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Original Article

Automating Distributed Systems Monitoring with CloudWatch, OpsGenie, and Grafana: A Comprehensive Guide

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Abstract - Modern cloud computing infrastructures are based on distributed systems and the need for such monitoring solutions is essential to keep them reliable and available, and in full use of their performance. The growth of operations then becomes unscalable using manual monitoring and requires an automation driven approach. In this paper, we provide a comprehensive framework for automating the distributed systems monitoring with Amazon Cloud Watch, OpsGenie and Grafana. These tools collectively provide a holistic view to monitoring by bringing real time telemetry together with intelligent alerting and advanced visualization. Our paper elaborates the architectural aspect of monitoring automation by data collection, event driven notification, anomaly detection, and dashboarding strategies. A methodology based on the use of a mathematical modeling approach is introduced in order to formalize key performance indicators (KPIs) such as latency (L), throughput (T) and system availability (A). Thorough empirical analysis in a cloud native environment is used to evaluate the proposed framework and shows how the framework decreases Mean Time to Detect (MTTD) as well as Mean Time to Resolve (MTTR) incidents. It is shown that operational efficiency, system resilience and downtime are minimized using automation. This research provides insights for system architects, DevOps engineers, and cloud practitioners seeking to implement an intelligent, automated monitoring strategy for large-scale distributed applications.

Keywords - Distributed Systems, Cloud Monitoring, Automation, CloudWatch, OpsGenie, Grafana, Incident Management, Anomaly Detection, Performance Metrics, DevOps.

1. Introduction

Distributed systems on cloud computing environments are growing more complicated, which makes the operational efficiency, fault tolerance, and real time observability very challenging. [1] Distributed systems have multiple nodes, service and data centers disjointly than traditional monolithic type, so manual monitoring becomes impractical and may become error prone. With increasing infrastructure needs of organizations, there is a need to automate intelligent monitoring solutions. Proactive Monitor is essential for automating distributed systems monitoring and for the tedious task of proactively detecting failures and minimizing downtime, or optimizing performance. [2] Current traditional monitoring approaches still exist in monolithic/static thresholds that typically require monitoring personnel to periodically check or drain alerts. [3] Rather, modern monitoring frameworks combine real time telemetry, intelligent alerting, and visual analytics to provide a fast incident response and system optimization.

1.1. The Role of Automation in Monitoring

Event driven architecture, machine learning algorithms for anomaly detection and intelligent alerting mechanisms used by automated monitoring solutions allow to detect and solve the issue without human intervention or as minimal as possible. Regarding the service, services like Amazon CloudWatch, OpsGenie, and Grafana fill the gap in the analysis of system performance in cloud computing!

- Amazon CloudWatch is a centralized service for monitoring AWS resources and collecting metrics, logs, and events across a wide range of AWS services, as well as application info viewed by using AWS CloudWatch Metric Streams in the AWS Cloud.
- OpsGenie is an intelligent alerting and oncall management solution, which ensures right people in the right place will take action at the right time.
- Grafana allows for advanced visualization and dashboarding into distributed system performance.

When these tools are put together, organizations enjoy end to end observability that allows them to proactively deal with incidents and automatically fix them.

1.2. Research Objectives

Through addressing the following research questions, this paper wants to deliver a complete study on automating distributed systems monitoring:

- What is the best practice of integrating CloudWatch, OpsGenie and Grafana into one monitoring solution?
- What are the main metrics and the indicators of the performance of such a system?
- Keeping automation at the core of the incident response times and system resiliency.
- How do we quantify the effectiveness of automated monitoring in terms of there being something that we can model mathematically?

1.3. Contributions of This Work

- Several contributions to the field of cloud monitoring and automation are made by this research.
- A methodical approach for putting together CloudWatch, OpsGenie, and Grafana to spin up a completely automated monitoring answer.
- Formulation of mathematical models for monitoring parameters comprising of system availability, latency and alerting efficiency.
- Experimental evaluation of the proposed monitoring framework in a real-world cloud environment.
- This is a discussion of DevOps best practices for implementation of automated monitoring.

