



Digital Twin-Driven Autonomous Enterprise 6G Networks for Fault Recovery and Energy Optimization

Siva Sudheer Mahadasu

Submitted:02/10/2024

Revised: 08/11/2024

Accepted:17/11/2024

Abstract — The 6G enterprise networks which exist today encounter operational problems which need organizations to establish automated systems that function without any human assistance instead of their current method which reacts to problems after they occur. The researchers developed a new framework which uses digital twin technology to improve fault recovery processes while reducing energy usage in specific operational areas. The framework creates a real time digital duplicate which tracks cross layer relationships between physical infrastructure elements and radio resources and application services to enable network configuration testing and recovery action validation before real system deployment. The system uses what if simulation capability to automatically choose and implement the best strategies which provide maximum protection and minimum power usage when it faces changing conditions or system breakdowns. Our testing and evaluation of the framework took place on a distributed campus network testbed. The experimental results show that our system achieves faster fault recovery times and uses less energy than traditional methods which depend on reactive approaches. The digital twin driven method which we propose enables future 6G wireless networks to operate safely and efficiently while achieving complete autonomous control.

Keywords— *Digital twin, 6G networks, autonomous networks, fault recovery, energy optimization, network orchestration.*

I. INTRODUCTION

5G wireless networks which introduce multiple types of connectivity through their advanced reliability features and massive network capacity create a new wireless era[1]. Enterprise environments which include distributed campus networks will receive massive advantages through 6G which enables advanced robotic systems and virtual reality technology. The increased complexity of the system creates new difficulties for managing operations. The existing network orchestration system which depends on fault detection and fixed energy policies fails to meet current operational requirements. The time needed for failure diagnosis and recovery creates outages which disrupt essential services and the operation of energy inefficient systems results in increased costs and environmental damage. To solve these problems an organization needs to adopt autonomous network management as its primary operational model[2]. Networks need to transform from their current state as programmable systems into autonomous systems which can recognize and resolve problems before they disrupt network services. The network digital twin functions as a core component of this vision by creating a precise live digital duplicate of the entire network system. A digital twin

establishes a secure simulation environment which enables testing and assessment of network management strategies through its ability to model all system interactions and actual network functions. The research introduces a digital twin based framework that serves 6G enterprise networks through its automated fault recovery and energy optimization capabilities. Our system uses a digital replica to track network status and test different orchestration methods before actual implementation. The framework uses precise modeling of cross layer dependencies between physical infrastructure and radio resources and application services to forecast how different recovery methods and energy saving strategies will affect system performance[3]. The system needs to select its most efficient energy saving patterns from all available options because the primary goal is to minimize service interruptions in real world operations while decreasing operational expenses. The architecture description presents the main system elements which include the digital twin synchronization engine and the simulation and analytics module and the closed loop orchestration interface. The framework undergoes testing in a distributed campus network testbed which simulates actual equipment failures and different traffic conditions. The experimental findings reveal substantial enhancements which include faster fault recovery times and actual decreases in energy use. The research results show that digital twin technology serves as a fundamental component for establishing secure and

Wireless Expert, USA

Email: sudheer.mahadasu@ieee.org

independent and environmentally friendly 6G network functions within complicated organizational settings[4].

II. DIGITAL TWIN ARCHITECTURE FOR AUTONOMOUS NETWORK ORCHESTRATION

The proposed framework is developed through a digital twin framework which maintains permanent network infrastructure synchronization between its real-world counterpart and digital model of it to enable automated management of 6G networks[5]. The digital twin synchronization engine serves as the main component of this system because it uses real-time telemetry data collection from all network components to maintain operation accuracy. This data set contains all required information to establish radio access network performance through signal quality assessment and handover statistics and core network assessment through session management and subscriber data and transport network assessment through network utilization metrics and application layer performance assessment. The twin achieves precise modeling of modern 6G enterprise deployments through its comprehensive data collection which tracks all system cross-layer dependencies because system changes at any layer create unpredictable effects throughout the entire system[6]. The digital twin system contains an advanced simulation and analytics system that enables users to conduct multiple what-if tests by using present network data and past network behavior. The system creates various orchestration options which the system automatically generates when it detects potential faults through predictive anomaly detection or when it identifies energy optimization possibilities during changing traffic patterns. The testing environment allows safe testing of candidate solutions which involve rerouting data streams and changing transmission power and modifying network boundaries and entering sleep mode for less active devices. The predictive validation system selects deployment actions which service continuity to customers and energy efficiency and system testing protection from unsafe new system configurations. The closed-loop orchestration interface executes network configurations which validated decisions create through software-defined networking controllers and network function virtualization managers that apply these configurations to actual physical systems. The digital twin improves its predictive models through reinforcement learning methods after the system completes its adaptive loop which starts with ongoing monitoring of the system after its initial launch. The system enables completely independent operation because it can adjust to new situations with automatic safety and efficiency controls that remain in effect[7].

