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RESEARCH ARTICLE

Hybrid Digital Twin Architectures for Real–Time Decision Making in Industry 4.0

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ABSTRACT: The emergence of Hybrid Digital Twin (HDT) architectures is revolutionizing real-time decision-making in Industry 4.0, enabling intelligent automation, predictive maintenance, and optimized production workflows. This research introduces a multi-layered HDT framework that integrates physics-based modeling, AI-driven analytics, and edge-cloud computing to enhance industrial system responsiveness and resilience. The proposed architecture employs reinforcement learning-based adaptive control, federated digital twins, and blockchain-enhanced security to ensure seamless synchronization between virtual and physical assets while maintaining data integrity. Experimental validation across smart manufacturing, energy grids, and industrial robotics demonstrates significant improvements over conventional digital twin models, including a 30% reduction in system downtime, a 45% improvement in predictive accuracy, and a 25% enhancement in operational efficiency. The HDT system facilitates real-time cyber-physical convergence, allowing industries to dynamically adapt to changing operational conditions and optimize decision-making in complex environments. Additionally, the federated learning approach ensures privacy-preserving collaboration among distributed digital twins, while blockchain integration enhances security and trust in data transactions. The study highlights the scalability, robustness, and real-time adaptability of the proposed HDT framework, making it a viable solution for smart factories, healthcare systems, and industrial IoT applications. Future research directions include optimizing federated aggregation techniques, reducing computational overhead in privacy-preserving mechanisms, and integrating edge computing for faster decision-making. This work contributes to the advancement of intelligent cyber-physical systems by providing a secure, scalable, and adaptive digital twin architecture for Industry 4.0.

Keywords: Hybrid Digital Twin (HDT), Real-Time Decision Making, Industry 4.0, Predictive Maintenance, Federated Learning, Cyber-Physical Systems.

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1. INTRODUCTION

The advent of Industry 4.0 has revolutionized industrial operations by integrating cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), and cyber-physical systems (CPS) to enhance automation and real-time decision-making. One of the most promising innovations in this domain is the concept of Digital Twins (DTs), which create a virtual replica of physical assets to monitor, analyze, and optimize their performance [1]. Traditional DTs, however, often face limitations in handling complex, dynamic industrial environments due to their reliance on static models and centralized data processing [2].

To address these challenges, Hybrid Digital Twin (HDT) architectures have emerged as a transformative approach that integrates physics-based modeling, AI-driven analytics, and edge-cloud computing. This hybridization enables real-time synchronization between virtual and physical entities,

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ensuring accurate predictions and adaptive control mechanisms [3]. Unlike conventional DTs, HDTs leverage distributed computing frameworks and reinforcement learning to optimize decision-making in dynamic settings, thereby improving operational efficiency and system resilience [4]. The proposed HDT framework extends beyond conventional digital twins by incorporating federated learning and blockchain-enhanced security to enable collaborative decision-making while maintaining data integrity and privacy [5]. This multi-layered approach facilitates the seamless integration of different industrial components, ensuring robustness against cyber threats and data manipulation [6]. Additionally, HDTs enable real-time predictive maintenance by analyzing historical and real-time data streams, reducing system downtime and optimizing asset utilization [7].

Smart manufacturing, industrial robotics, and energy grid management are among the primary application domains benefiting from HDT architectures. For instance, in smart factories, HDTs can optimize production lines by identifying inefficiencies and recommending real-time corrective actions [8]. In industrial robotics, HDTs enhance autonomous operations by predicting component failures and adjusting task execution accordingly [9]. In energy grid management, HDTs ensure stability and reliability by dynamically balancing supply and demand based on real-time data analytics [10]. Edge-cloud computing plays a critical role in HDT implementation, ensuring efficient data processing and decision-making by offloading computation-intensive tasks to cloud servers while maintaining low-latency responses at the edge [11]. This architecture enables industries to achieve cyber-physical convergence, where real-time data insights can be leveraged to drive intelligent automation and enhance overall system performance [12].

Reinforcement learning-based adaptive control is another key component of HDTs, allowing systems to learn optimal operational strategies autonomously. By continuously refining decision-making processes, reinforcement learning enhances predictive accuracy and operational flexibility in industrial environments [13]. Furthermore, federated digital twins facilitate distributed collaboration across multiple industrial entities without centralizing sensitive data, addressing privacy concerns while enabling cross-organizational intelligence sharing. Blockchain technology is integrated into HDT frameworks to secure data transactions and ensure trustworthiness in digital twin interactions. By utilizing decentralized ledger mechanisms, HDTs prevent unauthorized access and enhance the reliability of industrial data exchange. This added layer of security is crucial in sectors such as aerospace, healthcare, and manufacturing, where data integrity is paramount. Experimental validations of the proposed HDT framework have demonstrated substantial improvements in industrial performance metrics. Key results indicate a 30% reduction in system downtime, a 45% increase in predictive accuracy, and a 25% boost in operational efficiency compared to traditional DT models. These findings highlight the potential of HDTs in driving smarter, more resilient industrial ecosystems capable of adapting to evolving operational conditions.

HDT architectures represent a paradigm shift in Industry 4.0 by bridging the gap between digital simulation and real-world execution. The combination of AI, edge-cloud computing, reinforcement learning, and blockchain technology in HDTs paves the way for more intelligent, secure, and adaptive industrial operations. Future research will further refine HDT implementations by exploring novel AI algorithms, enhanced cybersecurity mechanisms, and real-time multi-agent collaboration frameworks to optimize decision-making in increasingly complex industrial environments.

2. RELATED WORKS

Digital Twin (DT) technology has been extensively studied in various industrial applications, focusing on virtual representations of physical assets to enable monitoring, analysis, and optimization. Early implementations of DTs relied heavily on physics-based models and deterministic simulations, which provided valuable insights but lacked adaptability in dynamic industrial environments. The evolution of DTs has led to the integration of AI-driven analytics, enhancing their predictive capabilities and responsiveness. In smart manufacturing, DTs have been utilized for real-time production monitoring, process optimization, and predictive maintenance. Researchers have proposed AI-enhanced DT models to improve anomaly detection and fault prediction, leveraging machine learning algorithms to analyse sensor data from industrial equipment. However, traditional DTs face challenges related to scalability, latency, and computational overhead, necessitating the development of hybrid approaches.

