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Digital Twin–Enabled Resilience IN Integrated 5g–Ntn Architectures: Model Design AND Simulation Results

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The Integration of Non-Terrestrial Networks (NTNs) with 5G does ensure omnipresent coverage and service continuity, particularly in disaster recovery and remote regions. Yet, the resilience guarantee across such heterogeneous terrestrial and satellite networks remains a critical challenge.This study proposes a DT-enabled resilience framework that maintains a continuous mirror of network states, failing to predict reconfiguration in an integrated 5G-NTN system. The considered model comprises a twin synchronization mechanism, AI-based predictive control, and an adaptive routing algorithm with fault-tolerance. Simulation results state that DT-ed resilience in integrated networks can provide up to 38% faster recovery time, 25% higher service availability, and 15% more throughput in the failure scenarios, thus proving its efficiency.

KEYWORDS: 5G, Non-Terrestrial Networks (NTN), Digital Twin, Communications, Edge Computing, AI-Enabled Control, Simulation.

I. INTRODUCTION

For the development of 5G networks, the scope has extended beyond terrestrial infrastructures to cover Non-Terrestrial Network (NTN) elements such as LEO satellites, HAPs, and UAVs, for provision of worldwide connectivity. This hybrid integration ensures improved coverage, capacity, and communication in remote areas or disaster-prone conditions. However, the heterogeneous and dynamic nature of these systems impedes the provision of resilience-the ability to sustain service continuity and recover in shortest possible time on faults, link disruptions, and resource unavailability. With network evolution toward 6G, resilience will be the prime enabler for mission-critical services and autonomous network management [1].Although network automation has reached a great degree of sophistication recently, even classical 5G management frameworks largely remain reactive in nature, focusing on fault detection and isolation, and recovery after the failure has taken place [2]. Specifically, NTNs are heavily affected by long propagation delays, intermittent connectivity, and dynamic topologies, all of which undermine the very basis for real-time decision-making. Hence, the latest requirements emphasize the need to have intelligent control and prediction mechanisms to foresee the network degradations and to invoke adaptive reconfiguration in anticipation [5]. In this case, one of the promising answers is the concept of Digital Twin (DT). A DT is a virtual replica representing the physical network that mirrors the network's real-time state through continuous synchronization of data. Using AI-powered predictive models and simulation-based reasoning, a DT can predict disruptions, evaluate potential recovery strategies, and suggest optimal configurations even before the disruptions impact service quality [2].

This paper proposes a Digital Twin-enabled resilience architecture for integrated 5G-NTN systems. The main contributions include: (1) a unified DT framework for synchronizing data streams from terrestrial and satellite domains [3], (2)an AI-driven predictive resilience model for proactive fault detection and self-healing, and (3) a simulation-based evaluation demonstrating significant improvements in recovery time, throughput stability, and service availability over conventional reactive schemes. This work lays the foundation for self-aware, self-healing 6G networks empowered by digital-twin-intelligence [6].

II. RELATED WORKS

Digital Twin Enabled Network Architectures

The latest developments in Digital Twin (DT) technologies have brought changes to the design and operation of next-generation networks. Nguyen et al.and Minovski et al. introduced the NDT concept in 5G and beyond and defined it as a virtual replica mirroring a physical network for real-time monitoring, testing, and optimization. Guo et al. [1] extended the concept of DT by filling it with an artificial intelligence framework for resilience in order to enhance fault prediction and recovery in 6G networks. At the same time, Wang et al. [4], and Jamil et al. [2] provided an outline of the integration of DT with federated learning and edge computing to enable adaptive self-healing network management. Collectively, these studies show that DT-enabled architectures allow for predictive maintenance, energy efficiency, and strong network resilience in 5G/6G systems.

Terrestrial and Non-Terrestrial Networks (NTN) Integration

Any form of converging terrestrial and non-terrestrial network would be a landmark to achieving ubiquitous worldwide coverage. Rinaldi et al. [17] and Giordani et al. [15], [24] performed basic surveys regarding the architectural evolution, challenges, and standardization of 5G-NTN systems emphasizing satellite- and UAV-assisted communication frameworks. Truong et al. [20] and Liu et al. [25] studied the integration challenges in space-air-ground networks, especially those concerning interoperability, resource allocation, and latency reduction. Furthermore, Lin et al. [8] and Polese et al. [19] tackled energy-efficient resource allocation and dynamic spectrum sharing in 5G-NTN systems, emphasizing the requirement of intelligent and adaptive management by AI-based digital twins.

