Digital Twin-Based Intelligent Network Management

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DOI: https://doi.org/10.51583/IJLTEMAS.2026.150800086

Received: 26 August 2026; Accepted: 05 September 2026; Published: 16 September 2026

ABSTRACT

Communication networks today are becoming more and more complex as a result of the introduction of 5G/6G technologies, the Internet of Things (IoT), cloud computing, edge computing, network virtualization, and software-defined networking (SDN). Existing methods of managing networks mostly depend on fixed configurations, manual monitoring, and dealing with faults after they occur, which makes them inadequate for coping with varying traffic conditions, changing resource needs, and unforeseen network failures. In order to meet these challenges, this paper puts forward an intelligent network management framework that combines Network Digital Twin (NDT) technology with Artificial Intelligence (AI) and Machine Learning (ML). This framework produces a real-time digital version of the actual communication network and keeps it updated by means of real-time network data. It is made up of six main layers: the physical network layer, the data collection and synchronization layer, the digital twin layer, the AI/ML analytics layer, the decision-making and simulation layer, and the control and feedback layer. The approach described enables real-time network monitoring, traffic prediction, detection of anomalies and faults, resource optimization, scenario-based simulation, and proactive network management. By analysing network behaviour, AI/ML models assist in making predictive decisions before any changes are implemented on the physical network, thus reducing operational errors, service interruptions, and network downtime. The performance of the proposed framework can be assessed using a number of key performance indicators such as latency, throughput, packet loss, resource utilization, fault detection time, prediction accuracy, energy efficiency, and synchronization delay. Combining NDT with AI/ML offers a promising way of achieving autonomous, adaptive, and proactive management of next-generation communication networks. Nevertheless, there are still a number of problems to be overcome, such as real-time synchronization, computational complexity, scalability, data security and privacy, communication latency, and the accuracy and reliability of the AI/ML models. Future research should concentrate on tackling these issues and on developing scalable, secure, and highly accurate AI-driven digital twin solutions for next-generation communication networks.

Keywords: Network Digital Twin, Artificial Intelligence, Machine Learning, 5G, 6G, Internet of Things, Software-Defined Networking, Network Management, Predictive Analytics, Edge Computing.

INTRODUCTION

Modern communication networks are increasingly becoming heterogeneous, distributed, virtualized, and software-defined. The integration of 5G, edge cloud computing, network function virtualization, software-defined networking, IoT, and network slicing introduces considerable complexity in the management of large-scale systems. Network operators must effectively manage substantial quantities of both physical and virtual resources to maintain the necessary levels of quality of service, reliability, security, and energy efficiency.

Most conventional network management systems depend on gathering operational data from physical network devices and responding to identified events or failures. Although these management strategies are typically adequate for traditional networks, they may fall short for the new heterogeneous, software-defined, and highly automated systems. For instance, network operators might not anticipate the repercussions of reconfiguring a network component to enhance specific key performance indicators (KPIs) such as traffic or link utilization. Therefore, it is essential for network operators to predict changes in system behavior proactively and to make well-informed decisions.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

A digital twin is a software-based representation of a physical object, process, or system that facilitates continuous or periodic data exchange with its real-world equivalent. While traditional model-based methods depend on a system description to create a digital replica, a digital twin offers enhanced flexibility by updating the model's information with data collected from the actual system. Although the concept of digital twins was initially introduced for industrial applications, recent research indicates their use in communication networks. The growing interest is attributed to the capability of developing a Network Digital Twin (NDT) that encompasses a description of network elements, topology, configuration, resources, traffic, and other attributes. Researchers emphasize that NDTs can be utilized to gather and analyze performance data from both physical and virtual network devices, thereby providing network insights.

LITERATURE REVIEW

Digital Twin Technology

A digital twin (DT) is a virtual software-based representation of a physical entity, allowing for regular or ongoing information exchange between the two. The concept of DTs aims to enhance the understanding of a physical object, process, or system by creating a digital version of it. Unlike a computer model that is based on specific assumptions regarding the behaviors of a real-world system, DTs offer increased adaptability by consistently updating their representations according to actual operational data.

DT technology has found applications in various fields, such as industrial systems, smart cities, and healthcare; however, current research is increasingly focused on utilizing DTs for communication network management. Specifically, network DTs can gather and analyze data from network devices.

