A Framework for Closed-Loop Automation in Autonomous Network Operations Centers: Reducing Mean-Time-to-Resolution in U.S. 5G Network Deployments: Closed-Loop Automation for Autonomous NOCs in 5G Networks

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ABSTRACT

As United States carriers densify fifth-generation (5G) radio access and transport infrastructure, Network Operations Centers (NOCs) face a sharp rise in alarm volume, event correlation complexity, and cross-domain fault interdependency that erodes Mean-Time-to-Resolution (MTTR) for service-impacting incidents. This paper proposes a five-layer closed-loop automation framework telemetry and data fusion, AI/ML-driven diagnosis, intent-driven decision and orchestration, automated remediation, and persistent knowledge management designed to compress the detect-diagnose-decide-act-verify incident lifecycle that dominates MTTR in autonomous NOC operations. The framework synthesizes intent-driven management automation principles, context-aware autonomous operation models, distributed telemetry and knowledge-management architectures, and machine-learning-based anomaly detection and traffic analytics drawn from the contemporary 5G/B5G literature. We map the framework against established network-autonomy maturity levels, discuss radio-access functional-split implications for fault-detection latency budgets, and present an illustrative MTTR stage-decomposition model contrasting manual and automated operation. The analysis indicates that the largest MTTR reduction opportunity lies in compressing the diagnose and decide stages through AI-assisted root-cause analysis and intent translation, rather than in the act stage alone. We conclude with open challenges cross-domain knowledge federation, model trust and explainability, and the transition path toward 6G-ready autonomous operations and outline a research agenda for closing the loop end-to-end in production 5G NOCs.

Keywords

Closed-loop automation; autonomous networks; Network Operations Center (NOC); Mean-Time-to-Resolution (MTTR); 5G; intent-driven management; AI/ML network analytics; zero-touch network and service management (ZSM); root-cause analysis; network slicing.

1. INTRODUCTION

The commercial maturation of fifth-generation (5G) networks in the United States has been accompanied by a parallel increase in operational complexity. Multi-vendor radio access networks (RAN), disaggregated functional splits across centralized and distributed units, network slicing, and edge-cloud-native cores have multiplied the number of independently monitored network functions that a Network Operations Center (NOC) must correlate during an incident. Traditional NOC workflows alarm triage, manual ticket routing, human-driven root-cause analysis, and scripted but operator-supervised remediation were designed for comparatively static fourth-generation (4G) architectures and now struggle to keep pace with the scale and dynamism of 5G deployments.

Mean-Time-to-Resolution (MTTR) remains one of the most consequential operational metrics for carriers, directly influencing service-level agreement (SLA) compliance, churn, and regulatory exposure for safety- and mission-critical services increasingly carried over 5G slices. Reducing MTTR is therefore not merely an efficiency exercise; it is a precondition for trustworthy autonomous operation of next-generation networks.

This paper makes three contributions. First, it consolidates recent advances in intent-driven management automation [1], context-based autonomous operation [2], distributed telemetry and knowledge management [7], [8], and AI/ML-based network analytics [6], [9], [16]–[23] into a coherent closed-loop automation framework purpose-built for autonomous NOC operation. Second, it explicitly connects RAN functional-split architecture [3] to the latency budgets available for fault detection and remediation, a linkage that is often treated separately from NOC automation literature. Third, it proposes an MTTR stage-decomposition model that isolates where closed-loop automation yields the greatest marginal benefit the diagnose and decide stages rather than assuming uniform gains across the incident lifecycle.

The remainder of the paper is organized as follows. Section 2 reviews related work on closed-loop and autonomous network operation. Section 3 examines RAN and transport architecture considerations that bound achievable MTTR. Section 4 surveys the standardization landscape for network autonomy. Section 5 presents the proposed framework. Section 6 develops the MTTR impact model. Section 7 surveys AI/ML techniques applicable to fault and anomaly detection. Section 8 discusses open challenges, and Section 9 concludes.

2. RELATED WORK ON CLOSED-LOOP AND AUTONOMOUS NETWORK OPERATION

Closed-loop automation in telecommunications draws heavily on the classical Monitor-Analyze-Plan-Execute over a shared Knowledge base (MAPE-K) pattern from autonomic computing, in which a control loop continuously observes system state, reasons over deviations, plans corrective action,

and executes it while updating a persistent knowledge base (Figure 1). Recent 5G-specific work has refined this pattern in two complementary directions: intent-driven translation of high-level operator goals into machine-executable policies, and context-aware, data-driven autonomous operation across network domains.

