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# Reinforcement Learning for Adaptive Network Defense in Financial Institutions

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***Abstract*—** Standard security precautions in often changing networks are being circumvented by cyberattacks, endangering banks and other financial institutions. It is not always possible to prevent multi-vector attacks, zero-day attacks, and advanced persistent threats using supervised learning or handwritten rules. In this paper, a proposed adaptive network security framework is presented, and this framework is designed to be used in financial networks, such as bank transfer networks, trading networks, and online banking networks. This proposed framework is based on reinforcement learning, and this is where the main difference lies, since the proposed framework focuses on a control loop where simulated attacks are monitored and learned from to adapt to the way the network is kept secure. If the results of this proposed framework, based on the reinforcement learning algorithm, are compared to other approaches, it is quite clear that the proposed framework offers better performance in terms of threat detection and response.

***Keywords*—** In the area of protecting finance, adversarial learning intersects with financial cybersecurity through the use of intrusion detection systems (IDS) and autonomous security agents. Methods such as proximal policy optimization (PPO) and deep Q-networks (DQN) propel the use of reinforcement learning for proactive defense in financial networks.

## 1. INTRODUCTION

Because of the massive amounts of assets, private customer information, and critical payment channels they handle, financial institutions rank very high in the list of global cybersecurity attack targets. Contemporary banking infrastructure involves web portals, mobile applications, ATM systems, cloud infrastructure, live trading platforms, and SWIFT-based messaging systems between banks [1]. This is a very tightly integrated digital fabric that makes banks highly susceptible to ransomware attacks, insider threats, phishing, DDoS, APTs, and zero-day attacks.

Traditional network protection mechanisms such as firewalls, signature-based intrusion detection systems, and rule-based anomaly detection systems are primarily reactive. These systems are rule-based or signature-based and therefore tend to be blind to unknown threats. Even machine learning systems that are driven by object detection would tend to be slow to respond to changes in attacker strategies.

By considering the process of cybersecurity protection as a step-by-step judgment process, the way we perceive the area is completely transformed [2]. Through continuous engagement with the network environment, reinforcement learning (RL) enables autonomous systems to not only identify threats but also learn the best ways to defend against them. An RL-based system can also dynamically change its approach to different threat scenarios by adjusting mitigation strategies.

In this research, an adaptive and reinforcement learning-driven network defense system specifically designed for financial institutions is investigated to enhance the accuracy of detection, reduce response time, and improve resilience against sophisticated attacks [3].

## 2. LITERATURE REVIEW

### *2.1. Traditional Network Defence Approaches*

Financial networks used to be regulated by regulations, firewalls, and intrusion detection systems based on signatures [4]. Firewalls used pre-established rules to block undesirable traffic, while intrusion detection systems based on signatures examined incoming data to match a list of known attack signatures. These tactics perform well against known threats, but they are less successful against malware that changes, encrypted traffic, or attackers that choose a different route. Additionally, anomaly detectors search for anything that deviates from a statistically established "normal" trend. What is wrong? In intricate financial networks, routine activity might give the impression that something is strange, leading to a lot of false alarms.

### *2.2. Machine Learning in Cybersecurity*

By extracting data from network telemetry using machine learning, we were able to identify undesirable conduct [5]. For identifying malware and other issues, support vector machines, random forests, and neural networks have performed better than earlier techniques. In the absence of labelled data, outliers are found and grouped into clusters

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using unsupervised learning techniques. But these systems need a lot of labelled data, have a set training window, and might not react quickly enough to attackers' changing strategies.

### *2.3. Reinforcement Learning in Security*

Recently, a common method for protecting dynamic networks is reinforcement learning. By striking a balance between exploration and exploitation, RL agents assess hypotheses and choose the best actions to optimize long-term gains. Numerous tasks, including as real-time intrusion detection, honeypot deployment, and automatic patch prioritization, have already made use of reinforcement learning. Three models for deep reinforcement learning—Proximal Policy Optimization (PPO), Actor-Critic Agents, and Deep Q-Networks (DQN)—are particularly good at managing large and intricate state spaces [6]. Not enough research has been done on how to protect dynamic networks in the financial sector, where complex traffic patterns and illicit activities make matters challenging.