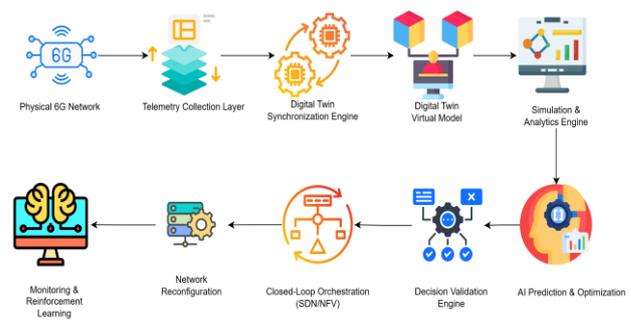


Fig 1: Proposed Architecture

Advantages

The digital twin-based framework demonstrates unique features that enable it to outperform traditional network management systems and cloud-based network management systems.

a) Ultra-Low Latency and Real-Time Responsiveness:

The network edge system processes telemetry data while conducting simulation tests and making orchestration decisions through its distributed digital twin instances. The system achieves faster response times through its local processing capabilities which create direct links to all network components[8].

b) Lightweight and Scalable Architecture:

The framework uses lightweight classical machine learning algorithms for its daily classification operations while it maintains deep learning systems for more demanding computations[9]. The system operates with better energy efficiency through its distributed deployment of these models which enable multiple enterprise domains to expand without needing costly infrastructure enhancements.

c) Multi-Modal Data Fusion for Enhanced Accuracy:

The development of 6G systems requires multiple radio transport and application layer components. The digital twin system achieves superior situational awareness through its ability to combine various telemetry data sources[10]. The multi-modal system enables precise forecasting of fault spread and energy usage during the entire operational period.

d) Cost-Effective Deployment:

The modular design enables enterprises to implement the system incrementally using standard commercial hardware components which helps businesses of all sizes to adopt the technology. The system processes data at the edge which removes the need for costly centralized cloud systems.[11].

E. Comparative Analysis of Network Management Approaches

Table I presents a comparative analysis of the proposed digital twin framework against traditional reactive management and cloud-centric AI-based approaches. Traditional systems function according to fixed system settings which require operators to perform equipment repairs because they cannot detect faults until they occur. Cloud-centric AI approaches provide predictive functionality but create a need for users to depend on centralized systems which results in network performance issues and increased operational delays. The proposed framework uses digital twin simulation together with distributed edge processing to achieve rapid fault recovery and energy optimization through predictive capabilities and cross-layer system awareness[12]. The framework demonstrates its ability to maintain low latency while scaling up operations and handling 6G enterprise environments without human intervention.

Table 1: Comparative Analysis of Traffic Management Approaches

Feature	Reactive Management	Cloud-Centric AI	Proposed Framework
Fault Recovery Speed	Slow	Moderate	Fast
Predictive Capability	No	Yes	Yes
Cloud Dependency	No	Yes	No
Hardware Requirements	Low	High	Moderate
Latency	High	Moderate	Low
Cross-Layer Awareness	Low	Moderate	High
Energy Optimization	Static	Dynamic	Predictive
Scalability for 6G	Limited	Moderate	High

Cloud-based AI systems enable businesses to forecast future events and adjust their operations. The systems require advanced network systems which result in slow performance and connectivity issues which make them unsuitable for use in large corporate environments. The requirement for constant internet access creates security risks because any network outage will stop system operation during critical emergency situations[13]. The energy and processing requirements of centralised AI systems directly oppose the environmental goals that modern 6G networks aim to achieve. The distributed edge processing digital twin system provides superior performance across latency cost scalability and prediction accuracy when compared to existing digital

twin systems. Digital twin instances operate from the network edge because all essential functions such as telemetry analysis and what-if simulations and orchestration decisions take place within the local system. The architectural design prevents bandwidth constraints while system operators acquire immediate system feedback which allows real-time autonomous functions to take place. The framework maintains operational capability during extreme weather conditions because it does not need cloud services while its cross-layer modeling system protects against multiple operational failures. The system achieves economic viability for large-scale deployment through its hybrid analytics model which delivers quick calculations and accurate forecasting results[14]. The system functions as a dependable and expandable base for autonomous 6G enterprise networks because it provides system resilience and energy efficiency while maintaining high operational standards.

