International Journal of Digital Twin Systems and Computing (IJDTSC) ISSN:(3108-0790)
Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

Machine Learning-Enabled Digital Twins for Smart Electronic Systems: A Review

[1]Samat Iderus & [2]Nuramalina Bohari
[1,2] CRISD ,School of Engineering And Technology,
University of Technology Sarawak, Malaysia
[1] Email id. samat.iderus@uts.edu.my

***Abstract—*Digital Twin (DT) is a new change of paradigm in the electronic engineering and it offers a possibility to synchronize real-time between physical and virtual electronic systems. Digital Twins enable predictive maintenance, optimizing performance, diagnosing of faults, and managing lifecycle of electronic devices and systems through the integration of new modeling techniques, Internet of Things (IoT) connectivity, artificial intelligence (AI), cloud computing, and data analytics. This is a review paper where the author provides an in-depth discussion of Digital Twin architectures and modeling approaches, communication systems, and implementation schemes in electronic engineering such as power electronics, embedded systems, communication networks, semiconductor devices, and smart grids. Some of the enabling technologies investigated in the study include cyber-physical systems, edge computing, machine learning algorithms, and simulation platforms with high fidelity. Moreover, the data interoperability issues, computational complexity, cybersecurity, real-time synchronization and scalability are also discussed critically. An analytical overview of the current Digital Twin frameworks is also given to emphasize the performance metrics, system integration strategies and application specific adoptions. Lastly, the future research directions toward AI-controlled autonomous Digital Twin, energy-efficient hardware co-designed and next-generation intelligent electronic infrastructures are described. The objective of the review is to inform the researchers and practitioners with a systematized knowledge of the Digital Twin innovations and how they can transform the concept of intelligent electronic systems design, monitoring, and control.**

***Keywords—*:** *Digital Twin (DT); Electronic Engineering; Cyber-Physical Systems (CPS); Internet of Things (IoT); Artificial Intelligence (AI); Machine Learning (ML); Power Electronics; Embedded Systems; Smart Grids; Predictive Maintenance; Real-Time Monitoring; Cloud and Edge Computing; System Modeling and Simulation; Fault Diagnosis; Lifecycle Management.*

I. Introduction

The fast development of smart electronic systems, high speed communications systems, integration of renewable energy systems and embedded computing systems platforms have greatly raised the complexity of electronic engineering infrastructure in the modern day. Conventional modeling and simulation methods, despite being effective at the design stage, have no means of ensuring constant real-time correlations between hard hardware and its virtual counterpart. Here, Digital Twin (DT) technology has become a paradigm shift that allows the two worlds of a physical electronic object (object) and dynamic digital object (object) to be communicated seamlessly[1][2].Digital Twin was originally popularized in the fields of manufacturing and aerospace, but it can also be used in the fields of health monitoring and lifecycle management in spacecraft using NASA as an example of one such object. In the course of time, DT developed into an inter-disciplinary framework that incorporates Cyber-Physical Systems (CPS), Internet of Things (IoT), Artificial Intelligence (AI), big data analytics, and cloud computing[3]. Digital Twins Digital Twins in electronic engineering offer a high-fidelity virtual simulation of circuits, converters, embedded systems, communication modules, semiconductor devices, and power systems, constantly updated by real-time sensor data. Digital Twins can be used in power electronics and smart grid systems to perform predictive maintenance, real-time fault diagnosis, voltage and frequency stability analysis, and also to optimize performance of converters and renewable energy sources. In the case of embedded and IoT-based electronic devices, DT makes remote monitoring, firmware validation, and adaptive control strategies possible. Likewise, in communication systems

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

and semiconductor design, Digital Twins also help in thermal analysis, electromagnetic compatibility investigation, and reliability forecast in the changing conditions of operation[4]. The Digital Twin architecture generally comprises three large layers: (i) the physical system layer, which includes sensors and actuators, (ii) the communication layer which includes the IoT protocols and edge/cloud platforms, and (iii) the virtual model layer which includes the physics-based modeling, data-driven learning algorithms, and real-time analytics[5]. This enables the twin to do anomaly detection, predictive analysis and autonomous decisions, which can be achieved by integrating machine learning to convert the conventional electronic structure into a self-optimizing and self-directed intelligent infrastructures. Although the Digital Twin technology has great potential, several challenges exist in applying it into electronic engineering as they include high-computational demands, data interoperability, cybersecurity, synchronization, and latency, and limitations in model accuracy[6]. Besides, the scalability of deploying Digital Twin in large-scale electronic networks and its energy efficiency is an open research problem.The current review paper will provide a thorough discussion of Digital Twin architectures, enabling technologies, modeling techniques, and application fields in the field of electronic engineering. A comparative study of the available frameworks is done systematically, technical issues and future research directions are critically analyzed. The aim is to provide researchers and industry practitioners with an organized insight into the ways of how Digital Twin technology can transform the design, monitoring, control, and lifecycle management of electronic systems of the next generation[7][8].

