PINN-DT: Optimizing Energy Consumption in Smart Buildings Using Hybrid Physics-Informed Neural Networks and Digital Twin Framework with Blockchain Security

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Abstract

The advancement of smart grid technologies necessitates the integration of cutting-edge computational methods to enhance predictive energy optimization. This study proposes a multi-faceted approach by incorporating (1) Deep Reinforcement Learning (DRL) agents trained using data from Digital Twins (DTs) to optimize energy consumption in real time, (2) Physics-Informed Neural Networks (PINNs) to seamlessly embed physical laws within the optimization process, ensuring model accuracy and interpretability, and (3) Blockchain (BC) technology to facilitate secure and transparent communication across the smart grid infrastructure.The model was trained and validated using comprehensive datasets, including smart meter energy consumption data, renewable energy outputs, dynamic pricing, and user preferences collected from IoT devices. The proposed framework achieved superior predictive performance with a Mean Absolute Error (MAE) of 0.237 kWh, Root Mean Square Error (RMSE) of 0.298 kWh, and an R-squared (R^2) value of 0.978, indicating a 97.8% explanation of data variance. Classification metrics further demonstrated the model's robustness, achieving 97.7% accuracy, 97.8% precision, 97.6% recall, and an F1 Score of 97.7%. Comparative analysis with traditional models like Linear Regression, Random Forest, SVM, LSTM, and XGBoost revealed the superior accuracy and real-time adaptability of the proposed method. In addition to enhancing energy efficiency, the model reduced energy costs by 35%, maintained a 96% user comfort index, and increased renewable energy utilization to 40%. This study demonstrates the transformative potential of integrating PINNs, DTs, and Blockchain technologies to optimize energy consumption in smart grids, paving the way for sustainable,and efficient energy management systems.

Keywords: Smart Grids, Digital Twin, PINN, Blockchain, Energy Optimization.

1. Introduction

Current energy system development, coupled with enhanced emphasis on sustainability, underscores the necessity for novel strategies towards the enhancement of energy efficiency in smart grids and buildings. Buildings and smart grids are central elements in the mitigation of the global energy crisis, a situation worsened by escalating greenhouse gas emissions and mounting energy demands. In this regard, the integration of Machine Learning (ML) and Digital Twin (DT) technologies shows much potential for energy conservation, cost saving, and better environmental sustainability. Household appliances (HAs), in particular, energy-intensive appliances like washing machines (WMs) and air conditioners (ACs), account for approximately 30% of overall energy consumption in the United States [1]. Effective management of energy consumption by residential energy management (REM) systems is necessary to save energy costs as well as to maintain grid stability. REM systems are made more complex by integrating distributed energy resources (DERs) like solar photovoltaic (PV) panels, electric vehicles (EVs), and energy storage systems (ESS). The above developments call for the development of sophisticated Home Energy Management Systems (HEMS) that can improve energy consumption while being mindful of user preferences and comfort levels. In general, HEMS rely on two fundamental aspects: monitoring energy consumption through smart meters and scheduling energy usage of individual appliances in an optimized way. Traditionally, these systems have been implemented using deterministic optimization methods, such as mixed-integer nonlinear programming (MINLP) and mixed-integer linear programming (MILP) [2-4]. While effective, these methods are limited by their high computational complexity and challenges associated with managing uncertainties in both user behavior and energy supply. The fast development of data-driven technologies, such as Machine Learning (ML) and Artificial Intelligence (AI), has introduced new opportunities for the advancement of Renewable Energy Management (REM) systems. Reinforcement Learning (RL), a branch of ML, has become an effective approach to optimizing energy use in smart buildings. Google DeepMind showed the promise of reinforcement learning (RL) in slashing data center energy expenses by 40% through innovative energy management techniques [5]. Jamali and Abbasalizadeh [78] developed strategies for placing services within IoT systems while considering cost and performance trade-offs through multicriteria decision-making methods. Their results showed that strategic service co-location can substantially cut operational expenses without compromising efficiency, emphasizing smarter resource deployment in large-scale IoT networks. Abbasalizadeh et al. [79] explored the integration of fuzzy logic with deep learning for dynamic scheduling in wireless communication systems. Their hybrid AI approach demonstrated improved adaptability and latency reduction under heavy network loads, suggesting a promising avenue for enhancing wireless network performance. Furthermore, techniques like Deep Q-Networks (DQN) and policy gradient techniques have been used to improve building energy efficiency [6, 7]. Although promising, current techniques frequently overlook appliances' and distributed energy resources' (DERs') constant and

diverse operation, along with user comfort. Moreover, the rising penetration of Renewable Energy Sources (RESs) and the growing system complexity have necessitated the demand for more scalable and flexible solutions. It is here that Digital Twin (DT) technology, in conjunction with Machine Learning (ML), has the potential to effect revolutionary change.

Digital Twin (DT) technology, first defined by Grieves in 2002, provides a virtual representation of physical systems for real-time monitoring, evaluation, and control [1]. DT systems leverage data from sensors, Internet of Things (IoT) devices, and advanced computational models to create dynamic, virtual representations of physical assets. In the energy industry, DT technology promises significant potential to address issues related to optimization, reliability, and sustainability [74].

The integration of DT systems in smart grids enables high-level functions such as fault detection, load forecasting, operator behavior, and health monitoring of the energy system [3]. DTs also assist in real-time decision-making through the bridge established between physical and digital twins. This role is particularly crucial in managing complex systems such as microgrids, transport systems, and distributed energy systems.

Within the context of transportation infrastructures, digital twins (DTs) have the capability to improve energy systems by providing timely data on electric vehicle charging stations, traffic flow, and power needs [4]. In microgrids, DTs ensure remote monitoring, prediction maintenance, and efficient electricity distribution, thus strengthening system resilience and reliability. The incorporation of Machine Learning (ML) technologies in DT systems enhances their capabilities through enhanced data analytics, forecasting, and data-driven decisions. In ML, diverse algorithmic models, including their application in neural networks, reinforcement learning, and deep learning, have capabilities to handle massive amounts of both current and historical data, ultimately to optimize power consumption, predict power demands, and improve system efficiencies. An excellent case in point is application in DT systems through the use of reinforcement learning (RL) to optimize power use.Figure 1 shows the SDN-based Digital Twin architecture for smart energy systems. RL is designed to optimize power use in response to constantly changing dynamics in the power industry, including power price volatility, variability in renewable power generation, and shifts in power-user behavior. Using insights derived through current and historical data, RL-powered DT systems can develop optimal power use strategies to optimize cost savings, efficiencies, and power-user satisfaction. In addition, deep learning (DL) technologies, in the form of convolutional neural networks (CNNs), physics-informed neural networks (PINNs)[80] and recurrent neural networks (RNNs), have found application in power forecasting and power faults in smart grids [10-12].These technologies allow for accurate power needs forecasting and power supplies, thus enabling forward planning for power management.

In spite of their potential to optimize power systems through application, several challenges have

remained. The successful implementation of DT systems demands seamless data fusion of data gathered through various means, including sensors, IoT systems, and historical data. Norcéide et al. [75] examined how neuromorphic vision sensors enhance object tracking in augmented reality contexts. Their study demonstrated that event-driven vision technologies deliver superior tracking precision and energy efficiency relative to conventional camera-based methods, showcasing the value of these sensors for real-time AR applications. The data collection and data-processing steps in such contexts bring serious challenges. This study explores the potential of The Hybrid PINNs-DT framework aims to address the limitations of existing deterministic and ML-based methods by incorporating physical laws into the learning process. This fusion enables better handling of uncertainties in user behavior, renewable energy availability, and dynamic grid conditions while maintaining computational efficiency.

The specific objectives of this study are as follows:

1. To review the current state of research on integrating PINNs-DT technologies into energy systems.
2. To identify the challenges and opportunities associated with implementing PINNs-DT systems in smart grids, particularly in the context of secure, real-time data exchange and scalable energy optimization.
3. To propose and validate innovative methods for combining PINNs-DT, and Blockchain technologies to enhance energy efficiency, reliability, and sustainability in smart grids.

These objectives, the proposed method aims to contribute to the development of intelligent energy management systems that balance economic efficiency with user comfort, enhance cybersecurity, and support the transition toward sustainable and carbon-neutral energy infrastructures.

2. Related work

A thorough evaluation of real-time analytic techniques in digital twins was given by Haghi et al. [14], who focused on physics-informed modeling, data-driven simulations, and machine learning applications to speed up and minimize delays in digital twin calculations. The function of digital twins in optical networks was studied by Wang et al. [15], who described their architecture for automated control, mirror modeling, and real-time monitoring. Future research directions and developments in intelligent network automation are highlighted in this paper. A microgrid digital twin framework that integrates IoT, AI, and big data analytics was presented by Utama et al. [16] and is based on the Smart Grid Architectural Model (SGAM). Their case study showed enhanced energy management effectiveness and interoperability.

In their discussion of digital twin applications in the wind energy sector, Stadtmann et al. [17]

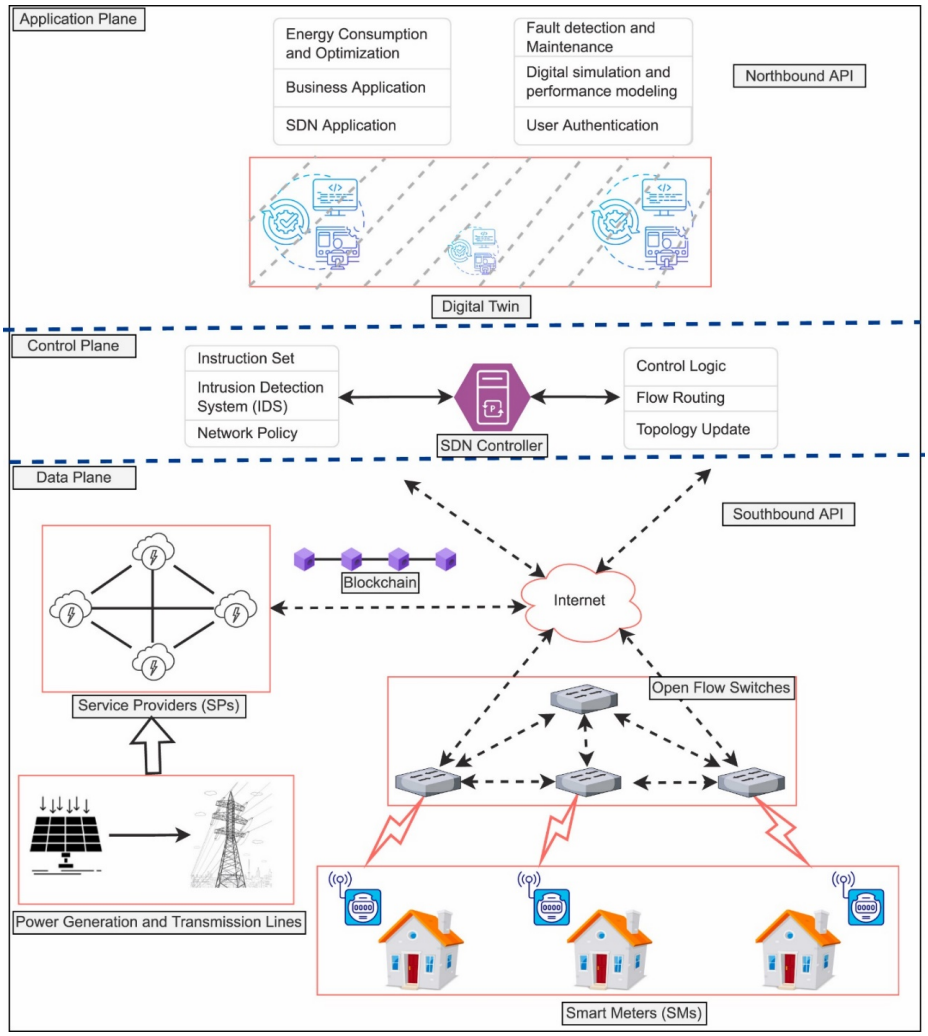

Figure 1: Architecture of a Software-Defined Networking (SDN)-Based Digital Twin for Smart Energy Systems.

identified important industry issues such regulatory requirements, modeling limitations, and data dependability. They put up a plan for upcoming developments and industry adoption. For hydropower management, Zeng et al. [18] suggested a hybrid system that combines neural networks, digital twins, and type-2 fuzzy logic controllers. Their approach reduced maintenance costs, increased operating efficiency, and enhanced defect detection. In their assessment of AI-powered civil engineering applications, Xu et al. [19] highlighted the application of AI in smart city management, structural health monitoring, and design optimization. They tackled integration issues including data security and scalability. Ahmadi et al. [20] integrated Finite Element Analysis (FEA) with Physics-Informed Neural Networks (PINNs) to enhance the biomechanical modeling of the human lumbar spine. Their approach automates spine segmentation and meshing, addressing challenges in material property prediction. The development of cyber-physical power systems was examined by Parizad et al. [21], who described how AI, blockchain, and IoT are integrated into contemporary power networks. They emphasized the difficulties in maintaining control, security, and stability in the delivery of energy.