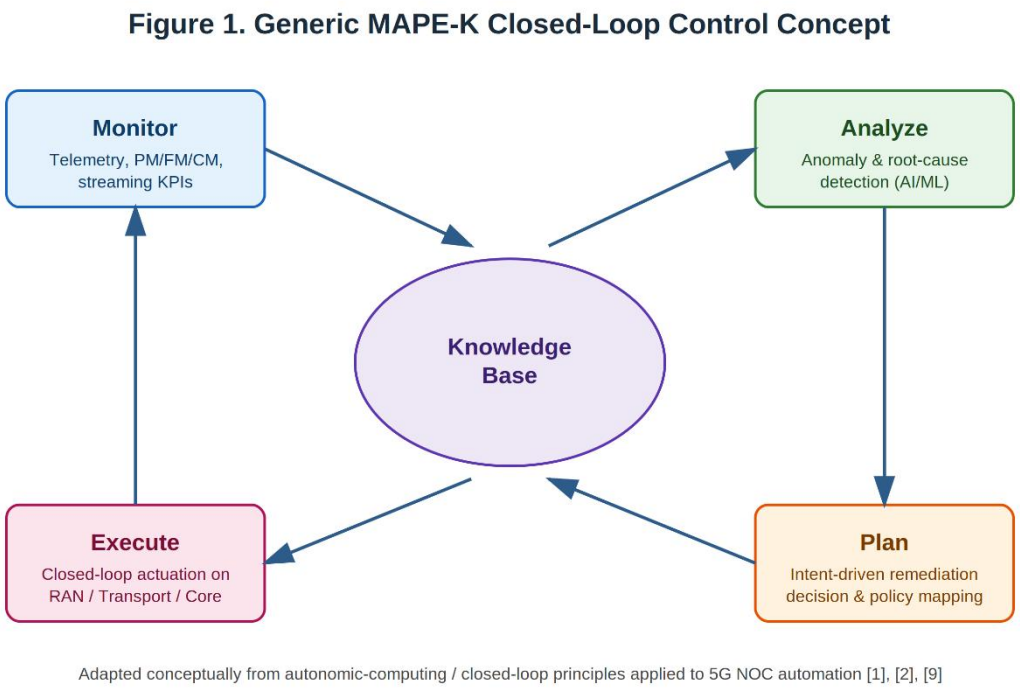

Figure 1. Generic MAPE-K closed-loop control concept underlying autonomous NOC automation.

Ahn and Jeong [1] propose an intent-driven management automation architecture for 5G mobile networks in which operator intents are translated into network configuration and monitoring policies, closing the loop between high-level objectives and low-level network actions a pattern directly relevant to reducing the decide stage of incident resolution. Wang, Ruiz, and Velasco [2] describe a context-based end-to-end autonomous operation model for beyond-5G (B5G) networks that conditions automated decisions on operational context (traffic profile, time-of-day, slice type), improving the relevance and safety of automated remediation actions. Koursioumpas et al. [6] present AI-driven, context-aware profiling for 5G and beyond networks, providing a profiling layer that can feed both intent translation and anomaly detection.

On the telemetry and knowledge side, Velasco, González, and Ruiz [7] describe distributed intelligence for pervasive optical network telemetry, demonstrating that pushing analytics closer to the data source reduces the latency of the monitor-to-analyze transition. Ruiz, Tabatabaeimehr, and Velasco [8] formalize knowledge management in optical networks, defining architecture and methods for capturing operational cases that can be reused across future incidents a capability this paper generalizes into the proposed framework's knowledge-management layer. Sulaiman et al. [9] apply multi-agent deep reinforcement learning to slicing and admission control in 5G Cloud-RAN, illustrating how learning-based agents can make and refine remediation decisions without full re-specification of policy rules.

Table 1 summarizes representative closed-loop and autonomous-operation studies most directly informing the proposed framework, contrasting their domain focus, underlying technique, and the stage of the incident lifecycle each primarily addresses.

