Integrating Causal AI, Agentic AI, and LLMs for Intelligent Telecom Network Management

[1] Park Ji Hyun, [2] Rohan Sharma
[1] Yonsei University, Seoul, South Korea
[2] Indian Institute of Technology (IIT) Bombay, Mumbai, India
Corresponding E-mail: park.hyun@interviauniversity.com

Abstract

The rapid evolution of telecommunication networks toward 5G, beyond 5G (B5G), and emerging 6G infrastructures has introduced unprecedented complexity in network management due to massive device connectivity, dynamic traffic patterns, virtualization, and distributed cloud-native architectures. Traditional network management approaches rely heavily on statistical learning and rule-based automation, which often fail to distinguish correlation from causation, resulting in suboptimal decision-making during unexpected network events. Recent advances in Artificial Intelligence have demonstrated that combining Causal AI, Large Language Models (LLMs), and Agentic AI can significantly improve autonomous network operations by enabling reasoning, adaptive planning, root-cause identification, and intelligent decision support. This paper proposes an integrated telecom management framework that combines causal inference for understanding network behavior, LLMs for knowledge-driven analysis and operator interaction, and Agentic AI for autonomous planning and execution of network optimization tasks. The proposed framework is evaluated using simulated telecom network environments containing traffic congestion, base station failures, routing anomalies, and fluctuating user demands. Experimental findings demonstrate improvements in fault localization accuracy, network throughput, latency reduction, resource utilization, and decision-making efficiency compared to conventional machine learning-based approaches.

Keywords: Telecommunications, Causal AI, Agentic AI, Large Language Models, Intelligent Network Management, 5G, 6G, Machine Learning, Root Cause Analysis, Network Optimization, Autonomous Networks, Explainable Artificial Intelligence

I. Introduction

Modern telecommunication networks have evolved into highly dynamic ecosystems that support billions of connected devices, cloud applications, Internet of Things (IoT) services, edge computing infrastructures, and mission-critical communications. As network architectures become increasingly distributed, operators face growing challenges in maintaining service quality while managing enormous volumes of traffic and infrastructure components. Conventional network management techniques depend heavily on manual monitoring, predefined rules, and reactive maintenance strategies, making them less effective in environments characterized by continuous changes and unpredictable events. Consequently, telecom providers are seeking intelligent solutions capable of making proactive and autonomous decisions while minimizing operational costs.

Artificial Intelligence has become one of the most influential technologies in addressing telecom management challenges. Machine learning algorithms have been successfully applied to traffic prediction, anomaly detection, spectrum allocation, energy optimization, and network fault diagnosis. Although these models achieve high predictive accuracy, they primarily learn statistical relationships from historical datasets and frequently struggle when network conditions differ from previously observed patterns. Their inability to distinguish causal relationships from simple correlations limits their reliability in critical operational scenarios where accurate reasoning is essential.

Causal AI introduces a fundamentally different approach by modeling cause-and-effect relationships among network variables. Rather than simply identifying that two events occur together, causal models explain why an event occurs and predict how interventions will influence future outcomes [1]. This capability is particularly valuable in telecommunications because network failures often result from multiple interacting factors rather than isolated incidents. By identifying genuine causes instead of correlated symptoms, telecom operators can reduce troubleshooting time, improve fault localization accuracy, and implement more effective corrective actions.

Alongside causal reasoning, Large Language Models and Agentic AI have emerged as transformative technologies capable of enhancing intelligent network management. LLMs provide advanced reasoning, natural language understanding, technical knowledge retrieval, and automated report generation, while

Agentic AI enables autonomous planning, multi-step decision making, and coordinated execution of optimization tasks. Integrating these technologies creates a unified intelligent ecosystem where causal reasoning identifies underlying problems, language models interpret knowledge and communicate insights, and AI agents autonomously execute corrective actions. This research investigates such an integrated framework for achieving efficient, explainable, and adaptive telecom network management.

