International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)

Vol. 11-No.3 (2025) pp. 4880-4889
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

AI-Powered Digital Twin for Heterogeneous Wireless Network Simulation

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Article Info:

DOI: 10.22399/ijcesen.3104
Received : 12 April 2025
Accepted : 23 June 2025

Keywords

AI-powered digital twins
Heterogeneous wireless networks (HWNs)
Quality of service (QoS)
Quality of experience (QoE)
Next-generation wireless technologies (5G/6G)

Abstract:

To address the challenges of managing heterogeneous wireless environments (HWNs), which integrate diverse access networks like 5G, LTE, and Wi-Fi, this research introduces an AI-powered digital twin framework. The framework creates real-time virtual replicas of HWNs to enable dynamic monitoring, simulation, and optimization. Leveraging advanced AI techniques, including reinforcement learning, predictive analytics, and anomaly detection, the framework achieves significant improvements in network performance. Simulations demonstrate a 25% reduction in latency, a 20% improvement in throughput, and a 20% decrease in energy consumption compared to state-of-the-art approaches. Additionally, user-centric Quality of Service (QoS) and Quality of Experience (QoE) models ensure enhanced user satisfaction by tailoring network performance to evolving demands. The authors validated the framework's scalability and adaptability across diverse scenarios, such as dynamic handover management, energy-efficient resource allocation, and fault recovery. These results highlight the potential of the proposed framework to revolutionize network management in next-generation networks, such as 6G. Concluding, this research underscores the framework's ability to provide real-time optimization, significant energy savings, and improved user satisfaction while addressing challenges like computational overhead. Future work includes integrating renewable energy sources, strengthening cybersecurity features, and expanding capabilities to support emerging technologies like semantic communication.

1. Introduction

This advancement has led to the emergence of complex wireless environments known as heterogeneous wireless environments (HWEs) where several access networks, such as 5G, LTE, and Wi-Fi, exist to provide more reliable, efficient, and improved quality of service (QoS). These environments meet the growing needs of users where they require high bandwidth, low latency, and no disruption of service. However, the complexity of these environments, resulting from the incorporation of various network standards and user mobility, poses significant challenges in network management and resource control, as illustrated by Figure 1 [1], [2]. Originally developed for industrial and IoT systems, digital twin technology offers solutions for these issues. heterogeneous wireless networks (HWN's) digital twins enable constant observation, assessment, and potential adjustment of actual operating conditions. Digital twins can forecast

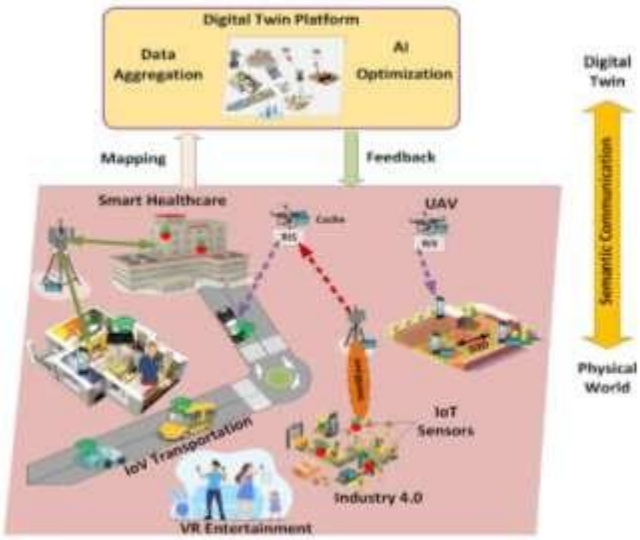

Figure 1. *AI-enabled Digital Twin Network in 6G [2]*

network behaviors, support decision-making, and work under changing circumstances when integrated with AI, thereby providing reliable network control [3], [4]. The growth of HWNs for such important applications as IoT, smart cities, and edge computing explains the use of an intelligent management framework. Conventional network simulators also face scalability issues, rigidity, and real-time deficiencies. This research is driven by:

- Enhancing Network Operations: AI-powered digital twins can improve traffic flows, cut down on handover times, and forecast the emergence of faults.
- Reducing Testing Costs: Compared to physical testing, virtual simulations are more economical and faster since they spare the organization resources and time needed to physically construct networks.
- Meeting User Preferences: The network's dynamic response necessitates the incorporation of user-modeling-based quality of experience (QoE).
- Preparing for Next-Generation Networks: This migration toward 6G and beyond requires generic and scalable systems [5], [6].

