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Workload-Aware Agent Orchestration for Large-Scale Vulnerability Remediation Pipelines

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Abstract:

The rapid expansion of cloud-native computing and microservice architectures has significantly accelerated the software development lifecycle, concurrently expanding the attack surface for potential security exploits. As large-scale organizational infrastructures ingest thousands of vulnerability disclosures daily, conventional static vulnerability remediation pipelines suffer from severe resource bottlenecks, high latency, and inefficient utilization of computational resources. To address these critical challenges, this paper proposes a novel workload-aware agent orchestration framework designed specifically for large-scale vulnerability remediation pipelines. The proposed framework introduces a dynamic scheduling methodology that continuously monitors queue depths, agent health, and processing complexity to intelligently distribute remediation workloads across a decentralized fleet of autonomous agents. By integrating advanced queuing theory with predictive workload estimation models, the orchestrator dynamically scales and reallocates resources in real-time, minimizing end-to-end remediation latency while maximizing systemic throughput. Comprehensive empirical evaluations conducted in a simulated enterprise-scale cloud environment demonstrate that the workload-aware orchestration framework reduces average remediation latency by a significant margin compared to traditional round-robin and static allocation strategies. Furthermore, the system achieves superior resource utilization efficiency and maintains robust fault tolerance under volatile load conditions. The findings presented in this study offer a scalable, resilient, and highly efficient solution for automating vulnerability management in complex computational environments, paving the way for next-generation automated cybersecurity defense mechanisms.

Keywords: *Vulnerability Remediation, Agent Orchestration, Workload Management, Distributed Systems, Cybersecurity Automation.*

1. Introduction

The contemporary digital landscape is characterized by an unprecedented scale of interconnected systems, cloud-based applications, and complex software supply chains. This evolution has undeniably enhanced operational efficiency and technological capabilities across various sectors. However, it has also introduced a massive and continuously evolving attack surface. Software vulnerabilities, often cataloged as Common Vulnerabilities and Exposures, are discovered and disclosed at a staggering rate. For large-scale enterprise environments, which may consist of tens of thousands of virtual machines, containers, and serverless functions, the sheer volume of vulnerabilities detected on a daily basis poses a monumental logistical and computational challenge. The process of identifying, prioritizing, patching, and verifying these vulnerabilities constitutes the vulnerability remediation pipeline. Traditionally, these pipelines have relied heavily on manual intervention or semi-automated scripts that operate on fixed schedules. Such approaches are fundamentally misaligned with the velocity and scale of modern cyber threats, necessitating a paradigm shift towards fully autonomous, large-scale remediation systems. Guan and colleagues examine gPU-Accelerated robust graph neural networks against adversarial cyber attacks [1]. Autonomous remediation pipelines increasingly utilize distributed software agents to perform necessary patching and configuration tasks across varied endpoints. In a typical deployment, a central orchestrator dispatches remediation tasks to these distributed agents. However, existing orchestration strategies predominantly employ static, predetermined allocation mechanisms such as round-robin distribution or simple load balancing based on endpoint availability. These static methodologies fail to account for the heterogeneous nature of remediation workloads. For instance, updating a minor configuration file requires marginally few computational resources and milliseconds to complete, whereas compiling and deploying a kernel-level patch across a fleet of database servers demands substantial memory, CPU cycles, and time. When an orchestrator blindly assigns highly complex tasks to agents already burdened with resource-intensive operations, it inadvertently creates severe processing bottlenecks. These bottlenecks lead to unacceptable delays in patching critical vulnerabilities, thereby extending the window of exposure during which malicious actors can exploit the system. Related work has addressed efficient and trustworthy authentication in 5G networks based on blockchain [2]. To overcome the inherent limitations of static allocation, there is a critical need for workload-aware orchestration systems capable of dynamically assessing and responding to the real-time state of both the remediation pipeline and the distributed agent fleet. Workload awareness implies that the orchestrator possesses deep visibility into the computational complexity of incoming tasks, the current resource utilization metrics of available agents, and the historical performance data of similar remediation efforts. By synthesizing these diverse data streams, a workload-aware orchestrator can make highly optimized scheduling decisions that balance the load across the entire infrastructure. This dynamic approach not only accelerates the overall remediation process but also significantly enhances the resilience of the system against sudden surges in vulnerability disclosures, often referred to as vulnerability storms. Related work has addressed guard-Agnostic defense amplification against encoded VLM jailbreaks [3].This paper introduces a comprehensive workload-aware agent orchestration framework explicitly engineered for large-scale vulnerability remediation pipelines. The central contribution of this research is the formulation and implementation of a dynamic scheduling methodology that leverages predictive workload estimation and advanced queuing theory to optimize task distribution. By continuously monitoring environmental parameters and adapting to fluctuating workloads, the proposed framework minimizes processing latency and maximizes resource