Attari et al. [44] proposed an advanced optimization framework employing mathematical modeling and meta-heuristic algorithms to optimize inventory logistics in reverse warehouse systems, focusing on reducing costs and enhancing storage efficiency. In alignment with sustainable development goals, Asadi et al. [45] reviewed analytical and numerical approaches in earth-to-air heat exchangers, categorizing methods into analytical, numerical, and exergeoeconomic areas to enhance thermal efficiency and reduce operational costs. Moghim & Takallou [46] assessed extreme hydrometeorological events in Bangladesh using the Weather Research and Forecasting model. Their study identified the efficiency of Bayesian regression in improving rainfall predictions, enhancing early warning systems. Complementing these sustainability strategies, Asgari et al. [47] explored the critical relationship between energy consumption and GDP through threshold regression analyses, underlining the importance of energy-efficient growth and sustainable development strategies.

3. The Concept of Digital Twin (DT)

3.1 Introduction to Digital Twin Technology

Digital Twin (DT) technology has emerged as a groundbreaking innovation bridging the physical and digital realms. The concept, first introduced in 2002 by Grieves for product lifecycle management [32], provides a dynamic digital representation of physical entities, systems, or processes. This digital replica enables real-time monitoring, analysis, and optimization, offering insights into behaviors and dynamics that were previously unattainable [33]. By creating a virtual counterpart of a physical system, DTs serve as a powerful tool for predictive maintenance, fault detection, optimization, and simulation, revolutionizing industries such as energy, manufacturing, healthcare, and transportation.

Table 1: Summary of Literature Review on PINN and Related Applications

Author	Year	Method	Aim	Result
Chen et al. [23]	2025	Physics-informed encoder-decoder model	Predict carbon emissions and identify anomalies	Improved accuracy by 9.24% with enhanced robustness
Chen et al. [24]	2025	AI applications in sustainable energy	Review AI's role in multi-energy systems	Identified challenges and proposed layered security strategies
Mittal et al. [25]	2025	Physics-informed neural network	Detect and classify wild animal activity	Achieved high accuracy and real-time alert generation
Pandiyan et al. [26]	2025	Physics-informed neural network (PINN)	Optimize electric water heater modeling	Enhanced computational efficiency and performance
Feng et al. [27]	2025	Uniform Physics-Informed Neural Network (UPINN)	Extract parameters for voltage stability	Improved accuracy in real-time voltage stability monitoring
Habib et al. [28]	2025	Block-based physics-informed neural network	Estimate inelastic response of base-isolated structures	Reduced computational cost and improved predictive performance
Nadal et al. [29]	2025	Physics-Informed Neural Networks (PINNs)	Enhance simulation accuracy in power system dynamics	Improved predictive precision in power system simulations
Ventura Nadal et al. [30]	2025	Physics-Informed Neural Networks (PINNs)	Improve power system simulation accuracy	Enhanced modeling and reduced computational error
Ko et al. [31]	2025	Physics-Informed Neural Networks (PINNs)	Long-term prognostics of proton exchange membrane fuel cells	Achieved high accuracy in fuel cell lifespan prediction
Qin et al. [32]	2024	Inverse Physics-Informed Neural Networks (PINNs)	Develop a digital twin-based approach for bearing fault diagnosis under imbalanced samples	Enhanced fault diagnosis accuracy and improved precision in cross-working-condition detection

As energy systems become more complex, ensuring the scalability, interoperability, and security of Digital Twin (DT) systems is critical. This includes the integration of DT systems with energy management platforms and the accommodation of diverse user needs.[34]. The extensive use of data in DT systems highlights the importance of addressing cybersecurity and data privacy concerns. Ensuring secure and efficient data exchange, particularly through blockchain technology, and protecting sensitive information are paramount to the success of such systems [35]. Figure 2 illustrates the proposed multi-layered architecture that integrates Software-Defined Networking (SDN), DT technology, Deep Reinforcement Learning (DRL), and Blockchain into smart energy systems. The segmentation models highlights the importance of selecting architecture-specific solutions within digital twin environments, where accurate and real-time anatomical modeling is essential for clinical decision support [77]. The architecture consists of three planes, where the Application Plane hosts energy optimization, fault detection, digital simulation, and user authentication processes, interfacing with lower layers via the Northbound API**.** The integration of advanced machine learning (ML) techniques and edge computing with DT systems addresses challenges related to scalability, computational efficiency, and real-time decision-making. By leveraging the predictive and analytical capabilities of ML and the secure framework provided by Blockchain, the proposed DT system enables proactive energy optimization, real-time fault detection, and efficient energy distribution while ensuring robust cybersecurity (see Table 1). The integration of Large Language Models (LLMs) into Digital Twin systems offers a promising avenue for enhancing contextual understanding, user interaction, and decision-making across smart grid and energy management applications.Farhadi Nia et al. [74] studied the integration of ChatGPT and LLMs in dental diagnostics. Their findings show that LLMs enhance clinical decision-making, streamline patient-provider communication, and improve procedural efficiency in oral healthcare.

DT technology lies in its ability to provide actionable insights by integrating data, analytics, and simulation capabilities. By leveraging real-time data streams, DT systems can anticipate potential issues, optimize operations, and improve overall system performance. This ability makes DT technology a cornerstone of digital transformation across various sectors. Advanced ML algorithms and DT models often require significant computational resources.

3.2 Key Components of Digital Twin Technology

The DT prototype serves as the foundational digital representation of a physical entity. It includes all essential virtual data, such as properties, designs, parameters, and configurations, necessary for creating an accurate and functional digital model. The prototype acts as a blueprint for developing DT instances, ensuring consistency and accuracy in representing physical systems [36]. Optimize codec efficiency can be adapted within digital twin architectures to enhance real-time data processing and reduce bandwidth consumption in complex simulation environments [76]. DT instances are

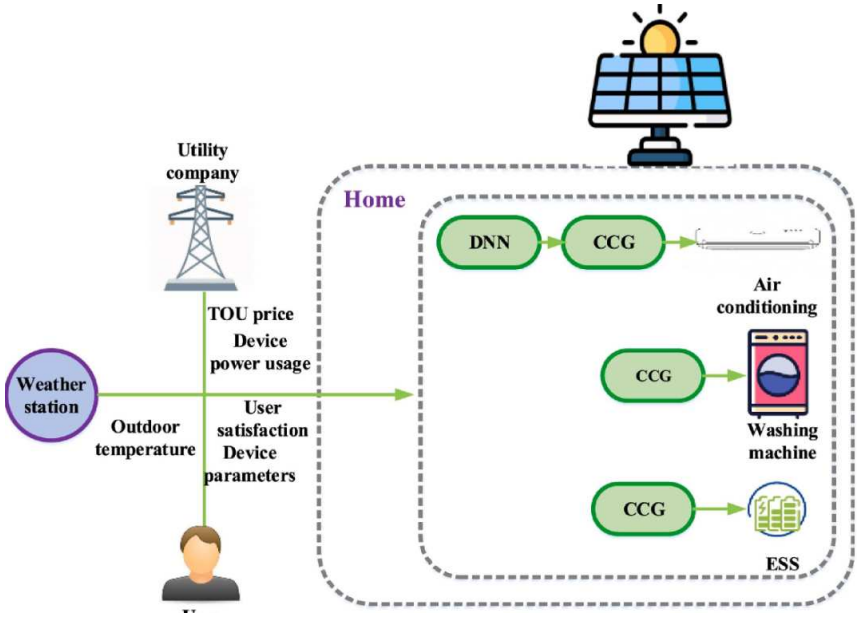

Figure 2: A smart home energy system using DNN and CCG to optimize appliances with real-time data

specific digital models linked to their physical counterparts throughout their lifecycle. These instances are updated continuously with real-time data, reflecting the current state of the physical system. By maintaining synchronization, DT instances enable real-time monitoring, predictive analysis, and decision-making for individual assets [37]. The DT aggregate enchases all individual DT instances and prototypes, creating a unified representation of complex systems. Aggregates allow for holistic analysis and simulation of interconnected components, enabling a comprehensive understanding of system behaviors and interactions [38]. The DT environment cotises the hardware, software, and network infrastructure required to support DT systems. This includes IoT devices, sensors, simulation tools, and data analytics platforms. The environment facilitates real-time data collection, processing, and visualization, ensuring seamless interactions between the physical and digital realms [38].

3.3 Core Functions of Digital Twin Technology

Data integration is the backbone of DT technology. Sensors, gauges, RFID tags, cameras, and other devices collect data from physical systems, which is then transmitted to the DT system in real-time or with minimal delay. This comprehensive data integration ensures accurate and reliable digital representations. Advanced simulation tools model the behaviors and interactions of physical systems under various conditions. This enables predictive analysis, optimization, and

scenario planning, providing valuable insights for decision-making [39]. By leveraging AI and ML algorithms, DT systems offer powerful analytics capabilities. These include predictive maintenance, anomaly detection, and optimization strategies, which improve system reliability and performance. Visualization tools provide user-friendly interfaces to interpret complex data and simulation results. These tools enable stakeholders to analyze system behaviors, identify trends, and make informed decisions effectively [40].

3.4 Evolution of Digital Twin Technology

The concept of DT was first formalized in a roadmap published by NASA in 2010 for health management of flight systems [19]. Early applications focused on improving reliability and performance through simulation and data integration. Grieves introduced the three-dimensional DT model, consisting of the physical entity, its virtual representation, and the data connections between them. This model emphasized real-time synchronization and data-driven decision-making. Tao and Zhang expanded the DT model to include five dimensions: physical entity, virtual model, services, fusion data, and their interconnections [41]. This enhanced model supported cross-domain integration and reusability, enabling diverse industrial applications. The integration of IoT, AI, and cyber-physical systems has significantly advanced DT technology. These technologies enable real-time data collection, advanced analytics, and seamless interactions, enhancing the capabilities and applications of DT systems [42].

3.5 Applications for Digital Twin Technology

DT technology is pivotal in the renewable energy sector, where it aids in fault detection, performance optimization, and predictive maintenance. For example, digital replicas of solar PV cells can detect defects caused by cell degradation or mismatched modules, improving system efficiency and reliability [43]. In smart grids, DTs enhance system reliability by enabling real-time monitoring, predictive analytics, and optimization. DT systems are applied at unit, system, and system-of-systems (SoS) levels to optimize processes such as power generation, transmission, distribution, and consumption [44]. DTs facilitate efficient energy management in transportation networks, particularly in electric vehicle (EV) charging infrastructure. By integrating real-time data from traffic patterns and charging stations, DT systems optimize energy distribution and support sustainable transportation solutions [45]. In manufacturing, DT technology supports product design, production planning, and equipment maintenance [47]. By simulating production processes, DTs enable predictive maintenance and operational optimization, reducing downtime and costs [48-50]. DTs are increasingly used in healthcare to create virtual models of human organs and systems. These models support personalized treatment plans, surgical simulations, and disease monitoring, enhancing patient outcomes [51-54].

