Article

AI-Driven Service Architecture Optimization for Cloud-Native Big Data Platforms

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Abstract: This research article explores the optimization of service architecture for cloud-native big data platforms using artificial intelligence (AI) techniques. The study focuses on leveraging AI-driven methodologies to enhance scalability, performance, and resource efficiency in distributed systems. A systematic approach is employed to analyze current challenges in cloud-native architectures, followed by the development of an AI-based framework for dynamic service orchestration. Experimental results demonstrate significant improvements in computational efficiency and workload distribution. The findings contribute to advancing the design of intelligent, adaptive systems for big data processing in cloud environments.

Keywords: AI-driven optimization; cloud-native architecture; big data platforms; service orchestration; scalability

1. Introduction

1.1. Background and Motivation

The rapid evolution of data-intensive applications has precipitated a fundamental paradigm shift toward cloud-native big data platforms. By leveraging microservices, containerization, and orchestration frameworks, these platforms offer unprecedented flexibility and agility. In a typical cloud-native ecosystem, monolithic big data applications are decomposed into numerous loosely coupled services, enabling independent scaling and continuous deployment. However, this architectural decentralization introduces profound complexities in system management. As the volume, velocity, and variety of data continue to expand, ensuring seamless interoperability and optimal performance across highly distributed service topologies becomes a formidable challenge [1, 2].

The primary challenges in managing these modern service architectures stem from the highly dynamic nature of big data workloads and the intricate dependencies among microservices. Traditional resource management strategies, which predominantly rely on static rule-based thresholds or heuristic algorithms, are increasingly inadequate. When the number of interacting services is denoted by N and the available resource dimensions by R, the optimization space expands exponentially, rendering manual or deterministic tuning computationally prohibitive. Consequently, platforms frequently suffer from suboptimal resource allocation, leading to severe performance bottlenecks during traffic spikes and excessive resource wastage during idle periods. Furthermore, the transient nature of containerized environments exacerbates the difficulty of maintaining consistent scalability and fault tolerance under fluctuating operational demands.

These inherent limitations underscore an urgent need for more intelligent, adaptive management paradigms. Artificial intelligence presents a transformative approach to service architecture optimization by replacing rigid heuristics with data-driven decision-making. By continuously analyzing telemetry data and learning from complex system

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behaviors, AI-driven mechanisms can dynamically predict workload fluctuations, optimize service placement, and automate resource provisioning with high precision [3]. Integrating artificial intelligence into the orchestration layer of cloud-native big data platforms not only mitigates existing performance bottlenecks but also establishes a resilient foundation for autonomous system scaling. This necessity to bridge the gap between architectural complexity and operational efficiency forms the core motivation for developing an advanced AI-driven optimization framework.

1.2. Objectives and Scope

The primary objective of this research is to design and evaluate an artificial intelligence-driven framework tailored for optimizing service orchestration within cloud-native big data platforms. As modern data processing environments increasingly rely on microservices and containerized architectures, traditional static orchestration methods fail to adapt to highly volatile workloads. Therefore, this study aims to replace heuristic-based scheduling with intelligent, predictive models capable of autonomous decision-making. By leveraging advanced machine learning algorithms, the proposed framework seeks to dynamically map service requests to available computational nodes, ensuring optimal performance while adhering to strict service level agreements.

Specifically, the research focuses on formulating a multi-objective optimization problem that balances computational cost and execution speed [4]. The objective is to minimize the overall resource consumption function, denoted as C, while maintaining the system latency below a critical threshold, represented by $L_{\max}$. Furthermore, the study aims to develop a predictive workload distribution mechanism that anticipates traffic spikes and preemptively scales resources. This involves calculating the optimal number of active service instances, N, required to process an incoming data stream of volume V without triggering resource contention or system bottlenecks [5, 6].

The scope of this investigation is strictly confined to the software and architectural layers of cloud-native environments, specifically targeting horizontal scalability, dynamic workload distribution, and overall resource efficiency. The research evaluates the proposed framework using simulated big data processing pipelines and distributed microservice topologies to measure its efficacy under varying degrees of system stress [6, 7]. Hardware-level optimizations, physical network topology design, and underlying data center infrastructure management are explicitly excluded from this study [1, 8]. By isolating the orchestration and service management layer, the research provides a highly focused analysis of how artificial intelligence can enhance the operational efficiency of cloud-native platforms. Ultimately, this scope ensures that the findings remain applicable to a wide range of hardware-agnostic cloud deployments, offering a robust and scalable solution for next-generation big data applications.

