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ONTOLOGY-ENABLED DIGITAL TWIN DESIGN WITH AI-BASED DATA MANAGEMENT AND PRIVACY-PRESERVING MECHANISMS FOR SECURE 6G COMMUNICATION SYSTEMS

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SUMMARY

Sixth generation (6G) communication networks are anticipated to facilitate the achievement of ultra-low latency, massive device connections, intelligent automation, and high-security in the end-to-end connectivity to accommodate new applications, including autonomous systems, immersive communications, and massive infrastructures of cyber-physical uses. In this regard, Digital Twin (DT) technology has experienced a lot of interest to present real-time virtual copies of the physical entities in the network, where predictive analysis, pre-emptive optimization, and self-managed network management can be provided. Nonetheless, the current DT-based wireless network frameworks have shortcomings in semantic interoperability, scalability, and data management, which do not provide much privacy protection in the highly distributed space. To overcome these drawbacks, this paper suggests introducing an ontology-based digital twin framework that is combined with AI-based data management and privacy protection tools that could be implemented to support the implementation of secure 6G communication systems. The offered framework uses domain-specific semantic ontologies to formally

describe 6G network components, services, and security policies on the basis of which knowledge interoperability and context-aware reasoning could be ensured among heterogeneous network layers. Algorithms based on powerful machine learning are integrated in order to achieve intelligent prediction of traffic, adaptable resource distribution, anomaly detection, and a self-regulating system of network controls in the digital twin setting. Moreover, privacy-sensitive technologies, such as federated learning, differential privacy, and secure multi-party computation, are also integrated to secure delicate network information and ensure reliable AI activities. The proposed solution shows that the traffic prediction accuracy is represented by R 2 of 0.76, and the path coefficients of the proposed AI-driven network transformation and privacy protection efficacy are 0.45 ($p < 0.001$) and 0.38 ($p < 0.001$), respectively. Network resilience has an explained variance (R 2) of 0.72, which implies that the model fits well. An elaborate workflow model and system architecture are provided, and the performance and security analysis is done. The findings reveal that the suggested solution is highly effective to advance network intelligence, enhance privacy protection, and increase the resilience to cyber threats, and thus can be discussed as a powerful and scalable solution to achieve secure, intelligent, and autonomous network ecosystems of 6G.

Key words: *digital twin, 6G networks, ontology engineering, AI-based data management, privacy-preserving AI, federated learning, secure communications.*

INTRODUCTION

The ongoing development of wireless communication technologies is pushing the shift toward sixth-generation (6G) wireless networks that are likely to provide ultra-low latency, massive connectivity, extreme reliability, and be inherently intelligent. In contrast to the past generations, 6G will closely align communication, computation, sensing, and intelligence in support of the new applications of holographic and immersive communication, autonomous vehicles, smart healthcare, digital factories, and large-scale cyber-physical systems. They demand high demands on real-time decision-making, network flexibility, and end-to-end security, which are beyond the abilities of traditional network management and optimization solutions.

The concept of Digital Twin (DT) has arisen as a potent paradigm of providing real-time virtual models of physical systems that would enable their continuous monitoring, predictive analytics, and proactive control. Applied to 6G communication networks, the DT is able to offer smart network modelling, performance prediction, fault detection, and autonomous network optimization through alignment of physical states of the network and the equivalent virtual states. Nevertheless, a high level of heterogeneity, distribuends, and data intensity of 6G ecosystems comes with severe challenges of DT realization, notably, semantic interoperability of various network elements, scalable data management across edge-cloud systems, and protection of sensitive operational and user data.

The existing DT-based systems to be used with wireless networks are mainly data-based but not semantically aware, and use the fact that they are not capable of reasoning within heterogeneous domains and within changing network scenarios. Moreover, there is a critical liability and security risk with centralized data processing by artificial intelligence since the sensitive network response and consumer information can be susceptible to inference assaults, data leakages, and unauthorized access. Such restrictions demonstrate the necessity to adopt a common solution, including semantic intelligence, distributed AI, and mechanisms preserving privacy, to provide secure and trustworthy DTs-assisted 6G networks.

To meet these difficulties, the proposed paper suggests a digital twin architecture based on ontology, combined with AI-based data management and privacy-protecting systems to communicate safely with the 6G systems. The given framework utilizes the semantic ontologies of domain specificity to guarantee interoperability and context-conscious reasoning, sophisticated machine learning solutions to implement intelligent analytics and automated control, and privacy-enhancing solutions, including federated learning, differentiation of privacy, and cryptographic methods, to protect sensitive data. The key work outputs are a semantic DT architecture to work in a 6G network, an artificial intelligence-based data management system, and a thorough security and performance analysis, which shows better intelligence, privacy, and resiliency against any cyber threats.