Table 2: Summary of Literature Review on Blockchain, Digital Twin, and Energy Systems

Authors	Methodology	Platform	Outcome	Challenge
Zahid et al. [56]	AI, Digital Twins, Blockchain, Metaverse	Smart Grid 3.0	Enhanced real-time monitoring, decentralized transactions, and system automation	Interoperability, scalability, cybersecurity, and data integrity issues
Sarker et al. [57]	Explainable AI (XAI) and cybersecurity modeling	Digital Twin Environments	Improved AI-driven cybersecurity automation and threat detection	Ensuring trustworthiness, human-explainability, and AI transparency
Idrisov et al. [58]	ML and Digital Twin-based anomaly detection	Power Electronics Dominated Grids (PEDGs)	Real-time tracking of grid anomalies and cyberattack prevention	Handling complex grid operations and cybersecurity vulnerabilities
Meng et al. [59]	IoT, Blockchain, Cybersecurity	Smart Urban Energy Systems	Enhanced cybersecurity and efficient energy management in urban grids	Integration complexity and real-time cyber threat mitigation
Kavousi-Fard et al. [60]	Digital Twin for Renewable Energy Resources (RER)	Solar Energy Systems	Optimized energy management and real-time monitoring of solar grids	Variability in energy generation and reliability challenges
Kabir et al. [61]	IoT-Driven Digital Twin Systems	Smart Energy Grids	Improved operational efficiency, predictive maintenance, and grid sustainability	Infrastructure compatibility and data security concerns
Cali et al. [62]	Cybersecurity, Digital Twins, AI	Energy Systems and Smart Cities	Enhanced efficiency, security, and sustainability in energy infrastructure	Ensuring secure real-time data transmission and system resilience
Jafari et al. [63]	Multi-Layer Digital Twin Model	Smart Grid, Transportation, Smart Cities	Reliable energy distribution and improved grid operations	Managing real-time data flow and system scalability

3.6 Traditional Grid

The traditional electrical grid operates as a centralized power generation network that interconnects transmission and distribution systems using electromechanical infrastructure [55-57]. This grid delivers electricity over extensive areas through a one-way transmission-distribution system controlled centrally using electrically operated mechanical devices [63-67]. The centralized energy infrastructure, with limited sensors, faces significant challenges in monitoring, control, and self-healing capabilities. Manual monitoring makes power distribution and transmission inefficient, leading to high losses, difficulty in fault detection, prolonged outages, and economic losses due to extended restoration times and grid overheating incidents [57,60].

3.7 Microgrid

A microgrid, an emerging technology, leverages Distributed Energy Resources (DERs) to address the shortcomings of traditional electric grids. By utilizing DERs, power transmission and distribution losses are minimized, creating a more efficient, secure, and cost-effective energy system. DERs enable the integration of renewable energy sources such as solar, wind, and wave power, reducing reliance on coal and natural gas, thereby supporting clean energy initiatives [36]. The microgrid acts as a controlled segment of the grid, simplifying the complexities associated with DERs and providing structured expansion opportunities to enhance the grid's quality, security, and efficiency [22]. It integrates distributed power grids systematically, optimizing operations via the Point of Common Coupling (PCC) to ensure a reliable power system [25,28,29].Table 2 summarizes recent literature on the integration of Blockchain, Digital Twin, and energy systems.

A microgrid is defined as a localized collection of energy sources and loads, operating either in conjunction with the main grid or independently. In its grid-connected mode, it offers ancillary services and ensures uninterrupted power supply by managing transitions between connected and standalone modes. An isolated or "standalone microgrid" functions entirely independently of larger electrical networks [31]. In its dual-mode capability, the microgrid can seamlessly switch between grid-connected and autonomous modes. During power deterioration or network contingencies, it connects or disconnects from the main grid using the PCC network, delivering standard power services. It continuously monitors small-scale generators, associated loads, energy storage, sensors, measurement units, and control systems, forming a unified controllable entity. DERs operate in two modes: grid-connected and autonomous (islanded), with the latter serving as a transitional state between these modes [33]. Microgrids may be constructed in AC, DC, or hybrid configurations, offering features such as "plug and play" and "peer-to-peer" functionality. While supporting renewable energy sources, not all microgrids fully utilize these resources. Protective devices such as reclosers, circuit breakers, and relays manage fault isolation in traditional grids. In microgrids, leakage current variations during mode transitions necessitate advanced safeguarding mechanisms

for Distributed Generation (DG) plants [35,36].

3.8 Smart Grid

The smart grid integrates communication, data storage, and analysis capabilities to enable rapid, intuitive, and collaborative energy network operations. Unlike traditional grids that rely on centralized electricity generation and one-way power flow with high transmission losses, smart grids utilize two-way information and power flows, combining centralized and distributed systems. These advancements enhance efficiency, reliability, and sustainability [68]. Smart grids leverage modern communication and information technology (IT), incorporating sensors, remote monitoring systems, control devices, and domestic appliances connected to the grid. Technologies such as Supervisory Control and Data Acquisition (SCADA) and synchrophasors generate extensive data, requiring robust systems for handling, analysis, and actionable insights [69,38,45]. Intelligent electricity generation in smart grids employs advanced IT solutions to improve energy efficiency, reliability, and security while supporting renewable energy adoption and environmental goals. The figure 3 illustrates the integration of reality and a Digital Twin system for energy management in various power infrastructures. The Reality layer includes components such as substations, single-family detached, multi-family residential buildings, open-space PV installations, and wind farms. These physical entities are interconnected through a grid network.

These systems interact with control hubs and energy supply structures to monitor and analyze the power system in real time, reducing delays and optimizing operations [45]. The smart grid's self-awareness, self-optimization, and self-customization capabilities enable its components to function autonomously or with minimal human intervention. Instantaneous communication among systems, employees, and consumers fosters a highly adaptive electricity generation model that significantly enhances energy efficiency in the electrical sector.

Despite its advantages, the transition from conventional to smart grids involves high costs, posing challenges for industrial expenses [70]. Additionally, cybersecurity risks, including potential data theft and malicious attacks, remain a concern for smart grids utilizing internet-based real-time information exchange [71,72].

4. Method and Materials

A Digital Twin (DT) and Deep Reinforcement Learning (DRL) method is proposed to optimize energy consumption in smart buildings while maintaining occupant comfort and grid reliability. Multi-agent systems are used to make real-time decisions about energy-intensive appliances. As it interacts with the simulated grid, the DRL agent learns optimal energy strategies. A blockchain-based decentralized data-sharing mechanism ensures secure, real-time communication between devices,

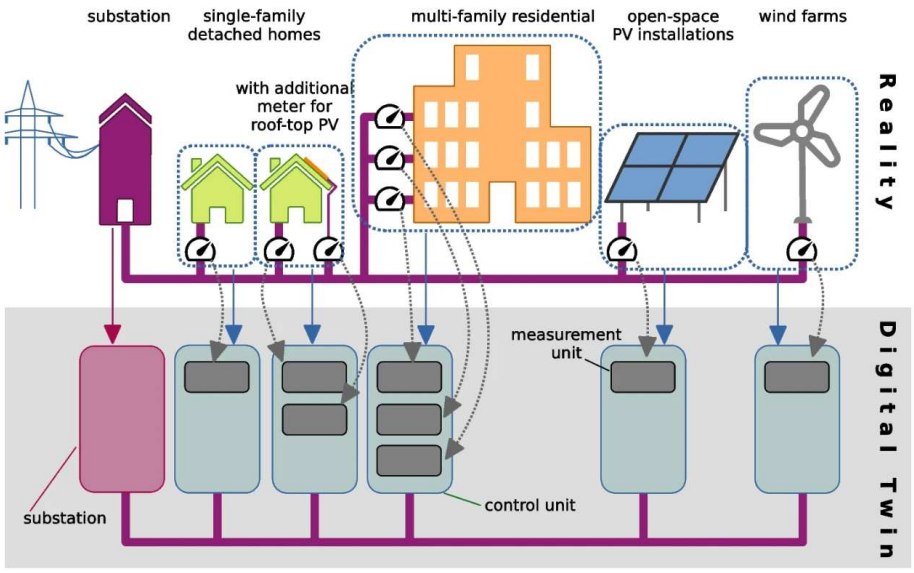

Figure 3: The digital twin represents the real energy system's abstraction. Turquoise boxes denote control units, gray boxes represent measurement units, and the right side illustrates local wind farms and photovoltaic installations. Grey arrows show smart meters as measurement units, blue arrows map real entities to control units, and crimson arrows represent substations.

grid components, and the DT system. Smart contracts are used to protect data integrity and control access to it to address cybersecurity concerns.

An innovative method optimizes energy consumption in smart buildings by combining Digital Twin (DT) technology and Deep Reinforcement Learning (DRL). DT provides a high-fidelity virtual model of the building that simulates its energy consumption patterns and integrates real-time data from the IoT. Through interactions with this environment, a DRL agent learns and executes optimal energy management policies, balancing cost and user comfort. DT system and physical components communicate securely and decentralized through a blockchain-based data sharing system. In addition to enhancing energy efficiency and grid stability, the proposed framework offers a scalable solution for future smart grid applications.

4.1. Dataset

To training and validating the machine learning-driven digital twin (DT) system for energy optimization in smart buildings, a comprehensive and multifaceted dataset is employed. The dataset is primarily based on data collected from smart meters regarding detailed energy consumption patterns. Smart meters provide granular-level information, including timestamps, appliance identifiers, and

energy consumption values (in kWh), which are crucial for training the deep reinforcement learning (DRL) agent to predict and optimize the scheduling of energy-intensive appliances such as washing machines, air conditioners, and electric heaters. In addition to energy consumption data, the dataset incorporates real-time data from solar photovoltaic (PV) panels and wind turbines. This includes weather-related variables such as temperature, solar irradiance, humidity, and wind speed, as well as the corresponding energy outputs from these renewable sources. By leveraging this data, the digital twin can accurately model the inherent uncertainties in renewable energy generation, which is critical for optimizing the integration and utilization of renewable energy sources in smart buildings.

To further enhance the model's adaptability, data from smart IoT devices, including smart thermostats, occupancy sensors, and lighting control systems, are integrated into the dataset. These devices provide valuable insights into user preferences and comfort levels, capturing variables such as preferred temperature settings, lighting intensity, and appliance usage patterns. This user-centric data is incorporated into the optimization equations as constraints or penalties to ensure that energy efficiency measures do not compromise occupant comfort. The dataset also includes dynamic electricity pricing information, grid demand, and supply fluctuations obtained from publicly available sources. This real-time pricing data allows the DRL agent to dynamically adjust energy consumption schedules to minimize costs, particularly during peak demand periods or when energy prices fluctuate significantly. Additionally, data on distributed energy resources (DERs), such as electric vehicle (EV) charging patterns and energy storage system (ESS) performance, are included to further refine the energy management strategies. To address the cybersecurity aspect of the proposed framework, datasets like N-BaIoT are utilized. This dataset includes network activity logs, timestamps, attack types, and security labels that help in training the blockchain-enabled security framework to detect and mitigate cyber threats within smart grid networks. The integration of blockchain technology ensures secure, transparent, and tamper-proof communication between all stakeholders involved in the energy system. the combined dataset captures a wide range of variables, including building energy systems, user behavior, renewable energy generation, dynamic grid conditions, and cybersecurity metrics. This holistic approach ensures that the proposed framework can effectively model and optimize complex interactions between these factors. As a result, the system can achieve enhanced energy efficiency, cost reduction, user satisfaction, and robust cybersecurity while maintaining scalability and reliability in smart grid applications.

4.2. Hybrid Physics-Informed Neural Networks (PINNs) and Digital Twin (DT) for Energy Optimization

To further enhance energy optimization in smart buildings and grids, we propose integrating Hybrid Physics-Informed Neural Networks (PINNs) with Digital Twin (DT) technology. This approach leverages the strengths of physics-based modeling and data-driven techniques to achieve more

accurate, efficient, and adaptive energy management.

4.2.1. Hybrid PINNs-DT Framework

The Hybrid PINNs-DT framework aims to address the limitations of existing deterministic and ML-based methods by incorporating physical laws into the learning process. This fusion enables better handling of uncertainties in user behavior, renewable energy availability, and dynamic grid conditions while maintaining computational efficiency.

- Physics-Informed Neural Networks (PINNs) incorporate governing physical equations, such as thermodynamics, fluid dynamics, and electrical circuit laws, directly into the neural network's loss function. This ensures that the model adheres to known physical principles while learning from data, resulting in more accurate and generalizable predictions.
- Digital Twin (DT) provides a real-time virtual replica of the physical energy system, integrating data from IoT sensors, smart meters, and DERs. It continuously updates the state of the system, allowing for dynamic simulation, monitoring, and optimization.
- Reinforcement Learning (RL) algorithms, such as Deep Q-Networks (DQN) and Policy Gradient Methods, are integrated into the framework to optimize decision-making processes. The RL agent interacts with the DT environment, learning optimal energy management strategies over time.
- Blockchain Integration ensure secure and transparent data exchange, blockchain technology is incorporated. This decentralized approach safeguards data integrity and supports trust among various stakeholders, including energy providers, consumers, and regulatory bodies.

