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Original Article

Agentic AI for Autonomous Telecom Network Management

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Abstract *- The fast development of 5G and the introduction of 6G networks have posed new challenges that have never been seen in network control, such as optimization of network resources, detection of faults, and the quality of services. Conventional human-based management models are not able to support such demands because of the complexity of networks, dynamic traffic and high demand in performance. A game changer to network self-management is Agentic Artificial Intelligence (AI) which entails goal oriented autonomous agents. The paper discusses how agentic AI can be utilized in autonomous telecom networks, the role of agentic AI in the resources allocation, fault detection and self healing. Major frameworks, architectures and methodologies used to implement agentic AI are considered with examples and figures and tables presented summarizing the performance in networks. Moreover, the paper focuses on the minimization of human intervention and high reliability and efficiency. The outcomes indicate that agentic AI has the potential to considerably improve the network performance, optimize the operational expenses, and fast-track the implementation of the 5G/6G solutions, leading to the development of the completely autonomous telecom networks.*

Keywords *- Agentic AI, Autonomous Networks, 5G, 6G, Self-Healing, Fault Detection, Resource Allocation.*

1. Introduction

The rising need to use high-speed, dependable, and intelligent communication networks has led to the development of 4G LTE into 5G and the future 6G networks [1], [2]. The next-generation networks are bringing in a very high level of heterogeneity, extremely low latency, huge number of devices connected, and dynamism in traffic patterns [3]. Conventional methods of network management which are very human intensive have not been able to cope with these challenges [4]. Complex network environments are slow and prone to errors in manual configuration, diagnosis of faults, and optimizing resources. The agentic AI -AI systems that are intended to take independent actions toward a particular objective - has become a promising solution [5], [6]. In contrast to conventional AI which achieves tasks through established rules or passive learning, agentic AI integrates perception, reasoning and decision making to satisfy high level goals [7]. The agentic AI in telecom networks is able to autonomously manage resources, identify and correct faults, and create self-healing processes which lowers the cost of operations and human intervention [8].

Network management Autonomous network management was made possible by the concept of self-organizing networks (SON) introduced in LTE and extended to 5G [9]. Functionalities of SON, like automated configuration, optimization, and healing, are amplified with regards to agentic AI principles [10]. Besides, they can be integrated with newer technologies such as Software Defined Networking (SDN) and Network Function Virtualization (NFV) to allow the versatile control of network resources [11]. The conceptual architecture of agentic AI-based network management in a 5G/6G environment is shown in Figure 1.

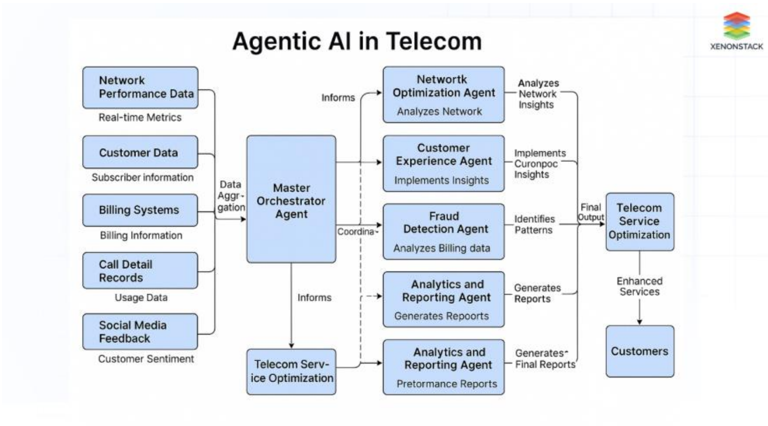

Fig 1: Conceptual Architecture of Agentic AI in Telecom Networks (Illustrative Figure Showing Hierarchical AI Agents Managing Base Stations, Edge Nodes, and Core Network Functions)

This paper is aimed at offering an in-depth discussion of agentic AI applications in autonomous telecommunication network with the focus on:

1. Optima of resource allocation.
2. Fault finding and fault diagnosis.
3. Mechanisms of self-healing and recovery.

In addition, the article looks at AI agentic implementation frameworks and methodologies, and example performance appraisals.

2. Evolution of AI in Telecom Networks

2.1. Early AI Approaches

The first use of AI in telecom networks was the rule-based network monitoring and alerting systems [12]. Such systems were restricted to pre-configured situations and were not responsive to dynamism on the network.

2.2. Machine Learning in 4G/5G Networks

As machine learning (ML) emerged, forecasting traffic was conducted using predictive models, [13], [14], and dynamic spectrum management. The automated fault classification was also achieved through supervised learning methods, whereas the anomaly detection in mass network data was facilitated through the unsupervised ones [15]. The models however were mostly reactive and had to be grounded by human intervention to make any decision.