Network Digital Twin

A network or its essential components, such as the radio access network (RAN), core network, routers, switches, virtual network operations, and resources, are represented by NDT. The ability of NDTs to support operations that will impact the production network but must first be confirmed in the DT environment is a crucial feature. This includes "what-if analysis," which describes the potential to implement recommended modifications and track how they affect the system. As a result, network operators can analyze failure scenarios, test different network topologies, and carry out additional experiments without interfering with the real network. In order to facilitate data-driven management and performance optimization, researchers examining 5G/B5G network simulation services show that these services gain by integrating network data with analytical and machine learning models.

AI and Machine Learning for Network Management

Network management, control, and optimization can be supported by combining AI/ML with NDT. AI/ML algorithms can be trained to carry out particular tasks, like traffic prediction, fault detection, resource allocation, and network setup, using the data gathered by network DTs.

For instance, a model that can forecast future network traffic can be constructed using supervised machine learning methods. In a similar vein, network traffic data can be analyzed by unsupervised machine learning algorithms to find patterns and abnormalities. Real-time resource allocation optimization and network management are possible with reinforcement learning. The network management process can change from "monitoring → manual reaction" to "monitoring → prediction → simulation → decision → action → validation" by integrating DT with AI/ML.

For many applications, AI's capacity to facilitate such proactive network management is essential.

Digital Twin and Zero-Touch Management

In zero-touch network/service management (ZSM), DTs are frequently used to gather information from network devices and facilitate the automatic orchestration and setup of network resources from beginning to

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

end. ZSM deals with "the automated delivery, deployment, orchestration, configuration, assurance, and optimization of network services and network resources," according to ETSI. Network digital twins can be employed to create zero-touch networks in the future since they are regarded as a crucial component of ZSM**.**

