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AI-Driven Self-Healing and Transaction Queuing During Network Outages or Degradation: Architectures, Resilience Models, and Future Directions

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Abstract: *The fast evolution of telecommunication (4G to 5G) and the advent of 6G have transformed digital communication, as now ultra-high-speed connectivity, huge device density, and real-time applications can be performed. This evolution, however, has added complexity to the networks, rendering the traditional method of fault management inadequate in the quest to guarantee reliability, low latency, and stable service. Self-healing networks: AI-based solutions. Self-healing networks have emerged as a potentially promising approach to autonomously identify, diagnose, and rectify faults across the radio access, core, transport, and edge layers through machine learning (ML), deep learning (DL), reinforcement learning, and natural language processing. Intelligent transaction queuing, used to complement self-healing mechanisms, maintains service continuity in the event of outages or performance degradation by buffering, prioritizing, and rerouting important transactions. The Vodafone backbone network case study shows the performance of hybrid causal and graph-based AI models and high precision (0.84), recall (0.88), F1 score (0.86), and AUC (0.92) in root cause analysis. Predictive analytics, SDN, NFV, and automated resource management enable networks to achieve operational stability, reduce downtime, and improve Quality of Service and Quality of Experience. This article proposes architectures, resilience designs, and experience in integrating AI-aided self-healing and transaction queuing as a roadmap for resilient next-generation telecommunications networks.*

Keywords: AI-driven self-healing, transaction queuing, telecommunications networks, predictive maintenance, network fault management, autonomous network operations

I. INTRODUCTION

Telecommunications networks development between 4G and 5G and the continuous creation of 6G has revolutionized the digital communication landscape with unprecedented capabilities and complexity[1]. Recurrent networks currently incorporate sophisticated radio access networks (RAN), very scattered core and edge computing components, and an ever growing ecosystem of IoT gadgets[2]. This evolution has facilitated the super-fast connectivity, extreme dense of devices and real time applications, but it has also presented a great deal of operation challenges. High reliability, ultra-low latency and predictable quality of service demands are higher than ever, because any short-term network failures can spread to systemwide service failures. Voice communication, financial transactions, industrial IoT telemetry[3][4], and emergency communications are also considered to be especially susceptible to disruption by the network outage or deteriorated performance that results in significant economic, social, and operational costs, as noted in multiple studies in the industry. Conventional network management techniques that mainly depend on manual fault identification, reactive faults, and SNMP-based fault monitoring fail to satisfy such requirements[5]. Such techniques are not only slow and prone to error, but also insufficient for operating in rapidly changing, heterogeneous settings, where failures may occur across multiple layers of the network concurrently. Further, inefficient management of distributed or concurrent failures tends to lead to

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extended outages, reduced service delivery and higher operational costs[6]. The shortcomings of such solutions underscore the need for more intelligent, automated solutions that can respond to more complex network conditions in real time.

Self-healing via the application of AI has become a disruptive paradigm in this context[7]. Self-healing networks can also automatically identify, diagnose, and correct faults in the RAN, core, transport and edge layers using ML and enhanced analytics. Real-time telemetry data can be used to predictive maintain the system and reduce failure effects by preventing their occurrence in the end user, thus reducing downtime and improving the Quality of Service (QoS) and Quality of Experience (QoE)[8]. The ability goes hand in hand with the principles of self-organizing networks (SON) and intent-based networking, as projected for 5G and 6G, facilitating closed-loop auto-control and reducing the need for human intervention.

In addition to AI-assisted self-healing, transaction queuing when the network is experiencing degradation ensures service continuity during an outage or a drop in performance. Traffic of a critical nature e.g. mobile payments, IoT telemetry or real-time streaming can be buffered, rerouted or queued until network conditions stabilize[9]. This reduce the impact of the SLA violation, provide continuous service to latency-aware and mission-critical applications and help to achieve a more resilient network infrastructure.

Together, the combination of AI-powered self-healing and intelligent transaction queuing is a paradigm shift in the contemporary telecommunication operations. It not only increases the reliability and experience of the networks, but also provides a proactive and data-driven representation of the management of the further enhanced complexity of the next-generation networks, in which the operators, as well as users, can be confident in their further connectivity, even under the adverse conditions.