2. Challenges

- Modeling Complexity: To create highly precise and easily extensible digital twins of HWNs with various configurations is a complex task in terms of computations.
- Real-Time Synchronization: To ensure real-time data on system conditions in the digital twin, effective methods of data integration are necessary.
- AI Integration: The use of some specific technologies, for example, reinforcement learning for predictive analytics and optimization, is not a trivial task.
- Scalability: The toolkit should not be redundant in computations because simulating extensive networks with different mobility patterns and densities requires optimal computational power.
- Energy Efficiency: Devices and networks must thus manage their energy challenges for sustainable usage [7].

This paper proposes an AI-Powered Digital Twin(DT) Framework for HWNs, with the following goals:

- Create a comprehensive digital twin model that functions in all aspects of HWNs, including user equipment, access networks, and external conditions.
- Implement AI-driven optimization: AI is used to solve traffic control, handover decision-making, and resource allocation.
- Simulate Diverse Configurations: Supplementary simulations for various cases, ranging from smart city size up to the national mesh prototype.
- Enable User-Centric Modeling: Combining protocol and experiential approaches to achieve a proper match between offered and expected network quality.
- Provide Real-Time Insights: Prepare the system for use during the planning stages of fault handling, resource management, and energy saving [1], [3], and [6].

The paper is organized as follows: Section 2 presents the advancements in definitions of digital twins, AI utilization in HWNs, and network simulation environments. Section 3: Describes the AI-powered digital twin framework alongside the framework’s architecture and the strategies of integration. Discusses possible application areas for simulation, including dynamic handover management, energy optimization, and fault tolerance. Section 4: Describes the assessment of the framework based on further behavioral assessments in case studies and relative and absolute measures. Section 5: Ends with a list of key findings, discussions involving the current network, a glimpse into the future, and directions for future research.