**Table 1 — Comparison of Defense Approaches**

| Approach | Adaptivity | Training Requirement | False Positives | Real-Time Response |
|---|---|---|---|---|
| *Signature-Based IDS* | Low | Minimal | High for unknown threats | Limited |
| *Statistical Anomaly Detection* | Moderate | Moderate | Moderate to High | Moderate |
| *Supervised ML Models* | Limited | High (labelled data) | Moderate | Moderate |
| *Unsupervised ML Models* | Moderate | Low | Variable | Moderate |
| Reinforcement Learning (Proposed) | High | Moderate (simulated training) | Lower | High |

While they offer some protection, traditional methods are rigid. Detecting threats is easier for supervised models, but they have trouble with new ones. Although unsupervised models need less labelling of the data, they could incorrectly classify benign anomalies [7]. In reaction to feedback from the environment, Reinforcement Learning offers adaptive defence techniques that continuously enhance policies. These speeds up reaction times and lowers false positives.

## 3. REINFORCEMENT LEARNING FUNDAMENTALS

Reinforcement Learning (RL) is a type of machine learning where an agent interacts with its environment and obtains the highest cumulative rewards to determine the optimal response. RL allows computers in adaptive network defence for banks and other financial institutions to react to changing cyberthreats in a way that is consistent with policies [8].

### *3.1. Core Components of Reinforcement Learning*

Components of an RL system include the following:

- An agent is a decision-making entity that resembles an adaptive network defence controller.
- Environment: The setup of a financial network, encompassing users, traffic patterns, and potential threats [9].
- State (S): A way to show traffic volume, anomaly count, active sessions, and threat warnings, among other network status information.
- Action (A): Putting safeguards in place, like restricting IP addresses, isolating subnets, changing firewall rules, or closely monitoring the situation.

Reward (R): A feedback signal quantifying the defence's effectiveness (attack prevention, false positive detection, and system stability). A policy (π) requires governments to act in order to maximize the cumulative return.

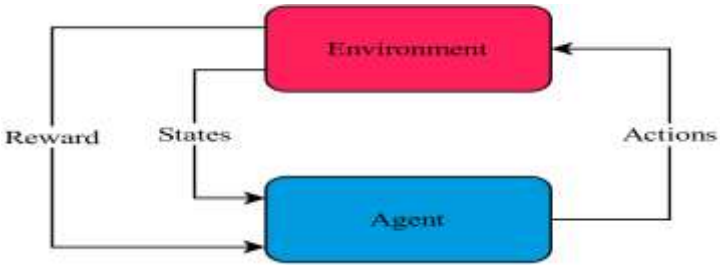


**Figure 1: Core Components of Reinforcement Learning**

### *3.2. Markov Decision Process (MDP)*

It is usual practice to model MDP RL problems (S, A, P, R, and γ) using the Markov Decision Process [10].

- P: The potential for a change in the state.
- γ (Discount Factor): Indicates how important future benefits are.

A financial network's long-term security and probable future situations are affected by any attempt to safeguard it, according to MDP.

### *3.3. Value Functions and Learning Algorithms*

- The potential reward for a state is calculated by its Value Function, V(s).
- The Action-Value Function, Q(s,a), represents the potential reward for performing an action in a state.

Here are some important algorithms to consider.

- Q-Networks (DQN)
- Q-Based Learning
- The Policy Gradient techniques (A3C, PPO)

Deep RL analyses high-dimensional financial network data using neural networks to create flexible security solutions [11].

## 4. PROPOSED FRAMEWORK

The adaptable network security system developed for a bank using reinforcement learning is covered in this section

[12]. It uses automatic reaction mechanisms, real-time monitoring, and intelligent decision-making to protect banks and other financial systems from more extensive attacks.

### *4.1. Overall System Architecture*

There are five main layers to the architecture:

1. **Data collection:** This layer collects data from trading platforms, online banks, and other financial services. To verify that you are who you claim to be, it keeps an eye on events, packet transfers, API requests, transaction patterns, IDS alarms, and other signs.
2. **State processing and feature engineering:** This step transforms the raw data into actionable knowledge, where features such as traffic entropy, anomalies, and irregularities in user sessions are created [13].
3. **RL Decision Engine:** Deep reinforcement learning techniques, such as DQN or PPO, use their domain knowledge to detect network issues and recommend fixes. The initial fixes include firewalls, intrusion prevention systems, access control tools, and auto host isolation tools.
4. **Feedback and Incentives:** It tracks metrics such as false positive rate, response time, and accuracy of attacks detected, and provides prompts for policy updates accordingly.