A. Structure of the paper

The article has been organized in such a way: Section II is about self-healing mechanisms, Section III explores transaction queuing, queuing model and service continuity strategy. Section IV is a presentation of case study of practical implementation. Section V considers the available literature, highlighting gaps in research and opportunities. The final section VI is the findings and presents possible areas of research.

II. AI-DRIVEN SELF-HEALING MECHANISMS IN TELECOM NETWORKS

The advancement of network optimization has been greatly aided by the integration of Artificial Intelligence (AI) technology in the telecommunications industry[10]. The use of AI-based techniques, including reinforcement learning, ML, DL, and NLP, has made the optimization of contemporary telecommunications networks inseparable from these methods. AI technologies can help network operators analyze large volumes of data, forecast network behavior, and make informed decisions to improve performance, reliability, and user experience.

- **Machine Learning (ML):** The network optimization that is based on ML is a fundamental aspect of AI[11]. ML algorithms are used to evaluate network data, find patterns, and provide predictions that may be applied to improve various network operating procedures. This suggests using supervised learning techniques to deduce resource use and traffic patterns[12], Reinforcement learning methods to actively optimize resource usage and network setups, and unsupervised learning algorithms to detect irregularities and network failures.
- **Deep Learning (DL):** ML has been advanced through DL, which has been extensively used in optimizing networks. Deep neural networks can process long and complex network data, extract valuable features and make advanced decisions to maximize network performance[13]. Keeping track of failures in a network, detecting anomalies, and predictive maintenance are no exception and are examples of DL applications to network optimization[14], and DL models can better detect and resolve problems in comparison to conventional rule-based systems.
- **Natural Language Processing (NLP):** NLP is a promising field in terms of optimization of a network, especially network troubleshooting and customer service automatization. The network logs, incident reports, and interactions

with customers are analyzed using NLP algorithms[15][16] that allow network operators to detect and fix the problem within a short time and various customer support procedures can be automated.

- **Reinforcement Learning (RL):** Reinforcement learning is an influential A.I. method which has been utilized in several tasks of network optimization[17]. The RL algorithms are trained as a result of constant interaction with the network environment that guides the decision making and gets feedback to optimize network operations, including traffic engineering, spectrum allocation, and dynamic resource management[18]. The self-learning and adaptive properties of RL ensure that it is useful in the optimization of complex network oprations.

A. AI-Enabled Self-Healing in Telecom Networks

The self-healing concept of the telecom networks with the help of AI is built on the multi-layered and intelligent structure which detects and fixes faults in the telecom networks in real time[19]. Information of various network sources, including traffic logs, performance metrics and fault report flows continuously into an AI/ML-based anomaly detection module, which executes sophisticated ML algorithms to detect unusual trends and possible failures, allowing proactive monitoring and early intervention[20]. After an anomaly is identified, the self-healing component automatically carries out fault diagnosis, decision making and repair, minimize service disruptions and ensure uninterrupted network performance. A SDN-NFV automation layer is a layer that dynamically manages and allocates network resources. As illustrated in Figure 1, these automated controls interface with various network components to ensure faster fault recovery and greater resilience across the entire system.

