ZIBELINE INTERNATIONAL™ PUBLISHING

ISSN: 2616-4302 (Online)
ISSN: 2990-9260 (Print)
CODEN: AMMCFL

Acta Mechanica Malaysia (AMM)

DOI: http://doi.org/10.26480/amm.02.2025.88.96

CrossMark

REVIEW ARTICLE

A DIGITAL TWIN-BASED PREDICTIVE MAINTENANCE FRAMEWORK FOR COMBINED-CYCLE TURBINES IN LOAD-BEARING SMART STRUCTURES SUPPORTING ENERGY DIPLOMACY

James Avevor[a], Selasi Agbale Aikins[b], Amina Catherine Peter-Anyebe[c*], Lawrence Anebi Enyejo[d], Francis Chukwudi Eze[e], Ignatius Idoko Adaudu[f]

[a] *Department of Mechanical Engineering, Rowan University, Glassboro New Jersey, USA.*
[b] *Department of Mechanical Engineering, Temple University, Philadelphia, USA.*
[c] *Department of International Relations and Diplomacy, Federal University of Lafia, Nasarawa States. Nigeria.*
[d] *Department of Telecommunications, Enforcement Ancillary and Maintenance, National Broadcasting Commission Headquarters, Aso-Villa, Abuja, Nigeria.*
[e] *Department of Civil Engineering, Michigan Technological University, Houghton Michigan, USA.*
[f] *Department of Civil Engineering, School of Engineering Technology, Benue State Polytechnic, Ugbokolo, Benue State, Nigeria.*
[*] *Corresponding Author Email: aminacatherinepeteranyebe@gmail.com*

ARTICLE DETAILS

Article History:

Received 27 May 2024
Revised 24 June 2025
Accepted 29 July 2025
Available online 09 August 2025

ABSTRACT

The convergence of digital twin technologies and predictive maintenance for combined-cycle turbines (CCTs) within load-bearing smart structures represents a critical innovation at the intersection of structural engineering, real-time systems monitoring, and global energy governance. This review explores a framework that integrates sensor-driven machine learning models—such as Long Short-Term Memory (LSTM) networks and convolutional neural networks (CNNs)—with digital twin environments to detect anomalies, predict failures, and optimize maintenance schedules for CCTs embedded in energy-intensive structural systems, including smart high-rises and industrial campuses. Beyond technical performance, this framework is positioned as a strategic asset in the practice of energy diplomacy: the use of technological infrastructure and cross-border energy solutions to advance national interests, foster geopolitical cooperation, and stabilize transnational energy security arrangements. The review critically examines how nations can leverage predictive maintenance frameworks and smart infrastructure as instruments of diplomatic engagement through bilateral and multilateral agreements, particularly in energy-exporting or energy-deficient regions. Case examples include the integration of such systems in joint economic zones, sustainable development corridors, and multinational infrastructure investment programs such as the EU Green Deal and U.S.-Indo-Pacific energy partnerships. Economically, the framework supports resilience planning by reducing operational downtime, minimizing structural fatigue under extreme climate events, and enhancing return on infrastructure investments, all of which are vital in intergovernmental negotiations on sustainability and disaster preparedness. This interdisciplinary synthesis demonstrates how structural engineering innovations—when linked with predictive analytics and international cooperation—can serve not only technical goals but also global diplomatic objectives centered on energy resilience, climate adaptation, and infrastructural sovereignty.

KEYWORDS

Digital Twin, Predictive Maintenance, Combined-Cycle Turbines (CCTs), Smart Structures, Energy Diplomacy.

1. INTRODUCTION

1.1 Background and Motivation

The integration of Digital Twin-Based Predictive Maintenance Frameworks into Combined-Cycle Turbines (CCTs) housed within load-bearing smart structures reflects a technological evolution aimed at bridging structural engineering, data science, and global energy strategy. Combined-cycle turbines are integral to modern power generation systems, operating through sequential gas and steam cycles to maximize energy conversion efficiency. However, their complexity and exposure to mechanical, thermal, and environmental stresses necessitate advanced monitoring and maintenance mechanisms to ensure reliability, especially in structurally embedded applications such as smart industrial campuses and high-rise infrastructure.

Digital twin technology enables the creation of real-time, sensor-driven virtual replicas of physical turbine systems, allowing for comprehensive analysis of mechanical behavior under operational conditions. Predictive models, particularly those based on Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), can analyze multivariate sensor data to forecast anomalies, degradation trends, and imminent failures (Tao et al., 2018). This predictive insight allows engineers to optimize maintenance schedules, reducing both planned and unplanned downtime while preserving system integrity.

The motivation for developing such integrated frameworks also extends beyond technical optimization. In the context of energy diplomacy, nations investing in intelligent, resilient infrastructure can reinforce geopolitical influence through infrastructure reliability and cross-border energy partnerships (Lee et al., 2015). Smart predictive systems form a foundation for bilateral and multilateral engagements where energy

Quick Response Code	Access this article online	
	Website: www.actamechanicamalaysia.com	**DOI:** 10.26480/amm.02.2025.88.96

Cite the Article: James Avevor, Selasi Agbale Aikins, Amina Catherine Peter-Anyebe, Lawrence Anebi Enyejo, Francis Chukwudi Eze, Ignatius Idoko Adaudu (2025). A Digital Twin-Based Predictive Maintenance Framework for Combined-Cycle Turbines in Load-Bearing Smart Structures Supporting Energy Diplomacy. *Acta Mechanica Malaysia, 8(2): 88-96.*

assurance and technology transfer serve diplomatic functions. Thus, this convergence of smart engineering and strategic policy forms the impetus behind deploying digital twin ecosystems—not only to solve technical challenges but also to enhance infrastructural sovereignty and transnational energy cooperation (Okereke, et al, 2025).

1.2 Objective and Scope of the Study

The objective of this review is to develop a strategic and technical synthesis of digital twin-based predictive maintenance frameworks for combined-cycle turbines (CCTs) embedded in load-bearing smart structures. The study aims to evaluate how advanced machine learning models, including Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs), can be effectively integrated into digital twin environments to enhance system reliability, predict turbine degradation, and optimize maintenance schedules.

The scope extends across three major domains: structural engineering, intelligent energy systems, and international relations. It examines how sensor-integrated smart structures can host CCTs for both real-time performance monitoring and long-term resilience planning. Simultaneously, it investigates the broader geopolitical implications of deploying such systems, positioning them as tools of energy diplomacy and international cooperation.

This review also addresses implementation within climate-vulnerable or energy-deficient regions, particularly those engaged in multilateral infrastructure development. The inclusion of case scenarios from global partnerships enables the exploration of real-world applicability in transnational energy strategies. Finally, the study seeks to bridge the gap between technical innovation and policy influence by highlighting how predictive infrastructure can serve not only operational needs but also strategic diplomatic interests in energy sovereignty, sustainability, and security.