Table 1. Representative Closed-Loop / Autonomous Operation Studies Informing the Proposed Framework

Study	Network Domain	Core Technique	Primary MTTR Stage Addressed	Key Limitation Noted
Ahn & Jeong [1], 2024	5G mobile / management plane	Intent-driven policy translation	Decide	Limited treatment of multi-domain intent conflict resolution
Wang, Ruiz & Velasco [2], 2024	B5G end-to-end	Context-based autonomous operation	Decide / Act	Context model granularity vs. real-time constraints trade-off

Study	Network Domain	Core Technique	Primary MTTR Stage Addressed	Key Limitation Noted
Koursioumpas et al. [6], 2022	5G and beyond	AI-driven context-aware profiling	Diagnose	Profiling overhead at very large network scale
Velasco, González & Ruiz [7], 2023	Optical / transport telemetry	Distributed pervasive telemetry	Detect	Coordination overhead across distributed telemetry agents
Ruiz, Tabatabaeimehr & Velasco [8], 2020	Optical networks	Knowledge management architecture	Verify / Knowledge reuse	Case representation generality across heterogeneous domains
Sulaiman et al. [9], 2022	5G C-RAN slicing	Multi-agent deep reinforcement learning	Decide / Act	Training stability and sample efficiency in production settings

Source: Compiled by the authors from [1], [2], [6], [7], [8], [9].

3. RAN AND TRANSPORT ARCHITECTURE CONSIDERATIONS FOR MTTR

The latency budget available for closed-loop detection and remediation is not solely a software question; it is bounded by the physical and functional architecture of the RAN and crosshaul transport network. Larsen, Checko, and Christiansen [3] provide a comprehensive survey of the functional splits proposed for 5G mobile crosshaul networks, ranging from low-layer splits (e.g., Option 8, Option 7.2) that demand very tight fronthaul latency and synchronization, to higher-layer splits (e.g., Option 2) that relax transport timing constraints at the cost of centralized processing flexibility.

This taxonomy matters directly for autonomous NOC design: a fault-detection and remediation loop operating over a tightly split fronthaul inherits a much smaller timing margin than one operating over a higher-layer split, because transport-induced latency competes with the latency budget available for telemetry transport, analytics, and actuation. Figure 2 illustrates the functional-split hierarchy and indicative order-of-magnitude latency budgets associated with each split option.

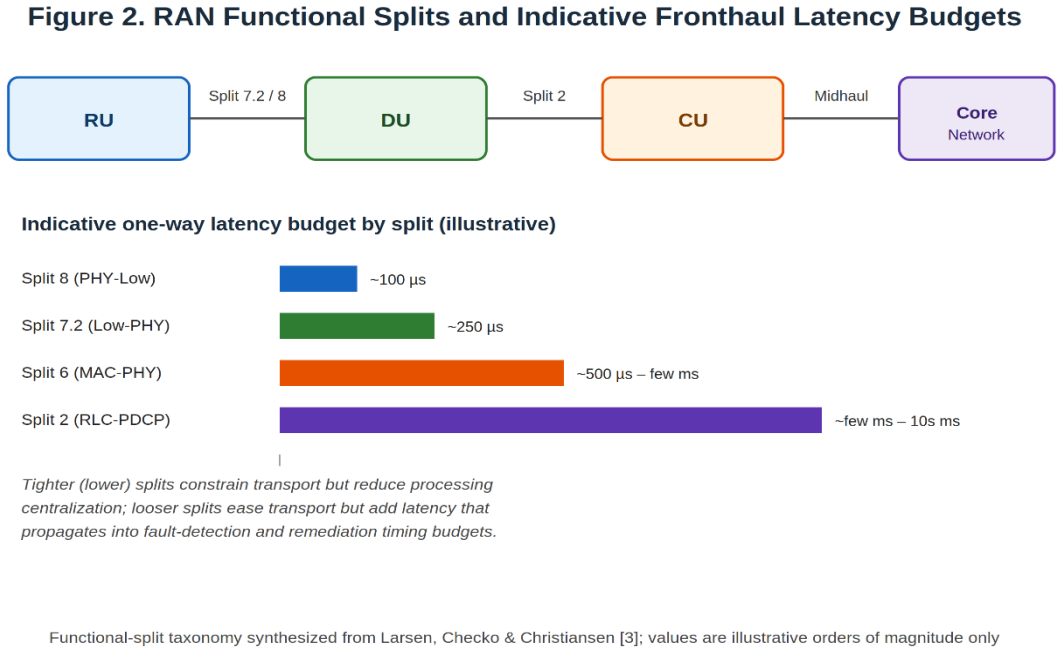

Figure 2. RAN functional splits and indicative fronthaul latency budgets relevant to closed-loop timing margins.