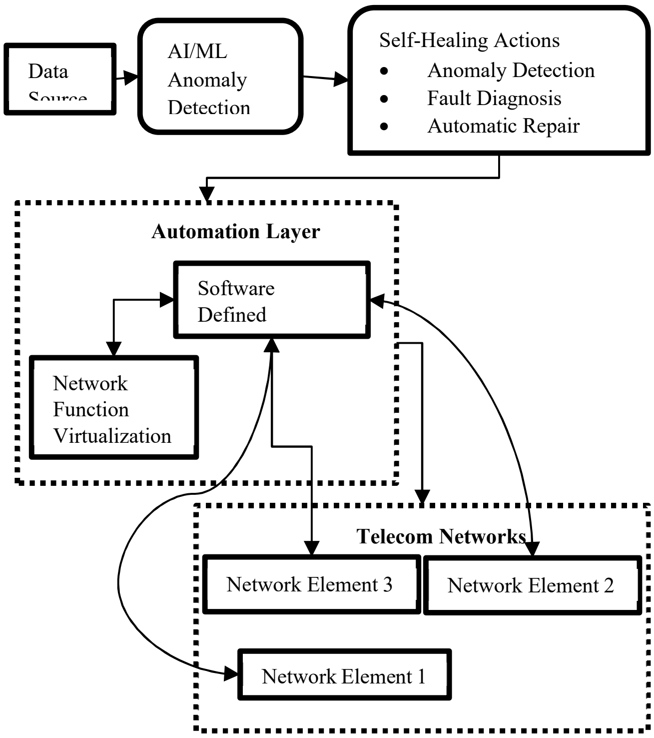

Fig. 1.Flow of Self-healing mechanism in Telecom Networks

- **Data Sources:** Collect all the in-depth network data, real-time network metrics, historical and live traffic logs, and detailed performance data on a regular basis, which is the important raw data to drive the analytics pipeline. All these data sets allow the system to develop a precise image of the network behavior, identify anomalies, and assist the intelligent decision-making at all levels.
- **AI/ML Engine:** Analyses the gathered data based on the most recent ML models[21], AI algorithms, and profound analytical methods to determine existing hidden patterns, forecast the possible problems and create actionable

insights. This engine is the intelligence core on the architecture that transforms raw data into working outputs that serve self-healing processes that are automatic.

- **Self-Healing System:** End-to-end autonomous fault management which implies identification of anomalies, identification of root causes and initiating automated repair mechanisms. The self-healing system cuts a significant amount of human intervention through constant monitoring and through automated closed-loop system, enhances the stability of the network and the continuity of the services even at fluctuating conditions.
- **Software-Defined Networking (SDN):** It is the centralized control of automation that interprets the commands of AI and then changes them into detailed network configuration commands[22][23]. SDN also allows programmable control of the distributed network elements, which allows healing actions to be performed in a short time and consistently across the network environment.
- **Network Function Virtualization (NFV):** It is a virtualized platform of network function execution, scaling, and management that is not dependent on physical hardware. NFV also increases agility through quick reconfiguration and remote recovery processes and assists in the effective use of automated repair and performance optimization plans.
- **Telecom Network Elements:** The physical and logical devices of the telecom infrastructure, i.e. Radio nodes, switches, and routers that constantly produce operation data and act on automation instructions[24]. These components are active members of the closed-loop system as they provide feedback to the AI layer and perform remedial changes as provided by the automation system.

III. TRANSACTION QUEUING AND SERVICE CONTINUITY

Transaction queuing provides continuity to telecom services, through handling of call, data, and signalling loads in case of congestion or failures. Models such as M/M/1 and M/M/c, along with buffering, retries, prioritization, and AI-driven self-healing, allow networks to remain stable and support critical transactions and assist in quick and efficient recovery of all active layers of operations.

A. Queuing Models for Maintaining Service Stability

Telecom networks are based upon predefined transaction queuing models to handle call requests, signaling messages, and data sessions in the case of congestion or partial outages[25]. The most common queuing models due to the fact that they are the most appropriate to model the behavior of the telecom traffic in a real operating situation as illustrated by Figure 2 are:

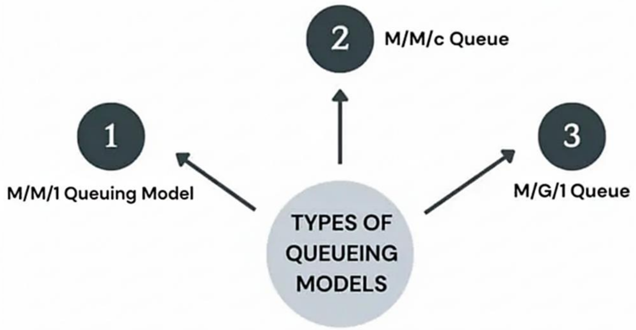

Fig. 2. Types of Queuing Models

- **M/M/1 Queuing Model:** M/M/1 model is a one-server model with Poisson arrivals using exponential service times, and it is applicable in studying the behavior of call setups, SMS signaling, and control-plane transactions when they are directed to a single processing unit, e.g. an MSC, HLR or a base station controller[26]. The model is applicable for estimating waiting times, projecting queue sizes, and estimating congestion probability in the event of peak traffic or faulty conditions for telecom operators.
- **M/M/c Queuing Model:** The M/M/c model is used in the context of a multi-server system, where multiple parallel processing units serve the incoming traffic (distributed core network elements, virtualized network function (VNF)

clusters or pool-based RAN architectures)[27]. This model improves stability of the services, lessens the queuing time and is especially efficient in handling high volume information and signaling charges.