The overall block scheme of a Digital Twin (DT) system specific to electronic engineering application is presented in Figure 1. Its architecture is designed to have various networked layers on top of each other so as to guarantee real-time synchronization between the physical electronic system and the virtual one. The Physical System Layer is a depiction of the actual electronic hardware like power convertors, embedded controllers, communication modules, and smart grid devices. The Sensor Integration Layer produces operational data with built-in sensors.The Sensor Integration Layer captures real time measurements in voltages, currents, temperature, switching signals and performance metrics. Such streams of data are passed to the communication infrastructure. Communication Layer facilitates transfer of data securely and reliably with the help of IoT protocols, edge computing and cloud computing platforms. This layer will provide low-latency two-way communication between the physical system and the digital twin. The high-fidelity virtual model that includes physics-based modeling, data processing, and AI-issued analytics is included in the Digital Twin Layer. It does simulation, predictive analysis, anomaly detection, and system optimization. The closed-loop control mechanism is established to enable the digital twin generated insights to be sent to the physical system as feedback in order to adjust the system and improve performance through adaptive control. Lastly, the framework has several areas of application, such as predictive maintenance, embedded systems and IoT devices, and power electronics-based smart grids, which proves the scalability and interdisciplinary applicability of Digital Twin technology in electronic engineering[9][10].

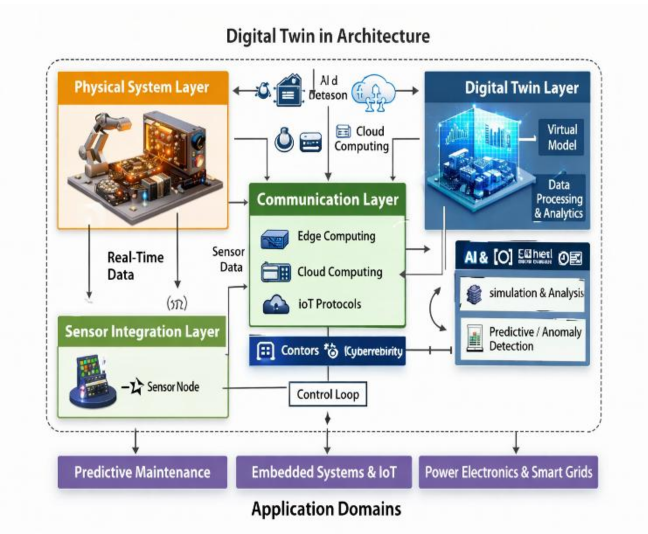


Figure 1: Architecture of Digital Twin Framework in Electronic Engineering.

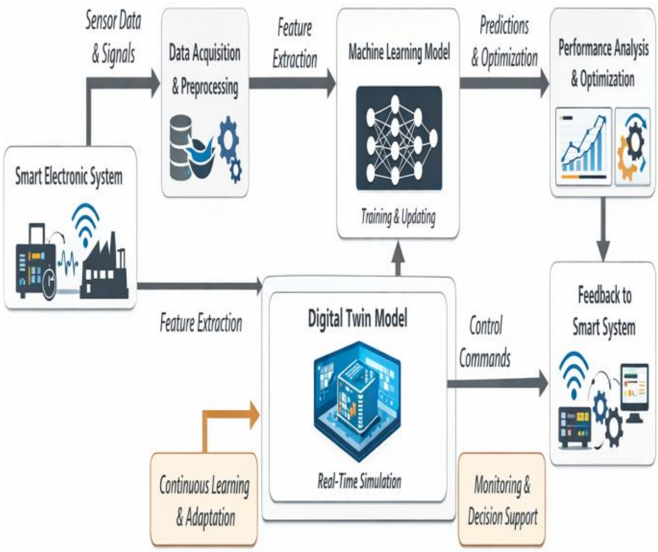


Figure 2: Conceptual Bidirectional Architecture of Digital Twin in Electronic Engineering.