1.4. Organization of the Paper

This paper is organized as follows.

- Section 2 presents background and existing work relevant to the distributed systems monitoring problem.
- Section 2 discusses the evaluation metrics used to assess ANP while keeping the overall architecture tipically defined by modern large scale recommendation systems in mind. Section 3 gives an architectural overview of the monitoring framework.
- Section 4 reviews important mathematical models that can appraise system performance.
- Section 5 discusses an empirical analysis of monitoring automation in the context of a cloud environment.
- Section 6 summarizes key findings and outlines directions for future research and limited effort to propose some challenges.
- Finally, Section 7 concludes the paper with final remarks and recommendations.

2. Background and Related Work

The process of monitoring distributed systems has gone from manual to intelligent automation. In order to meet the increasing requirements on scalable and adaptive monitoring frameworks, with the increasing of the cloud computing infrastructures' complexity, we have to defend lower cost. It will go through traditional monitoring methods, the cloud based evolution of observability, and automation's role in incident management. It also points out the shortcomings of current research and the reason for conducting the study.

2.1. Traditional Monitoring Approaches

In the past, system monitoring has been performed by periodic health checks, log based analysis and static threshold based alerts. Monitoring tools like Nagios, Zabbix, and Prometheus would be set up manually by the administrators to monitor important parameters like CPU utilization, memory consumption, latency in the network, etc. However, they also had a couple of major problems. [4] The static thresholds provided many false positives and unnecessarily raised alerts, while in the other cases, the critical anomalies were not noticed. The delay in issue resolution further augmented downtime and operational costs, given that manual log analysis had to be carried out first. [5] Also, traditional monitoring tools failed to scale in the distributed environment which demanded more dynamic observability when dealing in micro services and containerized workloads as well as multi cloud deployments. However, as cloud computing architectures evolved to be more complex, organizations had to rely on an alternative means of providing real–time telemetry, automated alerting and intelligent incident management. This demand resulted in the creation of cloud-native monitoring platforms that were more scalable and automated.

2.2. Evolution of Cloud-Based Monitoring

Introducing a paradigm shift, cloud-based monitoring solutions were moved from system health check based to observability. [6] Traditionally, monitoring refers to observing countable aspects of the system, namely, metrics, logs, and traces. Real-time performance indicators are captured on metrics, logs do the structured and unstructured event data storage for the forensic analysis, and traces map the flow of requests between microservices to detect bottlenecks. Built in monitoring solutions were introduced by major cloud providers to enable observability. Amazon CloudWatch is a service by Amazon Web Services (AWS) that collects and aggregates system metric, logs and events in real time. [7] With Azure Monitor, Microsoft Azure and with Operations Suite (formerly Stackdriver) by Google Cloud, a cloud native monitoring approach was launched. These tools still need integration with third party solutions for advanced alerting and visualization, and usually are used with OpsGenie and Grafana for that.

2.3 Intelligent Alerting and Incident Management

Intelligent alerting mechanisms introduced during later changes had improved the incident detection and the response times. An incident management platform such as OpsGenie provides automated alert routing and aims to minimize the number of times that a human has to intervene to handle monitoring operations. [8] Adaptive alerting is used to reduce noise by only sending at most one notification per redundant set of notifications and ranking at most one critical alert. It also includes on call scheduling and policies to escalate incidents so they will be addressed fast in the right teams. To reduce MTTD by as much as 40% and MTTR by 35%, the cloud monitoring tools must be integrated with intelligent alerting solutions like OpsGenie. [9] The result of this improvement is lower operational costs and higher system availability, that's why intelligent alerting becomes an integral part of a modern monitoring framework.

2.4 Advanced Visualization with Grafana

Data collection is necessary for effective monitoring but visualization of data is as important as data collection, which leads to quick decision making. [10] One such analytics and visualization tool is Grafana an open source platform, that allows users to create interactive dashboards that can be used with data from various cloud sources, e.g. Cloudwatch, Prometheus and InfluxDB. Grafana is different from static charts based monitoring interfaces which depend on charts,

rather it gives us real time streaming visualizations where engineers are able to see anything that is wrong instantly. The system observability is further boosted with threshold based alerting, and machine learning based trained anomaly detection using Grafana as well. Furthermore, studies reveal that 20% of the response times of organizations that make use of real-time dashboards in their monitoring workflow are reduced by quicker performance issue detection. Therefore, integration of visualization tools with a cloud-native monitoring framework is of great significance.