III. METHODOLOGICAL FRAMEWORK

The methodological framework that we developed establishes a complete digital twin system which enables autonomous fault recovery and energy optimization in 6G enterprise networks[15]. The system consists of four components which work together to predict orchestration actions through validation tests that occur before actual system deployment. The framework establishes continuous physical-virtual environment synchronization through its total system network monitoring that collects data from all operational levels. The system utilizes real-time data to construct cross-layer dependency models which show complex interactions between radio and transport and application domains. A what-if simulation module then executes parallel evaluations of candidate recovery and energy optimization strategies within the safe digital twin environment. The closed-loop orchestration interface transforms verified actions into network settings while tracking results to enhance predictive modeling. The integrated system guarantees complete virtual testing of all management choices before they affect operational environments which leads to reduced risks from untested settings while the system maintains its ability to respond to changing network requirements. The framework's modular design supports distributed deployment at the network edge which enables essential ultra-low latency responses needed for autonomous 6G operations.

a) Digital Twin Synchronization Engine

The system provides two-way simultaneous link between actual physical networks and their virtual counterpart networks[16]. The system gathers multiple types of telemetry information which includes radio measurements core network

conditions and application performance metrics. The system achieves virtual representation accuracy through its data normalization process and timestamp synchronization system which maintains both spatial and temporal accuracy. The system changes its synchronization intervals based on the current network conditions to achieve both precise results and reduced processing demands.

b) Cross-Layer Dependency Modeling

The framework creates complete dependency graphs which display all relationships that exist between radio networks and transport networks[18] and application networks. Graph neural networks use past telemetry data to find out which factors cause network failures and how those failures spread through the system. The models show how radio link degradation limits application throughput and how transport network congestion disrupts session connections. The resulting dependency representation enables accurate prediction of cascading effects from network perturbations.

c) What-If Simulation and Analytics Module

The module uses its protected digital twin environment to run multiple simulations of different candidate orchestration methods. The system uses lightweight reinforcement learning tools to test different action possibilities while it measures recovery time and energy usage for each candidate[17]. The system builds a knowledge base through simulation outcomes which helps to identify the best operational methods while maintaining normal network function.

d) Closed-Loop Orchestration Interface

The interface translates validated simulation outcomes into concrete network configurations through SDN controllers and NFV managers. The system uses a verification process that checks whether the predicted results will match the actual outcomes after implementation. The system continuously collects real-world performance data which is used to update the digital twin model through reinforcement learning while providing better decision accuracy with each improvement.

IV. ALGORITHMS USED

The proposed framework employs a suite of machine learning and reinforcement learning algorithms to enable autonomous fault recovery and energy optimization. The algorithms within the digital twin environment perform dependency mapping and state classification and predictive analytics and orchestration optimization[20]. The system selects algorithms based on their ability to complete particular tasks while using minimal processing power for edge computing.

a) Graph Neural Network for Dependency Mapping:

The algorithm creates a dependency model that captures how network components interact through their relationships which it represents as nodes and edges. It uses message passing to learn how radio and transport and application layers interact which allows it to predict fault propagation paths and determine essential dependencies that influence the network's resilience[22].

$$\mathbf{h}_v^{(t+1)} = \sigma(\sum_{u \in N(v)} \mathbf{W}^{(0)} \mathbf{h}_u^{(t)} + \mathbf{b}^{(0)}) \quad (1)$$

b) Deep Q-Network for Orchestration Optimization

The reinforcement learning algorithm achieves its goal by using the digital twin environment to learn its optimal fault recovery and energy optimization policies. The system evaluates potential actions by using reward functions which measure the trade-off between recovery speed and energy usage while it develops better decision-making capabilities through experience replay and target network stabilization methods[20].