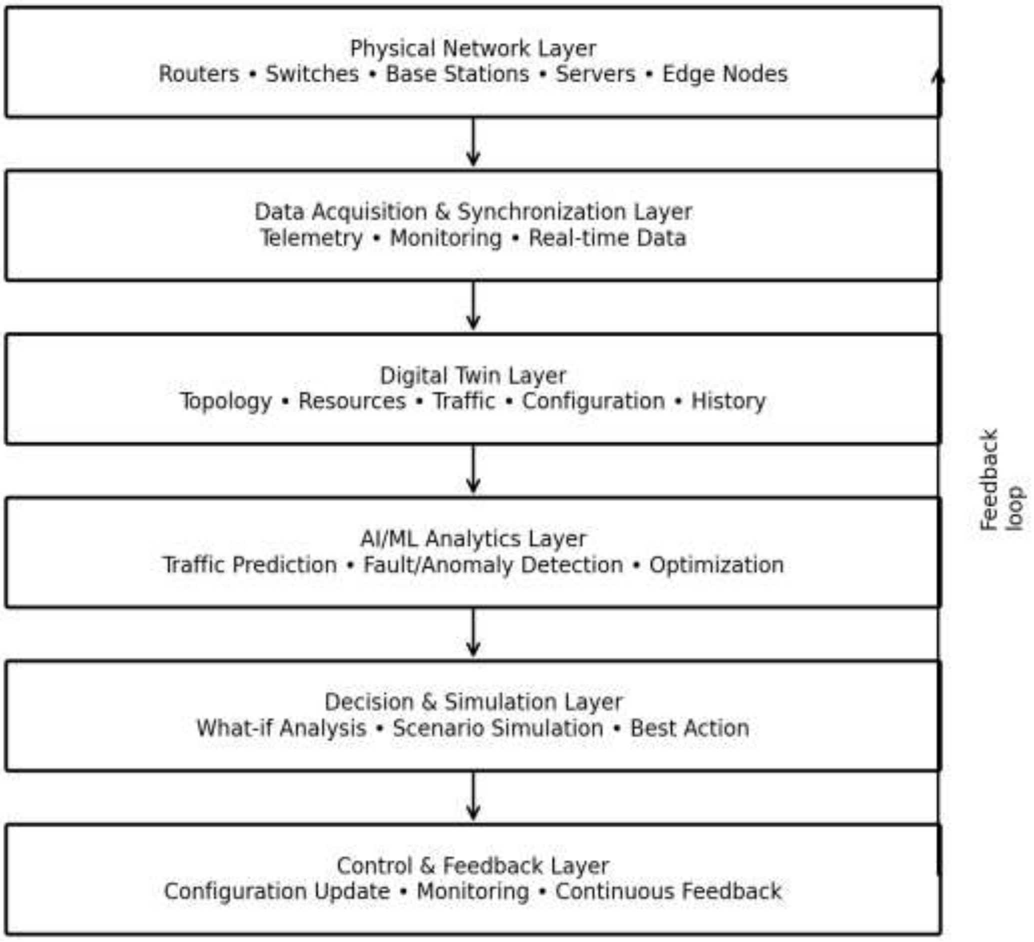
Research Gap

Even though the amount of research on NDTs has increased over the past few years, there are still a lot of important gaps that need to be filled.
First, instead of creating an end-to-end management framework that uses digital twins, the majority of publications concentrate on a specific area of NDT, such as design, simulation, or AI-driven optimization. Second, the majority of network management techniques, including NDTs, are mostly reactive or, at best, only act upon the discovery of an uncommon occurrence, such a failure or surge in traffic. Third, NDT's capacity to accurately depict real-world networks may be constrained by computational complexity. Fourth, large amounts of pertinent data are necessary for AI-based algorithms to function properly. Fifth, sensitive information regarding the network's architecture, configuration, traffic, and other elements may be included in NDT, meaning

PROPOSED DIGITAL TWIN-BASED INTELLIGENT NETWORK MANAGEMENT FRAMEWORK

System Architecture

Figure 1. Digital Twin-Based Intelligent Network Management Architecture



ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

The framework has six major components: 1) physical network layer, 2) data acquisition and synchronization layer, 3) digital twin layer, 4) AI/ML analytics layer, 5) decision and simulation layer, and 6) network control and feedback layer.

Physical Network Layer

Table 1. Components of the Proposed Framework

Layer	Main Components	Function
Physical Network Layer	Routers, switches, base stations, servers, edge nodes	Provides real network infrastructure and performance data
Data Acquisition & Synchronization	Telemetry, monitoring tools, data collectors	Collects real-time data and updates the digital twin
Digital Twin Layer	Topology, resources, traffic, configuration, history	Maintains a virtual representation of the physical network
AI/ML Analytics Layer	Prediction, anomaly detection, optimization	Analyzes network behavior and supports proactive decisions
Decision & Simulation Layer	What-if analysis, simulation, optimization	Tests possible configurations before implementation
Control & Feedback Layer	Controller, monitoring, feedback loop	Applies selected changes and validates performance

The physical network layer is made up of network infrastructure components such as routers, switches, base stations, servers, virtual network services, edge computing nodes, and more. Bandwidth utilization, packet loss, packet delay, jitter, CPU utilization, memory utilization, throughput, number of active users, signal measurements, network-function status, and energy consumption are just a few of the KPIs that can be used to evaluate the network's performance.

Data Acquisition and Synchronization Layer

Network data collection and delivery to the digital twin are handled by the data acquisition and synchronization layer. Telemetry data can be collected and processed by network monitoring technologies to extract pertinent information in an organized manner. The digital twin can then receive this data for synchronization, which entails updating the DT to reflect the real network's current status. Network synchronization can be expressed mathematically as $NDT_t = f(Net_t)$, where NDT_t is the state of the digital twin and Net_t is the state of the real network at time t. Minimizing ε_t will guaranty that the digital twin accurately depicts the real network as the synchronization error may be computed as $\varepsilon_t = \|Net_t - NDT_t\|$.