2.5. Gaps in Existing Research and Motivation for This Work

There still remain a lot of challenges in spite of the progress of cloud based monitoring. Second, cloud native monitoring stack with cloud watch, opsgenie and grafana was not elaborated. Current research is mainly done in discrete tools and not as a complete automation strategy. Second, the analysis of modeling of monitoring efficiency is generally lacking, with few formal analysis of system availability and anomaly detection efficiency. [11] Third, automated monitoring of real world cloud based environments is empirically almost an unexplored area, leaving little hope of quantitatively gauging the effect of automation on mitigation of potential incidents. This paper proposes a structured framework to automate distributed systems monitoring to address this issue. [12] This research brings together CloudWatch for real time telemetry, OpsGenie for intelligent alerting, and Grafana for advanced visualization into a complete proactive incident management and systems resilience offering. We evaluate the effectiveness of the proposed framework in a cloud native environment through quantitative performance modeling, as well as, empirical evaluation, showing its ability to minimize downtime and optimize utilization of the resources.

3. Architectural Overview of the Monitoring Framework

Project Bertava necessitates effective multi layered architecture ensuring real time observability, auto alerting and visualization. This section describes a structured framework of an automated approach to distributed systems monitoring on Amazon CloudWatch, OpsGenie and Grafana. [13] The architecture proposed has three main layers such as data collection and telemetry, event driven alerting and incident response, visualization and analytics. The effect of these layers is to increase system reliability, reduce downtime, and make the most of performance.

3.1. Architectural Components and Workflow

We design the monitoring framework as a modular system that contains three sub systems, namely, CloudWatch for telemetry collection, OpsGenie to facilitate the intelligent alerting and Grafana to present the dashboards. Four key stages are there in the system workflow:

- CloudWatch's continuous metric collection and log aggregation automatically collects system metrics, application logs, and systems performance indicator such as CPU utilization, memory usage, network latency and mistake rate, etc. All these logs are centralized and processed in real time.
- CloudWatch performs Event Processing and Anomaly Detection: alarms can be defined in terms of thresholds or machine learning based anomaly detection models. Structured notifications such as high latency, system failure or security breach occur.
- Alerts are routed to OpsGenie where escalation policies will determine the right oncall teams. Incidents are automatically classified, assigned and escalated based on predefined workflows using OpsGenie.
- Grafana, which able to retrieve and visualize real time data from CloudWatch, helps teams analyse a pattern and system trends, as well as correlating multiple data sources on interactive dashboards.

These components are seamlessly integrated and attempt to adopt a proactive approach to monitoring, to reduce Mean Time to Detect (MTTD) and Mean Time to Resolve (MTTR).

3.2. Data Collection and Telemetry Layer (CloudWatch)

The data collection and telemetry layer is responsible for capturing real-time metrics and logs from various distributed system components. [14] Amazon CloudWatch plays a pivotal role in this layer by collecting, storing, and analyzing telemetry data.

3.2.1. Key Performance Metrics Tracked

CloudWatch monitors a diverse set of performance metrics, including:

- System Metrics (S_i): CPU utilization, memory usage, disk I/O, and network bandwidth.
- Application-Level Metrics (A_j): Request latency, error rates, response time, and database query performance.
- Custom Metrics (C_k): User-defined metrics based on specific application needs.

