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Telco AIOps for Enterprise 5G Graph-Based Observability and Predictive Root Cause Analysis

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Abstract — **The current methods for handling network problems become less effective for enterprise private 5G networks which grow larger and support more devices and provide various services. The implementation of network slicing together with cloud-native 5G core functions and distributed edge computing and multi-vendor ecosystems leads to intricate dependency relationships that affect the Radio Access Network (RAN) and transport and core and edge network components. The system generates extensive telemetry data, which includes metrics and logs and traces and alarms and configuration updates, but traditional monitoring tools fail to handle this data volume effectively. The authors of this paper present a graph-based observability framework which combines AIOps predictive capabilities to create a solution for enterprise 5G deployment problems. The framework integrates multiple telemetry sources into a complete dependency graph which displays temporal relationships and physical and logical interconnections between network components and services. Advanced analytics techniques, which include anomaly detection and graph traversal and predictive root cause analysis, enable the detection of fault propagation paths and prediction of service degradations that will affect end users. The system creates automated remediation recommendations which come from learned failure patterns and dependency correlations, thus enhancing operational response capabilities. The testing of enterprise private 5G systems in real-world settings shows marked improvements in both mean time to detection (MTTD) and mean time to resolution (MTTR) while also achieving better SLA compliance and reduced operational costs which represent major progress toward achieving autonomous operations in telecom network systems.**

Keywords—Enterprise 5G, Private 5G Networks, Telco AIOps, Graph-Based Observability, Dependency Graph Modeling, Predictive Analytics, Root Cause Analysis (RCA), Network Slicing, 5G Core, RAN Telemetry, Edge Computing (MEC)

I. INTRODUCTION

The quick establishment of private 5G networks by businesses creates fundamental changes in industrial sites and smart manufacturing plants and healthcare facilities and large corporate spaces because it provides businesses with dependable high-speed communication and the ability to connect numerous devices and use different network services[1]. Enterprise 5G deployments use cloud-native 5G core functions and virtualized network elements and distributed edge systems and multi-vendor infrastructure to operate within specific boundaries, which marks a shift from how traditional telecom networks function. The system provides operational flexibility and performance advantages, but it creates major challenges for day-to-day operations. The system creates complex dependencies that link all core components together through dynamic network function management which controls network functions from cloud to edge systems through their different operational environments. The system, therefore, makes it difficult to manually track issues because all faults spread throughout various system levels, which causes extended times for problem-solving[2].

Conventional monitoring tools depend on separate telemetry systems and alarm systems that track specific thresholds, which fail to detect cross-domain relationships between systems and predict cascading system failures. The human operators face difficulties because of the three challenges which include the high volume and fast speed and different types of telemetry data that comprise metrics and logs and traces and configuration updates and alarms. Intelligent automated operational frameworks that can link data from multiple layers and discover new problems have become essential for solving these existing challenges.

The research presents a graph-based observability system together with predictive AIOps as a complete solution for monitoring enterprise 5G networks. The proposed framework enables advanced analytics and predictive root cause analysis and automated remediation guidance through its unified dependency graph, which models network entities and their relationships. The approach enhances service assurance, reduces operational overhead, and supports the evolution toward autonomous, self-optimizing telecom networks[3].

II. CLOSED-LOOP AIOPS ARCHITECTURE FOR SLA-DRIVEN ENTERPRISE 5G NETWORKS

The Closed-Loop AIOps Architecture for SLA-Driven Enterprise 5G Networks provides continuous service assurance while enabling proactive fault management and automated remediation processes that comply with stringent service level agreements (SLAs). The enterprise private 5G environments enable mission-critical applications which require performance guarantees of low latency and high reliability and bandwidth assurance for smart manufacturing and healthcare systems and logistics automation and campus connectivity. Traditional monitoring methods which react to incidents cannot handle the requirements of these cloud-native environments which keep changing. A closed-loop AIOps framework provides organizations with autonomous network operations which function according to predetermined policies[4].