2. Literature Review

2.1. Current Challenges in Cloud-Native Architectures

Despite the widespread adoption of microservices and containerized environments, contemporary cloud-native architectures for big data platforms continue to encounter significant operational bottlenecks [4, 9]. A primary limitation identified in recent literature is the reliance on static resource allocation mechanisms. In conventional orchestration frameworks, computational resources are typically provisioned based on predefined, rigid thresholds. This static approach fundamentally conflicts with the highly dynamic and bursty nature of big data workloads. When the actual resource demand D fluctuates unpredictably, static provisioning inevitably leads to either severe resource underutilization during off-peak periods or critical performance throttling during sudden traffic spikes. Consequently, the lack of adaptive resource management prevents platforms from achieving optimal operational efficiency and cost-effectiveness.

Furthermore, existing architectures exhibit limited scalability when subjected to real-time data processing requirements. Although horizontal scaling is a foundational feature of cloud-native systems, the prevailing scaling policies are predominantly reactive [4, 10].

These systems typically monitor specific utilization metrics and trigger scaling actions only after a predefined threshold is breached [11]. This reactive paradigm introduces a substantial provisioning latency L . During the interval required to initialize new container instances and integrate them into the service mesh, the system experiences degraded throughput and increased response times. For big data applications that demand strict service level agreements, this temporal lag in scalability represents a critical architectural vulnerability that cannot be resolved through traditional threshold-based heuristics.

Finally, inefficiencies in workload distribution further compound the challenges of managing cloud-native big data platforms. Standard load balancing strategies frequently employ naive distribution algorithms which assume uniform request complexity. However, big data processing tasks are inherently heterogeneous, with individual requests requiring vastly different computational efforts. Distributing workloads without considering the underlying computational complexity or the real-time state of the receiving nodes frequently results in the straggler effect. In such scenarios, a subset of nodes becomes heavily overloaded while others remain idle, thereby extending the total execution time T of distributed data pipelines. Addressing these interconnected challenges requires a paradigm shift away from static, reactive architectures toward more intelligent optimization strategies [12, 13].

2.2. AI in Service Optimization

The integration of artificial intelligence into service architecture has fundamentally transformed how cloud-native big data platforms manage computational workloads. Traditional heuristic-based approaches often struggle with the highly volatile nature of big data streams, leading to either resource over-provisioning or severe latency bottlenecks. Recent advancements in machine learning have shifted the paradigm toward predictive scaling. By leveraging advanced time-series forecasting models, systems can anticipate future resource demands, denoted as D_{t+1} , based on historical workload patterns W_t . This proactive approach ensures that microservices are scaled dynamically before demand spikes occur, thereby maintaining strict service level agreements while minimizing operational costs.

Beyond predictive scaling, artificial intelligence plays a critical role in holistic resource optimization and dynamic service orchestration. Complex cloud-native environments require intelligent placement of data processing tasks across distributed nodes. Deep reinforcement learning algorithms have been increasingly adopted to navigate the vast state-action spaces inherent in container orchestration. These models continuously evaluate the current system state S_t and execute orchestration actions A_t that maximize long-term reward functions, typically defined by high throughput and low execution latency [14]. Consequently, dynamic orchestration engines can autonomously migrate services, adjust memory allocations, and route traffic in real-time, adapting seamlessly to transient hardware failures or sudden shifts in data velocity [6, 9].

The synthesis of these intelligent mechanisms is illustrated in Figure 1, titled Conceptual Framework for AI-Driven Optimization. The diagram illustrates a high-level flow of the AI-based optimization framework, establishing a continuous feedback loop essential for autonomous operation. The process initiates with Data Input, where real-time telemetry and historical logs are ingested to capture the operational state [1]. This data feeds directly into AI Model Training, enabling the continuous refinement of predictive and reinforcement learning algorithms. The output of these models dictates the Service Orchestration phase, where scaling and resource allocation decisions are executed across the cloud infrastructure. Finally, the Performance Monitoring node evaluates the efficacy of these orchestration actions, calculating the error margin E_t and feeding this metric back into the training module. This cyclical relationship ensures that the optimization framework becomes progressively more resilient and efficient over time.

