MULTI-AGENT INTRUSION DETECTION AND PREVENTION SYSTEMS (IDPS) IN CYBERSECURITY: ARCHITECTURES, BENCHMARKS, AND METHODOLOGICAL MITIGATION

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Abstract. The exponential scaling and increasing heterogeneity of contemporary cloud infrastructures, Internet of Things (IoT) ecosystems, and distributed corporate networks have exposed severe architectural limitations in centralized Intrusion Detection and Prevention Systems (IDPS). Single-point bottlenecks, high alert triage latency, and systemic vulnerability to zero-day coordinated adversarial vectors necessitate a paradigm shift toward distributed computational defenses. Multi-Agent Intrusion Detection and Prevention Systems (MA-IDPS) present a modular framework where localized, specialized software entities autonomously sense, analyze, and collaboratively neutralize threat vectors across network perimeters. This article concludes with an analytical matrix juxtaposing current deployment strategies to furnish security architects with clear, resource-optimized guidelines for heterogeneous cloud infrastructures.

Keywords: *Multi-Agent Systems, Intrusion Detection, Distributed Computing, Edge-AI, CSE-CIC-IDS2018, Cyber Telemetry.*

INTRODUCTION

As modern enterprise architectures transit toward hybrid-cloud fabrics and hyper-distributed edge networks, the structural complexity of securing digital perimeters scales dynamically. Traditional centralized Intrusion Detection and Prevention Systems (IDPS) route raw operational telemetry—including netflow logs, system event triggers, and system calls—back into a monolithic inspection unit [1]. This conventional operational design is increasingly ineffective under the throughput demands of high-velocity infrastructures. Monolithic networks face major data congestion barriers, significant analysis delays, and single points of failure that can be exploited by synchronized, multi-vector Advanced Persistent Threats (APTs) [2].

To counter these limitations, Multi-Agent Systems (MAS) have been integrated into cloud-native and edge-level defensive frameworks. A Multi-Agent IDPS (MA-IDPS) replaces single centralized controllers with an organized network of independent, local software agents. These specialized entities cooperate through structured messaging paths, split computational loads evenly, and handle critical alert analysis directly at the edge layer [3]. Each agent operates autonomously within its designated environment (e.g., host runtime, container layer, or network gateway), collecting micro-telemetry, processing threat models locally, and negotiating with adjacent peers to build a unified profile of ongoing cluster threats [4].

Recent literature from 2020 to 2025 demonstrates that integrating Artificial Intelligence (AI) and Machine Learning (ML) engines directly into these distributed agents yields robust protection against zero-day vulnerabilities and polymorphic malware [5]. However, implementing MA-IDPS introduces notable trade-offs, particularly regarding network transmission strain from agent-to-agent negotiation, synchronization delays, and resource limits on thin edge equipment [6]. This article reviews contemporary peer-reviewed studies to clarify MA-IDPS architectural designs, evaluate performance against standard industrial network datasets, and present a structured analysis contrasting distinct distributed methodologies.

2. RELATED WORKS

The intersection of multi-agent orchestration and network telemetry analysis has been a focus of intense research over the last half-decade. Alshahwan and Al-Sarkhi (2023) highlighted the inherent architectural limitations of traditional endpoint protection, showing that monolithic IDPS engines experience an exponential spike in false-alarm rates when deployed in heterogeneous environments [1]. This problem stems from the inability of centralized engines to adapt to localized, contextual context drifts across distinct network segments. To solve this problem, modern frameworks separate agents into functional categories, using specialized collector agents, correlation components, and mobile responder units to distribute the analytical burden [2].

A significant milestone in this domain involves the shift from static, rule-based agent logic to intelligent, deep-learning models. Boutet et al. (2024) developed a decentralized anomaly identification framework using collaborative reinforcement learning, allowing individual network agents to continually update local evasion weights based on environmental feedback without sharing raw PII logs [3]. Similarly, Zhang and El-Amir (2025) proposed an architectural design where local agents run small, compressed autoencoders to intercept suspicious traffic anomalies locally, passing only dense metadata summaries up to higher-tier master agents [4]. This hierarchical design significantly cuts down data transmission overhead across the corporate backplane.