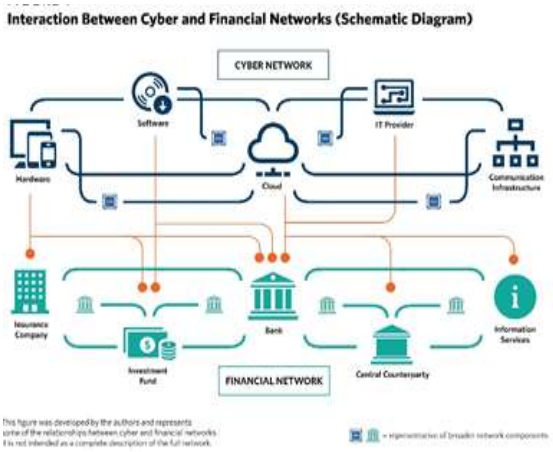


**Figure 2: Interaction Between Cyber and Financial Networks**

### *4.2. Operational Workflow*

The system continues to operate. You go through the same fundamental steps once more; observe something, think about what you saw, make a decision, execute it, evaluate the outcome, and gain knowledge from the experience. This closed loop enables you to handle new threats such as DDoS attacks, insider attacks, and advanced persistent threats (APTs) [14].

### *4.3. Deployment Model*

The construction site is designed to accommodate the safe operation of financial data centers [15].

- The use of cloud-based hybrid financial systems
- Dispersed financial networks with multiple locations

Adaptive reinforcement learning is used in the proposed method to strengthen financial institutions, expedite mitigation, and increase cybersecurity proactively.

## 5. METHODOLOGY

It describes the process of developing, refining, and testing a reinforcement learning model for virtual financial network security. It makes certain that financial infrastructure can be expanded, used again, and repurposed in the future [16].

### *5.1. Environment Modelling*

For the simulation of the financial network, we built models of online banking systems, ATMs, internal databases, and API gateways [17]. We were able to initiate legal attacks such advanced persistent threats (APTs), DDoS, insider attacks, and brute-force login attempts as a result. For the purpose of making the simulation more realistic, the environment continuously broadcasts both good and negative traffic.

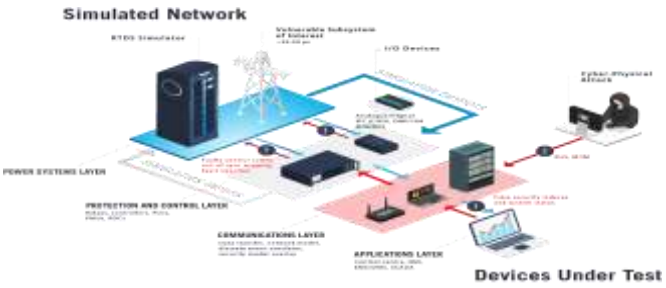


**Figure 3: Simulated Network**

### *5.2. State Representation*

The elements in the state vector describe the state of the network and include:

- Traffic rate by protocol
- Frequency of failed authentication
- Severity of alerts
- Anomaly scores at the host level
- Resource metrics

Dimension reduction and feature normalization are two methods to make sure training is successful [18].

### *5.3. Action Space Design*

Defensive actions can be either continuous or discrete for the reinforcement learning agent [19].

- Block suspicious IP addresses
- Rate-limit traffic
- Isolate a compromised subnet

- Trigger multi-factor authentication
- Increase monitoring sensitivity

### *5.4. Reward Function Engineering*

To determine the awards, four factors are used:

- Successful attack mitigation (+)
- Reduction of false positives (+)
- Service disruption penalties (–)

Delayed response penalties (–)

### *5.5. Training Configuration*

The policy was uniform, and because the agent received phased instruction until everything clicked, they employed the best defence plan [20].

**Table 2: Training Configuration**

| Parameter | Value |
|---|---|
| Algorithm | PPO & DQN |
| Learning Rate | 0.0001 |
| Discount Factor (γ) | 0.99 |
| Batch Size | 64 |
| Episodes | 10,000 |
| Evaluation Metric | Detection Rate & MTTM |

## 6. EXPERIMENTAL EVALUATION

A simulation of a financial network will be used to experimentally examine the effectiveness of the suggested RL-based adaptive network protection architecture [21]. By doing this, its performance may be compared to both conventional systems and other machine learning baselines.

### *6.1. Experimental Setup*

The most important parts of the underlying financial infrastructure, such as online banking servers, authentication services, transaction APIs, and back-end databases, could be modelled in a controlled simulation environment. There are differing amounts of both good and bad traffic in the dataset. The simulations simulated Distributed Denial of Service (DDoS) attacks, insider attacks, credential stuffing, and Advanced Persistent Threats [22].