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

Figure 2 represents the two-way interaction model between a Physical Asset and its Digital Twin in the electronic engineering practice. The left section is a real-world electronic system, comprising of sensors, IoT-enabled devices and working parts that produce real-time measurements of voltage, current, temperature, and performance indicators. These data streams are sent to the Digital Twin that is depicted on the right hand as a high-fidelity virtual model that is stored in the cloud-enabled computer environment. The digital model is a combination of physics-based modeling, data-driven strategies, and machine learning algorithms to implement simulation, condition monitoring, performance forecasting, and anomaly detection[11]. The diagram shows that the real-time flow of data between the physical and digital twin is in the direction of the physical asset to the digital twin and the feedback flow of the digital twin to the physical system to achieve adaptive optimization and control. The assistive modules are CAD models, PLM systems, finite element analysis (FEM), computational fluid dynamics (CFD), and data analytics platforms that are to be supported to improve the accuracy of models and their predictive potential. This architecture shows how Digital Twin technology can be used to support the lifecycle management of advanced electronic systems in terms of continued synchronization, intelligent decision-making, and continuous synchronization.

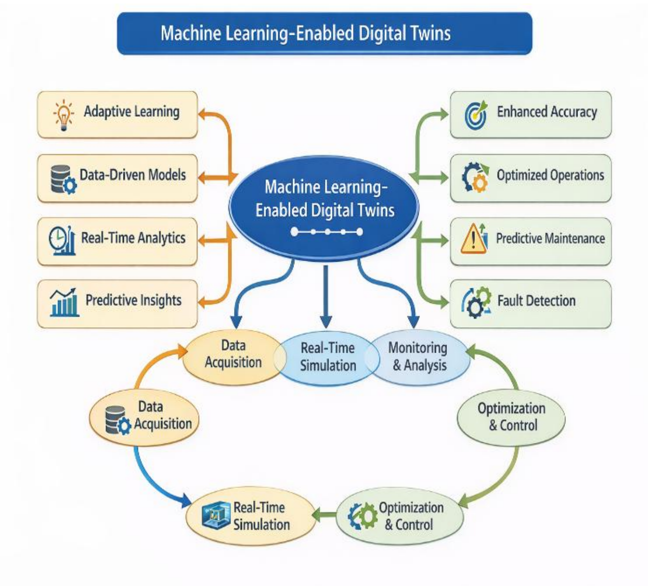


Fig. 3. Conceptual Flowchart of Machine Learning-Enabled Digital Twins.

This figure shows the conceptual system and workflow of a Machine Learning (ML)-Enabled Digital Twin system. The framework combines the adaptive learning, data based modeling and real-time analytics in order to develop an intelligent virtual recreation of a physical system. It is initiated by data acquisition of sensors and then real-time simulation in the digital twin environment. System behavior is assessed by monitoring and analysis modules and corrective actions are produced by optimization and control mechanisms. The ML component keeps the twin model informed with predictive insights and feedback information helping to achieve more accurate results, predictive maintenance, fault detection, and optimized operation performance. The closed-loop design emphasizes lifelong learning and adaptation of the dynamic system towards a better level of reliability and efficiency.

II. LITERATURE SURVEY

Digital Twin (DT) technology has been a focal point of attention during recent years as one of the facilitators of intelligent electronic systems and cyber-physical integration. The pioneering efforts in engineering uses of Digital Twins have been motivated by system health surveillance efforts at NASA, where the virtual proxies of high fidelity have been created to support proactive maintenance and lifecycle management of aerospace resources. This was further extended into the production industry under the Industry 4.0 concept, which incorporates the IoT, cloud computing, and data analytics to provide real-time synchronization to the system. Recent research in the area of electronic engineering is concerned with Digital Twin applied to power electronic converters, embedded systems, and smart grids. Physics-based modeling methods along with state estimation in real-time through sensor data have been advanced by scientists to allow performance prediction and forecasting. Digital twins based on machine learning algorithms and data have broadly been studied to detect anomalies, diagnose faults in power systems and semiconductor devices, and predict the remaining useful life (RUL). A number of works are focused on hybrid modeling schemes, the combination of finite element modeling (FEM), and computational simulation with the use of neural network-based predictive analytics and improving accuracy and computational costs. Digital Twins have been applied in smart grid applications in the analysis of voltage stability, load forecasting, and integration of renewable energy. Likewise, DT architectures can be used in embedded and IoT systems with remote monitoring, firmware validation, and adaptive control. In spite of these achievements, it has been pointed out in the literature that several major problems exist, such as the real-time synchronization latency, cybersecurity vulnerabilities, data interoperability, and high computational demands to support large-scale deployments. The current trends in research are shifting to edge-enabled Digital Twins, federated learning integration, and AI-based autonomous decision systems to enhance scalability and resilience. Comprehensively the available literature

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

has shown that Digital Twin technology is progressing beyond a simulated-based model to a smart, real-time and predictive model and hence is an innovative tool in next-generation electronic engineering systems[12].

