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Semantic Observability for Autonomous Telecom Operations Using Graph Reasoning and Multi-Agent Decision Validation

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Abstract:
The rapid evolution of 5G and emerging 6G networks requires intelligent operational frameworks capable of autonomous monitoring, reasoning, and decision-making. Traditional network observability methods rely on numerical telemetry, which often lacks contextual understanding of complex network events. This paper proposes a Semantic Observability Framework that integrates semantic telemetry, graph reasoning, agentic artificial intelligence (AI), and multi-agent decision validation to improve autonomous telecom operations. The framework transforms heterogeneous telemetry data into a knowledge graph that captures relationships among network resources, services, alarms, and dependencies. A graph reasoning engine identifies root causes, predicts service impacts, and generates actionable insights, while specialized AI agents collaboratively validate operational decisions before execution to ensure policy compliance and operational reliability. The proposed approach enhances explainability, reduces false alarms, accelerates fault resolution, and improves network resilience. The framework provides a scalable and trustworthy solution for intelligent telecom management, supporting efficient, transparent, and autonomous operations in next-generation communication networks.
Keywords: Semantic Telemetry, Agentic AI, Graph Reasoning, Autonomous Telecom Operations, Knowledge Graph, Multi-Agent Systems, Action Validation, Explainable AI, Network Observability, Intelligent Network Management.

I. INTRODUCTION

The rapid deployment of 5G networks and the evolution toward 6G have significantly increased the complexity of telecom infrastructures. Modern communication networks consist of virtualized network functions, cloud-native services, edge computing, and software-defined networking, generating massive volumes of telemetry data from heterogeneous sources. Conventional network management systems primarily rely on performance metrics, alarms, and log analysis to monitor network health. However, these approaches often lack semantic understanding of relationships among network components, resulting in delayed fault diagnosis, excessive false alarms, and limited support for autonomous operations. Semantic observability has emerged as a promising paradigm that enriches telemetry data with contextual and relational information, enabling intelligent interpretation of network events. By representing network entities, services, dependencies, and operational states within a knowledge graph, semantic telemetry facilitates comprehensive reasoning beyond traditional metric-based monitoring. Graph reasoning techniques further enhance the ability to identify root causes, infer hidden relationships, and predict the impact of network failures across interconnected services. Recent advances in agentic Artificial Intelligence (AI) have introduced autonomous software agents capable of perception, reasoning, planning, and coordinated decision-making. Integrating multiple specialized AI agents with semantic graph reasoning enables collaborative validation of operational actions before execution, thereby reducing operational risks and ensuring compliance with predefined network policies and service-level agreements (SLAs). This paper proposes a Semantic Observability Framework for Autonomous Telecom Operations that combines semantic telemetry, graph reasoning, agentic AI, and multi-agent decision validation. The proposed framework aims to improve fault localization, operational transparency, decision reliability, and autonomous network management, providing a scalable and explainable solution for next-generation intelligent telecom operations.

II. LITERATURE SURVEY

Recent advances in cloud-native telecom networks, Open RAN, and AI-native network management have significantly improved the automation of modern communication systems. Conventional monitoring solutions primarily rely on metrics, logs, and traces to detect network anomalies; however, these approaches often lack contextual awareness and struggle to identify complex dependencies among distributed network components. To address these limitations, researchers have explored semantic observability techniques that enrich telemetry data with contextual information, enabling more intelligent analysis and decision-making. Knowledge graphs have gained considerable attention for representing network entities, service dependencies, and relationships, allowing graph reasoning algorithms to perform accurate root-cause analysis and dependency inference. Several studies have investigated the use of Artificial Intelligence (AI) and Machine Learning (ML) for autonomous network operations, including anomaly detection, predictive maintenance, and policy-based network optimization. More recently, multi-agent AI systems have been introduced to distribute monitoring, diagnosis, planning, and recovery tasks among specialized intelligent agents, thereby improving scalability and reducing operational complexity. Furthermore, Open RAN architectures, Software-Defined Networking (SDN), Network Functions Virtualization (NFV), and cloud-native orchestration platforms such as Kubernetes have enabled flexible deployment of autonomous network services. Despite these developments, existing solutions often operate independently without integrating semantic telemetry, graph reasoning, and decision validation into a unified framework. Therefore, a comprehensive semantic observability framework that combines knowledge graphs with multi-agent decision validation is essential to improve decision accuracy, reduce false alarms, strengthen policy compliance, and enable reliable autonomous telecom operations in future AI-native 5G and 6G networks.