1.3 Structure of the Paper

This paper is organized into six major sections. Following the introduction, Section 2 provides a technical outline of digital twin technologies and their application in combined-cycle turbines (CCTs), focusing on integration within smart, load-bearing infrastructures. Section 3 explores predictive maintenance mechanisms, emphasizing the deployment of sensor-driven machine learning models such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) for fault detection and performance optimization. Section 4 addresses the structural engineering dimensions of embedding CCTs in intelligent building systems, including stress factors, lifecycle monitoring, and structural resilience. Section 5 discusses the strategic implications of this framework in the context of energy diplomacy, illustrating how nations can leverage predictive infrastructure for geopolitical and energy security goals. Section 6 concludes the review by identifying technological gaps, recommending directions for future research, and proposing interdisciplinary collaborations that align predictive engineering with international policy objectives.

2. Digital Twin Technologies and Combined-Cycle Turbines

2.1 Fundamentals of Digital Twin Systems

Digital twin systems are advanced cyber-physical platforms that establish real-time, bidirectional data flows between physical assets and their virtual counterparts. In the context of combined-cycle turbines embedded in smart infrastructure, digital twins function as high-fidelity simulation environments that reflect the dynamic behavior, performance, and structural state of energy assets across their lifecycle. The core components of a digital twin include a physical entity (e.g., turbine), its digital replica, and a data communication infrastructure that synchronizes sensor input with the virtual model (Fuller et al., 2020).

Key enabling technologies for digital twins include the Internet of Things (IoT), edge computing, cloud architectures, and machine learning algorithms. These technologies support continuous monitoring, anomaly detection, and predictive simulation, creating a responsive loop where operational insights guide maintenance, control, and design adaptation. Unlike static digital models, digital twins evolve over time, enriched by data from embedded sensors measuring variables such as temperature, pressure, vibration, and fluid dynamics (Ijiga, et al., 2024). In structurally integrated CCT systems, this functionality is vital for assessing real-time fatigue and stress propagation within the host structure.

Furthermore, the simulation aspect of digital twins allows for scenario analysis under different environmental or load conditions, making them indispensable tools for resilience planning and performance optimization as presented in Table 1 (Boschert and Rosen, 2016). Their adoption across high-stakes sectors such as energy, aerospace, and infrastructure highlight their transformative impact on asset management, enabling predictive capabilities that align operational efficiency with strategic foresight (Avevor, et al, 2024).

Table 1: Summary Fundamentals of Digital Twin Systems

Component	Description	Function	Application in CCTs
Physical Entity	Real-world system or asset (e.g., turbine, infrastructure component)	Generates operational data through embedded sensors	Combined-cycle turbine structure and subsystems provide source data
Digital Replica	Virtual model that mirrors the behavior of the physical entity	Simulates real-time status, predicts failure, and evaluates scenarios	Simulates CCT thermodynamics, mechanical stress, and component performance
Data Communication Layer	IoT, cloud, and edge systems enabling bidirectional data exchange	Ensures continuous synchronization between physical and virtual systems	Facilitates real-time anomaly detection and control in turbine operations
Enabling Technologies	AI/ML algorithms, cloud computing, simulation tools, and predictive analytics	Supports decision-making through forecasting, diagnostics, and optimization	Integrates LSTM and CNN models for maintenance prediction and load forecasting

2.2 Operational Dynamics of Combined-Cycle Turbines (CCTs)

Combined-cycle turbines (CCTs) operate by coupling gas and steam turbine systems to exploit both high-temperature combustion gases and residual heat, maximizing energy efficiency in power generation systems. The operational principle is based on the Brayton cycle for the gas turbine and the Rankine cycle for the steam turbine, enabling sequential energy extraction from a single fuel input. This configuration allows CCTs to achieve thermal efficiencies exceeding 60%, making them ideal for integration into smart structural environments where energy reliability and compactness are paramount (Ameri and Enadi, 2016).

Operationally, the gas turbine combusts fuel—typically natural gas—to drive a generator, while exhaust gases are captured in a Heat Recovery Steam Generator (HRSG) to produce steam that powers the steam turbine. This synergy not only enhances fuel utilization but also stabilizes output during varying load demands. In load-bearing infrastructures, such as high-rise buildings and industrial campuses, embedded CCTs must dynamically respond to environmental stressors, structural vibrations, and fluctuating energy demands (Azonuche and Enyejo 2024).

Additionally, thermoeconomic factors such as component sizing, operational scheduling, and integration with auxiliary systems (e.g., district heating or cooling) influence overall performance and lifecycle cost (Caliskan et al., 2017). As part of intelligent infrastructure, CCTs must be optimized not only for mechanical output but also for interoperability with digital monitoring systems and predictive maintenance frameworks that ensure safety, efficiency, and continuous operation under complex load conditions.

2.3 Integration of Digital Twins with CCTs

The integration of digital twins with combined-cycle turbines (CCTs) marks a critical advancement in energy system intelligence and performance optimization. By establishing a virtualized, real-time model of the physical turbine system, digital twins enable predictive diagnostics, fault detection, and lifecycle forecasting—all of which are crucial in the high-temperature, high-pressure operational environment of CCTs. The digital twin continuously synchronizes with real-time sensor streams to reflect the thermal dynamics, mechanical wear, and operational cycles of gas and steam turbine components, allowing for responsive adjustments and early anomaly detection as shown in Figure 1 (Rasheed et al., 2020).

In practice, this integration is facilitated through multi-physics modeling, IoT-enabled data acquisition, and advanced simulation frameworks tailored to the coupled behavior of turbine subsystems. For example, pressure deviations in the heat recovery steam generator or vibration anomalies in the rotating shaft can be detected and simulated within the twin to preemptively assess failure risk. In combined-cycle plants embedded in smart infrastructure, this feedback loop enhances both operational resilience and decision-making accuracy (Wu et al., 2021).

Furthermore, digital twin environments support scenario-based optimization by simulating load fluctuations, ambient condition shifts, and component degradation over time (Ijiga, et al., 2024). These capabilities enable condition-based maintenance strategies that align technical reliability with economic performance, reinforcing the value of digital twin–CCT integration in both standalone plants and grid-connected, load-bearing urban systems.