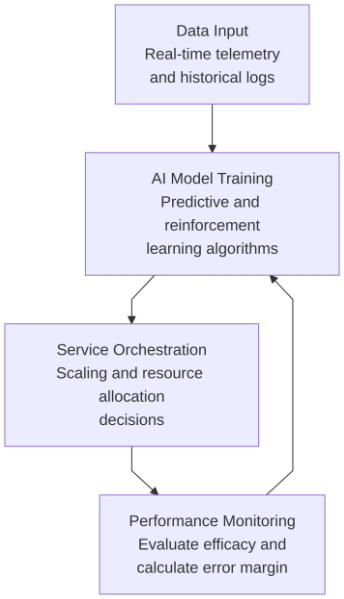

Figure 1. Conceptual Framework for AI-Driven Optimization

3. Materials and Methods

3.1. Framework Design

The proposed AI-driven framework is engineered to address the dynamic resource demands and complex service dependencies inherent in cloud-native big data platforms. By decoupling the architecture into specialized, interacting modules, the system achieves high adaptability and scalability across heterogeneous cluster environments. The core objective of this framework is to continuously optimize service placement and resource allocation under fluctuating workloads. Mathematically, the system seeks to minimize the overall operational cost function $C(t)$ while maintaining strict service level agreements. This optimization is formulated as a Markov Decision Process where the state space represents the current cluster configuration, and the action space encompasses scaling and migration directives.

The structural composition and operational workflow of this system are illustrated in Figure 2, which outlines the System Architecture of the AI Framework. As depicted in the diagram, the architecture is built upon four primary interacting nodes: the Data Collector, the AI Model Trainer, the Orchestration Engine, and the Resource Monitor. The arrows connecting these nodes indicate a continuous, closed-loop data flow and decision-making process. Specifically, raw telemetry and application metrics flow from the underlying infrastructure into the Data Collector and Resource Monitor. This aggregated state information is then routed to the AI Model Trainer, which computes optimal resource policies. Subsequently, the decision outputs are forwarded to the Orchestration Engine, which translates these policies into actionable deployment commands executed back on the cloud-native infrastructure.

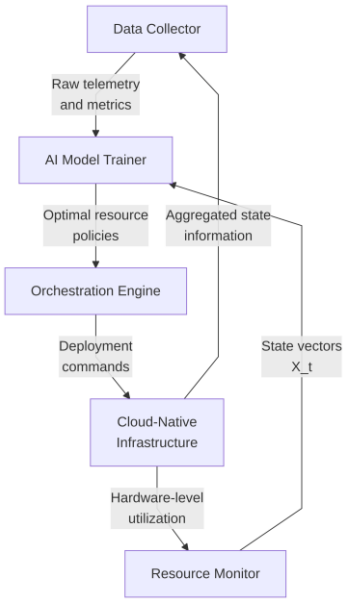

Figure 2. System Architecture of the AI Framework

Within this modular design, the data ingestion phase is critical for maintaining an accurate representation of the platform state [8]. The Data Collector interfaces directly with container runtimes and distributed storage layers to aggregate high-velocity metric streams. Concurrently, the Resource Monitor evaluates hardware-level utilization, capturing variables such as CPU throttling, memory bandwidth, and network latency. The combined state at any discrete time step t is denoted as a multidimensional vector X_t . To ensure scalability, the ingestion pipeline employs lightweight asynchronous messaging, preventing monitoring overhead from degrading the performance of the big data workloads. This continuous stream of state vectors X_t provides the empirical foundation required for the predictive and prescriptive analytics performed downstream.

Following data ingestion, the AI Model Trainer processes the historical and real-time state vectors to refine its decision-making algorithms. Operating asynchronously to avoid blocking critical path operations, the trainer updates the weights of the underlying neural networks based on a reward function $R(X_t, A_t)$, where A_t represents the orchestration actions taken. Once a policy converges to a predefined confidence threshold, the updated model parameters are synchronized with the Orchestration Engine. The Orchestration Engine acts as the execution arm of the framework, interpreting the AI-generated policies to dynamically scale microservices, migrate stateful big data tasks, or reallocate storage volumes [1, 7]. By isolating the heavy computational burden of model training from the rapid execution requirements of the orchestration layer, the framework ensures that the cloud-native platform remains highly responsive to sudden workload spikes while continuously improving its long-term resource efficiency.