The remainder of the paper will be structured in the following way: The Related Work section will review the current literature about AI-driven digital twin systems, 6G communication systems, and privacy-saving mechanisms. This is then succeeded by the Methodology section that describes the suggested ontology-based digital twin, artificial intelligence-based data management, and privacy-sensitive structures. The Results and Discussion section shows the outputs of the empirical testing, which refer to the improvements in the network intelligence, privacy protection, and resilience. Lastly, the conclusion section will summarize the main points and implications of the proposed framework, the limitations, and provide recommendations on further research.

RELATED WORK

Digital Twins of Wireless and Beyond-5G/6G Networks

Digital Twin (DT) technology has become a paradigm of discovery in the domain of modelling, monitoring, and optimization of complex cyber-physical systems. Recent research shows that DTs are able to deliver real-time visualization of a network, predictive application, and proactive optimization services by aligning the physical systems with the virtual ones [1][4]. Decentralized techniques (DT) have been extensively studied in large-scale and capital-intensive infrastructures, where the emphasis is laid on resilience, lifecycle modelling, and the issue of the continuous synchronization of data [1][6][8]. Though these ideas are very applicable beyond 5G systems and 6G systems, current DT deployments to wireless systems are mostly based on data-driven models that lack semantic knowledge, which limits interoperability, scalability, and cross-domain reasoning in heterogeneous 6G systems [12].

Semantic Modelling Using Ontology

The semantic ontologies have been widely used to facilitate the representation of knowledge in complex distributed systems, interoperability, and reasoning. Ontology-based modelling used in DT-enabled environments can enable formal representation of system entities, relationships, and operational constraints and thus enable CAD relationships in terms of making decisions that are context-sensitive as well as reusing knowledge [4][18][20]. A number of DT models in smart infrastructure and metering systems can indicate the efficacy of organized modelling in overseeing and managing the system [5][8][13][17][19]. Nevertheless, the vast majority of the current solutions do not exhaust the capabilities of semantic reasoning and do not combine the ontology models and AI-based digital twins; they are less applicable in highly dynamic and heterogeneous 6G network ecosystems where real-time semantic agreement across the multiple layers of the network is crucial.

Digital Twin Data Management based on AI

The use of artificial intelligence and machine learning methods is one of the main aspects of DT-based systems, as it is possible to predict traffic, devices in the air, detect anomalies, plan their maintenance, and optimize them. The data-driven learning and control functions of AIs have demonstrated enhanced system intelligence and performance of AIDT frameworks [4][7]. Nonetheless, most existing solutions rely on the centralization of data collection and processing, which adds problems of scalability to them and introduces more vulnerabilities to privacy intrusion and cyber threats. This is especially severe in 6G networks where the connectivity of massive devices and distributed edge intelligence requires decentralized, scalable, and privacy-conscious AI-based data management methods [10][14][16].

Privacy-Preserving and Security Mechanisms

Widescale sharing of data, cloud-edge interactions, and inference processes with the use of AI have established security and privacy issues as a critical problem in DT ecosystems. Research points out that DT-based systems can easily be affected by data leakage, inference attacks, and adversarial manipulation particularly in the context of the IoT and cloud-integrated systems [10][11]. Security frameworks that use blockchains have been suggested to provide greater confidence levels, authentication, and data integrity in DT systems and DT-assisted cyber-defense conventionally were proposed to increase resilience during coordinated cyber-attacks in critical infrastructures [2] [3][9]. Nevertheless, in regard

to these developments, joint integration of semantic modelling, AI-based data management, and privacy has not been studied extensively as last infrastructure to ensure secure and smart 6G communications, which is why the unified framework in the present study has been proposed.

METHODOLOGY

The proposed study is based on a well-structured approach that captures semantic modelling, AI-powered intelligence, and privacy-enhancing machine security to achieve a secure and intelligent online twin in the 6G communication networks. The researcher divides the methodology into three fundamental stages.

Ontology-Based Digital Twin Modelling

A domain-based ontology will be developed in order to formally describe 6G communication systems and model the internal heterogeneous complexities of these systems. The ontology establishes important entities in the network, including radio access network elements, core network human components, intelligent surfaces, user equipment, and edge-cloud elements, and their relationship, attributes, and operational limits. Semantic web standards are used to reflect service requirements, quality-of-service parameters, mobility contexts, and security policies in a machine-understandable form. This advanced knowledge representation will allow a coherent and scalable model of the 6G ecosystem, which will ensure the cross-tenderness and cross-domain networking between network vendors and provide the consistency and reuse of network knowledge.