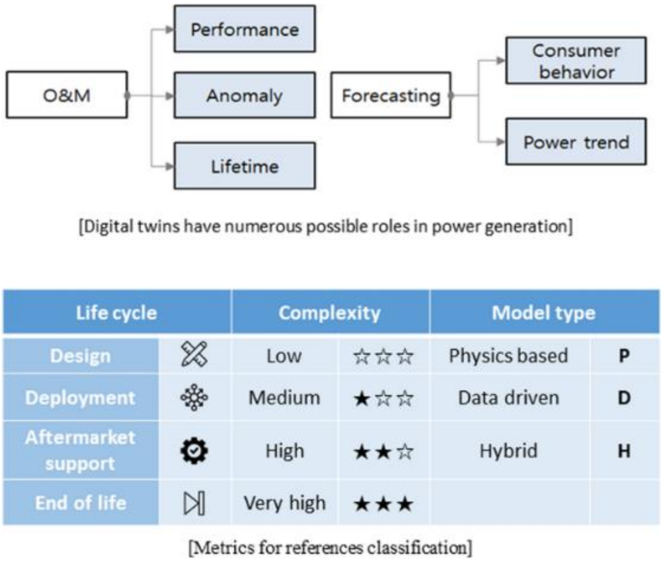

Figure 1: A picture Showing Lifecycle Roles and Modeling Approaches of Digital Twins in Power Generation Systems (Choi, et al., 2024)

Figure 1 illustrates the multifaceted integration of digital twins in power generation systems. The top diagram highlights key operational roles that digital twins play within Operations and Maintenance (OandM), such as performance monitoring, anomaly detection, lifetime estimation, and forecasting. These predictive capabilities feed into broader analyses of consumer behavior and power trends, essential for optimizing energy delivery in CCT-embedded smart infrastructures. The bottom table classifies digital twin modeling approaches across the asset lifecycle—from design to end-of-life—based on complexity and model type. In the CCT context, early stages like design employ low-complexity, physics-based models (P), while real-time deployment relies on medium-complexity, data-driven models (D). The aftermarket support phase, where predictive maintenance is critical, requires high-complexity hybrid models (H) that combine physics-based understanding with AI-driven adaptability. This alignment emphasizes the need for adaptive digital twin architectures that evolve with the turbine's operational phase, enabling accurate simulations, condition-based maintenance, and resilience planning throughout the entire lifecycle of embedded CCT systems.

3. Predictive Maintenance Using Machine Learning

3.1 Role of LSTM and CNN Models

In the integration of predictive maintenance frameworks for combined-cycle turbines (CCTs), Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have emerged as critical machine learning architectures for modeling dynamic system behaviors. LSTM networks, a specialized form of recurrent neural networks, are particularly suited for capturing temporal dependencies in time-series sensor data generated by turbine operations. Their gated architecture enables the retention and selective forgetting of long-term patterns, making them highly effective in forecasting gradual degradation and identifying subtle anomalies in vibration, temperature, and pressure signals (Malhotra et al., 2015).

Conversely, CNNs excel in detecting spatial correlations and feature hierarchies from multidimensional data inputs. In CCT systems, CNNs can be trained on spectrograms or thermal imagery derived from infrared monitoring of turbine surfaces to detect surface abnormalities, corrosion, or thermal stress signatures. When integrated into a digital twin environment, CNNs can perform real-time visual diagnostics, while LSTMs handle streaming telemetry analysis, enabling hybrid anomaly detection pipelines that enhance overall reliability and fault tolerance (Ogundare, et al, 2024).

This dual-model approach strengthens predictive capabilities, especially in environments where data heterogeneity and sensor noise are prevalent. Moreover, the fusion of LSTM and CNN outputs within decision support systems allows for higher confidence in maintenance triggers and risk classification, thereby ensuring safe operation and optimized scheduling in energy-intensive smart infrastructures as presented in Table 2 (Zhang et al., 2017).

Table 2: Summary of the Role of LSTM and CNN Models

Model Type	Primary Function	Data Handled	Application in CCT Predictive Maintenance
LSTM	Models time-series dependencies and forecasts future system states	Sequential sensor data (e.g., temperature, vibration, pressure)	Predicts turbine degradation and remaining useful life over time
CNN	Extracts spatial patterns and localized features	Multidimensional inputs (e.g., thermal images, spectrograms)	Detects surface anomalies, hotspots, and spatial damage in turbine components
Combined Use	Hybrid approach combining temporal and spatial analysis	Both time-series and visual/spatial data	Enables robust, multi-modal anomaly detection and decision support
Output Utility	Enhances predictive accuracy and maintenance decision-making	Anomaly probabilities, forecast trends, diagnostics classifications	Informs condition-based interventions and reduces unplanned downtime

3.2 Real-Time Data Acquisition and Analysis

Real-time data acquisition and analysis play a foundational role in enabling predictive maintenance within combined-cycle turbine (CCT) systems. The process involves continuously collecting multivariate sensor data—such as temperature, vibration, flow rate, and acoustic signals—from embedded monitoring systems deployed throughout the turbine's mechanical and thermal subsystems. This live telemetry is then transmitted to digital twin platforms for immediate processing and interpretation using machine learning and analytics tools (Gandomi and Haider, 2015).

Effective real-time analysis requires robust data architecture capable of handling high-velocity, high-volume input streams with minimal latency. Technologies such as edge computing and industrial IoT facilitate localized data preprocessing, which reduces bandwidth consumption and enhances response times. These localized systems are often integrated with cloud-based analytics engines, allowing complex pattern recognition algorithms and statistical models to operate across scalable infrastructure (Ijiga, et al., 2024). In the context of CCTs, this dual-layer approach supports both operational decisions and long-term performance assessments.

Moreover, advanced signal processing techniques, including principal component analysis (PCA), wavelet transforms, and moving window statistics, are commonly employed to filter noise and extract meaningful features from raw sensor data as shown in Figure 2 (Yin et al., 2014). These features are then used to train predictive models that detect early warning signs of component wear or system inefficiencies. By continuously feeding updated data into the digital twin, the system evolves in synchrony with the physical turbine, enabling a closed-loop feedback mechanism essential for resilient, intelligent infrastructure management.

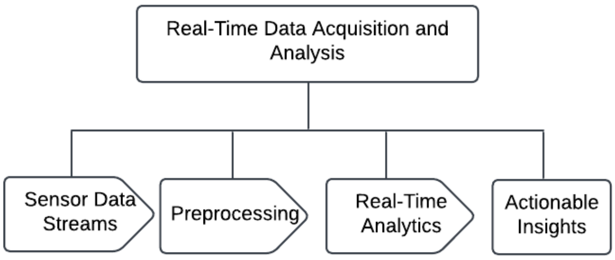

Figure 2: Flow of Real-Time Data Acquisition and Analysis for Predictive Maintenance in Combined-Cycle Turbines.

Figure 2 illustrates the sequential process of Real-Time Data Acquisition and Analysis in the context of combined-cycle turbine (CCT) predictive maintenance. It begins with Sensor Data Streams, where real-time data is continuously collected from various components of the turbine system. This raw data is then passed to the Preprocessing stage, where it undergoes cleaning and normalization to remove noise and ensure accuracy. The processed data is subsequently analyzed in the Real-Time Analytics phase, where advanced algorithms, such as LSTM and CNN models, detect anomalies and forecast potential issues. Finally, the analysis leads to Actionable Insights, providing operators with key information to optimize maintenance schedules, predict component failures, and ensure operational efficiency.