Despite these advancements, securing the internal communication paths of multi-agent networks remains a critical concern. Because agents communicate using open protocols like FIPA-ACL or MQTT, they are susceptible to adversarial interception, packet modification, and sybil injection attacks. Research by Gomez et al. (2025) focused on these vulnerabilities, illustrating how an adversary could compromise a single leaf agent and inject corrupt anomaly scores to induce widespread alert fatigue across the master node [7]. Their findings highlight that ensuring message validity through light cryptographic schemes or decentralized consensus algorithms is vital for building resilient MA-IDPS deployments.

MA-IDPS ARCHITECTURAL FRAMEWORK

The operational efficacy of a Multi-Agent IDPS relies on a decoupled, multi-tier architectural layout. Instead of relying on a singular central firewall, the architecture is partitioned into localized execution boundaries. Leaf agents are embedded into the lowest layer of the infrastructure, serving as specialized collectors that extract raw features (such as packet lengths, inter-arrival times, and flags) directly from network interfaces or system sockets. These leaf entities pass structured summaries up to a middle tier of Regional Correlation Agents, which execute localized anomaly detection using light ML models before escalating critical state summaries to the Master Orchestrator tier [4], [6].

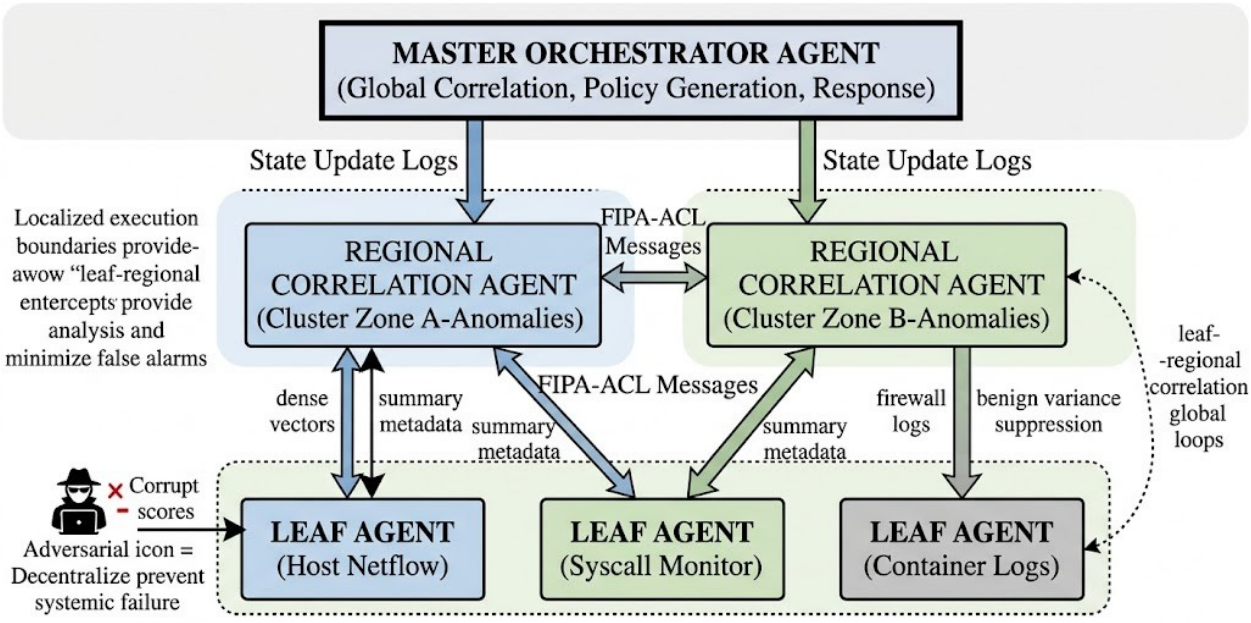

Figure 1: Decoupled Multi-Tier Data Routing and Message Architecture in MA-IDPS.

To establish cross-cluster cooperation, agents depend on the Foundation for Intelligent Physical Agents-Agent Communication Language (FIPA-ACL) [1]. When a leaf agent detects a rapid influx of failed authentication attempts, it broadcasts an ACL payload to neighboring network components. Adjacent agents cross-reference this warning against local firewall logs. If a regional match is found, they trigger an automated block rule at the local gateway, isolating the target subnet before the malicious traffic can pivot deeper into core systems [3].