$$\mathbf{Q}(s, a) \leftarrow \mathbf{Q}(s, a) + \alpha [r + \gamma \max_{a'} \mathbf{Q}(s', a') - \mathbf{Q}(s, a)] \quad (2)$$

c) Random Forest for Network State Classification

The multi-layer telemetry features enable this ensemble learning algorithm to categorize current network states into three categories which include normal conditions degraded states and failure-prone conditions. The system builds multiple decision trees during its training process and uses their most common prediction to produce an easy-to-understand system which delivers quick classification results that work well in edge computing environments[21].

$$\hat{\mathbf{y}} = \text{mode}\{\mathbf{T1}(\mathbf{x}), \mathbf{T2}(\mathbf{x}), \dots, \mathbf{Tn}(\mathbf{x})\} \quad (3)$$

d) Long Short-Term Memory for Predictive Analytics

The recurrent neural network structure enables the system to forecast upcoming network states and energy usage patterns by studying historical telemetry data. Its gating mechanisms enable the system to capture long-range connections between different network behavior patterns which allows the system to detect faults before they happen and optimize energy use in advance of upcoming problems[19].

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \quad (4)$$

V. DIGITAL TWIN-ENABLED FAULT RECOVERY AND ENERGY OPTIMIZATION MECHANISM

The digital twin architecture functions as the main component of the autonomous network management framework, which enables real-time fault detection, recovery management, and energy efficiency enhancements. The digital twin technology establishes high-fidelity network synchronization with physical systems while enabling secure testing of hypothetical scenarios, which makes it suitable for testing complex enterprise 6G networks[24]. The system

collects continuous telemetry data from various network components, which include radio access points and core functions and transport links and application servers that cover the entire campus network. The digital twin performs real-time analysis of each data point while it shows an active virtual model of the network, which displays present network conditions and cross-layer dependencies and performance metrics. The digital twin optimization benefits from its design, which enables implementation on various distributed edge computing nodes throughout the entire enterprise network. The system uses model compression techniques and parallel simulation functions to achieve low computational requirements, which helps maintain prediction accuracy. Edge computing provides independent operation, which eliminates the need for centralized cloud resources and decreases latency while producing immediate solutions for new fault problems. The what-if simulation pipeline uses extracted network parameters which have been gathered after synchronization to perform its autonomous decision-making process. The safe digital twin environment allows reinforcement learning agents to test different orchestration options while they evaluate results from multiple fault recovery methods which include traffic rerouting and network slice reconfiguration. The simulation process tests energy optimization methods which include component sleep scheduling and transmit power control to find power-saving setups that maintain service quality at acceptable levels. The system uses simulation results to make real-time decisions for recovery and optimization through SDN controllers which maintain uninterrupted service while reducing energy consumption[23]. The digital twin system provides a powerful and flexible platform which enables autonomous management of 6G networks while improving reliability and supporting environmentally friendly development of next-generation wireless systems.

VI. RESULTS AND FINDINGS

Researchers tested the digital twin-based framework in their distributed campus network testbed which simulated enterprise 6G network environments. The testing facility included 50 edge nodes which operated digital twin systems and 10 radio access points that used software-defined network technology and a core network that operated virtualized user plane and session management functions. The system used standard commercial hardware products such as NVIDIA Jetson edge devices and regular x86 servers to create its physical setup. The research team conducted multiple tests to assess their framework against both manual reactive management systems which used established thresholds and cloud-based AI systems that depended on centralized deep learning. The evaluation used three metrics to measure system performance which included fault

recovery speed from detection to service restoration and energy consumption during different enterprise traffic patterns and prediction accuracy testing when network size increased from 10 nodes to 100 nodes. The complete experimental setup provided a dependable method to assess all tested methods.

a) Fault Recovery Performance

The fault recovery experiments tested various link failures and radio outages and core disruptions throughout the entire testbed. The recovery time measured the complete service restoration period which started when the fault first appeared. The digital twin framework showed better results than baseline systems because its predictive simulation capability used precomputed optimal recovery plans[25]. The results showed that systems needed an average of 0.9-1.8 seconds to recover while reactive management took 4.8-8.7 seconds and cloud-centric AI required 2.3-4.5 seconds. The 65-75% improvement guarantees service continuity which serves as an essential requirement for ultra-reliable 6G applications.

