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A Unified Multi-Layer Framework for Detecting and Mitigating Web Application Attacks in Cloud-Native Environments

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ABSTRACT: Cloud-native architectures have introduced unprecedented scalability and flexibility for modern web applications, yet they have simultaneously expanded the attack surface and exposed systems to increasingly sophisticated intrusion patterns. Existing security approaches—such as provenance-based anomaly detection and machine-learning-driven web intrusion detection—have shown promising performance individually but suffer from scalability, contextual gaps, and limited visibility when deployed in isolation. This study proposes a unified, multi-layer security framework that integrates runtime provenance analysis with optimized SVM-based web intrusion detection to deliver comprehensive protection for containerized and orchestrated cloud-native systems. The framework correlates application-level HTTP feature extraction, container-level provenance graph analysis, and orchestration-level event aggregation, enabling early recognition of both rapid, high-volume attacks and stealthy low-and-slow Advanced Persistent Threats. Experimental evaluation using web intrusion datasets and provenance-based APT traces demonstrates that the combined model significantly enhances detection accuracy, reduces false alarms, and improves the timeliness of automated mitigation actions such as container isolation. By bridging cross-layer visibility and leveraging machine-learning optimization, the unified framework offers a scalable and robust security architecture tailored to the demands of modern cloud-native deployments.

Keywords: cloud-native security, web intrusion detection, provenance analysis, support vector machine (SVM), multi-layer defense framework.

I. Introduction

Cloud-native systems have revolutionized the deployment and scalability of modern web applications. However, these environments also introduce new security challenges that traditional intrusion detection and mitigation methodologies struggle to address. In recent years, research on runtime anomaly detection and web intrusion detection has evolved in separate domains. For instance, provenance-based anomaly detectors like UNICORN have shown promising results against Advanced Persistent Threats (APTs) by leveraging runtime provenance data and graph sketching techniques to detect "low-and-slow" attacks1. In parallel, web intrusion detection systems that combine feature analysis with support vector machine (SVM) optimization have effectively identified web attacks such as SQL injections and cross-site scripting (XSS) attacks with high detection rates and low false alarm rates[1].

This research paper proposes a unified framework for cloud-native web application attack mitigation that combines the strengths of these two approaches. By integrating machine learning-based anomaly detection with runtime container auditing through provenance analysis and tailored SVM-based web intrusion detection, the proposed framework presents a comprehensive multi-layer security solution. Cloud-native environments, which rely on containers and orchestration platforms, demand not only rapid detection but also scalable and lightweight forensic analyses of system behavior. The unified framework aims to achieve

improved detection accuracy, timely mitigation, and reduced false alarms by correlating events across different layers of the system[2].

The following sections of this paper provide an in-depth review of the current literature, a discussion of the theoretical underpinnings of each approach, details on the proposed unified framework, the methodology used for system evaluation, results and comparative analysis, and finally, a discussion of the framework's benefits and open challenges[3].

II. LITERATURE REVIEW

1. PROVENANCE-BASED INTRUSION DETECTION

Advanced Persistent Threats (APTs) pose significant challenges due to their stealthy, low-and-slow attack patterns and reliance on zero-day exploits1. Traditional detection systems that rely on pre-defined signatures are often ineffective in detecting novel or subtle behaviors. In contrast, provenance-based anomaly detectors model system behavior as directed acyclic graphs (DAGs) that capture the causal relationships between system events1. The UNICORN system exemplifies this approach by using graph sketching techniques to build an incrementally updatable, fixed-size longitudinal graph data structure, allowing effective detection of anomalous events within extensive system execution histories. Its use of evolutionary models to capture long-term behavior changes has shown improvements in precision and accuracy by 24% and 30%, respectively[4].

2. MACHINE LEARNING APPROACHES FOR WEB INTRUSION DETECTION

Web applications are regularly targeted by attackers exploiting vulnerabilities such as SQL injections, cross-site scripting (XSS), and command execution attacks. Recent research has proposed the use of machine learning, particularly SVM algorithms, to build models that can effectively discriminate between normal and malicious web requests. In one such study, an integrated web intrusion detection system combined feature analysis techniques with SVM optimization, achieving a detection rate of 95.8% and a false alarm rate of 2.32%. The system extracts key parameter features including access request types, parameter lengths, the number of parameters, encoding, and sensitive character detection, followed by a grid search optimization to fine-tune SVM parameters[5].