The collected data is stored in CloudWatch Logs and Events, where time-series analysis and anomaly detection can be performed. Mathematically, the system's performance can be represented as:

$$P(t) = \sum_{i=1}^{n} S_i(t) + \sum_{j=1}^{m} A_j(t) + \sum_{k=1}^{p} C_k(t)$$

Where P(t) is the overall system performance at time t, Si(t) represents system-level metrics, Aj(t) denotes application-level performance indicators, and Ck(t) accounts for custom-defined metrics. CloudWatch also supports anomaly detection using statistical models and machine learning algorithms to predict failures before they occur. The Exponential Weighted Moving Average (EWMA) algorithm is commonly used for detecting anomalies:

$$EWMA_t = \alpha X_t + (1 - \alpha) EWMA_{t-1}$$

Where X_t is the observed metric at time t and α is the smoothing factor.

3.3. Event-Driven Alerting and Incident Management Layer (OpsGenie)

The alerting and incident management layer ensures that anomalies and system failures are detected and escalated automatically. OpsGenie is responsible for managing alerts generated by CloudWatch, reducing alert fatigue, and enforcing on-call rotations.

3.3.1. Automated Alert Routing and Escalation

When CloudWatch detects a system anomaly, it sends alerts to OpsGenie via **Amazon SNS (Simple Notification Service)**. [15] OpsGenie then applies predefined rules to determine **priority levels, on-call schedules, and escalation paths**. The alerting process can be formulated as:

$$A_{ops} = f(A_{cw}, P_{crit}, S_{oncall}, E_{rules})$$

Where:

- A_{ops} represents the OpsGenie alert.
- A_{cw} is the CloudWatch-generated alarm.
- P_{crit} denotes the priority of the alert (e.g., critical, high, medium, low).
- S_{oncall} is the on-call schedule for the engineering team.
- E_{rules} represents the escalation rules for unresolved alerts.

OpsGenie minimizes incident response time by automating ticket creation, routing notifications via multiple channels (email, SMS, phone calls, mobile push notifications), and integrating with ITSM tools such as ServiceNow and Jira.

3.4. Visualization and Analytics Layer (Grafana)

The visualization layer plays a crucial role in analyzing system performance and correlating multiple data sources. [16] Grafana retrieves monitoring data from CloudWatch and presents it in custom dashboards, enabling engineers to identify performance trends, detect anomalies, and optimize system health.

3.4.1. Real-Time Dashboarding and Custom Alerts

Grafana provides interactive, real-time dashboards with various visualization options such as:

- Time-series graphs for tracking system trends over time.
- Heatmaps for visualizing load distribution and error patterns.
- Gauge charts for monitoring thresholds and critical system metrics.

Additionally, Grafana supports alert rule definitions, allowing users to set conditions based on statistical thresholds. For instance, an alert can be triggered if CPU utilization U_{cpu} exceeds a critical threshold T_{cpu}:

$$A_{graf} = \begin{cases} 1, & U_{cpu} > T_{cpu} \\ 0, & \text{otherwise} \end{cases}$$

Where A_{graf} represents an active alert.

By integrating CloudWatch, OpsGenie, and Grafana, organizations gain a real-time, automated monitoring framework that significantly improves system resilience and operational efficiency.

4. Mathematical Modeling and Performance Evaluation

The effectiveness of an automated monitoring framework depends on its ability to detect system anomalies, generate actionable alerts, and optimize incident response times. [17] To quantify these aspects, this section introduces mathematical models for evaluating system availability, latency, and alert efficiency. The performance of the proposed monitoring framework is analyzed using key metrics, including Mean Time to Detect (MTTD), Mean Time to Resolve (MTTR), and False Alert Rate (FAR).

4.1. System Availability and Reliability Model

In distributed systems, availability (A) is a critical metric that determines the proportion of time a system remains operational. It is given by:

$$A = \frac{U}{U + D}$$

Where:

- U is the total system uptime.
- D is the total downtime.

With the integration of CloudWatch, OpsGenie, and Grafana, automated incident detection reduces downtime by minimizing MTTD and MTTR. The system's improved availability can be modeled as:

$$A_{improved} = \frac{U}{U + (D - \Delta T)}$$

Where ΔT represents the reduction in downtime due to automated alerting and incident management.

A high-availability system aims to maintain AAA close to 1, meaning minimal downtime. The efficiency of automated monitoring can be evaluated by comparing the traditional manual monitoring model with the automated approach.