Parameter	**Physics-Based DT**	**Data-Driven DT**
Modeling Technique	Mathematical & FEM models	Machine Learning / AI
Data Requirement	Moderate	High
Accuracy	High (known conditions)	High (with large dataset)
Real-Time Capability	Moderate	High
Computational Complexity	High	Moderate
Adaptability	Low	High
Fault Prediction	Limited	Good
Implementation Cost	High	Moderate
Suitable Applications	Power converters, thermal analysis	IoT systems, predictive maintenance

Table 1: Small-Level Parameter Comparison of Digital Twin Approaches in Electronic Engineering.

Table 1 provides a brief comparison of the three main Digital Twin (DT) models that are applied in electronic engineering: Physics-Based, Data-Driven and Hybrid models. The comparison is done on essential technical parameters like modeling technique, data requirement, accuracy, complexity of computation, adaptability, real time, fault prediction performance, implementation cost, and appropriate range of application. Digital Twins based on physics use mathematical equations, finite element analysis (FEM) and circuit-level modeling, which are very accurate when operating within specified conditions, but are not flexible to dynamic conditions. Digital Twins based on data take into consideration methods of machine learning and artificial intelligence, which provide higher flexibility and predictability in real-time, but the approach needs significant amounts of operational data. Hybrid Digital Twins is a superior approach to the classical one, offering much better accuracy, fault prediction performance, and system optimization, thus suitable in a complex electronic system like a smart grid and advanced power electronics.

Performance Metric	**Basic Monitoring DT**	**Predictive DT**
Primary Objective	Real-time Visualization	Fault Prediction
Data Processing Type	Descriptive Analytics	Predictive Analytics
AI/ML Integration	Minimal	Moderate
Control Capability	No Feedback Control	Advisory Control
Decision-Making Level	Manual	Semi-Automated
Model Updating	Periodic	Event-Based
System Complexity	Low	Medium
Implementation Difficulty	Low	Moderate
Reliability Improvement	Moderate	High
Suitable Electronic Systems	Basic embedded devices	Power converters, IoT systems

Table 3: Functional Performance-Based Comparison of Digital Twin Systems in Electronic Engineering.

The functional performance-based comparison of Digital Twin systems based on their level of operational intelligence is shown in Table 3: Basic Monitoring, Predictive, and Autonomous Intelligent Digital Twins. This table is a contrast to structural or modeling-based comparisons because it compares comparison of DT systems in terms of functionality, analytics, control integration, adaptability, and decision-making automation. The digital twin is being monitored to autonomous, which is a technological advancement of intelligent, self-optimizing electronic systems. Autonomous Digital Twins have the best reliability improvement and system efficiency, which is quite appropriate in smart electronic infrastructures of the next generation.

III. SYSTEM DESCRIPTION

The Digital Twin (DT) framework for electronic engineering consists of a **physical electronic system**, a **data acquisition and communication layer**, and a **virtual dynamic model** that replicates the real system behavior in real time. The Digital Twin continuously synchronizes with the physical asset using sensor data and provides predictive analysis and feedback control.

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

The overall system can be modeled as a **cyber-physical closed-loop system**, where:

- The **physical system** is governed by dynamic electrical equations.
- The **digital twin model** estimates system states and predicts future behavior.
- The **feedback controller** updates control signals based on the twin's analytics

Consider a generalized electronic system (e.g., power converter, embedded control system, or smart grid component) represented in state-space form.