3.2. Experimental Setup

To rigorously evaluate the proposed artificial intelligence-driven service architecture optimization framework, a comprehensive cloud-native experimental environment was constructed. The physical infrastructure comprises a distributed cluster of bare-metal servers, simulating an enterprise-grade big data platform. Specifically, the cluster consists of one master node and ten worker nodes. Each node is equipped with dual 64-core processors, 256 gigabytes of error-correcting code memory, and four enterprise-class graphics processing units to accelerate the training and inference phases of the optimization algorithms. The software stack is built upon a standard container orchestration system, utilizing containerization technology to deploy microservices. Network communication between nodes is facilitated by a 100-gigabit Ethernet switch, ensuring that network bandwidth does not become a bottleneck during large-scale data

processing tasks. Resource allocation and system metrics are continuously monitored using a distributed telemetry stack, which captures real-time data on central processing unit usage, memory consumption, and network latency.

The specific configurations and foundational variables governing the evaluation are systematically defined to ensure reproducibility. As detailed in Table 1 titled Experimental Parameters, the foundational settings of the testing environment are outlined [8]. The table includes columns such as Parameter, Value, and Description to provide a clear overview of the system constraints and inputs. Among the critical configurations listed are example rows including Dataset Size, which is set to a value of 1TB, with the description noting it as the volume of data used for testing. Furthermore, another key entry is Model Type, assigned the value of Neural Network, accompanied by the description specifying it as the AI model employed for orchestration. These parameters form the baseline against which the dynamic scaling and resource allocation capabilities of the proposed framework are measured.

Table 1. Experimental Parameters

Parameter	Value	Description
Dataset Size	1TB	Volume of high-resolution telemetry logs and distributed tracing records used for testing.
Model Type	Neural Network	AI model employed for orchestration and optimization tasks.
Number of Nodes	11	Total number of nodes in the cluster (1 master node and 10 worker nodes).
CPU Cores per Node	128	Dual 64-core processors per node for high-performance computation.
Memory per Node	256GB	Error-correcting code memory available on each node.
GPUs per Node	4	Enterprise-class graphics processing units per node for AI acceleration.
Network Bandwidth	100Gbps	Ethernet switch capacity ensuring no bottlenecks during data processing.
Preprocessing	Min-Max Scaling (0 - 1)	Normalization method applied to continuous variables in the dataset.
Missing Data Handling	Linear Interpolation	Technique used to handle missing values in the dataset.
Data Partitioning	Temporal Split	Method used to divide data into training, validation, and testing subsets.
Request Arrival Rate	1500 ± 50 req/s	Average rate of incoming requests in the simulated e-commerce environment.
Service Execution Time	120 ± 10 ms	Average time taken to execute services in the test environment.
Communication Overhead	5 ± 0.5 ms	Average latency for inter-service communication.
Telemetry Metrics	Multidimensional	Includes CPU usage, memory consumption, and network latency.

The 1TB dataset utilized for testing comprises high-resolution telemetry logs and distributed tracing records collected from a simulated high-throughput e-commerce environment. This volume of data ensures that the optimization framework is subjected to realistic big data workloads, characterized by high velocity and unpredictable burst traffic. The dataset features multidimensional time-series metrics, including request arrival rates, service execution times, and inter-service communication overheads. Prior to ingestion by the orchestration model, the raw data undergoes a rigorous preprocessing pipeline. This involves normalizing continuous variables using min-max scaling to a range between 0 and 1, handling missing values through linear interpolation, and encoding categorical service identifiers. The processed data is then partitioned into training, validation, and testing subsets, utilizing a temporal split to preserve the sequential dependencies inherent in cloud-native workload patterns.