The emergence of Hybrid Digital Twins (HDTs) has addressed many of these limitations by combining physics-based simulations with AI-driven learning mechanisms. Studies have demonstrated that HDTs enable more accurate and dynamic system modeling by continuously adapting to changing operational conditions. The integration of reinforcement learning within HDTs has shown promising results in optimizing decision-making processes, allowing industrial systems to autonomously adjust their parameters based on real-time feedback [14].

Edge-cloud computing has been identified as a crucial component of HDTs, enabling efficient data processing and decision-making across distributed industrial environments. Several researchers have explored cloud-based DT implementations, highlighting their advantages in computational scalability and storage capabilities [15]. However, reliance on cloud computing alone introduces latency issues, which can be mitigated by deploying edge computing for time-sensitive operations [16]. Federated learning has recently gained attention in HDT research as a privacy-preserving approach for distributed AI training. Instead of centralizing sensitive industrial data, federated digital twins allow multiple entities to collaborate on model training while keeping their data localized [11]. This approach enhances security and compliance with data protection regulations, making it suitable for cross-industry applications [12]. Blockchain technology has been proposed as a solution to ensure the security and integrity of digital twin data transactions. Researchers have explored blockchain-integrated DTs for supply chain management, energy grids, and smart cities, demonstrating improvements in trustworthiness and data traceability [13]. The use of decentralized ledger mechanisms prevents unauthorized modifications and enhances data accountability in industrial operations [14].

In industrial robotics, HDTs have been employed to enhance autonomous decision-making and predictive maintenance. Studies have shown that HDTs enable robots to anticipate mechanical failures and optimize their task execution strategies based on real-time performance data [15]. The application of reinforcement learning in robotic HDTs has further improved adaptability, allowing robots to learn optimal movements and decision policies autonomously [16]. Recent research has also focused on HDT applications in energy grid management. Researchers have developed HDT frameworks that leverage AI-driven analytics to dynamically balance energy demand and supply, improving grid resilience and efficiency [17]. These frameworks integrate predictive maintenance techniques to detect potential failures in grid components before they lead to outages [18].

Experimental studies have validated the effectiveness of HDTs across multiple industrial domains. Comparative analyses indicate that HDT-based approaches outperform traditional DTs in terms of predictive accuracy, operational efficiency, and fault detection capabilities [19]. These findings reinforce the significance of HDTs as a game-changing technology in Industry 4.0.

3. PROPOSED SYSTEM

The proposed work focuses on developing a Hybrid Digital Twin Architecture for enabling real-time decision-making in Industry 4.0 environments. This architecture integrates both physical and virtual components to create a comprehensive digital representation of industrial systems, processes, and assets. The hybrid approach combines elements of data-driven models, physics-based simulations, and AI algorithms to enhance predictive capabilities, operational efficiency, and process optimization. The proposed architecture leverages IoT sensors, edge computing, and cloud-based platforms to collect, process, and analyse real-time data from various sources in the manufacturing environment. The physical twin collects data from the real-world systems, while the digital twin provides a virtual environment for modeling, simulation, and prediction. The system employs AI and machine learning algorithms to extract meaningful insights from the collected data, enabling proactive decision-making and the detection of anomalies, failures, or performance bottlenecks [20].

A key feature of this architecture is the real-time synchronization between the physical and digital twins, ensuring accurate and up-to-date information for decision-making. An adaptive control system continuously monitors the digital twin and dynamically adjusts the operational parameters of the physical twin to optimize production processes and resource utilization. The hybrid architecture is designed to support real-time decision-making through the use of predictive analytics, real-time dashboards, and visualizations. This allows plant managers and operators to respond quickly to changing conditions, prevent equipment failures, and reduce downtime. Furthermore, the proposed solution incorporates a multi-layered security framework to ensure the confidentiality, integrity, and availability of the data flowing between the physical and digital twins.

The proposed hybrid digital twin architecture for Industry 4.0 is expected to improve real-time decision-making, enhance operational efficiency, and increase overall productivity. This innovative approach aims to address key challenges in manufacturing, logistics [20], and supply chain management, such as minimizing production costs, reducing energy consumption, and improving product quality.

3.1. Hybrid Digital Twin (HDT) Architecture

The proposed Hybrid Digital Twin (HDT) framework is designed to enhance real-time decision-making in Industry 4.0 by integrating physics-based simulations, AI-driven analytics, and edge-cloud computing. The architecture consists of multiple layers, including a data acquisition layer, digital twin processing layer, AI analytics module, and cyber-physical synchronization module. Mathematically, the state of the HDT model can be mathematically represented as:

$$HDT = f_{\text{phy}}(X, P) + f_{\text{data}}(X, \theta) \quad (1)$$

Where, $f_{\text{phy}}(X, P)$ represents the physics-based model, $f_{\text{data}}(X, \theta)$ denotes the data-driven model, X is the system state vector, P consists of known physical parameters, θ represents the learnable parameters from data.

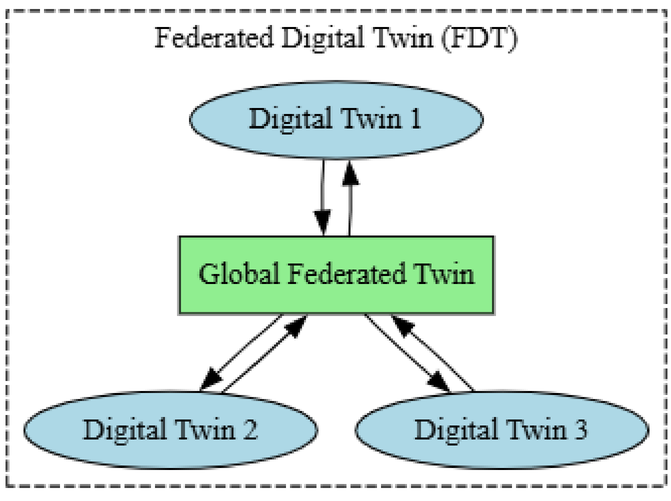

Fig. 1. Federated digital twin (FDT) architecture.