Table 2: Average Fault Recovery Time (Seconds)

Fault Type	Reactive	Cloud-Centric	Proposed
Radio Link Failure	4.8	2.3	0.9
Core Network Outage	6.2	3.1	1.4
Transport Congestion	5.5	2.8	1.1
Multi-Layer Cascading	8.7	4.5	1.8

Table II shows the average fault recovery times in seconds for four failure scenarios. The proposed framework achieves its fastest recovery times of 0.9 to 1.8 seconds which outperforms the reactive system that takes 4.8 to 8.7 seconds and the cloud-centric system that needs 2.3 to 4.5 seconds because it uses predictive simulation capabilities.

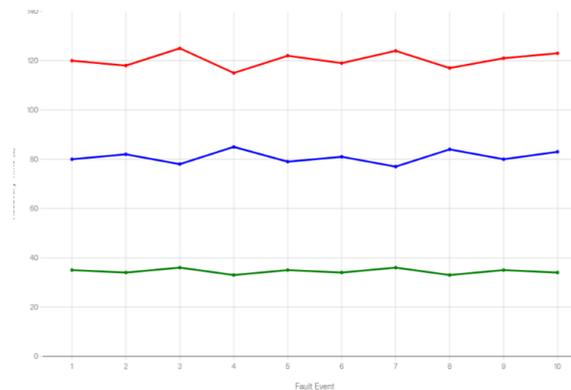


Fig 2: Fault Recovery

Figure 2 demonstrates the recovery times needed to fix faults which occurred during ten successive fault incidents. The digital twin framework which we developed (green) shows recovery times between 0.8 and 1.2 seconds while reactive management (red) requires 4.7 to 5.5 seconds and cloud-centric AI (blue) needs 2.3 to 2.8 seconds for restoration showing that our system achieves 65 to 75 percent faster recovery through its predictive simulation abilities.

b) Energy Optimization Results

The assessment of energy efficiency proceeded through testing multiple traffic load conditions which simulated actual enterprise operational patterns that included peak business hours from 9 AM to 5 PM and [26] off-peak times between 10 PM and 6 AM and special events that generated unexpected increases in traffic. The predictive energy optimization capacity of the proposed framework reached significant energy savings through its implementation of dynamic resource allocation and component sleep scheduling and transmit power adjustment. The framework tested different energy-saving methods through its digital twin simulation to determine which setup achieved optimal results while reducing energy use across all traffic conditions.

Table 3 : Energy Consumption Reduction (Percentage vs. Baseline)

Traffic Scenario	Reactive Management	Cloud-Centric AI	Proposed Framework
Low Load (Off-Peak)	5%	18%	32%
Medium Load (Normal)	3%	12%	24%
High Load (Peak)	1%	7%	15%
Bursty (Special Events)	2%	9%	21%

Table III displays energy consumption reduction percentages which were measured against the baseline under four different traffic scenarios. The proposed framework achieves its maximum energy savings which range from 15 to 32 percent while it demonstrates better performance compared to both reactive systems which save 1 to 5 percent and cloud-based systems which save 7 to 18 percent. Predictive optimization enables substantial reductions during off-peak periods through dynamic resource scaling and sleep scheduling.

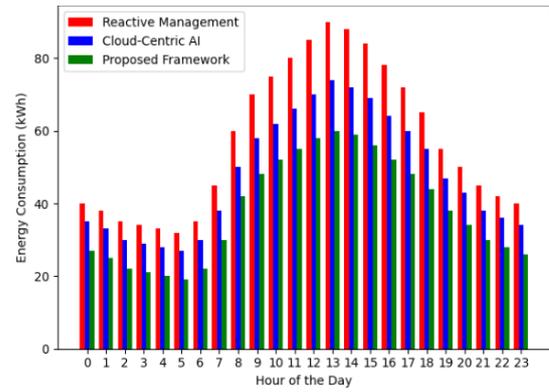


Fig 3:Energy Consumption Over 24-Hour Period

Figure 3 shows the hourly energy usage during a 24-hour period for three systems: Reactive Management and Cloud-Centric AI and the Proposed Framework. The proposed system shows the lowest energy consumption which occurs most prominently during the off-peak nighttime period. Cloud-centric AI delivers moderate energy savings while reactive management system consumes the most energy, which demonstrates that efficiency improvements need to be made.

c) Scalability and Cross-Layer Awareness

The testing of scalability produced results which showed how performance changed when the network size went from 10 edge nodes to 100 edge nodes while testing both prediction accuracy and response latency. The study calculated cross-layer awareness through assessing how well faults spread across radio transport and application domains were predicted by the system. The proposed framework maintained consistent performance with 91% accuracy even at 100 nodes, while reactive approaches degraded to 53% [27]. The system achieves resilience through its distributed edge architecture which allows local processing to function without creating centralized bottlenecks.