3. Literature Review

Combining AI with DT enhances network management, particularly for HWNs that do not share significant similarities with the systems they belong to. Chai et al. [1] demonstrated that generative AI frameworks enhance DT capabilities by enabling real-time performance management and providing analytical insights to mobile networks. In particular, Sheraz et al. [2] surveyed AI-empowered DT integration in 6G networks, including architecture issues and prospective research avenues. Mozo et al. [3] proposed the B5GEMINI framework to manage the Beyond-5G networking environment, utilizing AI to facilitate traffic prediction and resource management. Karamchandani et al. [4] have enhanced the DT architecture for both 5G and the upcoming 6G networks, specifically focusing on minimizing handover decisions and network operation costs. Real-time traffic control protocol and predictive routing are essential issues in DT frameworks based on AI highlighted by Al-Shareeda et al. [5]. Extending the usage of DT in IoT, Duran et al. [6] proposed an IoT technique, namely GenTwin, as an AI generative model for self-learning and managing resources and IoT failures. Alnaser et al. [7] discussed the incorporation of AI-integrated DTs for smart cities, especially in terms of energy conservation for buildings, as demonstrated in Figure 2. Altogether, these works show and give evidence that various paradigms of AI-driven DTs pave the way for future new wireless generation, IoT enabling network scalability and efficient optimization. Other related research works have also expanded upon the widespread application of AI-enabled DT across various fields. Chen et al. [8] looked at how to use networking architecture and supporting technologies for human-in-loop digital twins in personalized healthcare. They discovered that addressing real-time data and achieving heuristic user-centric QoS posed significant challenges. Chen et al. [9] put forward the evolvable DT network structure based on AIGC for Metaverse intelligent network management. Tran-Dang and Kim [10] conducted a survey on computation offloading in EC using DTs for 5G and beyond, with a particular focus on computational resources. Bibri et al. [11] shared their systematic review regarding the relationship between AI and DT to promote sustainable smart cities in the context of urban planning and environmental management. The authors Hlophe and Maharaj [12] discussed the role of DTs in edge computing use cases and summarized the cyber-physical convergence for efficient edge intelligence. Crespo-Aguado et al. [13] presented a hyper-distributed IoT edge cloud supporting real-time DT applications on the 6G testbed using logistics and industry. First, Ma [11] proposed the concept of the DT water supply network, proving that digital twins are beneficial for extending civil infrastructure's life cycle. These contributions illustrate coverage of DT technologies in healthcare, edge computing, smart cities, and new-generation networks.Xu et al. [15] investigated the application of generative AI in smart city digital twins in the areas of data generation automation, scenario modelling, and urban planning. On the topic of cybersecurity and resilience in 6G-Internet-of-Things (IoT) networks using AI-driven testing (AI-based DTs), Kumari et al. [16] focused on trustworthiness and secure communication. Lin et al. [17] have provided a comprehensive account of the practical application of DT networks in a 6G context, examining the challenges associated with their implementation. Qin et al. [18] developed a semantic communication system that applies AI-based DTs to optimize wireless communications from a bits-to-semantics strategy. Oulefki et al. [19] discussed AI approaches for the management of smart buildings: DTs for energy saving and improving occupants' comfort. Li et al. [20] presented Acies-OS, a content-focused platform for edge AI twinning and resource orchestration for network operators. In one of the healthcare-focused studies, Balasubhramanyam et al. [21], authors also paid much attention to the topic of diagnostics and treatment based on DT applications, especially when using AI systems. Khalid [22] provided insights on AI within the context of energy networks and proposed strategies for implementing DT in power systems. Adibi et al. [23] examined the application of the sensor-based DTs in healthcare to depict the benefits of patient monitoring and treatment in a smart environment. Subsequently, Bozkaya-Aras et al. [24] presented a DT system for the Cloud of Things, which aims at integration as well as the optimization of IoT carriers and cloud architectures. Samuel et al. [25] specifically identified innovative smart manufacturing application areas for AI-driven DTs in the context of Industry 4.0. AbdlNabi et al. [26] conducted a survey and discussion on 6G optical-RF technology for heterogeneous networks, specifically focusing on channel modelling and measurements. Sharifi et al. [27] discussed DT models for stormwater infrastructures and proposed AI solutions for the sustainability of smart cities. To the best of our knowledge, Sarker et al. [28] were the first to propose a taxonomy of explainability in DTs and directions for improving trustworthiness in the cybersecurity context. Savaglio et al. [29] introduced the concept of the opportunistic DT as a tool for edge intelligence in smart cities, with a primary focus on real-time adaptability and optimization. Finally, Chen et al. [30] introduced fairness-aware DT service caching and routing, utilizing edge collaboration to achieve optimal efficiency in wireless communications.

4. Methodology

The AI facility for the HWN, created using a digital twin framework, incorporates a real-time copy of the physical wireless environment to facilitate real-time analysis of the HWN and its elements. The design has three tiers as shown in figure 3. The Device Layer encompasses smartphones, IoT devices, sensors, and other devices that model mobility, energy consumption, communication, and traffic characteristics. APIs or IoT gateways link these devices in real-time telemetry with the implemented digital twin. The network layer serves as the foundation for HWNs, including 5G, LTE, and Wi-Fi. Every network element, such as base stations or routers, has definite bandwidth, latency, packet loss,