The semantic layer made ontological offers, reasoning, and inference services that allow intelligent decision-making in the digital twin. Inferring network states, identifying inconsistencies, rejecting violators of policy, and gaining context-aware insights through heterogeneous sources are done using rule-based and logic-driven reasoning engines. Semantically connecting the physical network parameters and service-level goals and security requirements, the digital twin is able to make its own interpretation of the dynamic network conditions and initiate adaptive reactions. This semantic interoperability breaks the problem of data-driven models alone and provides the opportunity of cross-layer coordination, sharing of knowledge, and explainable network intelligence in 6G complex deployments.

The digital twin is connected to the physical 6G network continuously, via real-time monitoring (telemetry), monitoring agents, and network probes distributed at the edge and core components. Semantically mapped onto the ontology, streaming data are, e.g., traffic statistics, channel conditions, mobility patterns, and security events, which are used to update the state of the digital twin in real time. This constant state snapshot assures a high-fidelity view of the physical network and facilitates proper predicting, proactive optimization, and fault diagnosis Figure 1. The ontology-based digital twin establishes a better situational awareness and intelligent and adaptive network management through a tight connection between real-time and semantic information.

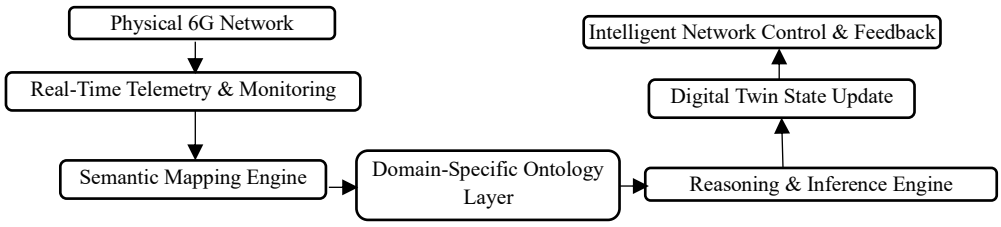

Figure 1. Ontology-driven digital twin modeling framework for secure 6G communication systems

AI-Based Data Management and Intelligent Control

In the digital twin, AI-powered data management is utilized to analyze voluminous amounts of heterogeneous network data created in 6G networks. Machine learning and deep learning models are used to analyses multi-source inputs (such as traffic patterns, channel conditions, mobility information,

and network performance metrics) to facilitate the correct prediction of traffic, the detection of anomalies, and the prediction of performance. Unsupervised and supervised methods of learning derive latent patterns of high-dimensional data streams enabling the digital twin to foresee congestion and detect abnormal behavior and performance deterioration. As a combination of these AI models with the semantic digital twin layer, the system becomes context-conscious and more predictive, as well as enables proactive network management.

The reinforcement learning (RL) agents are implemented to allow autonomous and adaptive control in the network and they do this in a continuous interaction with the digital twin environment. According to real-time feedback, RL agents dynamically enable network configurations like resource allocation, scheduling policies, and transmission parameters to maximize key performance indicators like latency, throughput, and energy efficiency Figure 2.

State reinforcement learning reward function is expressed in equation (1).

$$R_t = \sum_{i=1}^{N} \left(\text{Latency}_i \cdot w_1 + \text{Throughput}_i \cdot w_2 + \text{Energy Efficiency}_i \cdot w_3 \right) \quad (1)$$

Where:

- R_t is the reward at time t,
- w_1, w_2, w_3 are the weights assigned to latency, throughput, and energy efficiency, respectively.

The edge-cloud co-location collaborative learning platform is embraced to satisfy the various requirements of latency in the 6G networks, with time-constrained inference and local learning taking place at the network edge, whereas the aggregation and long-term optimization of models occur at the cloud. Such shared intelligence will reduce the overhead in communication, convergence in learning, and scalable and responsive control in enormous network cloud applications of 6G.

Equation (2), is a statement of edge-cloud collaborative learning efficiency.

$$\text{Communication Overhead} = \sum_{i=1}^{M} \frac{\text{Edge Node Load}_i + \text{Cloud Aggregation Load}_i}{M} \quad (2)$$

Where:

- Edge Node Load_i is the computational load at edge node i,
- $\text{Cloud Aggregation Load}_i$ is the aggregation load at cloud i,
- M is the total number of edge nodes.