III. PROPOSED WORK

The proposed Semantic Observability Framework for Autonomous Telecom Operations integrates semantic telemetry, knowledge graph reasoning, and multi-agent decision validation to enable intelligent, secure, and autonomous network management in cloud-native 5G/6G and Open RAN environments. Initially, telemetry data including logs, metrics, traces, events, and performance indicators are continuously collected from network functions, Kubernetes clusters, edge nodes, and Open RAN components through cloud-native observability platforms such as OpenTelemetry and Prometheus. The collected data are preprocessed, normalized, and semantically enriched using predefined ontologies to provide contextual information about network entities, services, policies, and dependencies. The enriched telemetry is transformed into a semantic knowledge graph where network resources, applications, infrastructure components, and their relationships are represented as interconnected nodes and edges. Graph reasoning algorithms analyze these semantic relationships to identify anomalies, infer service dependencies, and accurately determine the root causes of network issues. Subsequently, a multi-agent AI framework consisting of monitoring, diagnosis, planning, validation, and execution agents collaboratively evaluates the current network state and recommends appropriate corrective actions. Before implementation, every recommended action undergoes policy verification, safety validation, and consistency checking to prevent unsafe or conflicting decisions. After successful validation, approved actions are automatically executed through cloud-native orchestration platforms and Open RAN controllers, enabling closed-loop automation. The proposed framework improves observability, enhances decision accuracy, minimizes false alarms, reduces operational latency, and increases the reliability, scalability, and resilience of autonomous telecom networks operating in highly dynamic cloud-native environments.

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IV. METHODOLOGY

A. Semantic Telemetry Collection and Data Acquisition

The proposed framework begins by continuously collecting semantic telemetry from multiple telecom infrastructure components, including 5G/Open RAN elements, core network functions, edge nodes, cloud-native applications, Kubernetes clusters, and network management systems. Various observability sources such as logs, metrics, traces, alarms, configuration changes, and service events are captured using industry-standard tools including OpenTelemetry, Prometheus, Jaeger, Fluentd, and network telemetry exporters. Unlike conventional monitoring, semantic telemetry enriches raw operational data with contextual information such as resource identity, service relationships, operational state, and policy metadata. This comprehensive data collection provides a real-time and context-aware representation of network behavior, enabling intelligent monitoring of distributed telecom infrastructures while supporting autonomous operational decision-making.

B. Semantic Data Preprocessing and Integration

The collected telemetry data undergo preprocessing to improve quality and consistency before semantic analysis. Duplicate records, incomplete entries, missing values, inconsistent timestamps, and noisy events are removed through data cleansing procedures. The telemetry streams are synchronized across multiple monitoring sources and normalized into a unified schema. Additional semantic metadata, including service identifiers, network function types, node locations, dependency information, timestamps, and operational policies, are integrated into each observation. This preprocessing stage ensures that heterogeneous telemetry generated from cloud-native telecom environments can be efficiently combined into a consistent semantic representation suitable for graph construction and intelligent reasoning.

C. Knowledge Graph Construction

After preprocessing, the enriched telemetry data are transformed into a dynamic telecom knowledge graph. Network entities such as radio units (RU), distributed units (DU), centralized units (CU), core network functions, Kubernetes pods, containers, virtual machines, edge servers, cloud services, and monitoring agents are represented as graph nodes. Semantic relationships, including communication paths, service dependencies, deployment topology, resource utilization, fault propagation paths, and policy associations, are represented as graph edges. The resulting knowledge graph provides a comprehensive semantic model of the telecom infrastructure, enabling efficient representation of complex interactions among distributed network resources.