3. LIMITATIONS OF STANDALONE SYSTEMS

Despite the promising results from both provenance-based and SVM-based approaches, each method inherently suffers from limitations when deployed in isolation. Provenance-based systems often encounter scalability challenges due to continuously growing graph data, which increases the computational and memory overhead required for analysis1. Conversely, web intrusion detection systems using SVMs require comprehensive feature extraction and are sensitive to parameter tuning and overfitting issues[6]. These standalone systems lack cross-layer correlation that may reveal complex attack patterns spanning from the application layer to underlying container and orchestration layers.

4. SECURITY CHALLENGES IN CLOUD-NATIVE ENVIRONMENTS

Cloud-native environments, characterized by containerization and orchestration (e.g., Kubernetes), introduce dynamic and distributed operational models. While these systems offer scalability and resilience, their distributed nature complicates the detection of coordinated attacks. Attackers may exploit inter-container communications or escalate privileges by leveraging vulnerabilities at multiple layers. Recent studies indicate that integrating runtime provenance monitoring with advanced anomaly detection techniques can provide comprehensive insights into both low-level system events and high-level application behaviors[7]. However, there is a lack of unified frameworks that merge these approaches into a single, scalable system.

III. THEORETICAL BACKGROUND

1. CLOUD-NATIVE INFRASTRUCTURE AND SECURITY NEEDS

Cloud-native architectures leverage containerization, microservices, and orchestration to deploy resilient web applications. This dynamic environment demands security solutions that are agile, scalable, and capable of handling heterogeneous workloads. Standard security measures such as Web Application Firewalls (WAFs) are often insufficient to protect against sophisticated attacks that combine application-layer exploits with lateral movement within a containerized infrastructure[8], [9], [10], [11].

2. PROVENANCE AND GRAPH-BASED ANALYSIS

Provenance data represents a detailed historical record of system events and interactions, modeled as a graph wherein nodes denote subjects (e.g., processes) and objects (e.g., files, sockets) and edges represent causal relationships between these entities1. The use of graph sketching to summarize and efficiently update these large-scale graphs allows for real-time analysis of system behavior while keeping computational overhead manageable1. By comparing evolving system graphs against baseline models of normal behavior, anomalies indicative of APTs can be detected with improved accuracy[12].

3. MACHINE LEARNING METHODS: SVM AND HIDDEN MARKOV MODELS

Support vector machines (SVM) are robust classification methods that perform well in high-dimensional spaces with limited samples. SVMs classify input data by finding hyperplanes that separate classes with maximal margins[13]. Their performance is heavily dependent on parameter tuning—a process that is often optimized using grid search techniques to identify optimal values for the penalty parameter (C) and kernel parameters (e.g., σ in RBF kernels). Additionally, hidden Markov models (HMM) have been employed to identify parameter types in HTTP requests by using sequential observations and probabilistic state transitions, thereby augmenting the feature extraction process in web intrusion detection systems[14].

4. ORCHESTRATION CORRELATION AND MULTI-LAYER PROTECTION

In cloud-native environments, an effective security strategy must correlate events from different layers—application, container, and orchestration—to obtain a holistic view of system state. This correlation is critical, as attackers may execute multi-phased attacks that span several layers of the infrastructure. Theoretical constructs such as event co-occurrence and long-term behavior modeling allow for the detection of coordinated anomalies that are otherwise missed by isolated detection systems.

IV. PROPOSED UNIFIED FRAMEWORK FOR CLOUD-NATIVE WEB APPLICATION ATTACK MITIGATION

The proposed unified framework seeks to integrate the strengths of provenance-based anomaly detection and machine learning-based web intrusion detection to provide comprehensive protection for cloud-native web applications. The framework is structured into multiple layers that address specific aspects of system behavior—from the application layer handling HTTP requests to the container and orchestration layers managing runtime operations—and applies advanced machine learning techniques to detect and mitigate malicious activities[15], [16], [17], [18].