Table 2 maps representative functional-split options to their typical transport implications and the corresponding constraint

they place on autonomous NOC closed-loop timing, synthesizing the taxonomy in [3] with broader B5G/6G architectural surveys [4], [5] that anticipate even tighter integration of compute and transport resources.

Table 2. RAN Functional Split Options and Implications for Closed-Loop Timing Margins

Split Option	Split Point	Fronthaul Sensitivity	Implication for Closed-Loop NOC Timing
Option 8	PHY-RF (low-PHY)	Very high strict synchronization	Smallest residual margin for detection/remediation; favors edge-local automation
Option 7.2	Low-PHY split	High	Requires near-real-time edge analytics to avoid budget exhaustion
Option 6	MAC-PHY	Moderate	Allows limited regional aggregation of telemetry before analysis
Option 2	RLC-PDCP (higher layer)	Low relaxed timing	Greater centralization feasible; more headroom for AI/ML diagnosis
Multiple / hybrid splits	Mixed across sites	Variable	Requires split-aware orchestration of closed-loop placement decisions

Source: Synthesized by the authors from the functional-split survey in Larsen, Checko & Christiansen [3], with context from 6G architectural surveys [4], [5].

4. STANDARDIZATION LANDSCAPE AND NETWORK AUTONOMY LEVELS

Multiple standardization and pre-competitive research efforts provide architectural reference points for autonomous network operation. The 5G PPP Architecture Working Group's view on 5G architecture [10] defines reference points for management and orchestration that underpin closed-loop automation across domains. ETSI's white paper on fixed 5th generation advanced and beyond networks [11] extends autonomy considerations to converged fixed-mobile infrastructure, which is increasingly relevant as U.S. operators converge access technologies. The Hexa-X project's 6G vision [12] explicitly frames network autonomy as a graduated capability rather than a binary property, motivating the use of maturity-level models to describe how far a given NOC deployment has progressed toward full autonomy.

Figure 3 depicts a network-autonomy ladder, adapted from these reference architectures, ranging from fully manual operation (L0) to full autonomy (L5), with intent-driven management automation [1] situated as the mechanism that enables the transition from conditional (L3) to high (L4) automation by allowing operators to express goals rather than procedures.

Figure 3. Network Autonomy Ladder Relevant to Intent-Driven NOC Operation

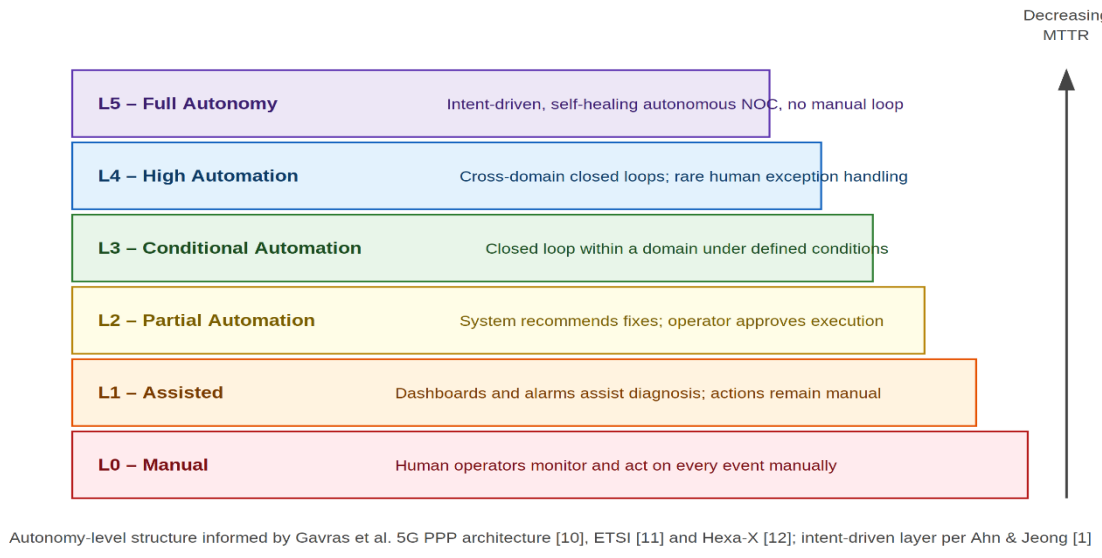

Figure 3. Network autonomy ladder relevant to intent-driven NOC operation, adapted from [1], [10], [11], [12].