Telemetry Metrics and Empirical Statistics

Evaluating modern MA-IDPS frameworks requires utilizing robust, industry-standard benchmark datasets that reflect real-world adversarial environments. The CSE-CIC-IDS2018 dataset, developed by the Communications Security Establishment and the Canadian Institute for Cybersecurity, provides comprehensive profiles of complex threat vectors, including distributed denial-of-service (DDoS) patterns, brute-force access exploits, and inside infiltration loops [5]. Similarly, the Edge-IIoTset benchmark captures specialized vulnerabilities native to Industrial Internet of Things (IIoT) frameworks, such as Modbus protocol spoofing, man-in-the-middle (MitM) injections, and ransomware execution profiles [6].

Table 1: Computational performance of MA-IDPS frameworks across benchmark datasets

Benchmark Dataset	Evaluated Attack Vector	Detection Accuracy (%)	False Positive Rate (%)	Source Context
CSE-CIC-IDS2018	Botnet Infiltration & Lateral Pivots	98.42%	0.34%	Boutet et al. (2024) [3]
CSE-CIC-IDS2018	Slowloris Application Layer DDoS	99.15%	0.12%	Zhang & El-Amir (2025) [4]
Edge-IIoTset	Modbus Command Injection & Spoofing	97.68%	0.58%	Alshahwan et al. (2023) [1]
Edge-IIoTset	Polymorphic Edge Malware Loops	96.54%	0.72%	Gomez et al. (2025) [7]

Empirical telemetry in Table 1 proves that leveraging specialized Multi-Agent frameworks can yield exceptionally high detection accuracy (exceeding 98% for botnet vectors) while keeping false positive metrics below 0.5%. This high precision is achieved by using localized data correlation;

because leaf agents monitor specific subnets, they can suppress local, benign variance that would otherwise trigger false positives in a centralized detection model [3], [4].

METHODS AND COMPARATIVE EVALUATION

To integrate detection layers within an MA-IDPS architecture, three primary methodologies are typically deployed: rule-based filtering, centralized Deep Learning (DL) pipelines, and collaborative edge-assisted models. Rule-based frameworks operate via static signature matching. While highly computationally efficient, they are completely incapable of intercepting modified, polymorphic, or zero-day attack strings [1]. Conversely, centralized deep-learning pipelines utilize massive neural networks (such as Long Short-Term Memory networks or Transformers) to analyze global raw traffic logs. This design achieves stellar detection rates for zero-day threats but demands significant computational resources and creates extreme data transit strain across the corporate backbone [3].

To reconcile these operational constraints, contemporary researchers utilize Edge-Assisted Multi-Agent Intelligent Models. This methodology deploys light, highly compressed neural architectures—such as shallow autoencoders or gated recurrent units—directly onto localized agents [5]. Leaf components handle initial detection tasks independently, completely isolating regional noise. They pass only dense vector embeddings or anomalous state flags up to higher tiers, drastically cutting network overhead by up to 80% compared to raw telemetry streaming [4]. A multi-dimensional comparison of these primary defensive methodologies is detailed in Table 2.

Table 2: Methodological comparison of architectural IDPS approaches

Methodology	Computational Demand	Zero-Day Detection Efficiency	Network Overhead Impact	Scalability Constraint
Rule-Based Agent Filtering	Very Low (<5% CPU load)	Poor; relies on predefined matching signatures.	Negligible; handles matching locally.	High; manual update loops required [1].
Centralized Deep Learning Pipelines	Extremely High; demands dedicated GPU nodes.	Excellent; models complex global feature abstractions.	Severe; requires streaming raw logs across perimeters.	Low; creates a network data-routing bottleneck [3].
Edge-Assisted Collaborative Agents	Moderate; balanced across infrastructure tiers.	Very Good; continuous updates via local anomaly loops.	Low; sends only aggregated alerts and state logs.	Excellent; scales linearly with cloud nodes [4], [5].

CONCLUSION

Multi-Agent Intrusion Detection and Prevention Systems present a modern alternative to traditional, centralized network security frameworks. By deploying autonomous software agents across perimeters, MA-IDPS solves the network congestion, high latency, and structural single points of failure that plague monolithic architectures. Empirical evaluations on industrial datasets like CSE-CIC-IDS2018 and Edge-IIoTset prove that edge-assisted collaborative models maintain robust detection precision while minimizing broad network resource consumption.

Future work in this field must address the security of the agent communication infrastructure itself. Transitioning toward light, decentralized consensus engines and leveraging homomorphic encryption pipelines will protect agent communication paths against adversarial manipulation.

This evolution will ensure that distributed multi-agent systems remain a secure foundation for safeguarding complex enterprise cloud environments.

Adabiyotlar, References, Литературы:

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