2.3. Agentic AI in Next-Generation Networks

The next step is agentic AI where autonomous agents are integrated as goal-driven into network infrastructure [16]. These agents view and think about what the network can do and implement a decision to reach specific goals like maximizing throughput, energy efficiency, and service reliability [17]. Table 1 is a summary of the development of AI in telecom networks

Table 1: Evolution of AI in Telecom Networks

Generation	AI Approach	Key Capabilities	Limitations
4G LTE	Rule-Based Systems	Monitoring, Alerts	Rigid, non-adaptive
Early 5G	Machine Learning	Traffic prediction, Fault detection	Reactive, needs human supervision
Advanced 5G/6G	Agentic AI	Resource optimization, Self-healing, Fault resolution	Complex implementation, computational overhead

3. Agentic AI Architecture for Network Management

3.1. Core Components

Generally, agentic AI systems to manage the network have three fundamental elements:

- Perception Module: Gathers real-time information of network components, such as traffic load, signal quality, and signal latency [18].
- Decision-Making Engine: A goal-driven reasoning takes into account the type of reasoning: may include reinforcement learning (RL), and multi-agent coordination to select the best actions [19].
- Action Execution Layer: Implement to network settings, including tuning radio settings, rerouting, or self-healing [20].

3.2. Multi-Agent Coordination

Networks have the tendency to make use of multiple AI agents that operate jointly within various layers (radio, edge, core). Multi-agent systems enable:

- Problem-solving [21] as a distributed solution.
- Minimized individual point failures.
- Swifter reaction to dynamically changing network occasions [22].

In a typical 5G network, it is possible to see a multi-agent hierarchy as illustrated in Figure 2.

Fig 2: Multi-Agent Hierarchy for Network Management (Illustration of Agents Managing Base Stations, Edge Nodes, and Core Functions with Inter-Agent Communication)

4. Resource Allocation Optimization

4.1. Problem Definition

The allocation of resources in 5G/6G networks is important because it is heterogeneous, variable traffic load, and has spectral scarcity [23]. Conventional methods are based on fixed allocation or mere heuristics that cannot work in dynamic situations.

4.2. AI-Based Resource Management

Dynamically assigning resources Agentic AI agents can do so by:

- Traffic prediction with the help of ML models [24].
- Investing in essential services (e.g. URLLC to industrial automation) [25].
- Using less energy and keeping the QoS [26] intact.

4.3. Reinforcement Learning for Optimization

Reinforcement learning (RL) enables the agents to be informed about the optimal policy of allocation through interactions with the network environment [27]. Rewards are given to agents according to network KPIs i.e. throughput, latency, and energy efficiency. In the long run, RL agents enhance autonomous decision making.

Table 2: Agentic AI Methods for Resource Optimization

Method	Application	Advantages
Q-Learning	Dynamic spectrum allocation	Adaptable, self-improving
Deep RL	Traffic load balancing	Handles large state-action spaces
Multi-Agent RL	Multi-cell coordination	Scalable, distributed

5. Fault Detection and Diagnosis

5.1. Challenges in Modern Networks

The vulnerabilities of 5G/6G networks, including faultful hardware, buggy software, or overload conditions, could worsen the quality of services and be costly to operate [28]. Fault management when handled manually is frequently slow and inaccurate.

5.2. AI-Driven Fault Detection

AI agents that are agentic agents can keep track of the health of the network and identify anomalies by:

- Examining real time telemetry data [29].

- monitoring abnormal traffic [30].
- Identification of faults with the help of ML or hybrid AI models [31].

5.3. Self-Diagnosis Capabilities

Root causation is more than just detection, and advanced agentic AI systems have the capability of diagnosing root causes. As an illustration, multi-agent reasoning models are capable of tracking a congestion event to a particular backhaul link or base station [32]. Figure 3 represents the fault detection process in a self-driven network