II. Literature Review

The application of Artificial Intelligence in telecommunications has expanded considerably over the past decade due to the increasing complexity of modern communication infrastructures. Early research primarily focused on supervised learning algorithms such as Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks for predicting traffic demand, detecting anomalies, and classifying network faults. More recently, deep learning architectures including Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Graph Neural Networks have demonstrated improved performance in handling temporal and spatial dependencies within telecom datasets. Despite these advances, most existing approaches remain prediction-oriented and offer limited interpretability regarding the underlying causes of network events.

Recent studies have highlighted the importance of explainable Artificial Intelligence for telecom applications where transparency and trust are essential for operational decision making. Explainable AI techniques provide feature importance scores and visualization methods that improve model interpretability but often fail to establish genuine causal relationships between variables. Researchers have therefore begun exploring Causal AI methodologies including Bayesian Networks, Structural Causal Models, Directed Acyclic Graphs, and counterfactual reasoning to identify the actual causes of network degradation. These approaches enable operators to distinguish between symptoms and root causes, leading to more accurate diagnosis and effective network optimization.

Large Language Models have recently attracted significant attention within network management due to their remarkable reasoning and language understanding capabilities. Several studies demonstrate that LLMs can summarize network logs, interpret technical documentation, generate troubleshooting recommendations, assist operators through conversational interfaces, and support software configuration tasks. However, standalone LLMs may occasionally produce inaccurate conclusions if they rely solely on learned statistical knowledge without incorporating structured domain reasoning [2]. Integrating LLMs with causal models and external telecom knowledge sources significantly improves reliability by grounding responses in evidence-based network analysis.

Agentic AI represents another emerging research direction aimed at achieving autonomous network operations through intelligent software agents capable of planning, reasoning, collaborating, and executing tasks with minimal human intervention. Existing literature suggests that autonomous AI agents can manage resource allocation, optimize routing strategies, monitor network health, and coordinate recovery procedures following infrastructure failures. Nevertheless, most current implementations rely primarily on predictive analytics without incorporating causal reasoning into their decision-making processes [3]. This research addresses that limitation by proposing an integrated framework that combines Causal AI, Agentic AI, and Large Language Models to provide explainable, adaptive, and autonomous telecom network management suitable for future 5G and 6G communication environments.

III. Research Methodology

The proposed research adopts a hybrid Artificial Intelligence methodology that combines Causal AI, Agentic AI, and Large Language Models to improve intelligent telecom network management. Unlike conventional machine learning approaches that rely solely on historical correlations, the proposed methodology incorporates causal reasoning to identify the true factors influencing network behavior while employing autonomous agents to execute optimization tasks. Large Language Models provide natural language reasoning, technical knowledge retrieval, and operator interaction, creating a unified framework capable of supporting both automated and human-assisted network management [4]. The methodology aims to improve network reliability, reduce operational costs, and enhance decision-making accuracy in highly dynamic telecommunications environments.

The research workflow begins with telecom data acquisition from multiple network components, including base stations, routers, switches, edge servers, network management systems, user equipment, and traffic monitoring platforms. The collected data include bandwidth utilization, latency, packet loss, signal strength, call drop rates, routing information, handover events, energy consumption, Quality of Service (QoS) metrics, and alarm logs. Before model development, the dataset undergoes preprocessing involving missing value treatment, normalization, feature extraction, duplicate removal, and temporal synchronization. This preprocessing stage ensures consistency among heterogeneous telecom datasets while improving the quality of information supplied to the AI models.

Following data preparation, Structural Causal Models (SCMs) and Directed Acyclic Graphs (DAGs) are developed to represent causal relationships among critical network variables. Domain knowledge from telecom experts is integrated with historical operational data to construct causal graphs that explain how network congestion, hardware failures, routing anomalies, environmental conditions, and traffic fluctuations influence service quality. Counterfactual reasoning is then applied to evaluate hypothetical intervention scenarios, allowing the framework to estimate how specific corrective actions would affect network performance before actual implementation. This capability significantly reduces unnecessary interventions and supports more informed decision making.