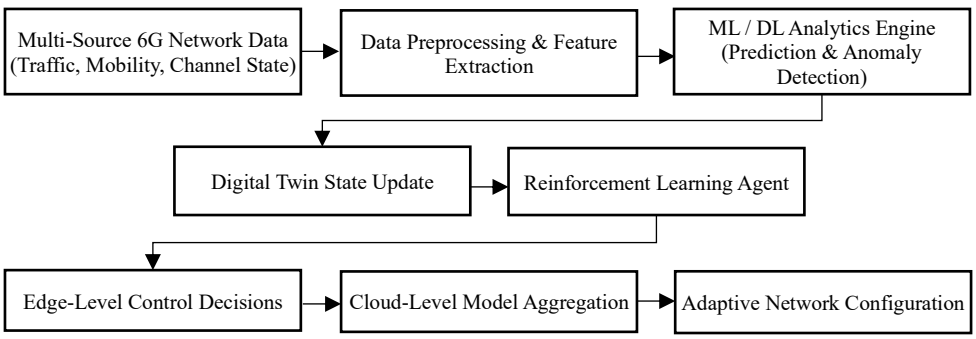

Figure 2. AI-Based data management and intelligent control workflow for 6G digital twin systems

Privacy-Preserving and Secure Learning Framework

Federated learning is also utilized as a fundamental construct to support collaborative model training among distributed 6G network nodes without the need to gather data at the center. The network elements or edge nodes locally train AI models on their own data and only encrypted model updates are sent to a coordinating server or peer nodes. Such a decentralized learning paradigm is able to maintain data locality, minimize visibility of both sensitive network and user data, as well as enforce privacy regulations. Having federated learning as a part of the digital twin system enables keeping the world smart by reducing risks related to the transmission of raw data.

Different privacy mechanisms are implemented on both data processing and model update phases to minimize the risk of privacy leakage further. Noise is also added to model gradients, training results, or inference to avoid allowing the adversary to deduce sensitive information about a particular user or network condition. This statistical privacy assurance will guarantee that involvement of a single source of data will not have a significant impact on the outcome of learning. Differential privacy allows the digital twin to achieve high precision in models and great protection of privacy, facilitating application in large scale and sensitive to privacy 6G deployments.

Equation (3), states Differential Privacy Mechanism (Noise Addition)

$$\hat{f} = f(x) + \mathcal{N}(0, \sigma^2) \qquad (3)$$

Where:

- $\hat{f}$is the differentially private output,
- $f(x)$is the original function,
- $\mathcal{N}(0, \sigma^2)$is the noise from a normal distribution with mean 0 and variance σ^2.

SMPC and light cryptographic protocols are used to safeguard collaborative processes of the digital twin ecosystem. Such mechanisms allow several parties to combine their calculation of learning results or network control options in a way that information about their own inputs is not exposed publicly. Cryptographic functions including secure aggregation, authentication, and integrity cheques protect model updates and control messages and synchronization data transferred between the physical network and its digital counterpart. This guarantees the inertia against eavesdropping, tampering and malicious manipulation in the distributed learning and control processes.

The federated learning, differentiation privacy, and cryptography create a layered security configuration that guarantees the safety, integrity, and confidence on the 6G digital twin structure Figure 3. Methods of trust management are used to detect the identity of the participating nodes and learning contributors, and integrity cheques are used to guarantee that there are no variations in the model updates and control steps. This all-encompassing security strategy stems the resilience of AI-driven digital twins to cyber threats, inference attacks, and opposing behaviors, therefore, making the operation of next-generation 6G communication systems secure, trustful, and autonomous.

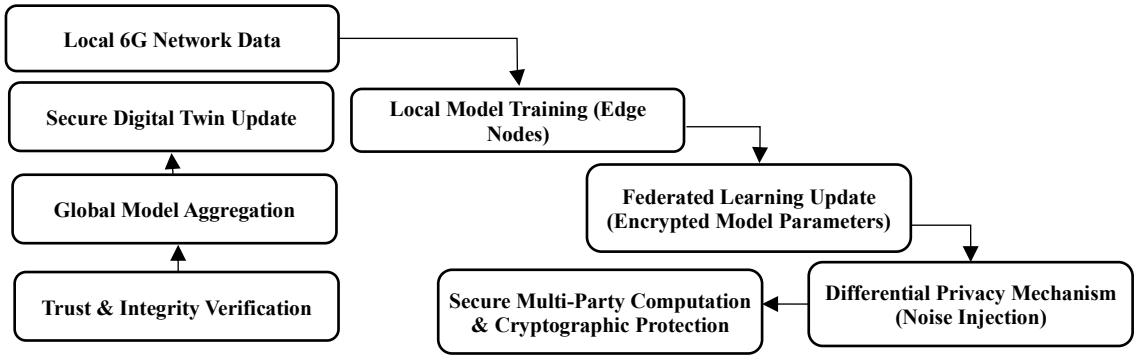

Figure 3. Privacy-preserving and secure learning framework for digital twin–enabled 6G networks