Table 3 summarizes the autonomy levels alongside the typical NOC operating model and the corresponding expectation for MTTR behavior at each level. The mapping is illustrative and intended to orient where the framework proposed in Section 5 is targeted (levels L3–L5), rather than to assert precise quantitative thresholds, which remain an open empirical question for carrier-specific validation.

Table 3. Network Autonomy Levels and Associated NOC Operating Characteristics

Level	Designation	Typical NOC Operating Model	MTTR Trend
L0	Manual	Operator-driven monitoring and remediation for every event	Highest, variable, operator-dependent
L1	Assisted	Dashboards/alarms assist; all actions manual	High, somewhat reduced via faster detection
L2	Partial automation	System recommends; operator approves execution	Moderate; decide stage partially compressed
L3	Conditional automation	Closed loop within a single domain under defined conditions	Reduced within domain-scoped incidents
L4	High automation	Cross-domain closed loops; rare human exception handling	Substantially reduced for most incident classes
L5	Full autonomy	Intent-driven, self-healing operation; no manual loop	Lowest, bounded primarily by physical/transport limits

Source: Adapted by the authors from 5G PPP architecture [10], ETSI [11], Hexa-X [12], and intent-driven automation principles [1]; level definitions are illustrative, not normative.

5. PROPOSED CLOSED-LOOP AUTOMATION FRAMEWORK

Building on the reviewed literature, this paper proposes a five-layer closed-loop automation framework for autonomous NOC operation, illustrated in Figure 4. The framework is deliberately layered so that each layer can be incrementally automated and validated independently, supporting a realistic migration path from current operator-supervised NOCs toward higher autonomy levels (Section 4).

Figure 4. Proposed Closed-Loop Automation Framework for Autonomous 5G NOCs

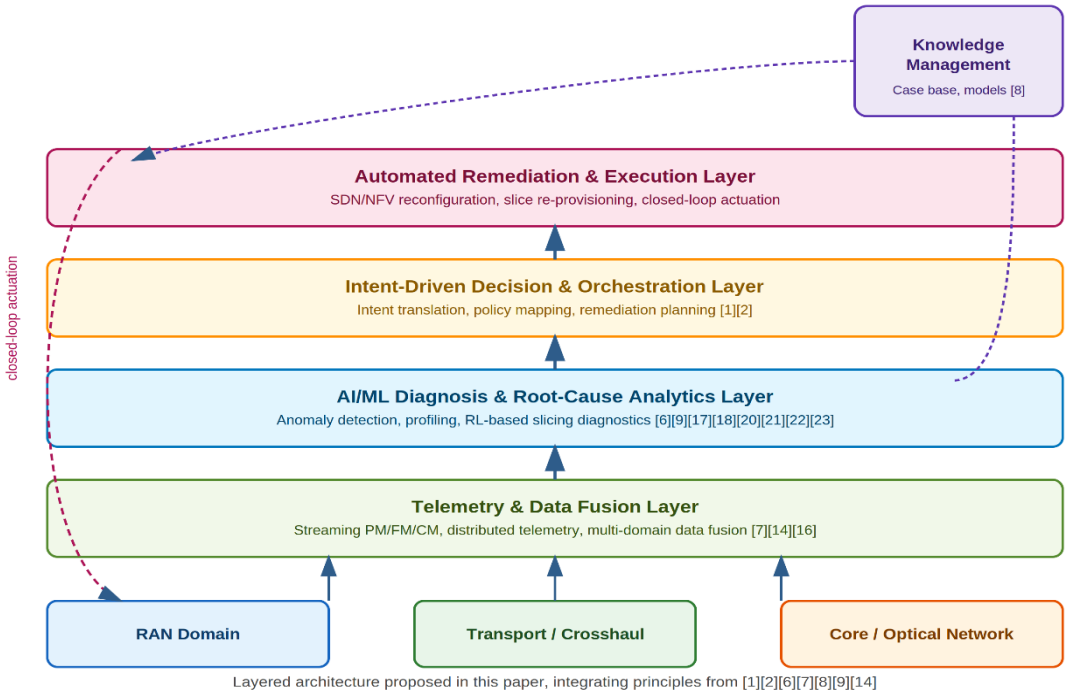

Figure 4. Proposed closed-loop automation framework for autonomous 5G NOCs, integrating telemetry fusion, AI/ML diagnosis, intent-driven decision-making, automated remediation, and persistent knowledge management.