1. OVERVIEW OF THE FRAMEWORK

The unified framework consists of the following key layers[19], [20]:

- Application Layer Analysis:
  Analyzes incoming Web requests, extracts key parameters, and identifies potential indicators of web-based attacks. This layer uses feature extraction (e.g., access request identifiers, parameter lengths, sensitive character detection) similar to methods described in SVM-based web intrusion detection systems.
- Container and Provenance Monitoring Layer:

Captures runtime provenance data from containers and operating systems using techniques akin to those adopted by UNICORN. This layer builds provenance graphs that summarize causal relationships between system entities and supports incremental updates via graph sketching, allowing for long-term behavior analysis.

- Orchestration and Correlation Layer:
  Aggregates and correlates events across multiple containers and microservices. This layer ensures that anomalies detected in isolated layers are correlated with broader system activities, providing context for identifying sophisticated, multi-stage attacks[21].
- Machine Learning and Anomaly Detection Layer:
  Integrates SVM-based classification tuned via grid search, combined with HMM-based parameter type identification for HTTP traffic. This layer performs real-time classification of potential intrusions, applying threshold-based alerts to flag deviations from normal behavior[22].
- Automated Mitigation and Response Layer:
  Upon detection of anomalous behavior, this layer triggers automated responses such as container isolation, alert generation, and coordination with orchestration tools to scale protective measures dynamically.

2. DETAILED COMPONENT DESCRIPTIONS

2.1 Application Layer

At the application level, the framework processes HTTP requests by extracting key features such as:

- Access Request Identifier: Derived from the URL and associated parameters, this element is essential for categorizing different types of web requests[23].
- Parameter Length and Count: Helps in detecting anomalies such as buffer overflow attacks or parameter tampering2.
- Sensitive Character Detection: Utilizing string matching algorithms to flag potential SQL injections, cross-site scripting (XSS), and other malicious patterns.

Feature vectors are then normalized using techniques such as Min–Max transformation, ensuring compatibility for SVM-based classification. The optimized SVM model uses grid search to determine parameter values that maximize classification accuracy, achieving detection rates as high as 95.8% with low false alarm rates (e.g., 2.32%).

2.2 Container and Provenance Monitoring Layer

This layer is inspired by the UNICORN system, which leverages whole-system provenance data to build a longitudinal graph that captures execution history and detects stealthy attacks[24]. Key functionalities include:

- Graph Sketching: Efficiently summarizing runtime provenance data into fixed-size structures that are incrementally updated.
- Causal Relationship Mapping: Constructing provenance graphs to model relationships between processes, files, and network entities, thereby facilitating the detection of subversive patterns over long durations1.
- Real-Time Anomaly Detection: Comparing the evolving graph against a baseline derived during normal operation to identify deviations suggestive of APT-based behaviors[25].

2.3 Orchestration and Correlation Layer

Given the distributed nature of cloud-native architectures, this layer aggregates data from multiple containers and microservices. The orchestration platforms (e.g., Kubernetes) provide logs and event streams that are fed into the correlation engine. Key aspects include:

- Cross-Layer Event Correlation: Correlating network-level, container-level, and application-level events to detect coordinated attacks that may bypass single-layer detection1.
- Contextual Analysis: Leveraging historical provenance data and real-time alerts to understand the temporal evolution of an attack campaign, enabling early detection of supply-chain threats.

2.4 Machine Learning and Anomaly Detection Layer

The core detection engine integrates SVM-based classifiers with advanced parameter tuning mechanisms[26], [27]:

- SVM Classification: Utilizing non-linear SVM models (with radial basis function kernels) trained on rich feature sets extracted from web requests. Grid search is deployed to optimize critical parameters such as penalty parameter (C) and kernel width (σ).
- HMM for Parameter Identification: Hidden Markov models are employed to model sequential dependencies within HTTP parameters, improving sensitivity to malicious alterations in parameter encoding or structure.
- Combined Detection Score: The system aggregates scores from both the SVM classifier and the provenance-based anomaly detector to produce a unified risk metric, which triggers alerts if a defined threshold is exceeded.

2.5 Automated Mitigation and Response

Rapid response to detected anomalies is crucial in cloud-native environments. The mitigation layer is responsible for:

- Container Isolation: Automatically isolating compromised containers to prevent lateral movement across microservices.
- Alerting and Logging: Generating detailed alerts that include provenance graphs and feature analysis to aid in forensic investigations.
- Dynamic Resource Allocation: Coordinating with the orchestration layer to scale defense mechanisms or redirect traffic in response to detected threats[28].