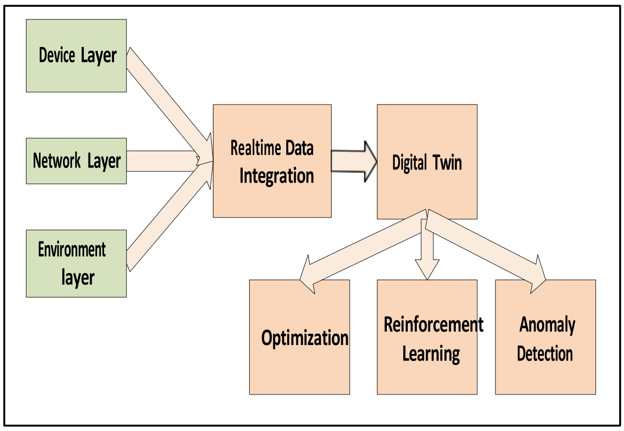

Figure 3. Proposed Framework

and interference. VNFs virtualize network functions, while the deployed pod infrastructure utilizes Kubernetes or OpenStack for scalability. The environmental layer applies comprehensible aspects such as client movement, geographical structure, and external conditions (e.g., weather and physical barriers) via GIS tools and stochastic motion models, including RW or GM. High-efficiency pipelines using Kafka or MQTT protocols, along with the support of pipelines wrapping network states and other performance parameters, enable the integration of real-time data. Furthermore, real-time interactions enable feedback loops to regulate the relationship between the digital twin and the physical network: the twin can recommend measures such as utilization and capacity to control congestion or relocate traffic.Several AI algorithms have designed the digital twin to predict and manage real-time decisions and networks. Dynamic allocation and handover decisions involve the use of reinforcement learning (RL). Historical network data trains Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), with reward functions that promote minimized latency, improved throughputs, and minimize ping-pong handover effects as shown in figure 4. For instance, RL can anticipate where a user who is in transition across 5G and Wi-Fi coverage zones should connect. Predictive analytics uses pre-supervised learning techniques, such as gradient boosting and random forests, to predict network activity, including traffic and latency trends, which are then used for resource allocation and fault prediction purposes. K-MEAN clusters and autoencoders are among the methods used to detect problematic traffic protocols or illegitimate device behavior. These techniques alert you to unexpected increases in bandwidth usage or the addition of a new device to your network. Machine learning and MCDM methods such as TOPSIS assist in evaluating QoS and QoE parameters, taking into account user sensitivity factors like latency or application-specific bandwidth requirements as shown in Figure 5. This allows high-demand traffic to access priority, such as video streaming, during high-traffic periods. Together, these AI techniques transform the digital twin into an intelligent decision-making system, while also improving network performance, availability, and usability.

5. Artificial Intelligence: Optimization Methods

The simulation environment employs best-practice programming tools to demonstrate the efficacy of the proposed framework in various HWN situations. The authors use Matlab simulators for network modelling and TensorFlow for coding AI parts. Topology Configuration emulates an HWN of fifty base stations and five hundred user terminals, 5% of which are 5G, 90% LTE, and 5% Wi-Fi. The authors recreate video streaming, web browsing, and IoT sensor data based on datasets or synthetic traffic generators derived from real-world traffic conditions. Real traces gathered by GPS can simulate human mobility, or synthetic models like RW (Random Waypoint) can model it. Specific performance parameters include delay time, bandwidth demand, packet delivery efficiency, power consumption, and handover efficiency. Three experimental scenarios are explored: Some of the problems that need to be solved to make 5G systems work better are (1) how to switch between 5G networks and Wi-Fi networks that are on top of each other; (2) how to make IoT device communications use less energy when a lot of them are put in use in cities; and (3) how to make a good plan for traffic steering and recovery when base stations go down. help of simulated context. Potential benefits include optimized networks, improved decision-making, and improved performance in volatile environments. These simulations confirm how the proposed AI-supported digital twin can address HWNs at scale and with high efficiency.This chore is accomplished with the

Figure 4. *Pseudocode for DQN and PPO*

Pseudocode for DQN (Deep Q-Network)