Digital Twin Layer

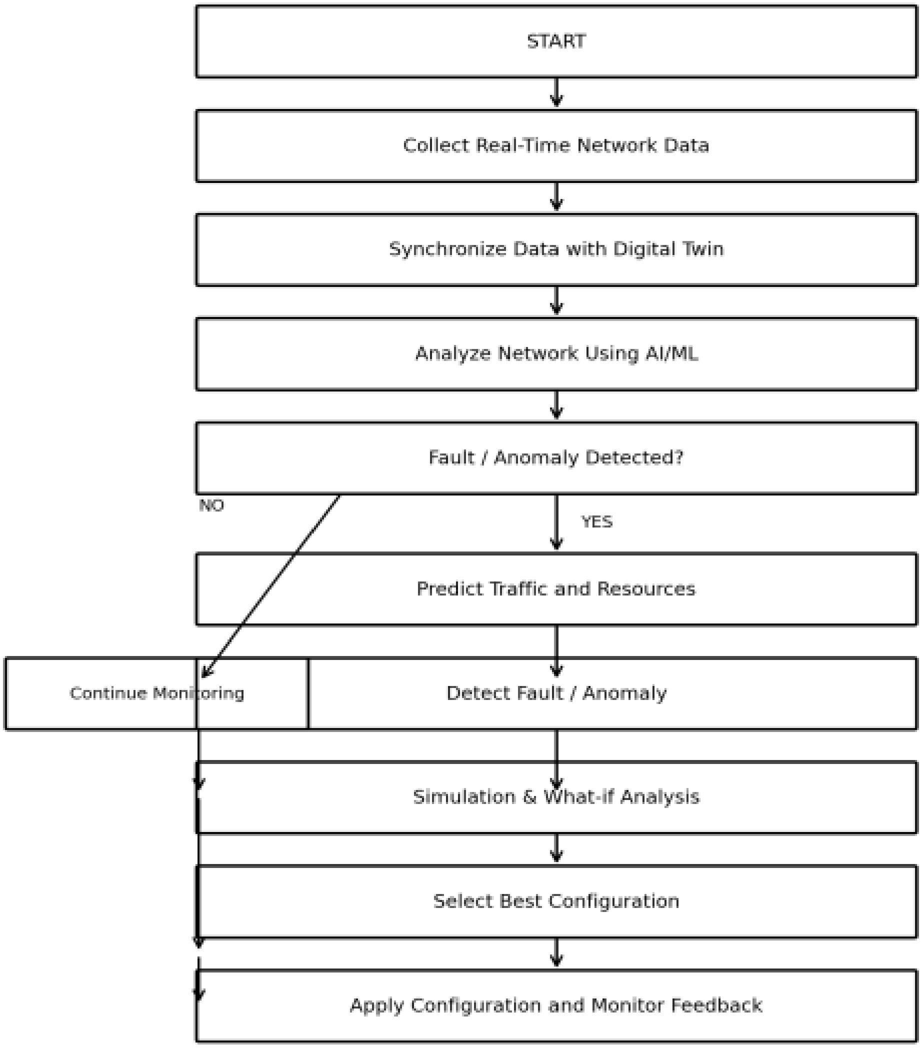
The network topology, link/node attributes, configuration, resources, traffic, service requirements, network-function status, and operational history are all included in the digital twin layer's accurate reproduction of the network. It makes use of simulation, emulation, analytical models, and AI/ML algorithms to guaranty that the digital twin accurately depicts the real network. As a result, the network elements in the digital twin can be

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

described as $N_{DT}=g(Net, Sim, Emu, Analytical, ML)$, where the input parameters that can be used to update the digital twin are represented by Net, Sim, Emu, Analytical, and ML.

AI/ML Analytics Layer

Figure 2. Proposed Intelligent Network Management Flow



The digital twin's data is processed by the AI/ML analytics layer, which facilitates modeling, simulation, and decision-making. For instance, given past data, an ML model can be trained to forecast future traffic patterns, as demonstrated below:

$\hat{T}_{t+1} = h(T_t, T_{t-1}, C_t)$, where T stands for traffic and C for additional network factors, including link characteristics or user behavior, that could affect traffic. Similar to this, an anomaly score can be used by an ML system to find anomalies in the network data:

$s(x)= \|x-\hat{x}\|$, where x is the actual value and $\hat{x}$ is the expected value that an ML model predicts. The method can identify a data point as anomalous if $s(x) > threshold$.

Decision and Simulation Layer

Table 2. Example What-if Analysis Scenarios

Scenario	Simulation Activity	Decision Outcome
Traffic increase	Simulate alternative routing/resource allocation	Select configuration with acceptable latency and