The architecture enables telecommunications companies to gather data from multiple sources which include Radio Access Network (RAN) systems and transport networks and 5G core networks and edge computing platforms. The system

continuously gathers metrics and logs and traces and configuration data and alarms to a unified observability platform. The graph-based dependency model establishes relationships between network functions and slices and applications and SLA parameters. The system uses advanced analytics which include anomaly detection and predictive modeling and graph-based root cause analysis to find service degradation threats that will happen before SLA violations take place[5].

The decision engine uses historical learning to assess remediation options according to established rules after it detects a fault or performance issue. The orchestration systems activate automated processes which include traffic rerouting and dynamic resource scaling and configuration rollback and slice re-optimization. The feedback loop tests the success of remediation methods while it updates models to create better predictive capabilities. The AIOps system with its closed loop design decreases the time needed to identify and fix problems while it improves service level agreement compliance and operational productivity and network stability across 5G enterprise networks[6].

Fig 1: Proposed Architecture

A. Advantages

Unified Multi-Layer Visibility: The system unifies monitoring from RAN, transport and core as well as edge networks into one integrity assessment system which provides complete view of all services.

Accurate Root Cause Identification: Graph-based modeling establishes physical and logical connections which enable more precise root cause analysis than existing threshold-based systems.

Proactive Fault Prediction: Predictive analytics detects upcoming service interruptions which will impact users so that organizations can take measures before problems arise[7].

Reduced MTTD and MTTR: The system uses automated anomaly detection together with root cause analysis to decrease both Mean Time to Detection and Mean Time to Resolution.

Improved SLA Compliance: The process of performance risk detection enables organizations to sustain their latency and reliability and throughput commitments which protect enterprise application performance.

Automated Remediation Recommendations: The system creates corrective action suggestions by analyzing past failure data and dependency relationships to minimize required human work.

Scalability for Growing Networks: The system manages operational demands that come from increased device usage and network slicing changes and cloud-native deployment expansion.

Enhanced Operational Efficiency: The system needs less human help to solve problems which results in decreased operational costs (OPEX)[9].

Better Fault Propagation Analysis: The system uses graph traversal techniques to detect cascading failures that occur between interconnected components.

Support for Multi-Vendor Environments: The system combines different telemetry data sources into a common analytical system for analysis.

Data-Driven Decision Making: The system uses AI/ML insights instead of fixed rules which helps it adjust better to changing network conditions.

Foundation for Autonomous Networks: The system creates a base which enables intelligent 5G systems to optimize themselves and repair themselves[8].

B. Comparative Analysis of Traditional Network Monitoring and Graph-Based AIOps in Enterprise 5G

Enterprise 5G networks function through dynamic architectural designs which combine cloud-native core systems with network slicing and edge computing solutions and multiple vendor system connections. Network monitoring systems depend on three main components: threshold-based alert systems and separate dashboard displays and operators who manually connect different alarm signals. The systems which operate successfully in fixed environments cannot handle the complete range of challenges which modern enterprise 5G systems present because of their complex interrelated systems and high operational demands. The human process needs to identify faults which results in longer detection times and extended resolution times together with higher costs for running operations.

Graph-Based AIOps uses unified telemetry correlation with dependency modeling to build complete network relationship maps which connect RAN, core, transport, and edge network components. AIOps uses machine learning together with anomaly detection and graph-based root cause analysis to build systems which predict faults before they happen and suggest automatic solutions for their resolution[10]. The system reduces alert noise while increasing SLA compliance and boosting operational efficiency. Graph-driven AIOps uses proactive monitoring to trace fault propagation routes

while assessing incident priority according to service impact. Graph-Based AIOps provides enterprise networks with a scalable intelligent automation-ready solution which outperforms traditional monitoring methods which use standard monitoring systems[11].