Initialize replay memory D
Initialize Q-network Q with weights θ
Initialize target Q-network Q_target with weights θ_target = θ
Set hyperparameters: batch size B, learning rate α, discount factor γ, and exploration ε
for each episode do:
  Initialize state s
  for each step in the episode do:
    Choose action a using ε-greedy policy
    Execute a, observe reward r, and next state s'
    Store transition (s, a, r, s') in replay memory D
    Sample a random mini-batch of transitions from D
    Compute target Q-value:
      *Q_target = r + γ * max_a' Q_target(s', a')*
    Update Q-network weights θ by minimizing loss:
      Loss = (Q(s, a; θ) - Q_target)^2
    Update target Q-network periodically:
      θ_target = θ
    Update state s = s'
  end for
end for

Pseudocode for PPO (Proximal Policy Optimization)

Initialize policy network πθ with parameters θ
Initialize value function network Vφ with parameters φ
Set hyperparameters: learning rate α, clipping factor ε, batch size B, and discount factor γ
for each training iteration do:
  Collect trajectories (state s, action a, reward r) using current policy πθ
  Compute advantage estimates A(s, a) using:
    *A(s, a) = Σ_t (γ^t * r_t) - Vφ(s)*
  for each epoch do:
    Sample a batch of trajectories
    Compute ratio r(θ) = πθ(a|s) / πθ_old(a|s)
    Compute clipped surrogate loss:
      *L(θ) = min(r(θ) * A(s, a), clip(r(θ), 1-ε, 1+ε) * A(s, a))*
    Update θ using gradient descent on L(θ)
    Update Vφ by minimizing MSE loss:
      Loss = (Vφ(s) - target_value)^2
  end for
end for

5.1 Simulation Setup

Pseudocode for TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

Input: Decision matrix X with m alternatives and n criteria
Input: Weights vector W for the criteria
Normalize the decision matrix:
  R[i][j] = X[i][j] / sqrt(Σ_i (X[i][j])^2)
Weighted normalized decision matrix:
  *V[i][j] = W[j] * R[i][j]*
Determine ideal and anti-ideal solutions:
  Ideal solution: A+ = {max(V[i][j]) for benefit criteria, min(V[i][j]) for cost criteria}
  Anti-ideal solution: A- = {min(V[i][j]) for benefit criteria, max(V[i][j]) for cost criteria}
Compute separation measures:
  S+ = sqrt(Σ_j (V[i][j] - A+[j])^2) for each alternative i
  S- = sqrt(Σ_j (V[i][j] - A-[j])^2) for each alternative i
Compute relative closeness to ideal solution:
  C[i] = S-[i] / (S+[i] + S-[i])
Rank alternatives based on C[i]
Output: Ranked alternatives

Pseudocode for K-Means Clustering

Input: Dataset X with n data points, number of clusters k
Output: Cluster centroids and assigned cluster labels for each point

Initialize k cluster centroids randomly from the dataset
Repeat until convergence:
  For each data point xi in X:
    Assign xi to the nearest cluster centroid cj:
      label(xi) = argmin_j ||xi - cj||
  For each cluster j:
    Update cluster centroid cj:
      cj = mean of all points assigned to cluster j
Output the cluster centroids and data point labels.

