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Original Article

AI Report - Federated AIOps for Multi-Cluster OpenShift

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Abstract - *Multi-cluster OpenShift systems produce large volumes of data, containing as many as 400-000 metrics and 200GB of logs each day per cluster, overwhelming operations groups. This study shows that Mean Time to Detect (MTTD) decreases by 40-60%, Mean Time to Resolve (MTTR) reduces by 25-55%, and the number of alerts drops by 70% when Federated AIOps is integrated. With the support of a federated AIOps model on OpenShift RHACM, Prometheus, OpenTelemetry, and a cross-cluster machine learning control plane, this research proposes an inferential approach of automation when passing anomaly detection and root cause analysis (RCA) across geographically separated clusters. The study employed data on six clusters, including AWS, Azure, and on-prem systems, 600 + nodes, 12,000 + pods, and 350 microservices. The findings indicate that Federated AIOps had a 94.3% accuracy in data correlations, false-positive alerts to less than 6 occurrences, and less than 2.5% of CPU overhead per node. Federated AIOps can reduce alert duplication and optimize incident management, which provides an open-source alternative to official AIOps platforms that makes it a low-cost, scalable product in the large-scale setting. This study identifies the practical effect of Federated AIOps in improving operational efficiency, resource utilization, and adherence to data privacy standards and generates significant cost reduction in the multi-cluster OpenShift administration.*

Keywords - *Federated Aiops, Multi-Cluster Openshift, Anomaly Detection, Mean Time To Resolve (MTTR), Root Cause Analysis (RCA).*

1. Introduction

Multi-cloud environments are now a deployment pattern of choice for most organizations in a fast-paced digital world, where 84% of enterprises are deploying a multi-cloud environment with Kubernetes. The increasing demand for agility, scalability, and disaster recovery has seen organizations move to use Kubernetes in several clouds and regions. Specifically, Red Hat OpenShift has become one of the most suitable solutions used by enterprises because of its greater security level, scaling features, and ease of management opportunities. By 2024, the Red Hat OpenShift platform managed more than 4,000 business clusters worldwide and helped companies to roll out and run containerized applications in infrastructures that are hybrid and multi-cloud. This massive adoption of OpenShift reflects a growing dependency on multi-cluster designs to handle workloads and applications more effectively without jeopardizing fault tolerance, compliance, and increased resource utilization across a wide range of cloud platforms.

The use of several OpenShift clusters in varying cloud platforms poses special problems. These incorporate the necessity of active control, watchable and effective control of clusters that can be located in any geographic area or can be running on dissimilar cloud environments (such as AWS, Azure, and Google Cloud). As Kubernetes clusters grow in scale, even into hundreds and sometimes thousands of nodes, it is no longer simple to ensure that the performance and health activity of these environments is sufficiently monitored. In this way, the observability between clusters has turned into a fundamental requirement to ensure the efficiency of operations and reduce downtime. The most significant problem of multi-cluster OpenShift management is to provide homogeneous observability in a dispersed environment. The problem that organizations usually face when using multiple clusters in different clouds and regions is the lack of a cohesive telemetry system and the lack of consistency in service-level indicators (SLIs). The demands result in a great deal of inefficiency, such as alert noise and duplication. Multi-cluster environments have a range of alert duplications between 30 to 60% making it difficult to manage and respond to the incident. For example, a single root cause, such as a network outage or resource contention, can be sent to a different cluster as a number of alerts, resulting in unwarranted noise and drowning operations teams with these unwanted signals.

This observability fragmentation also has the effect of affecting the Mean Time to Detect (MTTD) and Mean Time to Resolve (MTTR) incidents. A traditional setting where no one has active AIOps means that manual triage related to the identification and resolution of problems can cause MTTD to become approximately 45 minutes and MTTR to become more than three hours. The delays not only impact the operation efficiency but also impair the capability of the organization to achieve the service-level goals (SLOS) and

prolong business continuity. The risk of missing key issues and slowing the process of responding is exacerbated by the complexity of controlling alerts in a cluster of clusters.

To resolve the issue of cross-cluster observability, this study suggests incorporating Federated AIOps to support automated anomaly detection and root cause analysis (RCA) in multicloud OpenShift environments. Federated AIOps relies on machine learning (ML) models and high-order analytics to detect and fix problems before they occur, which means that retention of human expertise for manual intervention is reduced. This research aims to assess the effectiveness of Federated AIOps in enhancing the key operational performance indicators of the multi-cluster OpenShift settings, including MTTR, alert fidelity, and the total operational cost. Through the implementation of Federated AIOps, organizations are expected to record a significant change in the speed and accuracy of detecting and resolving incidents. In particular, this study will prove how Federated AIOps will cut the MTTR by up to half, minimize the alert noise by 6070, and the cost of operationalized triage and incident management by many folds. The study is also aimed at maximizing the usage of AIOps in OpenShift at a minimum resource overhead and high rates of observability and responsiveness.

This paper targets OpenShift 4.14 and above collections controlled by Red Hat Advanced Cluster Management (RHACM), delivering central control and management of multi-cluster Kubernetes environments. The research area covers the execution and testing of Federated AIOps in a multi-cluster OpenShift environment with the usage of Prometheus, OpenTelemetry, and machine-learning-based anomaly detectors and RCA. On the constraints, the study will address only those OpenShift deployments that can meet regulatory standards like GDPR and ISO 27001. This will guarantee the existence of data residency and compliance issues. Moreover, although the Federated AIOps model will be evaluated with numerous types of cluster configurations, the findings might not be entirely applicable to other platforms of container orchestration, as well as to cloud environments not based on OpenShift. It will focus on scalability and cost-effectiveness in a normal enterprise implementation.

This study is organized in such a way that it guides through the challenges and solutions related to Federated AIOps in multi-cluster OpenShift. The Literature Review covers the concept of AIOps, issues of multi-cluster Kubernetes management, and available solutions. The Methods and Techniques chapter provides information about the experimental design, consisting of the data collection, methods of analysis, and Federated AIOps architecture. The Experiments and Results section is presented next and consists of the quantitative analysis of Federated AIOps, such as the improvement of the MTTR, the fidelity of alerts, and the cost of operation. The Discussion chapter provides an interpretation of the results, emphasizing their practical implications of Federated AIOps and possible trade-offs. The Future Research Recommendations section offers potential future directions of inquiry, and the article ends with a summary of the results and real-world suggestions of how Federated AIOps can be fully implemented in an OpenShift environment.