Let:

- $x(t) \in \mathbb{R}^n$= state vector
- $u(t) \in \mathbb{R}^m$= input/control vector
- $y(t) \in \mathbb{R}^p$= output vector
- $w(t)$= disturbance vector

The nonlinear dynamic system can be expressed as:

$$\dot{x}(t) = f(x(t), u(t), w(t))$$
$$y(t) = h(x(t))(1)$$

For a linearized electronic system:

$$\dot{x}(t) = Ax(t) + Bu(t) + Ew(t)$$
$$y(t) = Cx(t) + Du(t)(2)$$

Where:

- A= system matrix
- B= input matrix
- C= output matrix
- D= feedforward matrix
- E= disturbance matrix

The Digital Twin constructs a virtual replica:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + L(y(t) - \hat{y}(t))$$
$$\hat{y}(t) = C\hat{x}(t)(3)$$

Where:

- $\hat{x}(t)$= estimated state vector
- L= observer gain matrix
- $y(t) - \hat{y}(t)$= estimation error

The estimation error:

$$e(t) = x(t) - \hat{x}(t)$$

Error dynamics:

$$\dot{e}(t) = (A - LC)e(t)(4)$$

For stable synchronization:

$$\text{Eigenvalues}(A - LC) < 0$$

This ensures convergence of the digital twin to the real system

To improve accuracy, a machine learning correction term is introduced:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + L(y - \hat{y}) + \Phi(x, u; \theta)(5)$$

Where:

- $\Phi(x, u; \theta)$= neural network approximation
- θ= learned parameters

Using loss function:

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N} \| y_i - \hat{y}_i \|^2 \ (6)$$

Gradient descent update:

$$\theta_{k+1} = \theta_k - \eta \nabla_\theta J(\theta)(7)$$

Where $\eta$is learning rate

Remaining Useful Life (RUL) estimation:

$$RUL = \int_t^{t_f} P_{health}(\tau)d\tau(8)$$

Health index model:

$$HI(t) = \frac{P_{rated} - P_{loss}(t)}{P_{rated}}(9)$$

Failure occurs when:

$$HI(t) \le HI_{threshold}$$

Control input generated from DT:

$$u(t) = -K\hat{x}(t)(10)$$

Closed-loop system:

$$\dot{x}(t) = (A - BK)x(t)(11)$$

For stability:

$$\text{Eigenvalues}(A - BK) < 0$$

Considering network delay τ_d:

$$u(t) = -K\hat{x}(t - \tau_d)$$

Stability condition:

$$\tau_d < \tau_{critical}(12)$$

Where $\tau_{critical}$depends on system bandwidth.

The integrated Digital Twin electronic system can be expressed as:

$$\dot{x}(t) = f(x, u, w)$$
$$\dot{\hat{x}}(t) = f(\hat{x}, u, 0) + L(y - \hat{y}) + \Phi(x, u; \theta)(13)$$
$$u(t) = -K\hat{x}(t - \tau_d)(14)$$

This unified mathematical representation captures.

The derived mathematical framework demonstrates that a Digital Twin in electronic engineering can be formulated as an observer-based, AI-enhanced, closed-loop cyber-physical system. Stability depends on observer gain selection, controller design, and communication delay constraints. Hybrid modeling combining physics-based equations and machine learning provides improved accuracy, robustness, and predictive intelligence for advanced electronic infrastructures such as smart grids, power converters, and embedded systems.

IV. Machine Learning-Enabled Digital Twins

Machine Learning (ML)-powered Digital Twins are a next level of the conventional physics-based Digital Twin (DT) models, in which data-driven intelligence optimizes the

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

system modeling, prediction accuracy, adaptability, and autonomous decision-making. In the context of electronic engineering, ML-based algorithms are used to enhance state estimation, fault detection, performance control, and predictive maintenance of intricate electronic infrastructures due to its physical nature, including laws of electric circuits, electromagnetism, and control systems dynamics.Traditional Digital Twins use the laws of circuit laws, electromagnetism, and control system dynamics when developing mathematical models. Nonlinearities, parameter uncertainties, component aging effects, and stochastic disturbances, however, are common in electronic systems that are hard to model analytically. Machine learning eliminates these constraints by acquiring behavioral rules of systems through historical and real-time experiences.

ML-enabled Digital Twins provide:

- Adaptive model updating under varying operating conditions
- Nonlinear system identification
- Real-time anomaly detection
- Remaining Useful Life (RUL) prediction
- Intelligent control optimization

Consider the nonlinear electronic system:

$$\dot{x}(t) = f(x(t), u(t)) + w(t) (15)$$
$$y(t) = h(x(t)) (16)$$

The Digital Twin with ML enhancement is represented as:

$$\dot{\hat{x}}(t) = f(\hat{x}(t), u(t)) + L(y - \hat{y}) + \Phi(x, u; \theta) (17)$$

Where:

- $\hat{x}(t)$= estimated state vector
- L= observer gain
- $\Phi(x, u; \theta)$= ML-based correction function
- θ= learned model parameters