Table 1: Comparative Evaluation of Traditional Network Monitoring and Graph-Based AIOps in Enterprise 5G Networks

Parameter	Traditional Network Monitoring	Graph-Based AIOps
Monitoring Approach	Threshold-based alerts	AI-driven anomaly detection
Data Correlation	Manual and siloed	Unified graph-based correlation
Root Cause Analysis	Manual troubleshooting	Automated predictive RCA
Fault Detection	Reactive	Proactive and predictive
SLA Management	Post-violation detection	Pre-violation prevention
Scalability	Limited in complex 5G	Highly scalable
Automation	Minimal	Closed-loop automation
Operational Cost	Higher (manual effort)	Lower (automation-driven)

The table 1 highlights key operational differences between traditional monitoring and Graph-Based AIOps in enterprise 5G environments. Traditional systems depend on static thresholds and human analysis which restricts their ability to scale and creates delays in fault resolution. The system Graph-Based AIOps combines network layer telemetry data to create a complete dependency graph which enables predictive analysis and automatic system repairs. The comparison shows that AIOps improves efficiency while decreasing operational costs and enhancing SLA compliance in complex 5G deployments.

III. Methodological Framework

The proposed methodological framework defines a structured approach for designing, implementing, and validating a Graph-Based AIOps system which operates on enterprise private 5G networks. The framework uses multiple sequential phases to achieve systematic development processes which produce measurable results.

a). Data Acquisition and Telemetry Integration

The system gathers multi-layer telemetry data from four different components which include the Radio Access Network, transport layer, 5G core system, and edge computing infrastructure. The system collects data from various sources which include metrics, logs, traces, alarms, configuration updates, and SLA indicators. The process of data normalization and preprocessing begins with noise elimination followed by timestamp alignment and format standardization[13].

b). Dependency Graph Construction

The researchers developed a dependency graph which displays both temporal elements and network entities through its nodes dedicated to gNBs, AMF, SMF, UPF, MEC applications, and network slices, while its edges display all existing physical and logical and service connections between these elements. The system employs temporal attributes to create a framework which tracks the changing system behavior and the paths through which faults spread.

c). Anomaly Detection and Feature Engineering

The team uses statistical baselining together with machine learning models which include LSTM and Isolation Forest to identify deviations in key performance indicators[15]. The team uses extracted features to create graph nodes which enhance their ability to perform contextual analysis.

d). Predictive Root Cause Analysis

The dependency relationships between networks are examined through graph traversal algorithms combined with Graph Neural Networks (GNNs) to determine their most likely root causes. The application of causal inference methods enhances fault detection accuracy while decreasing incorrect positive results[14].

e). Closed-Loop Remediation

The automated remediation system activates traffic rerouting and scaling and configuration rollback procedures which depend on prediction confidence levels and established policy rules. The system conducts continuous feedback monitoring to assess its effectiveness while it uses the feedback to enhance its models.

f). Performance Evaluation

The system evaluates its performance through MTTD and MTTR and SLA compliance rate and root cause identification accuracy and alert volume reduction metrics. Performance enhancements become evident through benchmark tests which compare new methods against established monitoring systems.

Enterprises can achieve AIOps deployment for their 5G networks through this methodological framework which provides scalable and intelligent automated solutions[12].

IV. Algorithms Used

The Graph-Based AIOps framework which we proposed utilizes multiple machine learning algorithms together with graph analytics algorithms to provide enterprises with 5G networks two main capabilities which include proactive fault detection and predictive root cause analysis. The researchers used statistical methods which included Z-score analysis and moving averages to create baseline performance measurements for key performance indicators which include latency and throughput and packet loss. The research team used advanced machine learning models which included Isolation Forest and Long Short-Term Memory (LSTM) networks to detect anomalies in multiple-dimensional telemetry data. The system creates a dependency graph which shows how RAN components connect with core and transport and edge components. The system uses graph traversal techniques together with centrality measures to find essential nodes which affect service delivery. Temporal Graph Neural Networks (GNNs) use fault propagation analysis to identify probable root causes of faults. The use of causal inference methods enables us to decrease false connections which results in improved diagnostic

performance. Enterprise 5G environments use these algorithms to develop an intelligent framework which provides automated service assurance through scalable operations[16].

