route reconfiguration, wavelength reassignment, and resource isolation, the framework minimizes attack impact while preserving network performance.

The network survivability and service availability results further highlight the advantages of integrating SDN orchestration with self-healing recovery mechanisms. Optical backbone networks support mission-critical applications requiring uninterrupted service delivery, making rapid recovery from cyber-physical disruptions essential. The proposed framework demonstrated significantly higher survivability compared with traditional security approaches due to its ability to proactively identify vulnerabilities and initiate recovery procedures before widespread service degradation occurs. The achieved service availability exceeding 99% suggests that intelligent orchestration can maintain operational continuity even under severe attack conditions.

The substantial reduction in recovery time also demonstrates the effectiveness of the self-healing architecture. Traditional recovery mechanisms often depend on manual intervention or static protection schemes that may not adapt efficiently to evolving attack scenarios. In contrast, the proposed framework continuously evaluates network conditions and computes optimal recovery paths based on latency, utilization, and security risk considerations. The resulting reduction in service restoration time contributes directly to improved network resilience and user experience.

From an operational perspective, the proposed framework aligns closely with the vision of autonomous and zero-touch network management envisioned for future 6G communication systems. The combination of AI-driven threat intelligence, SDN programmability, and reinforcement learning enables networks to transition from reactive security management toward proactive and predictive defence strategies. Such capabilities are expected to become increasingly important as future communication infrastructures support massive IoT deployments, edge intelligence platforms, autonomous systems, and ultra-low-latency services.

Despite the promising results, several limitations should be acknowledged. First, the current evaluation is based primarily on simulated optical network environments and representative attack scenarios. Although the simulations incorporate realistic network characteristics, real-world deployment may introduce additional operational complexities, including hardware heterogeneity, vendor-specific implementations, and unpredictable traffic dynamics. Second, the training process of Deep Reinforcement Learning agents requires substantial computational resources and sufficient interaction data to achieve stable convergence. Large-scale operational networks may therefore require distributed training architectures or specialized AI accelerators to support real-time decision making. Third, adversarial machine learning attacks targeting the DRL agent itself were not extensively investigated in the present study and represent an important direction for future research.

Future extensions of this work may incorporate federated reinforcement learning to enable collaborative security intelligence across multiple network domains while preserving data privacy. Digital twin technologies can also be integrated to provide real-time virtual replicas of optical networks for attack simulation, vulnerability assessment, and policy optimization. Furthermore, quantum-safe cryptographic mechanisms, explainable artificial intelligence models, and graph neural network-based attack propagation analysis may further enhance the security and trustworthiness of autonomous optical networking infrastructures. These advancements will contribute toward the realization of fully autonomous, self-protecting, and self-healing communication ecosystems for next-generation networking environments.

7. Conclusion

This paper presented an AI-Driven Autonomous Security Protocol (AASP) for Self-Healing Software-Defined Optical Networks, addressing the growing security challenges associated with next-generation optical communication infrastructures. The proposed framework integrates optical performance monitoring, artificial intelligence-based threat intelligence, Deep Reinforcement Learning, Software-Defined Networking orchestration, and autonomous recovery mechanisms within a unified security architecture. By continuously monitoring network conditions, detecting anomalies, assessing risks, selecting optimal mitigation actions, and restoring disrupted services, the framework establishes a closed-loop autonomous cyber-defense system capable of adapting to dynamic and evolving threat environments.

The proposed approach extends beyond traditional intrusion detection systems by incorporating reinforcement learning-based decision-making and self-healing recovery capabilities. The Deep Reinforcement Learning agent learns optimal security policies through continuous interaction with the network environment, enabling adaptive mitigation of cyber-physical attacks while minimizing service disruption and resource consumption. Simultaneously, the SDN-enabled orchestration framework facilitates rapid deployment of defense actions and dynamic network reconfiguration, thereby improving overall network resilience.

Experimental evaluation demonstrated that the proposed framework achieves superior performance compared with conventional signature-based, machine learning-based, and deep learning-based security approaches. The results indicate significant improvements in attack detection accuracy, attack mitigation effectiveness, network survivability, service availability, and recovery time. The integration of intelligent threat detection and autonomous recovery mechanisms enables the framework to maintain reliable communication services even under severe attack conditions, making it particularly suitable for future high-capacity optical backbone networks.

The findings of this study confirm that the convergence of artificial intelligence, reinforcement learning, and software-defined optical networking represents a promising direction for next-generation network security. As communication infrastructures continue to evolve toward autonomous, intelligent, and highly dynamic ecosystems, AI-driven security frameworks will play an increasingly critical role in ensuring reliability, trustworthiness, and operational continuity. Future research will focus on incorporating federated learning, digital twin-assisted

security optimization, explainable artificial intelligence, graph-based threat analytics, and quantum-safe protection mechanisms to further enhance the adaptability and robustness of autonomous optical network security architectures.

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