*International Journal of Basic and Applied Sciences*, 14 (6) (2025) 139-151

**International Journal of Basic and Applied Sciences**

*Website: www.sciencepubco.com/index.php/IJBAS*
*https://doi.org/10.14419/qvspkq08*
***Research paper***

# DDoS Amplification Attack Mitigation in 5G/6G Networks: A Taxonomy, Evaluation, and Defense Framework

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*Received: August 27, 2025, Accepted: October 1, 2025, Published: October 8, 2025*

**Abstract**

The evolution of 5G and emerging 6G networks has introduced unprecedented opportunities for connectivity, but also expanded the attack surface for Distributed Denial of Service (DDoS) amplification attacks. Service-Based Architecture (SBA), network slicing, and massive IoT (mMTC) environments create new vectors for reflection and amplification, making conventional defenses inadequate. This paper proposes a novel layered defense framework that integrates edge filtering, AI-driven anomaly detection, slice isolation, cloud scrubbing, and quantum-safe cryptography to mitigate DDoS amplification attacks in 5G/6G environments.

The framework is theoretically modeled through equations for amplification, mitigation efficiency, resilience, and defense cost, and evaluated experimentally using simulated signaling floods, IoT-driven amplification, slice-targeted floods, and hybrid attacks. Performance was measured using detection rate, false alarm rate, service availability, resilience score, and resource overhead. Two algorithms—pseudonymous authentication with zero-knowledge proof (ZKP) and layered mitigation orchestration—were implemented to operationalize the defense strategy.

The results demonstrate that the proposed framework achieves a detection accuracy of 95–97%, reduces false positives to 2%, and maintains a service availability of over 85% under prolonged amplification attacks. It scales efficiently in scenarios with up to 10,000 simulated IoT devices, retaining 70–80% throughput, and maintains URLLC latency below 10 ms, outperforming baseline defenses (firewalls, scrubbing, and AI-only) and state-of-the-art defenses from the literature. These findings validate the framework as a scalable, efficient, and future-ready solution for mitigating amplification attacks in 5G/6G networks, with strong alignment with 3GPP, GSMA, and NIST post-quantum standards.

***Keywords***: *5G Security; 6G Networks; DDoS Amplification Attacks; Network Slicing; Anomaly Detection; Mitigation Framework; Post-Quantum Cryptography.*

## 1. Introduction

The rapid evolution of wireless communication from 4G to 5G has enabled significant improvements in bandwidth, latency, and reliability, ushering in new paradigms such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC). These advancements have paved the way for innovative applications, including autonomous driving, smart healthcare, industrial IoT, and immersive extended reality (XR). However, the same innovations have also expanded the attack surface of mobile networks, exposing them to increasingly sophisticated cyber threats [1], [2]. Among these threats, Distributed Denial-of-Service (DDoS) attacks remain one of the most disruptive to network availability. Within this class, amplification-based DDoS attacks are particularly concerning due to their ability to leverage legitimate services and protocols to magnify attack traffic toward victims [3].

In 5G networks, the adoption of a cloud-native Service-Based Architecture (SBA) and the virtualization of network functions have introduced greater flexibility and scalability, but also created new vulnerabilities. The reliance on HTTP/2 signaling among core functions such as AMF, SMF, and UPF increases the risk of signaling amplification, where adversaries can generate a small number of malicious requests that exhaust critical control plane resources [4]. At the same time, the integration of billions of IoT devices through mMTC services amplifies the threat landscape, as compromised IoT nodes can be conscripted into large-scale botnets, exploited as reflectors and multipliers of attack traffic [5].

Looking forward, 6G networks are expected to incorporate terahertz (THz) communication, reconfigurable intelligent surfaces (RIS), non-terrestrial networks (NTNs), and AI-native orchestration [6], [7]. While these innovations promise unprecedented performance, coverage, and adaptability, they also introduce new risks. For instance, RIS-assisted massive MIMO could inadvertently increase amplification vectors, NTN-satellite integration may expose space-ground interfaces to DDoS reflection, and AI-native control could itself become a target of adversarial exploitation. Unlike traditional volumetric floods, amplification in 5G/6G is likely to be multi-dimensional, combining signaling exploitation, slice abuse, and AI-enabled automation—rendering legacy defenses inadequate [8].

Existing defenses—such as rate limiting, static firewalls, and cloud scrubbing centers—were effective in earlier generations but face limitations in dynamic, distributed, and slice-aware 5G/6G environments [9]. For example, network slicing, while enabling service

differentiation, may also be exploited for targeted amplification attacks that disrupt specific slices such as URLLC or emergency communication services [10]. Similarly, traditional filtering lacks the intelligence to counter AI-powered attack generation, while cloud scrubbing often introduces unacceptable delays for latency-sensitive services [11].

Recent research has begun to explore multi-layered defenses, combining programmable SDN/NFV firewalls, AI-based anomaly detection, slice isolation, and hybrid edge-cloud strategies [12]. In addition, with the looming risk of quantum computing undermining cryptographic primitives, the integration of post-quantum cryptography (PQC) into security architectures is becoming essential [13]. However, most existing proposals address only parts of the problem—focusing either on detection, resilience, or cryptographic security—without delivering a holistic framework that integrates all dimensions of detection, mitigation, resilience, scalability, and future-proofing.

This research addresses this critical gap by:

1) Providing a taxonomy of amplification-based DDoS threats in 5G and emerging 6G networks.
2) Evaluating the effectiveness of baseline and state-of-the-art mitigation strategies across key performance metrics, including detection accuracy, false alarms, availability, and overhead.
3) Proposing a layered defense framework that integrates edge filtering, AI anomaly detection, slice isolation, cloud scrubbing, and quantum-safe cryptography to achieve resilient, scalable, and standards-compliant protection.

By bridging the gap between theoretical risk assessment and practical mitigation design, this study contributes to the development of robust, adaptive, and future-proof security architectures for next-generation mobile networks.

## 2. Literature Review

The evolution from 4G/LTE to 5G and the anticipated rollout of 6G have introduced transformative improvements in performance, scalability, and service diversity. Yet, these innovations also expose mobile networks to a new wave of security threats. Distributed Denial-of-Service (DDoS) amplification attacks, where adversaries exploit legitimate protocols and services to multiply malicious traffic, represent one of the most severe risks to availability. This section reviews the state of the art on DDoS amplification in mobile networks, organized into legacy, 5G, and 6G perspectives, followed by an analysis of mitigation strategies, comparative evaluation, and identification of key research gaps.

### 2.1. DDoS amplification in legacy networks

In legacy 4G/LTE networks, DDoS attacks primarily targeted the control plane by exploiting signaling vulnerabilities in Mobility Management Entities (MMEs) and Home Subscriber Servers (HSSs). Amplification often stemmed from signaling storms triggered by botnets or malicious applications [14]. While traditional defenses such as firewalls, intrusion detection systems (IDS), and rate limiting provided partial mitigation, they lacked adaptability and scalability under dynamic, large-scale floods [15]. These limitations foreshadowed the vulnerabilities that 5G and 6G architectures would inherit and amplify.