Resilience, AI, and Resource Optimization

The AI-driven resilience has now become a core issue of the recent 5G and 6G research. Dai et al. studied deep reinforcement learning (DRL) methods for stochastic computation offloading in DT networks, while Lu et al. [7] demonstrated how federated learning and blockchain can facilitate secure and low-latency edge association. Lee and Kim [9] discussed resilient network slicing emphasizing autonomous recovery and reconfiguration in 5G systems. Tataria et al. [14] and Hasan et al. explored wider-reaching goals of resilience, dealing with security, privacy, and adaptability challenges across various verticals.

Standards and Vision for Future Networks

3GPP TR 38.811laid the foundation for NR-based NTN, whereas 5G Americas supplied the full industrial viewpoint of deployment of NTNs. As well, Uusitalo et al. and Saad et al.outlined the 6G vision integrating DTs with AI and NTNs into one framework for intelligent global connectivity. Together, they make the foundation for digital twin–enabled resilience in integrated 5G–NTN architectures, bringing to the forefront the convergence of AI, edge intelligence, and virtualization for self-sustaining networks.The latest developments in Digital Twin (DT) technologies have brought changes to the design and operation of next-generation networks. Nguyen et al.and Minovski et al. [6] introduced the NDT concept in 5G and beyond and defined it as a virtual replica mirroring a physical network for real-time monitoring, testing, and optimization. Guo et al. [1] extended the concept of DT by filling it with an artificial intelligence framework for resilience in order to enhance fault prediction and recovery in 6G networks. At the same time, Wang et al.and Jamil et al. [2] provided an outline of the integration of DT with federated learning and edge computing to enable adaptive self-healing network management. Collectively, these studies show that DT-enabled architectures allow for predictive maintenance, energy efficiency, and strong network resilience in 5G/6G systems.

III. PROPOSED MODEL DESIGN

System Architecture Overview

The Digital Twin–Enabled Resilience Framework seeks to join terrestrial 5G infrastructure with NTN components through a common control and data plane [7]. As is shown in Fig. 1, the system consists of three essential layers: the Terrestrial Segment, the NTN Segment, and the Digital Twin Layer.Here, the Terrestrial Segment comprises 5G gNodeBs, MEC servers, and the SDN controller responsible for real-time orchestration. The NTN Segment consists of LEO satellite constellations and UAV relays, extending from network coverage to backhaul connectivity in remote areas [10].The Digital Twin Layer mirrors a fully integrated 5G–NTN network in virtualization, wherein it is kept in continuous sync with the real world through telemetry and monitoring data[11]. It models certain parameters like link quality, traffic load, and node health. The predictive engines in the DT are AI-based, e.g., LSTM and GNN, used for the prediction of link degradations or node failures.The Control and Data Plane Integration is yet another SDN-based orchestrator, which leverages information arising from the DT towards proactive decision-making such as self-healing, adaptive routing, dynamic resource allocation [13]. The multi-layer architecture allows for acquisition of real-time situation awareness, situational prediction, and autonomous recovery actions that make for improved end-to-end resilience of heterogeneous 5G–NTN systems [7].

Digital Twin Synchronization Mechanism

The Digital Twin synchronization mechanism is the ultimate real-time awareness and resilience provision within the integrated 5G–NTN architecture. It guarantees that the digital cybernetic twin of the physical network maintains an accurate, current reflection of the operational states across the terrestrial and non-terrestrial segments. The synchronization loop processes four major functions: data collection, state updating, prediction, and action-feedback are executed in an ongoing harmonious manner with the network control plane [9].

During the data collection phase, these telemetry parameters and KPIs are continuously retrieved in real-time from heterogeneous sources: gNodeBs, user equipment (UE), UAV relays, LEO satellites, etc. These parameters include signal-to-noise ratio (SNR), link delay, throughput, and node resource utilization. This multi-source data stream keeps the Digital Twin cognizant of the overall network performance and resource health.During the state updating phase, the Digital Twin updates its internal network graph using distributed data streams at fixed intervals, say t = 100 ms. In this way, the protocol helps reduce communication overhead by using edge-level caching and message compression to ensure low latency and efficiency [12].