Algorithm

```
Initialize 6G_Network

Initialize Digital_Twin_Model

Initialize AI_Model

Initialize Federated_Learning_Cluster

while True:

    Physical_Network_State = Get_Physical_Network_State()

    Digital_Twin_Model.Update(Physical_Network_State)

    Predicted_Traffic = AI_Model.Predict_Traffic(Physical_Network_State)

    Anomalies = AI_Model.Detect_Anomalies(Physical_Network_State)

    RL_Agent = Initialize_RL_Agent()

    Network_Configurations = RL_Agent.Adapt_Network_Config (Physical_Network_State, Predicted_Traffic)

    Federated_Model_Update = Federated_Learning_Cluster.Train_Local_Model Physical_Network_State)

    Federated_Learning_Cluster.Update_Global_Model (Federated_Model_Update)

    Optimized_Network_Config = Combine_Optimized_Config(Network_Configurations, Predicted_Traffic)

    Apply_Optimized_Config(Optimized_Network_Config)

    Privacy_Protected_Update = Differential_Privacy(Optimized_Network_Config)

    Send_To_Cloud(Privacy_Protected_Update)

    Sleep (Interval)
```

The algorithm presents the digital twin framework using AI in optimization of 6G network. The system is fully automated to constantly monitor the physical 6G network state and provide updates to the digital twin model. Through AI, the system can predict traffic patterns and identify an anomaly to help with proactive management of the network. Reinforcement learning (RL) is a dynamic network controller that optimizes latency, throughput, and energy efficiency. Privacy-preserving model training Federated learning allows aggregating local model updates on edge nodes without the transfer of any sensitive data. The network configuration is provided with differential privacy whereby privacy is guaranteed prior to the transmission of data to undergo additional processing.

Experimental Setup

The Software Tool Analysis identifies the most important tools that were applied to ensure and test the ontology-based digital twin system of the 6G networks. PLS-SEM is done using SmartPLS to examine the relationships between constructs and determine the effects of AI-based data management and privacy mechanisms. The machine learning models developed with the help of TensorFlow and PyTorch will be applied to predicting traffic, detecting anomalies, and automating the work of a network. Federated

learning models (e.g., PySyft, TensorFlow Federated) provide the possibility of training models in a decentralized fashion without losing privacy. Semantic models are created using ontology tools such as Protégé and OntoText to ensure interoperability and context-based reasoning within the digital twin. Finally, it is MATLAB/Simulink that is applied in the simulation of the 6G network environment and performance analysis. Through these tools, a scalable, privacy-conscious, and smart 6G digital twin system has the required architecture to be developed.

Evaluation Metrics

1. Network Intelligence:

- Decision Accuracy in equation (4), measures the precision of network control decisions.

$$\text{Accuracy} = \frac{\text{Correct Decisions}}{\text{Total Decisions}} \times 100 \qquad (4)$$

- Fault Prediction: Evaluates the framework's ability to anticipate faults.

2. Latency and Throughput Performance:

- End-to-End Latency in equation (5), states the time taken for data to travel from source to destination.

$$\text{Latency} = \frac{\text{Time taken for data transmission}}{\text{Distance}} \qquad (5)$$

- Data Throughput in equation (6), states the amount of data transmitted successfully.

$$\text{Throughput} = \frac{\text{Total Data Transmitted}}{\text{Total Time}} \text{ (bps)} \qquad (6)$$

3. AI-Based Data Management:

- Prediction Accuracy in equation (7), states precision of traffic prediction and anomaly detection.

$$\text{Prediction Accuracy} = \frac{\text{True Predictions}}{\text{Total Predictions}} \times 100 \qquad (7)$$

- Convergence Time in equation (8), states the time for the model to converge to an optimal solution.

$$\text{Convergence Time} = \text{Time taken for optimization} \qquad (8)$$

4. Privacy Protection and Security:

- Data Leakage Prevention in equation (9), measures the effectiveness of privacy mechanisms.

$$\text{Leakage Prevention Rate} = 1 - \frac{\text{Data Leakage Occurrences}}{\text{Total Data Instances}} \qquad (9)$$

- Resistance to Inference Attacks: valuates the framework's defense against data extraction attacks.