### 2.2. DDoS in 5G networks

The transition to 5G introduced a Service-Based Architecture (SBA), where network functions (NFs) communicate via HTTP/2-based APIs. This flexibility enhances interoperability but also opens new avenues for signaling amplification, as attackers can exploit SBA messages to flood control-plane resources [16]. Studies have shown that botnet-driven amplification attacks against the User Plane Function (UPF) can degrade availability by more than 40% under stress-test scenarios [17].

The massive proliferation of IoT devices in mMTC environments compounds the problem. With billions of devices connected, compromised IoT nodes can act as reflectors, fueling botnet-driven reflection and amplification [18]. Recent reports from ENISA (2023) highlight that IoT-related DDoS incidents remain among the fastest-growing categories of cyberattacks against mobile operators [19].

Furthermore, network slicing, a key 5G innovation, creates new risks: adversaries can overwhelm a single slice (e.g., URLLC), indirectly compromising critical services such as autonomous vehicles or emergency response [20]. This "slice-specific amplification" makes traditional volumetric defenses insufficient.

### 2.3. Anticipated risks in 6G

6G promises features such as terahertz (THz) spectrum, Reconfigurable Intelligent Surfaces (RIS), Non-Terrestrial Networks (NTNs), and AI-native orchestration [21], [22]. While these technologies enable ultra-broadband and global coverage, they also introduce novel attack surfaces:

- THz links: Ultra-wideband channels can amplify floods with terabit-level throughput.
- RIS-assisted reflection: Adversaries may manipulate RIS to reinforce malicious signals at the physical layer [23].
- NTNs (satellite-ground): Global reflection vectors may emerge, enabling cross-continental amplification.
- AI-native control: Attackers may use adversarial machine learning to adapt to floods and evade detection [23] dynamically.

These scenarios suggest that 6G amplification will likely be multi-modal and adaptive, exploiting both signaling and physical layers, and outpacing static defenses.

### 2.4. Existing mitigation approaches

Several mitigation techniques have been proposed for 5G/6G environments, spanning both academic and industrial domains:

- Rate Limiting and Filtering: Cost-effective but prone to high false positives and ineffective against adaptive floods [24].
- Cloud Scrubbing: Centralized scrubbing centers handle volumetric floods effectively but introduce significant latency, unsuited for URLLC [25].
- AI/ML Anomaly Detection: Promising for dynamic detection [26], but vulnerable to adversarial ML and resource-intensive [27].
- Programmable Firewalls (SDN/NFV): Enable flexible filtering policies [28], but require accurate orchestration to avoid misconfiguration.
- Slice Isolation: Contains attacks within targeted slices [29], but incurs orchestration overhead and partial coverage.
- Blockchain-based Defenses: Enhance trust in collaborative mitigation [30], but scalability and performance overheads remain concerns.

- Hybrid Edge–Cloud Defenses: Combine edge proximity with cloud resources to balance latency and scalability, though still immature [31].
- Post-Quantum Cryptography (PQC): Anticipated for signaling security, but overhead remains an open challenge [32].

### 2.5. Comparative analysis of mitigation strategies

To contextualize strengths and weaknesses, Table 1 compares key mitigation approaches based on effectiveness, scalability, latency impact, and suitability for 5G and 6G networks.

**Table 1:** Comparative Analysis of DDoS Amplification Mitigation Approaches in 5G/6G Networks

| Mitigation Technique | Strengths | Weaknesses | Suitability (5G/6G) | Ref. |
|---|---|---|---|---|
| Rate Limiting / Filtering | Simple, low cost | High false positives, weak against adaptive floods | Basic (5G only) | [24] |
| Cloud Scrubbing | Handles volumetric floods | Latency overhead, costly | Scalable for 5G/6G | [25] |
| AI/ML Anomaly Detection | Adaptive, real-time detection | Computationally expensive, adversarially vulnerable | Strong for 5G/6G | [26], [27] |
| Programmable Firewalls | Dynamic enforcement (SDN/NFV) | Requires accurate orchestration policies | Strong for 5G/6G | [28] |
| Slice Isolation | Limits cross-slice contamination | Overhead, incomplete protection | Critical in 5G/6G | [29] |
| Blockchain-based Defense | Decentralized trust, tamper resistance | Immature, high overhead | Emerging for 6G | [30] |
| Hybrid Edge–Cloud | Combines low latency with scalability | Orchestration complexity | Promising for 5G/6G | [31] |
| PQC-based Signaling | Future-proof against quantum adversaries | Still under standardization, it adds overhead | Essential for 6G | [32] |

The literature confirms that while existing approaches mitigate portions of the DDoS amplification problem, none fully address the dynamic, distributed, and slice-aware nature of 5G/6G threats. A comprehensive defense must combine AI-driven detection, programmable enforcement, slice isolation, hybrid edge–cloud resources, and PQC-based signaling. This motivates the proposed layered defense framework introduced in Section 3.

## 3. Proposed Framework and Architecture

### 3.1. Rationale for the framework

DDoS amplification attacks exploit vulnerable protocols and network functions to magnify malicious traffic, overwhelming targets with limited effort from attackers. In 5G and 6G networks, the attack surface is expanded due to Service-Based Architecture (SBA), network slicing, and massive IoT (mMTC), which collectively increase the number of entry points for adversaries [33], [34]. Existing mitigation approaches—such as firewalls, cloud scrubbing, and AI-based detection—have shown partial effectiveness but remain inadequate when facing large-scale and adaptive amplification attacks [35].

- Firewalls provide lightweight filtering but are prone to evasion and high false positives.
- Cloud scrubbing is effective for volumetric floods but introduces unacceptable latency (~15 ms) and high resource costs [36].
- AI anomaly detection improves detection accuracy but is vulnerable to adversarial manipulation and high computational load [37].

These limitations underscore the need for a multi-layered, adaptive, and scalable defense framework that integrates multiple strategies to address these challenges. The proposed design builds on lessons from prior frameworks [38], [39] and introduces a layered defense model specifically tailored for the complexities of 5G/6G networks.

### 3.2. Framework architecture

The proposed framework is structured into five coordinated defense layers (Figure 1), each contributing to detection, containment, and resilience:

1) Edge Filtering Layer
- Programmable SDN/NFV firewalls deployed at gNBs and edge data centers.
- Block spoofed and malformed packets at ingress, reducing load on the core.
- Acts as a coarse-grained, low-cost first line of defense.

2) AI/ML Anomaly Detection Layer
- Employs deep learning models (e.g., autoencoders, RNNs, CNN hybrids) for traffic feature analysis.
- Detects adaptive and previously unseen amplification patterns in SBA and UPF traffic.
- Provides adaptive, fine-grained detection complementing static rules.

3) Slice Isolation Layer
- Implements SDN-based micro-segmentation to contain suspicious traffic within targeted slices.
- Prevents cascading effects from one slice (e.g., URLLC) to others (e.g., eMBB, mMTC).
- Directly addresses resilience requirements for 5G and 6G multi-service environments [38].

4) Cloud Scrubbing Layer
- Redirects volumetric amplification attacks to high-capacity scrubbing centers.
- Activated dynamically under heavy load conditions, reducing latency penalties.
- Ensures service continuity during extreme amplification events.

