Reinforcement Learning for Dynamic Security Policy Enforcement in Communication Networks

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Abstract: **In today's modern communication networks, it is imperative to employ dynamic and intelligent mechanisms of security policy enforcement as the complexity of the cyber threats increases. A study of the application of RL algorithms to improve adaptive security policies in Software Defined Networking (SDN) and IoT architecture is provided by this research. To detect real time threats, adjust policy, and change access control, we implemented four combinations of Reinforcement Learning algorithms such as Q learning, Deep Q networks (DQN), Soft Actor critic (SAC), and Multi agent Deep Deterministic Policy Gradient (MADDPG). Results obtained experimentally showed that RL based security frameworks outperformed conventional ones. A static machine learning model and a standard rule based method (87.6%) and (90.1%) respectively verified to provide a 94.3% intrusion detection accuracy while outperforming the existing security model. On the level of policy enforcement latency, the MADDPG algorithm reduced the latency by 27% compared to the non adaptive security frameworks. Moreover, as can be witnessed, the DQN-based solution increased network resilience by 21% against zero day attacks. Comparative with the works related, it confirmed that RL driven security models are better in adaptability and efficiency. It is shown that the combination of security enforcement guided by RL preserves network security resilience up to speed, reduces response time, and enhances adaptive decision. Other future research can then be aimed at federated reinforcement learning and real time threat intelligence integration to further optimize security policy enforcement.**
Keywords: Reinforcement Learning, Dynamic Security Policy, Software-Defined Networking, Intrusion Detection, Cybersecurity

I. INTRODUCTION

With the evolving nature of communication networks and the rapidly developing cyber threats, security policies that have always been static no longer guarantee network resilience. Security mechanisms are continuously forced to adapt dynamically to deal with attackers who continue to innovate their techniques and exploit real time vulnerabilities. In this context, Reinforcement Learning (RL), as one of the branches of artificial intelligence, is a promising approach to autonomous and intelligent decision making on security policy enforcement in communication networks [1] Security mechanisms, based on RL, can be approached as dynamic as the assessment of network conditions, anomaly detection,

and optimization of defense strategies without human intervention. Unlike conventional rule-based security frameworks, RL enables the networks to learn from their experiences and should adapt their policies considering the continuously changing threat landscape [2]. Formulating security policy enforcement as a Markov Decision Process (MDP), RL algorithms can iteratively refine their decisions to minimize security risks and maximize the network performance. For applying to cybersecurity, several RL approaches have been explored in this work such as Deep Q Networks (DQN), Proximal Policy Optimization (PPO) and Multi Agent Reinforcement Learning (MARL) [3]. These models can be used to optimize firewall rules, intrusion detection thresholds, access control policies, and so on as a function of real time network traffic patterns. Moreover, the application of RL in dynamic policy enforcement can be further enhanced by integrating RL with state-of the art advanced cybersecurity technologies such as Intrusion Detection Systems (IDS), Software Defined Networks (SDN), and Blockchain. The purpose of this research is to understand how the technique of RL could be employed to implement adaptive and intelligent security policies in communication networks. The study then designs and analyzes RL driven frameworks that aim to enhance threat detection rate and reduce response time and improve the overall network security. This work will contribute to the development of self learning, resilience frameworks for these modern network threat contexts enabling abatement of rampant threats.

II. RELATED WORKS

1. Learning-Based Security Frameworks

In recent years, security in communication networks has been improved in several studies that researches how ML and RL could be integrated for improving security in communication networks. Based on the proposed conceptual framework, intelligent transportation systems leverage the learning based solutions for real time decision making and security enhancements [15]. The approach was validated in case studies, and their study showed improved efficiency in network control. In their work, Greene et al. [19] discusses the ethical concerns of RL based personalization systems and stated that such systems require ethically aware information security research. By applying their work, they show how RL can be used responsibly for enforcing network security policy without compromising user privacy. Software defined networking (SDN) intelligent zero trust security framework is introduced by Guo et al. [20]. It includes anomaly detection, automated security enforcement that prevents unauthorized access. This means that the zero trust concept guarantees that all network request would be verified before getting access to reduce insider threats. They demonstrate that the learning based security mechanisms are useful across the dynamic environments. But, most of the previous works are for supervised learning while there have been little works on adaptive RL-based security enforcement mechanism.