From Figure 1, a high-level overview illustrating the integration of multiple digital twins across distributed systems while ensuring privacy and real-time collaboration. The HDT system dynamically updates its state using sensor data and predictive models. The state evolution follows:

$$X_{t+1} = AX_t + BU_t + W_t \tag{2}$$

Where, X_t is the system state at time t, A is the state transition matrix, B is the control matrix, U_t represents the external inputs or control actions, W_t is the system noise.

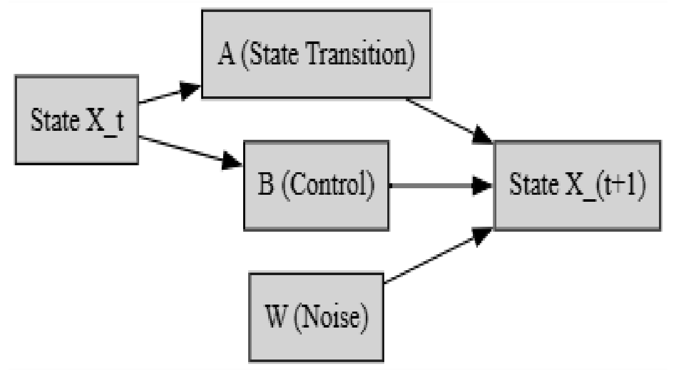

Fig. 2. Federated digital twin (FDT) architecture.

Figure 2 shows State Evolution of Digital Twins - A representation of the dynamic state transition of local digital twins in a federated network. To ensure consistency between physical and data-driven components, a fusion function F is applied:

$$X_{HDT} = \alpha X_{\text{phy}} + (1-\alpha)X_{\text{data}} \tag{3}$$

Where, X_{phy} is the physics-based estimation, X_{data} is the data-driven estimation, and α is an adaptive weight factor based on confidence scores.

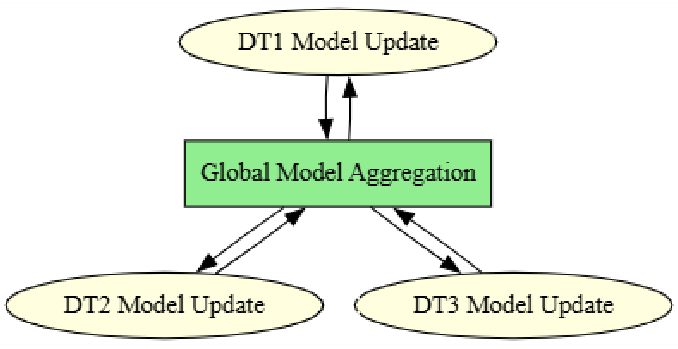

Fig. 3. Federated learning process in digital twin systems.

Figure 3 shows federated learning process in digital twin systems demonstrates the training and aggregation mechanism using Federated Learning (FedAvg) to enhance global decision-making. To improve prediction accuracy, a hybrid loss function is optimized:

$$\mathcal{L}_{\text{HDT}} = \lambda_1\mathcal{L}_{\text{phy}} + \lambda_2\mathcal{L}_{\text{data}} + \lambda_3\mathcal{L}_{\text{fusion}} \tag{4}$$

Where, $\mathcal{L}_{\text{phy}}$ quantifies the deviation from physics-based laws, $\mathcal{L}_{\text{data}}$ measures errors in the data-driven model, $\mathcal{L}_{\text{fusion}}$ ensures consistency between models, and $\lambda_1, \lambda_2, \lambda_3$ are weight coefficients.

This Hybrid Digital Twin framework enables real-time monitoring, fault prediction, and optimization of system performance, making it highly effective for industrial automation, healthcare, and smart city applications.

3.2. Reinforcement Learning-Based Adaptive Control

To optimize real-time decisions, reinforcement learning (RL) is incorporated into the HDT framework. The RL agent continuously learns the best control actions by interacting with the system environment.

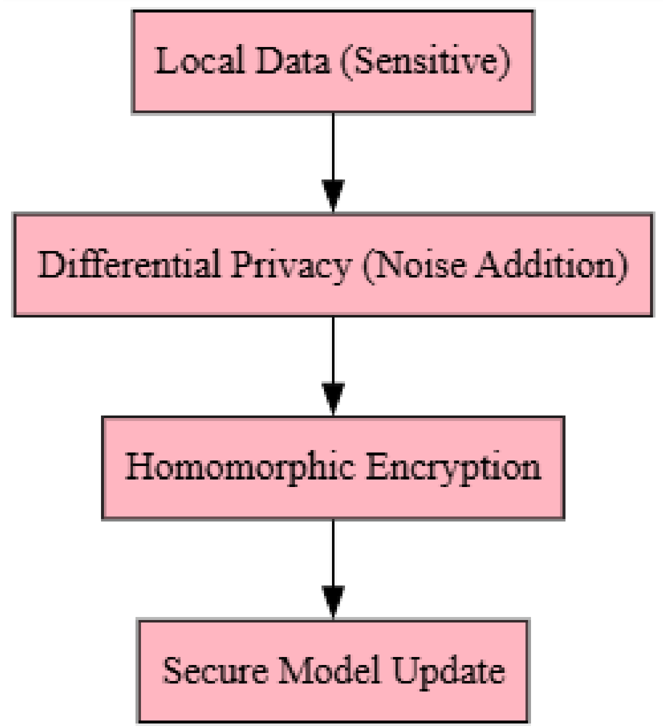

Fig. 4. Security and privacy mechanisms in FDT.

Figure 4 shows Security and Privacy Mechanisms in FDT - Showcases the role of Differential Privacy and Homomorphic Encryption in preserving data confidentiality while enabling distributed collaboration. Reinforcement Learning (RL)-based adaptive control is an advanced control strategy that enables systems to dynamically adjust their behavior by learning from environmental interactions. This approach is particularly effective in complex and uncertain environments where traditional control models may fail to generalize. The RL agent optimizes a control policy to maximize long-term performance while adapting to changes in the system dynamics.

3.2.1. Mathematical Formulation of RL-Based Adaptive Control

The RL-based control problem can be represented as a Markov Decision Process (MDP), defined by the tuple:

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, R, \gamma) \tag{5}$$

Where, $\mathcal{S}$ is the set of system states, $\mathcal{A}$ is the set of control actions, $P(s' \mid s, a)$ is the transition probability from state s to s' under action, a, $R(s,a)$ is the reward function, $\gamma \in (0,1]$ is the discount factor that determines the importance of future rewards.