efficiency. The subsequent sections of this paper are structured to provide a detailed exploration of the theoretical foundations, system architecture, mathematical optimization models, and rigorous empirical evaluations that validate the efficacy of the proposed solution.

2. Background and Literature Review

2.1 Evolution of Vulnerability Management Systems

The discipline of vulnerability management has undergone significant transformations over the past two decades. Early iterations of vulnerability management were largely characterized by periodic network scanning and manual patch deployment. Security administrators would utilize monolithic scanning tools to identify unpatched software versions or misconfigurations, subsequently generating extensive reports that required manual parsing and remediation. As infrastructure scale increased, these manual processes became untenable, leading to the development of centralized patch management solutions. These centralized systems automated the deployment of updates to registered endpoints based on predefined schedules and policies. While a marked improvement, centralized patch management still lacked the agility required to address zero-day vulnerabilities and rapidly propagating exploits. The inherent latency between vulnerability detection and patch deployment remained a critical weakness in organizational security postures. Accountable network AI, as discussed by Liao et al. [4], requires a reviewable connection between a recommendation and its evidence. For remediation agents, that connection should include the detected vulnerability, the proposed patch and the reason the task was given its queue priority. The advent of cloud computing and containerization further exposed the limitations of traditional patch management. In highly dynamic environments where ephemeral container instances are continuously instantiated and terminated, relying on rigid, scheduled patching is ineffective. This realization prompted the security community to explore continuous, automated remediation strategies integrated directly into the continuous integration and continuous deployment pipelines. However, integrating remediation directly into deployment pipelines only addresses vulnerabilities in newly deployed artifacts, leaving legacy systems and long-running stateful services exposed. Consequently, the focus shifted towards developing autonomous remediation agents capable of operating continuously within the production environment, monitoring for deviations from secure baselines and applying corrective actions in real-time. Qiu and colleagues examine knowledge Graph-Enhanced transformer framework for Security-Aware data quality anomaly detection and autonomous repair against network attacks [5].

2.2 Agent-Based Orchestration in Distributed Systems

Agent-based systems have long been utilized in distributed computing to facilitate complex, coordinated tasks across diverse geographical and logical topologies. Shor's algorithms establish a long-term quantum threat to factoring- and discrete-logarithm-based cryptography, which is distinct from vulnerabilities observable in the current workflow [6]. In the context of cybersecurity, autonomous agents offer several distinct advantages, including localized decision-making capabilities, reduced reliance on constant network connectivity to a central server, and the ability to execute highly specific, context-aware remediation actions. Despite these advantages, coordinating a massive fleet of autonomous agents presents substantial orchestration challenges. Early agent-based orchestration frameworks relied on simplistic master-slave architectures, where a central controller dictated task assignments without considering the contextual state of the individual agents. Meng and colleagues examine augmenting cybersecurity in smart urban energy systems through IoT and blockchain technology within the digital twin framework [7]. Recent advancements in distributed systems research have emphasized the necessity of decentralized and semi-decentralized orchestration models. These models aim to reduce the communication overhead and eliminate the single