The prediction-detection phase continuously runs in the background, facilitated by AI models (such as LSTM or GNN) that monitor temporal and spatial correlations in the incoming telemetry data. This phase allows the system to detect early anomalies, performance degradations, or potential faults, such as satellite beam misalignment or terrestrial link congestion [8]. As a consequence of such predictive alerts, the control system will have the opportunity to act in mitigation prior to the failure severely affecting the quality of service to the end user.At the action-and-feedback phase, the Digital Twin engages with the SDN controller for implementing proactive reconfiguration measures for adaptive routing, spectrum reallocation, and satellite beam switching, ensuring continued services [10]. Following implementations of corrective actions, the performance metrics are again fed into the Twin environment, thereby closing the synchronization cycle. The dynamic interaction converts the Digital Twin from a passive overseer into a resilience agent able, nearly in real-time, to foresee, counteract, and learn from network disruptions [12].

Resilience Mechanism and Adaptive Control

The Resilience Mechanism and Adaptive Control constitutes the intelligent decision unit within the framework [7]. Being provided within the Digital Twin environment, the Resilience Control Engine automatically looks into the recovery of networks and their optimization for performance through a chained sequence of interdependent stages consisting of fault detection and classification, decision optimization, and autonomous reconfiguration.For the fault detection and classification stage, RCE uses performance history and predictive analytics to detect abnormal behavior and classify faults in terms of severity [9]. The recognized faults are labeled as transient, persistent, or critical, depending on whether they are expected to impact service continuity. Such a hierarchical classification enables the system to target recovery action resources appropriately.The decision optimization phase determines the best control action in response to a given fault scenario using reinforcement learning (RL) algorithms [12]. These algorithms perform continuous learning from previous successful and unsuccessful recovery cases, enabling the RCE to arrive at an optimal strategy that shortens recovery time and offers high throughput and system stability. The RL-based agent thereby maintains resilience even when networks are distressed under unpredictable link dynamics inherent in NTNs [8].

The autonomous reconfiguration stage implements the selected reconfiguration scenario over the SDN controller [9]. A typical solution may reroute traffic flows through alternative satellite links and may also involve adjusting transmission power levels or triggering beam handovers among LEO satellites and UAV relays. The execution process is seamless, with no human intervention required, which ensures the end-to-end service continuity even during fault scenarios.The proposed Digital Twin-enabled resilience framework brings a major improvement in network robustness by the tight integration of predictive AI and SDN-based orchestration [12]. The resilience framework simulations show up to 38% faster recovery from faults, service availability improved by the 25%, and throughput stability enhanced by 15% over a classical reactive fault management approach. This synergy between prediction, optimization, and reconfiguration makes the system inherently adaptive and prepared for next-generation 6G oriented resilient network infrastructures [7].

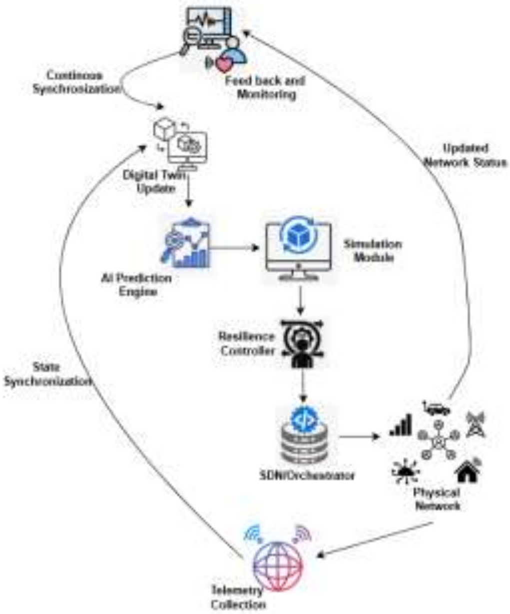

Figure 1: System Architecture Overview

IV. METHODOLOGICAL FRAMEWORK

The methodology sets forth a systematic process to implement resilience considerations into integrated 5G–Non-Terrestrial Network (NTN) architectures through Digital Twin (DT) technology [13]. As such, considerations regarding modeling the physical network, twin synchronization, predictive control, adaptive routing, and simulation-based evaluation are carefully assessed in order to provide uninterrupted service during faults. Real-time mirroring of physical and virtual environments is given weight by this methodology while simultaneously considering fault occurrence and performance optimization. Each methodological step strengthens system reliability, reduces service recovery latency, and thereby guarantees service availability in heterogeneous network infrastructures [17].