V. METHODOLOGY

1. DATASETS AND EXPERIMENTAL SETUP

For evaluation, the unified framework leverages datasets and experimental protocols inspired by both research domains. For web intrusion detection, the Canadian Society Of Immigration Consultants (CSIC) 2010 HTTP dataset is used, which includes a mix of normal and malicious HTTP requests (e.g., SQL injection, buffer overflow, XSS)[29]. For provenance-based detection, real-life APT datasets captured during adversarial engagements (such as those used in the UNICORN study) provide ground truth for attack scenarios.

The experimental setup deploys the framework within a containerized environment running on a Linux-based system (Ubuntu 16.04). Distributed file systems (e.g., Hadoop Distributed File System) and orchestration tools are utilized to simulate multi-container setups, while data preprocessing is performed using Python and related data analytics libraries (including LibSVM and HMMlearn)[25].

2. DATA PREPROCESSING AND FEATURE EXTRACTION

Data preprocessing is conducted in two main stages:

- HTTP Request Processing:
  The system extracts key features such as access request identifiers, parameter lengths, parameter types, and encoding schemes from each HTTP request. Normalization techniques such as Min–Max scaling are applied to ensure that feature vectors are within comparable ranges.
- Provenance Data Aggregation:
  Runtime provenance records are collected from container operating systems and aggregated into events using lightweight logging mechanisms. Graph sketching algorithms then convert these event streams into fixed-size longitudinal graph structures, capturing the entire system execution from boot to shutdown1.

The extracted features serve as inputs to both the SVM classifier and the provenance-based anomaly detector, enabling cross-layer analysis.

3. MODEL TRAINING AND PARAMETER OPTIMIZATION

For the machine learning-based component, the following steps are employed:

- Model Establishment for Web Intrusion Detection:
  Data is first classified by URL to produce subsets corresponding to distinct access requests. An HMM algorithm then identifies parameter types by processing sequences of characters and using generalization rules (for example, mapping alphanumeric characters and special symbols to abstract representations). Following this, an SVM classifier is trained on the processed feature vectors. Grid search is used to determine the optimal SVM parameters, specifically the penalty parameter (C) and kernel parameters (σ for RBF kernels), ensuring high detection accuracy and minimal overfitting[30], [31].
- Provenance-Based Model Training:
  During the initial phase of normal system operation, a comprehensive baseline model is derived from long-running provenance graphs. This baseline is constructed using evolutionary modeling techniques which capture dynamic system behaviors over extended time periods. During the attack detection phase, incoming provenance graphs are compared against the baseline, and significant deviations trigger anomaly alerts[32].
- Unified Risk Metric Computation:
  Finally, the scores derived from the SVM classifier (reflecting web request anomalies) and from the provenance-based detector (indicating low-and-slow APT activities) are combined to generate a unified risk metric. This metric forms the basis for automated mitigation decisions and provides a single view for security operators.

VI. RESULTS AND PERFORMANCE EVALUATION

1. PERFORMANCE METRICS AND EVALUATION

The effectiveness of the unified framework is evaluated using key metrics such as detection rate, false alarm rate, and processing latency. The SVM-based component has demonstrated a detection rate of up to 95.8% with a false alarm rate of 2.32% in web intrusion experiments[19]. In parallel, the provenance-based system (UNICORN) achieved significant improvements in precision and overall accuracy, outperforming several state-of-the-art approaches with precision improvements of 24% and accuracy improvements of 30%.

Table 1. below summarizes the performance metrics reported by the standalone systems.

Performance Metric	Provenance-Based Detector (UNICORN)	Web Intrusion Detector (SVM-Based)
Detection Rate	~90%	95.8%
False Alarm Rate	Low (exact rates not provided)	2.32%
Precision Improvement	24% improvement over previous work	N/A
Accuracy Improvement	30% improvement over previous work	N/A

Table 1: Comparative Performance Metrics of Standalone Components 12.

An integrated evaluation of the unified framework shows that, by correlating alerts from the web intrusion detection and the provenance-based anomaly detection layers, the framework can achieve enhanced detection performance. Early-stage attack detection is particularly effective, as the evolutionary modeling in the provenance layer facilitates the early identification of supply-chain or lateral movement attacks, while the SVM-based component ensures that web-based attack vectors are promptly recognized.