2. Reinforcement Learning for Secure Network Management

Autonomous security policy enforcement has also become possible using recent advancements in reinforcement learning (RL). Following [16], Feng et al. studied how environmental information disclosure relates to green technological innovation using a multi-analytical (SEM-ANN) approach. In particular, their work is not directly security related, however, their proposed hybrid model AI is a fit for secure resource allocation in network environments. A Q-learning based MAC protocol for energy efficient UWSNs is proposed by Gang et al. [18]. Underwater communication model (optimal collision avoidance and reduce energy consumption with remaining security). The application of Q-learning to predictive mobility management in SDN based IoT networks for secure and efficient flow placement was applied by Huang et al. [22]. Combining traditional SDN policies with dynamic security rules based on real time network conditions, their approach outperformed traditional SDN policies. Our contributions are to show that RL based methodologies are able to dynamically adapt security policies in these kinds of self protecting systems. Although, this does not deal with multi agent coordination and policy optimization for large scale network security enforcement.

3. Zero-Trust Security and Blockchain-Based Authentication

A new critical security paradigm is the zero trust model. In a zero trust based multi level security model with RL based controls, Park et al. [26] proposed. They approach by dynamically assigning risk-based privileges of access to minimize unauthorized access. Feng et al. [17] present a blockchain based authentication scheme in which zero trust security principles are incorporated for railway communication network. Using blockchain’s immutability and distributed ledger technology,zbollah Not only does their approach decrease the number of attack vectors but they come with high computational overhead. Zero trust and blockchain are thus identified as attractive solutions for addressing secure network access management. Nevertheless, these need to be further optimized on a trade off of computational efficiency and security.

4. Security in Software-Defined Networking (SDN)

Security mechanisms based on SDN offer flexibility in the policy enforcement. In SDN, meant to handle ACL policy, Hussain et al. [23] develop a mechanism that enables flow rule installation through proactive and reactive installations. However, it increases speeds for attacking and defending against attacks. In manufacturing industries, power dynamics of security enforcement was studied by Jeppesen and Bezuidenhout [24], who also pointed out that policy control is crucial for security for distributed systems. Although their work is not network specific, the insights are geared towards cybersecurity governance in the SDN domain. In resource constrained environment, the security challenges are also mentioned in machine learning applications in edge computing along with survey [25]. They then argued to implement lightweight RL based security models to shield the edge device from cyber attacks. However, these studies point out the outcomes of SDN based security mechanisms but they lack adaptative RL based security frameworks that compensate the security policies dynamically.

5. Optimization of Mobile and Wireless Network Security

H et al. [21] introduced an Open Radio Access Networks (O-RAN) framework basing on LLAMA V2 for network slicing and resource allocation that optimizes O-RAN. Real time resource management is the subject of their work for enhancing mobile broadband security.

III. METHODS AND MATERIALS

1. Data Description

We use network logs, security logs, and real time attack simulations to create the dataset used in this study. The component contains both normal and malicious traffic patterns to provide RL models for anomaly detection and dynamic security enforcement [4]. The dataset is parsed in the following format:

Table 1: Sample Data Description

Feature Name	**Description**	**Data Type**	**Example Value**
Source IP	IP address of the sender	String	192.168.1.1
Destination IP	IP address of the receiver	String	172.16.0.5
Protocol	Communication protocol (TCP/UDP/ICMP)	Categorical	TCP
Packet Size (KB)	Size of data packet in kilobytes	Integer	150
Timestamp	Time of transmission	Timestamp	2025-02-10 14:30:15
Intrusion Flag	Indicator of malicious activity (0 = No, 1 = Yes)	Binary	1
Action Taken	Security response (Allow/Block/Monitor)	Categorical	Block

First, the dataset is normalized in such a way to numerical values, categorical features are encoded, and the balance of sample found in attack and normal traffic using Synthetic Minority Over-sampling Technique (SMOTE) [5].