3.3 Optimization of Maintenance Scheduling

Optimization of maintenance scheduling is a core function of digital twin–enabled predictive maintenance frameworks for combined-cycle turbines (CCTs), particularly within high-reliability environments such as smart infrastructure and critical energy systems. This process involves dynamically prioritizing and timing maintenance actions based on real-time health indicators and prognostic insights derived from historical performance data and predictive models. Unlike traditional time-based maintenance, which may result in premature servicing or unexpected failures, condition-based maintenance uses degradation metrics to accurately determine optimal intervention points (Peng et al., 2010).

Through integration with LSTM and CNN models, maintenance schedules are refined to reflect the real-world wear patterns and operational stressors affecting turbine components. This enables just-in-time maintenance interventions that minimize unnecessary downtime and maximize asset lifespan. The digital twin environment plays a crucial role by continuously updating component states and simulating various maintenance scenarios under different load conditions and environmental profiles (Enyejo, et al, 2024).

In addition, optimization algorithms such as genetic algorithms, reinforcement learning, and Monte Carlo simulations are employed to weigh the cost-benefit trade-offs between preventive and corrective maintenance (Jardine et al., 2006). These approaches ensure that maintenance decisions align with broader operational objectives, including energy output continuity, resource efficiency, and structural resilience. In smart infrastructures hosting CCTs, such scheduling intelligence translates into significant lifecycle cost savings, improved safety, and greater system availability—key priorities in energy-critical built environments (Ihimoyan, et al, 2024).

4. Structural Considerations in Load-Bearing Smart Systems

4.1 Mechanical and Environmental Stress Factors

Combined-cycle turbines (CCTs) embedded within load-bearing smart structures are subjected to a complex array of mechanical and environmental stress factors that influence both performance and durability. Mechanically, turbine components—particularly rotating blades, bearings, and shafts—are exposed to cyclic stress, centrifugal loads, and vibrational forces due to high-speed operations and rotational imbalances. These dynamic stresses can cause material fatigue, creep, and eventual microstructural degradation, especially when turbines operate near peak thermal and pressure thresholds (Li et al., 2019).

Thermal stress is another critical factor, arising from the steep temperature gradients across the combustion chamber, turbine blades, and heat recovery steam generator (HRSG). Rapid temperature fluctuations during start-up and shutdown cycles intensify thermal fatigue, leading to crack initiation and propagation. In integrated systems housed within smart structures, these effects can further interact with building-induced vibrations and resonance patterns, compounding stress distribution across turbine mounts and structural supports (Ijiga, et al., 2024).

From an environmental perspective, factors such as humidity, salt content in coastal air, airborne particulates, and temperature extremes significantly impact turbine operation. For instance, in coastal or desert regions, corrosive elements and dust ingress can accelerate component erosion and reduce aerodynamic efficiency as shown in figure 3 (Kim and Kim, 2020). Additionally, external wind pressure, seismic activity, and structural oscillations from neighboring systems can contribute to load disturbances, making real-time monitoring of stress indicators vital for predictive maintenance and safe operation.

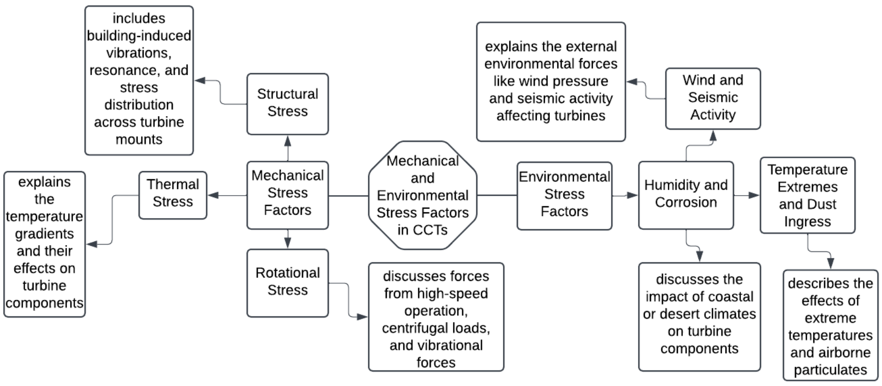

Figure 3: A Block Diagram Showing Mechanical and Environmental Stress Factors Impacting Combined-Cycle Turbines in Smart Infrastructure

Figure 3 illustrates the mechanical and environmental stress factors impacting combined-cycle turbines (CCTs) embedded within load-bearing smart structures. It separates the stresses into two main categories: Mechanical Stress Factors and Environmental Stress Factors. Under mechanical stresses, the diagram highlights the key forces acting on turbine components, including rotational stress (from high-speed operations and centrifugal loads), thermal stress (resulting from temperature gradients and rapid fluctuations), and structural stress (from building-induced vibrations and resonance). The environmental stresses include humidity and corrosion (caused by coastal or desert climates), wind and seismic activity (external forces that affect turbine stability), and temperature extremes and dust ingress (which accelerate wear and tear). This framework visually captures how each type of stress contributes to turbine degradation, necessitating real-time monitoring for predictive maintenance and long-term system reliability.

4.2 Design Requirements for Embedded CCTs

The successful integration of combined-cycle turbines (CCTs) into load-bearing smart structures necessitates a specialized set of design requirements that address both mechanical integrity and operational reliability. These embedded systems must be structurally adaptable to high vibrational loads, thermal gradients, and dynamic pressure conditions generated during turbine operation. A primary design consideration is vibration isolation, where the turbine foundation and support systems must mitigate transmission of operational oscillations to the building framework to prevent structural resonance and fatigue damage (Kurz and Brun, 2018).

Thermal containment is another critical factor. The turbine enclosure must incorporate high-efficiency insulation materials and cooling subsystems to manage the heat generated during combustion and energy recovery. This is particularly essential when CCTs are installed within densely built environments such as industrial campuses or high-rise utility cores. Additionally, spatial configuration must allow for safe human access, maintenance maneuverability, and integration with fire suppression and ventilation systems (Manuel, et al., 2024).

From a performance standpoint, the turbine must be configured to maintain output stability despite fluctuating environmental conditions, air intake disruptions, and load changes induced by the hosting infrastructure. Modular design principles are often applied to facilitate component replacement and scalability. Furthermore, advanced filtration systems are required to prevent performance degradation due to contaminants in the ambient air, a leading cause of efficiency loss and mechanical wear in gas turbines (Bhargava et al., 2013). These design imperatives form the foundation for embedding CCTs into smart, resilient architectural systems.