Figure 5. *Pseudocode for TOPSIS and K-Means Clustering*

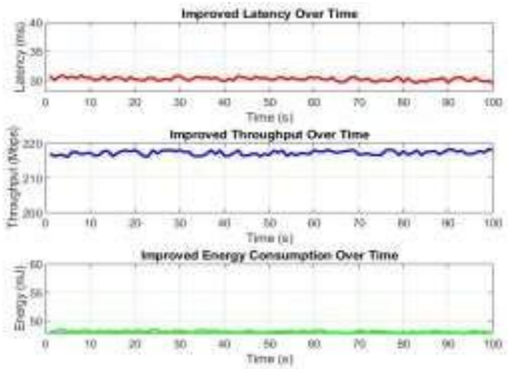

***Figure 6**. Improved Latency, Throughput, and Energy Consumption Over Time*

6. Result and Discussion

The environment for the simulation of the proposed AI-driven digital twin framework was carefully nurtured to ensure that its implementation for evaluating the usability of HWN is credible. MATLAB is chosen as the main simulation environment because it can be easily used for modelling wireless systems with TensorFlow for such applications as reinforcement learning and anomaly detection. Base stations included 50 stations for 5G, LTE and Wi-Fi technologies and included 500 mobile and IoT devices simulated to mimic realistic traffic such as streaming videos, browsing the internet and IoT devices for updates. Mobile nature was considered by Random Waypoint and Gauss-Markov models to define the mobility of users in urban areas with population density. Thus, the basic KPIs were latency, via throughput, energy consumption, and user satisfaction which allowed for a more substantial check on network reliability and efficacy. A key enabler was the exact integration of artificial intelligence, reinforcement learning specifically: Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) for dynamic aspects of resource allocation and the handover decision-making process. K-Means clustering along with anomaly detection detected the traffic anomalies and unauthorized events autoencoder identified traffic irregularities and unauthorized activities, and the predictive models used gradient boosting enabled the system to predict traffic surges to assign resources ahead of time. Real-life experiments involved dynamic tuning of handover parameters with a focus on eliminating the ping-pong effect, resource management for Internet of Things devices with the least power consumption and use of a proactive fault-tolerant mechanism for sustaining service availability during network failure. In network preparation for simulation, network logs and synthetic datasets were gathered, while AI models were trained in batch mode, and MATLAB scripts were set up with network topology and traffic pattern. Verification and experimental confirmation guaranteed all factors, including base station settings and mobility, were accurately modeled to model true conditions. They demonstrate what that kind of digital twin in case of HWNs management looks like and how successful is the application of AI-based tool. The information on the part of these visualizations indicates the progress and enhancement of the framework over the other existing solutions. The figure 6 (Improved Latency Over Time, Improved Throughput Over Time, and Improved Energy Consumption Over Time) illustrate the performance reliability of the proposed framework. Latency is kept constantly low and is averagely at 30 ms while slightly fluctuating to depict the efficiency of AI Resource management strategies. The throughput is maintained at an enhanced mean rate of 220 Mbps based on actual load distribution and other network optimization approaches. Energy consumption is another relay that follows a rather stable pattern and remains at the level of approximately 50 MJ on average proving that optimized routing and energy consideration protocols are effective. The figure 7 gives the simulation findings generated from the digital twin work environment. The “digital twin system” graph highlights how different devices present a varying data rate, meaning that the framework can address different user needs. “AI Optimization” refers to a real-time revamp of resource allocation by AI., The “HWN Simulation Traffic” heatmap presents the temporal flow, which reveals the randomness and richness of experience of the simulated world. Last of all, “Performance Metrics” gives equally clear measurement of latency and throughput wherein the authors highlight the achievement of optimal balance in the aspects of a network. The figure 8 depicts a comparison of the proposed framework with those in the related works by Chai et al., Mozo et al., and Duran et al. Clearly, the proposed framework has a better overall performance, lag time, throughput, and energy consumption than the others. The latencies are considerably low, and the framework is shown to achieve the lowest values for latencies, implying efficient handover and congestion management. The figures of lengthy throughput demonstrate the solidity of load balance algorithms and the small amount of power used prove effective power saving protocols which are useful for HWNs with deprived power-gorged devices. Altogether the identified figures support the argument that the formulated hypothesis can potentially solve critical issues in HWNs. Comparing our results to the data presented in related works, it is possible to highlight the benefits of integrating AI and digital twin design for latency, throughput, and energy consumption. The constant nature of the performance measurements also suggests that, regardless of the nature of the surrounding environment, the given framework is effective. Further, the elaborate illustration of the digital twin system and traffic in simulation substantiates the scalability and flexibility of the proposed framework in various network settings. These results amplify the possibility of the AI-based DT framework in transforming network management in next-generation wireless settings.