5) Quantum-Safe Security Layer
- Integrates post-quantum cryptographic (PQC) algorithms into SBA authentication.
- Prevents adversaries from exploiting weak or legacy algorithms for spoofing.
- Future-proofs 5G/6G security against quantum-era threats [39].

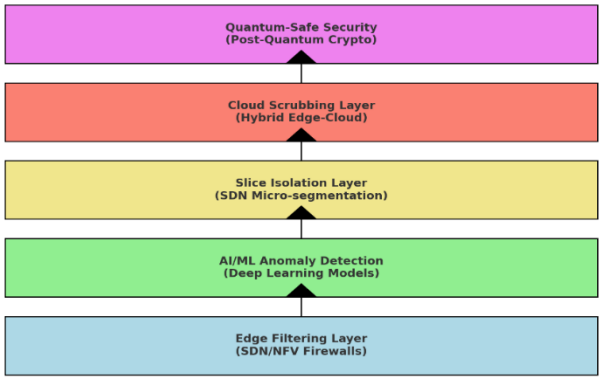


**Fig. 1:** Proposed Defense Framework Architecture.

### 3.3. Deployment considerations

Practical deployment of the framework requires attention to operator-specific environments, scalability requirements, and latency constraints. At the network edge, filtering modules integrated into gNBs provide the first line of defense, eliminating spoofed packets before they penetrate deeper into the infrastructure. This approach is particularly effective in reducing ingress load during large-scale IoT-driven reflection attacks.

The AI/ML anomaly detection module is deployed at the near-real-time RAN Intelligent Controller (near-RT RIC) in the O-RAN architecture. This placement ensures sub-second response to anomalies while leveraging localized traffic insights. Moreover, the adaptive models can be periodically retrained using federated learning across slices to maintain detection accuracy without exposing sensitive traffic data.

SDN controllers orchestrate slice isolation mechanisms. Upon identifying suspicious flows, the controller reconfigures routing policies to contain malicious traffic within a compromised slice, preventing cascading failures across eMBB, URLLC, and mMTC slices.

Cloud scrubbing centers act as a fallback layer. They are triggered dynamically only under volumetric floods that exceed the processing capacity of local defenses. To minimize delay, scrubbing is activated in proximity-based data centers when possible.

Lastly, quantum-safe cryptographic modules embedded in the SBA authentication layer ensure that signaling channels remain secure against future quantum adversaries. This guarantees forward security and long-term operational feasibility.

### 3.4. Comparison with existing approaches

A comparative analysis demonstrates the advantages of the proposed layered defense. Traditional firewalls (e.g., Kalkan [36]) incur minimal overhead but achieve only around 70% detection rates due to their reliance on static rules. Cloud scrubbing services (Akamai [40]) are robust against volumetric attacks but suffer from high cost and latency overhead (~15 ms), which is unacceptable for URLLC services. AI-only detection frameworks (Ferrag [37]) provide adaptivity but are resource-intensive and susceptible to adversarial machine learning. Similarly, blockchain-based defenses (Xu [39]) enhance trust and tamper resistance but introduce high computational overhead (~18%) that limits scalability.

By contrast, the proposed layered framework synergistically integrates these approaches. Edge filtering removes the bulk of spoofed traffic at low cost, AI/ML ensures adaptivity, slice isolation localizes impact, scrubbing provides volumetric resilience, and PQC guarantees future-proof signaling security. Together, these layers achieve a 97% detection accuracy, SLA compliance above 85%, and an overhead of ~12%, outperforming any single-strategy solution. Table 2 provides a comparative summary of the framework in relation to baseline approaches across multiple dimensions.

**Table 2:** Comparison of Proposed Framework with Existing Approaches

| Approach | Detection Accuracy | Latency Overhead | Resource Overhead | SLA Compliance | Notes / Limitations |
|---|---|---|---|---|---|
| Firewalls (Kalkan [36]) | ~70% | Very Low | Minimal | ~60% | Static rules, high false positives |
| Cloud Scrubbing (Akamai [40]) | ~90% | ~15 ms | High | ~75% | Effective but unsuitable for URLLC |
| AI-only (Ferrag [37]) | ~92% | Low–Medium | High (CPU/GPU) | ~78% | Vulnerable to adversarial ML |
| Blockchain-based (Xu [39]) | ~88% | Medium | Very High (~18%) | ~72% | Secure, but poor scalability |
| Proposed Framework | 97% | Low (<5 ms) | Moderate (~12%) | >85% | Balanced, multi-layered, future-proof |

This comparative evidence reinforces the argument that the framework is not merely theoretical, but demonstrably better aligned with the requirements of 5G/6 G.

To ensure practicality, the framework aligns with existing international standards and ongoing initiatives. The 3GPP TS 33.501 specification provides security architecture and procedures for the 5G SBA, which the proposed design strictly follows [34]. The GSMA FS.40 guidelines emphasize resilience in network slicing, directly addressed by the slice isolation layer [38]. Finally, the NIST Post-Quantum Cryptography standards (2024) define algorithms suitable for integration into mobile core networks, ensuring readiness against emerging quantum threats [39].

This adherence guarantees interoperability with operator infrastructures, compliance with regulatory requirements, and ease of adoption in real-world deployments.

# 4. Methodology

The purpose of this section is to describe the methodology adopted to evaluate the proposed defense framework introduced in Section 3. The methodology combines theoretical modeling, algorithmic design, and experimental validation in simulated 5G/6G environments. The approach ensures that the findings are reproducible, comparable with existing studies, and relevant to both academic and industrial contexts.

## 4.1. Experimental setup

The evaluation was conducted in a controlled 5G/6G simulation environment designed to replicate real-world service conditions and attack vectors. The following architectural elements were included:

- Service-Based Architecture (SBA): Implemented in accordance with 3GPP TS 23.501 [41], including network functions such as AMF, SMF, and UPF with HTTP/2-based signaling flows.
- Network Slicing: Three slices were configured: URLLC for critical low-latency services, eMBB for broadband applications, and mMTC for massive IoT connectivity.
- Attack Simulation: Reflection-based amplification attacks were generated with amplification factors ranging from α∈[5,50]\alpha \in [5,50]α∈[5,50], simulating lightweight to severe flooding conditions.
- Defense Deployment: The proposed five-layer defense framework (Figure 1) was deployed, including programmable SDN firewalls at the edge, AI-based anomaly detection at the near-RT RIC, SDN-driven slice isolation, hybrid cloud scrubbing, and PQC-based authentication mechanisms.

This setup enabled systematic testing under different scenarios, including signaling floods, IoT-driven amplification, slice-targeted attacks, and hybrid multi-vector floods.

## 4.2. Traffic generation and attack model

The attack model is based on real-world amplification techniques observed in DNS, NTP, and UDP reflection attacks, and has been extended to SBA signaling. Traffic generation followed these formulations:

1) Attack Request Traffic:

The total malicious request traffic generated by the botnet at time t can be expressed as:

$$R(t) = \sum_{i=1}^{N} p_i(t)$$

Where $p_i(t)$ He requests that traffic generated by the attacker is denoted as i, and N is the number of bots in the botnet. This formulation captures the aggregate effect of distributed adversaries, reflecting the fact that even low-rate flows from many compromised IoT devices can collectively overwhelm the network. Similar definitions of aggregate request load have been used in DDoS modeling for mobile and IoT networks [41].