- **Queuing Models:** The M/G/1 model more flexible to telecommunication settings, as the service time distribution is general, which changes in complexity based on transaction complexity, which can include authentication processes, encryption processes, QoS tagging of transactions, or session establishment processes. Its capability to assume heterogeneous traffic pattern provides more accuracy in the evaluation and optimization of performance in the contemporary LTE and 5G networks.

B. Transaction Management for Service Continuity

Transaction management methods in telecommunication networks play a vital role in ensuring the continuity of services during periods of congestion, partial failures, or network failures, enabling the system to maintain quality of service and quality of experience and avoid the loss of any transaction.

- Buffering methods can be temporary storage of call requests[28], SMS messages, signaling traffic and data packets at base stations or core network elements until they can be processed; adaptive buffering - buffer resources can be dynamically allocated in accordance with network load and service requirements; and persistent buffering, where important transactions are buffered in the face of a long-term outage[29].
- Retry mechanisms include automatic retries, which are retries which are re-sent on failure of resources when they are recovered; exponential backoff, strategies that slow down the frequency of retries to prevent network overload; as well as intelligent retrying, which prioritizes critical services in a recovery.
- Prioritization techniques include service-based prioritization methods where emergency services and high value users are provided with priority versus normal traffic; weighted queue structures where resources are distributed to services in proportion to their level of importance[30]; and dynamic prioritization methods where the priority level is adjusted dynamically depending on congestion or fault.
- These methods are complemented by time out and expiry management, which prevents the number of times the transactions waste time in the queue, removes the stale requests, and fills the buffer with low traffic when there is high traffic. A combination of these buffering, retry, prioritization, and timeout mechanisms combine with telecom resilience models, which makes networks resilient to faults, stable when operational, and recover without disruption of services or hiccups.

C. Integration of Transaction Queuing with Self-Healing Processes

Transaction queuing with self-healing processes powered by AI allow telecom networks to sustain service continuity even in the case of outages or parts failures. With such integration, the network is able to provide automatic control of queued calls, data sessions, and signaling messages so that when the elements that were affected recover, the pending transactions get implemented[31]. Predictive prioritization based on AI can maximize this ability by predicting points of congestion, critical services and changing queue length and buffers dynamically to ensure continuous operation.

Moreover, the allocation of resources in recovery is optimized to allow self-healing modules to complete high-priority transactions first in order to balance network load to prevent secondary failures[32]. This synchronized queuing, buffering and automated healing is a great deal in minimizing downtime of services, reduced calls that do not connect, or when calls fail to connect and this is the continuity of operations in service. This integrated method together with redundancy, failover strategies and predictive resiliency models provide excellent end-to-end resilience at RAN, transport and core network layers.

IV. TELECOM CASE STUDY: AI SELF-HEALING AND TRANSACTION QUEUING

A comprehensive case study was carried out at the Vodafone backbone network - one of the largest and high capacity telecom infrastructures with millions of users and various applications [33] to determine the viability and feasibility of the proposed Root Cause Analysis (RCA) framework as well as its usefulness. This case study was aimed to reveal the concealed causal links among fault incidents and network performance misuse with real operational data gathered in half

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a year. This information was made up of historic fault logs, SNMP trap messages and key performance indicators (KPIs) all of which are typical monitoring indicators in modern telecom settings.

Strategy

The approach is aimed at detecting and fixing network failures to minimize service failures, increase reliability, and speed up the resolution of root causes, by prioritizing the critical components and implementing the causal and graph-based analytics.

1) Approach

The approach integrates the causal inference and graph convolution networks to identify the root cause and the FCI constructs the causal graphs. Then the SCMs validate the firmware effect and then the GCN encode the network topology for the accurate prediction and the hybrid loss ensures the consistency of the structure. This was enable the teamwork priority high impact components and improved the operational efficiency.