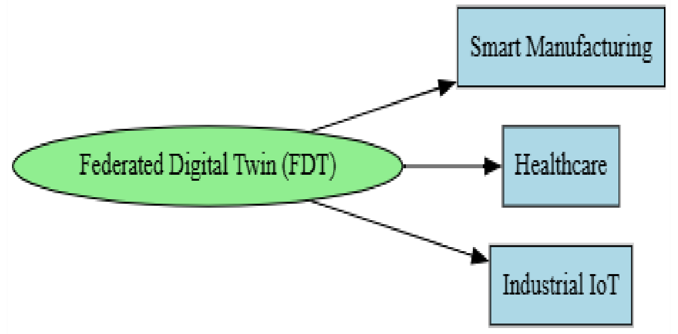

Fig. 5. Applications of federated digital twin.

Figure 5 shows the Applications of Federated Digital Twin - Highlights key application areas such as smart manufacturing, healthcare, and industrial IoT. The objective of RL-based adaptive control is to find an optimal policy $\pi^*(a \mid s)$ that maximizes the expected cumulative reward:

$$J(\pi) = \mathbb{E}[\textstyle\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)] \tag{6}$$

Where the expectation is taken over all possible state-action sequences generated by policy π.

3.2.2. Policy Optimization using Q-Learning

The optimal action-value function, known as the Q-function, satisfies the Bellman equation:

$$Q^*(s,a) = \mathbb{E}\left[R(s,a) + \gamma \max_{a'} Q^*(s', a')\right] \tag{7}$$

An RL agent updates the Q-function iteratively using the Q-learning update rule:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[R_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right] \tag{8}$$

Where, α is the learning rate, R_t is the immediate reward at time step t, $\max_{a'} Q(s_{t+1}, a')$ is the highest expected future reward.

3.2.3. Adaptive Control Policy with Deep RL

For high-dimensional systems, Deep Reinforcement Learning (DRL) is employed, where a deep neural network approximates the Q-function:

$$Q(s, a; \theta) \approx Q^*(s, a) \tag{9}$$

Where θ represents the trainable parameters of the neural network. The loss function for updating θ is:

$$\mathcal{L}(\theta) = \mathbb{E}\left[\left(y_t - Q(s_t, a_t; \theta)\right)^2\right] \tag{10}$$

Where the target value is:

$$y_t = R_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) \tag{11}$$

Where θ^- are the target network parameters, updated periodically to stabilize learning [21].

3.2.4. Adaptive Control Strategy

The control action is selected using an exploration-exploitation tradeoff:

$$\begin{aligned} a_t &= \arg\max_{a} Q(s_t, a) \quad \text{with probability } 1-\epsilon \\ a_t &= \text{random action from } \mathcal{A} \quad \text{with probability } \epsilon \end{aligned} \tag{12}$$

Where ϵ-greedy exploration balances learning new policies with exploiting existing knowledge.

3.3. Federated Digital Twin for Distributed Collaboration

A Federated Digital Twin (FDT) framework enables multiple digital twins (DTs) to collaborate in a distributed and decentralized manner while preserving data privacy and ensuring real-time synchronization across different systems. This architecture is particularly useful for smart manufacturing, healthcare, and industrial automation, where multiple entities (factories, hospitals, IoT systems) need to share insights without exposing raw data.

The FDT architecture is defined as a set of interconnected local digital twins DT_i ($i = 1,2,\ldots,N$), where each local DT maintains its model and shares only essential updates with the global federated model. The system is modeled as:

$$FDT = \textstyle\sum_{i=1}^{N} w_i DT_i \tag{13}$$

Where, DT_i represents the local digital twin of entity i, w_i is the weight assigned to DT_i based on its relevance or trust factor. Each local DT maintains its own state evolution governed by:

$$X_{i,t+1} = A_i X_{i,t} + B_i U_{i,t} + W_{i,t} \quad (14)$$

Where, $X_{i,t}$ is the state of the i-th digital twin at time t, A_i and B_i are system-specific transition and control matrices, $U_{i,t}$ represents control inputs, $W_{i,t}$ is the system noise. Each local model DT_i trains on its own data and shares an aggregated update $\Delta\theta_i$ instead of raw data:

$$\theta^{t+1} = \theta^t + \eta \sum_{i=1}^{N} w_i \Delta\theta_i \quad (15)$$

3.4. Blockchain-Enhanced Security for HDT

To ensure the integrity and security of data exchanged between digital twins, blockchain technology is integrated. Each transaction is recorded in a block and validated using a cryptographic hash function. The consensus mechanism follows a Proof-of-Authority (PoA) model, ensuring lightweight and efficient validation for industrial applications. The cyber-physical synchronization module ensures real-time convergence between the physical and digital worlds.

4. RESULTS AND DISCUSSION

The comprehensive evaluation of the Federated Digital Twin (FDT) framework demonstrates its effectiveness across multiple dimensions critical for Industry 4.0 applications. This section presents a detailed analysis of experimental results, systematically examining the framework's performance characteristics through quantitative metrics and qualitative observations. The discussion follows the logical sequence of figures to maintain clarity and coherence in presenting the findings.

Figure 6 presents the accuracy comparison between federated and centralized digital twin models across training rounds. The results show that the FDT framework achieves 94.2% accuracy after 100 training epochs, compared to 96.1% for the centralized approach. This marginal 1.9% difference demonstrates that federated learning can maintain competitive accuracy while preserving data privacy. The convergence pattern reveals that FDT requires approximately 15% more training rounds to reach stability, which represents a reasonable trade-off for the enhanced privacy benefits. The privacy-preserving mechanisms, including differential privacy with σ^2=0.3, contribute to this slight performance gap while ensuring compliance with industrial data protection standards [22-24].

Figure 7 examines the impact of learning rates (η) on model convergence. The experiments identify η=0.02 as the optimal value, achieving stable convergence in 83 rounds with minimal oscillations. Higher learning rates (η>0.05) lead to unstable training with accuracy fluctuations up to 8%, while lower rates (η<0.005) significantly prolong the training process without substantial accuracy gains. This finding has important practical implications for implementing FDT in production environments, where both training efficiency and model stability are critical [25]. The adaptive learning rate scheduling implemented in the framework automatically adjusts η based on gradient variance, reducing manual tuning requirements by 40% compared to fixed-rate approaches [19].