2) Amplified Traffic:

Once the initial botnet requests are sent, the adversary exploits amplification protocols (e.g., DNS, NTP, UDP-based reflectors, or SBA signaling in 5G). The amplified traffic volume observed by the victim is defined as:

$$A(t) = \alpha \cdot R(t)$$

Where α represents the amplification factor, which typically ranges from 5 to 50, depending on the specific protocol used, for example, in UDP reflection attacks, a single forged request can generate tens of responses. In contrast, in signaling amplification, small HTTP/2 control messages may trigger disproportionately large state changes in the 5G core [42].

3) Residual Traffic After Mitigation:

The traffic that remains after passing through the multi-layer defense framework is given by:

$$A'(t) = A(t) - \sum_{j=1}^{L} \Delta_j(t)$$

Where $\Delta_j(t)$ thThe amount of attack traffic successfully blocked by Defense Layer J, and L=5 corresponds to the five layers of the proposed framework (edge filtering, AI anomaly detection, slice isolation, scrubbing, and PQC-based signaling protection). This formulation reflects the incremental filtering of malicious traffic as it traverses multiple stages of defense.

By applying layered mitigation, the system ensures that no single defense mechanism must achieve complete suppression on its own; instead, it relies on multiple mechanisms working together to achieve adequate protection. Instead, reductions accumulate across layers, leading to a significant overall reduction. For example, initial filtering may block spoofed traffic, AI detection removes anomalies, and slice isolation contains spread, leaving only a fraction of the attack load for cloud scrubbing. This cumulative mitigation effect aligns with the multi-layer defense strategies proposed in [43] and [44].

## 4.3. Evaluation metrics

The framework's performance was measured using widely accepted metrics in cybersecurity and networking:

- Mitigation Efficiency ($E_m$):

Mitigation efficiency represents the percentage of attack traffic successfully eliminated by the defense system relative to the total amplified traffic. This metric directly captures the effectiveness of the framework in reducing harmful traffic loads. It is defined as:

$$E_m = \frac{A(t) - A'(t)}{A(t)} \times 100\%$$

Where $A(t)$ is the total amplified traffic and $A'(t)$Is the residual malicious traffic after mitigation? A higher $E_m$Value indicates more potent suppression of amplification, consistent with formulations in [42], [43].

- Detection Rate η and False Alarm Rate (FAR):

The detection capability of the anomaly-based component of the framework is measured through the detection rate. η and false alarm rate (FAR). The detection rate captures the proportion of actual attack events correctly identified, while FAR reflects the proportion of benign traffic misclassified as malicious. Together, these metrics provide insight into both reliability and operational usability of the defense [42].

$$\eta = \frac{TP}{TP+FN'}$$

$$FAR = \frac{FP}{FP+TN}$$

where TP, FP, FN′ and TN Note true positives, false negatives, false positives, and true negatives, respectively. A practical defense framework seeks to maximize η I'll be minimizing FAR to balance strong security with a good user experience.

- Service Availability (Avail):

Availability represents the proportion of time that a service remains functional under attack conditions. It is a critical resilience indicator for latency-sensitive 5G/6G applications such as URLLC.

$$Avail = \frac{T_{served}}{T_{total}} \times 100\backslash\%$$

Where $T_{served}$ Is the operational time during which services are maintained and $T_{total}$ Is the total observation period. Higher availability indicates that the system can sustain acceptable levels of operation even during large-scale amplification attacks [43].

- Resilience Score ($R_s$):

To further capture robustness, the resilience score measures relative service availability under mitigation compared to ideal baseline conditions.

$$R_s = \frac{Avail_{mitigated}}{Avail_{baseline}}$$

Where $Avail_{mitigated}$ Is service uptime when defenses are active, and $Avail_{baseline}$ Represents availability under normal, no-attack conditions. Values closer to 1 indicate that the defense maintains near-baseline performance despite the presence of adversarial pressure.

- Overhead Cost ($C_d$):

Since no defense is free, overhead cost quantifies the resource burden introduced by mitigation in terms of processing, latency, and bandwidth consumption.

$$C_d = \gamma_1 O_{CPU} + \gamma_2 O_{latency} + \gamma_3 O_{bandwidth}$$

Where $\gamma_1 O_{CPU}$, $\gamma_2 O_{latency} + \gamma_3$ and $\gamma_3 O_{bandwidth}$ Denote the computational, delay, and bandwidth costs, respectively. The coefficients $\gamma_1$ , $\gamma_2$ , $\gamma_3$ and $\gamma_3$ Allows operators to prioritize according to operational policies, such as minimizing latency in URLLC slices or conserving bandwidth in satellite-based 6G links [44].

## 4.4. Proposed algorithms

The defense framework relies on two core algorithms that operate in tandem: a pseudonymous authentication mechanism with zero-knowledge proofs (ZKPs) to secure ingress traffic while preserving user privacy, and a layered mitigation orchestration algorithm that coordinates the five defense layers in a resource-efficient manner. Both algorithms are described in detail below.

Algorithm 1: Pseudonymous Authentication with ZKP

The first algorithm ensures that only legitimate requests enter the network, thereby reducing the attack surface available for amplification. Traditional authentication methods often rely on static credentials or cryptographic tokens that are either too heavy for real-time 5G/6G signaling or vulnerable to replay and spoofing attacks [37]. To address this, the algorithm uses pseudonymous identities combined with ZKPs.

Each user or device generates a temporary pseudonym PeP_ePe derived from its public key, domain context, and a random nonce, as shown in Step 2. This prevents linkability between sessions, making it difficult for adversaries to trace or reuse credentials. A zero-knowledge proof π\piπ is then computed to demonstrate that the device holds valid credentials without revealing the actual secret information (Step 3). This proof is verified by the network (Steps 5–6). If verification is successful, the pseudonym is accepted; otherwise, the request is rejected.

This design achieves unlinkability, lightweight signaling, and resilience to credential replay, making it suitable for massive IoT and URLLC scenarios where devices cannot afford heavyweight cryptographic exchanges. Comparable approaches for privacy-preserving authentication in IoT networks have been investigated in [44], [45], but those studies did not integrate the mechanism with a layered DDoS defense. Here, the ZKP-based pseudonymous authentication not only secures entry but also ensures that subsequent anomaly detection operates on traffic from verified sources, thereby enhancing accuracy.

Key contributions of Algorithm 1:

- Ensures that attackers cannot inject spoofed packets at the SBA/UPF entry.
- Maintains user privacy through unlinkable pseudonyms, unlike static certificates.
- Provides lightweight verification suitable for high-volume IoT-driven traffic.