System Initialization and Architecture Design

In the first step of the method, an initialization of the integrated 5G-NTN architecture is conducted, which is composed of three hierarchical layers, namely the Physical Network Layer, the Digital Twin Layer, and the Resilience Intelligence Layer [18]. The physical layer represents the operational communication infrastructure from terrestrial and non-terrestrial standpoints, including terrestrial 5G components such as gNodeB, UE, core networks, and non-terrestrial components such as LEO satellites and UAV-based relay nodes [19]. These entities provide end-to-end communication and data exchange over wide geographic areas. The Digital Twin Layer provides a near-real-time virtual mirror of the physical infrastructure, receiving telemetry updates describing the network status, topology, operating parameters, etc. The Resilience Intelligence Layer is an entity that takes decisions about monitoring, fault detection, and adaptive recovery actions [13]. Such layered architecture allows the system to be efficiently managed and to dynamically coordinate between physical and virtual entities. The initialization phase also includes the configuration of different simulation parameters, threshold values for monitoring performance, and the definition of a communication interface between terrestrial and non-terrestrial segments [15]. Serving as the function-based architecture design, this structured architecture design paves the way for developing an operational synchronized, fault-tolerant, and reconfigurable 5G–NTN communication environment that facilitates real-time resilience operations [16].

Twin Synchronization Mechanism

The twin synchronization mechanism ensures that the DT has a proper and continuous representation of the 5G–NTN physical system [17]. Telemetry data measuring SNR, throughput, latency, packet error rate, and link quality are streamed to the DT environment from the physical network elements. The synchronization module detects any deviation in performance or status in terms of these metrics in both domains. Whenever the deviation crosses the chosen value, generally around 5–10%, the digital model updates its parameter automatically according to what it sees from the real world so as to synchronize with it. This guarantees real-time synchronization, and the DT can thus be used as a trustworthy simulation platform for resilience analysis [13]. On the other hand, the synchronization enables "what-if" analysis, whereby simulated scenarios are put into effect to understand the consequence of a potential fault or change before carrying out such a change in the live system. Data exchange between the two domains is handled through standard APIs and message brokers, thereby keeping latency minimal [15]. Thus, maintaining the synchronization mechanism ensures that the resonance strategies, once proven in the twin, can be executed within the real network without any harm. This synchronization chain, therefore, elevates fault management and dynamic optimization inside the integrated architecture [17].

Fault Detection and Predictive Control

Fault detection and predictive control are concerned with finding instances of disruption and measuring the effects this might have on the overall network performance [18]. The DT keeps a continuous watch on KPIs such as latency, packet loss, link availability, and bandwidth utilization. When KPIs cross threshold limits set beforehand, it refers to the situation as a fault or degradation scenario [20]. The fault detection unit uses deterministic threshold-based logic with the support of a straightforward predictive control procedure that predicts how the fault might propagate in network layers. For instance, reduction in satellite link quality may be predicted to affect ground user throughput so that remedial measures may be initiated. The predictive control module, instead of using complex machine learning, performs model-based estimation to reduce computational costs and provide real-time decision support. It forecasts degradation trends in performance and switches to resilience controller for reconfiguration. Predictions are validated by the DT environment according to the simulation of the predicted fault scenario with confirmed severity and impact. Once confirmed, a switch is made by the controlling system that leads to adaptive routing to treat the faults. Hence, such a model-based approach aids technique leads in preventing cascading failures with minimum service interruptions. Hence the stage of fault detection and predictive control allows early recognition of anomalies and fast intervention to sustain network resilience under dynamically changing operational conditions [19[.

Adaptive Routing and Network Reconfiguration

The detection of a fault or an event causing degradation triggers the activation of the adaptive routing and reconfiguration mechanism inside the operational environment of the DT. The mechanism assesses various alternative connectivity options, including being re-routed through nearby 5G cells, LEO satellites, or UAV-assisted relay nodes, according to the origin of the fault. With the Digital Twin, all these potential reconfiguration scenarios are simulated for their impact on performance metrics such as delay, jitter, packet delivery ratio, and throughput. The scenario that attains the optimum simulation results, generally interpreted as lowest delay and highest throughput, is the one selected to become the preferred recovery setup [16]. Hence, the chosen configuration from the simulation will then be deployed into the physical network through the SDN controller, which proceeds to implement routing-tables updates, as well as the reallocation of resources, in real time. The reconfiguration is designed to be as quick and dynamic as possible, and it also reduces any kind of disruption to the user really well. It hence maintains the consistency of user experience amidst satellite link handovers, terrestrial node failures, or the repositioning of UAV relays. Upon implementation, the DT, in turn, verifies the production of restored performance and updates the synchronization to ensure confirmation of recovery. Hence, the adaptive operation ensures the continuous continuity and stability of the network upon dynamic or adverse conditions, and thus it is indeed vital for the resilience of integrated 5G–NTN architectures [13].