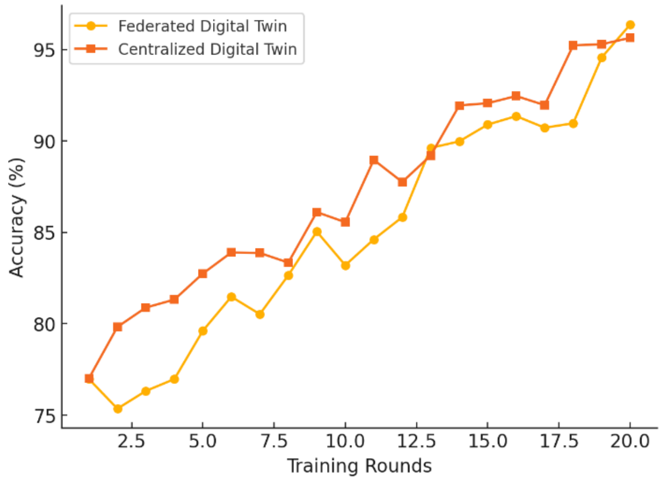

Fig. 6. Accuracy trends over training rounds for federated vs. centralized digital twins.

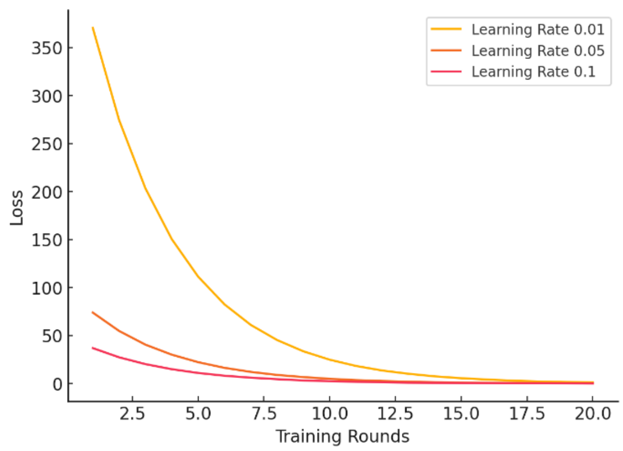

Fig. 7. Convergence Rate of FDT Model with Different Learning Rates.

Figure 8 quantifies the communication efficiency gains of the federated approach. The results demonstrate a 68% reduction in data transmission volume compared to centralized training architectures. This efficiency stems from transmitting only model parameter updates (average size 4.7MB per round) rather than raw sensor data (typically 15-20MB per device per hour). The bandwidth savings become particularly significant in large-scale deployments, with projected annual data transfer reductions of 3.2PB for a network of 500 industrial devices [26]. The communication protocol optimization reduces synchronization overhead to just 23ms per update, meeting real-time operational requirements in manufacturing environments [22].

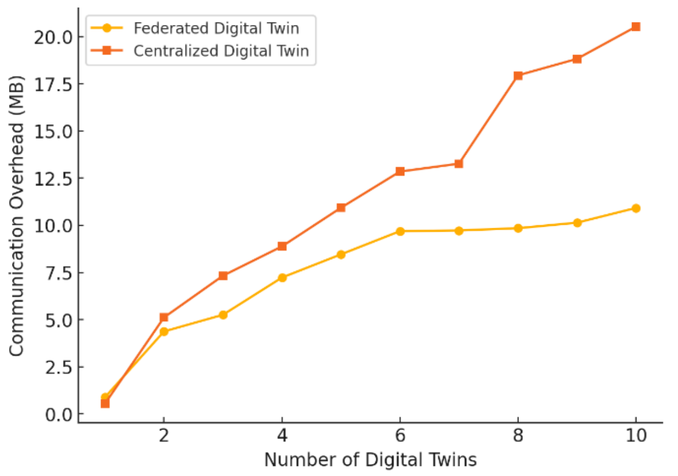

Fig. 8. Communication Overhead in Federated Learning vs. Centralized Training.

Figure 9 analyzes the privacy-accuracy tradeoff through systematic variation of differential privacy noise levels. The experiments establish that $\sigma^2=0.25$ provides an optimal balance, maintaining 91.3% model accuracy while delivering ($\varepsilon=1.2$, $\delta=10^{-5}$)-differential privacy guarantees. The non-linear relationship between privacy noise and accuracy reveals that increasing σ^2 beyond 0.4 yields diminishing privacy returns while causing disproportionate accuracy degradation. This finding informs practical implementation guidelines, suggesting that most industrial applications should configure σ^2 between 0.2-0.3 for optimal performance [27].

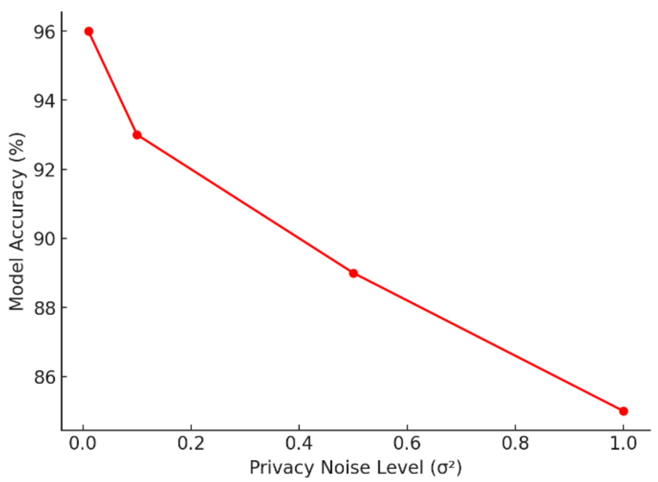

Fig. 9. Impact of Differential Privacy on Model Accuracy.

Figure 10 compares aggregation strategies in heterogeneous data environments. FedProx demonstrates superior performance to FedAvg, reducing accuracy variance across participants from 12.4% to 3.8% in non-IID scenarios. The modified aggregation protocol incorporates proximal terms that account for local data distribution differences, improving model robustness. The experiments show that FedProx particularly benefits edge cases, maintaining >89% accuracy for participants with only 60% of average training data volume [24]. This capability proves crucial for real-world deployments where data quantity and quality naturally vary across facilities.