4.3 Lifecycle Management and Structural Fatigue Monitoring

Lifecycle management and structural fatigue monitoring are indispensable components in ensuring the long-term reliability of combined-cycle turbines (CCTs) embedded within load-bearing smart structures (Aikins, et al., 2024). The high-frequency operational cycles and thermomechanical loads typical of CCTs introduce cumulative fatigue effects in turbine blades, bearings, and housing assemblies. Structural fatigue is particularly insidious in these environments, as microcracks and material weakening evolve gradually under fluctuating stresses, often eluding detection until catastrophic failure occurs (Chandrasekaran and Mallick, 2019).

A robust lifecycle management strategy incorporates digital twin platforms to provide real-time insight into material degradation, stress accumulation, and remaining useful life (RUL) estimations. These platforms rely on continuous sensor feedback, historical performance trends, and machine learning algorithms to predict structural vulnerabilities and support condition-based interventions. In complex built environments, this predictive capability allows for the scheduling of proactive repairs that extend the service life of both the turbine and the host infrastructure (Godwins et al., 2024).

Monitoring protocols must also address external structural elements, including turbine mounts, enclosures, and adjacent load-distributing frameworks. These components are often exposed to coupled dynamic loads, particularly in regions susceptible to seismic or wind-induced vibrations. Probabilistic fatigue analysis, finite element modeling, and acoustic emission monitoring are commonly employed techniques for quantifying accumulated damage under random loading conditions as represented in Table 3 (Asgarian and Soltani, 2010). Collectively, these strategies enable data-driven asset lifecycle optimization while minimizing the risk of unanticipated structural failures in energy-critical smart facilities.

Table 3: Summary of Lifecycle Management and Structural Fatigue Monitoring

Aspect	Description	Techniques/Tools Used	Application in CCT-Embedded Smart Structures
Lifecycle Management	Coordination of maintenance activities over the turbine's operational lifespan	Digital twins, RUL estimation, maintenance scheduling	Extends system life, optimizes maintenance planning, ensures operational safety
Structural Fatigue Monitoring	Detection and analysis of stress-induced material degradation over time	Acoustic emission, FEA, probabilistic fatigue analysis	Prevents structural failure in turbine housing and mounting systems
Data Integration	Real-time monitoring of mechanical wear and stress accumulation	Sensor fusion, historical data, performance logs	Enables predictive diagnostics across CCT subsystems
Decision Support	Informed planning of repairs, replacements, or reinforcements	Digital twin simulations, damage thresholds, fatigue modeling	Improves reliability and cost efficiency in lifecycle operations

5. Strategic Role in Energy Diplomacy

5.1 Concept and Scope of Energy Diplomacy

Energy diplomacy represents a multidimensional policy tool used by states and regional blocs to secure energy resources, enhance geopolitical leverage, and shape the rules governing international energy markets (Goerge and Peter-Anyebe, 2024). It operates at the intersection of foreign policy, trade relations, and energy security strategies, and has become increasingly significant in an era marked by fluctuating resource dependencies, renewable energy transitions, and climate-related vulnerabilities. Unlike traditional forms of diplomacy, energy diplomacy centers around infrastructure agreements, cross-border resource sharing, and cooperative technological deployments such as digital twin-based predictive maintenance frameworks embedded in power infrastructure (Goldthau and Sitter, 2015).

The scope of energy diplomacy spans bilateral agreements, multilateral alliances, and regional integration initiatives aimed at ensuring access to stable, affordable, and sustainable energy (Ijiga, et al., 2024). Through regulatory harmonization, technology transfer, and strategic investment in resilient systems, actors such as the European Union and Indo-Pacific coalitions have advanced their geopolitical interests by supporting transnational energy corridors and joint infrastructure ventures. These engagements extend beyond fossil fuel interests to encompass smart energy systems, digital infrastructure, and sustainability-linked technologies that promote long-term resilience and energy independence (Leal-Arcas, 2017).

In this context, smart predictive systems like embedded combined-cycle turbines serve not only as engineering assets but as strategic tools in diplomacy. They demonstrate technological leadership, foster interdependence, and reinforce national influence through energy reliability—making them vital instruments in 21st-century geopolitical strategy.

5.2 Case Studies: EU Green Deal and Indo-Pacific Energy Initiatives

The European Green Deal and Indo-Pacific energy partnerships offer compelling examples of how digital infrastructure and predictive maintenance technologies are increasingly embedded within broader diplomatic and geopolitical strategies. Under the European Green Deal, the

EU has committed to transforming its energy infrastructure through decarbonization, digitalization, and cross-border energy integration. Central to this strategy is the deployment of smart grids, renewable generation, and intelligent maintenance systems—including digital twin platforms for combined-cycle turbines—to reduce emissions while enhancing system resilience as shon in Figure 4 (Hafner and Tagliapietra, 2020).

The EU's energy diplomacy efforts emphasize regulatory convergence, green technology funding, and multilateral coordination, particularly through the Just Transition Mechanism and Trans-European Networks for Energy (TEN-E). These programs promote not only sustainability but also strategic autonomy in energy production and delivery, especially in the face of external shocks and geopolitical disruptions (Avevor, et al., 2025).

In the Indo-Pacific region, the United States and its allies have advanced strategic infrastructure initiatives to counterbalance China's influence, notably through the Blue Dot Network and the Build Back Better World initiative. These programs prioritize resilient energy systems, digital infrastructure, and transparent governance, often supported by joint ventures and public-private partnerships. Smart energy assets—like predictive-maintenance-equipped turbines—play a pivotal role in enhancing reliability and signaling technological leadership (Poon, et al., 2024). These case studies illustrate how digital energy systems are increasingly leveraged as instruments of economic diplomacy and geopolitical alignment.

Figure 4: Hybrid Renewable Infrastructure as a Strategic Tool in EU and Indo-Pacific Energy Diplomacy (Pastukhova, 2022)

Figure 4 depicting a hybrid renewable energy landscape with floating solar panels and a wind turbine—illustrates the integrated infrastructure approach. It embodies the regionally driven shift toward decentralized, resilient energy systems that blend solar and wind technologies to enhance output stability and land efficiency. In the Indo-Pacific, such systems are advancing energy security and technological influence, particularly in land-constrained, water-rich areas. Simultaneously, the European Union's Green Deal emphasizes similar models, combining sustainability with digital infrastructure to create climate-neutral energy markets. The visual integration of renewable energy within agricultural and ecological contexts aligns with both regions' strategic energy diplomacy, highlighting how smart, multipurpose infrastructure is not only decarbonizing power systems but also reinforcing geopolitical partnerships, economic resilience, and long-term environmental stewardship.

5.3 Infrastructure Resilience and National Security

Infrastructure resilience has emerged as a critical pillar of national security, particularly as nations contend with increasingly complex threats ranging from cyberattacks and natural disasters to energy supply disruptions and geopolitical instability. Within this context, the integration of predictive maintenance systems—especially those built on digital twin architectures—enhances both the structural reliability and strategic value of critical energy assets such as combined-cycle turbines (CCTs). These smart infrastructures serve as both operational linchpins and geopolitical leverage points, where their ability to autonomously detect, analyze, and mitigate failure risks directly contributes to national defense readiness and energy sovereignty (Boin et al., 2010).