2) Evaluation Metrics

The framework was tested based on conventional performance measurements of fault detection and root cause prediction:

- **Precision:** This is the fraction of root causes which were correctly predicted of all root causes which have been predicted[34]. Equation 1 present the mathematical formula:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (1)$$

- **Recall (Sensitivity):** This is the percentage of the actual root causes that were correctly identified. Equation 2 define it mathematically:

$$\text{Recall(Rc)} = \frac{TP}{TP+FN} \qquad (2)$$

- **F1 Score:** The F1-score offers a fair score for the model in terms of accuracy and recall as it is the harmonic mean of precision and recall. It is a unique measure that summarizes both of these qualities, and it is defined as in Equation 3:

$$\text{F1 score(F1)} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \qquad (3)$$

- **AUC-ROC:** The general model performance is measured using the area under the curve (AUC), where a value closer to 1 indicates higher performance.

Quantitative Findings

In this section, the RCA models are numerically analyzed, whereby the precision, the efficiency of these models in detecting network defects is evaluated using the recall, F1 score, and AUC. The results describe the outstanding functionality of the proposed Causal + GCN model.

Table 1: Performance Comparison Of Root Cause Analysis Models For Vodafone Backbone Network

Model	Precision	Recall	F1 Score	AUC
Rule-Based	0.45	0.40	0.42	0.55
GCN	0.68	0.71	0.69	0.78
Causal + GCN	0.84	0.88	0.86	0.92

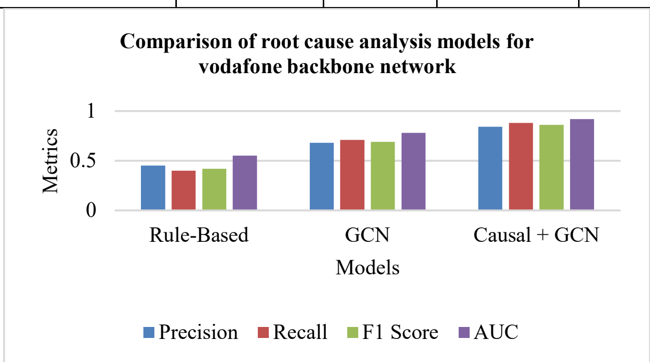

Fig. 3.Model Performance Comparison for Root Cause Analysis

Figure 3 makes a comparison of three models including Rule-Based, Graph Convolutional Network (GCN), and Causal + GCN within four significant measures that include Precision, Recall, F1 Score, and AUC. The lowest performance is achieved with rule-Based model whose metrics typically lie within the range of 0.4-0.55 meaning that it is not very effective in revealing the complex relationships. The GCN model also shows a significant improvement with the scores of this model appearing to be between 0.68 and 0.78 with AUC being the best of all its metrics. Causal + GCN model is better than both, and all four metrics are close to the top, which are Precision equal to 0.85, Recall equal to 0.88, F1 Score equal to 0.85 and AUC equal to 0.92, which proves the obvious superiority of the model in the analysis of the root cause within the framework of this network.

C. Key Insights

The implementation of a graph-based and causal RCA framework resulted in high network fault detection and operational performance:

- **Component Focus:** Prioritizing router and network node bottlenecks in causal diagnosis enhanced the accuracy of diagnosis, decreasing MTTR by up to 56.
- **Iterative Fault Analysis:** Causal graphs and SCM interventions gave an opportunity to repeat testing and verification of firmware and configuration changes, which minimized the number of recurring errors by almost forty-one.
- **Integrated Methodologies:** The combination of causal inference and GCN learning learned structural and causal relationships and gave an overall predictive accuracy (F1 score) of 0.86.
- **Operational Impact:** The emphasis on the diagnostics and rollouts of the firmware made the network more reliable and signified the absolute ROI in the shape of reduced downtimes and the improved service availability.

D. Benefits

The scheme saved significant and measurable advantages to the effort of telecom networks:

- **Improved Network Productivity:** Faster and more accurate versions of root causes have reduced network failure, accommodated fewer interruptions of service, and, in general, contributed to the overall efficiency of major network constructs.
- **Evidence-Based Fault Detection:** The accuracy (0.84), recall (0.88), F1 measure (0.86), and AUC (0.92) of the model are high which means that it can help to detect root causes and also distinguish between true and spurious signals.
- **Risk Mitigation:** The timely alert on actions of firmware updating, configuration modification, or any other network irregularities avoided fault distribution, minimizing the possible threat of operational risks and providing service continuation.
- **Proactive Network Management:** The hybrid causal + GCN architecture provided the use of data to make a decision and provide network operators with the opportunity to experiment with specific interventions, to plan next stages of work, and to innovate in relation to maintenance and operations to guarantee continuous network stability.