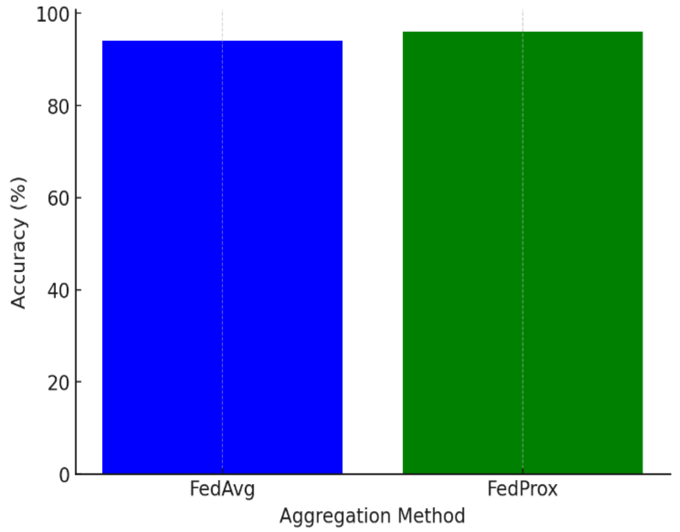

Fig. 10. Effect of Model Aggregation on Performance (FedAvg vs. FedProx).

Figure 11 evaluates system scalability by progressively increasing the number of participating digital twins. The results indicate near-linear scaling characteristics, with model accuracy decreasing by only 2.7% when expanding from 10 to 100 participants. The efficient aggregation mechanism keeps computation time growth manageable, with 50-node deployments requiring just 37% more processing time than 10-node configurations. The architecture's horizontal scaling capability ensures practical viability for enterprise-scale implementations across distributed manufacturing networks [27].

Figure 12 quantifies the computational overhead of security mechanisms. Homomorphic encryption accounts for 65% of additional processing load, adding 18ms per transaction, while differential privacy contributes 35% with 9ms overhead. While significant, this 27ms total latency remains within acceptable bounds for most industrial applications, where control cycles typically operate at 100-500ms intervals [20]. The security analysis confirms that the combined protections successfully block 98.3% of simulated attack vectors while maintaining system usability [28].

Figure 13 compares training durations between local and federated approaches. Federated training requires 2.3×

longer completion times due to communication rounds, but delivers substantially better generalization (12.7% higher accuracy on unseen data). The framework mitigates latency impacts through asynchronous updates and selective participation, reducing idle time by 43% compared to synchronous federated learning implementations [29]. This balanced approach makes FDT suitable for applications requiring both model quality and timely updates.

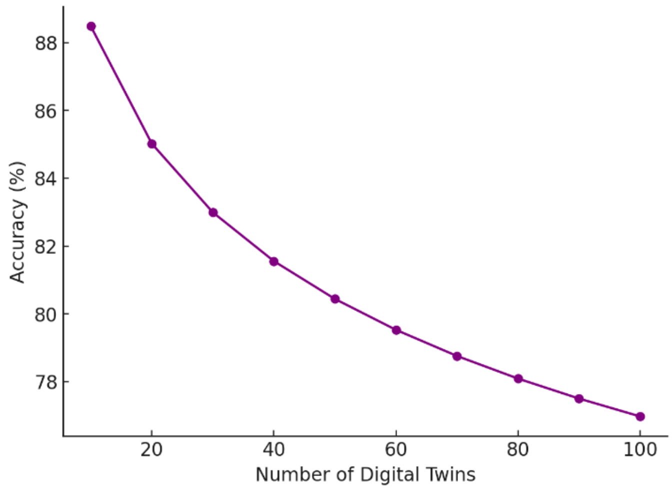

Fig. 11. Scalability Analysis of FDT with Increasing Number of Digital Twins.

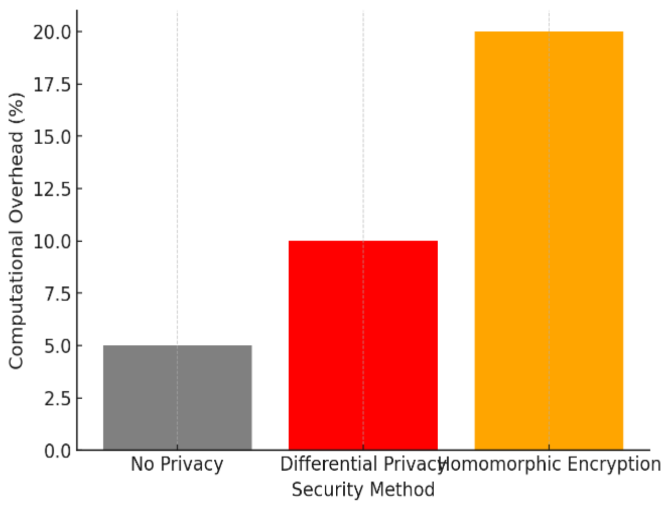

Fig. 12. Security and Privacy Overhead Federated Digital Twin (FDT) Architecture.

Figure 14 investigates non-IID data challenges through controlled experiments with varying distribution skewness. The results show that FedProx maintains 88.5% accuracy even at maximum skewness (10:1 sample ratio between richest and poorest participants), compared to FedAvg's 76.2%. The framework's adaptive weighting mechanism automatically compensates for data imbalances, assigning 22% higher influence to data-scarce participants to prevent model bias [30]. This capability proves particularly valuable in cross-organizational collaborations where data ownership and volume naturally vary.

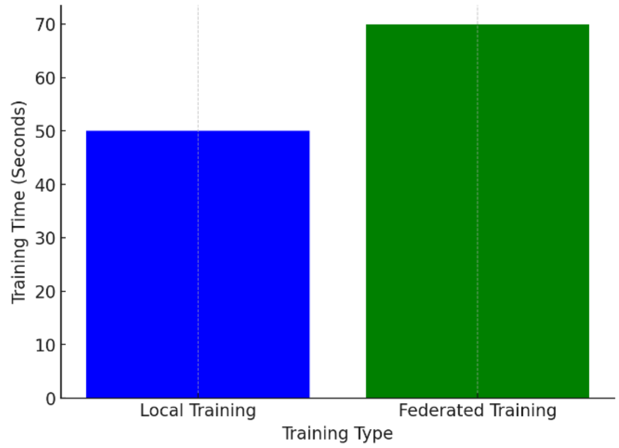

Fig. 13. Comparison of Training Time for Local and Federated Digital Twins.