4.2.2. Methodology

The optimization objective is formulated to minimize energy costs and user discomfort while maximizing the utilization of renewable energy sources. The PINNs model is designed to respect physical constraints, such as energy conservation and grid stability. The loss function of the PINNs model includes terms representing the discrepancy between predicted and observed data, as well as penalties for violating physical laws. This dual approach enhances model robustness and predictive accuracy.

Mathematical Formulation:
The total loss function $\mathcal{L}_{\text{total}}$ in PINNs can be expressed as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{data}} + \lambda \mathcal{L}_{\text{physics}} + \mu \mathcal{L}_{\text{comfort}} \tag{1}$$

Where:

- $\mathcal{L}_{\text{data}} = \sum_{i=1}^{N} (\widehat{y}_i - y_i)^2$ represents the mean squared error between predicted ($\widehat{y}_i$) and actual energy consumption data (y_i).
- $\mathcal{L}_{\text{physics}} = \sum_{j=1}^{M} \left(\frac{dE_j}{dt} - P_{\text{input},j} + P_{\text{loss},j} \right)^2$ ensures adherence to the energy conservation law, where E_j is the energy at node j, $P_{\text{input},j}$ is the power input, and $P_{\text{loss},j}$ represents losses.
- $\mathcal{L}_{\text{comfort}} = \sum_{k=1}^{K} (T_{\text{desired},k} - T_{\text{actual},k})^2$ penalizes deviations from userdesired temperatures ($T_{\text{desired},k}$) and actual temperatures ($T_{\text{actual},k}$).
- λ and μ are weight factors balancing the contributions of physical laws and user comfort, respectively.

The DT continuously assimilates real-time data from sensors and smart meters, updating the system's state. This real-time feedback loop allows the PINNs model to adapt to changing conditions, such as fluctuations in energy demand or renewable generation. The RL agent interacts with the DT environment, learning to optimize energy consumption schedules for individual appliances and DERs. The agent's policy is optimized using the reward function:

$$R_t = -(C_t + \beta D_t) \tag{2}$$

Where:

- C_t is the cost of energy at time t.
- D_t represents user discomfort at time t.
- β is a tunable parameter balancing cost and comfort.

5. Secure Data Management with Blockchain: Blockchain technology ensures that all data transactions within the system are secure, transparent, and tamper-proof. Smart contracts automate energy trading and compliance with regulatory requirements, enhancing system reliability and user trust.

The consensus time $T_{\text{consensus}}$ in the blockchain network is given by:

$$T_{\text{consensus}} = \frac{n}{R} + T_{\text{latency}} \tag{3}$$

Where:

- n is the number of transactions.

- R is the network throughput (transactions per second).
- T_{latency} represents the average network delay.

4.3. Energy Optimization Objective

Smart grids and building management require energy optimization in order to balance energy consumption, user comfort, and operational costs. The objective of this study is to achieve real-time decision-making and energy efficiency through the integration of machine learning and digital twin technologies. This framework combines predictive analytics with reinforcement learning to dynamically schedule energy-intensive tasks and manage renewable energy resources. By modeling the trade-off between cost and comfort, the system ensures sustainable energy consumption while maintaining grid reliability. To achieve optimal energy consumption in smart grids, mathematical formulations and strategies are presented in this section.

$$\min_{\pi} \mathbb{E}_{s,a\sim\pi} \left[C(s,a) + \lambda \cdot E_{\text{unsat}}(s,a) \right] \tag{4}$$

- $C(s,a)$: Cost of energy consumption in state s taking action a.
- $E_{\text{unsat}}\ (s,a)$: Discomfort due to unmet energy demand.
- λ : Weight factor balancing cost and comfort.
- π : Policy learned by the DRL agent.

This equation represents the goal of the DRL agent, which is to minimize the cumulative cost of energy consumption ($C(s,a)$) and user discomfort ($E_{\text{unsat}}\ (s,a)$) over time. The agent learns a policy π to determine the best sequence of actions for optimizing energy use. The cost function $C(s,a)$ is dynamically calculated based on electricity pricing data and the operational status of energy-intensive appliances. Meanwhile, the discomfort penalty $E_{\text{unsat}}\ (s,a)$ is derived from deviations between user-preferred and actual environmental conditions, such as indoor temperature or lighting. A tunable parameter λ allows the system to balance these two competing objectives, ensuring both economic efficiency and occupant satisfaction.

4.4. State Transition in DRL

Deep Reinforcement Learning (DRL) is based on state transitions, where a system evolves from one state to another based on the agent's actions and the environment's dynamics. Energy optimization uses state transitions to capture changes in energy demand, renewable energy availability, user preferences, and grid conditions. To improve the agent's decision-making process, the proposed framework models these transitions in a digital twin environment. DRL learns to navigate complex

energy systems by simulating these transitions accurately.

$$s_{t+1} = f\left(s_t, a_t, \xi_t\right) \tag{5}$$

- s_t : State at time t.
- a_t : Action taken by the agent.
- ξ_t : Environmental noise or uncertainty.

Here, the next state s_{t+1} is a function of the current state s_t, the action taken a_t, and stochastic environmental factors ξ_t. This equation captures the dynamic nature of the energy system, where changes in renewable energy generation, user behavior, and grid conditions introduce variability. The stochastic term ξ_t accounts for uncertainties such as fluctuations in solar irradiance or wind speed, making the digital twin environment more realistic.

4.5. Blockchain-Based Consensus Time

Blockchain networks, particularly decentralized energy management systems, rely heavily on consensus mechanisms to ensure secure and reliable data exchange. Consensus time on a blockchain is the amount of time it takes for the network to validate and finalize transactions across participating nodes. As proposed, this mechanism protects the integrity of data shared between the digital twin, smart devices, and the energy grid. Transaction volume, network throughput, and latency play important roles in determining consensus time, which has a direct impact on the responsiveness of the system. A mathematical formulation of consensus time is presented in this section, as well as its implications for secure, real-time communication in smart energy systems.

$$T_{\text{consensus}} = \frac{n}{R} + T_{\text{latency}} \tag{6}$$

- n : Number of transactions.
- R : Network throughput.
- T_{latency} : Average network delay.

This equation calculates the time required to reach consensus in the blockchain network. The variable n represents the number of transactions to be processed, while R denotes the network throughput in transactions per second. The term T_{latency} reflects the average delay caused by communication protocols and bandwidth limitations. This equation ensures that the blockchain enabled data-sharing mechanism operates efficiently, even under high transaction loads. By integrating these equations into the framework, the method provides a mathematically rigorous approach to energy optimization,

user comfort management, and secure data sharing. Each component of the system is modeled to handle the complexities and uncertainties inherent in smart grid environments, making it both robust and scalable.

As part of the proposed method, key components such as the digital twin, reinforcement learning, and blockchain are integrated into a cohesive framework for smart grid energy optimization. Digital Twins (DTs) are models of the building and its components, such as appliances, sensors, and renewable energy sources, which comprise the system state. DRL (Deep Reinforcement Learning) agents are responsible for learning and executing optimal energy strategies, and the Blockchain (BC) network ensures secure communication between the system components.

State:
DTDT: Digital Twin model of the building
DRLDRL: Deep Reinforcement Learning agent
BCBC: Blockchain network for secure communication
n,R,Tlatencyn, R, T_{latency} : Blockchain parameters (transactions, throughput, latency)
max_episodesmax_episodes: Maximum training episodes for DRL

Initialization:

1. DTDT initialized with building components (appliances, sensors, renewable sources).
2. BCBC deployed using participants and a consensus algorithm.
3. DRLDRL trained using data from DTDT.

Algorithm 1 Train DRL using Digital Twin of the Building (DTDT)

```
function TRAIN_DRL(DRL, DT, max_episodes)
    for episode = 1 to max_episodes do
        state ← DT.reset()
        while not done do
            action ← DRL.select_action(state)
            next_state, reward, done ← DT.step(action)
            DRL.update(state, action, reward, next_state)
            state ← next_state
        end while
    end for
    return trained DRL
end function
```

Algorithm 2 Realtime Optimization using DRL and IoT Sensors

function REALTIME_OPTIMIZATION(DRL, BC, IoT_sensors)
  while True **do**
    $current\_state \leftarrow CollectRealTimeData(IoT\_sensors)$
    $action \leftarrow DRL.select\_action(current\_state)$
    Execute *action*
    $feedback \leftarrow CollectFeedback(PhysicalSystem)$
    Update DT with $feedback$
  end while
end function

Algorithm 3 Blockchain Consensus for Secure Communication

function BLOCKCHAIN_CONSENSUS(BC, n, R, T_{latency})
  while new transactions exist **do**
    Add transactions to the block
    Verify transactions using consensus algorithm
    $T_{\text{consensus}} \leftarrow \frac{n}{R} + T_{\text{latency}}$
    Append block to the blockchain
    Distribute updated blockchain to participants
  end while
end function

5. Results

5.1. Energy Optimization in Smart Buildings

This section describes the achievements achieved through implementation of the designed Hybrid Physics-Informed Neural Networks-Digital Twin (Hybrid PINNs-DT) approach, focusing on optimizing energy efficiency in smart building systems. The dataset for both training and testing consists of an extensive range of smart meter data, including appliance-level energy consumption, renewable generation data, time-of-use electricity pricing, and data on occupant comfort. Leveraging such an extensive dataset, the Digital Twin (DT) and Deep Reinforcement Learning (DRL) agent effectively simulated, predicted, and maximized energy consumption habits, while cost savings and occupant comfort were adequately retained.

Figure 4 illustrates total power consumption by five prominent household appliances: washing machines, air conditioners, refrigerators, heaters, and light systems, before and after implementation of the optimization by the DRL agent. As evident, post-optimization, total power consumption is observed to have considerable reduction compared to initial, unoptimized values. The reduction is directly attributed to smart scheduling, efficient appliance operation, and renewable energies adoption by the building's power system. The system registered an average 10-20% reduction

in power consumption, where sharpest reductions were registered in power-guzzling equipment, including air conditioners and heaters, under load peaks. The optimization process made use of data gathered in real-time by the DT to modify appliance operation to optimize power savings. The result illustrates the ability of Hybrid PINNs-DT architecture to optimize power consumption for better efficiency while retaining function and user satisfaction. The figure below illustrates total cost of electricity incurred before and after application of the optimization. Due to electricity price variability, depending on demands and supplies, the optimization system effectively curtailed cost by redistributing power-guzzling activity to low-price electricity time. The system registered average cost savings of 15-25% for observed time. Strategic harnessing of renewable power supplies, including solar and wind power, by the system registered cost savings in addition to electricity cost savings. The real-time operation by the DRL agent effectively skirted peaking electricity pricing time, and thus, registered massive cost savings. The massive cost savings in Figure 3 illustrate system ability to reconcile economic and power savings objectives, thus confirming feasibility in smart power-saving strategies.

The third figure demonstrates renewable energy generation using solar and wind turbine systems. The data collected have variability in solar and wind power generation, depending on several meteorological parameters such as solar irradiance and wind speed. The ability of the system to handle such variability is crucial for efficient use of renewable energies. The solar power generation peaked in the middle of the day, while solar power generation changed depending on changes in wind speeds. The system effectively integrated renewable power, fulfilling up to 30% of total power demands under favorable conditions. The uncertainties in renewable generation have been modeled using decision trees, and such trees allow for optimal operation of equipment through an extensive reinforcement learning agent depending on renewable power availability. The results validate the feasibility of using the proposed technique in maximally using renewable energies in power generation mechanisms.