4.2. Mean Time to Detect (MTTD) and Mean Time to Resolve (MTTR)

4.2.1. Mean Time to Detect (MTTD)

MTTD is the average time taken to identify system failures or anomalies. Traditional monitoring methods rely on periodic manual checks, leading to higher detection times. Automated monitoring using CloudWatch and machine learning-driven anomaly detection reduces MTTD significantly. Mathematically, MTTD is defined as:

$$MTTD = \frac{\sum_{i=1}^{N} T_{detect,i}}{N}$$

Where:

- $T_{detect,i}$ is the time taken to detect the i^{th} anomaly.

- N is the total number of anomalies detected.

The effectiveness of anomaly detection can be enhanced using statistical forecasting models such as Exponential Weighted Moving Average (EWMA), which predicts deviations in performance metrics.

4.2.2. Mean Time to Resolve (MTTR)

MTTR represents the average time required to mitigate an incident after detection. It includes incident triage, notification, root cause analysis, and resolution. With OpsGenie's automated alert routing and escalation policies, MTTR can be minimized. Mathematically, MTTR is given by:

$$MTTR = \frac{\sum_{i=1}^{M} \quad T_{resolve,i}}{M}$$

Where:

- $T_{resolve,i}$ is the time taken to resolve the i^{th} incident.
- M is the total number of incidents resolved.

An effective monitoring system aims to reduce both MTTD and MTTR, thereby minimizing downtime and improving system availability.

4.3. False Alert Rate (FAR) and Alert Precision

A major challenge in monitoring systems is false alarms, which contribute to alert fatigue and inefficient incident management. The False Alert Rate (FAR) measures the proportion of false alerts generated relative to total alerts:

$$FAR = \frac{F_A}{T_A}$$

Where:

- F_A is the number of false alerts.
- T_A is the total number of alerts generated.

Ideally, a robust monitoring system maintains a low FAR while ensuring high recall, meaning that all critical incidents are detected without excessive false positives.

The precision of alerting (P_{alert}) is given by:

$$P_{alert} = \frac{T_P}{T_P + F_P}$$

Where:

- T_P is the number of true positive alerts.
- F_P is the number of false positive alerts.

A well-optimized monitoring system maintains P_{alert} close to 1 while keeping FAR as low as possible.

4.4. Performance Evaluation through Simulated Workloads

To validate the efficiency of the proposed monitoring framework, we conduct an empirical evaluation using simulated workloads in a cloud environment. [18] The following performance metrics are measured:

- System Uptime (UUU) and Downtime (DDD) before and after automation.
- Reduction in MTTD and MTTR due to automated alerting.
- False Alert Rate (FAR) and Precision (PalertP_{alert}Palert) of the monitoring system.

The simulated environment includes a distributed application running on AWS with CloudWatch logging, OpsGenie alerting, and Grafana visualization. We collect data over a period of one month and compare system performance before and after automation.

A summary of the experimental results is presented in Table 1, showcasing the improvements achieved with automation.

Table 1. Performance Improvement with Automated Monitoring

Metric	Traditional Monitoring	Automated Monitoring	Improvement (%)
System Availability (AAA)	99.2%	99.95%	+0.75%
Mean Time to Detect (MTTD)	15 min	3 min	-80%
Mean Time to Resolve (MTTR)	40 min	12 min	-70%
False Alert Rate (FAR)	18%	5%	-72%
Alert Precision (PalertP_{alert}Palert)	76%	92%	+21%

The results indicate that automated monitoring significantly improves system reliability, reduces detection and resolution times, and enhances alert accuracy.

5. Empirical Case Study and Experimental Validation

We also conducted an empirical case study of a distributed application deployed in a real world cloud environment in order to empirically evaluate the proposed automated monitoring framework. We present the experimental setup, the data collection methodology, the performance metrics and the results achieved from the experiment. Thus, the subject of this study is trying to show how CloudWatch, OpsGenie, and Grafana automation changes distributed systems' reliability, incidents' response efficiency, and alerts' accuracy.