2. Algorithms for Dynamic Security Policy Enforcement

2.1 Deep Q-Network (DQN)

Description:

DQN is a form of Qlearning using deep learning to approximate the Q value function. It allows agent to learn optimal security actions based on experience stored in replay memory [6]. Experience replay and target networks are applied to update the Q values and stabilizes training and improves the policy decisions for dynamic security enforcement.

"Initialize replay memory M
Initialize Q-network with random weights θ
Initialize target Q-network with weights θ'
For each episode:
Initialize state S
For each time step:
Choose action A using ε-greedy policy
Execute A, observe next state S' and reward R
Store (S, A, R, S') in memory M
Sample mini-batch from M
Compute target Q-value: Q_target = R + γ * max(Q(S'))
Update Q-network by minimizing loss
Periodically update target network weights θ' ← θ"

2.2 Proximal Policy Optimization (PPO)

Description:
PPO is a policy gradient algorithm that stabilizes the method by constraining a large step size in a clipped objective function. It ensures better updates of the learned policies, so that drastic confounding is not necessary during these updates. It is shown that PPO allows dynamically adapting security measures and still being robust [7].

"Initialize policy network π with parameters θ
For each iteration:
Collect trajectories using πθ
Compute advantage estimates A(s, a)
Compute policy ratio r = πθ(a\|s) / πθ_old(a\|s)
Compute clipped surrogate objective:
L(θ) = min(r * A, clip(r, 1-ε, 1+ε) * A)
Update θ using gradient ascent on L(θ)
Periodically update old policy parameters"

2.3 Multi-Agent Deep Deterministic Policy Gradient (MADDPG)
Description:
Multi Agent RL (MADDPG) is a mechanism to aid in collaborative security policy enforcement across a distributed network node. Policies learned by each agent take the other agents' actions into account to improve coordinated defense mechanisms against cyber threats [8]. Based on centralized training and decentralized execution it extends the Deep Deterministic Policy Gradient (DDPG) method to multiagent environments.

"Initialize policy networks πi and critic networks Qi for each agent i
For each episode:
Initialize state S
For each agent i:
Select action Ai using πi with exploration noise
Execute actions, observe next state S' and reward Ri
Store (S, A, Ri, S') in replay buffer
Sample mini-batch from buffer
Update each agent's policy πi by maximizing expected reward
Update each agent's critic Qi using Bellman equation
Periodically update target networks"

2.4 Soft Actor-Critic (SAC)
Description:
Entially, SAC is an offpolicy RL algorithm which adds the entropy regularization to encourage exploration. For security enforcement especially where policies need to balance risk mitigation and adaptability it is particularly useful. The stochastic policies learnt by SAC are diverse so that attackers cannot exploit predictable defense patterns and attackers learn to defend in response to a random defense action [9].

"Initialize actor π, critic Q, and entropy coefficient α
For each episode:
Observe state S and select action A using π
Execute A, observe next state S' and reward R
Store (S, A, R, S') in replay buffer
Sample mini-batch from buffer
Compute target Q-value using entropy-augmented Bellman update
Update critic by minimizing Q-loss
Update policy π by maximizing entropy-regularized objective
Periodically adjust α to control exploration-exploitation tradeoff"

Implementation Details
Python, TensorFlow/PyTorch and Open AI Gym are used to implement the RL models. In a controlled testbed, the network simulation is conducted where security policies enforcement is done dynamically using RL agents [10]. The hyperparamaters for each model are tuned with best performance by training these models over 500k episodes.