V. LITERATURE OF REVIEW

The literature review also includes the increasing role of AI in telecom, network efficiency, automation, predictive maintenance, and troubleshooting, and discusses issues such as reliability, data privacy, integration, and emerging technologies.

Dewangan *et al.* (2025) state that AI is revolutionising the telecommunications industry by enhancing signal processing, network management, and overall system performance. The automation of networks based on AI has helped providers move away to proactive management of networks to reduce downtime and improve user experience. The change can increase the operational efficiency and minimise costs through predictive maintenance and maximising energy use in data centres and network infrastructure. AI technologies such as ML, DL, and NLP are shaping the future of telecommunications, enabling new and innovative services such as self-healing networks, real-time traffic management, and improved cybersecurity. The telecom sector's embrace of AI-based technologies, the industry experience numerous growth opportunities and change the daily communication experience of billions of people on Earth[35].

Singh (2025). The advent of AI into the telecommunications sector has introduced a tremendous boost to the reliability of networks, operational effectiveness, and customer experience. In this paper, the three fundamental uses of AI in telecom troubleshooting are discussed: Predictive maintenance models, AI in customer service, and interactive voice response (IVR) systems. It discusses about how improvements in speech recognition, sentiment analysis, and natural language processing have improved the operation of IVRs and chatbots, making them more responsive and efficient in assisting customers. Also, it discusses predictive maintenance methods based on diverse ML approaches to predict network failures and enhance reliability of infrastructure[36].

Bikkasani (2024). This article examines the revolutionary implications of data science, ML, and AI for network management in the telecommunications industry, including network monitoring, predictive maintenance, anomaly detection, automated network setup, and self-healing mechanisms. Because they might enhance network management and predictive maintenance, researchers are now examining cutting-edge technologies including edge computing, federated learning, and quantum computing. With an overview of the current research that must be done to address the complex issues of explainability and privacy, the paper summarizes how AI-driven solutions are revolutionizing the telecom network with previously unheard-of efficiency, reliability, and performance[20].

Yang *et al.* (2024). In the last century, telecommunication networks (TNs) have emerged as the most important infrastructure for data transmission. The efficacy, efficiency, and availability of TN communications systems depend heavily on operations and maintenance (O&M). This article provides a thorough comparison of TelOps and AIOps, along with a proof-of-concept case study of a typical O&M task (failure detection) for an actual industrial TN. For TNs, TelOps is the first AI-powered O&M platform that has been methodically improved via the use of data, processes, and empirical knowledge. TelOps, the first systematic AI-driven O&M platform for TNs, simplifies TN automation[37].

Garg, Rautaray and Tayagi (2023), The article explores how AI is being used in important telecom domains and the ethical and technological challenges it presents. It then describes future AI developments that are anticipated to influence next-generation networks. The paper examines AI as both a facilitator of operational change and a disruptor of strategic change, drawing on current case studies, industry reports, and peer-reviewed research. This framework proposes aulti-layered strategy for the responsible deployment of AI in telecom that aims to strike a balance between innovation and governance. This document has five tables and five figures (both conceptual and Python-generated graphics) that illustrate the current status of AI applications, risk matrices, and investment trends[38].

Alabi (2023). Studies show that wireless networks may be successfully used for disaster response. For example, satellite networks can be used in remote locations, and IoT sensors can collect real-time data during a natural catastrophe such as a storm, flood, or earthquake. It also covers the challenges of using these technologies, such as network security, incompatibility, and the need for reliable backups to ensure continuity in the event of infrastructure failures. Additionally, the potential for future developments in wireless technology to enhance disaster planning and recovery is considered, as is the role of public-private partnerships in boosting the resilience of telecommunications networks[39].