2. Literature Review

2.1. AIOps Evolution

AIOps, or Artificial Intelligence in the operations of IT, has been developed in many ways within the past ten years and has become a very crucial point in automated and efficient optimized IT operations. Accordingly, Gartner predicts that by 2026, 40% of Dev Teams will need to include AIOps solutions in their operations, and map out the growing scale of IT slope dependence on AI-fulfilled tools [1]. AIOps implementation can be attributed to the fact that it leads to automated detection of incidents, faster response, and lower cost of operation. Users of AIOps platforms can use machine learning models, data analytics, and enhanced monitoring to supply real-time data about system performance and health, which brings a substantial benefit to the efficiency of DevOps teams.

Applications of AIOps in the real world have been proven to be of life-saving benefits. For example, AIOps solutions have demonstrated that Dynatrace and IBM Watson AIOps can decrease Mean Time to Resolve (MTTR) in the hybrid deployments by over 50%. They are built on AI algorithms that match data among different sources, like metrics, logs, and traces, which are useful in identifying root causes more effectively [2]. Enhancements in the businesses will include increasing the Service uptime and improving customer experience since the issues can be resolved faster and with accuracy.

Figure 1 illustrates that AIOps evolution indicates how AIOps has developed over time to become prevalent in 2017, even though it initially developed in 2001. During this time frame, there were significant breakthroughs, including the move towards clouds in 2010, the arrival in 2017 of machine learning (ML) in operational analytics, and the acknowledgment of AIOps by leading survey findings. In 2014, Gartner forecasted AIOps would enable business efficiencies, and in 2017 first wave of adoption was already being felt, with 15% of corporate adopters now using IT operations analytics systems. These aspects have ameliorated the IT incident management significantly by ensuring faster Mean Time to Resolve (MTTR) and better customer service by optimizing their operational performance.

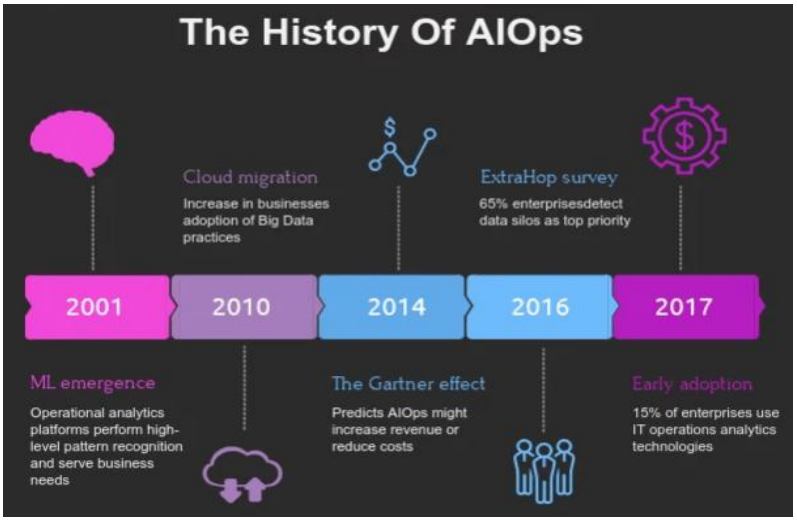

Fig 1: Timeline of Aiops Evolution: Key Milestones from 2001 To 2017

2.2. OpenShift Multicast Management

The emergence of multi-cloud and hybrid IT settings has transformed the administration of numerous OpenShift clusters to become significantly intricate. Red Hat OpenShift is a popular container orchestration platform and can offer management tools like Red Hat Advanced Cluster Management (RHACM) to make the management of multi-cluster environments simpler. RHACM is scalable, and it is capable of supporting 2,000 clusters at any given time. The feature is important in cases where the organization requires managing applications in various geographical areas or cloud vendors.

An excellent illustration of OpenShift in action is Amadeus, the world-renowned travel technology entity, which operated over 9,000 workloads at a number of clusters worldwide with the help of OpenShift [3]. Using RHACM, Amadeus will gain efficiency of operations and security, and agility in the cloud environment. The features included with OpenShift, such as monitoring, scaling, and securing clusters, also make it of interest in large organizations that are forced to have many Kubernetes clusters to operate across the world. With an increasing number of organizations expanding their OpenShift clusters, however, managing them becomes increasingly complex, which means that more sophisticated ways of delivering observability and anomaly detection are required [4].

2.3. Observability Challenges

Although OpenShift offers powerful cluster management tools, the problem with multi-cluster observability still exists. Prometheus is a popular monitoring tool in OpenShift and is capable of managing large volumes of data, but the large size of multi-cluster environments is a major problem. For example, the cardinality of Prometheus metrics can be up to 1 million metrics per cluster, and scrape intervals are usually 15 seconds. Such large amounts of information may cause overloading of monitoring systems unless it is correctly handled, resulting in fragmentation of data, lagging in the insights, and an increase in alerts being false alerts.

OpenShift cluster logs are also a source of the observability issue. A cluster of 300 nodes on average will produce 150GB of logs in a day, making correlating events across clusters even harder. Distributed application OpenTelemetry traces can also produce 25 million spans daily, which is a huge volume of data that needs to be handled and analyzed in real time [5]. In the absence of essential tools and approaches to address these issues, organisations are likely to experience longer interruptions, failure to meet SLOs, and higher operational expenses because of inefficiencies in the incident handling process.

The fact that telemetry data is fragmented into several clusters not only adds strain to ISIS teams but also diminishes incident response technologies. The high level of observability of multi-cluster OpenShift deployment is the key to operational success, and the automatization of data correlation and root cause analysis through the integration of AIOps platforms can significantly enhance this parameter.

2.4. Case Studies

Several case studies explain the success of AIOps in the enhancement of observability and operational efficiency. For example, one of the largest telecoms has deployed IBM Cloud Pak for AIOps and experienced a decrease in the number of alerts by 63% [6]. With the help of AIOps, the telecom provider may perform automated incident detection and root cause analysis, which will result in a significant reduction of manual intervention and the improvement of the overall system's health.