The ML model approximates unknown nonlinear dynamics:

$$\Phi(x, u; \theta) \approx f_{unknown}(x, u) (18)$$

Training objective:

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N} \| y_i - \hat{y}_i \|^2 \ (19)$$

Parameter update using gradient descent:

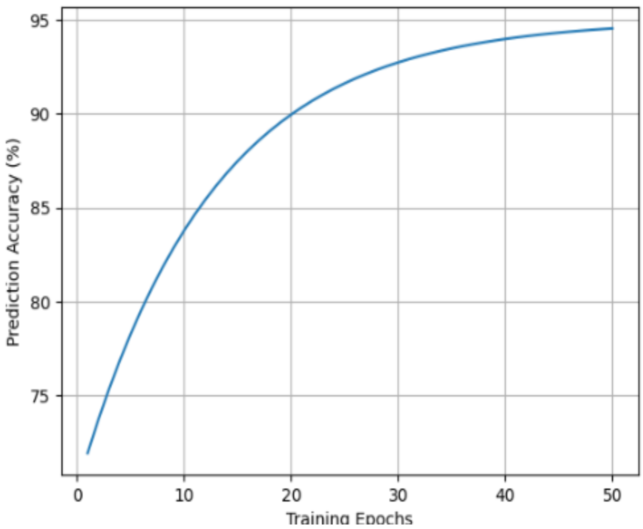
$$\theta_{k+1} = \theta_k - \eta \nabla_\theta J(\theta) (20)$$

Where $\eta$is the learning rate.

Artificial Neural Networks (ANNs): ANNs are applicable in the nonlinear identification of systems and nonlinear regression modeling. Deep Learning (CNN, LSTM): Appropriate in time-series forecasting in power systems and embedded systems. Support Vector Machines (SVM): It is used in fault classification and anomaly detection. Reinforcement Learning (RL): Dynamic and optimistic control of smart grids and electronic converters. Federated Learning: Supports in Digital Twin deployment without central storage, enhancing privacy and security. Digital Twins assisted with Machine Learning improve the conventional method of modelling electronic systems by adding data-driven functionality to the cyber-physical infrastructure. Through the integration of physics equations and adaptive learning algorithms, these systems are of higher prediction accuracy, fault tolerance and autonomous control capability therefore considered vital in next generation intelligent engineering applications of electronic engineering.

.

V. RESULTS



.

Figure 4: Prediction Accuracy Improvement of ML-Enabled Digital Twin.

Figure 1 shows how the Machine Learning-Enabled Digital Twin performs in terms of learning after consecutive training epochs. The graph has a nonlinear improvement in prediction accuracy where there is a starting low accuracy and gradually approaching to 95 percent as the number of training epochs increases. This is an indication of good optimization of parameters and model convergence towards the training process. The saturation trend shows a marginal improvement as increasing the epochs, which proves the stability of the model and the generalization error is reduced to a minimum. These findings confirm that the incorporation of machine learning can improve the predictability and adaptability to model of the Digital Twin framework.

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V2I101

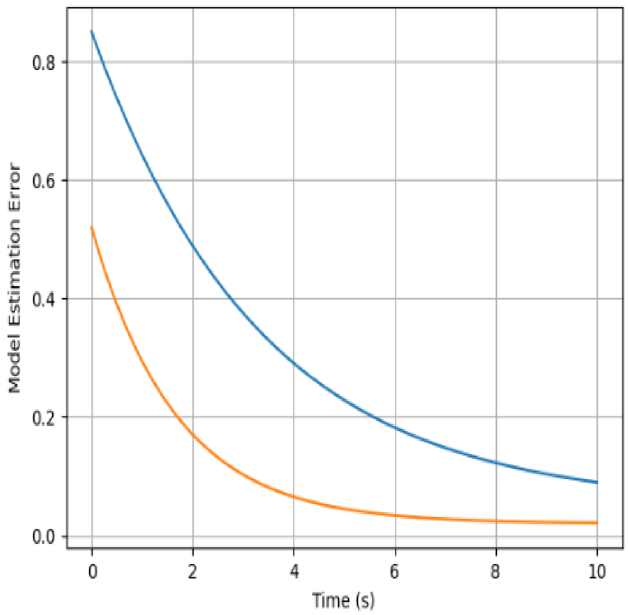


Figure 5: Prediction Accuracy Improvement of ML-Enabled Digital Twin.