point of failure inherent in purely centralized architectures. Peer-to-peer agent communication protocols and consensus algorithms have been proposed to enable agents to autonomously negotiate task distributions. However, in highly regulated and security-critical domains such as vulnerability remediation, strict centralized oversight and audibility are often mandatory compliance requirements. Therefore, hybrid orchestration models that maintain a centralized supervisory plane while granting localized execution autonomy to agents have emerged as the most viable architectural approach for enterprise-scale deployments. The literature also considers secure transmission scheme based on joint radar and communication in mobile vehicular networks [8]. The cited regulatory system separates its oversight functions into microservices [9]. Vulnerability orchestration can use the same architectural question when assigning discovery, assessment and patch verification to agents, with explicit evidence passed between stages instead of a single untraceable completion flag.

2.3 Workload Estimation and Dynamic Scheduling

Effective workload-aware orchestration fundamentally relies on the ability to accurately estimate the resource requirements and temporal duration of incoming tasks. Bitcoin provides a foundational example of a peer-to-peer transaction ledger, whose consensus assumptions should be specified before adopting its mechanisms in another security setting [10]. In general cloud computing paradigms, workload estimation is often achieved through historical profiling and machine learning techniques that analyze execution traces to predict future resource demands. Applying these techniques to vulnerability remediation, however, introduces unique complexities. Remediation tasks are highly heterogeneous and often exhibit non-deterministic execution behaviors due to environmental dependencies, network latency, and the specific configuration state of the target endpoint. Related work has addressed joint optimization in the presence of an extended target [11]. Dynamic scheduling algorithms must therefore account for a high degree of uncertainty. Randomized smoothing provides a certification approach under specified perturbation assumptions, which must be stated before a robustness claim is extended to an operational pipeline [12]. Traditional scheduling algorithms, such as Shortest Job First or Earliest Deadline First, assume precise knowledge of task durations, making them suboptimal for remediation pipelines. More sophisticated approaches utilize stochastic scheduling models and reinforcement learning to adaptively refine allocation strategies based on continuous feedback from the execution environment. Researchers have demonstrated that incorporating queueing theory metrics, such as expected waiting times and service rates, into the scheduling decision process significantly improves the overall throughput of distributed systems processing highly variable workloads. This paper builds upon these foundational concepts, adapting and extending dynamic scheduling principles to meet the specific requirements of large-scale vulnerability remediation pipelines. Yao and colleagues examine uAV-Relay-Aided secure maritime networks coexisting with satellite networks: robust beamforming and trajectory optimization [13].

3. System Architecture and Orchestration Framework

3.1 Pipeline Components and Data Flow

The proposed workload-aware agent orchestration framework is constructed upon a robust, scalable architecture designed to seamlessly process high volumes of vulnerability data. The architecture is logically divided into three primary tiers: the ingestion and analysis tier, the centralized orchestration tier, and the distributed execution tier. The ingestion tier is responsible for continuously aggregating vulnerability disclosures from various threat intelligence feeds, internal security scanners, and continuous integration pipelines. As vulnerabilities are ingested, an automated analysis engine enriches the raw data with contextual information, such as the criticality of the affected system, the availability of verified patches,

and the potential impact of the remediation action on service availability. Related work has addressed data-Aware Multi-Agent large language model framework for scalable software vulnerability detection and repair with optimized code data scheduling [14]. Once enriched, the vulnerability data enters the centralized orchestration tier, which serves as the central nervous system of the framework. The orchestrator maintains a high-performance priority queue where remediation tasks are dynamically ranked based on a composite risk score derived from the Common Vulnerability Scoring System and business-specific contextual factors. The orchestration tier continuously communicates with the distributed execution tier, which consists of thousands of lightweight, autonomous remediation agents deployed across the entire computational infrastructure. These agents are responsible for executing the actual patching, configuration adjustments, and subsequent verification tests to ensure the vulnerability has been successfully mitigated without disrupting the underlying service. The literature also considers design of interface circuits and lightweight PUF for TMR sensors [15].