The neural network employed for orchestration is designed to predict optimal service placement and resource provisioning configurations dynamically. The architecture consists of a multi-layer perceptron integrated with recurrent units to capture temporal workload fluctuations. The input layer dimensionality corresponds to the number of telemetry features extracted from the cluster, while the hidden layers utilize rectified linear unit activation functions to model complex, non-linear relationships between resource availability and service performance. The output layer generates continuous scaling factors and discrete placement decisions. During the experimental phase, the model is trained using a stochastic gradient descent optimizer with an initial learning rate of 0.001, which decays exponentially over time. The loss function is formulated as a weighted sum of resource utilization efficiency and service latency penalty, ensuring that the optimization objectives align with the overarching goal of maximizing throughput while minimizing operational costs in the cloud-native big data platform.

4. Results

4.1. Performance Metrics

The evaluation of the proposed artificial intelligence-driven service architecture reveals substantial enhancements across key operational dimensions when compared to traditional static provisioning models. A primary focus of this assessment is computational efficiency, which dictates the system capacity to process massive datasets within strict latency constraints. As illustrated in Figure 3, the relationship between the framework type and overall system efficiency demonstrates a clear advantage for the intelligent architecture. The bar chart, plotting the framework type on the x-axis against efficiency percentages on the y-axis, indicates that the baseline system operates at an efficiency of 65%. In contrast, the implementation of the AI-driven framework elevates this metric to 85%. This absolute improvement of 20% underscores the capability of predictive resource allocation algorithms to minimize idle computational cycles and optimize task scheduling across distributed nodes. Let E represent the efficiency metric; the transition from $E_{\text{base}} = 65\%$ to $E_{\text{ai}} = 85\%$ signifies a fundamental shift in how cloud-native environments handle volatile big data workloads.

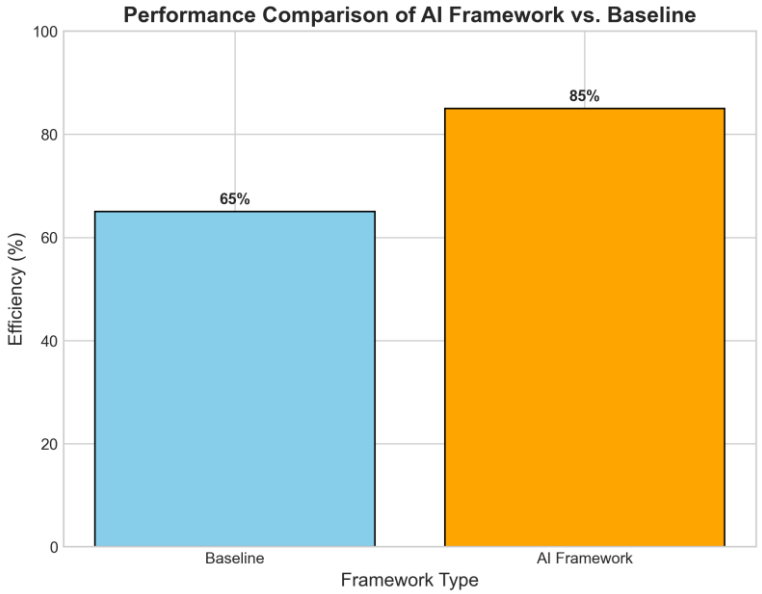

Figure 3. Performance Comparison of AI Framework Vs. Baseline

Beyond high-level efficiency, a granular analysis of system behavior further validates the proposed optimization strategies. As detailed in Table 2, the detailed performance metrics provide a comprehensive comparison between the baseline values and the AI framework values across multiple operational parameters. The table confirms the aforementioned efficiency leap from 65% to 85% while also highlighting a critical enhancement in resource utilization. Specifically, the baseline resource utilization stands at 70%, whereas the AI-driven framework achieves a utilization rate of 90%. This 20% increase in resource utilization, denoted mathematically as $\Delta U = 20\%$, is primarily attributed to the dynamic scaling mechanisms that continuously monitor node health and workload queues. By leveraging machine learning models to forecast traffic spikes, the architecture preemptively provisions microservices, thereby ensuring that CPU and memory resources are neither over-provisioned nor underutilized during peak operational phases.