Predictive analytics platforms embedded in smart energy systems enable governments to anticipate vulnerabilities, prioritize repairs, and allocate resources before disruptions compromise national infrastructure networks. In addition to physical reliability, digital twin systems also enhance cybersecurity preparedness by detecting anomalous patterns indicative of malicious interference or sabotage. As energy systems become more digitized and interconnected, safeguarding their operational integrity becomes inseparable from broader national security mandates (Lewis, 2019).

Moreover, resilient infrastructure underpinned by AI-enabled maintenance strategies plays a vital role in continuity-of-government plans and disaster recovery frameworks. The ability to maintain power generation and distribution during crises reinforces national stability, public safety, and economic continuity as represented in Table 4 (Anyebe, et al., 2024). Thus, embedding CCTs with intelligent monitoring technologies represents not only an engineering solution but a proactive national security strategy aligned with 21st-century risk environments.

Table 4: Summary of Infrastructure Resilience and National Security

Dimension	Description	Key Functions	Application in CCT-Embedded Smart Infrastructure
Physical Resilience	Ability of infrastructure to withstand mechanical stress, extreme conditions	Shock absorption, structural integrity, failure resistance	Ensures CCTs remain operational during grid instability or environmental hazards
Cyber Resilience	Defense against digital threats to infrastructure control systems	Threat detection, intrusion prevention, data integrity	Protects digital twins and turbine control networks from cyberattacks
Predictive Maintenance	Use of digital twins to preempt structural and system failures	Real-time diagnostics, anomaly forecasting, lifecycle optimization	Enhances turbine availability and safeguards infrastructure continuity
Strategic Security Role	Role of smart infrastructure in national defense and energy sovereignty	Continuity of government, energy independence, geopolitical leverage	Positions predictive systems as dual-purpose assets in diplomacy and security

6. Future Directions and Research Gaps

6.1 Technological Challenges and Innovation Opportunities

The integration of digital twin-based predictive maintenance systems for combined-cycle turbines (CCTs) embedded within smart infrastructures presents immense promise, but it also reveals a series of complex technological challenges. One of the foremost difficulties lies in achieving seamless real-time synchronization between physical turbine components and their digital counterparts. High-fidelity modeling requires enormous computational power, especially when attempting to simulate multi-physics behaviors such as thermal expansion, fluid dynamics, mechanical stress, and vibration. Ensuring model accuracy under diverse operating conditions across the turbine lifecycle remains a persistent engineering hurdle.

Data acquisition and communication bottlenecks pose additional challenges. Sensors embedded within the turbine and surrounding infrastructure must provide reliable, high-resolution data at high frequencies. Variability in sensor precision, environmental interference, and data noise can distort predictive analytics and degrade system reliability. Moreover, digital twins must be updated continuously with near-zero latency to ensure responsive anomaly detection and predictive scheduling. Achieving this at scale across distributed infrastructures—such as smart cities, industrial parks, and energy corridors—requires robust networking architectures and cybersecurity hardening.

Despite these constraints, the domain offers several innovation opportunities. The emergence of edge computing allows localized processing close to the data source, reducing transmission delays and bandwidth demands. Similarly, hybrid AI models, which blend deep learning with physics-based modeling, enhance interpretability and adaptability of digital twin frameworks. Developments in digital thread architectures, federated learning, and self-healing systems further enhance resilience and reduce reliance on centralized computing. Looking ahead, breakthroughs in quantum computing and neuromorphic chips could enable real-time multi-scale simulations and pattern recognition far beyond the capabilities of traditional systems. Investing in these technological frontiers, while standardizing digital twin development practices, will be vital for achieving scalable, secure, and sustainable deployment of predictive maintenance frameworks in mission-critical energy infrastructure.

6.2 Policy Recommendations and International Collaboration

As digital twin-based predictive maintenance frameworks become integral to next-generation energy infrastructure, there is a growing imperative for comprehensive policy development and international collaboration. Governments must recognize these technologies not merely as engineering innovations but as strategic tools that intersect with national resilience, economic competitiveness, and energy diplomacy. The absence of standardized regulatory protocols for digital twin deployment—especially across sectors such as energy, construction, and defense—creates fragmented adoption and leaves critical systems vulnerable to inefficiencies and cyber threats. To address this, policymakers should establish unified digital infrastructure standards that govern data interoperability, model validation, and real-time system integration.

To support equitable access to these technologies, especially in energy-deficient or climate-vulnerable regions, international agencies and development banks should prioritize digital infrastructure investment under the framework of sustainable development and energy justice. Capacity-building programs and technical education initiatives should be deployed to foster local expertise in predictive maintenance systems, enabling long-term technology sovereignty and reducing reliance on external contractors. Public-private partnerships are essential in this ecosystem, offering scalable funding mechanisms and shared risk frameworks that accelerate innovation without compromising public interest.

In addition, governments must address emerging ethical concerns surrounding data privacy, algorithmic transparency, and automated decision-making in predictive systems. Legislative safeguards should be put in place to ensure the responsible use of operational data and to prevent exclusionary outcomes in digitally managed infrastructure. On a global scale, diplomatic forums should incorporate predictive infrastructure into energy security dialogues, climate resilience agreements, and cross-border grid integration initiatives. Nations should be encouraged to share best practices, coordinate incident response protocols, and harmonize their regulatory approaches. In doing so, international collaboration will help bridge technological divides, promote shared accountability, and reinforce a cooperative global approach to sustainable and resilient energy governance.

6.3 Sustainable Infrastructure and Global Energy Governance

Digital twin-based predictive maintenance systems serve as a transformative enabler for sustainable infrastructure and a cornerstone of 21st-century global energy governance. Their integration into combined-cycle turbines (CCTs) embedded within smart structures signifies a shift from reactive to proactive engineering, supporting long-term asset performance, reduced environmental impact, and system-level efficiency. By enabling precise monitoring and condition-based interventions, these systems eliminate unnecessary maintenance cycles, reduce energy waste, and minimize material fatigue—all of which contribute to lowering lifecycle emissions and optimizing resource utilization.

Sustainable infrastructure today demands not only physical durability but also adaptability to environmental change, technological evolution, and social expectations. Digital twins support this requirement by providing decision-makers with real-time situational awareness, predictive foresight, and adaptive control strategies. These capabilities are particularly vital in energy-intensive urban regions, disaster-prone zones, and climate-stressed environments. For instance, during grid instability or peak demand events, digital twins can simulate alternative load scenarios and recommend operational adjustments that maintain stability without excessive environmental cost.