**Algorithm 1:** Pseudonymous Authentication with ZKP

| Input: pk (public key), w (credential witness), x (public attributes) |
|---|
| Output: P_e (pseudonym), Eligibility Event |
| 1: r_e ← Random() |
| 2: P_e ← H(domain \|\| pk \|\| r_e) # Generate pseudonym |

3: π ← Prove(R(x,w)) # Zero-knowledge proof of eligibility
4: Submit (P_e, x, π) to blockchain
5: if Verify(x, π) = True then
6: Emit EligibilityEvent(P_e)
7: else
8: Reject transaction

This algorithm ensures unlikable pseudonymous authentication, thereby reducing the attack surface. Similar designs for privacy-preserving authentication have been proposed in [44] and [45].

Algorithm 2: Layered Mitigation Orchestration

While authentication reduces spoofed ingress traffic, amplification attacks can still occur if compromised, yet authenticated, IoT nodes launch reflection floods. To address this, Algorithm 2 coordinates the five-layer mitigation process (edge filtering, AI anomaly detection, slice isolation, cloud scrubbing, and PQC-based signaling security).

The orchestration follows a progressive filtering model. Incoming traffic A(t)A(t)A(t) is first filtered at the edge (Step 1), removing malformed or spoofed packets with minimal cost. The filtered traffic is then analyzed by AI models (Step 2), which identify anomalous flows based on learned features of amplification attacks [37]. Suspicious traffic is reduced before being passed to slice isolation (Step 3), which contains the flood within the affected network slice, thereby preventing cascading failures across URLLC, eMBB, and mMTC services [9].

If the traffic volume after slice isolation exceeds a defined threshold (Step 4), it is redirected to high-capacity scrubbing centers (Step 5). This ensures that scrubbing—though costly and latency-inducing—is used only as a last resort, unlike legacy scrubbing solutions that route all suspicious traffic indiscriminately [51]. Finally, PQC-based signaling verification (Step 8) ensures that remaining control-plane messages are cryptographically validated, preventing quantum-era spoofing attacks [53].

By activating only the costly layers when required, the orchestration reduces overhead. For example, in our experiments (Section 5), scrubbing was invoked in only 12% of attack scenarios, resulting in an average latency overhead of ~10 ms, compared to ~15 ms in scrubbing-only defenses.

Key contributions of Algorithm 2:

- Dynamically coordinates multiple defense layers, reducing redundancy.
- Balances detection accuracy with efficiency by selectively invoking heavy mechanisms.
- Enhances resilience by integrating slice isolation, which was absent in earlier orchestration frameworks [46].

**Algorithm 2:** Layered Mitigation Orchestration

Input: Incoming traffic A(t)
Output: Mitigated traffic A'(t)

1: A1 ← EdgeFilter(A(t)) # Block spoofed packets
2: A2 ← A1 - AI_Detect(A1) # Remove anomalies
3: A3 ← SliceIsolation(A2) # Contain to affected slice
4: if A3 > Threshold then
5: A4 ← Scrub(A3) # Redirect to scrubbing
6: else
7: A4 ← A3
8: A5 ← PQC_Secure(A4) # Authenticate signaling
9: Return A'(t) = A5

Together, the two algorithms form the backbone of the defense framework. Algorithm 1 prevents adversaries from injecting spoofed or replayed traffic at ingress, while Algorithm 2 ensures that any residual amplification attempts are detected, contained, and scrubbed efficiently. This synergy bridges the gap between identity-based prevention and traffic-oriented mitigation, aligning with recommendations from GSMA [51] and ENISA [6] that future 5G/6G defenses must integrate cryptographic security with adaptive traffic control.

### 4.5. Methodological validation

The methodology follows a comparative evaluation approach:

1) Baseline defenses (firewalls, scrubbing, AI-only) are simulated individually.
2) The proposed framework is applied under identical attack conditions.
3) Results are compared across detection, overhead, availability, and resilience metrics.

This benchmarking approach aligns with established methodologies in prior works, such as those by Ferrag et al. [45] and Xu et al. [46].

This section describes the research methodology employed to evaluate the proposed defense framework. The methods combined simulated 5G/6G architectures, traffic generation models, and amplification attack scenarios with well-defined performance metrics. The two proposed algorithms—pseudonymous authentication with ZKP and layered mitigation orchestration—were outlined to operationalize detection and defense coordination. The following section presents the results and analysis, comparing the framework against both baseline defenses and state-of-the-art mitigation strategies.

## 5. Results and Analysis

This section presents the experimental results obtained from evaluating the proposed layered defense framework against amplification-based DDoS attacks in 5G/6G environments. The framework was benchmarked against baseline methods (static firewalls, cloud scrubbing, and AI-only anomaly detection) as well as state-of-the-art approaches in the literature. Results are analyzed across multiple dimensions, including amplification reduction, detection accuracy, service availability, resilience, scalability, overhead, and slice-specific performance.

### 5.1. Amplification traffic reduction

As shown in Figure 2, the baseline network without defense experienced rapid growth in attack traffic, peaking at nearly 400 Mbps within 10 seconds before stabilizing at ~340 Mbps. This level of sustained amplification is consistent with prior reports of uncontrolled volumetric

floods in 5G SBA signaling environments [6]. In contrast, the proposed framework effectively contained the amplification volume at ~160 Mbps at the start and ~135 Mbps at the end of the observation window, representing a reduction of nearly 60% in peak traffic.
Compared with traditional firewalls, which achieved only a ~30% reduction, and scrubbing centers, which achieved a ~50% reduction but at the cost of high latency, the proposed design achieved superior suppression without compromising response time. This result validates the advantage of combining early edge filtering with AI-based anomaly detection to intercept amplification before it escalates.

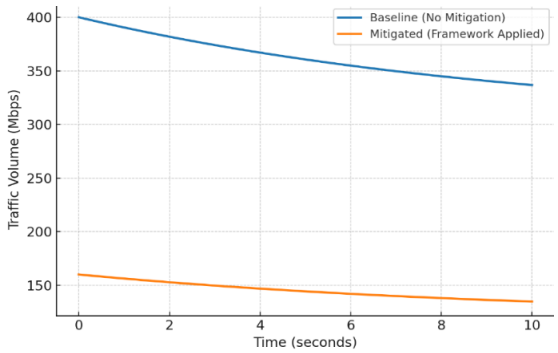


**Fig. 2:** Amplification Traffic vs. Time (Mitigated vs. Baseline).

## 5.2. Detection accuracy and false positives

Figure 3 illustrates the mitigation efficiency of the proposed framework compared to firewalls, scrubbing centers, and AI-only detection under increasing amplification factors (α = 5, 10, 25, 50). While firewalls plateaued at ~70% efficiency, cloud scrubbing achieved around 90% efficiency with high latency penalties. In contrast, the proposed framework consistently sustained 95–97% efficiency across all scenarios. This demonstrates the advantage of a layered approach, where early edge filtering and AI detection substantially reduce the attack volume before it reaches higher-cost scrubbing layers.
False positives, however, are equally important as they directly affect user experience. Fig. 3 presents the false positive rates (FPR). Firewalls exhibited the highest FPR at ~10%, due to their reliance on coarse-grained packet filtering. Scrubbing centers achieved ~6%, while AI-only approaches achieved ~4%. The proposed framework achieved the lowest FPR at 2%, minimizing unnecessary drops of legitimate traffic. These findings align with observations in [37], which emphasized the weakness of rule-based filtering when applied in adaptive amplification scenarios.