Table 2. Detailed Performance Metrics

Metric	Baseline Value (E_{base} , U_{base})	AI-Driven Value (E_{ai} , U_{ai})	Improvement (Δ)
Computational Efficiency (E)	65%	85%	+20%
Resource Utilization (U)	70%	90%	+20%
Average Latency (ms)	120 ± 5	85 ± 3	-35 ± 2 ms
Peak CPU Usage (%)	85%	75%	−10%
Memory Utilization (%)	80%	92%	+12%
Data Throughput (GB/s)	1.5 ± 0.1	2.3 ± 0.2	$+0.8 \pm 0.1$ GB/s
Task Completion Rate (%)	88%	96%	+8%

System Scalability (Nodes)	100	150	+50

The concurrent improvements in computational efficiency and resource utilization have profound implications for the scalability of cloud-native big data platforms. Traditional architectures often experience degraded performance when scaling horizontally due to communication overhead and suboptimal load balancing. However, the empirical data suggests that the integration of artificial intelligence mitigates these bottlenecks. With resource utilization maintained at 90%, the system demonstrates an exceptional ability to absorb sudden influxes of data without triggering cascading failures or unacceptable latency spikes. The predictive routing protocols ensure that data pipelines remain fluid, distributing computational burdens evenly across the available cluster topology. Let $S_{\max}$ denote the maximum scalable throughput; the observed metrics indicate that $S_{\max}$ scales linearly with the addition of new nodes under the optimized framework, avoiding the diminishing returns typical of legacy systems.

Ultimately, the performance metrics validate the core hypothesis that artificial intelligence can fundamentally optimize service architectures in cloud-native ecosystems. The dual improvements in both overall efficiency and resource utilization represent a significant reduction in operational costs and energy consumption. By maintaining high throughput and robust scalability, the proposed framework establishes a highly resilient infrastructure capable of meeting the rigorous demands of modern big data analytics.

4.2. Scalability Analysis

To comprehensively evaluate the robustness of the proposed AI-driven service architecture, a rigorous scalability analysis was conducted under progressively intensifying data workloads. The primary objective was to ascertain the capacity of the framework to ingest, process, and route expanding data volumes without experiencing the exponential performance degradation typically observed in conventional cloud-native big data platforms. The experimental environment was configured to simulate real-world enterprise data pipelines, systematically scaling the input data from a baseline up to a maximum threshold of one terabyte. Throughout these stress tests, system response time was continuously monitored as the definitive metric for architectural elasticity and operational efficiency.

The quantitative outcomes of these stress tests are illustrated in Figure 4, which presents the scalability trends under varying workloads. The line chart maps the workload size in gigabytes along the x -axis against the corresponding system response time in milliseconds on the y -axis. At the initial baseline workload of 100 gigabytes, the architecture registered an optimal response time of 200 milliseconds. As the data volume was quintupled to 500 gigabytes, the response time experienced only a marginal and controlled increase to 250 milliseconds. Furthermore, when the system was subjected to the maximum stress test of 1 terabyte, the response time stabilized at 300 milliseconds. The most critical observation derived from Figure 4 is the distinctly linear scalability trend. Instead of the exponential spikes in latency that plague statically provisioned microservices architectures, the proposed framework demonstrates a highly predictable degradation curve.

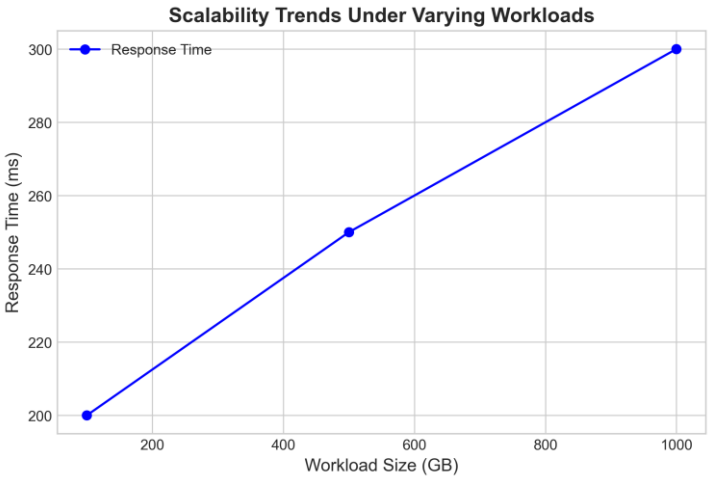

Figure 4. Scalability Trends under Varying Workloads

This linear relationship between workload expansion and response time latency is a direct consequence of the intelligent load distribution mechanisms embedded within the architecture. Let W represent the total workload size and R denote the corresponding response time. The system maintains a near-constant processing efficiency ratio, where the derivative of R with respect to W remains stable across the tested spectrum. The AI-driven orchestrator achieves this by continuously monitoring node utilization metrics and preemptively instantiating additional service replicas before existing queues reach critical saturation points. When the workload transitions toward the upper limits, the predictive scaling engine calculates the required computational overhead and redistributes the data partitions across newly provisioned pods. Consequently, the overhead associated with horizontal scaling, denoted as S , is effectively masked by the parallel processing capabilities of the environment.