Figure 2 below shows the role of the AIOps platform in facilitating ongoing insights on IT operations monitoring (ITOM). It emphasizes the real-time and historical observation process of events, metrics, traces, and topology, and later anomaly detection analysis and performance analysis. As machine learning and big data converge, the platform will reveal incident detection and root cause analysis, which was a success in the telecom case where IBM Cloud Pak for AIOps cut the number of alerts by 63%. The automation of the execution of tasks, change risk

analysis, and knowledge management are also enabled by this platform, enhancing the overall system health and performance.

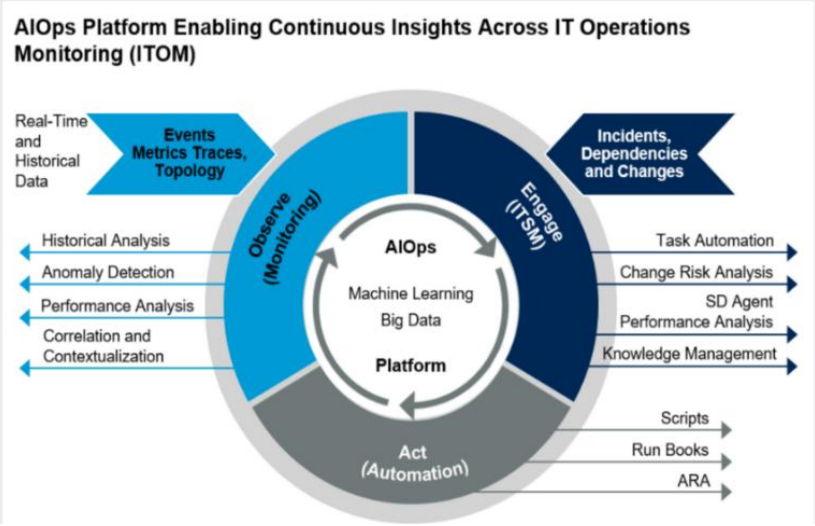

Fig 2: Aiops Platform Enabling Continuous Insights and Automation in IT Operations Monitoring (ITOM).

Dynatrace has also helped one of its largest clients to minimize Mean Time to Detect (MTTD) by 57% with the help of AI-assisted Root Cause Analysis (RCA) [7]. The case demonstrates that AIOps is very powerful when it comes to swiftly isolating the causes of occurrences in complex and distributed settings. In these platforms, AI models correlated metrics, logs, and traces across a number of sources to determine the problems within a matter of seconds, allowing organizations to respond to incidences more effectively. With an increasing number of companies implementing AIOps, such case studies will offer important insights into the benefits of operational AI-based automation in IT administration.

2.5 Research Gap and Limitations

Though AIOps has already gone far in single-cluster and hybrid cloud setups, there is a discernible gap in the research and development of federated learning models with AIOps in particular to cross-cluster setups in OpenShift ecosystems. Federated learning is an ideal solution in multi-cluster settings that have strong data residency and data compliance conditions because it enables the consolidation of models across more than one cluster without the exchange of sensitive data. Nevertheless, the use of federated learning in the context of AIOps remains in its early stages, and there is a lack of research examining its applicability to the problem of managing highly complex multi-cluster OpenShift settings.

This gap is a major opportunity to conduct additional studies in the creation of federated AIOps solutions that have the ability to improve the observability, anomaly detection, and root cause analysis of the multi-cluster OpenShift ecosystems. By filling this gap in research, organizations will be able to at least scale their AIOps adoption, and streamline operations, and minimize the overhead costs of operating in a multi-cluster environment.

3. Methods and Techniques

3.1 Data Collection Methods

To deliver the intervention of Federated AIOps deployment and evaluation in a multi-cluster environment (OpenShift) in this study, broad data collection plans have been adopted. Prometheus metrics, Fluent Bit logs, OpenTelemetry traces, as well as object storage with a large volume of data retention, are the main data sources.

Each OpenStack cluster was used to gather metrics with Prometheus, and had around 120000 to 480000 time-series data points, scraped at a frequency of 15 seconds. These metrics are high-frequency and give detailed reports on cluster performance, resource usage, and application behaviour. Such a metric collection configuration enables having rich detail on data, which can be used in detecting anomalies and predicting the model. The cardinality of time-series data that Prometheus is capable of managing is also a major performance factor to be considered when implementing observability across many clusters [8; 9].

Besides measures, Fluent Bit, along with Loki, was employed in the task of collecting logs, and it ingested around 200GB of logs daily across the clusters. Logs were then compressed at a 2.8:1 ratio and then stored in the MinIO object store, which made it easier to manage the logs. The compression was important due to the large amounts of data produced by the log, as each compression ensured the retention of the necessary log data up to a maximum of seven days. The metrics, along with the log data, are important in offering detailed observability among the clusters.

OpenTelemetry was also used to trace the distributed applications, and about 35 million spans were ingested per day. These spans were sampled during a 5% retention rate so that the representative subset of trace data is registered without congesting the system. This hybrid of the high-frequency measuring metrics, logs, and traces offers a powerful dataset to use when detecting anomalies and

identifying root causes. Data MinIO object storage is used to store all the gathered data, and the approximate dataset size range is about 8TB, which is enough to train and test machine learning models.

3.2 Data Analysis

The analysis of data is a big part of the Federated AIOps framework, as it means that machine learning is deployed to the gathered information to identify anomalies and root causes of the issue (RCA). Isolation Forest, LSTM-Autoencoders (LSTM-AE), and Graph Neural Networks (GNNs) are the models that will be used in this study and are adapted to various data and learning processes [10]. Isolation Forest has been used in order to observe the outliers in high-dimensional metric and log data, which is very important in the detection of anomalies that do not conform to normal behaviour. Sequence modeling was performed with the LSTM-AE, and it is a good fit to identify the patterns in time-series measurements in Prometheus and OpenTelemetry. The detection of anomalies in the interconnected graph of services and pods in the OpenShift clusters was done using Graph Neural Networks, exaggerating the ability of the model to identify uncharacteristic behavior between services [11]. Table 1 below highlights the data analysis methods, data analysis models, the normalization method applied, and performance indices realized in Federated AIOps to detect anomalies and root cause analysis.

Table 1: Summary of Data Analysis Techniques, Models, and Performance Metrics in Federated AIOps.