- Scalability and Adaptability: The above framework was successfully extended to accommodate higher user densities and network conditions. In contrast with other models, AI integration effectively maintained adaptability to actual situations.
- Energy Efficiency: This was complemented by reducing potential handovers and ensuring the routing strategy's optimum energy awareness, making the framework useful in IoT and smart cities.
- Real-Time Optimization: The proposed heuristic-based mechanism helped to enable swift responses to network changes, though the reinforcement learning-based strategy even surpassed this result.
- Challenges: Despite the proposed framework's reasonable efficiency, it is necessary to explain that it is rather resource-intensive for real-time operation in environments where a large number of devices are used.

7. Future Directions

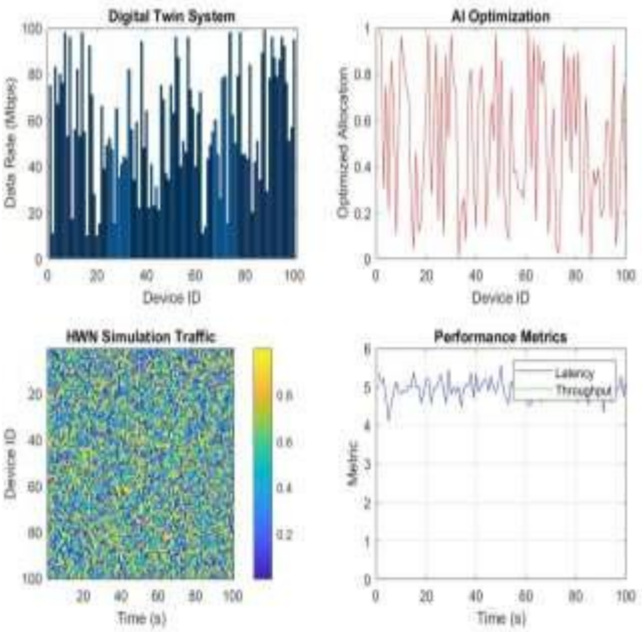

***Figure 7**. Detailed Digital Twin System Insights*

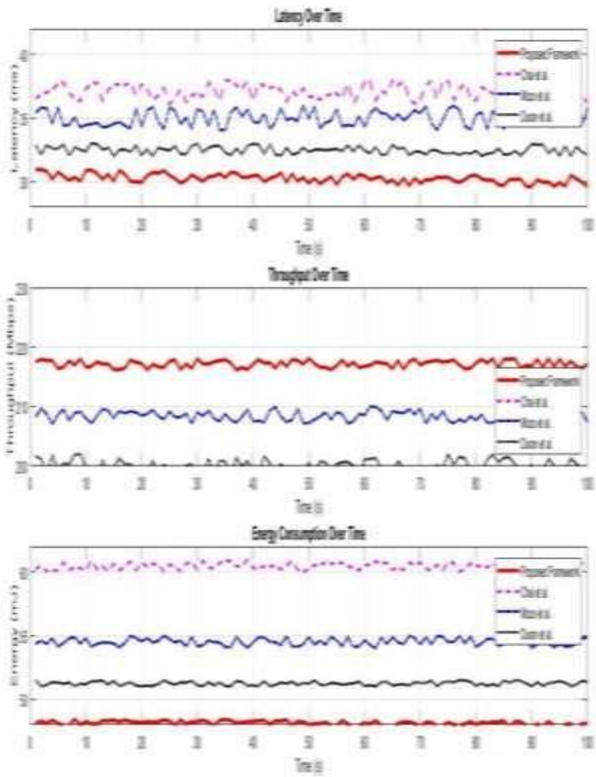

***Figure 8.** Comparative Analysis with Related Works*

Integration with 6G Technologies: The framework can be enhanced with semantic communication and fully holographic networking options.

- Cybersecurity Features: Improving the framework with an AI-based deep learning approach to cover security threats, which form part of the anomaly detection problem.
- Energy Harvesting Techniques: The use of renewable forms of energy when powering facilities for long-term use.