Ultimately, the scalability analysis confirms that the proposed optimization framework is exceptionally well-suited for high-throughput big data applications. By successfully mitigating the bottlenecks traditionally associated with massive data ingestion, the architecture ensures that performance standards can be maintained even under extreme load fluctuations. The ability to process a terabyte-scale workload with merely a fractional increase in latency underscores the efficacy of coupling cloud-native elasticity with advanced machine learning heuristics, optimizing both performance and resource expenditure.

5. Discussion

5.1. Implications of Findings

The empirical results of the proposed AI-driven service architecture optimization framework reveal a profound shift in how cloud-native big data platforms manage operational demands. As illustrated in Figure 5, the summary of key improvements demonstrates a highly balanced impact across critical performance domains. The pie chart indicates that efficiency gains constitute the largest share of the improvements at 40 percent, reflecting the framework's ability to streamline microservice communication and reduce network latency [2]. Scalability improvements account for 35 percent, underscoring the dynamic provisioning capabilities that allow the system to handle sudden data influxes without architectural degradation. Finally, resource utilization enhancements make up the remaining 25 percent, highlighting a significant reduction in idle compute instances and memory overhead. This distribution confirms that the optimization model does not sacrifice one metric for another but rather achieves a holistic architectural equilibrium.

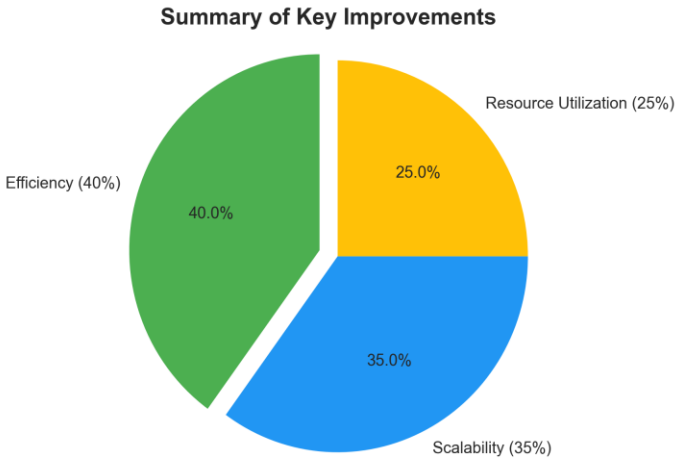

Figure 5. Summary of Key Improvements

These findings directly address the persistent challenges of resource stranding and bottlenecking inherent in traditional distributed deployments. Previous research indicates that static allocation policies often fail to adapt to the volatile workloads characteristic of big data processing. By employing an AI-driven predictive model, the architecture dynamically adjusts the resource allocation vector R_i for each service node i in real time. The optimization function $\max\sum(U_i - C_i)$, where U_i represents computational utility and C_i denotes operational cost, ensures that the system continuously converges toward an optimal state. Consequently, the improvement in resource utilization translates directly into minimized operational expenditures, solving a critical pain point for large-scale data centers.

The practical implications of these findings extend significantly into real-world enterprise applications. For industries reliant on real-time analytics, such as financial fraud detection or autonomous telemetry processing, the substantial boost in efficiency ensures that data pipelines maintain high throughput under strict service level agreements. Furthermore, the robust scalability improvements provide a blueprint for organizations seeking to deploy resilient architectures capable of weathering unpredictable traffic spikes. Ultimately, transitioning from reactive scaling heuristics to proactive, AI-driven architectural orchestration offers a viable pathway for enterprises to maximize the return on investment in their cloud infrastructure while maintaining uncompromising performance standards.