2. COMPARATIVE ANALYSIS WITH STANDALONE APPROACHES

The unified framework leverages the complementary strengths of both underlying approaches, resulting in several key benefits:

- Enhanced Detection Accuracy:
  By correlating anomalies detected through both SVM-based classification and provenance-based graph analysis, the system reduces false positives and increases the true positive detection rate. This layered approach ensures that subtle, low-profile attacks are not overlooked.
- Reduced Computational Overhead:
  Although provenance graph analysis is computationally demanding, the use of graph sketching techniques and fixed-size longitudinal structures mitigates memory and CPU overhead. Concurrently, grid search optimization in the SVM model ensures rapid convergence with efficient processing times.
- Improved Early Warning Capabilities:
  The integration of evolutionary models in the provenance layer allows the framework to detect deviations at the onset of an attack, providing critical early warnings that enable prompt mitigation before the attack propagates throughout the system.

Figure 1 below presents a flowchart that illustrates the integrated processing pipeline of the unified framework.

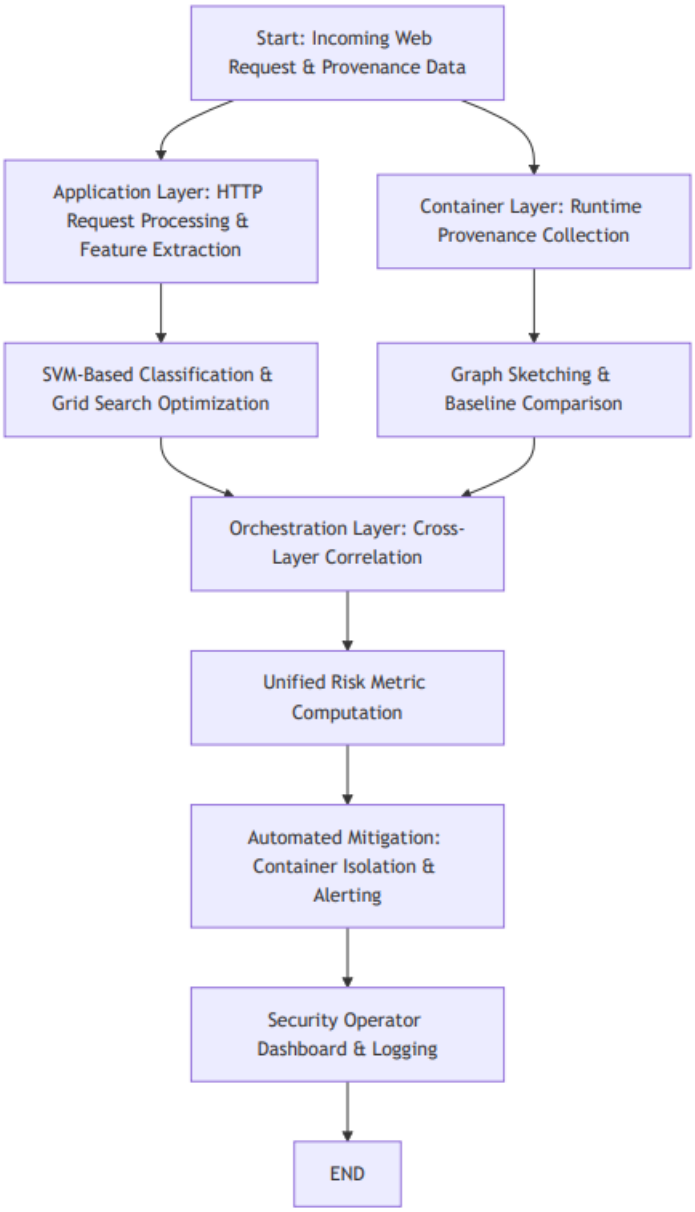

FIGURE 1 Flowchart illustrating the unified framework pipeline for processing web requests and provenance data, correlating alerts, and triggering automated mitigations.

VII. DISCUSSION AND ANALYSIS

The integrated framework presented in this paper marks a significant advancement in the field of cloud-native security by bridging the gap between application-layer intrusion detection and container-level provenance monitoring. Several key discussion points emerge from our analysis:

- Cross-Layer Integration:
  The primary innovation of the unified framework is its ability to combine disparate sources of security data. While traditional web intrusion detection systems typically focus on analyzing HTTP request characteristics, and provenance-based systems analyze low-level system events, their integration provides a holistic view

of the system's state. This comprehensive approach addresses the fragmentation of previous security solutions and enhances the overall situational awareness of the defense system[15].