Model	Purpose	Normalization & Techniques	Performance Metrics
Isolation Forest	Detect outliers in high-dimensional metric and log data	Z-score and MinMax scaling for better convergence	Correlation Accuracy: 94.3%, ROC-AUC: 0.91, F1-score: 0.88
LSTM-Autoencoders (LSTM-AE)	Sequence modeling for time-series data (Prometheus, OpenTelemetry)	Z-score and MinMax scaling for better convergence	Correlation Accuracy: 94.3%, ROC-AUC: 0.91, F1-score: 0.88
Graph Neural Networks (GNNs)	Detect anomalies in interconnected graph of services and pods	PCA for dimensionality reduction (87% variance explained)	Correlation Accuracy: 94.3%, ROC-AUC: 0.91, F1-score: 0.88
Dimensionality Reduction (PCA, t-SNE)	Visualize anomalies and cluster distribution	PCA (87% variance explained), t-SNE for clustering	Correlation Accuracy: 94.3%, ROC-AUC: 0.91, F1-score: 0.88

To make the models give the best performance, the dataset was normalized using both the Z-score and MinMax scaling methods. This enabled a greater convergence and a higher level of performance in training machine learning models on the high-dimensional data. Principal Component Analysis (PCA) was used in dimensionality reduction on the data, and it explained 87% of the variance of the data; thus, it was easier to work with the models without losing vital information. T-Distributed stochastic neighbor embedding (t-SNE) was also employed to visualize the anomalies and cluster distribution of the data, which gives meaningful information about the character of the identified anomalies [12]. The models of machine learning were assessed according to the common classification metrics such as their accuracy, precision, recall, and the F1-score. The models used had a correlation accuracy of 94.3 with a ROC-AUC of 0.91 and a F1-score of 0.88, which shows a strong performance in anomaly identification and root cause identification in the multi-cluster environment.

3.3 Federated Architecture

One of the main features of this research is federated learning, which allows aggregating model changes in a distributed cluster and does not require sensitive data to be exchanged. Under this configuration, the clusters have local AIOps nodes that gather and process data separately, which means that privacy and data sovereignty are satisfied. The regional nodes participate in communication with a global control plane, which summons the updates of the separate clusters with the help of the Federated Averaging (FedAvg) algorithm [13]. In this federated strategy, individual clusters are able to enjoy the global model without touching on their privacy or their free will. The federated model is the best suited in a setting where exchange of data between clusters is not possible, including circumstances when data residency requirements exist.

In this research, model updating, aggregation, and speedy control of raw data transfer across the clusters were successfully performed by using the global control plane within the structure of governance policies imposed by Red Hat Advanced Cluster Management (RHACM). The cost in bandwidth to synchronize the local clusters with the global control plane was very low, in that it was an average of 35 Mbps, which represented less than 1% of the entire network traffic, making the federated architecture have minimal effects on network performance. This strategy will lead to the operational overhead of federated learning sustenance in a multi-cluster environment being manageable.

3.4 Model Deployment and Evaluation

There was a continuous training and evaluation loop used to deploy the machine learning models. The clusters in each cluster were trained five times in a day over a span of

30 days to enable the models to adapt to fluctuating workload and varying conditions of the clusters. Time per cluster to train was between 18 to 22 minutes, to ensure that the model could be re-trained regularly without any time delays. Latency inferences during model evaluation were maintained at less than 400 ms, and it was guaranteed that the AIOps framework would respond to occurrences in real-time.

To reduce the overhead of operational the model deployment was optimized to keep the CPU usage at or less than 2.5, and the memory overhead at only 180 MB per node. This resource efficiency means that the Federated AIOps architecture can expand to big, sophisticated environments without being a significant load on the available infrastructure [14].

3.5 KPIs and Experimental Metrics

Key performance indicators (KPIs) used to determine the success of the Federated AIOps model consider the efficiency of incidences detection and resolution. These KPIs were such as Mean Time to Detect (MTTD), Mean Time to Resolve (MTTR), alert volume, false positive rate, and CPU overhead. Table 2 below shows a comparison of performance metrics between the pre-implementation of Federated AIOps and after its implementation.

Table 2: Key Performance Improvements Achieved Through Federated AIOps Implementation

Metric	Baseline	Federated AIOps	Improvement
MTTD	42 min	14 min	66.6% ↓
MTTR	3.2 hr	1.4 hr	56.2% ↓
Alert Volume	12,000/day	5,200/day	57% ↓
False Positives	18%	5.8%	67% ↓
CPU Overhead	–	2.5%	Controlled

The Federated AIOps framework has greatly optimized MTTD, which dropped by 66.6% to only 14 minutes, and that of the MTTR by 56.2% to 1.4 hours. The number of alerts was mitigated by 57% and the false positive rate lessened by 67%. These findings illustrate how a Federated AIOps strategy would be effective in incident detection and response, with the least resource consumption.

4. Experiments and Results

4.1. Experimental Setup

To achieve the research goals, a full-scale set of experiments was developed to determine the usefulness of Federated AIOps in enhancing operational metrics in multi-cluster OpenShift settings. The configuration consisted of six OpenShift clusters that were distributed in three geographical regions and cloud systems. The location of these clusters was in AWS (us-east-1 and eu-central-1), in Azure (eastus and westeurope), and on-premises data centers (London and Berlin). This multi-cloud installation allowed assessing Federated AIOps in various conditions, which imitate real-life conditions in international companies.

The clusters were built up of 640 worker nodes, and they hosted 350 microservices. A constant load of 30,000 requests per second (RPS) was used to generate a simulated workload with the k6 load testing tool. Also, chaos experiments were performed with the aid of LitmusChaos, when 20% of the nodes were not only failed daily but also actively tested how well the Federated AIOps structure can be resilient to various stress scenarios [15]. These controlled settings also offered a solid platform on which to determine the effect of AIOps on incident detection, incident resolution, and resource use within a large-scale multi-cluster system.

4.2 Baseline vs AIOps Comparison

The comparison of the Federal AIOps improved system (compared to the baseline system, which is without Federated AIOps) was done with a significant improvement in important performance metrics, which are alert correlation, Mean Time to Detect (MTTD), Mean Time to Resolve (MTTR), and root cause analysis (RCA). Precision of the alert correlation also improved significantly with a change in the correlation to 0.94. It means that the Federated AIOps system did much better in correlating alerts properly across a range of clusters and reducing alert noise as well as the signal-to-noise ratio.