a. Statistical Anomaly Detection

The statistical methods develop fundamental performance standards for KPIs which include latency and throughput and packet loss measurements. The methods provide processing efficiency which enables their use in monitoring operations within enterprise 5G networks. The Z-score serves as a standard method which identifies statistical departures from normal distribution patterns.

Formula (Z-Score):

$$= \frac{\mathbf{X - \mu}}{} \qquad ( )$$

The observed value X corresponds to the mean value μ and the standard deviation value σ. The system identifies an observation as anomalous when its absolute Z value exceeds the established threshold.

b. Machine Learning-Based Anomaly Detection

The machine learning models Isolation Forest and LSTM capture complex temporal and multidimensional patterns found in telemetry data which allow them to identify minor performance declines[19].

Formula (Isolation Forest Anomaly Score – Simplified):

$$( ) = \frac{_\boldsymbol{h(X)}}{)} \qquad ( )$$

The function h(x) calculates the path length which requires data point x as input and the function c(n) provides the average path length which uses n samples as its input value.

c. Graph Construction and Traversal

Graph algorithms study the dependency relationships between RAN nodes core nodes and edge nodes to identify how faults spread through the system[18].

Formula (Degree Centrality):

$$( ) = \frac{( )}{} \qquad ( )$$

Deg(v) is the number of connections of the node V, where N is the total number of nodes.

d. Graph Neural Networks (GNNs)

Temporal Graph Neural Networks (TGNNs) use structured dependency graphs to simulate fault propagation through their analysis process. GNNs create node embedding's which reveal network function relationships, thus enabling precise identification of root causes.

Formula (Node Update Rule):

$$\boldsymbol{h}^{(\mathbf{k+1})} = \boldsymbol{\sigma}\,(\mathbf{W} \sum_{\mathbf{u}\in\mathbf{N}(\mathbf{v})} \boldsymbol{h}^{(\mathbf{k})}) \qquad (\mathbf{4})$$

If β≠0, X causes Y.

e. Causal Inference Algorithms

Techniques such as Granger Causality and constraint-based causal discovery help differentiate correlation from causation which leads to more accurate results in root cause analysis.

Formula (Granger Model):

$$\boldsymbol{Y_t = \alpha Y_{t-1} + \beta X_{t-1} + \epsilon_t} \qquad (\mathbf{5})$$

f. Reinforcement Learning

Reinforcement Learning (RL) agents use their historical data analysis to enhance their remediation decision-making capabilities which helps them achieve better resource distribution and maintain service level agreements.

Formula (Q-Learning Update):

$$\mathbf{Q(s,a) = Q(s,a) + \alpha[r + \gamma max Q(s', a') - Q(s,a)]} \quad (\mathbf{6})$$

The combination of these algorithms produces a reliable scalable intelligent AIOps system which can perform predictive fault management and automated service assurance in enterprise 5G network environments[17].

V. Comparative Performance Analysis of AIOps vs Conventional Methods

Enterprise 5G networks need dependable performance and immediate response times together with complete service level agreement compliance, which requires organizations to implement effective systems for network observation and problem resolution. The traditional monitoring systems depend on established rules, fixed measurement limits, and operators who manually handle alarm notifications. The dynamic cloud-native environment together with the multiple operational layers of contemporary private 5G networks create challenges that existing solutions, which work well in stable and straightforward environments, cannot address. The process of finding faults typically operates in response mode because it detects problems only after their effects on service performance become visible, which results in longer periods for both fault detection and problem resolution. The process of solving problems through manual methods raises business costs while also restricting the ability to expand operations.