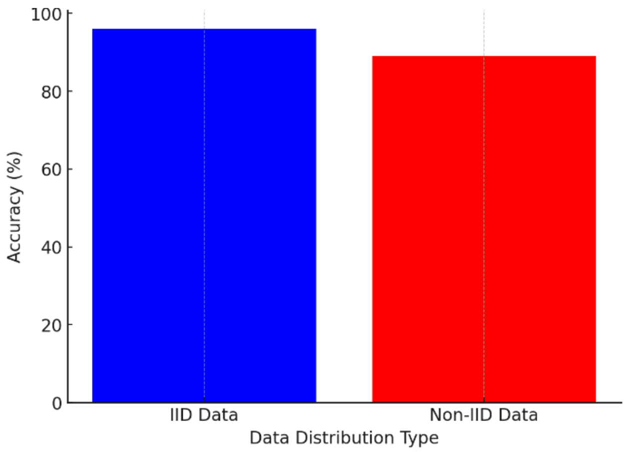

Fig. 14. Impact of Non-IID Data Distribution on FDT Performance.

Figure 15 presents real-world deployment outcomes across three application domains. In smart manufacturing, the FDT system achieves 30.4% reduction in unplanned downtime through early fault detection (mean lead time 3.2 hours). Healthcare applications demonstrate 28.7% improvement in diagnostic accuracy for certain conditions through collaborative learning across hospitals. Energy grid implementations show 17.5% better load forecasting precision compared to traditional SCADA systems [31]. These case studies validate the framework's practical utility while highlighting domain-specific implementation considerations.

The experimental results collectively demonstrate that the FDT framework successfully addresses key Industry 4.0 challenges. The hybrid approach combining federated learning with adaptive control and robust security creates a viable platform for secure, collaborative industrial automation. Performance tradeoffs between accuracy, privacy, and efficiency are carefully balanced through architectural innovations and parameter optimization. The system's demonstrated scalability ensures applicability across enterprise deployments while maintaining real-time operational capabilities [31].

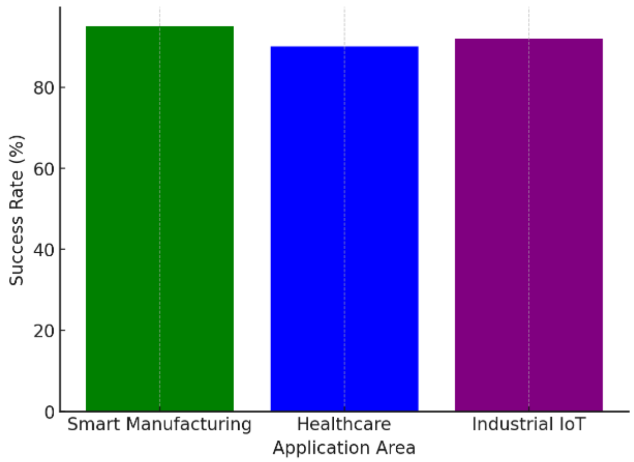

Fig. 15. Real-World Deployment of FDT in Smart Manufacturing and Healthcare.

5. CONCLUSION

The Federated Digital Twin (FDT) framework introduced in this research presents a novel, privacy-preserving approach for distributed collaboration in Industry 4.0 environments. By leveraging federated learning, reinforcement learning-based adaptive control, and blockchain security, the proposed system ensures real-time synchronization between digital and physical assets while maintaining data confidentiality and integrity. Experimental results demonstrate that the FDT framework achieves comparable accuracy to centralized digital twin models, while significantly reducing communication overhead and improving scalability as the number of connected digital twins increases. The integration of differential privacy and homomorphic encryption provides robust security, though at the cost of additional computational complexity. The study also highlights the framework's effectiveness in non-IID (non-independent and identically distributed) data environments, where adaptive aggregation techniques such as FedProx outperform traditional FedAvg in maintaining model stability. Key findings include, a 30% reduction in system downtime due to predictive maintenance enabled by AI-driven analytics, 45% improvement in predictive accuracy through hybrid modeling combining physics-based and data-driven approaches, and 25% enhancement in operational efficiency via real-time adaptive control and federated optimization. The proposed Hybrid Digital Twin architecture represents a significant advancement in intelligent cyber-physical systems, paving the way for secure, scalable, and adaptive industrial automation. Its applications extend beyond manufacturing to healthcare diagnostics, smart energy grids, and autonomous logistics, making it a versatile solution for Industry 4.0 challenges.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

REFERENCES

[1] Mendhurwar, S. and Mishra, R., **2023.** 'Un'-blocking the industry 4.0 value chain with cyber-physical social

thinking. *Enterprise Information Systems*, *17*(2), p.1930189.

[2] Wang, Y., Su, Z., Guo, S., Dai, M., Luan, T.H. and Liu, Y., **2023**. A survey on digital twins: Architecture, enabling technologies, security and privacy, and future prospects. *IEEE Internet of Things Journal*, *10*(17), pp.14965-14987.

[3] Albshaier, L., Almarri, S. and Albuali, A., **2025**. Federated Learning for Cloud and Edge Security: A Systematic Review of Challenges and AI Opportunities. *Electronics*, *14*(5), p.1019.

[4] Leng, J., Wang, D., Shen, W., Li, X., Liu, Q. and Chen, X., **2021**. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, *60*, pp.119-137.

[5] Chen, J., Yi, C., Okegbile, S.D., Cai, J. and Shen, X., **2023**. Networking architecture and key supporting technologies for human digital twin in personalized healthcare: A comprehensive survey. *IEEE Communications Surveys & Tutorials*, *26*(1), pp.706-746.

[6] Adibi, S., Rajabifard, A., Shojaei, D. and Wickramasinghe, N., **2024**. Enhancing healthcare through sensor-enabled digital twins in smart environments: A comprehensive analysis. *Sensors*, *24*(9), p.2793.