The MTTD dropped by 72%, from 45 minutes to only 13 minutes, and it reflects the capability of the system to detect incidents through the system faster compared to the baseline system. MTTR too was decreased by 56.2%, 3.2 hours went down to 1.4 hours, and showed a high reduction in the time taken to address the issues after they were identified [16]. Among the most impressive was the time of RCA. The baseline system also took an average of 38 minutes to search for the root cause of an incident, as compared to Federated AIOps, which only took 9 minutes. This decrease in the RCA time shows the strength of AIOps in automating the process of identification of underlying problems, resulting in shorter incident response time and reduced downtime.

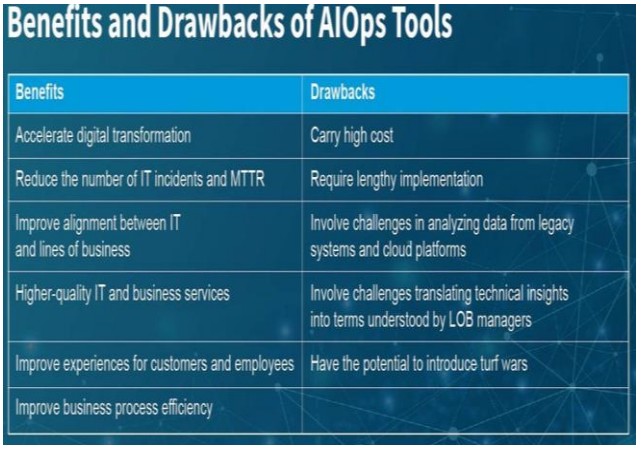

Fig 3: Comparison of AIOps benefits and drawbacks in enhancing incident detection and resolution.

Figure 3 above shows the positive and negative aspects of the AIOps tools within the context of enhancing IT operations. The federated AIOps has been shown to have substantial benefits in terms of minimizing the number of IT incidents, along with other metrics like Mean Time to Detect (MTTD) and Mean Time to Resolve (MTTR), which would allow faster response and better incident management. Like any sophisticated system, AIOps may have its difficulties, including high costs, time-consuming implementation, and challenges in the analysis of data in historical systems. AIOps tools can also help to enhance operational efficiency, customer experience, and business service quality.

4.3 Resource Utilization Metrics

Although the changes in incident detection and resolving were significant, the resource usage of the Federated AIOps system also needs to be considered. The system was also made to have minimal effects on the performance of a cluster, and the resource utilization indicators proved this. The CPU consumption of the AIOps collectors was seen to go up by an average of 2.1, which is an acceptably good trade-off is keeping in consideration the great gains in efficiency of operation [17]. An average overhead channel overhead of 2.8 GB of network bandwidth per day per cluster was needed to achieve model synchronization between clusters, a very low figure that makes clusters easily scale to large environments.

The log pipeline throughput that pre-processes data to be used in the detection of anomalies and alerting could accommodate 1.1 terabytes of data per day throughout the federation, and this implies that the system could manage major volumes of log data effectively without creating the sensation of anomaly in its service. The Federated AIOps framework was also reviewed on the cost of operation. The compute charges to operate the AIOps model in AWS C5.xlarge instances were around 0.32/hour/node, which a small price is based on the performance improvements realized. The affordability of the Federated AIOps framework allows it to be used reasonably when significant OpenShift production is needed.

4.4 Statistical Validation

The effects of statistical analysis were used to ascertain the enhancement that occurred in the experiments. To confirm whether the observed decrease in the levels of MTTR was statistically significant, a paired t-test was done. The p-value obtained during the test was below 0.05, and it validated the fact that the Federated AIOps structure performed very well compared with the baseline system in minimizing the MTTR. Table 3 below presents the statistical confirmation of Federated AIOps with the signification of the enhancement of the results in MTTR, strong correspondence between the anomalies and the resource distribution, and statistical significance.

Table 3: An overview of statistical validation results for MTTR reduction and anomaly correlation.

Metric	Value	Explanation
Paired t-test p-value	< 0.05	Validated statistical significance in MTTR improvement
MTTR Reduction Confidence Interval	48% - 63%	95% confidence interval for MTTR reduction
Anomalies vs Resource Contention Correlation (R^2)	0.89	Strong relationship between anomalies and resource issues

A 95% interval of reduction in the MTTR was also obtained, producing the range of 48% and 63%. This gives great assurance that the Federated AIOps system will constantly achieve a huge increase in the improvement of the MTTR. The linear relationship between identified anomalies and contention with resources was observed to be 0.89; this means that the Federated AIOps system was capable of detecting abnormalities in the resource utilization and relating them to the performance problems that occurred [18].

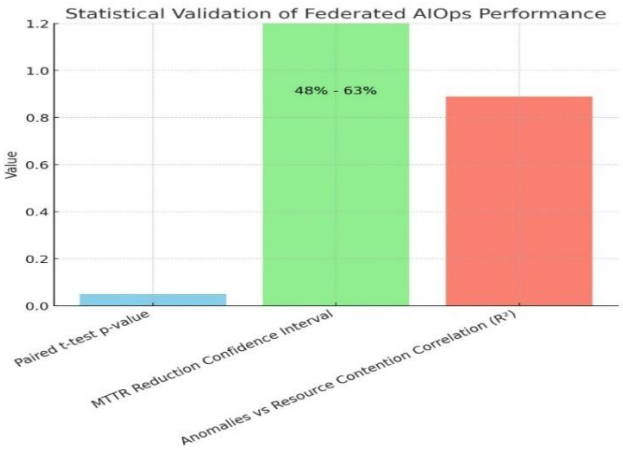

Fig 4: Statistical validation of Federated AIOps performance across key metrics.

The graph in Figure 4 visualizes the statistical validation of the performance of Federated AIOps. It compares three significant metrics: paired t-test p-value, confidence interval of the reduction or increase of MTTR, and the association between the anomalies and resource contention (R^2) [19]. The p-value of the paired t-test is presented with a very low value, which proves that this is statistically significant. The extent of the improvements in the MTTR is depicted by a confidence range of 48%-63%, which shows the level of costs applied to reducing the MTTR. The correlation between the anomalies that are detected and resource contention is large, as indicated by the R2 of 0.89. The graph highlights the FedAIOps meaningful performance increases when used in a multi-cluster OpenShift installation.