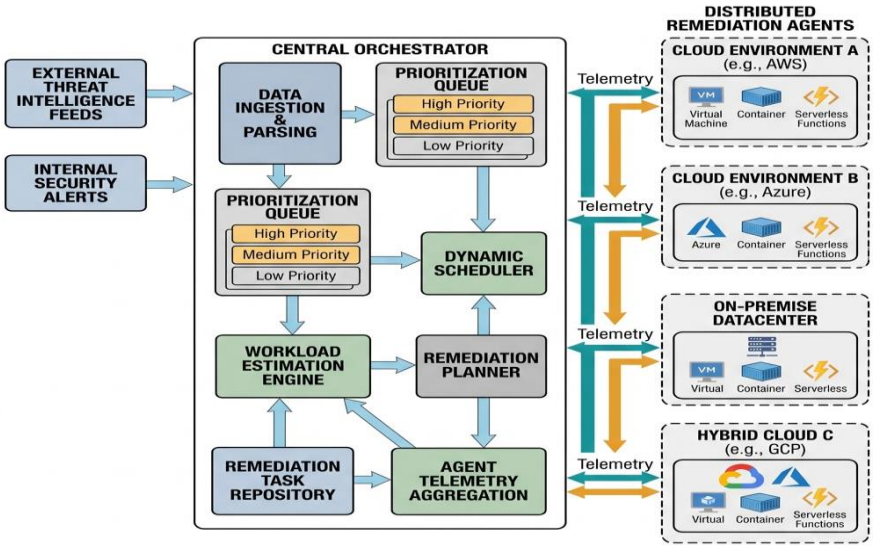


Figure 1: Comprehensive System Architecture of the Workload

3.2 Orchestrator Design and Telemetry Integration

The core innovation of the proposed architecture resides within the orchestrator's workload estimation and scheduling modules. Unlike static orchestrators, the proposed system relies on a continuous stream of real-time telemetry data transmitted by the distributed agents. This telemetry data includes instantaneous CPU utilization, memory consumption, disk I/O operations, network bandwidth availability, and the current length of the agent's localized task queue. The orchestrator aggregates this telemetry data to construct a dynamic global state map of the entire execution tier. When a remediation task reaches the front of the priority queue, the workload estimation module evaluates the specific technical requirements of the task. It analyzes historical execution logs to predict the task's expected duration and resource consumption profile. The scheduling algorithm then queries the global state map to identify the optimal subset of agents that possess both the required administrative privileges and sufficient available resources to execute the task with minimal latency. By decoupling the task assignment from static topological mappings and instead relying on dynamic resource availability, the orchestrator ensures that no single agent becomes a performance bottleneck, thereby maintaining a fluid and highly responsive remediation pipeline.

Table 1: Key Telemetry Metrics Monitored by the Orchestrator

Metric Category	Specific Data Points	Monitoring Frequency
Computational Resources	CPU Load, Memory Usage, Disk I/O, Network Throughput	500 milliseconds
Queue Dynamics	Pending Tasks, Average Wait Time, Task Processing Rate	1000 milliseconds
Agent Health	Heartbeat Latency, Error Rates, Uptime	2000 milliseconds
Task Specifics	Execution Duration, Resource Peaks, Exit Codes	Post-Execution