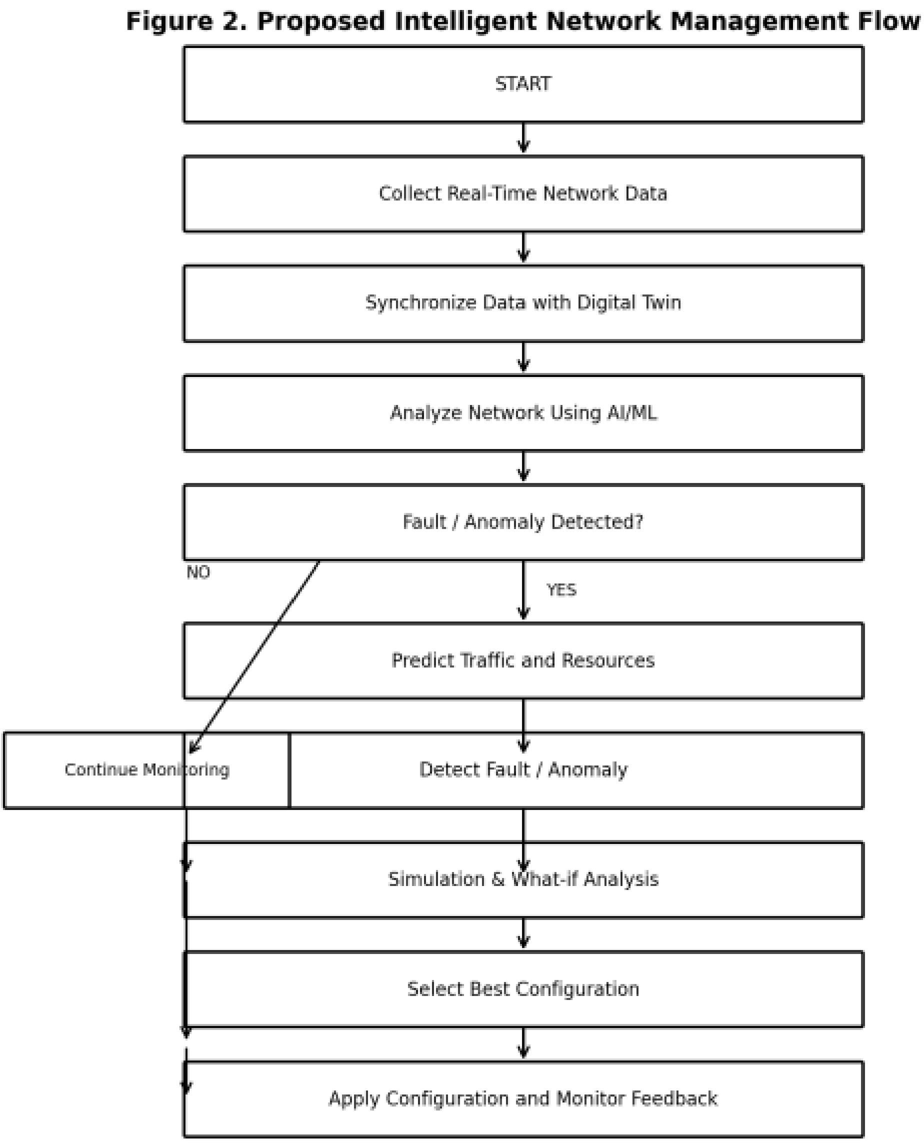
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

		throughput
Link/node failure	Simulate failure and recovery scenarios	Recommend alternate path or resource configuration
Unusual traffic	Analyze anomaly score and expected behavior	Trigger proactive management action

The decision-making layer evaluates the digital twin's condition and recommends network modifications that might be necessary to achieve the intended performance. For instance, the network operator wants to maintain the service level, maximize link utilization and throughput, and decrease latency, packet loss, and link utilization. These goals can be expressed as follows: min Lat + PL + Del + En max Th + Ut subject to SL $\geq$ SL_min, where Lat, PL, Del, En, Th, Ut, and SL stand for network latency, packet loss, delay, energy consumption, throughput, utilization, and service level, respectively. To accomplish these optimization objectives, the decision-making layer can suggest particular network configurations or actions. Specifically, in the aforementioned example, the decision-making layer can recommend different routing paths for

Control and Feedback Layer

Figure 3. Proposed Intelligent Network Management Flow



The network control layer can receive the suggested network configuration and use it to update the real network. The network monitoring layer and the digital twin can be used to examine how the new network