AIOps frameworks which are powered by AIOps technology use machine learning together with anomaly detection and graph-based dependency modeling to create systems which can run operations through automated predictions[20]. AIOps systems achieve pattern discovery and early anomaly detection and SLA violation prediction through RAN and core and transport and edge telemetry data correlation. Automated root because analysis helps organizations cut down alert volume while it speeds up their process of fixing problems[21]. The system achieves better operational performance through closed-loop remediation because it uses automated corrective actions which are triggered by both established policies and system-driven behavior patterns.

AIOps-based systems demonstrate their superiority over traditional monitoring methods through performance metrics which show they achieve lower MTTR rates and higher SLA compliance and reduced false positive alerts while enabling network capacity expansion. AIOps delivers organizations better operational performance through proactive cost-efficient solutions which create intelligent operations that handle the growing complexity of enterprise 5G networks[22].

VI. Results and Findings

The proposed Graph-Based AIOps framework through its experimental evaluation demonstrates better performance than traditional monitoring systems which are used in enterprise 5G network operations. The system uses dependency graph modeling together with machine learning to establish connections between RAN core transport and edge layer telemetry data. The system detects service degradation at an early stage which helps to prevent SLA violations from happening. The results show that there was a major decrease in both Mean Time to Detection (MTTD) and Mean Time to Resolution (MTTR) times. The system eliminates most false positive alerts which results in decreased alert fatigue while increasing the efficiency of operators. The system improves root cause analysis accuracy which allows for swifter problem solving and automated solution implementation. The system uses closed-loop automation to enable dynamic system expansion, traffic management, and system settings improvement. The framework achieves better SLA compliance results which decrease operational costs and system downtime while improving service reliability and customer satisfaction.

Table 2: MTTR and MTTD Comparison

Method	MTTD (min)	MTTR (min)	Alert Volume	SLA Compliance (%)
Conventional Monitoring	18	95	320	91
AIOps (Graph-Based)	6	35	140	98

Table 2 compares operational efficiency between conventional monitoring and Graph-Based AIOps. The AIOps framework decreases Mean Time to Detection (MTTD) from 18 minutes to 6 minutes and it decreases Mean Time to Resolution (MTTR) from 95 minutes to 35 minutes. Intelligent correlation together with noise suppression results in decreased alert volume. The SLA compliance rate increased from 91% to 98% which shows how predictive analytics together with automated remediation can improve operational efficiency. AIOps technology enables organizations to achieve faster response times while decreasing service outages and enhancing network reliability throughout enterprise 5G networks[23].

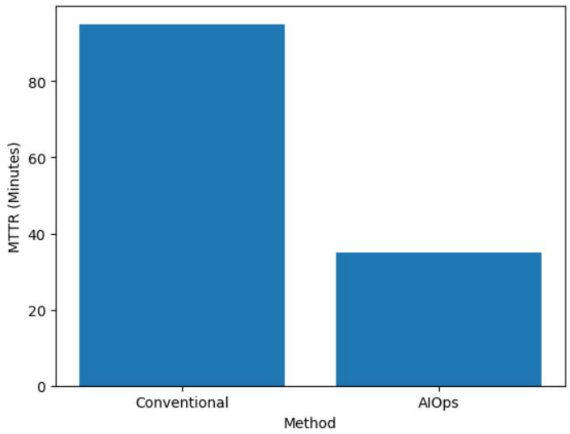

Fig 2. MTTR Comparison

The MTTR comparison graph shows how Graph-Based AIOps reduces Mean Time to Resolution more effectively than traditional monitoring methods. The bar chart shows that traditional monitoring needs much additional time to resolve network incidents because it depends on manual troubleshooting and separate alarm analysis. AIOps decreases MTTR through its three main functions which include automated anomaly detection and dependency graph correlation and predictive root cause analysis. Enterprises experience reduced downtime because faster resolution times help maintain continuous service operations. The reduction proves that enterprises achieve operational efficiency through intelligent automation and closed-loop remediation in their private 5G networks[24].