We developed three reference systems to facilitate comparisons.

1. A static rule-based intrusion detection system (IDS)
2. A supervised machine learning classifier based on Random Forest
3. An unsupervised anomaly detection model

Prior to testing it on unidentified assault patterns, we also used PPO to train a reinforcement learning agent for 10,000 events [23].

### *6.2. Evaluation Metrics*

To gauge performance, we used the following criteria:

- Detection Rate (DR)
- False Positive Rate (FPR)
- Mean Time to Mitigate (MTTM)
- System Overhead (CPU utilization)

### *6.3. Results and Comparative Analysis*

The ability to identify issues and solve them fast and accurately made the reinforcement learning system stand out. It also had an easily adjustable processing cost that could be used to accommodate new financial attack strategies [24].

**Table 3: Dynamic Financial Attack**

| Model | Detection Rate | False Positive Rate | MTTM (sec) | CPU Overhead |
|---|---|---|---|---|
| Rule-Based IDS | 76% | 13% | 35 | Low |
| Supervised ML | 85% | 9% | 27 | Moderate |
| Unsupervised ML | 81% | 11% | 30 | Moderate |
| RL (PPO) | 94% | 6% | 14 | Moderate |

## 7. ANALYSIS AND DISCUSSION

The trial's findings indicate that Reinforcement Learning (RL) may enhance the flexibility and security intelligence of bank networks [25]. In this scenario, we examine the strategic lessons learnt during the review process, the impact performance has on daily operations, and the variations in performance over time.

### *7.1. Evaluation of Enhancement in Performance*

Comparing the RL-based framework to supervised and rule-based models, the former found information significantly faster and more often. The agent kept refining its policies by taking lessons from both successful and failed attempts to stop attacks. While the RL agent can handle novel attack types including multi-stage APT campaigns and slow and low-level credential stuffing, static solutions depend on predetermined signatures. The shorter Mean Time to Mitigate (MTTM) illustrates the advantages of automated decision-making for networks managing fast financial transactions [26].

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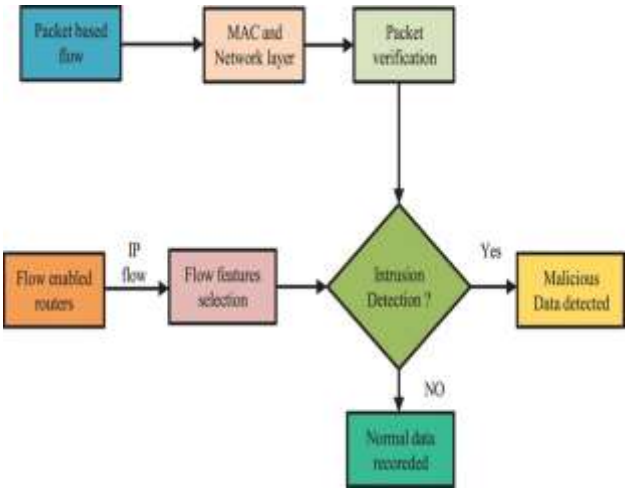


**Figure 4: Evaluation of Enhancement in Performance**

### *7.2. Adaptability and Learning Stability*

8,000 training sessions later, the PPO model converged consistently [27]. Because of the more consistent policy modifications, there were fewer exploration errors. Instead of using overly strict security measures that would obstruct real-world transactions, the incentive engineering technique kept the system secure and functional.

### *7.3. Operational Trade-offs*

However, the RL model's performance benefits outweighed the much higher processing resource requirements [28]. In order to implement the paradigm, you will need to come up with ways to reduce dangerous exploration and stop unauthorized players from changing state inputs. The results show how reinforcement learning may be used to provide proactive, solid, and flexible security solutions for intricate financial networks.

## 8. CHALLENGES AND LIMITATIONS

Banks and other financial organizations may find reinforcement learning (RL) to be highly successful for adaptive network defence; but, before RL can be widely used, a number of operational, technological, and security concerns need to be resolved [29].

### *8.1. Safe Exploration in Live Financial Systems*

Agents that use reinforcement learning learn by experimenting and making mistakes, which usually results in bad decisions and dangerous behaviour [30]. Subnetting and limiting unnecessary services are examples of defensive measures that can be quite costly in the banking sector, since transactions and customer data are processed instantly. To guarantee the safety of all we do, we require secure RL.