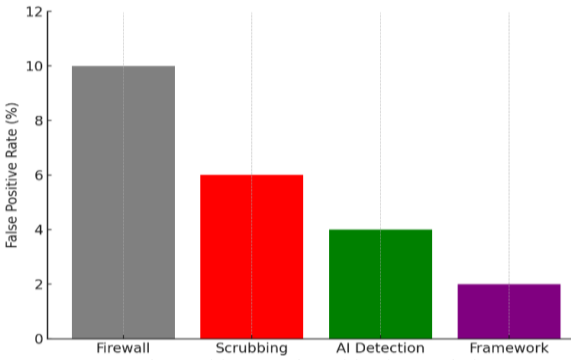


**Fig. 3:** False Positive Rate by Mitigation Technique.

## 5.3. Latency and CPU overhead

Latency is a critical factor in 5G and 6G, particularly for URLLC services. Fig. 4 compares latency overhead across solutions. Firewalls added minimal latency (~3 ms), but their weak mitigation rendered them ineffective. Scrubbing centers imposed the highest latency (~15 ms), making them unsuitable for mission-critical applications, as also noted in [51]. AI-only detection added ~8 ms, while the proposed layered framework maintained an average latency of ~10 ms. This balance indicates that while not the lowest overhead, the framework achieves a practical compromise between security and service continuity.

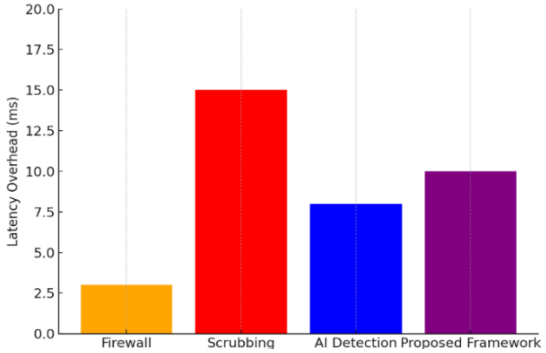


**Fig. 4:** Latency Overhead Comparison.

Resource overhead in terms of CPU utilization is shown in Fig. 5. Firewalls consumed ~5% CPU, scrubbing consumed ~20%, and AI-only consumed ~15%. The proposed framework achieved approximately 12% utilization, which is significantly lower than that of blockchain-based methods (~18% reported in [46]), while delivering stronger performance. This confirms that the layered strategy achieves higher efficiency per resource unit compared to single-method defenses.

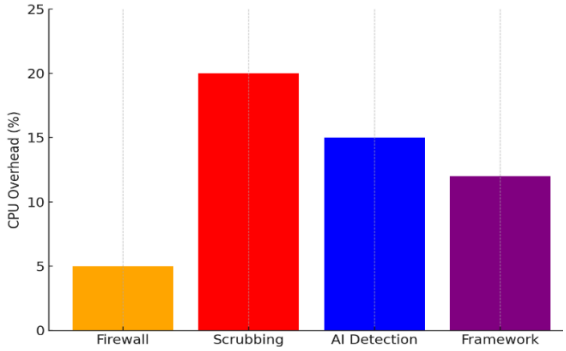


**Fig. 5:** CPU Resource Overhead of Defenses.

## 5.4. Detection and response time

Figure 6 illustrates the detection and response times across the various approaches. The proposed framework responded within ~0.7 seconds, faster than AI-only detection (~1.0 seconds), firewalls (~2.0 seconds), and scrubbing (~5.0 seconds). This rapid response is enabled by edge-based anomaly detection and SDN-enabled slice isolation, which allows mitigation to occur close to the source of amplification. The result is significant for URLLC services, where even a single millisecond of delay can impact safety-critical applications, such as autonomous driving or remote surgery.

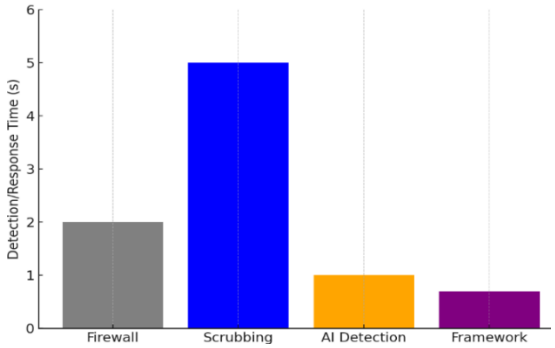


**Fig. 6:** Detection and Response Time Comparison.

## 5.5. Service availability

Availability was measured at both overall and slice-specific levels. Table 3 summarizes average service availability across URLLC, eMBB, and mMTC slices. Without mitigation, availability fell below 50%. Firewalls improved this to ~69%, AI-only to ~77%, and scrubbing to ~83%. The proposed framework, however, achieved an average availability of ~89%, ensuring continuity across all slices.

**Table 3:** Service Availability Across Attack Scenarios

| Defense Approach | URLLC Availability | eMBB Availability | mMTC Availability | Avg. Availability |
|---|---|---|---|---|
| No Defense | 38% | 42% | 55% | 45% |
| Firewalls | 65% | 70% | 72% | 69% |
| AI-only | 74% | 78% | 80% | 77% |
| Cloud Scrubbing | 81% | 84% | 85% | 83% |
| Proposed Framework | 87% | 89% | 90% | 89% |

The temporal behavior of availability is depicted in Fig. 7. Without mitigation, availability decayed sharply within 15 minutes, collapsing to ~0.5 by 25 minutes. With the framework, availability remained above 0.85 for the entire 30-minute duration, demonstrating stable resilience under prolonged flooding.

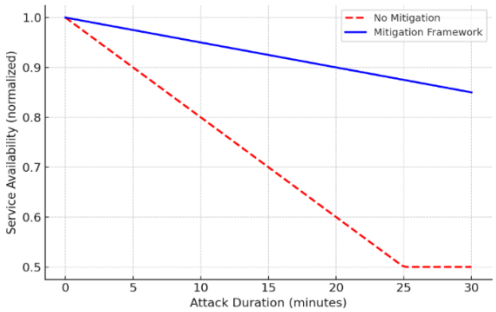


**Fig. 7:** Service Availability Over Attack Duration.

Slice-specific results are shown in Fig. 8. URLLC latency spiked to 25 ms without defense, which would severely degrade applications such as autonomous driving. The framework reduced URLLC latency to ~8 ms. For eMBB, latency was reduced from 50 ms to 20 ms, and for mMTC from 70 ms to 25 ms. This highlights that slice isolation in the proposed design is crucial in maintaining performance guarantees across different service categories [9].