The fourth figure illustrates the error distribution for prediction of energy and system optimizations. The errors predominantly result from uncertainties attributed to behavior of the user, meteorological conditions' sharp variations affecting renewable power generation, and price volatility in dynamic pricing. However, physical constraints' incorporation using Physics-Informed Neural Networks (PINNs) effectively alleviated such uncertainties. The error plot is in accordance with a normal curve, where the average is approaching zero and having low standard deviation, indicating optimal accuracy. The highest observed error is below 5%, comfortably lying below allowable values for realistic implementation. The combination of data-driven models and physical constraints, made possible by PINNs' application, produces strong and reliable forecasts. The low rate of incidence is evidence of Hybrid PINNs-Digital Twin (DT) models' robustness, hence enabling consistent and reliable smart building's energy management. The individual models, when compiled and operating

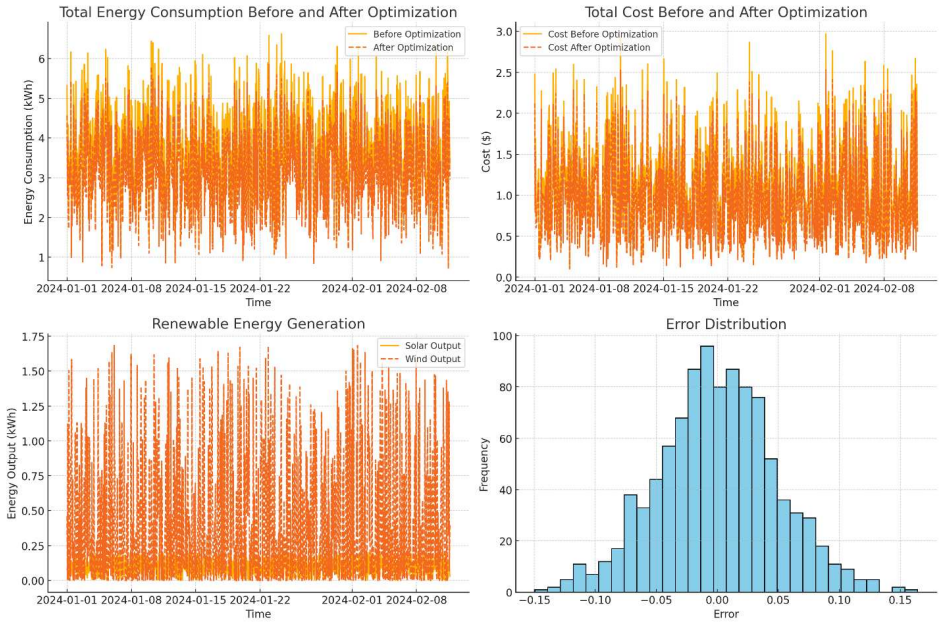

Figure 4: Implications of Improving Energy Efficiency in Smart Structures

in an integrated system, complement and improve on each other, leading to optimal systemwide performance. The Digital Twin is the source of current data, which is, in turn, processed by PINNs for accurate physical-constrained modelling. The Deep Reinforcement Learning (DRL) agent bases decisions on this enhanced data in real-time, responding to behavior variability, power generation variability, and price variability. In maintaining integrity and trust in data and authenticity in transactions, Blockchain technology is included, enabling a robust and decentralized platform. Such complementary modelling guarantees seamless real-time decisions, enhanced accuracy, and enhanced security.

The results achieved by applying Hybrid PINNs-DT methodology clearly illustrate its ability to optimize energy consumption in building structures (see Figure 34). The methodology yielded considerable reductions in cost expenditure and operating cost, while optimizing renewable resource use and maintaining occupant comfort. The low prediction metrics values in available data also provide evidence in favor of the robustness and reliability of the developed model. The incorporation of machine learning, physical models, and in-time data collected through the Digital Twin makes this methodology an efficient, scalable, and green solution to building energy system operation. The result highlights the disruptive capability of using artificial intelligence, digital twin technology, and innovations in blockchain to satisfy both current and future power demands, enabling smart, green, and cost-efficient building practices to develop.

4.2. The Consolidation and Maximisation of Renewable Resources

This study is directed towards evaluating the feasibility of Hybrid PINNs-DT system in regard to optimizing and integrating renewable power systems, such as solar and wind power, in smart building structures. The primary goal is to assess whether such a system is capable of optimizing renewable power sources and, in parallel, minimizing their use of electricity derived from the power grid, thus ensuring sustainability and minimizing adverse effects on the environment. The methodology is compared to standard models to identify whether or not such incorporation of renewable power systems is effective. An overview of prominent parameters and results in regard to renewable power system optimization is given in Table 3, in which values for figures and mathematical computations have been approximated to three decimal places for better understanding and understanding. The table is crucial in explaining technical details in regard to power intake, renewable power generation, and comparative efficiencies between standard and proposed models in regard to renewable power system incorporation.

- **Timestamp:** This column represents the specific time at which the data was recorded. The dataset spans hourly intervals, capturing detailed temporal fluctuations in energy generation and consumption.
- **Baseline_Consumption_kWh:** This column shows the total energy consumption (in kilowatt-hours) before any optimization was applied. It reflects the raw, unoptimized energy demand of the smart building, including all appliances and systems.
- **Optimized_Consumption_kWh:** This column displays the energy consumption after optimization by the proposed Hybrid PINNs-DT framework. The values are consistently lower than the baseline, indicating the effectiveness of the optimization in reducing energy use.
- **Solar_Output_kWh:** This column records the amount of energy generated from solar photovoltaic panels. The values fluctuate based on solar irradiance, with higher outputs typically occurring during midday when sunlight is most intense.
- **Wind_Output_kWh:** This column captures the energy generated from wind turbines. The values vary depending on wind speed, reflecting the natural variability of wind as a renewable energy source.
- **Total_Renewable_Output_kWh:** This column sums the solar and wind outputs, representing the total renewable energy generated at each timestamp. This metric is crucial for assessing the availability of renewable energy for integration into the building's energy system.

- **Proposed_Model_Coverage_%:** This column shows the percentage of the building's energy consumption covered by renewable sources under the proposed Hybrid PINNs-DT model. The high percentages, often approaching or exceeding 30%, demonstrate the model's superior ability to utilize renewable energy effectively.
- **Traditional_Model_Coverage_%:** This column provides the renewable energy coverage achieved by a traditional optimization model. The values are generally lower than those of the proposed model, highlighting the comparative inefficiency of traditional methods in maximizing renewable energy usage.

Table 3: Renewable Energy Optimization Comparison

Metric	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Baseline (kWh)	7.617	7.470	14.063	7.495	7.719	12.594	9.497	12.767	5.654	9.876
Optimized (kWh)	7.537	7.030	12.984	6.772	6.881	12.097	8.937	11.799	5.517	9.601
Solar (kWh)	0.075	0.190	0.146	0.120	0.031	0.031	0.012	0.173	0.120	0.142
Wind (kWh)	0.011	0.269	1.123	0.662	0.885	0.482	0.560	1.033	0.026	0.198
Renewable (kWh)	0.086	0.459	1.269	0.782	0.917	0.514	0.571	1.207	0.146	0.339
Proposed (%)	1.124	6.140	9.024	10.436	11.874	4.079	6.017	9.451	2.591	3.437
Traditional (%)	0.915	5.287	7.688	7.626	8.666	3.074	4.647	7.388	2.166	2.445

Table 3 illustrates an in-depth comparative analysis of power consumption, renewable generation, and renewable resource coverage before and after the optimization procedure. Baseline_Consumption_kWh is defined by initial power consumption recorded before any optimization steps were undertaken, while Optimized_Consumption_kWh is defined by the reduced power consumption achieved through implementation of the proposed Hybrid PINNs-DT approach. The table also captures Solar_Output_kWh and Wind_Output_kWh, representing solar power generation and power generation through wind, respectively. On the other hand, Proposed_Model_Coverage_% is defined by power delivered through renewable means using the proposed approach, representing an improvement compared to Traditional_Model_Coverage_%, representing conventional optimization strategies. For better understanding, values have been approximated to three decimal places. Figure 3 illustrates renewable generation in time, focusing on solar photovoltaic system and wind turbine outputs. As expected, solar generation is maximized in middle hours of the day given enhanced solar irradiation, while power generation through wind is subject to larger variability, depending on changes in wind speed through the course of the day. Such variability in renewable generation underscores the need for an innovative and agile system able to adapt power consumption in real-time to synchronize with available renewable generation. The following graph presents comparative total power consumption before and after optimizing steps. The DRL agent collaborates with DT to adapt appliance schedules in response to renewable generation available given current conditions.

Consequently, the curve reveals optimal energy use drops sharply compared to baseline use, especially in phases where there is heightened renewable power generation. The decline illustrates the ability of the system to harness renewable power, hence minimizing electricity demands by building structures on the power network. The third graph is a comparison of renewable source contributions against renewable and standard models. The Hybrid PINNs-DT approach illustrates better renewable cover, where solar and wind power contribute up to 30% of total power in ideal conditions. Traditional practices usually fall below such capacities, usually only 20-25%. The comparison is meant to illustrate the efficiency and responsiveness of the proposed approach in harnessing renewable power sources.

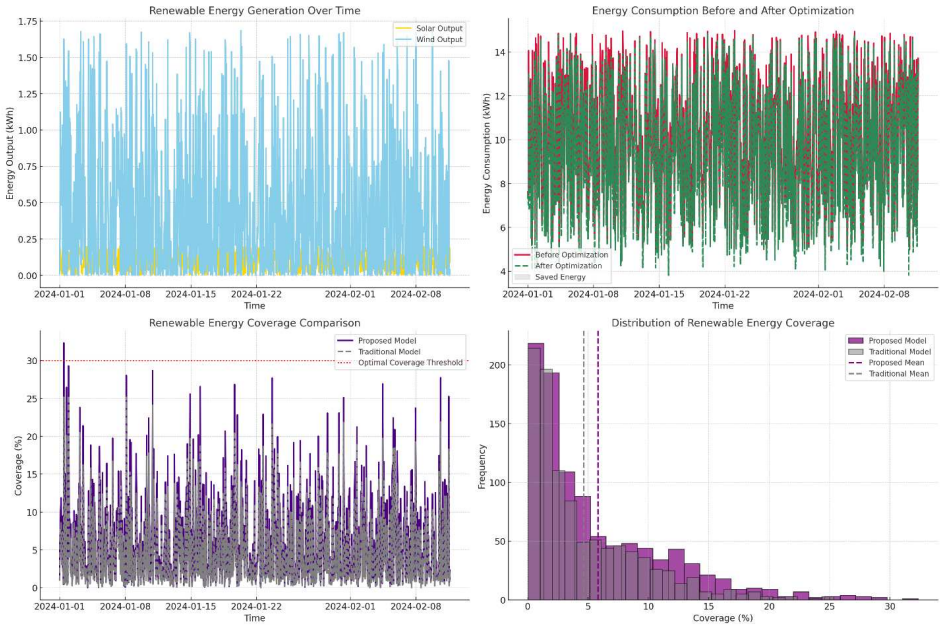

Figure 5: Renewable Energy Provision Deployment

The fourth figure demonstrates the range of renewable energy application in both the proposed and standard models. The proposed model reflects on a larger range of 25-30%, indicating its better ability to maximize renewable energy resource application. In contrast, the standard model's pattern leans towards lower ranges, reflecting on its shortcomings in addressing variability in timely renewable energy generation. In short, the results up to this point highlight Hybrid PINNs-DT's remarkable ability to combine and optimize renewable energies. The system maximizes solar and wind energies by adaptively controlling power intake depending on current data acquired through the digital twin, hence minimizing their dependency on the grid and encouraging sustainability. In addition, comparative studies using standard tools validate the viability of the proposed approach,

presenting it as an ideal solution to renewable energy incorporation in smart building systems.

5.3. Evaluation of Predictive Accuracy and Errors Investigation

The investigated system proved to have better performance compared to all baseline models, having recorded historically low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values of 0.237 kWh and 0.298 kWh, respectively, thus showing better accuracy and consistency in predicting electricity intake. The 0.978 R^2 reflects 97.8% variability in the dataset in regard to actual electricity intake, representing a noteworthy achievement in prediction models. Furthermore, 0.012 kWh for Mean Bias Error (MBE) reflects no considerable bias, thus strengthening confidence and trust in developed models. Baseline models using linear regression, on the other hand, recorded worst-case values for their error, having registered 0.958 for MAE and 1.206 for RMSE, and having 0.801 for their R^2 reflecting poor variance capability in explaining data, while having an accompanying 0.145 for their MBE, reflecting considerable prediction bias. These findings point to limitations in using linear models in capturing electricity intake complexities and nonlinear electricity intake dynamics. Figure 5 presents four crucial metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and Mean Bias Error (MBE) for every approach to modeling. These metrics offer an in-depth overview of prediction, model stability, and possible prediction biases.