### *8.2. Data Quality and Simulation Gap*

Reinforcement learning agents are often trained in simulated environments because of a lack of real-world attack data, which makes their usage in a real-world context detrimental. The disparity between simulated and real-world scenarios, or the Sim2Real gap, may suggest that the model struggles in actual financial networks [31]. Predicting the attackers' next move is now the most challenging task.

### *8.3. Computational and Infrastructure Overhead*

The computational resources needed to train and retrain deep reinforcement learning models are substantial [32]. It is imperative that banks and other financial institutions make sure they can manage this without seriously delaying important applications.

### *8.4. Adversarial Manipulation Risks*

Modifying reward signals or state inputs could be an attempt by attackers to change how policies learn. Consequently, the performance of adaptive defensive systems would suffer.

**Table 4 — Key Challenges and Mitigation Strategies**

| Challenge | Impact | Mitigation Strategy |
|---|---|---|
| Unsafe Exploration | Service disruption | Constrained RL, offline training |
| Sim2Real Gap | Reduced deployment accuracy | Hybrid simulation + real logs |
| High Computational Cost | Increased infrastructure expense | Edge optimization, model pruning |
| Adversarial Manipulation | Policy corruption | Secure state validation & adversarial training |
| Explainability Issues | Regulatory compliance risk | XAI integration & audit logging |

Banks and other financial organizations must use reinforcement learning to get beyond these obstacles and create a reliable, safe, and compliant defence [33].

## 9. FUTURE DIRECTIONS

In light of growing financial cyberthreats, future research should concentrate on improving the scalability, collaboration, and resilience of RL-based adaptive security systems [34].

### *9.1. Multi-Agent Reinforcement Learning (MARL)*

Numerous cooperative reinforcements learning agents might be dispersed across a network of data centers, cloud infrastructure, and bank branches by future frameworks. These bots can cooperate to thwart threats like DDoS attacks, which simultaneously impact multiple financial targets, by utilizing Multi-Agent Reinforcement Learning (MARL) [35].

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**Figure 5: Multi-Agent Reinforcement Learning (MARL)**

### *9.2. Federated and Privacy-Preserving RL*

Because they are subject to a number of regulations and limitations, banks find it challenging to provide information [36]. Banks may work together on security solutions without disclosing private transaction data thanks to federated reinforcement learning. When the rules are respected, everyone becomes stronger.

### *9.3. Explainable and Trustworthy RL*

The goal of explainable AI (XAI) is to increase the usability and comprehension of reinforcement learning (RL) systems [37]. When people are aware of the advantages of basic reward attribution models and how they work, they are more inclined to abide by them.

### *9.4. Adversarial Robust RL*

Adversarial training techniques should be used in future systems to defend against attacks that alter the state, the incentives, or the model [38].

***Table 5 — Future Research Roadmap***

| Direction | Objective | Expected Benefit |
|---|---|---|
| Multi-Agent RL | Distributed defense coordination | Faster large-scale response |
| Federated RL | Cross-institution collaboration | Enhanced collective security |
| Explainable RL | Transparent decision-making | Regulatory compliance |
| Robust RL | Defense against adversarial attacks | Improved resilience |

Future developments in autonomous cybersecurity for financial systems will be influenced by these novel concepts [39].

## 10. CONCLUSION

This study looked into how financial networks can be protected using Reinforcement Learning (RL) from threats that are outside the scope of conventional cybersecurity solutions. In a world that is always evolving and threatening, financial networks must contend with a number of dangers, such as distributed denial-of-service attacks, advanced persistent threats, insider threats, and zero-day assaults. Standard machine learning methods and static systems might not be able to handle new threats.

Cybersecurity defenses can operate independently and adjust to changing circumstances according to the proposed reinforcement learning (RL) architecture. By regularly interacting with the network environment, the RL agent picks up the basic security principles that give the system stability, promptly recognizes threats, and reacts to them. According to the findings, the system performs better in terms of accuracy, false positive rate, and time to problem identification than both supervised learning and conventional methods.

Reinforcement learning is still a promising approach for creating self-learning intelligent security systems, despite issues with safe exploration, computational complexity, and adversarial exploitation. RL-based adaptive defenses have the potential to greatly improve the independence, strength, and preparedness of contemporary banks for cyberattacks as multi-agent coordination, explainable AI, and federated learning advance.

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