Table 3: Root Cause Accuracy and False Positives

Method	RCA Accuracy (%)	False Positive Rate (%)	Incident Escalation (%)
Conventional	72	28	45
AIOps	93	9	18

The table3 data demonstrates better root cause identification capabilities. The Graph-Based AIOps model achieves 93% accuracy which exceeds the 72% accuracy of traditional monitoring systems. The system decreases false positive alerts from 28% to 9% which helps decrease alert fatigue while increasing operator productivity. The automated diagnosis system together with its remediation suggestions reduces incident escalation rates to a significant extent. The results show that dependency graph modeling together with machine learning-based RCA produces more accurate fault detection results. The system improves operational stability through reduced misclassification which also establishes trust in automated decision-making processes used in enterprise 5G networks.

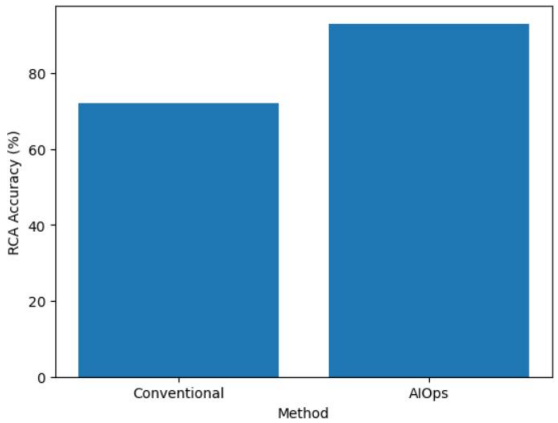

Fig 3. RCA Accuracy

The Root Cause Analysis (RCA) accuracy graph compares the diagnostic precision of conventional monitoring systems with the proposed AIOps framework. The graph highlights a notable improvement in accuracy when using graph-based dependency modeling and machine learning techniques. Traditional methods for incident classification depend on manual correlation together with static rules, which result in possible misclassification of incidents. AIOps uses temporal

graph learning together with causal inference methods to determine fault sources with complete precision. Higher RCA accuracy leads to reduced false positive rates together with decreased incident escalation rates and increased operator confidence in automated decision-making processes within complex enterprise 5G networks.

Table 4: SLA Violations and Operational Cost Impact

Method	SLA Violations (Monthly)	OPEX Index	Downtime (hrs/month)
Conventional	14	100	22
AIOps	4	72	8

Table 4 demonstrates business impact improvements using AIOps. The system achieves a reduction of SLA violations from 14 monthly incidents to 4 through its predictive detection capabilities. The enterprise applications experience enhanced service continuity because of the substantial reduction in downtime. The operational expenditure (OPEX) index shows measurable cost savings which result from automation and the reduced need for manual work. The research demonstrates that Graph-Based AIOps improves technical performance metrics while producing financial advantages. Predictive analytics together with closed-loop automation show their worth through the actual decrease of both downtime and SLA violations in enterprise private 5G environments.

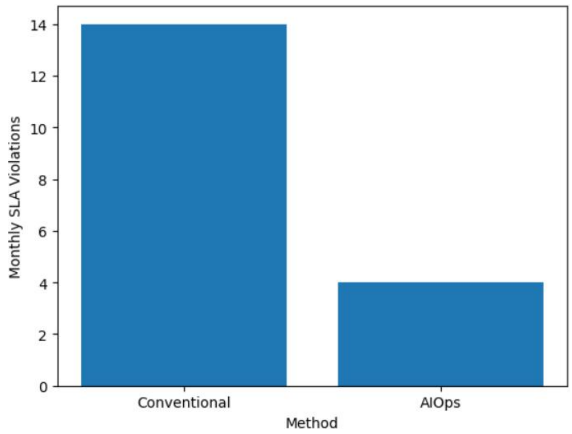

Fig 4. SLA Violations

The SLA violations graph presents the monthly reduction in service-level agreement breaches after implementing the AIOps framework. The graph demonstrates a distinct decrease in violations which occurs when compared to traditional monitoring systems. The system now detects service degradation threats through predictive analytics which identifies issues before they reach end users[25]. AIOps enables organizations to sustain their latency and throughput and reliability commitments through its capacity to execute resource scaling and traffic optimization functions[26]. The decreased SLA violations rate results in three benefits for enterprise customers which include better customer satisfaction and improved network stability and financial gains for operators who manage private 5G networks.