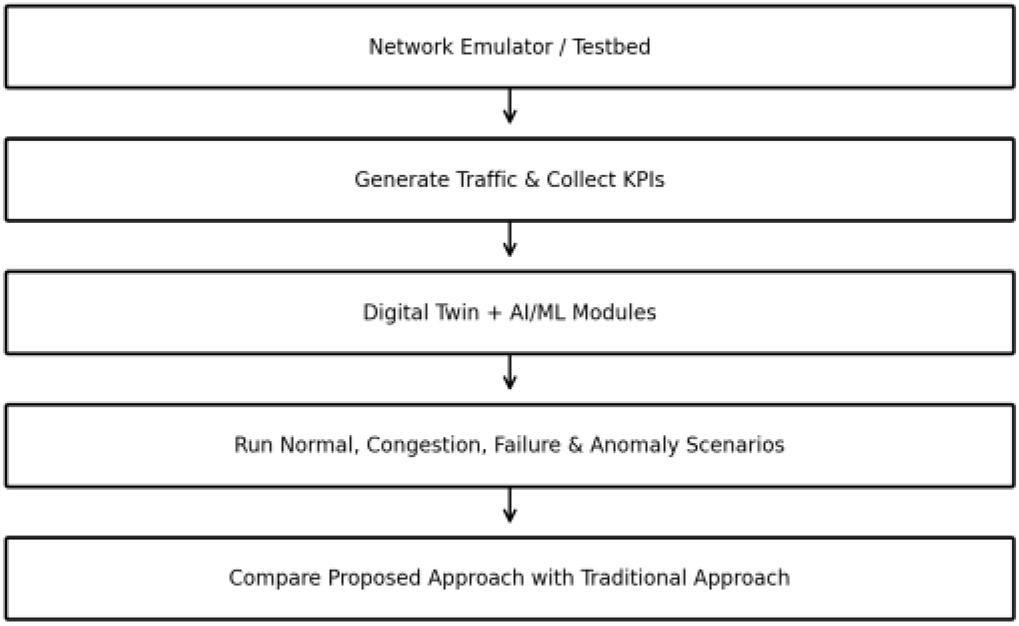
INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING,
MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)
ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

configuration would impact the network's performance. By modifying the settings in response to actual measurements and anticipated performance in the digital twin, this feedback loop enables ongoing network performance improvement. It is important to remember that many facets of intelligent network management depend on this kind of closed-loop control.

METHODOLOGY

Figure 4. Testbed and Evaluation Methodology

Figure 3. Testbed and Evaluation Methodology



A testbed or network emulation environment can be used to assess the suggested system. A software-defined network controller and network simulation/experimental platform, as well as tools for generating network traffic and gathering network data, would be one potential configuration. A digital twin model of the network, an ML prediction/anomaly detection module, a decision module, and a dashboard may also be included in the testbed.

The performance of the suggested framework (Approach B) and the traditional network management approach (Approach A) will be compared in the testbed trials. Normal traffic, traffic congestion, link/node failure, traffic anomalies, and variations in the network usage level are some of the traffic scenarios that can be used.

TESTING

Table 3. Testing Strategy

Testing Type	Test Scenario	Expected Result
Functional Testing	Add node, link failure, increased traffic, configuration change	Digital twin state/topology is correctly updated
Fault Detection Testing	Link/router failure, packet loss, congestion, CPU overload, unusual traffic	Fault or anomaly is identified
Prediction Testing	Future traffic prediction and classification	Prediction accuracy is evaluated using standard metrics
Network Performance Testing	Latency, throughput, packet loss,	Overall network performance

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

	resource use	is measured
Stress Testing	Increasing network size and traffic load	Scalability and robustness are evaluated

The testing process will involve four major stages: functional, performance, prediction, and resilience testing.

Functional Testing

The suggested system's ability to accurately update the digital twin replica will be confirmed through functional testing. It is possible to define many test cases:

Expected Results of the Test Case

The topology is updated when a network node twin is added.

Link failure Identification of the modification

Increased traffic Modification of usage levels

Modification of the network configuration The virtual model's update

Normalization of the twin state during network recovery

Fault Detection Testing

It is possible to test the system's ability to recognize and react to different types of network failures.You can use the test scenarios listed below:

Expected Results of the Test Case

Link failure: Finding the problem

Finding the problem with the router

high loss of packets Finding the problem

Finding the problem with traffic congestion

CPU overload Identification of the issue

Unusual traffic patterns Finding the problem

Prediction Testing

Standard performance indicators can be used to assess an ML model:

$MSE = 1 / n \sum_{i=1}^{n} |x_i - x^{i}|$ | $RMSE = \sqrt{1 / n \sum_{i=1}^{n} (x_i - x^{i})^2}$

The performance measures accuracy, precision, recall, F1-score, and ROC-AUC can be applied to classification-based prediction tasks.