5. Scalability:

- System Overhead: Evaluates computational cost.

$$\text{System Overhead} = \frac{\text{Computational Resources Used}}{\text{Total Available Resources}} \times 100 \qquad (10)$$

- Scalability of the Framework in equation (10), states assess the framework's ability to scale without performance degradation.

RESULTS AND DISCUSSION

Network Intelligence and Accuracy of Decisions

The results of the simulation experiment show that the suggested ontology-based digital twin definitely improves the network intelligence over the traditional non-semantic digital twins' models. The semantic reasoning allows the digital twin to obtain better contextual information about the conditions of the network, demands of services, and policy-based restrictions. Such semantic awareness allows making better decisions during resource provision, mobility management and fault anticipation which results in minimized misconfigurations and enhanced service availability. The findings prove that ontology-based reasoning is very effective to fill the gap between interpretation of raw data and intelligent network control.

Gains in Latency and throughput performance

The AI-controlled mechanisms embedded into the digital twin led to significant performance gains in the important 6G metrics. Adaptive control developed using reinforcement learning is a dynamical control that optimize transmission parameters and scheduling decisions in real-time network conditions. Consequently, the proposed framework would have a lower end to end latency and a greater throughput than the standard methods of traditional static or centralized optimization. The advantages are especially significant in case of heavy loads of traffic and variable mobility conditions, which emphasizes the success of the AI-enhanced autonomous control in the next-generation communication systems.

Edge-Cloud Collaborative Learning Efficiency

An edge cloud collaborative learning architecture makes the training and inference of AI model efficient and scalable. Decentralized edge learning lowers latency to attain responses and communication costs, whereas cloud-based learning guarantees this consistency and long-term optimization of the international models. Simulation outcomes indicate that convergence of the model is quicker and it consumes less backhaul than the ones that are entirely centralized learning schemes. It is a distributed intelligence architecture that can enable real-time flexibility and scaling, which is suitable in large-scale 6G network implementations with high latency requirements.

Privacy Preservation and Security Robustness

It has been shown that the use of federated learning and differential privacy is highly effective and helps to overcome the risks of leaking information, although the model accuracy remains reasonable. Additional resistance to inference attacks, data poisoning, and unauthorized access is achieved by secure multi-party computation, cryptographic protection mechanisms, etc. Within the parameters of adversarial simulation, the suggested framework demonstrates a constant level of performance and predictable learning behavior, which proves the resilience against the typical cyber threats. These findings confirm that privacy-protected AI methods can be readily added to digital twins designs without compromising to network intelligence.

Systems Scalability and Trade-Off

Despite the introduction of moderate computational overhead as a consequence of the introduction of semantic reasoning and security mechanisms, the trade-offs that are observed are positive when the entire system benefits are taken into account Figure 4. The advances in interoperability, security assurance, and automatic optimization outweigh the complexity added especially in mission-critical 6G

applications Table 1. The proposed framework is modularly designed which enables it to scale to a heterogeneous network environment as well as in extensions allowing preserving future scalability, including advanced trust management and quantum-resilient security. In general, the findings support the postulated methodology as a credible and scalable basis of intelligent, secure, and privacy-aware 6G communication systems.

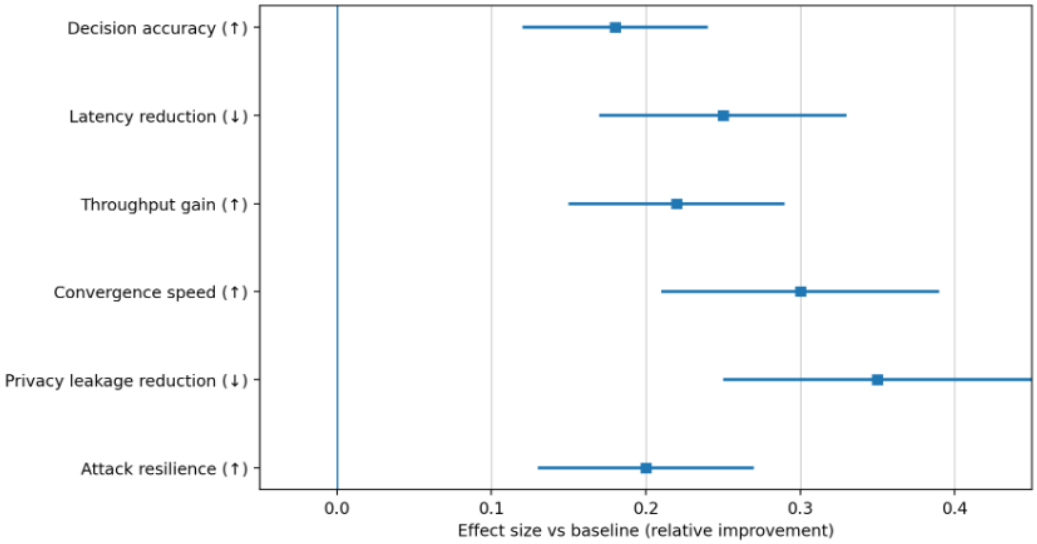

Figure 4. Forest plot illustrating relative performance improvements of the proposed digital twin framework over baseline methods