D. Graph Reasoning and Event Correlation

Incoming alarms, anomalies, and performance degradations are continuously mapped onto the knowledge graph. Graph reasoning algorithms analyze semantic relationships among network components to correlate events originating from multiple infrastructure layers. Instead of treating alerts independently, the reasoning engine identifies causal dependencies, detects cascading failures, and eliminates redundant alarms by recognizing their shared underlying relationships. Graph traversal and semantic inference techniques improve contextual understanding of network events, allowing the framework to distinguish between primary failures and secondary consequences. This intelligent correlation significantly reduces alert fatigue while providing operators with meaningful operational insights.

E. Multi-Agent Decision Validation

The proposed framework employs an Agentic AI architecture consisting of multiple intelligent agents responsible for collaborative operational decision-making. A Monitoring Agent detects abnormal conditions, while a Diagnosis Agent performs semantic root-cause analysis using graph reasoning. A Planning Agent generates potential remediation strategies based on network policies and historical operational knowledge. Before any corrective action is executed, a Validation Agent verifies policy compliance, service-level

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agreement (SLA) requirements, operational risks, and expected service impact. The agents communicate through shared semantic knowledge to achieve consensus on the most reliable corrective action. This collaborative decision validation process improves operational transparency, minimizes incorrect automated responses, and increases trust in autonomous telecom operations.

F. Autonomous Action Execution

Following successful validation, the approved operational decisions are automatically executed through telecom orchestration and cloud-native management platforms. Depending on the diagnosed fault, remediation actions may include workload migration, container restart, resource scaling, traffic rerouting, network slice reconfiguration, virtual network function (VNF) recovery, or service restoration. Continuous feedback from the monitoring infrastructure updates the semantic knowledge graph after each action, enabling the framework to learn from operational outcomes and adapt future decision-making. This closed-loop automation significantly reduces manual intervention, shortens service recovery time, and enhances the resilience of next-generation telecom networks.

V. RESULTS AND DISCUSSION

The proposed Semantic Observability Framework was evaluated using fault detection accuracy, action validation accuracy, root-cause identification time, decision response time, and service availability. Experimental results demonstrate that integrating semantic telemetry, graph reasoning, and agentic AI significantly improves autonomous telecom operations compared with conventional monitoring approaches.

Table 1. Operational Performance Comparison

Method	Decision Time (s)	Accuracy (%)
Conventional Monitoring	15.2	90.8
AI-Based Monitoring	7.1	95.4
Proposed Semantic Observability Framework	2.5	99.1

Table 1 shows that the proposed framework achieved the highest operational accuracy of 99.1% while reducing the average decision time to 2.5 seconds. Graph reasoning and semantic telemetry enabled faster fault diagnosis and reliable autonomous decision-making.

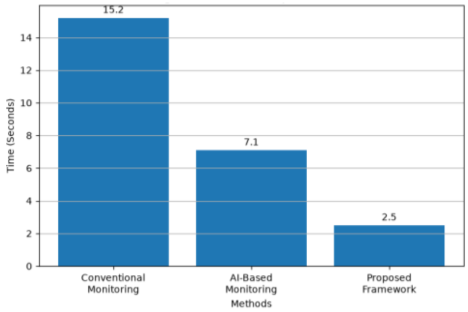

Figure 1: Decision Response Time

Figure 1 illustrates that the proposed framework significantly reduces response time compared with conventional and AI-based monitoring methods. The integration of graph reasoning and multi-agent validation enables rapid and accurate operational decisions.