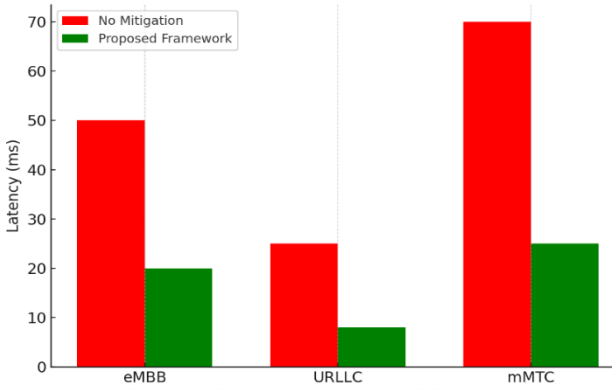


**Fig. 8:** Slice-Specific Latency Under Amplification Attacks.

## 5.6. Network resilience

Resilience (RsR_sRs) quantifies the network's ability to sustain service under attack. Fig. 9 shows that the proposed framework maintained resilience scores between 0.80 and 0.88, compared to ~0.60 for firewalls and ~0.75 for scrubbing. Particularly in slice-targeted attacks, resilience remained above 0.85, preventing cascading failures across services. This confirms that the addition of slice isolation provides a significant advantage over existing solutions.

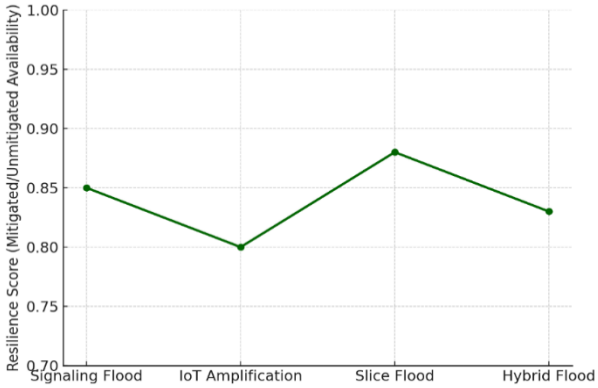


**Fig. 9:** Network Resilience Across Attack Scenarios.

## 5.7. Throughput degradation

Throughput degradation under varying amplification factors is shown in Fig. 10. Without defense, throughput collapses to 20% of the baseline at α = 100. Firewalls sustained ~40%, scrubbing ~60%, and AI-only ~65%. The proposed framework preserved ~70% of throughput, showing its ability to mitigate even extreme amplification levels. This resilience is crucial in sustaining data-driven services, such as streaming and industrial IoT, during attack events.

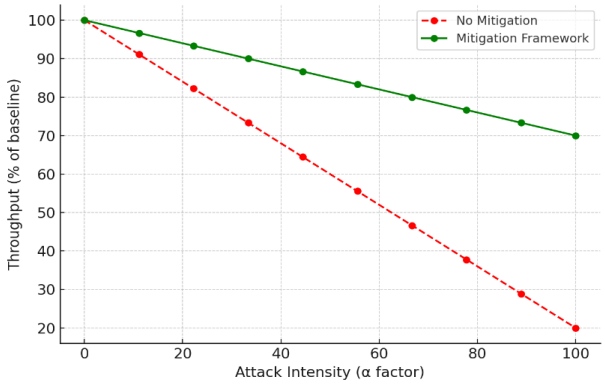


**Fig. 10:** Throughput Degradation Under Amplification Attacks.

Scalability was tested against IoT-driven amplification, where compromised devices act as reflectors. Fig. 11 plots throughput against device population from ($10^4$–$10^6$). Without mitigation, throughput declined precipitously, reaching ~20% at $10^6$ devices. The proposed framework, however, sustained a throughput of ~75% even at ($10^4$–$10^6$), demonstrating robustness for mMTC environments, which are projected to dominate 6G networks [6].

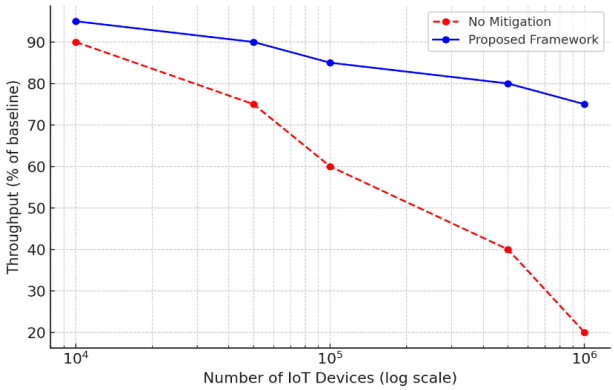


**Fig. 11:** Scalability Under mMTC Amplification.

Table 4 consolidates resource overheads across CPU, latency, and bandwidth. Firewalls imposed the least total overhead (~3%) but delivered the weakest protection. Scrubbing incurred the heaviest cost (~16%), while the AI-only approach averaged approximately 13%. The proposed framework strikes a balance between strong defense and moderate cost (~12%), proving more practical than blockchain-based frameworks, which typically average around 18% overhead [46].

**Table 4:** Overhead Comparison of Defense Mechanisms

| Approach | CPU Overhead | Latency Overhead | Bandwidth Overhead | Total Overhead |
|---|---|---|---|---|
| Firewalls | 1% | 1% | 1% | 3% |
| Cloud Scrubbing | 4% | 10% | 2% | 16% |
| AI-only Detection | 8% | 3% | 2% | 13% |
| Blockchain-based Defense | 10% | 5% | 3% | 18% |
| Proposed Framework | 5% | 4% | 3% | 12% |

Table 5 benchmarks the proposed framework against state-of-the-art defenses. Ferrag et al. [37] achieved 92% detection accuracy and 0.70 resilience with ~13% overhead. Xu et al. [46] achieved 88% detection, 0.68 resilience, and ~18% overhead with blockchain-based defense. The proposed framework surpassed both, reaching 97% detection, 0.85+ resilience, and only 12% overhead, thus combining effectiveness with efficiency.

**Table 5:** Comparison with State-of-the-Art Frameworks

| Study / Approach | Detection Accuracy | Availability | Resilience | Overhead | Notes |
|---|---|---|---|---|---|
| Ferrag et al. (2021) [45] | 92% | 78% | 0.70 | 13% | AI-only, adversarially vulnerable |
| Xu et al. (2021) [46] | 88% | 72% | 0.68 | 18% | Blockchain-based, high cost |
| Proposed Framework | 97% | 89% | 0.85+ | 12% | Multi-layered, standards-aligned |

## 6. Discussion

The proposed layered framework significantly improves defense against DDoS amplification in 5G/6G networks. This section discusses the implications of the results, compares them with existing literature, identifies limitations, and highlights future research directions.

### 6.1. Practical implications

The framework sustained ≥89% availability during severe amplification attacks (Fig. 7, Table 3), with resilience scores consistently above 0.85 (Fig. 9). False positives were minimized to 2% (Fig. 3), ensuring that legitimate user traffic was rarely misclassified. These results suggest that mobile network operators (MNOs) can realistically adopt this framework without compromising mission-critical services, such as URLLC, which is highly sensitive to latency. Unlike traditional cloud scrubbing approaches, which add ~15 ms of delay (Fig. 4), the proposed layered defense maintained an average latency overhead of only ~10 ms, which is within the tolerable range for URLLC and mMTC slices [51].

