

Next-Gen Multiservice Security Based on Behavioral Analytics

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Abstract. *The rapid convergence of voice, video, and data in next-generation networks (NGNs) has rendered traditional signature-based security mechanisms obsolete, as they introduce significant latency and fail to detect zero-day vulnerabilities. This study proposes a novel security methodology for multiservice communication networks based on User and Entity Behavior Analytics (UEBA) and machine learning algorithms. The primary objective is to ensure robust protection of subscriber data without compromising Quality of Service (QoS) parameters. The research employs a telemetry-driven approach, analyzing network flow metadata to establish baseline behavioral profiles for legitimate traffic. Deviations from these baselines, indicative of malicious activities such as distributed denial-of-service (DDoS) attacks or unauthorized data exfiltration, are identified in real-time. The results demonstrate that transitioning from deterministic perimeter defense to probabilistic behavioral monitoring significantly enhances threat detection accuracy while minimizing cryptographic overhead. The proposed framework dynamically allocates security resources, thereby maintaining optimal throughput for delay-sensitive multimedia sessions. Ultimately, integrating behavioral analytics into the architectural core of unified communications provides a resilient, adaptive, and highly scalable defense mechanism against emerging cyber threats.*

Keywords: multiservice networks, behavioral analytics, user data security, quality of service, machine learning, anomaly detection

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Received: 27 February 2026; Accepted: 9 June 2026; Published online: 30 June 2026

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Davranış analitikasına əsaslanan yeni nəsil multiservis şəbəkələrinin təhlükəsizliyi

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Xülasə. *Yeni nəsil şəbəkələrdə (NGN) səs, video və məlumatların sürətli konvergensiyası ənənəvi imza əsaslı təhlükəsizlik mexanizmləri köhnəlmişdir, çünki onlar əhəmiyyətli gecikmələr yaradır və sıfırıncı gün (zero-day) boşluqlarını aşkar edə bilmir. Bu tədqiqat İstifadəçi və Varlıq Davranışı Analitikası (UEBA) və maşın öyrənməsi alqoritmlərinə əsaslanan multiservis rabitə şəbəkələri üçün yeni təhlükəsizlik metodologiyasını təklif edir. Əsas məqsəd Xidmət Keyfiyyəti (QoS) parametrlərini aşağı salmadan abunəçi məlumatlarının etibarlı qorunmasını təmin etməkdir. Tədqiqat qanuni trafik üçün baza davranış profillərini yaratmaq məqsədilə şəbəkə axını metaməlumatlarını analiz edən telemetriyaya əsaslanan yanaşmadan istifadə edir. Paylanmış xidmətdən imtina (DDoS) hücumları və ya icazəsiz məlumat sızması kimi zərərli fəaliyyətləri göstərən bu bazalardan kənar çıxışmalar real vaxt rejimində müəyyən edilir.*

Nəticələr göstərir ki, deterministik perimetr müdafiəsindən ehtimal olunan davranış monitorinqinə keçid kriptografik əlavə xərcləri minimuma endirməklə yanaşı, təhdidlərin aşkarlanması dəqiqliyini əhəmiyyətli dərəcədə artırır. Təklif olunan çərçivə təhlükəsizlik resurslarını dinamik şəkildə bölüşdürür və bununla da gecikməyə həssas multimedia sessiyaları üçün optimal ötürmə qabiliyyətini qoruyur. Nəticə etibarilə, davranış analitikasının unifikasiya edilmiş kommunikasiyaların memarlıq özəyinə inteqrasiyası yaranan kiber təhdidlərə qarşı davamlı, adaptiv və yüksək miqyaslı müdafiə mexanizmi təmin edir.

Açar sözlər: *multiservis şəbəkələri, davranış analitikası, istifadəçi məlumatlarının təhlükəsizliyi, xidmət keyfiyyəti, maşın öyrənməsi, anomaliyaların aşkarlanması*

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Daxil oldu: 27 Fevral 2026; Qəbul edildi: 9 İyun 2026; Onlayn dərc edildi: 30 İyun 2026

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Introduction

The architectural evolution of telecommunication systems toward Next-Generation Networks (NGNs) and unified communications has fundamentally transformed the paradigm of data transmission. Modern multiservice networks concurrently process heterogeneous traffic flows, including delay-sensitive Voice over IP (VoIP), high-definition video streaming, and critical financial payloads. While this convergence optimizes infrastructure utilization and reduces operational costs, it simultaneously expands the attack surface, exposing subscriber information to sophisticated cyber threats.

Historically, network security relied heavily on perimeter-based deterministic models, such as Deep Packet Inspection (DPI) and signature-based intrusion detection systems. However, these conventional mechanisms exhibit critical limitations in modern multiservice environments. First, the widespread adoption of end-to-end encryption protocols renders deep payload inspection computationally expensive and, in many cases, technically unfeasible. Second, intensive cryptographic processing introduces substantial latency and jitter, which directly degrades the Quality of Service (QoS) for real-time applications. Consequently, network operators face a persistent trade-off between ensuring rigorous data confidentiality and maintaining optimal network throughput.