5.1. Experimental Setup and System Architecture

The microservices architecture consisted of multiple EC2 instances, RDS databases, S3 storage and a Kubernetes cluster running containerized applications that were running on top of an AWS based platform and the experiment was performed on the architecture. [19] This architecture was then integrated with the monitoring framework as:

- Metrics such as CPU, memory, network I/Os and API response times of application services were sent to Amazon CloudWatch for aggregation.
- Intelligent alerting, escalation policies and on call scheduling was handled by OpsGenie.
- For the real time visualization and dash boarding, Grafana is deployed on a dedicated monitoring server.

Several scenarios were posed for these varying workloads: normal, peak, and failure (system failure) scenarios, over period of one month and tested our design. The experiment aims at measuring the framework's capability to detect anomalies, emit alert, and reducing response time to incident.

5.1.1. Workload Simulation

Synthetic workloads were generated using the Synthetic Downloads feature of Apache JMeter and from AWS Load Testing tools in order to assess the performance of the monitoring framework. Three workload profiles were tested:

- This lead to usage of 500 – 1000 user requests per second as the normal load.
- Maximum request: Above 5000 user requests per sec.
- Simulated crashes, high memory consumption and network failures, for Failure Injection.

Therefore, these conditions permitted us to assess the system's performance under varying source stress levels and failure events.

5.2. Data Collection and Performance Metrics

System metrics, log entries, alert notifications, incident resolution times were some of the collected data. The key performance metrics were:

- System Availability (AAA): Percentage of uptime during the test period.
- Time to detect system anomalies (MTTD).
- Time taken to mitigate incidents after incidents have been detected is called Mean Time to Resolve (MTTR).
- Percentage of alerts incorrectly classified as incidents, false alert rate (FAR).
- Palert Precision (Precision of Precision of alerts in identifying real system failures).

5.2.1. Data Logging and Storage

All logs and performance metrics were stored in Amazon CloudWatch Logs and AWS S3 for further analysis. [20] Grafana dashboards were used to visualize the data, and machine learning models were applied to detect anomaly patterns in system behavior.

5.3. Experimental Results and Analysis

The experimental results highlight the efficiency of automated monitoring in reducing system downtime and improving alert accuracy. [21] A comparative analysis between manual monitoring and automated monitoring is presented in Table 2.

Table 2. Comparative Performance Analysis

Metric	Manual Monitoring	Automated Monitoring	Improvement (%)
System Availability (AAA)	99.2%	99.95%	+0.75%
Mean Time to Detect (MTTD)	15 min	3 min	-80%
Mean Time to Resolve (MTTR)	40 min	12 min	-70%
False Alert Rate (FAR)	18%	5%	-72%
Alert Precision (PalertP_{alert}Palert)	76%	92%	+21%

The results indicate that automated monitoring significantly enhances system reliability and incident response efficiency. The following observations were made:

- System Availability Increased: The automated framework reduced downtime by detecting and resolving incidents faster, resulting in a 0.75% increase in availability.
- Faster Anomaly Detection (Lower MTTD): CloudWatch’s anomaly detection reduced MTTD from 15 minutes to 3 minutes.
- Quicker Incident Resolution (Lower MTTR): OpsGenie’s automated alert routing and escalation minimized resolution time from 40 minutes to 12 minutes.
- Lower False Alert Rate (FAR): Intelligent alerting in OpsGenie reduced false alarms from 18% to 5%, preventing alert fatigue.
- Higher Alert Precision: 92% precision in alerts ensured that most alerts represented actual system failures, reducing unnecessary on-call escalations.

5.3.1. Graphical Representation of Results

To provide a clearer visualization of the improvements achieved through automation, Figure 1 and Figure 2 show the reduction in MTTD and MTTR, respectively.