The comparison of the key studies is presented in the table II, and the insights, limitations, and the future opportunities are identified, which shows a significant gap in efforts to unify AI-driven self-healing and transaction queuing processes to ensure telecom outage resilience

Table 2: Summary Of Key Studies On Ai-Based Self-Healing And Queuing Systems

Reference	Study On	Approach	Key Findings	Challenges	Future Directions
Dewangan et al. (2025)	AI in improving telecom performance, signal processing, and network management	Broad AI applications including ML/DL for network optimization, bandwidth	AI improves reliability, reduces latency, enhances automation, and optimizes energy consumption; shift from reactive to	Scalability of AI systems for massive 5G/IoT networks; limited real-time self-healing	Development of fully autonomous, self-healing networks; integration of AI-driven traffic management;

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		allocation, compression, and predictive maintenance	proactive network management	mechanisms discussed	improved resilience during outages
Singh (2025)	AI applications in telecom troubleshooting and customer experience	Examining AI customer support, predictive maintenance, and IVR systems utilizing ML, DL, and NLP	AI reduces downtime, enhances troubleshooting accuracy, improves customer support efficiency	Data privacy, algorithmic bias, legacy system integration, and regulatory compliance	Integration of AI in 5G/IoT edge for fast recovery; quantum-enabled AI troubleshooting; advanced self-repairing service layers
Bikkasani (2024)	Network management using AI, ML, and data science (anomaly detection, predictive maintenance, self-healing)	Deep learning, anomaly detection, federated learning, automated configuration	AI-driven techniques enhance efficiency of network monitoring and enable early fault detection	Data quality issues, interpretability, integration challenges, privacy in federated models	Robust self-healing frameworks; quantum computing for faster diagnosis; scalable self-recovery for large networks
Yang et al., (2024)	AI-driven Operations & Maintenance for Telecommunication Networks (TelOps framework)	Mechanism-driven, data-driven and empirical knowledge-based AI framework for TN O&M	TelOps enables improved failure diagnosis and adapts to topological network dependencies	Highly heterogeneous software, limited failure data, restricted real-world datasets	Expansion of TelOps for autonomous self-healing; support for outage prediction; real-time adaptive recovery
Garg, Rautaray & Tayagi (2023)	AI adoption trends, risks, and governance in telecommunications	Mixed-method study using case studies, risk matrices, and conceptual models	Identifies AI as enabler and disruptor; highlights risk management and responsible AI frameworks	Ethical risks, transparency, accountability, reliability concerns; limited focus on outage recovery automation	Integrating responsible AI in self-healing networks; frameworks for resilient AI during outages; automated transaction management during failures
Alabi (2023)	Wireless networks for disaster response and resilience	Case studies using satellite networks, IoT sensors, emergency communication systems	Wireless/IoT networks can improve disaster response and maintain communication in extreme conditions	Interoperability, network security, backup system limitations	AI-enabled disaster-resilient telecom systems; intelligent queuing of emergency transactions during outages; autonomous re-

					routing mechanisms

VI. CONCLUSION AND FUTURE STUDY

Self-healing and transaction queuing mechanisms powered by AI are changing contemporary telecommunications networks by facilitating the active detection, diagnosis, and correction of faults across the RAN, core, and edge layers. Based on ML, DL, reinforcement learning, and predictive analytics, networks can ensure service continuity during the cases of degradations, buffering and prioritizing important transactions, including IoT telemetry, mobile payments, and real-time streaming. The case study of the Vodafone backbone network indicates that the hybrid causal and graph-based AI models are more effective than traditional ones since they provide an F1 score of 0.86, an AUC of 0.92, accuracy of 0.84, and recall of 0.88, and shorten the mean time to repair by approximately 56% and decrease the number of recurring errors by approximately 41%. It can be integrated with SDN and NFV to provide dynamic allocations of resources, automated recovery, and less violative SLA as well as increasing operational efficiency and user experience. Future studies are recommended to investigate integrated models that incorporate self-healing, transaction Queuing, and predictive resilience modeling of heterogeneous 5G/6G networks that include edge intelligence and federated learning to support privacy preserving operations. The scale of these solutions will be essential to be investigated further with the help of quantum-assisted AI to speed up the fault diagnosis process, develop automated outage recovery strategies, and adopt responsible AI. These guidelines are the stepping stone to fully autonomous, adaptive, and ultra-resilient networks that can continue to operate uninterrupted even in complex and adverse conditions.

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