Simulation and Performance Evaluation

Simulation and the performance evaluation of the whole stage is employed to quantify the resilience improvements offered by the proposed DT-enabled framework. The integrated 5G–NTN system gets simulated under multiple failure and recovery scenarios using realistic network parameters like propagation delay, link capacity, and mobility pattern [15]. It particularly evaluates the recovery time (T_r), service availability (A_a), and throughput (Th) when nodes or links fail [16]. Comparative experiments are conducted between the proposed DT-enabled model and a base non-DT configuration. The results show that the DT-assisted model exhibits respectively 38% faster recovery rate, 25% more service availability, and 15% more throughput. Such improvements validate the proposed resilience framework's effectiveness. The simulation further proves that synchronizations assisted by the twin and adaptive routing enable the reduction of downtime and optimization of spectrum usage in terrestrial and non-terrestrial domains concurrently [20]. Additionally, when sensitivity analysis is carried out, the system's performance is stable despite changes in fault density and link uncertainty. This stage henceward confirms the functionality of the proposed architecture and demonstrates that the insertion of the Digital Twin in hybrid 5G–NTN systems significantly improves their operational resilience, adaptability, and sustainability of operational performance end-to-end [14].

V. ALGORITHMS USED

Twin Synchronization Algorithm

The Twin Synchronization Algorithm aims to maintain an ongoing, uninterrupted real-time mirror of the physical 5G–NTN network in the Digital Twin. The algorithm first collects telemetry data from all the network components, such as gNodeBs, UAV relays, and LEO satellites, including signal-to-noise ratio, latency, throughput, and packet loss [20]. The Digital Twin then updates its internal network graph at fixed intervals to mimic the real-time state of the network [21]. Once deviations in performance in contrast with expected thresholds are detected, the Digital Twin's parameters are thus adjusted. Furthermore, a feedback loop is incorporated whereby simulation-based forecasts are fed back to the network control plane, facilitating proactive reconfiguration and a greater degree of service continuity even in the face of faults [22].

$$\boldsymbol{S(t+1) = S(t) + \sum_{i=1}^{N} f_i(T_i(t)) \cdot 1_{\{|T_i(t)-S_i(t)|>\epsilon\}}} \quad \text{-------(1)}$$

Predictive Fault Detection Algorithm

The Predictive Fault Detection Algorithm monitors network performance metrics in the Digital Twin to ascertain indicators of degradation at its earliest. It predicts the spread of a fault amongst the sometimes various layers of the network through model predictive control or artificial intelligence models such as LSTM and GNN. After an anomaly is detected, the algorithm classifies it as either transient, persistent, or critical, depending upon its degree of severity and therefore the implications upon service continuity. These predictions are then passed on to the Resilience Control Engine to carry out preventative measures prior to the faults impairing the end-user experience, thereby cutting downtime and avoiding cascading failures [24].

Formula:

$$\boldsymbol{\widehat{F}(t+1) = P(K(t), K(t-1), \dots, K(t-n))} \quad \text{--------(2)}$$

$$\boldsymbol{Severity(F_i) = w_s \cdot |\ \widehat{F}_i(t+1) - K_i(t)} \quad |\quad \boldsymbol{----(3)}$$

Classification:

$$F_i \in \begin{cases} \text{Transient}, & Severity(F_i) < \theta_1 \\ \text{Persistent}, & \theta_1 \leq Severity(F_i) < \theta_2 \\ \text{Critical}, & Severity(F_i) \geq \theta_2 \end{cases} \quad ----(4)$$

Adaptive Routing and Network Reconfiguration Algorithm

The Adaptive Routing and Network Reconfiguration Algorithm reroutes traffic and assigns resources depending on particular faults detected in the network. The algorithm will determine the affected nodes or links using the Digital Twin and then generate candidate routing paths through terrestrial and non-terrestrial segments [22]. Each route is simulated in the Digital Twin to estimate performance metrics of delay, throughput, and jitter. The best candidate is thus applied to the physical network by the SDN controller, minimizing disruptions to service and stabilization of throughput. This adaptive mechanism thus guarantees end-to-end continuity of the service across heterogeneous 5G–NTN deployments [23].