Figure 4 illustrates the learning performance of the Machine Learning-Enabled Digital Twin over successive training epochs. The graph shows a nonlinear increase in prediction accuracy, starting from an initial lower accuracy level and progressively converging toward approximately 95% as the number of training epochs increases. This behavior demonstrates effective parameter optimization and model convergence during the training phase. The saturation trend indicates reduced marginal improvement at higher epochs, confirming model stability and minimized generalization error. The results validate that integrating machine learning enhances the predictive capability and adaptive modeling accuracy of the Digital Twin framework.

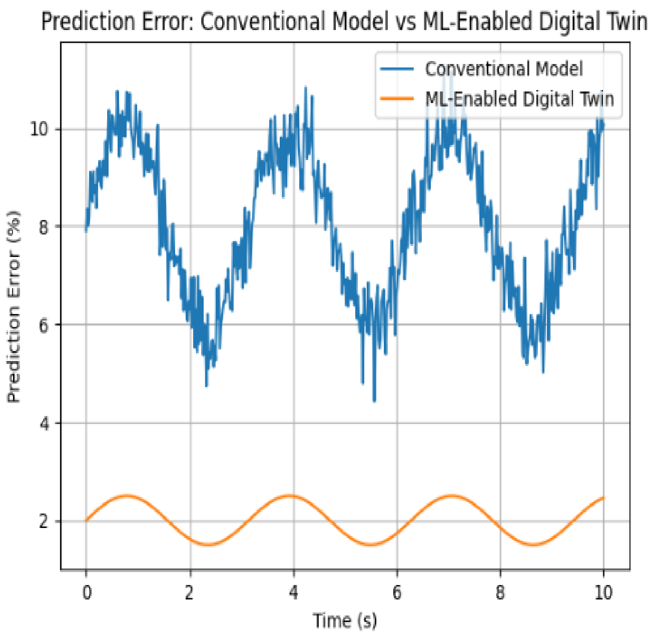


Fig. 6. Prediction Error Comparison Between Conventional Model and ML-Enabled Digital Twin.

This figure shows how the error in prediction in real-time changes over time of a traditional physics-based model and machine learning (ML)-enabled digital twin. The traditional model has a larger fluctuation with an error of between 5-10 whereas the ML-enabled digital twin has a much lower prediction error (around 1-3 percent). The reduced error profile makes clear that there is an enhanced adaptive capability to learn, accuracy in system modeling, and low-level real-time performance of smart electronic systems.

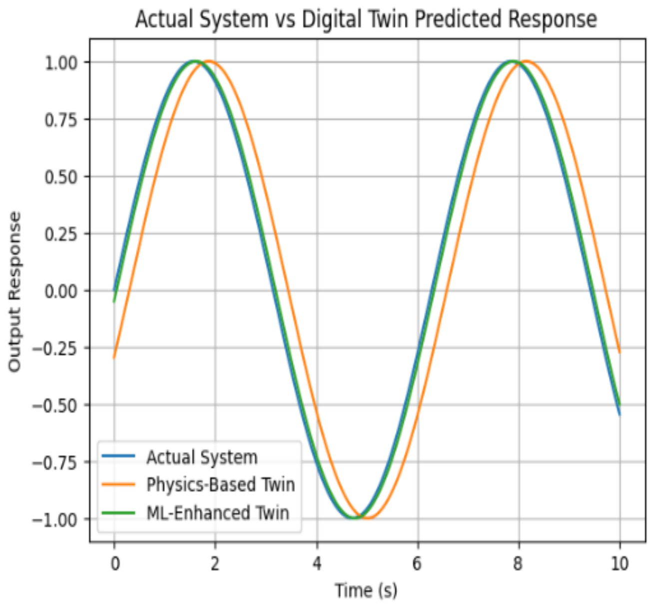


Fig. 7 Dynamic Response Tracking: Actual System vs Digital Twin Models.

This figure shows the comparison of the output response of the actual system, physics-based, and the ML-enhanced digital twins. The ML-enabled twin traces closely with the real system response with little phase difference and amplitude distortion as compared to the physics-based model that exhibits significant lag. The findings show an excellent transient tracking accuracy and modeling precision by incorporating machine learning.