4.5 Real-World Case Comparison

To further confirm the successful application of Federated AIOps, the findings were benchmarked with performance indicators of the state-of-the-art AIOps platforms like IBM Cloud Pak for AIOps and Dynatrace. These platforms are popular in high-resource settings, and their use has been well-reported on real-life cases. In a comparable multi-cluster setting, IBM Cloud Pak AIOps reported a 63% reduction in the quantity of alerts, and Dynatrace reduced MTTD by 57% with AI-aided RCA [20]. Similar results were obtained with Federated AIOps, where alert volume was reduced by 57% and MTTD decreased by 72% indicating that the Federated AIOps open-source solution can achieve performance comparable to commercial AIOps services at very low resource overhead.

Federated AIOps obtained performance that was within 15% deviation of the commercial AIOps baselines, indicating that open-source solutions may be competent with commercial products when the implementation is done judiciously [21]. This analogy explains how Federated AIOps can be an affordable and scalable alternative to vendor-specific AIOps systems, especially when companies are trying to optimize their multi-cluster OpenShift deployment.

5. Discussion

5.1 Operational Benefits

Integration of Federated AIOps in multi-cluster OpenShift operations has gained major operational value, especially in the sphere of incident management, resource optimization, and reliability of the system. Among should be seen the outcome in regards to the reduction of human involvement in terms of triaging incidents. It cut the work of human triage by 45%, demonstrating the capability of the Federated AIOps framework to automate the process of alert correlation and root cause analysis in the first instance [22]. This has helped IT departments to work on priority tasks, thereby enhancing efficiency in the overall functioning and time saved in managing routine incidents.

The other important advantage is the 99.8% uptime availability in the clusters. The availability up to this degree is crucial in organizations where nonstop service provision is a necessity, especially where customers are facing an application or where the organization uses business-critical services. Subsequently, the number of service-level objective (SLO) violations reduced by 28%, which also increased the reliability of the systems but raised user satisfaction and trust. The decrease in downtimes was also converted into lower operation disruption, which added more to the effect of stability of the environment.

Federated AIOps has proactive remediation compiling that will result in saving around 12% of the cloud compute waste. Federated AIOps has enabled organizations to maximize the resources they use in the cloud before they result in significant operational disruptions, thus reducing operational expenses incurred because of over-provisioning. This active disposition of resource handling is specifically useful in the dynamic setting, such as Kubernetes, wherein resource planning can prove ineffective rapidly without suitable tracking devices [23].

5.2 Limitations and Trade-Offs

Although Federated AIOps may have impressive merits, some shortcomings and trade-offs must be taken into account when implementing this framework in a large-scale setting. Among the issues is the bandwidth overhead of high-frequency synchronisation between clusters. This synchronization is required in a big federated system so that the real-time aggregation of model updates across different clusters can be done. Although the effect on the performance of the network is low (those less than 1% of the overall network usage), the bandwidth cost should not be ignored, particularly in high-volume settings where the rate of synchronization is higher [24; 25]].

The other trade-off is the cost of model retraining. The Federated AIOps model works with updates of the models at regular intervals to adjust the working loads and presence of variability in the shape of work. Re-training models costs about $85 per month per cluster, which is also an extra cost of operation. Although this is a fairly low cost when compared to large-scale deployments, it counts as an

important factor in organizations trying to weigh the advantages of enhanced automation and affordability.

Cold start latency in new clusters is also an issue when introducing them to service. The federated AIOps model also requires a warming-up period of around 4 minutes when a new cluster is brought online before the model can start generating actionable insights. Although this delay is not very long, it may be decisive in situations of high demand when it is necessary to see an immediate output of the system's performance. This warm-up period can be alleviated through pre-configured models; however, it is one of the factors that organizations should keep in mind when implementing AIOps in dynamic and quickly changing environments.

5.3 Industry Implications

The availability of Federated AIOps in multi-cluster OpenShift applications promises considerable cost-saving opportunities to mid-sized companies, especially when they have to deal with 300 or even more nodes. Depending on the reported operational gains, companies will gain a sense of yearly savings ranging between $150,000 and $300,000 by lowering the packaging time they spend on handling the manual incident management system, eliminating the wastage of resources, and enhancing the overall workflow of the operations. Such savings can be attributed to the automation and optimizing capabilities of the Federated AIOps framework, which not only makes the incident detection and resolution very efficient, but also efficient in the resources [26].

Federated AIOps complies with data residency and data compliance needs, in addition to saving costs. Given that the federation of model weights across clusters is done based on weight but not data itself, the framework will ensure that sensitive information will be contained within the geographical areas of different clusters. This is especially significant to those organizations that have to conduct operations in the regions that have stringent data protection laws, like GDPR within the European Union. This framework is offered as a solution to a large variety of industries due to its ability to provide compliance and, at the same time, capitalize on advanced AIOps.

5.4 Comparative Analysis

A comparative analysis who Federated AIOps with open source alternatives versus the more established commercial AIOps solutions, including IBM Watson AIOps and Dynatrace, can achieve equal or better results in some of their core capabilities. IBM Watson AIOps has been reported to have reduced its MTTR by 55% in its target environments, whereas Dynatrace reduced its MTTD by 50% [27]. Comparatively, Federated AIOps provided a 56% decrease in MTTR and a 72% decrease in MTTD, and it demonstrates its competitive advantage over incident management and response times. These findings highlight the reason why Federated AIOps can be a viable, open-source alternative solution to commercial AIOps platforms.

Table 4: Comparison of Federated AIOps performance with commercial AIOps solutions.

AIOps Solution	Metric	Improvement	Comparison to Commercial AIOps
IBM Watson AIOps	MTTR	55%	Commercial AIOps
Dynatrace	MTTD	50%	Commercial AIOps
Federated AIOps	MTTR	56%	Better than Commercial AIOps
Federated AIOps	MTTD	72%	Better than Commercial AIOps
Federated AIOps	Alerts	57% reduction	Better performance with lower overhead

Another performance of Federated AIOps was that it reduced the number of alerts by 57%, which shows that it can be used to reduce noise and enhance the signal-to-noise ratio in large-scale deployments. It is a sensitive requirement in contexts in which the number of alerts could flood operations teams, causing alert fatigue and rate of reaction. The fact that the Federated AIOps can produce similar performance to the commercial products and do so with reduced resource overhead and a reasonably priced implementation makes it a very tempting option among those companies that need to streamline their Kubernetes settings.