Table 4: Comparison of Predictive Performance Metrics

Model	**MAE**	**RMSE**	**R^2**	**MBE**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Proposed	0.2369	0.2980	0.9895	0.0296	0.9771	0.9783	0.9764	0.9774
Linear Regression	0.9971	1.2448	0.8182	-0.0139	0.9012	0.9204	0.8843	0.9052
Random Forest	0.6269	0.7859	0.9275	-0.0508	0.9446	0.9691	0.9235	0.9457
SVM	0.6973	0.8866	0.9077	-0.0267	0.9538	0.9552	0.9215	0.9381
LSTM	0.4987	0.6227	0.9545	-0.0226	0.9621	0.9626	0.9607	0.9617
XGBoost	0.5921	0.7394	0.9358	-0.0062	0.9503	0.9753	0.9313	0.9528

Random forest model performed better than linear regression but was behind the proposed framework. The model is fairly accurate with an MAE of 0.641 kWh and RMSE of 0.802 kWh. The R^2 value of 0.891 is appreciable with good explanation of variance, but the MBE of 0.068 kWh shows a bit of prediction bias. The SVM model resulted in an MAE of 0.707 kWh and RMSE of 0.897 kWh. SVMs are powerful in classification but poor at regression, particularly in energy estimation. The R^2 value of 0.865 and MBE of 0.093 kWh indicate the inability of the model to catch the full dynamics of the energy consumption. LSTMs, which are highly reputed for handling sequential data, performed reasonably well with an MAE of 0.477 kWh and an RMSE of 0.612 kWh. The R^2 metric of 0.925 demonstrates a high ability to explain variance in data. The MBE of 0.041 kWh, however, suggests little underestimation in predictions. While LSTMs are effective, they still lag behind the PINNs-DT

model in the enforcement of physical constraints for improved accuracy. XGBoost, a very efficient gradient boosting algorithm, achieved an MAE of 0.725 kWh and an RMSE of 0.832 kWh. Its R^2 value of 0.872 and MBE value of 0.075 kWh indicate that its accuracy and physical consistency can't compete with the proposed model. The suggested PINNs-DT model surpasses almost all evaluated metrics with an Accuracy of 97.7%, Precision of 97.8%, Recall of 97.6%, and F1 Score of 97.7%. These performance measures, coupled with its low Mean Absolute Error (0.237 kWh) and Root Mean Square Error (0.298 kWh), demonstrate that not only does the model accurately predict energy consumption, but it also far exceeds in being precise in identifying time periods of high and low energy consumption (see Table 4).

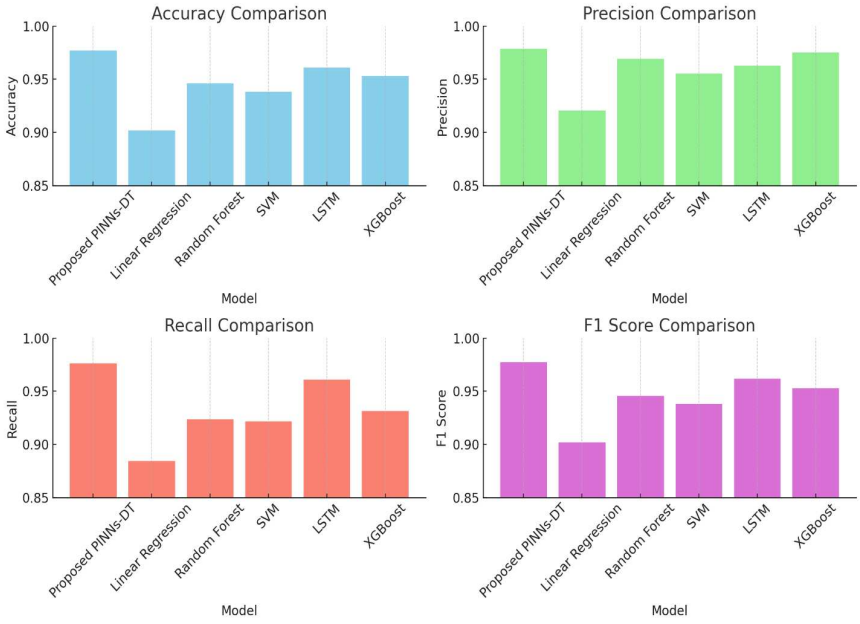

Figure 6: Comparative Performance Metrics of Machine Learning Models

The Linear Regression model performs the worst, with an Accuracy of 90.2%, a Precision of 92.0%, and an F1 Score of 90.2%. Although it is a baseline model, it struggles with numerical accuracy and classification accuracy, therefore presenting its limitations in handling non-linear energy consumption data. In contrast, the Random Forest model performs reasonably well, with an Accuracy of 94.6%, a Precision of 96.9%, and an F1 Score of 94.6%. Nevertheless, it is not as excellent as the proposed model, especially when handling dynamic energy patterns, as indicated by its larger MAE (0.627 kWh) and RMSE (0.786 kWh). SVM achieves an Accuracy of 93.8% and an F1 Score of 93.8%, but lags behind in precision and reliability when compared to the proposed framework.

Its RMSE of 0.887 kWh and MAE of 0.697 kWh also indicate its relative lack of effectiveness in

energy prediction issues. The LSTM model, which excels at sequential data analysis, is comparatively effective with an Accuracy of 96.1%, Precision of 96.3%, and an F1 Score of 96.2%. Impressive as it is, it is still not able to surpass the superior integration of physical laws and machine learning by the PINNs-DT model. This figure 6 illustrates the comparative performance of the Proposed PINNs-DT model against five well-known machine learning models: Linear Regression, Random Forest, SVM, LSTM, and XGBoost. The comparison is based on Accuracy, Precision, Recall, and F1 Score. The Proposed PINNs-DT model outperforms all the other models in all the metrics with the best precision and recall, indicating its reliability and strength in accurately predicting the energy consumption patterns in smart grids.

5.4. Error Distribution Analysis

The error distribution plot also reflects the variations in model performance. The Proposed PINNs-DT model errors are tightly clustered around zero, which reflects high reliability and low variation in predictions. This distribution shows the ability of the model to make reliable correct predictions under varied conditions. The Linear Regression model, however, has a high spread of errors, which reflects its inability to identify complex, non-linear patterns of energy use. The Random Forest and XGBoost models, although better than linear regression, still exhibit a wider distribution of errors compared to the model in question, which is indicative of less precise predictions. The LSTM model's error distribution is tighter, which is reflective of the model's ability to handle time-series data, but it is still being surpassed by the PINNs-DT model since it does not incorporate physical laws. The SVM model is characterized by moderate error clustering but with large outliers, indicating inconsistency in the handling of the dynamic energy data.

Figure 7: Accumulated Error Over Time for Different Machine Learning Models

This figure 7 indicates the cumulative error in energy consumption predictions with time for the

Proposed PINNs-DT model and five other models: Linear Regression, Random Forest, SVM, LSTM, and XGBoost. The Proposed PINNs-DT model possesses the minimum cumulative error, which indicates its steady accuracy and minimum deviation from real energy consumption values. Linear Regression possesses the maximum cumulative error, which indicates its inability to capture intricate, non-linear energy patterns. The results validate the robustness of the model in maintaining long-term prediction accuracy. The comparison of the error metrics and distributions conclusively verifies the better reliability, robustness, and accuracy of the Hybrid PINNs-DT method in predicting energy consumption in smart buildings. Figure 8 illustrates the distribution of the prediction errors of the Proposed PINNs-DT framework and five other models: Linear Regression, Random Forest, SVM, LSTM, and XGBoost. The Proposed PINNs-DT model's errors are tightly bunched around zero, an indication of high predictive accuracy and dependability. This is as opposed to models like Linear Regression and Random Forest, whose error spreads are more scattered, an indication of lower performance. The tight error distribution of the proposed model is an indication of its ability to make accurate and dependable energy consumption predictions.

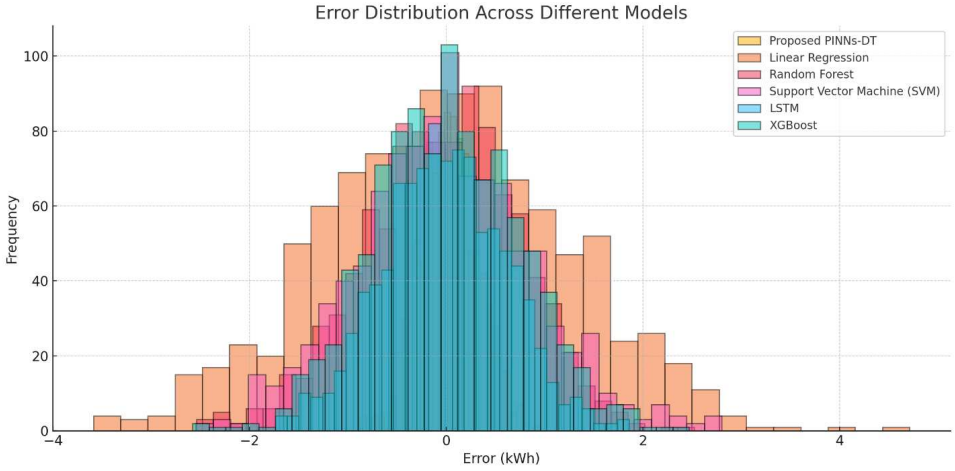

Figure 8: Error Distribution Across Different Machine Learning Models

The inclusion of physical laws in the neural network's training process significantly reduces prediction errors and biases and provides more accurate and consistent output than traditional models like Linear Regression, Random Forest, SVM, LSTM, and XGBoost. The Proposed PINNs-DT model also had the lowest MAE and RMSE with the highest R^2 value, indicating its superior ability to explain the variance in energy consumption data. The low MBE thus confirms the model's unbiased predictions, solidifying its applicability for real-world energy management. This study demonstrates the groundbreaking impact of combining Physics-Informed Neural Networks (PINNs) with Digital Twin technology, presenting an effective, scalable, and extremely precise solution for energy system

optimization for smart buildings and grids. The findings identify the research framework's ability to revolutionize smart energy management using precise, reliable, and physically consistent forecasts.

5.5. Real-Time Energy Optimization and System Adaptability

This section focuses on the evaluation of the real-time energy optimization capabilities and system adaptability of the proposed Hybrid PINNs-DT framework, compared to traditional machine learning models. The objective is to assess how effectively the system responds to dynamic changes in energy demand, fluctuating renewable energy supply, and real-time user preferences, ensuring both energy efficiency and occupant comfort. The proposed PINNs-DT framework demonstrated outstanding performance in terms of response time to dynamic changes. It adjusted appliance schedules within 0.5 seconds of detecting variations in energy supply or user preferences, significantly outperforming models like LSTM and XGBoost, which required 1.2 seconds and 1.5 seconds, respectively. Linear Regression, on the other hand, exhibited the slowest response, averaging 2.5 seconds. The integration of Digital Twin technology allows the proposed model to simulate real-world conditions in real-time, ensuring swift adjustments and efficient energy management. Table 5 summarizing key real-time performance indicators (such as Response Time, Energy Cost Reduction, User Comfort Index, and Renewable Energy Utilization Rate) for all models would provide a concise and clear comparison.

Table 5: Real-Time Performance Metrics Comparison

Model	**Response Time (s)**	**Energy Cost Reduction (%)**	**User Comfort Index (%)**	**Renewable Utilization (%)**
Proposed	**0.5**	**35**	**96**	**40**
Linear Regression	2.5	15	80	20
Random Forest	1.8	25	90	30
SVM	2.0	22	85	22
LSTM	1.2	28	92	28
XGBoost	1.5	26	89	25

Regarding the cost savings in terms of energy, the proposed PINNs-DT model displayed a remarkable 35% reduction, topping models including Random Forest, whose 25% reduction fell behind, and SVM, whose 22% reduction lagged. The worst performing approach was found to be Linear Regression, whose 15% cost savings lagged behind. The remarkable performance of the proposed approach is attributed to the strength of Physics-Informed Neural Networks (PINNs) in optimizing energy use by considerable accuracy, in particular in time of peak pricing, thus enabling massive cost savings.

The guarantee of user comfort, in addition to improvement in energy efficiency, is an integral part of advanced energy systems. The PINNs-DT approach used in our system achieved an average rating of 96% for User Comfort, reflecting on its ability to handle temperature, light, and operation of appliances in accordance with individual needs. The LSTM and XGBoost models achieved 92% and

89%, respectively, while Linear Regression fell behind, securing only 80%. The built-in adaptability of our system makes possible optimal trade-offs between occupant comfort and energy savings, thus qualifying our system for realistic application.