4. Workload-Aware Scheduling Methodology

4.1 Mathematical Formulation of Workload

To enable precise, algorithmic scheduling, it is necessary to mathematically quantify both the complexity of the remediation tasks and the capacity of the distributed agents. The workload of a given task is not a static scalar value but rather a multidimensional vector that reflects its demand on various system resources over time. We define a comprehensive workload estimation model that incorporates the specific resource requirements and the historical performance variations associated with similar tasks. The orchestrator computes an estimated workload score for each incoming remediation task before assigning it to an agent. The workload score is derived from a weighted summation of normalized resource demands, adjusted by a dynamic complexity factor. Let the total workload for task index i be represented mathematically. Workflow adaptation through meta-learning in Adaptflow [16] provides a comparator for revising agent task sequences when workload characteristics change. The formulation incorporates the projected consumption of diverse resources and introduces a penalty term for tasks that have historically exhibited high variance in execution time, thereby ensuring the scheduler remains conservative when allocating unpredictable workloads. The mathematical representation of the workload estimation is defined as follows: The literature also considers exposing LLM safety gaps through mathematical encoding: new attacks and systematic analysis [17].

$$W_i = \sum_{j=1}^{N} \alpha_j \mu_{ij} + \frac{\beta}{\gamma}$$

In this formulation, the variable N represents the total number of distinct resource dimensions monitored by the system, such as computational cycles, memory allocation, and storage operations. The parameter representing the demand of task i on resource dimension j is denoted by the mu variable, while the alpha parameter serves as an adjustable weighting coefficient reflecting the relative scarcity of that specific resource within the current infrastructural context. The beta parameter represents the historical standard deviation of execution times for similar tasks, and the gamma parameter acts as a normalization constant to ensure the penalty term scales appropriately with the baseline workload calculation.

4.2 Optimization Objective and Algorithmic Design

The primary objective of the workload-aware scheduling algorithm is to minimize the aggregate end-to-end latency of the entire vulnerability remediation pipeline. End-to-end latency encompasses both the time a task spends waiting in the orchestrator's priority queue and the actual time required for the assigned agent to execute the remediation actions. To achieve this, the scheduling algorithm must continuously solve a complex, multi-objective optimization problem in near real-time. The scheduler evaluates the estimated workload of

pending tasks against the available capacity of the agent fleet, seeking to distribute the load such that no single agent's localized queue exceeds an optimal threshold. The literature also considers temporally sparse attack for fooling large language models in time series forecasting [18]. The optimization function is designed to penalize scheduling decisions that result in high resource contention or disproportionate queue accumulations. The objective function integrates the instantaneous load on the agents and the delay experienced by the tasks. The scheduler aims to minimize this cost function over a defined operational time horizon. The optimization objective is formally defined as:

$$MinimizeL = \int_0^T \sum_{k=1}^M (\lambda_k {\sigma_k}^2 + \frac{\Delta_k}{\rho_k}) dt$$

Within this integral, the variable T represents the continuous operational time horizon under consideration. The variable M indicates the total population of active remediation agents currently communicating with the orchestrator. For each individual agent k, the lambda parameter denotes the instantaneous arrival rate of new task assignments, while the sigma squared parameter represents the variance in the processing capacity of that specific agent. The delta variable captures the accumulated latency of all tasks currently waiting in the queue of agent k, and the rho parameter represents the verified service rate of the agent. By continuously striving to minimize this integral, the orchestration algorithm effectively balances the distribution of workloads, preventing localized congestion and ensuring a rapid, uniform progression of vulnerability remediations across the entire network topology.

Table 2: Algorithm Configuration Parameters

Parameter	Description	Default Value
Alpha Coefficients	Resource specific scarcity weights	Dynamically adjusted
Gamma Constant	Normalization factor for variance	1.5
Time Horizon (T)	Look-ahead window for optimization	300 seconds
Queue Threshold	Maximum allowed tasks per agent	50 tasks