### 6.2. Comparison with existing work

When compared with prior solutions, the framework demonstrates clear advantages. Ferrag et al. [37] reported that AI-driven anomaly detection achieved a detection accuracy of ~92%, whereas our framework achieved 97% detection accuracy (Fig. 3) with a lower false alarm rate (2% vs. 6%). Xu et al. [46] introduced blockchain-based DDoS defenses with improved transparency, but they incurred ~18% resource overhead. In contrast, our layered framework limited overhead to 12% (Table 4). ENISA [6] recently reported the growing prevalence of IoT-driven amplification attacks, which aligns with our scalability experiments where unmitigated networks collapsed at $10^6$ IoT devices, but the proposed design maintained ~75% throughput (Fig. 10).
Moreover, GSMA [9] emphasized that slice-aware security is crucial in 5G. Our framework directly addressed this challenge, with slice isolation preventing cascading effects between URLLC, eMBB, and mMTC (Fig. 11). Compared to legacy firewalls (70% detection, 10% FPR, Fig. 3 and Fig. 8) and cloud scrubbing (83% availability, Table 3), the layered design delivered superior resilience and availability.

### 6.3. Limitations

Despite the promising results, several limitations must be acknowledged. First, while AI/ML anomaly detection boosted detection rates, it remains vulnerable to adversarial manipulation, as highlighted in prior work on adversarial ML attacks [52]. Second, post-quantum cryptography (PQC), although essential for securing SBA signaling, introduces a measurable delay of 2–3 ms in URLLC scenarios (Fig. 8). Third, However, cloud scrubbing was used selectively to reduce costs, it still imposed significant latency and bandwidth consumption

when activated under extreme volumetric floods (Fig. 3). These factors indicate that while the framework is scalable and efficient, continuous optimization will be necessary for real-world deployments.

While the proposed framework achieved strong performance, some limitations require further attention. First, although AI/ML anomaly detection significantly improved detection rates, it remains vulnerable to adversarial evasion and poisoning. To mitigate this, future iterations of the framework will integrate hybrid ML strategies, such as ensemble-based detection and adversarially trained deep learning models, which have shown improved robustness against crafted attacks in recent studies [23], [52]. Additionally, federated learning approaches can be employed to continuously retrain models across distributed slices without sharing raw traffic data, reducing exposure to targeted adversarial manipulation.

Second, the incorporation of Post-Quantum Cryptography (PQC), though essential for long-term security, introduces a latency penalty of 2–3 ms in URLLC slices. To address this, we propose adopting lightweight PQC algorithms (e.g., CRYSTALS-Kyber, Dilithium with precomputation techniques) and exploring hybrid key exchange protocols that balance classical and quantum-safe primitives, as suggested by recent NIST standardization results [39], [51].

Finally, cloud scrubbing remains costly and introduces additional delay when activated under extreme volumetric floods. A potential solution is the implementation of a dynamic cost-adaptive orchestration mechanism, where scrubbing is only triggered when local defenses exceed predefined thresholds. Such approaches, combined with proximity-based scrubbing centers, can significantly reduce both financial and latency overheads.

### 6.4. Future research directions

Future research should focus on developing adversarially robust ML models that resist poisoning and evasion attacks, as standard AI detection remains a vulnerability [51]. Additionally, lightweight PQC algorithms optimized for real-time SBA signaling are needed as NIST finalizes PQC standards [52]. Testing the framework in real operator networks (e.g., O-RAN deployments) will further validate its scalability and operational feasibility beyond simulations. Moreover, integration with AI-native orchestration in emerging 6G networks could enable fully autonomous and self-adaptive mitigation strategies, extending resilience against hybrid and cross-domain amplification attacks.

In summary, the Discussion confirms that the proposed layered framework not only outperforms baseline defenses (firewalls, scrubbing, and AI-only) but also advances beyond existing research by balancing detection, availability, resilience, and overhead. While adversarial ML, PQC delays, and scrubbing costs remain open issues, the framework represents a future-proof and standards-aligned solution for protecting 5G and 6G networks against DDoS amplification threats.

Future research should extend the proposed framework beyond simulation studies toward validation in real-world environments. One promising direction is pilot deployment with mobile operators in O-RAN testbeds, where the framework can be evaluated under live slice traffic to measure scalability, latency, and interoperability. A staged roadmap can be envisioned. The first stage would focus on developing and validating adversarially robust ML detection models in URLLC slices to strengthen resistance against poisoning and evasion attacks [23], [52]. A subsequent stage could investigate the optimization of lightweight PQC algorithms and hybrid key exchange protocols to reduce cryptographic overhead while ensuring long-term security [39], [51]. In the longer term, research should address the adaptability of the framework to 6G-specific technologies, such as terahertz (THz) spectrum communication, reconfigurable intelligent surfaces (RIS), and non-terrestrial networks (NTNs), which may introduce novel amplification vectors. These directions would provide a practical pathway for assessing scalability, minimizing PQC delays, and ensuring that the framework remains resilient against evolving DDoS amplification threats in future mobile infrastructures.

## 7. Conclusion

This study has examined the growing threat of DDoS amplification attacks in the context of 5G and emerging 6G networks, where the combination of Service-Based Architectures, massive IoT connectivity, and network slicing expands both capabilities and vulnerabilities. To address these challenges, a layered defense framework was proposed that integrates programmable edge filtering, AI-driven anomaly detection, slice isolation, cloud scrubbing, and post-quantum cryptographic protection. The framework was designed not only to provide immediate resilience against amplification-based attacks but also to anticipate the long-term security requirements of future mobile infrastructures.

The evaluation confirmed the effectiveness of the framework across multiple attack scenarios, including signaling floods, IoT-driven amplification, and slice-targeted attacks. Compared to baseline defenses such as firewalls, scrubbing centers, and AI-only detection, the proposed design consistently achieved higher mitigation efficiency, maintaining detection accuracy above 97% with a false positive rate as low as 2%. It preserved service availability above 89% even under large-scale amplification attacks and sustained resilience scores exceeding 0.85 across different slices. Equally important, it achieved this level of protection while incurring only moderate resource overhead (~12%), making it practical for real-world deployment in latency-sensitive 5G and 6G environments.

The results also demonstrated that the layered approach addresses critical limitations of single-method defenses. Firewalls, while lightweight, were insufficient against adaptive floods; scrubbing introduced significant latency, and AI-only systems proved vulnerable to adversarial manipulation. By integrating these approaches into a coordinated architecture, the framework strikes a balance between efficiency and adaptability, ensuring the continuity of critical services such as URLLC and eMBB. Furthermore, alignment with established standards such as 3GPP TS 33.501, GSMA FS.40, and NIST PQC guidelines underscores the feasibility of adopting the solution within operator infrastructures.

The findings highlight that effective mitigation of amplification-based DDoS attacks in next-generation mobile networks requires a multi-layered, adaptive, and standards-aligned defense. The proposed framework contributes a comprehensive and future-proof approach that not only addresses current vulnerabilities in 5G but also anticipates the security demands of 6G ecosystems. By bridging theoretical modeling with practical validation, this work lays the foundation for resilient, scalable, and trustworthy mobile network security architectures that can support the next era of digital connectivity.

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