5.1 Telemetry and Data Fusion Layer

This layer aggregates streaming performance management (PM), fault management (FM), and configuration management (CM) data from RAN, transport, and core domains. Following the distributed telemetry principles of Velasco, González, and Ruiz [7], analytics functions are pushed close to data sources where feasible to minimize the detect-stage latency identified in Section 3. Near-real-time performance estimation techniques for converged fixed-mobile networks [13], together with traffic and latency analyses for multi-band optical transport [14] and 5G slicing/fronthaul traffic [15], inform the data-fusion rules used to correlate cross-domain signals into candidate incident contexts before they reach the analytics layer.

5.2 AI/ML-Driven Diagnosis and Root-Cause Analytics Layer

The diagnosis layer consumes fused telemetry to detect anomalies and infer probable root causes. It draws on a broad base of network analytics research: context-aware profiling [6], industrial-prognosis-style data fusion and machine learning [16], big-data behavioral analysis of cellular networks [17], context-extraction and resource-mapping engines [18], SDN/NFV-integrated traffic clustering and forecasting [19], location- and mobility-aware resource management [20], user-anomaly detection in mobile wireless networks [21], multi-source data analytics frameworks for access selection and traffic steering [22], and context-aware traffic identification toolkits [23]. Collectively, these works support a diagnosis layer capable of distinguishing transient performance fluctuations from genuine service-impacting faults and of narrowing the candidate root-cause set before escalation to the decision layer.

5.3 Intent-Driven Decision and Orchestration Layer

Rather than encoding exhaustive if-then remediation rules, the decision layer follows the intent-driven management paradigm of Ahn and Jeong [1] and the context-based autonomous operation model of Wang, Ruiz, and Velasco [2]: operators express high-level intents (e.g., service-level objectives, risk tolerance for automated action), and the layer translates diagnosed root causes into a ranked set of candidate remediation actions consistent with both the diagnosis and the prevailing operational context. This separation of concerns allows the same diagnostic evidence to be acted on differently depending on context for example, peak-hour traffic versus maintenance-window conditions without rewriting detection logic.

5.4 Automated Remediation, Execution, and Closed-Loop Feedback

Approved remediation actions are executed through software-defined networking (SDN) and network function virtualization (NFV) control interfaces across RAN, transport, and core domains, consistent with reinforcement-learning-based slicing and admission control approaches [9]. Execution outcomes are verified against the original intent and fed back into the knowledge-management layer, which follows the architecture and case-based methods proposed by Ruiz, Tabatabaeimehr, and Velasco [8], so that future occurrences of structurally similar incidents can be diagnosed and remediated with reduced latency, progressively shortening MTTR over successive incident cycles.

6. MTTR STAGE DECOMPOSITION AND EXPECTED IMPACT

To reason about where closed-loop automation yields the greatest benefit, it is useful to decompose an incident's total resolution time into five stages: Detect, Diagnose, Decide, Act, and Verify. Near-real-time performance estimation studies [13] and latency-focused traffic analyses [14], [15] suggest that, in predominantly manual NOC workflows, the Diagnose stage correlating symptoms across domains to identify root cause typically dominates total resolution time, followed by Decide (selecting and authorizing a remediation action).

Figure 5 presents a schematic comparison of relative stage durations under a baseline, largely manual NOC and under the proposed closed-loop automated NOC. The comparison is illustrative rather than measured, intended to communicate where automation investment should be prioritized: the framework in Section 5 targets disproportionate compression of the Diagnose and Decide stages through AI-assisted root-cause analytics and intent translation, in addition to incremental gains in Detect (via distributed telemetry) and Act (via automated SDN/NFV execution).