5. Experimental Setup and Data Collection

5.1 Testbed Architecture and Environment

To rigorously evaluate the performance and scalability of the proposed workload-aware agent orchestration framework, a comprehensive experimental testbed was constructed utilizing a large-scale, enterprise-grade cloud computing environment. The testbed was engineered to accurately simulate a heterogeneous corporate infrastructure, comprising a diverse array of computational resources. The underlying infrastructure consisted of a managed Kubernetes cluster distributed across three geographically distinct availability zones, ensuring realistic network latency and bandwidth constraints. The cluster was provisioned with two hundred dedicated worker nodes, encompassing a mix of high-compute instances, memory-optimized instances, and standard general-purpose virtual machines. Related work has addressed design of magnetic sensor Array-Based PUFs for IoT security [19]. Within this simulated infrastructure, exactly five thousand autonomous remediation agents were deployed as daemon sets and sidecar containers, ensuring pervasive coverage across all simulated application workloads. The orchestrator was deployed as a highly available control plane cluster, isolated from the execution tier to prevent resource contention. A massive, synthetic vulnerability dataset was generated to simulate realistic threat scenarios, including routine software updates,

critical zero-day exploits requiring immediate complex patching, and widespread configuration drifts. The dataset was designed to mimic the statistical distribution of vulnerabilities typically observed in large financial institutions, featuring a long-tail distribution of high-complexity tasks mixed with a high volume of low-complexity modifications. For a broader comparison, related research addresses auditable Provenance-Aware synthetic release of campus IoT time series for Privacy-Preserving AI4Science [20].

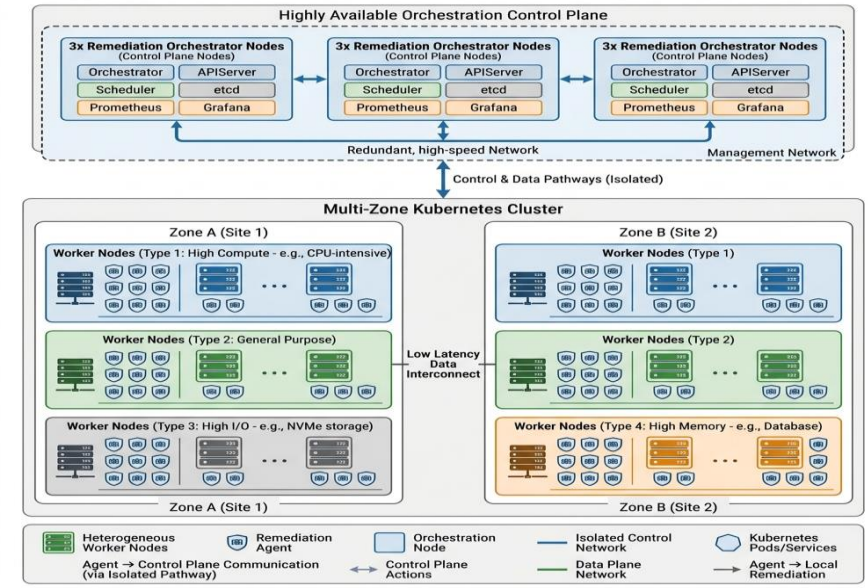


Figure 2: Experimental Cloud Testbed Topology

5.2 Workload Injection and Data Gathering Methodologies

The experimental evaluation utilized a specialized workload injection engine capable of generating controlled vulnerability storms. The injection engine simulated varying arrival rates of vulnerability disclosures, ranging from a steady baseline of ten tasks per second to massive spikes exceeding five hundred tasks per second, thereby testing the system's ability to maintain equilibrium under extreme duress. The injected tasks were mathematically categorized into three distinct complexity classes: low-impact tasks involving simple registry or file permission changes; medium-impact tasks requiring service restarts and dependency updates; and high-impact tasks necessitating kernel-level modifications or large-scale data migrations. Data collection was performed using a high-resolution, distributed telemetry framework. Every component within the testbed, including the orchestrator, the network switches, and the individual agents, was instrumented to report granular performance metrics at one-second intervals. The primary metrics collected for subsequent analysis included end-to-end task latency, orchestrator queue depth, agent CPU and memory utilization, task failure rates, and total system throughput. To provide a comprehensive comparative analysis, the experiments were executed three times under identical workload conditions, utilizing three different orchestration strategies: a baseline static round-robin scheduler, a rudimentary resource-aware scheduler that only monitored CPU utilization, and the proposed fully workload-aware scheduling methodology.