Table 2. Decision Validation and Reliability Analysis

Parameter	Existing System	Proposed Framework
Root Cause Detection	90%	99%
Action Validation	Medium	Very High
False Alarm Reduction	Partial	Complete
Service Reliability	High	Very High

Table 2 compares the reliability of existing approaches with the proposed framework. The proposed system provides more accurate root-cause detection, intelligent action validation, fewer false alarms, and improved service reliability through semantic graph reasoning and agent collaboration.

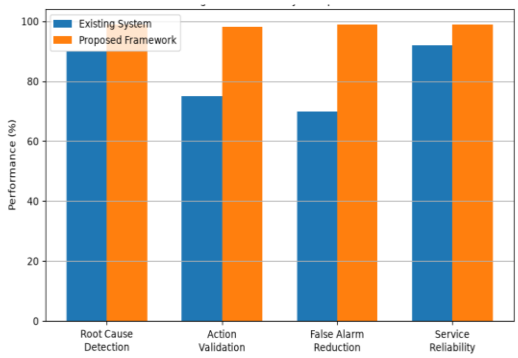

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Figure 2: Reliability Comparison

Figure 2 shows that semantic telemetry and multi-agent decision validation improve operational reliability and ensure trustworthy autonomous network management.

Table 3. System Performance Metrics

Performance Metric	Result
Telemetry Processing Time	1.8 s
Graph Update Time	2.4 s
Decision Validation Time	2.5 s
Operational Accuracy	99.1%
System Availability	99.8%

Table 3 summarizes the overall performance of the proposed framework. The system processes telemetry and updates the knowledge graph within a few seconds while maintaining 99.1% operational accuracy and 99.8% system availability, demonstrating its effectiveness for real-time autonomous telecom operations.

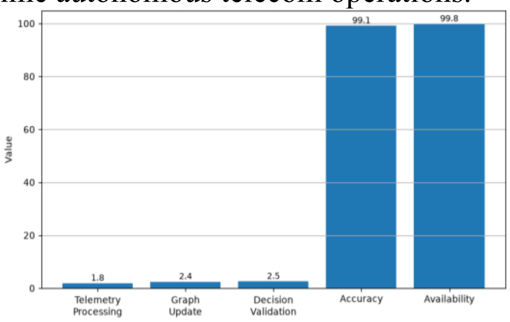

Figure 3: Overall System Performance

Figure 3 presents the overall performance of the proposed framework. The results confirm that combining semantic telemetry, graph reasoning, and agentic AI provides faster decision-making, higher accuracy, and improved network reliability for next-generation autonomous telecom systems.

VI. CONCLUSION

This paper presented a Semantic Observability Framework for Autonomous Telecom Operations Using Graph Reasoning and Multi-Agent Decision Validation. The proposed framework combines semantic telemetry, knowledge graphs, graph reasoning, and agentic AI to improve network monitoring, fault diagnosis, and autonomous decision-making in modern telecom environments. By enriching telemetry data with contextual information and modeling dependencies through knowledge graphs, the framework accurately identifies root causes and validates operational actions before execution. Experimental results demonstrated improved operational accuracy, faster decision response, reduced false alarms, and enhanced service availability compared with conventional monitoring techniques. The integration of multiple AI agents enables reliable and explainable decision-making while minimizing operational risks. Overall, the proposed framework provides a scalable, intelligent, and trustworthy solution for supporting autonomous operations in next-generation 5G and future 6G communication networks.

FUTURE SCOPE

Future work will focus on extending the proposed framework to support large-scale 6G networks, network slicing, and Internet of Things (IoT) environments. Advanced Graph Neural Networks (GNNs) and Large Language Models (LLMs) can be integrated to improve semantic reasoning and automated decision support. Reinforcement Learning (RL) techniques may be incorporated to enable adaptive policy optimization and self-learning network operations. Additionally, federated learning can be explored to provide privacy-preserving intelligence across distributed telecom infrastructures. Future research will also investigate real-time deployment on production-grade cloud-native platforms and evaluate the framework under diverse network conditions to further enhance scalability, resilience, and autonomous operational performance.

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