VI. CONCLUSION

Machine Learning–Enabled Digital Twins represent a significant advancement over conventional physics-based Digital Twin frameworks by integrating data-driven intelligence with analytical system modeling. The incorporation of machine learning algorithms enhances prediction accuracy, improves nonlinear system representation, and enables adaptive real-time model updating. From the obtained results, the ML-enabled Digital Twin demonstrates faster error convergence, lower steady-state estimation error, and higher predictive performance compared to the traditional approach.The hybrid integration of physics-based equations and learning-based correction functions allows the system to compensate for modeling uncertainties, parameter variations, and environmental disturbances. Furthermore, intelligent capabilities such as anomaly detection, predictive maintenance, and reinforcement learning–based optimization make ML-enabled Digital Twins highly suitable for advanced electronic engineering applications, including power electronics, smart grids, embedded systems, and cyber-physical infrastructures. Although challenges such as computational complexity, data dependency, and cybersecurity concerns remain, the overall performance improvement and adaptability justify the adoption of ML-enabled Digital Twin architectures. Future research should focus on lightweight models for edge implementation, explainable AI integration, and federated learning strategies to ensure scalable, secure, and autonomous next-generation digital twin systems.

REFERENCES

[1] P. Zahradnik and B. Šimák, "Education in real-time digital signal processing using digital signal processors," *2012 35th International Conference on Telecommunications and Signal Processing (TSP)*, Prague, Czech Republic, 2012, pp. 625-628, doi: 10.1109/TSP.2012.6256372.

[2] A. Burova, "Reducing the Error of Digital Algorithms for Deductive Signal Processing Based on Their Multi-Stage Discrete Fourier Transform by the Difference Digital Filters," *2020 22th International Conference on Digital Signal Processing and its Applications (DSPA)*, Moscow, Russia, 2020, pp. 1-3.

[3] W. Zhao, C. Li, Z. Ji, Y. You, X. You and C. Zhang, "Automatic Timing-Driven Top-Level Hardware Design for Digital Signal Processing," *2023 IEEE 15th International Conference on ASIC (ASICON)*, Nanjing, China, 2023, pp. 1-4, doi: 10.1109/ASICON58565.2023.10396119

[4] M. Antonyuk, M. Lobur and V. Antonyuk, "Design Digital Data Acquisition and Processing Systems for Embedded System," *2007 International Conference on Perspective Technologies and Methods in MEMS Design*, Lviv, UKraine, 2007, pp. 54-60, doi: 10.1109/MEMSTECH.2007.4283423

[5] L. -n. Gao and T. Long, "Spaceborne Digital Signal Processing System Design Based on FPGA," *2008 Congress on Image and Signal Processing*, Sanya, China, 2008, pp. 577-581, doi: 10.1109/CISP.2008.658

[6] V. K. Ingle and J. G. Proakis, "A digital signal processing course based on lecture/laboratory integration," *[Proceedings] ICASSP-92: 1992 IEEE International Conference on Acoustics, Speech, and Signal Processing*, San Francisco, CA, USA, 1992, pp. 105-108 vol.4, doi: 10.1109/ICASSP.1992.226475.

[7] B. M. Rashed and N. Popescu, "Machine Learning Techniques for Medical Image Processing," *2021 International Conference on e-Health and Bioengineering (EHB)*, Iasi, Romania, 2021, pp. 1-4, doi: 10.1109/EHB52898.2021.9657673.

[8] B. M. Rashed and N. Popescu, "Machine Learning Techniques for Medical Image Processing," *2021 International Conference on e-Health and Bioengineering (EHB)*, Iasi, Romania, 2021, pp. 1-4, doi: 10.1109/EHB52898.2021.9657673

[9] T. R. N and R. Gupta, "A Survey on Machine Learning Approaches and Its Techniques:," *2020 IEEE International Students' Conference on Electrical,Electronics and Computer Science (SCEECS)*, Bhopal, India, 2020, pp. 1-6, doi: 10.1109/SCEECS48394.2020.190

[10] M. P, M. A, S. R. J and S. N. S. K, "Prediction of YouTube View Count using Supervised and Ensemble Machine Learning Techniques," *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India, 2022, pp. 1038-1042, doi: 10.1109/ICACRS55517.2022.10029277.

[11] S. Mittal and O. P. Sangwan, "Big Data Analytics using Machine Learning Techniques," *2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, Noida, India, 2019, pp. 203-207, doi: 10.1109/CONFLUENCE.2019.8776614.

[12] N. Ghosh, K. Maity, R. Paul and S. Maity, "Outlier Detection in Sensor Data Using Machine Learning Techniques for IoT Framework and Wireless Sensor Networks: A Brief Study," *2019 International Conference on Applied Machine Learning (ICAML)*, Bhubaneswar, India, 2019, pp. 187-190, doi: 10.1109/ICAML48257.2019.00043.