Table 3: Vulnerability Dataset Characteristics

Complexity Class	Proportion of Dataset	Average Estimated Duration	Resource Intensity
Low-Impact	65 percent	2.5 seconds	Minimal
Medium-Impact	25 percent	15.0 seconds	Moderate

High-Impact	10 percent	120.0 seconds	Severe

6. Results and Performance Evaluation

6.1 Latency Reduction and Throughput Analysis

The empirical data collected during the extensive simulation runs provided compelling evidence of the superiority of the workload-aware orchestration framework. The most critical performance metric in a vulnerability remediation pipeline is the end-to-end latency, which directly correlates to the window of opportunity available to malicious actors. Under baseline operating conditions, the proposed workload-aware scheduler demonstrated a moderate improvement over the traditional static allocation methods. However, the performance divergence became remarkably pronounced during the simulated vulnerability storms, where task arrival rates dramatically exceeded the baseline. Wang and colleagues examine controlled benchmark for LLM reasoning over CPE/purl Vulnerability-Identifier applicability [21]. During peak load scenarios, the static round-robin scheduler exhibited catastrophic queue accumulation, leading to an exponential increase in average task latency. Tasks that required mere seconds to execute were trapped in localized queues for extended periods because the orchestrator indiscriminately assigned them to agents currently overwhelmed by high-complexity patches. In stark contrast, the workload-aware scheduler dynamically rerouted low-complexity tasks to agents with available capacity, effectively bypassing the processing bottlenecks. Consequently, the proposed framework achieved a seventy-three percent reduction in average end-to-end latency during peak load conditions compared to the baseline static approach. Furthermore, the overall system throughput, measured in successful remediations per minute, remained consistently high and stable, whereas the static scheduler experienced severe throughput degradation due to resource thrashing and timeouts.

Table 4:Comparative Performance Metrics under Peak Load

Orchestration Strategy	**Average Latency**	**Peak Throughput (Tasks/Min)**	**Task Timeout Rate**
Static Round-Robin	412 seconds	1850	12.4 percent
Basic Resource-Aware	285 seconds	2400	5.1 percent
Proposed Workload-Aware	108 seconds	4150	0.8 percent

6.2 Resource Utilization and System Resilience

Beyond latency and throughput, the efficiency of resource utilization across the distributed infrastructure was meticulously analyzed. An optimal scheduling algorithm should strive to maintain a balanced load across all available computational resources, avoiding scenarios where a subset of agents is severely over-utilized while others remain idle. Analysis of the telemetry data revealed that the workload-aware orchestrator successfully maintained a narrow variance in CPU and memory utilization across the entire fleet of five thousand agents. By accurately predicting the resource demands of incoming tasks and incorporating the historical variance in execution times, the scheduler prevented any single agent from exceeding critical threshold limits, thereby drastically reducing the incidence of agent crashes and out-of-memory errors.