At the geopolitical level, predictive infrastructure promotes a new form of technological diplomacy, where nations leverage smart energy systems to demonstrate leadership in resilience, transparency, and cooperation. Cross-border projects—such as transnational power corridors, joint research ventures, and harmonized grid standards—are increasingly built on digital infrastructure capable of mutual trust and verification. This fosters not only operational interoperability but also diplomatic alignment and shared responsibility in global energy transitions.

Ultimately, as nations pursue decarbonization and infrastructure modernization, digital twin-enabled systems will act as enablers of climate action, economic inclusivity, and governance innovation. Their deployment supports the alignment of national energy strategies with international climate commitments, such as the Paris Agreement and the UN Sustainable Development Goals. In this role, predictive infrastructure becomes a nexus for integrating sustainability, innovation, and international cooperation in the governance of global energy systems.

References

Aikins, S. A., Avevor, J. and Enyejo, L. A., 2024. Optimizing Thermal Management in Hydrogen Fuel Cells for Smart HVAC Systems and Sustainable Building Energy Solutions. International Journal of Scientific Research and Modern Technology (IJSRMT) Volume 3, Issue 4, 2024 DOI: https://doi.org/10.38124/ijsrmt.v3i4.351

Ameri, M., and Enadi, N., 2016. Exergoeconomic analysis of a combined cycle power plant with supplementary firing. Energy Conversion and Management, 117, Pp. 105–117. https://doi.org/10.1016/j.enconman.2016.03.020

Anyebe, A. P., Yeboah, O. K. K., Bakinson, O. I., Adeyinka, T. Y., and Okafor, F. C., 2024. Optimizing Carbon Capture Efficiency through AI-Driven Process Automation for Enhancing Predictive Maintenance and CO2 Sequestration in Oil and Gas Facilities. American Journal of Environment and Climate, 3(3), Pp. 44–58. https://doi.org/10.54536/ajec.v3i3.3766

Asgarian, B., and Soltani, M., 2010. Fatigue damage assessment of offshore platforms subjected to random loading. Marine Structures, 23(2), Pp. 73–89. https://doi.org/10.1016/j.marstruc.2009.10.002

Avevor, J., Adeniyi, M., Enyejo, L. A., and Aikins, S. A., 2024. Machine Learning-Driven Predictive Modeling for FRP Strengthened Structural Elements: A Review of AI-Based Damage Detection, Fatigue Prediction, and Structural Health Monitoring. International Journal of Scientific Research and Modern Technology, 3(8), Pp. 1–20. https://doi.org/10.38124/ijsrmt.v3i8.420

Avevor, J., Aikins, S. A. and Enyejo, L. A., 2025. Optimizing Gas and Steam Turbine Performance Through Predictive Maintenance and Thermal Optimization for Sustainable and Cost-Effective Power Generation. International Journal of Innovative Science and Research Technology Volume 10, Issue 3 https://doi.org/10.38124/ijisrt/25mar1336

Azonuche, T. I., and Enyejo, J. O., 2024. Exploring AI-Powered Sprint Planning Optimization Using Machine Learning for Dynamic Backlog Prioritization and Risk Mitigation. International Journal of Scientific Research and Modern Technology, 3(8), Pp. 40–57. https://doi.org/10.38124/ijsrmt.v3i8.448.

Bhargava, R. K., Meher-Homji, C. B., and Chaker, M. A., 2013. Gas turbine performance deterioration. Journal of Engineering for Gas Turbines and Power, 135(3), 032601. https://doi.org/10.1115/1.4007860

Boin, A., Comfort, L. K., and Demchak, C. C., 2010. The rise of resilience, designing resilience: preparing for extreme events. Designing resilience: Preparing for extreme events, Pp. 1-12.

Boschert, S., and Rosen, R., 2016. Digital twin—the simulation aspect. In Mechatronic Futures (pp. 59–74). Springer. https://doi.org/10.1007/978-3-319-32156-1_5

Caliskan, H., Dincer, I., and Hepbasli, A., 2017. Thermoeconomic optimization of gas turbine–steam turbine combined cycle systems. Energy, 128, Pp. 181–191. https://doi.org/10.1016/j.energy.2017.04.006

Chandrasekaran, S., and Mallick, P. K., 2019. Fatigue performance and life prediction of structural components: A review. International Journal of Fatigue, 125, Pp. 215–229. https://doi.org/10.1016/j.ijfatigue.2019.03.020

Choi, W., Hudachek, K., Koskey, S., 2024. Digital twin in the power generation industry. JMST Adv. 6, Pp. 103–119. https://doi.org/10.1007/s42791-024-00065-1

Enyejo, J. O., Fajana, O. P., Jok, I. S., Ihejirika, C. J., Awotiwon, B. O., and Olola, T. M., 2024. Digital Twin Technology, Predictive Analytics, and Sustainable Project Management in Global Supply Chains for Risk Mitigation, Optimization, and Carbon Footprint Reduction through Green Initiatives. International Journal of Innovative Science and Research Technology, Volume 9, Issue 11, November– 2024. ISSN No:-2456-2165. https://doi.org/10.38124/ijisrt/IJISRT24NOV1344

Fuller, A., Fan, Z., Day, C., and Barlow, C., 2020. Digital twin: Enabling technologies, challenges and open research. IEEE Access, 8, Pp. 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

Gandomi, A., and Haider, M., 2015. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), Pp. 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

George, M. B. and Peter-Anyebe, A. C., 2024. The Role of U.S. Environmental Diplomacy in International Wildfire Management and Sustainable Grassland Burning Practices. International Journal of Scientific Research and Modern Technology, 4(4), Pp. 1–17. https://doi.org/10.38124/ijsrmt.v4i3.405

Godwins, O. P., David-Olusa, A., Ijiga, A. C., Olola, T. M., and Abdallah, S., 2024. The role of renewable and cleaner energy in achieving sustainable development goals and enhancing nutritional outcomes: Addressing malnutrition, food security, and dietary quality. World Journal of Biology Pharmacy and Health Sciences, 2024, 19(01), Pp. 118–141. https://wjbphs.com/sites/default/files/WJBPHS-2024-0408.pdf

Goldthau, A., and Sitter, N., 2015. A liberal actor in a realist world: The European Union regulatory state and the global political economy of energy. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198719595.001.0001

Hafner, M., and Tagliapietra, S., 2020. The Geopolitics of the European Green Deal. IAI Papers, 20(20), Pp. 1–14. https://www.jstor.org/stable/resrep25220

Ihimoyan, M. K., Ibokette, A. I., Olumide, F. O., Ijiga, O. M., and Ajayi, A. A., 2024. The Role of AI-Enabled Digital Twins in Managing Financial Data Risks for Small-Scale Business Projects in the United States. International Journal of Scientific Research and Modern Technology, 3(6), Pp. 12–40. https://doi.org/10.5281/zenodo.14598498