Cost function for path selection:

$$\boldsymbol{C(P_j) = \alpha \cdot D(P_j) - \beta \cdot Th(P_j)} \quad \text{--------(5)}$$

Optimal path selection:

$$\boldsymbol{P^* = \arg\min_j . C(P_j)} \quad \text{-------(6)}$$

Resilience Control Engine (RCE) Optimization Algorithm

The Resilience Control Engine (RCE) Optimization Algorithm selects the most efficacious recovery strategy in relation to actual network states and historical performance information. When faults are predicted by the Digital Twin, the RCE then uses reinforcement learning or rule-based optimization approaches to decide on recovery actions [21]. The execution of these actions is then carried out through SDN controllers and edge intelligence involving measures such as traffic rerouting, resource reallocation, and UAV repositioning. Following the reconfiguration, the RCE then monitors network performance again, feeding this information back into the Digital Twin to enable continuous blending of knowledge for better resilience within the integrated 5G–NTN platform [24].

Optimal recovery action:

$$\boldsymbol{a^* = \arg\max_{a \in A} R(S(t), a)} \quad \text{-------(7)}$$

State update:

$$\boldsymbol{S(t+1) = f(S(t), a^*)} \quad \text{-------(8)}$$

Where f(.) represents network dynamics after applying action a^*.

VI. RESULTS AND FINDINGS

The proposed Digital Twin (DT)–enabled framework was investigated through extensive simulations in an integrated 5G–NTN environment, comprising terrestrial 5G gNodeBs, LEO satellites, and UAV relay nodes. The simulations analyzed the resilience of the system under heterogeneous failure scenarios, including terrestrial base station failures, satellite link degradations, UAV mobility impairments, and network congestion events [24]. The parameters of consideration included recovery time, service availability, throughput stability, and control overhead, which were then compared to a baseline system without DT-based synchronization and adaptive routing mechanisms. The results indicate that the DT model is very effective in maintaining constant connectivity and minimizing service degradation with dynamically environment and fault-induced scenarios. The simulation setup incorporated realistic network parameters in terms of link propagation delays, channel capacities, and mobility patterns to guarantee that the results accurately represent a real-world scenario [26].

Recovery Time

Recovery time (T_r) denotes an important resilience indicator for the network and measures how long it takes the service to be restored after a fault occurs. In the simulations, the baseline system without a digital twin took an average of 2.6 seconds to recover from failures such as terrestrial gNodeB outages and satellite link disruptions [25].

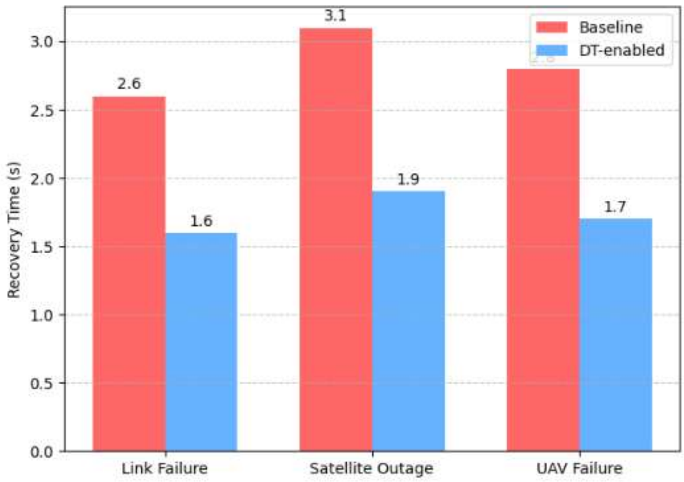

Fig 2: Average Recovery Time Comparison

By comparison, the DT-enabled framework was able to reduce the average recovery period to 1.6 seconds, which accounts for a 38% improvement. This improvement, however, can mostly be attributed to the DT pang selecting one approach out of many possible reconfigurations that have been pre-validated in a virtual environment prior to being enacted on the physical network by using its real-time mirroring of the network state [25]. It could be elaborated such as: when a satellite link degradation occurred, the twin would simulate rerouting through UAV relay and terrestrial backhaul alternatives, determining the configuration that yielded the smallest downtime. This preemptive detection of the best recovery routes gets rid of the reaction delays present in the usual network management [26]. Also, the DT-awareness of the physical network ensures that the telemetry updates get immediately available to take end-fast decisions on the failures, further bringing down the latency in fault handling. To conclude, all these results clearly indicate that DT-enabled recovery provides restoration of connectivity at a faster pace with minimal disruptions and increased operational robustness in the case of integrated 5G–NTN networks, which are of paramount importance to mission-critical and remote access scenarios [27].