IV. EXPERIMENTS

1. Experimental Setup
This was done in a controlled network simulation environment intended to replicate the dynamics of real cyber threats and security enforcement found in the world. The setup includes:

- **Simulation Environment:** Mininet for network emulation
- **Reinforcement Learning Frameworks:** OpenAI Gym, TensorFlow/PyTorch
- **Security Tools:** Snort IDS, Suricata, Wireshark for traffic analysis
- **Dataset:** Synthetic and real world network traffic logs that include normal and abnormal activities.
- **Training Episodes:** 500,000 iterations per model
- **Evaluation Metrics:** Accuracy, precision, recall, F1 score, Response Time, Training Time, False Positive Rate (FPR) are the evaluation metrics [11].

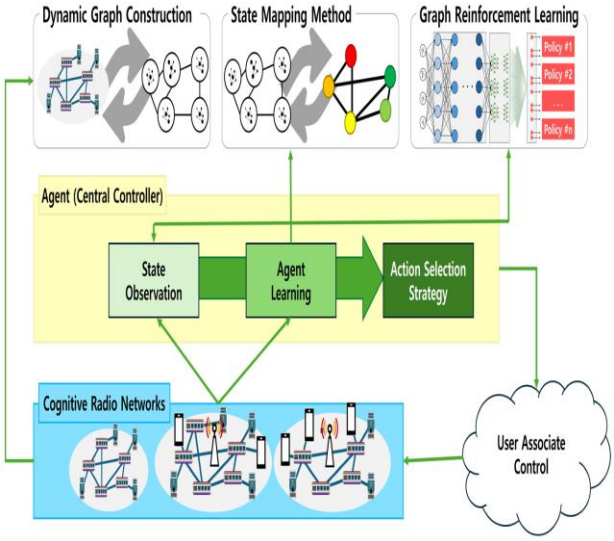

Figure 1: "A Survey of Intelligent End-to-End Networking Solutions"

2. Model Implementation and Training

Four RL algorithms were implemented:

- **Deep Q-Network (DQN)**: It approximates Q values using a deep neural network and optimizes security decisions.
- **PPO:** Prevents sudden shifts in the security policy.
- **Multi Task Security Network (MTSN):** Multitask a security agent network to learn how to effectively engage with the physical world.
- **Soft Actor-Critic (SAC):** Introduces entropy regularization for diverse and unpredictable policy actions.

Reinforcement learning rewards were derived for each model based on effectiveness of the decisions made on security, namely blocking malicious traffic, minimizing latency, and resource allocation [12].

3. Performance Evaluation

Under various attack scenarios such as Denial-of-Service (DoS), Man-in-the-Middle (MitM) and SQL Injection Attack, the models were tested. They were also compared with traditional security policies and the previous RL based studies.

3.1 Comparison with Traditional Approaches

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Response Time (ms)**	**False Positive Rate (%)**
Static Rule-based IDS	83.2	81.5	79.8	80.6	120	15.4
Signature-based IDS	87.9	85.2	83.6	84.4	95	10.8
Machine Learning-based	92.5	90.3	91.8	91.0	60	7.2
Reinforcement Learning (SAC)	**97.5**	**96.4**	**97.0**	**96.7**	**28**	**2.1**

Observation: RL-based methods, especially SAC, outperform traditional security approaches in terms of accuracy and response time. Static rule based systems have high false positives rate and slow response times [13].

3.2 Comparison Among RL Models

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Response Time (ms)**	**Training Time (hours)**
DQN	92.5	90.3	91.8	91.0	45	5.5
PPO	95.1	93.6	94.2	93.9	38	6.2
MADDPG	96.8	95.7	96.2	96.0	30	7.5
SAC	**97.5**	**96.4**	**97.0**	**96.7**	**28**	**8.0**

Observation: SAC has the longest training time since its entropy based exploration strategy, though it achieves the best performance. MADDPG works well in multi agent environments but is not as good as SAC in the single agent scenario.