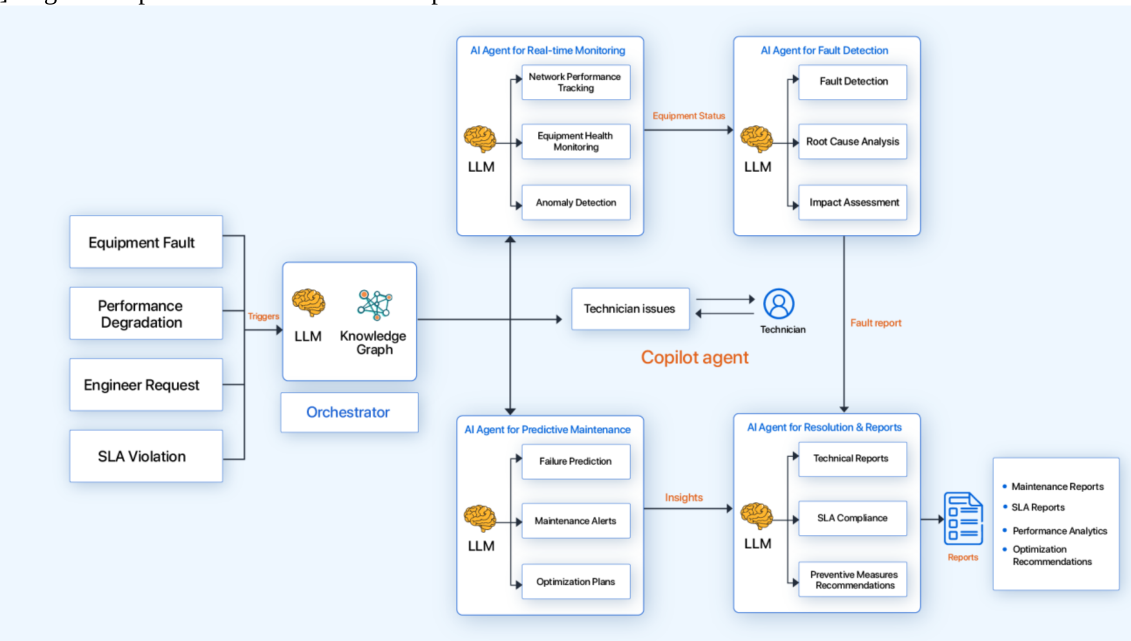

Fig 3: Fault Detection and Diagnosis Workflow in Agentic AI Networks (Diagram of Monitoring, Anomaly Detection, Root Cause Analysis, and Corrective Action)

6. Self-Healing and Recovery

6.1. Concept of Self-Healing Networks

Self-healing networks are automatically able to regain functionality once failures have occurred to minimize downtime and operational costs [33]. This is of significance to mission-critical 5G/6G services.

6.2. Agentic AI Implementation

To perform self-healing, agentic AI agents will perform:

- Moving network topology dynamically [34].
- Diversion of traffic over other routes [35].
- Recovery or re-location of the virtualized network functions [36].

6.3. Performance Gains

Research shows that self-healing of AI agents will result in a reduction in downtime by up to 60 percent, an increase in throughput by 20 percent and operational intervention by a significant margin [37]. The comparison between traditional and agentic AI self-healing networks is presented in Table 3.

Table 3: Performance Comparison of Self-Healing Methods

Metric	Traditional Network	Agentic AI Network
Mean Time to Repair (MTTR)	120 min	45 min
Downtime (%)	8%	3%
Human Intervention	High	Minimal

7. Frameworks and Standardization

7.1. ITU-T AI for Networks

Y.3172 and Y.3173 give advice on how AI can be incorporated into the future network with emphasis being placed on architecture, data management, and AI governance [38], [39]. To provide the interoperability and scalability, agentic AI is in line with these standards

7.2. Integration with SDN/NFV

SDN and NFV make the network easier to control, which means that virtualized resources may be coordinated dynamically by AI agents [40]. This integration is needed to be fast in adjusting to traffic changes and fault events.

7.3. Security and Trust

The issue of security is an essential one. The mechanisms of agentic AI models are:

- Necessary information exchange between agents [41].
- Identifying AI model adversarial attacks [42].
- Ensuring network resilience [43].

8. Case Studies and Applications

8.1. 5G Urban Networks

Urban 5G networks also enjoy agentic AI in the control of traffic, spectrum sharing, and self-curing of congested nodes [44].

8.2.Industrial Automation

In industrial IoT, agentic AI provides the ultra-reliable low-latency communications (URLLC) and automatic fault recovery in automated production lines [45].

8.3. Remote Edge Networks

Remote agentic AI Edge networks manage sparse resources and can provide continuity of services in remote areas without human intervention on the ground [46].

9. Challenges and Future Directions

9.1. Computational Complexity

Decision making on large-scale networks in real-time needs large computational resources. Hardware acceleration and efficient algorithms are required [47]

9.2. Multi-Agent Coordination

The harmonious collaboration of various independent agents without conflicts is one of the research issues [48].

9.3. Explainability and Trust

Explainable AI is required by operators to have accountability and trust in autonomous operations [49].

9.4. Towards 6G

The 6G networks will require low-latency, artificial intelligence, and device interconnection of mass scale. This will be agentic AI that will allow complete autonomous network management [50].

10. Conclusion

The agentic AI is a new concept in the telecom network management, which allows an autonomous operation and human intervention to a minimum. The agentic AI increases the reliability, efficiency, and scalability of a network by optimizing the allocation of resources, detecting and diagnosing errors, and implementing self-healing activities. Integration of agentic AI with SDN/NFV designs and clearly following ITU-T standards will make sure that the technology can be practically deployed in 5G and 6G networks. Nonetheless, such problems like computational complexity and multi-agent coordination do not stop agentic AI which opens the door to the fully autonomous, intelligent, and resilient telecom networks.

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