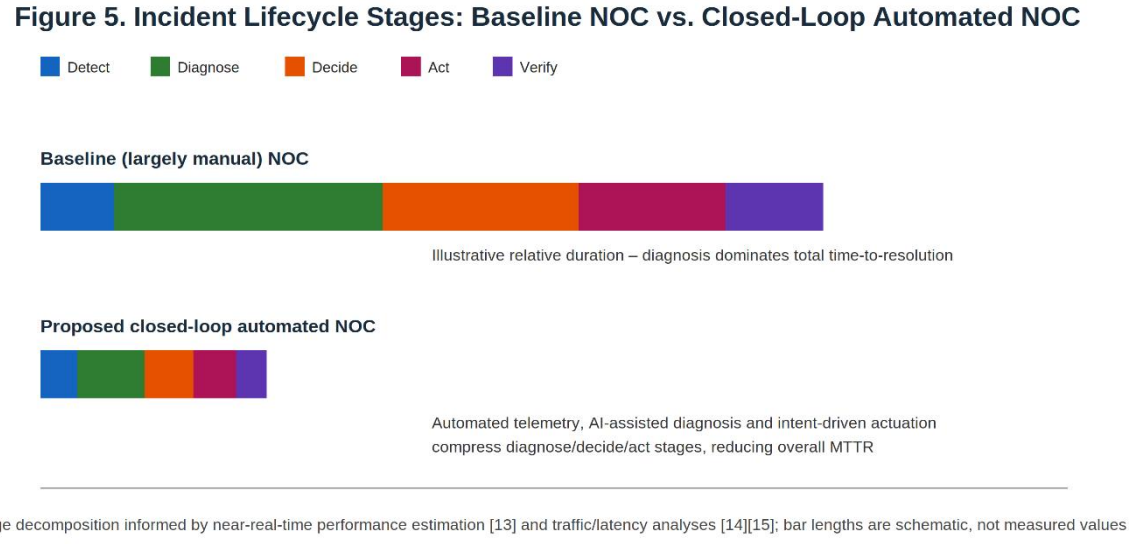

Figure 5. Schematic comparison of incident lifecycle stage durations: baseline (manual) NOC versus the proposed closed-loop automated NOC.

Table 4 summarizes, for each lifecycle stage, the primary automation lever proposed in this framework, the supporting literature, and the qualitative MTTR impact expected. Quantitative validation against carrier-specific incident logs is identified as necessary future work (Section 8).

Table 4. MTTR Stage Decomposition, Automation Levers, and Expected Qualitative Impact

Lifecycle Stage	Dominant Manual Bottleneck	Proposed Automation Lever	Supporting Literature	Expected Impact
Detect	Siloed, polling-based monitoring across domains	Distributed, streaming telemetry fusion	[7], [13]	Moderate reduction
Diagnose	Manual cross-domain correlation and root-cause hunting	AI/ML anomaly detection and context-aware profiling	[6], [16]–[23]	High reduction
Decide	Sequential approval chains and rule-based playbooks	Intent-driven decision translation	[1], [2]	High reduction
Act	Manual or semi-scripted configuration changes	Automated SDN/NFV remediation execution	[9]	Moderate reduction
Verify	Manual confirmation and ticket closure	Closed-loop verification with knowledge-base update	[8]	Moderate reduction

Source: Synthesized by the authors from [1], [2], [6], [7], [8], [9], [13], [16]–[23]; impact ratings are qualitative judgments, not measured outcomes.

7. AI/ML TECHNIQUES FOR FAULT AND ANOMALY DETECTION IN 5G NETWORKS

A wide range of AI/ML techniques has been proposed for the analytics demands of 5G network operations, each addressing a different facet of the diagnosis problem. Table 5 surveys representative techniques drawn from the literature underlying the diagnosis layer of the proposed framework (Section 5.2), organized by technique family, target analytics task, and reported application domain.