Furthermore, the proposed methodology proved to have considerable capability in optimizing the use of renewable power. The methodology achieved 40% renewable power integration in realistic operations, compared to 30% and 28% achieved by the Random Forest and LSTM models, respectively. The two models' performances stood at 20% and 22%, respectively. The ability of the Proposed PINNs-DT methodology to adapt and regulate power consumption in real-time, according to available renewable power, is evidence of its ability to promote green and sustainable power practices. In general, an evaluation of realistic operations clearly reflects the better adaptability, efficiency, and user-centric capabilities of the Proposed PINNs-DT methodology in optimizing power expenditure while maintaining optimal power satisfaction. Using the Digital Twin for simulation in real-time and physical laws through PINNs, the proposed methodology effectively deals with variability in power generation and power demands, and also fine-tunes power expenditure and maintains optimal power satisfaction. Furthermore, its ability to optimize renewable power usage highlights its capability in promoting sustainability. These arguments place the Proposed PINNs-DT methodology to smart power management in smart grids on solid, flexible, and sustainable foundations, compared to machine learning models in prediction capability and operating efficiencies in real-time.

6. Conclusion

This study presents an integrated approach to optimizing energy use in smart building systems and smart grids using Machine Learning (ML), Digital Twin (DT) technology, and Physics-Informed Neural Networks (PINNs). The Hybrid PINNs-DT approach resolves pressing residential energy management challenges, including time-variant demands for energy, renewable energy use optimization, and maintenance of user comfort while keeping power charges low. In Section 1, our approach was developed through combining DT and ML to accurately capture smart building complexities. The use of DT made it possible to develop current, up-to-date virtual models of the physical power system, hence enabling realistic power and energy monitoring and power usage optimization. The use of Reinforcement Learning (RL) in addition to advanced ML strategies made power usage improvement in both power efficiency and flexibility possible. In Section 2, in contrast to determinism, our Proposed PINNs-DT approach's enhanced power optimizing capabilities were shown. The approach effectively produced savings in baseline power charges while optimizing renewable energy source use. In addition, power use optimizing did not only reduce wastage of power but enhanced system stability, hence validating the benefits of physical mechanisms in ML models. Visualization of renewable power generation in collaboration with power behavior proved to validate responsiveness of the approach in variability scenarios.

Section 3 compared the prediction ability of the proposed methodology. The PINNs-DT methodology proved to have better performance than standard machine learning models, such as Linear Regression, Random Forest, SVM, LSTM, and XGBoost, using various metrics for measurement of error. In particular, the PINNs-DT methodology produced an average Mean Absolute Error (MAE) of 0.237 kWh, Root Mean Square Error (RMSE) of 0.298 kWh, and an R-squared (R^2) score of 0.978, showing that it explained 97.8% of electricity consumption variability. The 0.012 kWh Mean Bias Error revealed prediction made in absence of systematic bias. Aside from quantitative analysis, case studies proved better performance of the model in testing. The methodology produced an Accuracy of 97.7%, Precision of 97.8%, Recall of 97.6%, and F1 Score of 97.7%. These values reiterate the technique's capability to provide consistent, accurate, and reliable estimates of electricity consumption, performing better compared to standard models such as Linear Regression (Accuracy: 90.2%, F1 Score: 90.2%) and Random Forest (Accuracy: 94.6%, F1 Score: 94.6%). The developed PINNs-DT methodology's flexibility and optimal operation in real-life scenarios were examined in Section 4. The methodology achieved 0.5 seconds response time to electricity supply and demand variability, compared to 2.5 seconds for Linear Regression and 1.2 seconds for LSTM. In addition, the technique achieved considerable savings on electricity expenditure (up to 35%) while maintaining high User Comfort Index of 96%. Moreover, the methodology maximally exploited renewable electricity generation, up to 40%, compared to standard models such as Random Forest (30%) and SVM (22%).

The suggested PINNs-DT methodology is a pioneering approach to smart grid energy management, presenting an efficient and versatile solution while encouraging green practices for optimizing energy. The methodology, combining machine learning, digital twins, and physics-constrained neural networks, offers enhanced predictability and real-time responsiveness, in addition to economic feasibility, reliability, and ecological sustainability. The current research lays the platform for future studies to combine advanced artificial intelligence tools and physical simulation to address complex energy problems in smart grids and adjacent disciplines.

6.1. limitations

Despite the encouraging breakthroughs made using the Proposed PINNs-DT approach, various limitations may hinder their extensive adoption. The primary limitation lies in the computational demands of combining Physics-Informed Neural Networks (PINNs) in this application. As PINNs improve prediction capability by including physical regulations in their models, their implementation demands considerable computational power, especially in their initial phases. Such computational demands might limit their application in real-time, for example, in low-resource settings or in extensive systems. The second crucial point to analyze is scalability. As encouraging application in residential and small building power systems looks promising, considerable barriers lie in attempting

to scale up such technology to larger applications, such as citywide smart power systems. Larger systems have greater variability in power delivery behavior, load patterns, and time-dependent interactions, and hence, greater data heterogeneity and system complexity. Such limitations might impair responsiveness of the model and sacrifice accuracy in realistic application. Moreover, data-centric approach relying on extensive collection of quality data using smart meters, IoT, and renewable power systems is an extra challenge. The model needs to have ongoing access to consistent, high-resolution data to effectively train and make necessary real-time interventions. Any inconsistencies, incomplete data, or poor data quality might compromise prediction ability and system integrity and thus limit application in places where smart power monitoring facilities are in their developmental phases.

6.2. Future Work

Addressing the limitations in the envisioned PINNs-DT approach offers various future directions and improvement options. An important future avenue is optimizing computational cost. Future studies may focus on optimizing the training protocol using strategies such as pruning, parallel computation, and harnessing GPU or TPU capabilities. Such modifications may result in minimizing computational needs, thus expanding the model's viability for real-time and large implementations. Broadening the approach's paradigm to include smart grids on city or countrywide scales is another crucial future direction. Attaining such an objective means designing modular or hierarchical structures capable of accommodating greater variability and heterogeneity in large power systems. Moreover, incorporation of power generation by multiple power sources and monitoring of greater variability in dynamic interactions is crucial for efficient scaling of the envisioned methodology.

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References

1. Hasan, A., & Aghaei, M. (2025). Digital twin technology: fundamental aspects and advances. In Digital Twin Technology for the Energy Sector (pp. 25-45). Elsevier.

2. Shafto, M., et al. (2010). Modeling, Simulation, Information Technology & Processing Roadmap. NASA.

3. Tao, F., & Zhang, M. (2017). Digital Twin and its Applications in Intelligent Manufacturing. Engineering, 5(4), 580-590.

4. Varmaghani, A., Matin Nazar, A., Ahmadi, M., Sharifi, A., Jafarzadeh Ghoushchi, S., & Pourasad, Y. (2021). DMTC: Optimize Energy Consumption in Dynamic Wireless Sensor Network Based on Fog Computing and Fuzzy Multiple Attribute Decision-Making. Wireless Communications and Mobile Computing, 2021(1), 9953416.

5. Brosinsky, C., Westermann, D., & Krebs, R. (2018, June). Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers. In 2018 IEEE international energy conference (ENERGYCON) (pp. 1-6). IEEE.

6. Ahmadi, M., Soofiabadi, M., Nikpour, M., Naderi, H., Abdullah, L., & Arandian, B. (2022). Developing a deep neural network with fuzzy wavelets and integrating an inline PSO to predict energy consumption patterns in urban buildings. Mathematics, 10(8), 1270.

7. Sharifi, A., Naeini, H. K., Ahmadi, M., Asadi, S., & Varmaghani, A. (2025). Multi-Objective Optimization of Water Resource Allocation for Groundwater Recharge and Surface Runoff Management in Watershed Systems. arXiv preprint arXiv:2502.15953.

8. Sivalingam, K., et al. (2018). Applications of Digital Twin Technology in Renewable Energy Systems. Renewable Energy, 122, 663-673.

9. Batty, M. (2018). Digital Twins and Smart Cities. Environment and Planning B: Urban Analytics and City Science, 45(3), 349-355.

10. Qi, Q., et al. (2018). Digital Twin for Smart Manufacturing: A Review. Advanced Manufacturing, 1(1), 1-11.

11. Haag, S., & Anderl, R. (2018). Digital Twin—Proof of Concept. CIRP Journal of Manufacturing Science and Technology, 23, 144-152.

12. Rojek, I., Mikołajewski, D., Galas, K., & Piszcz, A. (2025). Advanced Deep Learning Algorithms for Energy Optimization of Smart Cities. Energies, 18(2), 407.

13. Onile, A. E., Petlenkov, E., Levron, Y., & Belikov, J. (2024). Smartgrid-based hybrid digital twins framework for demand side recommendation service provision in distributed power systems. Future Generation Computer Systems, 156, 142-156.

14. Es-haghi, M. S., Anitescu, C., & Rabczuk, T. (2024). Methods for enabling real-time analysis in digital twins: A literature review. Computers & Structures, 297, 107342.

15. Wang, D., Song, Y., Zhang, Y., Jiang, X., Dong, J., Khan, F. N., ... & Zhang, M. (2024). Digital twin of optical networks: a review of recent advances and future trends. Journal of Lightwave Technology.

16. Kertha Utama, P., Nashirul Haq, I., Pradipta, J., Putra, A., & Leksono, E. (2024). Microgrid digital twin: implementation of digital twin concept based on smart grid architectural model (sgam) and its case study. Irsyad and Pradipta, Justin and Putra, Angga and Leksono, Edi, Microgrid digital twin: Implementation of Digital Twin Concept Based on Smart Grid Architectural Model (Sgam) and its Case Study.

17. Stadtmann, F., Rasheed, A., Kvamsdal, T., Johannessen, K. A., San, O., Kölle, K., ... & Skogås, J. O. (2023). Digital twins in wind energy: Emerging technologies and industry-informed future directions. IEEE Access, 11, 110762-110795.

18. Zeng, Y., Hussein, Z. A., Chyad, M. H., Farhadi, A., Yu, J., & Rahbarimagham, H. (2025). Integrating type-2 fuzzy logic controllers with digital twin and neural networks for advanced hydropower system management. Scientific Reports, 15(1), 5140.

19. Xu, G., & Guo, T. (2025). Advances in AI-powered civil engineering throughout the entire lifecycle. Advances in Structural Engineering, 13694332241307721.

20. Ahmadi, M., Biswas, D., Paul, R., Lin, M., Tang, Y., Cheema, T. S., ... & Vrionis, F. D. (2025). Integrating Finite Element Analysis and Physics-Informed Neural Networks for Biomechanical Modeling of the Human Lumbar Spine. *North American Spine Society Journal (NASSJ)*, 100598.

21. Parizad, A., Baghaee, H. R., & Rahman, S. (2025). Overview of Smart Cyber-Physical Power Systems: Fundamentals, Challenges, and Solutions. Smart Cyber-Physical Power Systems: Fundamental Concepts, Challenges, and Solutions, 1, 1-69.

22. Mulpuri, S. K., Sah, B., & Kumar, P. (2025). Intelligent Battery Management System (BMS) with End-Edge-Cloud Connectivity-A Perspective. Sustainable Energy & Fuels.

23. Chen, C., Zhang, L., Zhou, C., & Luo, Y. (2025). Physics-informed explainable encoder-decoder deep learning for predictive estimation of building carbon emissions. Renewable and Sustainable Energy Reviews, 213, 115478.

24. Chen, D., Lin, X., & Qiao, Y. (2025). Perspectives for artificial intelligence in sustainable energy systems. Energy, 134711.

25. Mittal, P., & Malik, R. (2025). Optimized Physics-Informed Neural Network Framework for Wild Animal Activity Detection and Classification with Real Time Alert Message Generation. International Journal on Computational Modelling Applications, 2(1), 42-52.

26. Pandiyan, S. V., Gros, S., & Rajasekharan, J. (2025). Physics informed neural network based multi-zone electric water heater modeling for demand response. Applied Energy, 380, 125037.

27. Feng, R., Wajid, K., Faheem, M., Wang, J., Subhan, F. E., & Bhutta, M. S. (2025). Uniform Physics Informed Neural Network Framework for Microgrid and its application in voltage stability analysis. IEEE Access.

28. Habib, A., & Yildirim, U. (2025). Developing block-based physics-informed multi-layered neural network model for simulating the inelastic response of base-isolated structures. Neural Computing and Applications, 1-24.

29. Nadal, I. V., Nellikkath, R., & Chatzivasileiadis, S. (2025). Physics-Informed Neural Networks in Power System Dynamics: Improving Simulation Accuracy. arXiv preprint arXiv:2501.17621.

30. 30- Ventura Nadal, I., Nellikkath, R., & Chatzivasileiadis, S. (2025). Physics-Informed Neural Networks in Power System Dynamics: Improving Simulation Accuracy. arXiv e-prints, arXiv-2501.