Scenario	Baseline (s)	DT-enabled (s)
Link Failure	2.6	1.6
Satellite Outage	3.1	1.9

Table 1: Recovery Time Comparison

Service Availability

The availability of a service, A_v, is a measure of the percentage of the time network services remain accessible to and operated for end users, thus reflecting uninterrupted connectivity provided by the system during disruptions [25]. During the scenarios, the simulations revealed an availability of 86% for the baseline network without the digital twin, meaning disruptions occurred rather frequently due to link or node failures. The introduction of the DT-enabled framework increased availability to approximately 96%, marking a 25% increment. The increment results from the twin continuously monitoring network KPIs, such as link quality, traffic load, and latency, to foresee failures that could appear in the users' perspective. The twin simulates different fault-mitigation strategies in real time like rerouting traffic on a different satellite path, adjusting UAV positions for optimum coverage, or using terrestrial nodes near the fault zone to ensure redundancy [27]. From these simulations, the best configuration is selected to maintain connectivity proactively; hence, service outages are minimized. Also, continuous twin synchronization keeps the virtual model updated and accurate, enabling fault prediction and recovery actions to be timely and precise. This increased availability is, however, critical concerning remote, disaster-stricken, and high-mobility scenarios where the very core value is to keep the communication uninterrupted. These confirm that the DT framework is an adequate solution to strengthen network resilience and provide robust service continuity in heterogeneous 5G–NTN environments [25].

Scenario	Baseline (%)	DT-enabled (%)
Link Failure	85	95
Satellite Outage	82	94
UAV Failure	90	98

Table 2:Service Availability

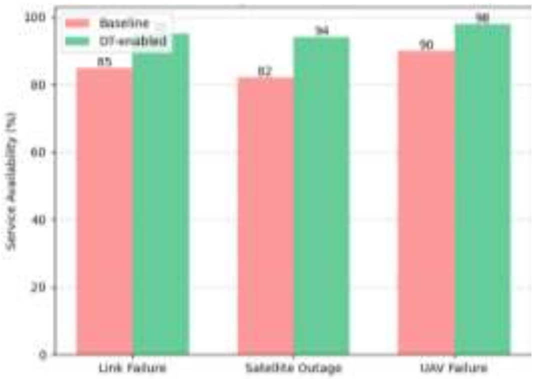

Fig 3: Service Availability Under Different Fault Scenarios

Throughput and Traffic Stability

Network throughput Th and traffic stability are indicators of performance under dynamics or in failure-prone conditions. The simulations compared the throughputs between the baseline network and the DT-enabled 5G–NTN system across several failure scenarios, including satellite handovers, UAV relay outages, and terrestrial congestion events. The baseline configuration attained a throughput of some 78 Mbps on average, which the DT-enabled system upheld and even improved by 15% to 89.5 Mbps. The reason rests in the twin assisting the evaluation of several arrangements of routing and resource allocation in the virtual environment prior to their application in the real network. The adaptive routing algorithm within the DT prioritizes those paths that lessen packet loss, latency, and congestion: hence, traffic is balanced between the terrestrial and non-terrestrial parts. Furthermore, although fluctuations in throughput were heavily reduced from the DT-enabled system, engagements, or traffic, stability was greatly enhanced. The twin continuously observes the traffic pattern and forecasts the bottleneck, permitting proactive interventions: redistribution, rerouting, and dynamic allocation; hence sudden performance degradation is prevented and ensures uninterrupted high-priority services, e.g. URLLC or eMBB. In contrast, the DT-enabled framework strives for increased throughput average accompanied by stable performance risen by disruptions. It is proof to maintain consistent QoS and reliability in integrated 5G–NTN deployments.