Network Performance Testing

Table 4. Performance Evaluation Metrics

Performance Metric	Purpose
Average Latency	Measures communication delay

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

Throughput	Measures successfully transmitted data
Packet Loss Rate	Measures lost packets
Resource Utilization	Measures use of network resources
Fault Detection Time	Measures time required to identify a fault
Fault Recovery Time	Measures time required to recover from a fault
Prediction Accuracy	Measures accuracy of AI/ML predictions
Synchronization Delay	Measures delay between network and digital twin
Energy Efficiency	Measures energy consumption and optimization

Several key performance indicators (KPIs) can be utilized to evaluate the performance of the proposed system, including average latency, throughput, packet-loss rate, resource utilization, time to detect a fault, time to recover from a fault, prediction accuracy, and digital-twin synchronization delay.

Stress Testing

Another important aspect of testing involves assessing the impact of the network size and traffic on the system's performance. This information can help estimate how much the framework can scale.

The proposed Digital Twin-Based Intelligent Network Management framework provides an integrated approach for real-time monitoring, synchronization, prediction, simulation, decision-making, and closed-loop control. The evaluation described in the methodology is designed to compare the proposed approach with a traditional network management approach under normal traffic, congestion, link/node failure, traffic anomalies, and changing network usage levels. The framework is expected to support earlier fault identification, improved resource utilization, proactive traffic management, and safer configuration changes through what-if analysis. Numerical performance values should be populated after execution of the proposed testbed experiments; therefore, this section does not introduce unsupported experimental percentages or accuracy values.

Evaluation Area	Metrics	Expected Outcome
Traffic Prediction	Prediction accuracy, RMSE/MSE	Higher predictive accuracy / lower error
Fault Detection	Detection time, precision, recall, F1-score	Faster and reliable identification
Network Performance	Latency, throughput, packet loss	Lower delay/loss and higher throughput
Resource Management	CPU/memory/link utilization, energy	Efficient utilization of available resources
Digital Twin Synchronization	Synchronization delay/error	Closer representation of physical network state
Resilience	Recovery time after failures	Faster restoration of network services

Table 5. Expected Evaluation Outcomes

RESULTS

The proposed **Digital Twin-Based Intelligent Network Management** framework provides a proactive approach to monitoring and managing next-generation communication networks. The framework continuously synchronizes the Digital Twin with the physical network using real-time network data. AI/ML analytics can then be used for traffic prediction, anomaly detection, fault identification, and resource optimization.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VIII, August 2026

The testing methodology evaluates the framework using functional, fault detection, prediction, network performance, and stress testing. The main performance indicators include latency, throughput, packet loss, resource utilization, fault detection time, fault recovery time, prediction accuracy, and Digital Twin synchronization delay.

DISCUSSION

The suggested framework is an intelligent network management system that enables closed-loop control by utilizing the ideas of digital twins, network data, and AI/ML. By examining the network's behavior in the digital twin prior to physically altering the network hardware, the framework enables network operators to make well-informed decisions. One key feature of digital twins is their ability to facilitate what-if analysis, allowing network operators to test many scenarios in order to identify the most advantageous one. The AI/ML model's ability to forecast future network conditions and facilitate proactive fault management is another benefit of the framework. Lastly, the framework can maximize the use of network resources, which is essential for 5G and upcoming 6G networks.

However, a number of issues need to be resolved in order to properly

CONCLUSION

In order to develop an intelligent management system that uses real-time network data for closed-loop control and predictive analytics, this study proposes a Digital Twin-Based Intelligent Network Management framework that draws upon network data, virtual replicas, and artificial intelligence. The framework can help network operators make well-informed choices regarding resource allocation and network setup. Its main benefit is that it enables what-if analysis, which takes into account the anticipated effects of different network configurations prior to their actual implementation in the network.

The scientific community and standards organizations are paying more and more attention to NDT technology. As evidence that NDT is viewed as a crucial component, the 3GPP has been investigating the management aspects of NDTs and is currently transitioning from Release-19 research to more thorough investigations for future releases.

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