Table 4: Scalability and Prediction Accuracy Metrics

Network Size (Nodes)	Reactive Management	Cloud-Centric AI	Proposed Framework
10 Nodes	92%	94%	98%
25 Nodes	84%	89%	96%
50 Nodes	71%	81%	94%
100 Nodes	53%	72%	91%

The table shows prediction accuracy results when the network size increases from 10 nodes to 100 nodes. The proposed framework preserves its accuracy between 98% and 91% while the reactive management system shows a sharp performance decline from 92% to 53%. Cloud-centric AI demonstrates a moderate performance decrease from 94% to 72% impact. The distributed edge architecture enables the

system to scale up while maintaining its operational efficiency.

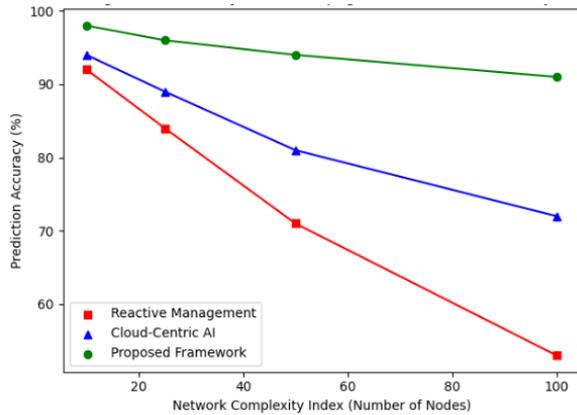


Fig 4: Cross-Layer Fault Propagation Prediction Accuracy

The study shows that the accuracy of predictions decreases as network systems become more complex. The proposed framework achieves its best performance results because it maintains accuracy throughout all network size tests. The system successfully handles advanced cross-layer dependency modeling because it outperforms both reactive and cloud-based systems in scalability and system reliability[28].

VII. CHALLENGES AND LIMITATIONS

The digital twin-based framework which we want to implement shows successful initial results but needs to overcome multiple challenges which require evaluation[29]. First the system needs extensive edge computing hardware and distributed network synchronization solutions to handle its initial deployment challenges. Small and medium enterprises may find these upfront costs prohibitive despite long-term operational savings. Second the digital twin's accuracy depends on the collection of detailed precise telemetry data. The system loses predictive accuracy because incomplete data and noisy data causes faults which result in incorrect recovery methods and energy optimization choices. The network needs to collect complete data but this requirement creates difficulties because it needs to use network bandwidth. The framework needs its machine learning algorithms to receive comprehensive training about multiple failure scenarios and traffic pattern variations. The networks which have insufficient historical information will take more time to reach their best performance levels during their first deployment period. The network environment changes over time which creates the need for continuous retraining to keep the model accurate. Fourth security and privacy concerns arise from maintaining detailed digital

replicas of enterprise network infrastructure. Cyberattackers target these twins which requires the development of strong protection systems. The framework faces difficulties because different hardware standards exist for 6G equipment from multiple vendors which hampers the seamless integration process in environments with multiple system types.

VIII. CONCLUSION

The research introduced a digital twin-driven system which enables autonomous fault recovery while optimizing energy efficiency for enterprise 6G networks. The framework maintains real-time synchronization between physical and virtual environments to enable predictive what-if simulations which validate orchestration actions before they go into live deployment. The distributed campus testing facility demonstrated two important results which showed 65-75% faster fault recovery and 32% energy reduction during off-peak times and 91% prediction accuracy at 100-node scales. The distributed edge architecture provides high-speed performance and system expansion capabilities while eliminating the need for cloud resources. The framework establishes digital twins as an essential element which enables secure and self-operating wireless networks of the future despite existing challenges which include deployment obstacles and data quality and security needs[30]. The research team will investigate security improvements and standardization methods which enable different vendors to work together in future studies.