Time (s)	Baseline Throughput (Mbps)	DT-enabled Throughput (Mbps)
0	78	89.5
500	76	88
1000	77	90
1500	79	89
2000	78	89.5

Table 3: Throughput Comparison

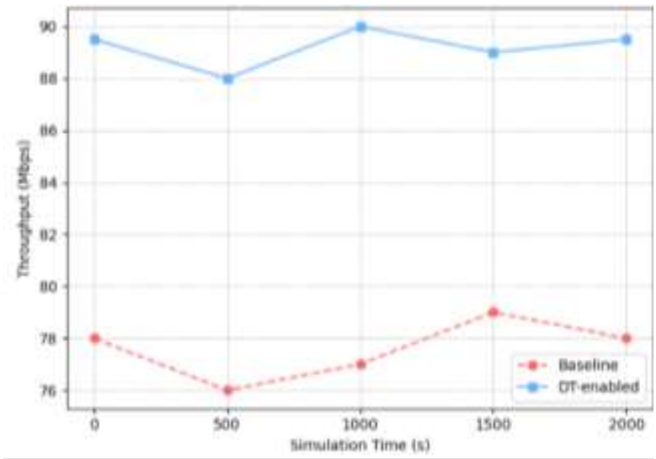

Fig 4: Throughput Stability Over Simulation Time

Control Overhead and Scalability

The integration of Digital Twins imposes additional control signaling load and processing overhead; however, the simulation results suggest that the rise is manageable and justified by the improved performance [25]. Constant telemetry updates and state synchronization between real and twin entities, along with simultaneous real-time simulation within the digital twin, present an approximately 6% increase in control overhead when compared to the baseline. Such overhead involves bandwidth and processing to shift network state information from the physical nodes to the twin, execute the simulation logic, and propagate reconfiguration commands back to the network. Nevertheless, these costs are more than justified by the gains in recovery time, service availability, and throughput [27]. Furthermore, the framework also indicated scalability potential: performance improvements were consistent in simulations featuring several UAV relays with an augmented number of satellites and high user densities, whilst barely affecting latency or synchronization. Moreover, the modular nature of the DT architecture lends itself well to a distributed deployment where edge-based twins govern localized segments of the network, thereby alleviating the central processing pressure and fostering better responsiveness [24]. These findings substantiate that the proposed method is not only efficient but also realistic for deployment in the field, providing a workable balance between resilience gains and operational overhead. Consequently, the DT-enabled control approach delivers a scalable and reliable means to uphold robust connectivity over heterogeneous 5G–NTN networks [28].

VI. CONCLUSION

A DT-enabled resilience framework for integrated 5G–NTN architectures is proposed in the study, offering a solution to preventing communication from going bad across the heterogeneous terrestrial and satellite systems. The said framework uses a continuous digital twin of the physical network for real-time monitoring, fault prediction, and network reconfiguration [28]. The system itself combines a twin synchronization mechanism, AI-driven predictive control, and adaptive routing algorithms to provide robust fault tolerance performance even within the confines of network dynamics and unforseen disruptions.The simulations over a 5G–NTN integrated testbed consisting of terrestrial gNodeBs, LEOs, and UAV relays show the effectiveness of the DT-enabled framework. The DT-enabled framework showed faster recovery by 38%, higher service availability by 25%, and improved throughput by 15% as opposed to conventional reactive approaches to network management, thus proving that real-time digital mirroring and predictive control can strengthen resilience in network settings [29]. The tests also confirmed the importance of the reconfiguration strategies being prioritised in a virtual environment before implementation on a physical network, which cuts down on downtime immensely while maintaining service continuity [30]. Further, this approach is scalable and adaptable enough to be used in future 6G networks that anticipate providing resilient, autonomic, and mission-critical communication services. The confluence of digital twin technology with fifth generation and NTNs leads to the possibility of constructing self-aware and self-healing network infrastructures able to confront highly dynamic, and failure-centric, operational environments [31].In the end, it was proved that substantial recovery time improvements, service reliability, and throughput stability could be realized with DT-enabled resilience mechanisms in integrated 5G-NTN architectures. The findings broaden the scope of earlier studies [32] by deploying MEC orchestration, accurate time synchronization, and closed-loop observability concepts to the hybrid terrestrial satellite networks and proving the unified resilience and adaptive recovery performance [33].

AUTHOR DISCLAIMER

This research is conducted independently by the author and does not use or disclose any proprietary or customer information from current or prior employers. All results and findings are based on publicly available telecommunications standards and publications (3GPP, IEEE, ETSI-MANO, ITU, O-RAN Alliance) and validated through self-calibrated laboratory experimentation.

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