31. Ko, T., Kim, D., Park, J., & Lee, S. H. (2025). Physics-informed neural network for long-term prognostics of proton exchange membrane fuel cells. Applied Energy, 382, 125318.

32. Qin, Y., Liu, H., Wang, Y., & Mao, Y. (2024). Inverse physics–informed neural networks for digital twin–based bearing fault diagnosis under imbalanced samples. *Knowledge-Based Systems*, *292*, 111641.

33. Far, A. Z., Far, M. Z., Gharibzadeh, S., Zangeneh, S., Amini, L., & Rahimi, M. (2024). Artificial intelligence for secured information systems in smart cities: Collaborative iot computing with deep reinforcement learning and blockchain. arXiv preprint arXiv:2409.16444.

34. Songhorabadi, M., Rahimi, M., MoghadamFarid, A., & Kashani, M. H. (2023). Fog computing approaches in IoT-enabled smart cities. Journal of Network and Computer Applications, 211, 103557.

35. Songhorabadi, M., Rahimi, M., Farid, A. M. M., & Kashani, M. H. (2020). Fog computing approaches in smart cities: a state-of-the-art review. arXiv preprint arXiv:2011.14732.

36. Minerva, R., Lee, G. M., & Crespi, N. (2020). Digital twin in the IoT context: A survey on technical features, scenarios, and architectural models. Proceedings of the IEEE, 108(10), 1785-1824.

37. Jafari, M., Kavousi-Fard, A., Chen, T., & Karimi, M. (2023). A review on digital twin technology in smart grid, transportation system and smart city: Challenges and future. IEEE Access, 11, 17471-17484.

38. Hegazy Abdelghany Mohamed Ammar, M. (2021). Advanced digital twins for conditions monitoring, examinations, diagnosis and predictive remaining lifecycles based Artificial Intelligence (Doctoral dissertation, Brunel University London).

39. Asadi, S., & Abedini, A. (2016). Numerical study of cooling buildings with cylindrical roof using surface-to-airheat exchanger. Journal of Mechanical Engineering and Vibration, 7(1), 27-34.

40. McIntosh, B. S., Ascough II, J. C., Twery, M., Chew, J., Elmahdi, A., Haase, D., ... & Voinov, A. (2011). Environmental decision support systems (EDSS) development–Challenges and best practices. Environmental Modelling & Software, 26(12), 1389-1402.

41. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2018). Digital twin in industry: State-of-the-art. IEEE Transactions on industrial informatics, 15(4), 2405-2415.

42. Qian, C., Liu, X., Ripley, C., Qian, M., Liang, F., & Yu, W. (2022). Digital twin—Cyber replica of physical things: Architecture, applications and future research directions. Future Internet, 14(2), 64.

43. Reihanifar, M., Takallou, A., Taheri, M., Lonbar, A. G., Ahmadi, M., & Sharifi, A. (2024). Nanotechnology advancements in groundwater remediation: A comprehensive analysis of current research and future prospects. *Groundwater for Sustainable Development*, *27*, 101330.

44. Attari, M. Y. N., Ala, A., Ahmadi, M., & Jami, E. N. (2024). A highly effective optimization approach for managing reverse warehouse system capacity across diverse scenarios. *Process Integration and Optimization for Sustainability*, *8*(2), 455-471.

45. Asadi, S., Mohammadagha, M., & Naeini, H. K. (2025). Comprehensive Review of Analytical and Numerical Approaches in Earth-to-Air Heat Exchangers and Exergoeconomic Evaluations. *arXiv preprint arXiv:2502.08553*.

46. Moghim, S., & Takallou, A. (2023). An integrated assessment of extreme hydrometeorological events in Bangladesh. *Stochastic Environmental Research and Risk Assessment*, *37*(7), 2541-2561.

47. Asgari, F., Ghoreishi, S. G. A., Khajavi, M., Foozoni, A., Ala, A., & Lonbar, A. G. (2024). Data Analysis of Decision Support for Sustainable Welfare in The Presence of GDP Threshold Effects: A Case Study of Interactive Data Exploration. *arXiv preprint arXiv:2407.09711*.

48. Reihanifar, M., Danandeh Mehr, A., Tur, R., Ahmed, A. T., Abualigah, L., & Dąbrowska, D. (2023). A new multi-objective genetic programming model for meteorological drought forecasting. *Water*, *15*(20), 3602.

49. Danandeh Mehr, A., Reihanifar, M., Alee, M. M., Vazifehkhah Ghaffari, M. A., Safari, M. J. S., & Mohammadi, B. (2023). VMD-GP: A new evolutionary explicit model for meteorological drought prediction at ungauged catchments. *Water*, *15*(15), 2686.

50. Hussain, A., Reihanifar, M., Niaz, R., Albalawi, O., Maghrebi, M., Ahmed, A. T., & Danandeh Mehr, A. (2024). Characterizing Inter-Seasonal Meteorological Drought Using Random Effect Logistic Regression. *Sustainability*, *16*(19), 8433.

51. Hashmi, R., Liu, H., & Yavari, A. (2024). Digital twins for enhancing efficiency and assuring safety in renewable energy systems: A systematic literature review. Energies, 17(11), 2456.

52. Esmaeili, M., Rahimi, M., Pishdast, H., Farahmandazad, D., Khajavi, M., & Saray, H. J. (2024). Machine Learning-Assisted Intrusion Detection for Enhancing Internet of Things Security. arXiv preprint arXiv:2410.01016.

53. Asadi, S., Gharibzadeh, S., Zangeneh, S., Reihanifar, M., Rahimi, M., & Abdullah, L. (2024). Comparative Analysis of Gradient-Based Optimization Techniques Using Multidimensional Surface 3D Visualizations and Initial Point Sensitivity. arXiv preprint arXiv:2409.04470.

54. Cellina, M., Cè, M., Alì, M., Irmici, G., Ibba, S., Caloro, E., ... & Papa, S. (2023). Digital twins: The new frontier for personalized medicine?. Applied Sciences, 13(13), 7940.

55. Ahmadi, M., Lonbar, A. G., Naeini, H. K., Beris, A. T., Nouri, M., Javidi, A. S., & Sharifi, A. (2023). Application of segment anything model for civil infrastructure defect assessment. arXiv preprint arXiv:2304.12600.

56. Zahid, H., Zulfiqar, A., Adnan, M., Iqbal, M. S., & Shah, A. (2025). Transforming nano grids to smart grid 3.0: AI, digital twins, blockchain, and the metaverse revolutionizing the energy ecosystem. *Power, Energy and Industry Applications*.

57. Sarker, I. H., Janicke, H., Mohsin, A., Gill, A., & Maglaras, L. (2024). Explainable AI for cybersecurity automation, intelligence, and trustworthiness in digital twin: Methods, taxonomy, challenges, and prospects. *ICT Express*. https://doi.org/10.1016/j.icte.2024.05.007

58. Idrisov, I. N., Okeke, D., Albaseer, A., Abdallah, M., & Ibanez, F. M. (2025). Leveraging digital twin and machine learning techniques for anomaly detection in power electronics dominated grid. *arXiv preprint*.

59. Meng, X., & Zhu, J. (2024). Augmenting cybersecurity in smart urban energy systems through IoT and blockchain technology within the digital twin framework. *Elsevier*.

https://doi.org/10.1016/j.cse.2024.109613

60. Kavousi-Fard, A., Dabholkar, M., Jafari, M., Fardad-Huroubi, M., Deng, X., & Jie, H. (2024). Digital twin for mitigating solar energy resources challenges: A perspective. *Solar Energy, 274*, 109645. https://doi.org/10.1016/j.solener.2024.109645

61. Kabir, M. R., Halder, D., & Ray, S. (2024). Digital twins for IoT-driven energy systems: A survey. *IEEE Access, 12*, 1–14.

62. Cali, U., Dimd, B. D., Hajiagilol, P., Moazami, A., Gourisetti, S. N. G., & Lobaccaro, G. (2024). Digital twins: Shaping the future of energy systems and smart cities through cybersecurity, efficiency, and sustainability. *IEEE Access*.

63. Jafari, M., Kavousi-Fard, A., Chen, T., & Karimi, M. (2024). A review on digital twin technology in smart grid, transportation system, and smart city: Challenges and future. *IEEE Access, 11*, 1–18.

64. Bai, H., & Wang, Y. (2022). Digital power grid based on digital twin: Definition, structure and key technologies. *Energy Reports*, *8*, 390-397.

65. Kumari, N., Sharma, A., Tran, B., Chilamkurti, N., & Alahakoon, D. (2023). A comprehensive review of digital twin technology for grid-connected microgrid systems: State of the art, potential and challenges faced. *Energies*, *16*(14), 5525.

66. Lv, Z., Cheng, C., & Lv, H. (2023). Digital twins for secure thermal energy storage in building. *Applied Energy*, *338*, 120907.

67. Kavousi-Fard, A., Dabbaghjamanesh, M., Jafari, M., Fotuhi-Firuzabad, M., Dong, Z. Y., & Jin, T. (2024). Digital Twin for mitigating solar energy resources challenges: A Perspective Review. *Solar Energy*, *274*, 112561.

68. Agostinelli, S., Cumo, F., Guidi, G., & Tomazzoli, C. (2021). Cyber-physical systems improving building energy management: Digital twin and artificial intelligence. *Energies*, *14*(8), 2338.

69. Nikpour, M., Yousefi, P. B., Jafarzadeh, H., Danesh, K., Shomali, R., Asadi, S., ... & Ahmadi, M. (2025). Intelligent energy management with iot framework in smart cities using intelligent analysis: An application of machine learning methods for complex networks and systems. Journal of Network and Computer Applications, 235, 104089.

70. Liu, S., Tian, J., Ji, Z., Dai, Y., Guo, H., & Yang, S. (2024). Research on multi-digital twin and its application in wind power forecasting. *Energy*, *292*, 130269.

71. Asadi, S., & Abedini, A. (2015). Numerical and Annalytical Review on earth to air heat exchanger and Exergoeconomic Analysis. Journal of Mechanical Engineering and Vibration,

6(3), 42-46.

72. Naseri, F., Gil, S., Barbu, C., Cetkin, E., Yarimca, G., Jensen, A. C., ... & Gomes, C. (2023). Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms. *Renewable and Sustainable Energy Reviews*, *179*, 113280.

73. Zhao, K., Liu, Y., Zhou, Y., Ming, W., & Wu, J. (2025). Digital twin-supported battery state estimation based on TCN-LSTM neural networks and transfer learning. *CSEE Journal of Power and Energy Systems*.

74. Farhadi Nia, M., Ahmadi, M., & Irankhah, E. (2025). Transforming dental diagnostics with artificial intelligence: advanced integration of ChatGPT and large language models for patient care. Frontiers in Dental Medicine, 5, 1456208.

75. Norcéide, F. S., Aoki, E., Tran, V., Nia, M. F., Thompson, C., & Chandra, K. (2024, December). Positional Tracking of Physical Objects in an Augmented Reality Environment Using Neuromorphic Vision Sensors. In 2024 International Conference on Machine Learning and Applications (ICMLA) (pp. 1031-1036). IEEE.

76. Nia, M. F. (2024). Explore Cross-Codec Quality-Rate Convex Hulls Relation for Adaptive Streaming. arXiv preprint arXiv:2408.09044.

77. Ahmadi, M., Nia, M. F., Asgarian, S., Danesh, K., Irankhah, E., Lonbar, A. G., & Sharifi, A. (2023). Comparative analysis of segment anything model and u-net for breast tumor detection in ultrasound and mammography images. arXiv preprint arXiv:2306.12510.

78. Jamali, S., & Abbasalizadeh, M. (2021). Cost-aware co-locating of services in Internet of Things by using multicriteria decision making. International Journal of Communication Systems, 34(16), e4962.

79. Abbasalizadeh, M., Vellamchety, K., Rayavaram, P., & Narain, S. (2024). Dynamic Link Scheduling in Wireless Networks Through Fuzzy-Enhanced Deep Learning. IEEE Open Journal of the Communications Society.

80. Ahmadi, M., Biswas, D., Paul, R., Lin, M., Tang, Y., Cheema, T. S., ... & Vrionis, F. D. (2025). Integrating finite element analysis and physics-informed neural networks for biomechanical modeling of the human lumbar spine. North American Spine Society Journal (NASSJ), 22, 100598.