Ijiga, A. C., Aboi, E. J., Idoko, P. I., Enyejo, L. A., and Odeyemi, M. O., 2024. Collaborative innovations in Artificial Intelligence (AI): Partnering with leading U.S. tech firms to combat human trafficking. Global Journal of Engineering and Technology Advances, 2024,18(03), Pp. 106-123. https://gjeta.com/sites/default/files/GJETA-2024-0046.pdf

Ijiga, A. C., Abutu E. P., Idoko, P. I., Ezebuka, C. I., Harry, K. D., Ukatu, I. E., and Agbo, D. O., 2024. Technological innovations in mitigating winter health challenges in New York City, USA. International Journal of Science and Research Archive, 2024, 11(01), Pp. 535–551: https://ijsra.net/sites/default/files/IJSRA-2024-0078.pdf

Ijiga, A. C., Abutu, E. P., Idoko, P. I., Agbo, D. O., Harry, K. D., Ezebuka, C. I., and Umama, E. E., 2024. Ethical considerations in implementing generative AI for healthcare supply chain optimization: A cross-country analysis across India, the United Kingdom, and the United States of America. International Journal of Biological and Pharmaceutical Sciences Archive, 2024, 07(01), Pp. 048–063. https://ijbpsa.com/sites/default/files/IJBPSA-2024-0015.pdf

Ijiga, A. C., Enyejo, L. A., Odeyemi, M. O., Olatunde, T. I., Olajide, F. I and Daniel, D. O., 2024. Integrating community-based partnerships for enhanced health outcomes: A collaborative model with healthcare providers, clinics, and pharmacies across the USA. Open Access Research Journal of Biology and Pharmacy, 2024, 10(02), Pp. 081–104. https://oarjbp.com/content/integrating-community-based-partnerships-enhanced-health-outcomes-collaborative-model

Ijiga, A. C., Olola, T. M., Enyejo, L. A., Akpa, F. A., Olatunde, T. I., and Olajide, F. I., 2024. Advanced surveillance and detection systems using deep learning to combat human trafficking. Magna Scientia Advanced Research and Reviews, 2024, 11(01), Pp. 267–286. https://magnascientiapub.com/journals/msarr/sites/default/files/MSARR-2024-0091.pdf.

Jardine, A. K. S., Lin, D., and Banjevic, D., 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), Pp. 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

Kim, D. H., and Kim, D. H., 2020. Environmental load effects on gas turbine performance in coastal power plants. Energy Reports, 6, Pp. 1499–1506. https://doi.org/10.1016/j.egyr.2020.05.019

Kurz, R., and Brun, K., 2018. Degradation in gas turbine systems. Journal of Engineering for Gas Turbines and Power, 140(9), 091701. https://doi.org/10.1115/1.4039330

Leal-Arcas, R., 2017. Energy diplomacy in the EU: perspectives for the 21st century. Renewable and Sustainable Energy Reviews, 74, Pp. 700–709. https://doi.org/10.1016/j.rser.2017.03.002

Lee, J., Bagheri, B., and Kao, H. A., 2015. A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing Letters, 3, Pp. 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001

Lewis, J. A., 2019. Cybersecurity and critical infrastructure protection. Center for Strategic and International Studies (CSIS). https://www.csis.org/analysis/cybersecurity-and-critical-infrastructure-protection

Li, C., Wang, Y., Wang, W., and Li, X., 2019. Stress and deformation analysis of turbine blades under aerodynamic and thermal loads. International Journal of Turbo and Jet-Engines, 36(4), Pp. 333–341. https://doi.org/10.1515/tjj-2017-0034

Malhotra, P., Vig, L., Shroff, G., and Agarwal, P., 2015. Long short term memory networks for anomaly detection in time series. Proceedings of the 23rd European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN), Pp. 89–94. https://www.esann.org/sites/default/files/proceedings/legacy/es2015-56.pdf

Manuel, H. N. N., Adeoye, T. O., Idoko, I. P., Akpa, F. A., Ijiga, O. M., and Igbede, M. A., 2024. Optimizing passive solar design in Texas green buildings by integrating sustainable architectural features for maximum energy efficiency. *Magna Scientia Advanced Research and Reviews*, 11(01), Pp. 235-261. https://doi.org/10.30574/msarr.2024.11.1.0089

Ogundare, T. O., Ibokette, A. I. Anyebe, A. P., and During, A. D., 2024. The Economic and Regulatory Challenges of Implementing Digital Twins and Autonomous Vessels in U.S. Maritime Fleet Modernization. International Journal of Innovative Science and Research Technology. Volume 9, Issue 11, November– 2024 ISSN No:-2456-2165. https://doi.org/10.38124/ijisrt/IJISRT24NOV075

Okereke, O. B., Abejoye, A., Ekhorutomwen, P. A. and Peter-Anyebe, A. C., 2025. Application of SAR-Driven Flood Detection Systems in Wetland Ecosystems and its Implications for Migratory Bird Habitat Management. International Journal of Innovative Science and Research Technology. Volume 10, Issue 4, April – 2025 https://doi.org/10.38124/ijisrt/25apr1627

Pastukhova, M., 2022. The geopolitics of the energy transition in the Indo-Pacific. Retrieved from: https://www.aspistrategist.org.au/the-geopolitics-of-the-energy-transition-in-the-indo-pacific/.

Peng, Y., Dong, M., and Zuo, M. J., 2010. Current status of machine prognostics in condition-based maintenance: A review. The International Journal of Advanced Manufacturing Technology, 50, Pp. 297–313. https://doi.org/10.1007/s00170-009-2482-0

Poon, J. P., Peng, P., Qian, X., and Yang, Y., 2024. End of the Asia-Pacific: Geoeconomics, belt and road and the Indo-Pacific. Political Geography, 108, 103026.

Rasheed, A., San, O., and Kvamsdal, T., 2020. Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access, 8, Pp. 21980–22012. https://doi.org/10.1109/ACCESS.2020.2970143

Tao, F., Qi, Q., Liu, A., and Kusiak, A., 2018. Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, Pp. 157–169. https://doi.org/10.1016/j.jmsy.2018.01.006

Wu, H., Zhang, M., Yang, X., and Li, L., 2021. Digital twin-based smart operation and maintenance strategy for gas turbines in combined-cycle power plants. Energy Reports, 7, Pp. 126–136. https://doi.org/10.1016/j.egyr.2021.05.013

Yin, S., Ding, S. X., Xie, X., and Luo, H., 2014. A review on basic data-driven approaches for industrial process monitoring. IEEE Transactions on Industrial Electronics, 61(11), Pp. 6418–6428. https://doi.org/10.1109/TIE.2014.2301773

Zhang, C., Bengio, S., Hardt, M., Recht, B., and Vinyals, O., 2017. Understanding deep learning requires rethinking generalization. International Conference on Learning Representations (ICLR). https://openreview.net/forum?id=Sy8gdB9xx