Table 5. Survey of AI/ML Techniques for Network Fault and Anomaly Analytics

Technique Family	Representative Study	Target Analytics Task	Application Domain
Multi-agent deep reinforcement learning	Sulaiman et al. [9]	Slicing and admission control decisions	5G Cloud-RAN
Context-aware AI profiling	Koursioumpas et al. [6]	User/network context profiling for anomaly relevance	5G and beyond networks
Data fusion + classical ML (industrial prognosis)	Diez-Olivan et al. [16]	Fault prognosis from multi-sensor fusion	Industry 4.0 / adapted to network ops
Big-data behavioral analytics	Jiang et al. [17]	Network behavior insight from large-scale traffic data	Cellular networks / Industry 4.0
Context-extraction and profiling engines	Magdalinos [18]	Resource mapping from contextual signals	5G network resource management
SDN/NFV-integrated clustering & forecasting	Le et al. [19]	Traffic clustering and demand forecasting	5G traffic management
Location/mobility-aware resource management	Karneyenka, Mohta & Moh [20]	Resource allocation tied to mobility patterns	5G Cloud-RAN
Anomaly detection on user-activity data	Parwez, Rawat & Garuba [21]	User-activity and anomaly detection	Mobile wireless networks
Multi-source data analytics frameworks	Barmpounakis et al. [22]	Access selection and traffic steering	5G networks

Technique Family	Representative Study	Target Analytics Task	Application Domain
Context-aware traffic identification	Xu & Duan [23]	Traffic identification for smart networking	5G (TrICK framework)

Source: Compiled by the authors from [6], [9], [16]–[23].

These techniques are complementary rather than competing: behavioral and traffic analytics [17]–[23] typically establish the normal-operating baseline against which context-aware profiling [6] and reinforcement-learning-based agents [9] detect and act on deviations, while data-fusion methods adapted from industrial prognosis [16] provide a general methodological bridge between sensor-level signals and actionable fault hypotheses. The proposed framework's diagnosis layer (Section 5.2) is designed to be technique-agnostic at the architectural level, allowing operators to substitute or ensemble these methods as production data and operational maturity permit.

8. Discussion: Open Challenges and Future Directions

8.1 Cross-Domain Knowledge Federation

The knowledge-management architecture proposed by Ruiz, Tabatabaeimehr, and Velasco [8] was developed primarily for optical transport networks. Extending case-based knowledge reuse across RAN, transport, and core domains each with different vendors, telemetry schemas, and failure modes requires federation mechanisms that preserve case relevance while avoiding overfitting to a single domain's fault signatures.

8.2 Trust, Explainability, and Operator Oversight

As autonomy levels rise toward L4–L5 (Section 4), operators must retain meaningful oversight of AI-driven decisions, particularly for safety- and mission-critical 5G slices. Intent-driven frameworks [1], [2] help by keeping the operator's expressed goals legible, but the underlying diagnostic models [6], [9], [16]–[23] still require explainability mechanisms proportionate to the consequence of the automated action being authorized.

8.3 Functional-Split-Aware Automation Placement

Section 3 showed that fronthaul functional-split choice materially affects the timing margin available for closed-loop automation. Future work should treat automation-layer placement (edge versus regional versus centralized) as a joint optimization with functional-split selection, rather than a downstream consequence of an architecture decided independently, particularly as 6G research [4], [5], [12] anticipates even tighter compute-transport integration.

8.4 Empirical Validation of MTTR Gains

The MTTR stage-decomposition model in Section 6 is qualitative. A natural next step is controlled before/after measurement of stage-level durations in production NOCs adopting the proposed framework incrementally for example, deploying only the telemetry-fusion and diagnosis layers first to isolate the marginal MTTR contribution of each layer and validate the prioritization argued for in this paper.

9. CONCLUSION

This paper proposed a five-layer closed-loop automation framework for autonomous Network Operations Centers, targeting reduced Mean-Time-to-Resolution in U.S. 5G network deployments. By synthesizing intent-driven management automation [1], context-based autonomous operation [2], functional-split architecture constraints [3], standardization-derived autonomy levels [10]–[12], distributed telemetry and knowledge management [7], [8], and a broad base of AI/ML network analytics [6], [9], [16]–[23], the framework offers a structured migration path from operator-supervised NOC operation toward higher levels of autonomy. The accompanying MTTR stage-decomposition analysis suggests that the greatest gains lie in compressing the diagnose and decide stages rather than in actuation alone a prioritization that should inform where carriers invest first when automating NOC operations. Realizing these gains in production will require addressing cross-domain knowledge federation, explainability commensurate with operational risk, and functional-split-aware placement of automation, each identified here as a concrete direction for future research as networks evolve toward 6G.

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