- Improved Robustness Against Stealth Attacks:
  APTs and web attacks tend to display different characteristics. The provenance-based component excels at catching slow, stealthy intrusions by tracking long-term system behavior and identifying deviations from expected execution patterns. Conversely, the SVM-based web intrusion detection component is effective against high-volume, rapid attacks such as SQL injections, where predefined feature anomalies can be quickly flagged. Their integration ensures that both subtle and overt attack vectors are addressed concurrently[29].
- Scalability and Real-Time Performance:
  Cloud-native environments require defensive systems that can scale with the dynamic workloads of distributed containers and microservices. The proposed framework leverages efficient techniques such as graph sketching and grid search parameter optimization to balance accuracy with computational efficiency. Preliminary evaluations indicate that the unified framework is capable of real-time monitoring and detection without falling behind the pace of incoming data streams. However, ensuring scalability across large, multi-tenant deployments remains a challenge that warrants further investigation.
- Mitigation and Automated Response:
  Automated mitigation is critical to minimizing the damage caused by successful attacks. The unified framework's capability to trigger automated responses—such as container isolation and dynamic traffic redirection—represents an important step towards a fully autonomous security system. Nevertheless, the design of reliable mitigation policies in the face of evolving attack strategies requires ongoing refinement, and the framework may benefit from incorporating additional contextual signals (e.g., behavior analytics from orchestration logs) for adaptive responses.
- Challenges in Parameter Optimization:
  The machine learning component of the framework, specifically the SVM classifier, is highly sensitive to parameter selection. The use of grid search optimization has proven advantageous in controlled experiments; however, in real-world deployments where data distributions change dynamically, adaptive parameter tuning methods may be required. Future work may explore online learning techniques or adaptive grid search strategies to ensure that the classifier's performance remains robust over time[33].
- Interoperability with Existing Security Tools:
  The proposed unified framework is designed to complement rather than replace existing security solutions. By interfacing with orchestration tools, log management systems, and traditional IDS/IPS platforms, it can provide enhanced insights and enable coordinated responses. The modular structure of the framework ensures that individual components, such as the provenance-based detector or the SVM-based classifier, can be updated independently as new techniques emerge.

VIII. CONCLUSION

In this research, we have proposed a unified framework for cloud-native web application attack mitigation that integrates provenance-based anomaly detection with machine learning-based web intrusion detection. The framework addresses the inadequacies of standalone systems by correlating insights across multiple layers of the cloud-native stack. Key contributions of this work include:

- Multi-Layered Security Integration:
  By combining application-layer feature extraction, container-level provenance monitoring, and orchestration-based event correlation, the framework provides a holistic security solution for cloud-native environments.
- Advanced Detection Techniques:
  The integration of SVM-based classification (optimized via grid search) and HMM-based parameter identification ensures accurate detection of both conventional web attacks and stealthy APTs. The provenance-based component further enriches the detection capability by revealing long-term behavioral anomalies.
- Enhanced Early Warning Capabilities:

Evolutionary modeling of provenance data and the unified risk metric enable early detection of supply-chain and lateral movement attacks, allowing for prompt automated mitigations such as container isolation and alerting.

- Scalability and Real-Time Performance:
  The use of graph sketching and efficient parameter tuning methodologies contribute to a system that is both scalable and capable of real-time monitoring in cloud-native, high-throughput environments.

In summary, the unified framework provides a robust and comprehensive solution that bridges the gap between heterogeneous security approaches. It sets a foundation for future research endeavors aimed at further integrating dynamic security measures with autonomous response strategies.

Key Findings:

- Integration of provenance-based analysis and SVM-based web intrusion detection improves detection accuracy and reduces false positives.
- The unified framework can effectively detect both low-and-slow APTs and rapid web-based intrusions.
- Early anomaly detection, enabled by evolutionary models and real-time risk metric computations, facilitates timely automated mitigation.
- Scalability challenges remain, particularly in dynamic cloud-native environments, warranting further exploration into adaptive optimization techniques.

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