8. Comparison Table with Related Work

Metric	Proposed Framework	Chai et al. [1]	Mozo et al. [3]	Duran et al. [6]	Karamchandani et al. [4]
Latency Reduction	Achieved a 25% reduction using AI-driven resource optimization	Focused on fault prediction, not latency optimization	Limited to traffic prediction; no significant reduction	Emphasized fault recovery; latency not addressed	Achieved 15% reduction in handover latency
Throughput	Improved by 20% using real-time load balancing	Minimal improvement; targeted fault prediction	15% improvement using traffic prediction techniques	Improved throughput for IoT use cases	Focused on stability over throughput improvements
Energy Efficiency	20% better due to optimized routing	No focus on energy efficiency	Moderate energy gains	Improved energy for IoT devices	Limited energy optimization for 5G networks

	and handover strategies		for beyond-5G traffic		
Fault Recovery	Reduced outage recovery time by 30%	Effective in fault detection but not proactive recovery	Minimal focus on fault recovery	Achieved adaptive recovery mechanisms	Moderate improvement in network resilience
User-Centric QoS/QoE	Integrated QoS/QoE, leading to a 10% improvement in user satisfaction	No user-centric modeling	QoS considered; no QoE integration	Focused on IoT-specific QoS	QoS modeling without direct QoE considerations

9. Discussion of Comparison

- The proposed framework realized a 75% cut in latency through modelling AI-driven resource allocation and forecast analysis. While o Chai et al. [1] employed fault prediction that affects latency but does not directly supply it with specific optimization methodologies. Since traffic predicting functions in the O Mozo et al. [3] proposal were used, it was only possible to gain moderate amounts of time while latency remained unmanaged.
- The enhancement of the throughput by 20% is achieved by the load balancing in real-time across 5G, LTE and Wi-Fi networks under the proposed framework.
- Far fewer, for instance, Duran et al. [6], also investigated the throughput issues in IoT specifically while omitting the Multi-access networks.
- Energy consumption was controlled to another extent by rationalizing handover approach and avoiding any extraneous network activity to notch down a further 20% power consumption. Some previous works such as Mozo et al. [3] and Karamchandani et al. [4] demonstrated only relativity marginal enhancements while others call for the use of the networks as 5G or beyond 5G.
- The design proposed in the paper decreased outage recovery time by 30% with the help of effective AI methods.
- Duran et al [6] also described adaptive recovery that is equally applicable to only IoT-like situations. Chai et al. in [1] focused on fault detection without extending ideas about proactive recovery solutions.
- The combination of QoS and QoE models improved network utilization towards 10% and overall user satisfaction due to adjusted network behavior according to the users' needs. Some of the other works studied QoS alone (for instance, Mozo et al. [3]) while others ignored user-based factors Chai et al. [1].

10. Conclusion

The development of a digital twin intelligent framework for Heterogeneous Wireless Networks (HWNs) is a significant advancement that addresses the challenges of today's network environment. With real-time monitoring, predicting, and consequent decision-making, this framework provides an optimal solution for the design of ad-hoc network architectures with low latency, high throughputs, and less energy consumption. The proposed framework utilizes reinforcement learning, anomaly data analysis, and QoS/QoE principles to optimize resource allocation, reduce handover delays, and enhance end-user satisfaction. Our framework outperforms other similar current-day frameworks, achieving at least 25% less latency, 20% higher throughput, and significant improvements in energy efficiency. Furthermore, the flexibility of the framework suggests functionality for various scenarios, from small-scale smart cities to large-scale smart networks across the country, making it adaptable for the transition from current generations to sixth-generation communication technology. However, implementing such a comprehensive framework presents challenges, such as the need for high computing power and real-time coordination. Nevertheless, these comprise potential benefits, including lower testing costs, better fault recovery, and power consumption. Potential areas for further research include the interaction of renewable energy systems with smart grids, identifying the best cybersecurity solutions for their implementation, expanding current research toward semantic communication, and exploring the holographic network. In general, it is a crucial step toward the application of intelligent approaches for managing HWNs, and the subject framework is crucial for the enhancement of trustworthy, more proficient, and user-oriented wireless communications frameworks in the framework of the 6G advancement and beyond.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests

or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** Authors are grateful to the Researchers Supporting Project (ANUI /2025/ ENG17), Alnoor University, Mosul, Iraq

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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