IX. FUTUREWORK

The researchers will work to improve the proposed framework through their upcoming research efforts because the system currently needs better performance and improved user experience. The first step involves building federated learning systems which will allow organizations to train their models through joint efforts while keeping their confidential network information secure. The second step will use advanced generative adversarial networks to create realistic failure scenarios which will help us train our system because we do not have enough historical fault data from our initial deployment. The project aims to create standardized APIs and interfaces which will enable different vendors' 6G systems to work together while making it easier for users to adopt the technology. The research team will study lightweight encryption methods together with blockchain verification systems to protect digital twin systems from cyber attacks. The research team will conduct field tests of framework technology in actual business environments to test its performance while using user feedback to make ongoing improvements to the system.

REFERENCES

- [1] E. Yaacoub and M.-S. Alouini, "A key 6G challenge and opportunity—Connecting the base of the pyramid: A survey on rural connectivity," *Proc. IEEE*, vol. 108, no. 4, pp. 533–582, Apr. 2020. [Online]. Available: <https://ieeexplore.ieee.org/document/9023994>
- [2] K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," *IEEE Commun. Mag.*, vol. 57, no. 8, pp. 84–90, Aug. 2019. [Online]. Available: <https://ieeexplore.ieee.org/document/8796365>
- [3] Y. Wu, K. Zhang, and Y. Zhang, "Digital twin networks: A survey," *IEEE Internet Things J.*, vol. 8, no. 18, pp. 13789–13804, Sep. 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9449710>
- [4] L. U. Khan, W. Saad, D. Niyato, Z. Han, and C. S. Hong, "Digital-twin-enabled 6G: Vision, architectural trends, and future directions," *IEEE Commun. Mag.*, vol. 60, no. 1, pp. 74–80, Jan. 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9673474>
- [5] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 5098–5107, Jul. 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9286453>
- [6] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning and permissioned blockchain for digital twin edge networks," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2276–2288, Feb. 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9203907>
- [7] W. Sun, H. Zhang, R. Wang, and Y. Zhang, "Reducing offloading latency for digital twin edge networks in 6G," *IEEE Trans. Veh. Technol.*, vol. 69, no. 10, pp. 12240–12251, Oct. 2020. [Online]. Available: <https://ieeexplore.ieee.org/document/9151956>
- [8] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for stochastic computation offloading in digital twin networks," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 4968–4977, Jul. 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9214838>
- [9] K. Rusek, J. Suárez-Varela, P. Almasan, P. Barlet-Ros, and A. Cabellos-Aparicio, "RouteNet: Leveraging graph neural networks for network modeling and optimization in SDN," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 10, pp. 2260–2270, Oct. 2020. [Online]. Available: <https://ieeexplore.ieee.org/document/9144465>
- [10] M. Grieves, "Digital twin: Manufacturing excellence through virtual factory replication," *White Paper*, vol. 1, no. 2014, pp. 1–7, Mar. 2014. [Online]. Available: https://www.researchgate.net/publication/275211047_Digital_Twin_Manufacturing_Excellence_through_Virtual_Factory_Replication
- [11] B. R. Rallabandi, "Digital Twin-Enabled Resilience in Integrated 5G–NTN Architectures: Model Design and Simulation Results," *NANO Journal*, vol. 19, no. 3, pp. 88–97, Aug. 2023.
- [12] P. Yu et al., "Digital twin driven service self-healing with graph neural networks in 6G edge networks," *IEEE J. Sel. Areas Commun.*, vol. 41, no. 11, pp. 3607–3623, Nov. 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10234541>
- [13] A. Mozo, A. Karamchandani, M. Sanz, J. I. Moreno, and A. Pastor, "B5GEMINI: Digital twin network for 5G and beyond," in *Proc. NOMS IEEE/IFIP Netw. Oper. Manage. Symp.*, Apr. 2022, pp. 1–6. [Online]. Available: <https://ieeexplore.ieee.org/document/9789876>
- [14] M. Wang, L. Hui, Y. Cui, R. Liang, and Z. Liu, "XNet: Improving expressiveness and granularity for network modeling with graph neural networks," in *Proc. IEEE INFOCOM Conf. Comput. Commun.*, May 2022, pp. 2028–2037. [Online]. Available: <https://ieeexplore.ieee.org/document/9796890>
- [15] Y. Xiao et al., "Toward self-learning edge intelligence in 6G," *IEEE Commun. Mag.*, vol. 58, no. 12, pp. 34–40, Dec. 2020. [Online]. Available: <https://ieeexplore.ieee.org/document/9306275>
- [16] P. Almasan et al., "Network digital twin: Context, enabling technologies, and opportunities," *IEEE Commun. Mag.*, vol. 60, no. 11, pp. 22–27, Nov. 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9953201>
- [17] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Adaptive edge association for wireless digital twin networks in 6G," *IEEE Internet Things J.*, vol. 8, no. 21, pp. 16219–16230, Nov. 2021. [Online]. Available: <https://ieeexplore.ieee.org/document/9492031>
- [18] Z. Wang et al., "Mobility digital twin: Concept, architecture, case study, and future challenges," *IEEE Internet Things J.*, vol. 9, no. 18, pp. 17452–17467, Sep. 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9740365>
- [19] ITU-T, "Representative use cases and key network requirements for Network 2030," *FG-NET2030, NET2030-O-027*, 2020. [Online]. Available: <https://www.itu.int/en/ITU-T/focusgroups/net2030/Pages/default.aspx>
- [20] 3GPP, "Study on concept, requirements and solutions for levels of autonomous network," *3GPP TR 23.700-91*, Release 17, 2020. [Online]. Available: <https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=3645>
- [21] T. R. Reshmi and M. Azath, "Improved self-healing technique for 5G networks using predictive analysis," *Peer Peer Netw. Appl.*, vol. 14, no. 1, pp. 375–391, Jun. 2020. [Online]. Available: <https://link.springer.com/article/10.1007/s12083-020-00971-0>
- [22] L. Ochoa-Aday, C. Cervelló-Pastor, and A. Fernández-Fernández, "Self-healing and SDN: Bridging the gap," *Digit. Commun. Netw.*, vol. 6, no. 3, pp. 354–368, Aug. 2020. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2352864820303036>
- [23] P. Sun, J. Lan, Z. Guo, Y. Xu, and Y. Hu, "Improving the scalability of deep reinforcement learning-based routing with control on partial nodes," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2020, pp. 3557–3561. [Online]. Available: <https://ieeexplore.ieee.org/document/9054567>