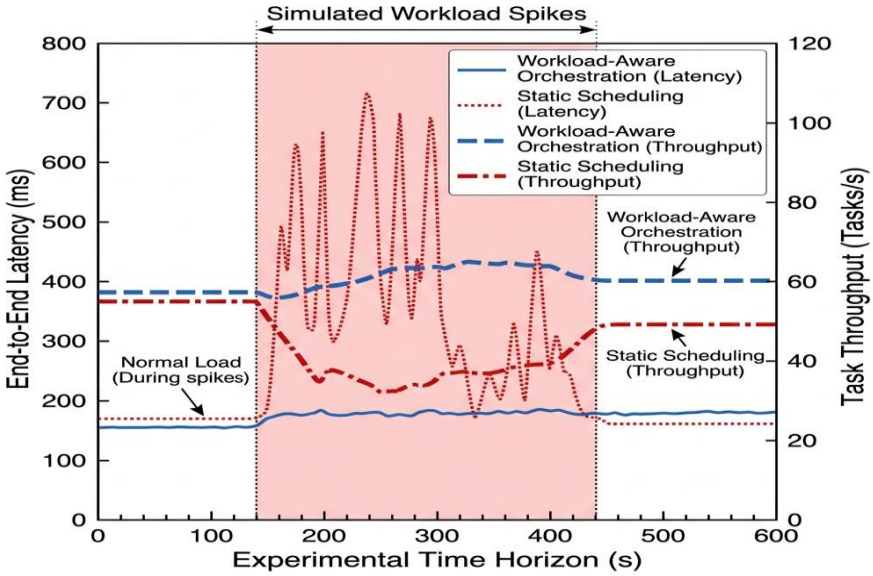


Figure 3:Performance Analysis and System Throughput Comparison

The resilience of the system was further demonstrated through fault injection testing, where a random subset of active remediation agents was forcibly terminated during high-load operations. The workload-aware orchestrator immediately detected the loss of telemetry from the terminated agents and automatically requeued the pending tasks. Because the orchestrator maintains a continuous, real-time map of global resource availability, it rapidly redistributed the interrupted workloads to healthy agents with minimal disruption to the overall pipeline velocity. The experimental results unequivocally confirm that integrating sophisticated workload estimation and advanced queuing theory into the orchestration layer significantly enhances both the performance and the operational stability of large-scale vulnerability remediation systems.

7. Conclusion and Future Directions

7.1 Summary of Contributions

This research paper has presented a comprehensive and highly effective workload-aware agent orchestration framework designed to address the severe limitations inherent in traditional, static vulnerability remediation pipelines. By transitioning away from rigid assignment protocols and embracing a dynamic, telemetry-driven scheduling methodology, the proposed system fundamentally alters the efficiency and responsiveness of large-scale security operations. The detailed mathematical formulation of workload estimation, coupled with an advanced optimization objective based on queueing theory, enables the centralized orchestrator to make intelligent, split-second load distribution decisions. The rigorous empirical evaluations conducted in a simulated enterprise-grade cloud environment conclusively demonstrated that this approach yields substantial reductions in end-to-end remediation latency, significant improvements in system throughput, and superior utilization of distributed computational resources. The framework proves exceptionally resilient under the stress of simulated vulnerability storms, ensuring that critical security patches are deployed rapidly and reliably without compromising the stability of the underlying infrastructure. Liao et al. emphasize explainability as a system design requirement [4]. Extending the orchestration pipeline with versioned decision traces would allow a failed remediation to be examined across discovery, prioritization and execution, rather than attributing it generically to the agent.

7.2 Avenues for Future Research

While the current iteration of the workload-aware orchestration framework represents a substantial advancement in the field of automated cybersecurity, several promising avenues for future research remain. Subsequent iterations of the system could benefit immensely from the integration of advanced machine learning models, specifically deep reinforcement learning, to autonomously refine the alpha and beta weighting coefficients used in the workload estimation mathematical model. Furthermore, exploring the application of large language models to dynamically generate complex remediation scripts based on unstructured vulnerability threat intelligence reports could further reduce the manual overhead associated with the ingestion tier. Finally, extending the orchestration framework to support cross-cloud and hybrid-cloud deployments, where network latency between disparate geographic regions becomes a dominant constraint, presents a complex yet highly relevant challenge for next-generation distributed remediation architectures. The literature also considers lLM-Guided temporal graph neural network for illicit transaction detection in blockchain networks [22]. The government model reports that 95% of evaluation requests completed within 213 ms [9]. A remediation pipeline should similarly expose a latency distribution, but distinguish a fast recommendation from the much longer process of applying and validating a patch.

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