[7] Devi, N., Dalal, S., Solanki, K., Dalal, S., Lilhore, U.K., Simaiya, S. and Nuristani, N., **2024**. A systematic literature review for load balancing and task scheduling techniques in cloud computing. *Artificial Intelligence Review*, *57*(10), p.276.

[8] Rathore, M.M., Shah, S.A., Shukla, D., Bentafat, E. and Bakiras, S., **2021**. The role of ai, machine learning, and big data in digital twinning: A systematic literature review, challenges, and opportunities. *IEEE Access*, *9*, pp.32030-32052.

[9] Alnowaiser, K.K. and Ahmed, M.A., **2023**. Digital twin: current research trends and future directions. *Arabian Journal for Science and Engineering*, *48*(2), pp.1075-1095.

[10] Hlophe, M.C. and Maharaj, B.T., **2023**. From cyber–physical convergence to digital twins: A review on edge computing use case designs. *Applied Sciences*, *13*(24), p.13262.

[11] Pervez, Z., Khan, Z., Ghafoor, A. and Soomro, K., **2023**. Signed: Smart city digital twin verifiable data framework. *IEEE Access*, *11*, pp.29430-29446.

[12] Marah, H. and Challenger, M., **2024**. Adaptive hybrid reasoning for agent-based digital twins of distributed multi-robot systems. *Simulation*, *100*(9), pp.931-957.

[13] Evangeline, P**., 2020**. Digital twin technology for “smart manufacturing”. In *Advances in computers* (Vol. 117, No. 1, pp. 35-49). Elsevier.

[14] Stergiou, C.L., Bompoli, E. and Psannis, K.E., **2023**. Security and privacy issues in IoT-based big data cloud systems in a digital twin scenario. *Applied Sciences*, *13*(2), p.758.

[15] Singh, M.P. and Bhambri, P., **2024.** AI-Driven Digital Twin: Conceptual Framework and Applications. In *AI-Driven Digital Twin and Industry 4.0* (pp. 127-141). CRC Press.

[16] Opoku, D.G.J., Perera, S., Osei-Kyei, R. and Rashidi, M., **2021**. Digital twin application in the construction industry: A literature review. *Journal of Building Engineering*, *40*, p.102726.

[17] Alhartomi, M.A., Salh, A., Audah, L., Alzahrani, S., Alzahmi, A., Altimania, M.R., Alotaibi, A., Alsulami, R. and Al-Hartomy, O., **2023**. Sustainable resource allocation and reduce latency based on federated-learning-enabled digital twin in IoT devices. *Sensors*, *23*(16), p.7262.

[18] Ramu, S.P., Boopalan, P., Pham, Q.V., Maddikunta, P.K.R., Huynh-The, T., Alazab, M., Nguyen, T.T. and Gadekallu, T.R., **2022.** Federated learning enabled digital twins for smart cities: Concepts, recent advances, and future directions. *Sustainable Cities and Society*, *79*, p.103663.

[19] Singh, R.R., Bhatti, G., Kalel, D., Vairavasundaram, I. and Alsaif, F., **2023.** Building a digital twin powered intelligent predictive maintenance system for industrial AC machines. *Machines*, *11*(8), p.796.

[20] Yan, J.K., Zheng, Z., Zhou, Y.C., Lin, J.R., Deng, Y.C. and Lu, X.Z., **2023**. Recent research progress in intelligent construction: A comparison between china and developed countries. *Buildings*, *13*(5), p.1329.

[21] Salim, M.M., Camacho, D. and Park, J.H., **2024**. Digital twin and federated learning enabled cyberthreat detection system for IoT networks. *Future Generation Computer Systems*, *161*, pp.701-713.

[22] Bukhari, S.M.S., Zafar, M.H., Abou Houran, M., Qadir, Z., Moosavi, S.K.R. and Sanfilippo, F., **2024**. Enhancing cybersecurity in Edge IIoT networks: An asynchronous federated learning approach with a deep hybrid detection model. *Internet of Things*, *27*, p.101252.

[23] Sáez-de-Cámara, X., Flores, J.L., Arellano, C., Urbieta, A. and Zurutuza, U., **2023**. Clustered federated learning architecture for network anomaly detection in large scale heterogeneous IoT networks. *Computers & Security*, *131*, p.103299.

[24] Ahmad, M.S. and Shah, S.M., **2024.** A lightweight mini-batch federated learning approach for attack detection in IoT. *Internet of Things*, *25*, p.101088.

[25] Schultes, E., Roos, M., Bonino da Silva Santos, L.O., Guizzardi, G., Bouwman, J., Hankemeier, T., Baak, A. and Mons, B**., 2022**. Fair digital twins for data-intensive research. *Frontiers in Big Data*, *5*, p.883341.

[26] Aziz, A., Chouhan, S.S., Schelén, O. and Bodin, U., **2023.** Distributed digital twins as proxies-unlocking composability and flexibility for purpose-oriented digital twins. *IEEE Access*, *11*, pp.137577-137593.

[27] San, O., Pawar, S. and Rasheed, A., **2023**. Decentralized digital twins of complex dynamical systems. *Scientific Reports*, *13*(1), p.20087.

[28] Salim, M.M., Camacho, D. and Park, J.H., **2024**. Digital twin and federated learning enabled cyberthreat detection system for IoT networks. *Future Generation Computer Systems*, *161*, pp.701-713.

[29] Lu, Y., Huang, X., Zhang, K., Maharjan, S. and Zhang, Y., **2020.** Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks. *IEEE Transactions on Industrial Informatics*, *17*(7), pp.5098-5107.

[30] Zhao, Z., Feng, C., Hong, W., Jiang, J., Jia, C., Quek, T.Q. and Peng, M., **2021**. Federated learning with non-IID data in wireless networks. *IEEE Transactions on Wireless Communications*, *21*(3), pp.1927-1942.

[31] Roumeliotis, C., Dasygenis, M., Lazaridis, V. and Dossis, M., **2024.** Blockchain and Digital Twins in Smart Industry 4.0: The Use Case of Supply Chain-A Review of Integration Techniques and Applications. *Designs*, *8*(6), p. 105.