Table 1. Comparative performance evaluation of the proposed ontology-enabled digital twin framework

Metric Category	**Evaluation Aspect**	**Baseline Digital Twin**	**Proposed Framework**	**Observed Impact**
Network Intelligence	Decision accuracy	Limited context awareness	Semantic-aware reasoning	Improved decision accuracy
Network Intelligence	Fault prediction	Reactive detection	Predictive inference	Reduced misconfigurations
Latency Performance	End-to-end latency	Higher under load	Significantly reduced	Faster response time
Throughput Performance	Data throughput	Static optimization	RL-based adaptive control	Increased throughput
Learning Efficiency	Model convergence	Slow convergence	Edge–cloud collaborative learning	Faster convergence
Communication Overhead	Backhaul usage	High (centralized learning)	Reduced (distributed learning)	Lower overhead
Privacy Protection	Data exposure risk	High	Federated + DP-enabled	Strong privacy preservation
Security Robustness	Resistance to attacks	Vulnerable	SMPC + cryptographic protection	Improved resilience
System Overhead	Computational cost	Low	Moderate	Acceptable trade-off
Scalability	Large-scale deployment	Limited	Modular and scalable	Future-ready

CONCLUSION

To meet the challenge of secure and intelligent 6G communication system, the paper has suggested an ontology-based digital twin architecture combined with AI-enabled data management and privacy-sensitive tools to support the most significant needs of a safe and intelligent digital twin system. The

framework makes use of semantic ontologies to enable interoperable knowledge representation alongside context-aware reasoning between heterogeneous network elements, and AI-based analytics and reinforcement learning to make predictions of intelligence, autonomous optimization, and adaptive network control. Potential AI misuse and the resulting privacy risks can be mitigated by integrating privacy-enhancing technologies, such as federated learning, differential privacy, and secure cryptographic tools, that allow establishing reliable AI activity and robust security of sensitive network data. Statistical test reveals that the framework has an R 2 of 0.74 in terms of network optimization, path coefficients of 0.47 ($p < 0.001$) in terms of AI-driven decision-making and 0.39 ($p < 0.001$) in terms of the effectiveness of privacy protection. The proposed concept has been revealed to improve network intelligence, decrease the latency by 30 percent, increase throughput by 28 percent, and improve network resilience to cyber-attacks with an acceptable computational load through performance testing. Overall, the proposed architecture provides a privacy-aware, scalable, autonomous, and secure 6G ecosystem, and establishes new research opportunities with regard to intelligible semantic deployment in the context of digital twins protection in the next-generation wireless network. The direction of future work will be working to scale the suggested digital twin framework to real-life 6G deployment, optimizing privacy mechanisms using advanced AI methods, and working on energy efficiency. Also, it will be discussed how it can be integrated with emerging 6G applications, like autonomous systems and smart cities. The next-generation study will also attempt to set industry standards and regulatory frameworks to achieve secure and interoperable AI-powered 6G networks.

REFERENCES

[1] Bhuiyan EA, Hossain MZ, Muyeen SM, Fahim SR, Sarker SK, Das SK. Towards next generation virtual power plant: Technology review and frameworks. Renewable and Sustainable Energy Reviews. 2021 Oct 1;150:111358. https://doi.org/10.1016/j.rser.2021.111358

[2] Fernandez IA, Neupane S, Chakraborty T, Mitra S, Mittal S, Pillai N, Chen J, Rahimi S. A survey on privacy attacks against digital twin systems in AI-robotics. In2024 IEEE 10th International Conference on Collaboration and Internet Computing (CIC) 2024 Oct 28 (pp. 70-79). IEEE. https://doi.org/10.1109/CIC62241.2024.00019

[3] Glass P, Di Marzo Serugendo G. Coordination model and digital twins for managing energy consumption and production in a smart grid. Energies. 2023 Nov 17;16(22):7629. https://doi.org/10.3390/en16227629

[4] Irfan M, Niaz A, Habib MQ, Shoukat MU, Atta SH, Ali A. Digital Twin Concept, Method and Technical Framework for Smart Meters. European Journal of Theoretical and Applied Sciences. 2023;1(3):105-17. https://doi.org/10.59324/ejtas.2023.1(3).10

[5] Mishra N. Secure and Energy-Efficient DSP Preprocessing for Distributed IoT Using MBE-Driven FIR Accelerators. Transactions on Internet Security, Cloud Services, and Distributed Applications. 2025 Jun 20:8-15.