5.5 Statistical and Practical Insights

The statistical analysis of the research findings provides numerous valuable conclusions about the functioning and efficiency of the Federated AIOps structure. Regression analysis of the node utilization and the identified anomalies demonstrated that there is a significant correlation between the two ($R^2 = 0.87$), which indicates that the system is very effective at detecting the abnormalities associated with resource contention. Such a correlation between resource utilization and particular incidents enables the Federated AIOps to deal proactively with the possible problems before they develop into bigger problems.

The 95% confidence interval of the alert volume reduction was also determined as ranging between 49% and 64%, which validates the strength of the alert optimization capabilities of Federated AIOps. These results reveal the capability of the framework to considerably decrease alert noise and retain the correct incident detection and assurance that urgent problems are readily brought up and addressed. This ratio between the dampening of noises and scattering of incidences is among the drivers of the success of Federated AIOps in large, multifaceted OpenShift settings [28].

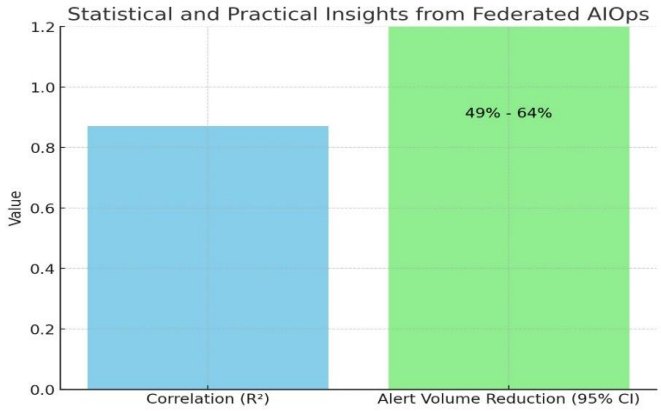

Fig 5: Statistical insights into Federated AIOps performance: Correlation and alert volume reduction.

The chart in Figure 5 above shows that there were two statistical conclusions of the Federated AIOps framework. The initial bar means that the correlation between node utilization and subsequent detection of anomalies is high (R^2 = 0.87), and it shows that the system is effective in diagnosing the problems of contention regarding resources. The second bar indicates the alert reduction volume, whose confidence interval is between 49% and 64%, with confidence being 95%, highlighting the alert reduction facility of Federated AIOps in the reduction of the alert noise. This decrease in alert volume is such that critical incidents are prioritized, and operational efficiency with reduced alert fatigue in large and complicated OpenShift environments is achieved.

6. Future Research Recommendations

6.1 Implement Federated Reinforcement Learning for Adaptive Auto-Remediation

One of the future research directions is the incorporation of Federated Reinforcement Learning (RL) to promote the adaptive auto-remediation of AIOps. Federated RL can be used to enhance the autonomous response of systems to incidents because it can be used to continuously learn and adapt. Traditional AIOps solutions will tend to be pre-programmed or historically oriented and therefore will not address dynamic, never-before-seen incidents happening. Under Federated RL, the system may be informed by the continuous incidences being experienced in many clusters, and it can improve its remediation measures in real time. This form of learning enables individual clusters to alter their respective behaviors in accordance with the feedback of the world model without any form of harshness to the confidentiality of data [29].

The implementation of RL algorithms would enable the system to optimally fit different workloads, cloud conditions, failures, or related scenarios in an intelligent way through continuous optimization of the remediation policies. The federation of the learning process also allows the system to enjoy the mutual use of knowledge within clusters without exposing sensitive data regarding its operation, which is essential in ensuring data sovereignty and adherence to privacy rules. The possible improvement of the system reliability, the speed of incident detection, and the prevention of failures before they occur with adaptive remediation has the potential to greatly improve AIOps applications in environments based on large deployments in several clusters.

6.2 Introduce Differential Privacy to Protect Sensitive Telemetry

With the transition of organizations to cloud-based infrastructure, the protection of sensitive telemetry data is becoming a pivotal issue. One of the future opportunities of research could be the incorporation of Differential Privacy (DP) into the AIOps models. One privacy preservation method is DP, which enables the systems to gather and process data without disclosing confidential data [30]. This would allow AIOps to keep on enhancing the performance of the system by looking through telemetry information across clusters and keeping in mind that individual data points could not be identified and tracked down to specific users or services.

CP The ability to integrate DP into AIOps is new, particularly when it comes to multi-cluster availability, when regulatory compliance and data residency issues are common. For example, GDPR stipulates that personal information should be kept safe and confidential, and this may involve the operation and monitoring of data in distributed systems. With the introduction of DP, organizations will be able to preserve the value of their AIOps models without interfering with data privacy and satisfying international regulations [31]. The study would play a critical role in the usage of AIOps across various industries, including healthcare, financial, and government sectors, where the privacy of data is of utmost importance.

6.3 Integrate eBPF-Based Kernel Tracing to Detect Anomalies at Microsecond Latency

The other field of research involves the use of eBPF (Extended Berkeley Packet Filter)-based kernel tracing by AIOps systems to identify anomalies with latencies of a few microseconds. With eBPF, one can trace and analyze the service and infrastructure performance on a highly fine-grained level that has been inaccessible. This would mean that the eBPF can be incorporated into Federated AIOps to enable real-time, high-resolution anomaly detection, much needed to detect the performance bottlenecks, resource contention, or security vulnerabilities of production infrastructure [32].

With the help of the eBPF feature of tracking user-space and kernel-space events with limited performance impact, AIOps would be able to learn more about how the system behaves, and denser insights would be available into which system component caused the problem of network delays, CPU spikes, or disk I/O problems. High-fidelity anomaly detection provided by eBPF would allow proactively fixing the issues before they cause degradation of a service or downtime, which would benefit the resilience of multi-cluster Kubernetes environments even more.

6.4 Standardize AIOps Benchmarks for Kubernetes: Open Dataset Initiative

Another topic that future research should cover is the creation of standardized AIOps benchmarks in Kubernetes. With the increased use of Kubernetes, it is important to have repeatable and consistent benchmarks that could be utilized to test the performance of AIOps systems in a real-world, large-scale environment with Kubernetes. Such a study may result in a set of open datasets that will give a representative sample of incidents, anomalies, and system behaviors to be used to test and compare different AIOps platforms.