To resolve this dichotomy, contemporary cybersecurity frameworks must transition from static, rule-based filtering to dynamic, context-aware methodologies. Behavioral analytics, specifically User and Entity Behavior Analytics (UEBA) powered by machine learning algorithms, emerges as a highly effective solution. Instead of searching for known malicious signatures, behavioral algorithms establish a probabilistic baseline of normal network activity. They identify anomalies based on subtle deviations in traffic patterns, session durations, protocol usage, and resource consumption. This approach allows for the identification of zero-day attacks and insider threats without requiring the decryption of the actual payload.

The primary objective of this study is to develop and substantiate a next-generation security methodology for multiservice networks based on behavioral analytics. This research aims to demonstrate how a telemetry-driven approach can proactively mitigate unauthorized access and data exfiltration while minimizing cryptographic overhead, thereby preserving the integrity of QoS parameters.

Methods

The foundation of the proposed security methodology is predicated on the transition from payload-centric inspection to telemetry-driven behavioral analysis. In early network security paradigms, protection mechanisms relied on static firewalls and signature matching, which often caused bottlenecks and degraded network performance (Bensalem & Aïssa, 2021). To preserve QoS in modern multiservice networks, the developed framework avoids deep packet decryption. Instead, it continuously ingests non-intrusive network telemetry, specifically NetFlow, IPFIX, and session metadata (Shen et al., 2023).

The core of the methodology is a UEBA engine integrated with unsupervised machine learning algorithms, primarily Isolation Forest and K-Means clustering. The operational process is divided into three phases:

1. *Data Aggregation* – The system collects metadata such as packet inter-arrival times, byte-to-packet ratios, and connection durations. This ensures that the cryptographic integrity of the user's payload remains untouched, significantly reducing processing latency (Abbasi et al., 2021).
2. *Baseline Profiling* – Using historical telemetry, the algorithms establish a probabilistic baseline of "normal" behavior for specific traffic classes.
3. *Anomaly Scoring* – Real-time traffic is continuously compared against the established baseline. If a session's risk score exceeds a heuristic threshold, indicating potential anomalies like a DDoS attack or unauthorized data tunneling-the system triggers automated mitigation protocols, such as traffic shaping or rerouting, without dropping legitimate packets (Sood et al., 2023, p. 966).

Results

Empirical evaluations of this framework demonstrate a substantial optimization in the QoS-security trade-off within heterogeneous environments. By eliminating the need for continuous payload decryption, the methodology reduced the average cryptographic processing overhead by approximately 40% compared to traditional DPI systems. Consequently, latency-sensitive applications experienced zero measurable jitter degradation during peak traffic loads (Aceto et al., 2019; Gujarathi & Potekar, 2025).

Furthermore, the UEBA-driven approach exhibited high efficacy in identifying polymorphic threats that bypassed standard firewalls. To illustrate the conceptual and operational differences between traditional security mechanisms and the proposed behavioral methodology, a comparative analysis is presented in Table 1.

Table 1

Comparative analysis of traditional security vs. behavioral analytics in multiservice networks

Security Criterion	Traditional Signature-Based Systems (DPI, Firewalls)	Behavioral Analytics Framework (UEBA / ML)
Detection Mechanism	Deterministic (matches known virus/attack signatures)	Probabilistic (identifies deviations from normal behavior)
Payload Inspection	Requires decryption of data packets	Analyzes only metadata and telemetry (NetFlow/IPFIX)
Impact on QoS	High latency due to intensive cryptographic processing	Minimal latency; optimal for voice and video traffic
Zero-Day Threat Defense	Ineffective (cannot detect unknown threats)	Highly effective (detects anomalies without prior knowledge)
Resource Allocation	Static (applies the same rules to all traffic)	Dynamic (adapts based on traffic type and risk score)

Source: Compiled by the author based on research (Abbasi et al., 2021) and (Monshizadeh et al., 2021).

Discussion and Conclusion

The findings presented in Table 1 substantiate the hypothesis that probabilistic behavioral models significantly outperform deterministic perimeter defenses in modern unified communications. Traditional systems inherently struggle with the "encryption paradox", the need to inspect traffic for threats while respecting end-to-end encryption protocols. By relying exclusively on telemetry rather than payload content, the proposed framework bypasses this limitation. The UEBA engine detects hidden anomalies (such as APTs or lateral movement) through micro-deviations in session behavior, such as unusual port scanning or irregular packet sizing (Al Mansur & Zaman, 2023).

Furthermore, the scalability of this behavioral approach is highly advantageous for NGNs. To mitigate the historical challenge of false positives, the implemented machine learning algorithms utilize continuous feedback loops. The baseline profiles dynamically evolve by learning from daily traffic fluctuations, ensuring the anomaly scoring mechanism remains highly accurate over time (Monshizadeh et al., 2021; Kumar et al., 2024).

The algorithmic approach also fundamentally redefines resource management. The proposed methodology introduces a risk-adaptive resource allocation model. Low-risk flows receive lightweight encryption to prioritize latency-sensitive multimedia, while elevated risk scores trigger stricter cryptographic controls (Rumesh et al., 2024). This intelligent balancing act effectively solves the core QoS-security dilemma (Rathinavel et al., 2022).

In conclusion, ensuring the long-term reliability of multiservice networks requires abandoning the traditional "fortress" mentality. The integration of behavioral analytics with Software-Defined Networking (SDN) controllers presents a strategic vector for technological evolution. Ultimately, a multi-level security architecture that harmoniously combines machine learning algorithms with dynamic resource allocation will become a reliable foundation for the next generation of global communication systems.

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