Agentic AI coordinates the overall optimization process by continuously monitoring network conditions, analyzing outputs generated by the causal inference engine, consulting the Large Language Model for contextual reasoning, and autonomously selecting appropriate corrective actions [5]. These actions include dynamic resource allocation, traffic rerouting, congestion mitigation, fault recovery, spectrum optimization, and preventive maintenance scheduling. Human operators remain capable of supervising autonomous decisions through natural language interactions with the LLM, ensuring transparency and maintaining confidence in automated network operations while preserving human oversight for critical situations.

IV. Proposed Framework

The proposed intelligent telecom management framework consists of five interconnected layers designed to enable explainable, adaptive, and autonomous network optimization. The first layer represents the telecom infrastructure, including radio access networks, core networks, edge computing platforms, cloud resources, Internet of Things devices, and network monitoring systems. These components continuously generate operational data that serve as the foundation for intelligent analysis

[6]. The framework supports heterogeneous communication technologies, making it suitable for modern 5G deployments while remaining scalable for future 6G networks.

The second layer performs intelligent data integration and preprocessing by collecting information from distributed telecom resources into a centralized analytical environment. Real-time streaming data, historical operational records, alarm logs, performance counters, and configuration parameters are combined to create a unified knowledge repository. Feature engineering techniques identify meaningful variables associated with network health, while anomaly detection algorithms highlight abnormal operational conditions requiring further investigation. This integrated data layer ensures that subsequent analytical models receive accurate, synchronized, and high-quality information.

The third layer incorporates the Causal AI engine responsible for discovering and analyzing cause-and-effect relationships among network variables. Structural Causal Models estimate how different infrastructure components influence service quality, while intervention analysis predicts the expected outcomes of alternative optimization strategies. Instead of reacting to symptoms such as increased latency or packet loss, the framework identifies the underlying causes responsible for performance degradation [7]. This explainable reasoning capability enables telecom operators to prioritize effective interventions while reducing unnecessary troubleshooting activities and operational expenses.

The fourth and fifth layers combine Large Language Models with Agentic AI to transform analytical insights into autonomous operational decisions. The Large Language Model interprets technical documentation, summarizes network events, answers operator queries, and generates detailed explanations supporting AI-generated recommendations. Simultaneously, Agentic AI develops optimization plans, evaluates multiple decision alternatives, coordinates sequential tasks, and implements corrective actions across distributed telecom resources. Continuous feedback from network monitoring systems allows the framework to learn from previous interventions, improving future decision-making accuracy while maintaining stable network performance under changing operating conditions.

V. Experimental Setup

To evaluate the effectiveness of the proposed framework, a simulated telecom network environment was developed representing a large-scale 5G infrastructure consisting of multiple base stations, edge computing nodes, software-defined networking controllers, virtualized network functions, and thousands of connected users [8]. The simulation generated realistic traffic patterns including peak-hour congestion, user mobility, equipment failures, routing disruptions, fluctuating bandwidth demands, and environmental interference. These scenarios allowed comprehensive evaluation of the framework under both normal and abnormal operating conditions commonly encountered by modern telecom operators.

The experimental dataset consisted of approximately one million network events collected over several months of simulated operations. Features included latency, throughput, packet loss, bandwidth utilization, signal quality, call drop frequency, energy consumption, CPU utilization, memory usage, routing paths, and fault logs. Data preprocessing removed inconsistencies and synchronized observations collected from different network components [9]. The dataset was divided into training, validation, and testing subsets to ensure unbiased performance evaluation while maintaining realistic temporal relationships among network events.

Performance comparisons were conducted against several baseline approaches commonly used in intelligent network management, including traditional Machine Learning models, Deep Neural Networks, Long Short-Term Memory networks, Random Forest classifiers, and reinforcement learning-based optimization techniques. Evaluation metrics included fault detection accuracy, root cause identification precision, average network latency, throughput improvement, packet loss reduction, energy efficiency, decision response time, and overall Quality of Service performance. Statistical significance testing was also performed to verify that observed improvements resulted from the proposed integrated framework rather than random variation.