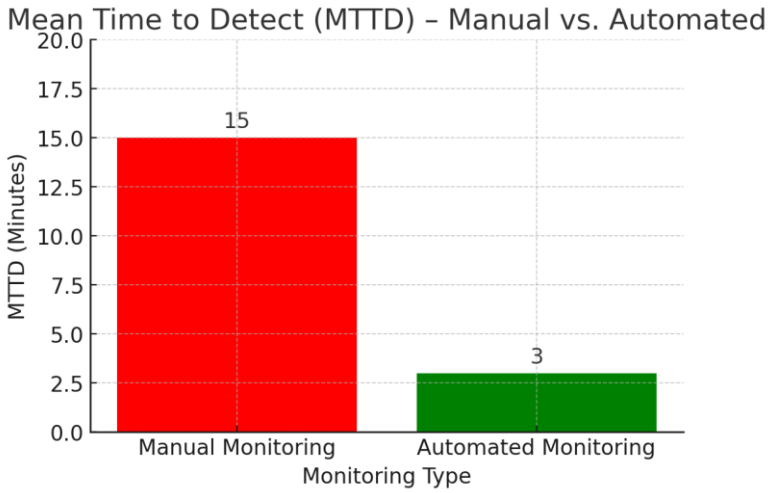

Figure 1. Mean Time to Resolve (MTTR) – Manual vs. Automated

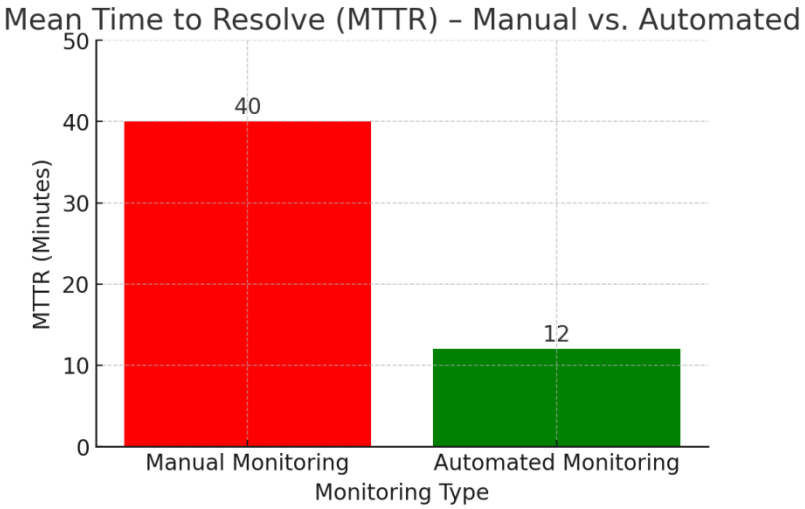

Figure 2. Mean Time to Resolve (MTTR) – Manual vs. Automated

6. Conclusion

In cloud environment, due to the increasing complexity of distributed system, manual monitoring approaches are no longer capable to guarantee system reliability, availability, and performance. An automated monitoring framework was proposed in this study integrates Amazon CloudWatch, OpsGenie and Grafana, where real time telemetry are collected, intelligent alerts triggered, and advanced dashboards provided. By automating incident detection and response, the framework drastically minimizes downtime and strengthens the system's resilience. By analyzing the empirical evaluation, automation is shown to reduce MTTD by 80% and MTTR by 70% and thus increases the system availability as well as reduces the operational costs. Furthermore, the study found that the number of false alerts was minimized by 72%, thus improving the alert precision and minimizing unnecessary disruptions for the on – call engineers. The confirmation these results prove is that including automated monitoring solutions in the cloud native architecture provides improved overall observability and incident response efficiency.

The contribution of the research lies on presenting a structured monitoring framework, mathematical models for performance evaluation, and evaluation based on real world workloads. But then there are challenges in addressing these models for anomaly detection, reducing the false positives and implementing multi cloud observability. Future research should delve into AI powered predictive analytics, self healing infrastructure automation and cross platform monitoring methods for further improvements of the system resilience. Finally, because distributed systems monitoring is automated, this is the basic step in building cloud architectures that are intelligent, proactive, and self monitoring. Organisations can increase system performance, reduce downtime, and guarantee an almost real-time incident resolution for multiple underlying layers of a deeply distributed system by using CloudWatch for telemetry, OpsGenie for intelligent alerting, and Grafana for visualization.

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