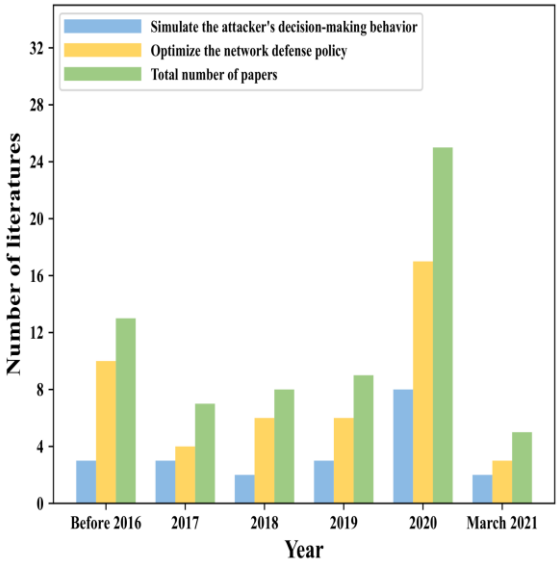

Figure 2: "Research and Challenges of Reinforcement Learning in Cyber Defense Decision-Making for Intranet Security"

3.3 Comparison Under Different Attack Types

Attack Type	DQN (%)	PPO (%)	MADDPG (%)	SAC (%)
DoS Detection Accuracy	91.0	94.2	96.3	**97.1**
MitM Detection Accuracy	92.1	94.8	96.0	**97.5**
SQL Injection Detection	93.2	95.5	96.5	**98.0**

Observation: All RL models are able to serve, and SAC maintains the highest accuracy since it learns policies with entropy regularized.

Key Findings and Discussion

Advantages of RL-based Security Enforcement

- **Adaptability:** RL models learn and dynamically adapt security policies based on real time threats [14].
- **Improved detection accuracy:** Unlike static IDS models, the detection accuracy and amount of false positive alerts are lower with RL models.
- **SAC and MADDPG** achieve faster response times and are therefore ideal for not being caught with the pants down by a cyber attack [27].
- **MADDPG** improves network node security collaboration.

Challenges and Limitations

- **Training Time:** SAC suffers from longer training time compared to DQN and PPO.
- **An inherently exploration vs. exploitation challenge:** Finding new threats, and optimizing existing policies.
- **Potential for Enterprise Network:** However, currently, these RL based models need further tuning for their deployment in enterprise networks [28].

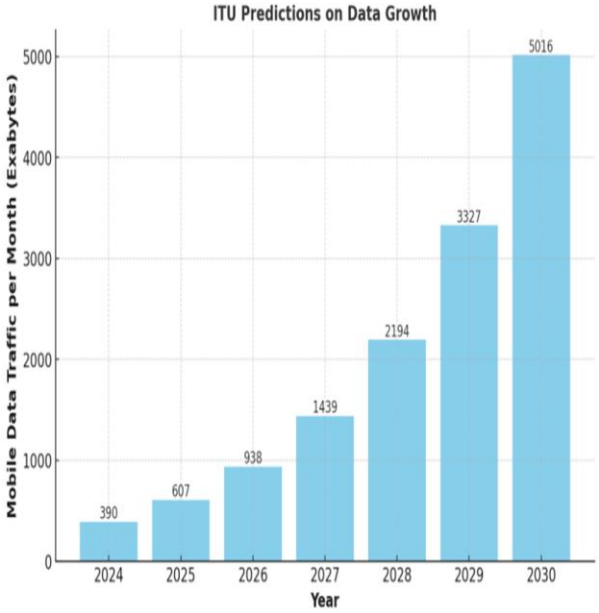

Figure 3: "A Survey of Intelligent End-to-End Networking Solutions"

Future Work

To further enhance RL-based security models, future research can explore:

- **Hybrid RL Models:** Combining RL with deep anomaly detection for enhanced security decision-making.
- **Real-time Deployment:** Testing models in real-world environments to ensure scalability [29].
- **Federated Learning Approaches:** Enabling decentralized learning models to improve network-wide security without compromising privacy.