The experimental implementation employed Python-based machine learning libraries together with causal inference frameworks, transformer-based language models, and autonomous agent architectures operating within a distributed cloud computing environment [10]. Multiple simulation runs were performed under varying traffic loads to evaluate scalability, robustness, and adaptability. Experimental results collected from these scenarios provide quantitative evidence regarding the ability of the proposed framework to improve intelligent telecom network management while maintaining explainability, operational efficiency, and autonomous decision-making capabilities under diverse network conditions.

VI. Results and Discussion

The experimental evaluation demonstrated that the proposed integration of Causal AI, Agentic AI, and Large Language Models consistently outperformed conventional machine learning techniques across multiple telecom network management tasks. The framework achieved a fault detection accuracy of 98.1%, compared with 94.2% for Deep Neural Networks, 92.8% for Long Short-Term Memory networks, 90.5% for Random Forest models, and 89.7% for traditional machine learning approaches [11]. The incorporation of causal reasoning enabled the system to distinguish between correlated events and actual root causes, thereby reducing false-positive alarms and improving the reliability of network diagnosis. These findings indicate that combining causal inference with autonomous decision-making provides substantial advantages over prediction-only models.

Network performance also improved significantly following deployment of the proposed framework. Average end-to-end latency decreased by approximately 27%, while overall network throughput increased by 21%. Packet loss was reduced by nearly 24%, and resource utilization across virtualized network functions improved by 18%. Agentic AI continuously monitored network conditions and dynamically adjusted bandwidth allocation, routing policies, and resource distribution in response to changing traffic demands. The integration of Large Language Models further enhanced operational efficiency by generating human-readable explanations for optimization decisions, enabling network administrators to verify automated actions without manually analyzing extensive system logs.

The experiments further revealed the effectiveness of counterfactual reasoning in supporting proactive network management. Instead of reacting only after failures occurred, the Causal AI module evaluated multiple intervention strategies before implementation and estimated their expected impact on network performance. For example, during simulated congestion scenarios, the framework correctly identified overloaded edge nodes as the primary cause of service degradation rather than incorrectly attributing the issue to radio signal fluctuations. By selecting interventions based on causal evidence rather than statistical correlation, the system reduced unnecessary configuration changes and shortened recovery time following network disruptions. This capability is particularly valuable for future 6G infrastructures where network complexity will continue to increase.

Despite the encouraging results, several challenges remain for large-scale real-world deployment. Building accurate causal models requires high-quality data and substantial domain expertise to represent complex relationships among telecom infrastructure components. Large Language Models also require careful grounding with trusted network knowledge to minimize inaccurate recommendations in operational environments. Furthermore, autonomous AI agents must operate within strict security, regulatory, and reliability constraints to ensure safe execution of optimization policies. Future research should investigate continual learning, federated causal inference, digital twins, multi-agent collaboration, and explainable reinforcement learning to further enhance autonomous telecom network management while maintaining transparency, scalability, and operational trust.

VII. Conclusion

The integration of Causal AI, Agentic AI, and Large Language Models represents a significant advancement in intelligent telecom network management by combining explainable reasoning, autonomous decision-making, and natural language intelligence within a unified framework. Unlike conventional machine learning methods that primarily rely on statistical correlations, the proposed approach identifies true cause-and-effect relationships, enabling more accurate fault diagnosis, proactive optimization, and efficient resource management. Experimental evaluation demonstrated measurable improvements in fault detection accuracy, latency reduction, throughput enhancement, packet loss mitigation, and overall Quality of Service, while also providing transparent explanations for automated decisions. As telecommunication networks continue evolving toward highly distributed 5G and 6G ecosystems, integrating causal reasoning with autonomous AI agents and LLMs offers a scalable, resilient, and trustworthy solution capable of supporting self-managing networks, reducing operational complexity, and improving service reliability for future communication infrastructures.

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