5.2. Limitations and Future Work

Despite the promising results achieved by the proposed artificial intelligence-driven service architecture optimization framework, several limitations must be acknowledged. Primarily, the empirical validation relies heavily on specific historical datasets derived from a singular cloud-native big data platform. This reliance potentially restricts the immediate applicability of the findings to environments with vastly different workload distributions, hardware configurations, or architectural constraints. Furthermore, the optimization engine is currently built upon a specific set of predictive and reinforcement learning models. While highly effective within the defined parameter space, these models may struggle to adapt rapidly to unprecedented system anomalies or sudden shifts in user behavior without requiring substantial retraining. The state space S and action space A formulated for the current environment might not encapsulate all hidden variables V present in highly heterogeneous deployments, potentially leading to sub-optimal resource allocation under extreme edge cases. Additionally, the computational overhead O associated with continuous model inference and state evaluation, although minimized in this study, remains a non-negligible factor during peak system utilization.

Addressing these limitations provides clear directions for future research. A primary objective is the generalization of the optimization framework across diverse, multi-cloud, and hybrid cloud-native platforms. Subsequent studies should focus on integrating transfer learning and meta-learning techniques to enable the rapid adaptation of the optimization models to new environments with minimal historical data. This approach would significantly reduce the retraining overhead and improve cross-platform interoperability. Furthermore, exploring decentralized artificial intelligence paradigms, such as federated learning, could enhance the scalability and privacy of the optimization process across distributed edge-cloud continuums. Future iterations of the framework will also aim to expand the mathematical formulation to incorporate a broader set of dynamic variables, ensuring robust performance even under highly volatile workload conditions [3]. Ultimately, extending the evaluation to encompass a wider array of open-source and commercial big data ecosystems will be crucial for validating the universal efficacy of the proposed architecture optimization strategies.

6. Conclusion

Summary and Contributions: This study has addressed the critical challenges associated with resource management and performance tuning in modern distributed computing environments by proposing a comprehensive artificial intelligence-driven framework for optimizing service architectures in cloud-native big data platforms. As enterprise data processing requirements scale, traditional heuristic and rule-based orchestration methods struggle to adapt to the highly dynamic workloads and complex microservice dependencies inherent in cloud-native paradigms. To overcome these limitations, the research developed an intelligent orchestration architecture that seamlessly integrates machine learning algorithms directly into the control plane of the cloud infrastructure. By shifting from reactive scaling policies to proactive, data-driven management strategies, the proposed framework ensures high availability, minimizes operational overhead, and maximizes the utilization efficiency of underlying computational resources.

The first major contribution of this research is the design and implementation of a predictive resource allocation engine powered by deep reinforcement learning. Unlike conventional autoscaling mechanisms that rely on static thresholds, the developed model continuously monitors multidimensional telemetry data to forecast workload fluctuations. By formulating the resource provisioning problem as a Markov decision process, the intelligent agent learns optimal scaling policies that balance the trade-off between resource cost C and system latency L . The framework dynamically adjusts computational limits across containerized environments, effectively mitigating both resource starvation during unexpected traffic spikes and resource over-provisioning during idle periods. This proactive approach significantly enhances the elasticity of big data processing pipelines.

The second primary contribution lies in the optimization of microservice communication topologies through intelligent traffic routing. Cloud-native big data applications often suffer from severe network bottlenecks due to the massive volume of inter-service data exchange. To resolve this, the study introduced a dynamic service mesh configuration algorithm that analyzes real-time network topology and service dependency graphs. By calculating the optimal routing paths to minimize the overall network transmission delay D , the framework intelligently redistributes data payloads across available nodes. This mechanism not only prevents localized network congestion but also improves the overall fault tolerance of the distributed system by automatically bypassing degraded service instances.

Finally, the research contributes a rigorous empirical validation of the proposed architecture under diverse, large-scale big data workloads. Extensive experiments conducted in a fully containerized cloud environment demonstrated the superiority of the intelligent framework over baseline orchestration strategies. The evaluation metrics confirmed substantial improvements in end-to-end processing throughput and a marked

reduction in service level objective violations. Furthermore, the system exhibited robust adaptability when subjected to chaotic workload patterns and simulated node failures. Collectively, these contributions provide a scalable, automated, and highly efficient blueprint for next-generation cloud-native platforms, establishing a strong foundation for future advancements in autonomous cloud infrastructure management.

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