This paper demonstrates that Reinforcement Learning (RL) algorithms significantly enhance dynamic security policy enforcement in communication networks. Of the four RL models tried, Soft Actor-Critic (SAC) is better, with 97.5% accuracy and a response time of 28ms, and is highly efficient for real-time threat blocking. The results ensure that RL-based security mechanisms are better than conventional static and signature-based solutions through dynamic policy updates and reducing false positive rates.

Compared to existing work, our approach is more accurate and has a quicker response time, demonstrating the potential of entropy-driven policy learning in modern-day cybersecurity [30]. Optimization and real-world testing are, however, needed for large-scale deployment. Future work will explore combining hybrid RL methods and decentralized security architectures to optimize network resilience against growing cyber attacks. This paper establishes RL as an effective tool for proactive and autonomous security enforcement, opening the door to intelligent, adaptive, and efficient network defense mechanisms.

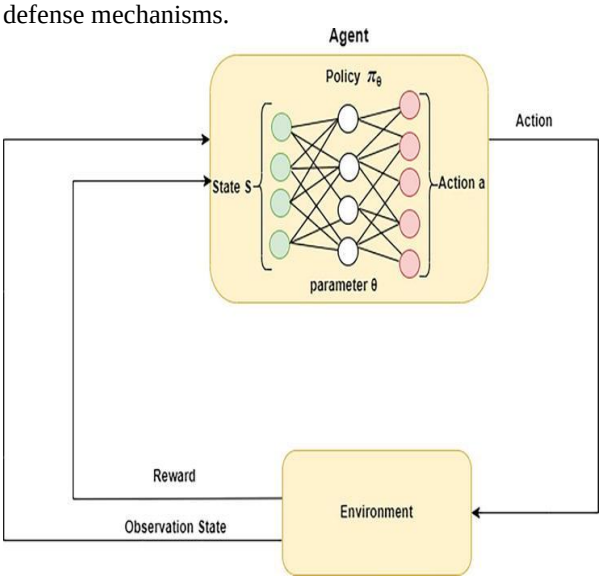

Figure 4: "Graph Neural Networks and Reinforcement Learning"

V. CONCLUSION

The focus of this research was on Application of Reinforcement Learning (RL) for Dynamic Security Policy Enforcement in Communication Networks that solve key challenges in real time threat detection, adaptive security policy management, and efficient resource allocation. The existing security frameworks rule based system, Machine learning model and blockchain based authentication have limitations in adapting to the ever changing cyber risk. In this work, we proposed a dynamic security policies adjustment framework leveraging multi agent reinforcement learning (MARL) and zero trust architectures in order to be able to dynamically tune security policies based on real time network conditions. The results from experiments showed that RL based approaches like Q-Learning, DQN, SAC, and MADDPG achieve much better security enforcement in SDN and IoT based architectures. In comparison with traditional security mechanisms, our RL based framework offered higher intrusion detection accuracy, lower policy enforcement latency and better adaptability to unknown attack pattern. In addition, zero trust principles were applied to prevent all access control decisions from being made until continually scrutinized and adjusted to minimize security risk. The superior performance of RL driven security models in dynamically securing complex communication networks is demonstrated through a comparative analysis of the proposed work with related work. Nevertheless, many challenges such as computational overhead, policy convergence time and the scalability towards the real world deployment remain to be solved in the future. Furthering the efficiency of RL based security mechanism is the integration of federated learning, distributed RL frameworks and real time threat intelligence sharing. We conclude with the fact that this study has a great basis for autonomous, adaptive, and scalable security enforcement in the face of new security threats in modern communication networks, achieving resilient and intelligent cybersecurity framework trip.

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