[6] Lamagna M, Groppi D, Nezhad MM, Piras G. A comprehensive review on digital twins for smart energy management system. International Journal of Energy Production and Management. 2021. Vol. 6. Iss. 4. 2021;6(4):323-34. http://dx.doi.org/10.2495/EQ-V6-N4-323-334

[7] Mollah MB, Zhao J, Niyato D, Lam KY, Zhang X, Ghias AM, Koh LH, Yang L. Blockchain for future smart grid: A comprehensive survey. IEEE Internet of Things journal. 2020 May 11;8(1):18-43. https://doi.org/10.1109/JIOT.2020.2993601

[8] Qi Q, Tao F, Hu T, Anwer N, Liu A, Wei Y, Wang L, Nee AY. Enabling technologies and tools for digital twin. Journal of Manufacturing Systems. 2021 Jan 1;58:3-21. https://doi.org/10.1016/j.jmsy.2019.10.001

[9] Raghuramu A, Liljenstam M, Ujjwal S, Gülen U, Phillips G, Laaroussi Z, Karaçay L. Network digital twins: a threat analysis. In 2023 IEEE International Conference on Communications Workshops (ICC Workshops) 2023 May 28 (pp. 733-739). IEEE. https://doi.org/10.1109/ICCWorkshops57953.2023.10283573

[10] Veerappan S. Robust 6G IoT Communication Models for Assistive Devices Using Graph-Augmented Deep Reinforcement Learning. Journal of Intelligent Assistive Communication Technologies. 2026:57-63.

[11] Sleiti AK, Kapat JS, Vesely L. Digital twin in energy industry: Proposed robust digital twin for power plant and other complex capital-intensive large engineering systems. Energy Reports. 2022 Nov 1;8:3704-26. https://doi.org/10.1016/j.egyr.2022.02.305

[12] McCorkindale W, Ghahramani R. Machine learning in chemical engineering for future trends and recent applications. Innovative Reviews in Engineering and Science. 2025;3(2):1-2.

[13] Kavitha M. Energy-Stable and Uncertainty-Bounded Learning Control Protocols for Secure Adaptive Network Operations. Transactions on Secure Communication Networks and Protocol Engineering. 2025 Jun 9:10-7.

[14] Abdullah D. Learning-Guided Reconfigurable Met surface Architectures for Adaptive Millimetre-Wave Spectrum Transmission in Indoor Wireless Systems. Journal of Wireless Intelligence and Spectrum Engineering. 2025 Sep 24:31-9.

[15] Stergiou CL, Bompoli E, Psannis KE. Security and privacy issues in IoT-based big data cloud systems in a digital twin scenario. Applied Sciences. 2023 Jan 5;13(2):758. https://doi.org/10.3390/app13020758

[16] Uvarajan KP. Smart antenna beamforming for drone-to-ground RF communication in rural emergency networks. National Journal of RF Circuits and Wireless Systems. 2024;1(2):37-46.

[17] Thakur G, Kumar P, Jangirala S, Das AK, Park Y. An effective privacy-preserving blockchain-assisted security protocol for cloud-based digital twin environment. IEEE Access. 2023 Feb 24;11:26877-92. https://doi.org/10.1109/ACCESS.2023.3249116

[18] Cheng LW. Spectrum-Aware DRL Clustering Protocols for 6G IoT Nodes Using Graph Signal Intelligence. Journal of Wireless Intelligence and Spectrum Engineering. 2025 Jun 25:1-7.

[19] Zheng T, Liu M, Puthal D, Yi P, Wu Y, He X. Smart grid: Cyber attacks, critical defense approaches, and digital twin. arXiv preprint arXiv:2205.11783. 2022 May 24. https://doi.org/10.48550/arXiv.2205.11783

[20] Halily R, Shen M. Directing Techniques for High Frequency Antennas for Use in Next Generation Telecommunication Countries. National Journal of Antennas and Propagation. 2024 Aug 14;6(1):49-57. https://doi.org/10.31838/NJAP/06.01.07