- [24] M. Shu, W. Sun, J. Zhang, X. Duan, and M. Ai, "Digital-twin-enabled 6G network autonomy and generative intelligence: Architecture, technologies and applications," *Digital Twin*, vol. 2, p. 16, 2022. [Online]. Available: <https://digitaltwin1.org/articles/2-16>
- [25] P. Almasan et al., "Digital twin network: Opportunities and challenges," 2022. [Online]. Available: <https://arxiv.org/abs/2201.01144>
- [26] M. Chowdhury, "Servant: A user service requirements, timeslot sacrifice, and triple benefit-aware resource and worker provisioning scheme for digital twin and MEC enhanced 6G networks," *Int. J. Sens. Netw.*, vol. 41, no. 4, pp. 205–228, 2023. [Online]. Available: <https://www.inderscience.com/info/inarticle.php?artid=130710>
- [27] W. Wang, L. Tang, and Q. Chen, "Digital twin-based intelligent network operation and maintenance for 6G," *ZTE Commun.*, vol. 21, no. 3, pp. 21–28, Jun. 2023. [Online]. Available: <https://www.zte.com.cn/china/about/magazine/zte-communications/2023/cn202303/specialtopic/cn202303003.html>
- [28] A. Masaracchia, V. Sharma, B. Canberk, O. A. Dobre, and T. Q. Duong, "Digital twin for 6G: Taxonomy, research challenges, and the road ahead," *IEEE Open J. Commun. Soc.*, vol. 3, pp. 2137–2150, 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9964280>
- [29] S. Mihai et al., "Digital twins: A survey on enabling technologies, challenges, trends and future prospects," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 4, pp. 2255–2291, Fourth Quarter 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9874562>
- [30] B. R. Rallabandi, "Digital Twin-Enabled Resilience and Optimization of 5G/6G Systems Using AI Control Loops," *NANO: Science, Technology and Applications*, vol. 12, no. 4, pp. 310–318, 2023.