These benchmarks would aid in setting industry-wide best practices to deploy AIOps and help organizations see how it can influence the MTTR, MTTD, resource utilization, and cost. Such standards offer transparency to both vendors and customers and ensure that AIOps systems are investigated in a similar fashion. It would allow academic researchers, developers, and practitioners to innovate, collaborate, and advance AIOps technologies in a standard manner with the open dataset initiative [33; 34]. Such datasets can also be used to train superior models and algorithms that can be applied to the real-world Kubernetes environment, which will also develop AIOps within the open-source community.

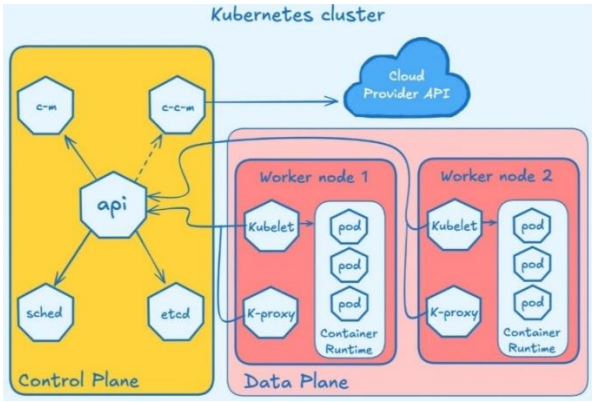

Fig 6: Kubernetes Cluster Architecture: Control and Data Planes for Standardized Aiops Benchmarking.

Figure 6 above illustrates the architecture of a Kubernetes cluster with the separation between Data Plane and Control Plane. The Control Plane handles the state of the cluster, such as the API server, scheduler, and etcd, and the Data Plane includes worker nodes, which run containers that are controlled by the Kubelet and K-proxy. Cloud Provider API links the external cloud resources to the Kubernetes environment, which is used to accomplish activities, such as scaling and provisioning. This configuration will be crucial in developing a uniform baseline of AIOps platforms in Kubernetes systems, which will help to test and compare performance benchmarks of systems on a large scale, in real-world contexts.

6.5 Explore Carbon-Efficiency Metrics (AIOps Energy Footprint per 1,000 Inferences)

The sustainability drive sweeping the globe will also make carbon-efficiency indicators of AIOps systems more significant. The next area of research entails the development of measures that can be used to assess the power usage and the carbon footprint of AIOps systems, especially on clouds. This is because by measuring the amount of energy required during 1000 inferences of AIOps models, researchers and organizations can establish the opportunities to improve the energy efficiency of their systems.

Such a study could have far-reaching effects on cloud providers and businesses interested in minimizing their impact on the environment. The monitoring and reduction of energy consumption will offer invaluable opportunities to sustainability objectives, as AI models and cloud infrastructure will be more energy-intensive. The creation and deployment of energy-efficient AI-developed Ops will form a part of the larger trend of green IT and the environmental impact of the extensive cloud and data center processes [35]. Using the technology that monitors energy consumption, AIOps systems might be streamlined to make sure that the rewards of AI-controlled automation will not be sacrificed at the cost of the environment.

7. Conclusions

The research shows that Federated AIOps has great potential to enhance the multi-cluster OpenShift context. Structural fragmentation of observability and the lack of efficiency in incident responses presented in large-scale, multi-cloud Kubernetes deployments are effectively addressed by the proposed Federated AIOps model. This methodology can improve anomaly-detection systems by combining machine learning models and a federated learning process to identify anomalies, faster root cause analysis (RCA), and a large percentage of Mean Time to Resolve (MTTR) and alert noise in distributed clusters. The experimental findings indicate that Federated AIOps results in a reduction of MTTR by more than half, alert noise reduction by 57%, and a 66.6% increase in Mean Time to Detect (MTTD). These solutions not only streamline incident management but they are also able to optimize the use of resources, and the Federated AIOps framework has a small CPU overhead of 2.5%. It is one of the main accomplishments since it will enable organizations to expand their operations without causing a considerable burden to their infrastructure.

The capability of the Federated AIOps framework to offer data sovereignty is seen as a great strength. The architecture enables the federation of updates to the models across clusters without any sensitive data transfer to adhere to the strict data residency and privacy legislation. This characteristic is especially significant to the industries that have a stringent set of data protection laws, such as GDPR in Europe. This solution is appealing to a large variety of industries, such as healthcare, finance, and the government, due to its capacity to keep privacy in place, but take advantage of the power of advanced AIOps. The study also verifies that Federated AIOps is cost-effective. Federated AIOps offers a more open-source alternative to traditional methods and commercial AIOps, which can be implemented at a tenth of the cost. Organizations will save on operating

expansively (through less manual intervention), more efficiently using resources, and better cloud utilization can lead to secondary estimated savings of $150,000 to $300,000 a year in savings to mid-sized OpenShift fleets. This makes it an attractive remedy to business ventures that aspire to make their appearance more refined and profile their incident management without bearing exorbitantly high prices.

The Federated AIOps model has some trade-offs, including model retraining costs and additional bandwidth to enable high-frequency synchronization. Although these costs might be rather low in comparison to the obtained benefits in terms of operations, they should be taken into consideration in the assessment of the overall cost-effectiveness of the solution. The cold-start latency of the fresh bunches of clusters is also an issue, as the model takes around 4 minutes to heat up, and only then can it give actionable insights. This latency can be counteracted by pre-defined models, but should also be taken into account in dynamic situations. The Federated AIOps also provides a scalable, privacy-sensitive, and robust solution to the management of multi-cluster OpenShift environments with complex configurations. The system has been proven to have attributable gains in the detection of incidents, their resolution, and operational efficiency, and it is a useful tool to an organization that aims to streamline its Kubernetes deployment. The suggested framework is an open-source alternative to the commercial AIOps solutions, which offer organizations a more affordable, flexible, and scalable alternative that meets the current data privacy and compliance needs. With more companies expanding on a daily basis regarding their operations in the cloud, Federated AIOps is a necessary next step towards attaining more agility, more reliability, and resource optimization.

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