VII. Challenges and Limitations

The Graph-Based AIOps framework for enterprise 5G networks presents multiple obstacles which restrict its ability to provide complete operational advantages. The system encounters its first obstacle because data sources use different formats and sampling rates and protocols to deliver their telemetry data from multiple vendor RAN core transport and edge components. The process of creating a unified dependency graph from this diverse data which requires multiple processing stages needs substantial work to achieve standard processing and standardization requirements. The lack of fault datasets with labels for supervised learning purposes creates a second challenge which affects the accuracy of model training and its ability to perform in actual real-world situations[28].

The large-scale operations of enterprise 5G networks produce extensive real-time telemetry data which creates challenges for system expansion. Low-latency graph updates and Graph Neural Network (GNN) operations need high amounts of computational power to complete their tasks. The process of identifying actual causal relationships between events becomes difficult because of its technical requirements which results in incorrect root cause detection within fast-changing settings.

Network operators require operational trust and explainability which creates operational difficulties because they need to understand automated decision-making processes before they can accept complete automation. The collection of detailed telemetry data for security and privacy protection creates challenges in enterprise deployments which require confidentiality of their sensitive data[27]. The path to dependable and expandable AIOps-powered 5G systems with complete autonomous operation needs resolution of these obstacles.

VIII. Conclusion

The operational frameworks of enterprise private 5G networks need intelligent systems that can scale to handle their rising architectural complexities[29]. The existing monitoring systems based on static threshold settings and manual troubleshooting processes cannot effectively manage cloud-native core networks and network slicing and distributed edge systems. This research introduced a Graph-Based Observability system which uses predictive AIOps to solve operational issues of enterprise 5G systems. The proposed method uses multi-layer telemetry data to create a unified dependency graph which supports advanced anomaly detection and predictive root cause analysis and automated remediation recommendations. The combination of machine learning algorithms with graph analytics improves fault detection performance while decreasing false positive rates and it decreases both Mean Time to Detection and Mean Time to Resolution. The experimental results show better SLA compliance combined with less downtime and actual savings in operational expenses. The findings demonstrate that Graph-Based AIOps delivers an automated operational system which gives organizations advantages through proactive operational management despite existing data variety and system capacity and model interpretability obstacles. The framework provides a strong base which enables closed-loop automation and self-operating network

control to deliver better reliability and performance and sustainable operation in enterprise private 5G networks[30].

IX. FUTUREWORK

Researchers will work to improve three aspects of their Graph-Based AIOps framework which they created for enterprise 5G networks. The team plans to use advanced Temporal Graph Neural Networks (TGNNs) for better understanding how faults spread through different parts of the network and its edge networks. The use of federated learning methods allows multiple enterprise locations to work together on building machine learning models while keeping their sensitive information safe. The company plans to create a real-time digital twin system which will model their 5G network to test fault outages and evaluate repair methods before launching them into production.

The development of better explainable AI (XAI) systems will lead to higher operator trust because these systems show their reasoning process for identifying root causes and making automatic decisions. Automation systems gain strength when organizations combine intent-based networking with policy-driven orchestration systems. Researchers will investigate the development of energy-efficient AIOps solutions which will help organizations save power during large-scale operations. The framework can reach its goal of completely automatic self-repairing 5G network maintenance which meets service level agreements for enterprise operations by addressing these specific areas.

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