A Digital Twin Industrial Energy Monitoring System

Sahin Mondal[1], Rutik Panhalkar[2], Sanket Kondhalkar[3], Omkar Chaure[4]

[1,2,3,4,]DepartmenT of Electrical Engineering, NGI Polytechnic, Pune

ABSTRACT

Digital Twin have been in the focus of research in recent years, trying to achieve the vision of industry 4.0. in the domain of industrial energy systems, they are applied to facilitate a flexible and optimized operation. With help of digital twins, the industry can participate even stronger in the ongoing renewable energy transition. Current Digital Twin implementations are often application-specific solutions without general architectural concepts and their structures and namings differ, although the basic concepts are quite similar. For this reason, we analyzed concepts, architectures, and frameworks for Digital Twins in the literature to develop a technology-independent Generic Digital Twin Architecture (GDTA),summarising the applications of energy digital twins throughout a site's lifecycle, and constructing a proposal of how to apply the technology to industrial sites and local areas to enable a reduction in carbon and other environmental footprints. The review concludes by identifying key challenges that face uptake of energy digital twins and a framework to apply the energy digital twins.

Keywords: Digital twin industry 4.0; Cyber-physical system; Service-oriented web; Sustainable energy; Renewable energy

INTRODUCTION

Digitalization is changing the way business is conducted within industrial value chains, facilitated by the rapid development of communication and information technology

[1]. This process is also referred to as the fourth industrial revolution or Industry 4.0. The goal is a highly optimized and customized production, as well as enhanced automation and adaption capabilities

[2]. To realize these visions of Industry 4.0, the Digital Twin (DT) is one of the most promising enabling technologies The concepts and capabilities of DTs are not clearly defined and sometimes hard to grasp. This is caused by the fact that DTs can be applied for various tasks in different life-cycle phases and industrial domains. Thus, different interpretations of a DT exist, driven by specific use casesSubstantial research is currently underway to identify ways, such as new process technology, process systems integration, green fuels, and digitalisation, to minimise greenhouse gas emissions from the process and energy industries.

LITRATURE REVIEW

Digitalization is changing the way business is conducted within industrial value chains, facilitated by the rapid development of communication and information technology

[1]. This process is also referred to as the fourth industrial revolution or Industry 4.0. The goal is a highly optimized and customized production, as well as enhanced automation and adaption capabilities

[2]. To realize these visions of Industry 4.0, the Digital Twin (DT) is one of the most promising enabling technologies

[3]. Industry 4.0 and the sustainable energy transition share important characteristics and can mutually benefit from each other

[4]. Information and communication technology helps to increase energy efficiency and the interaction of industry with smart grids which facilitates the integration of renewable energy sources.

[5]DTs are also the key enabler for such applications, as their common functionality includes monitoring, diagnostic, prediction, and controlling general,

[6] a DT can be defined as "a formal digital representation of some asset, process or system that captures attributes and behaviors of that entity suitable for communication, storage, interpretation or processing within a certain context"

[7]. Averybasicconcept for structuring a DT defines three different aspects: the physical space, the virtual space, and the connection between them to exchange data and information

[8]. A similar concept is known from the industrial domain as Cyber–Physical System (CPS) or more specifically as Cyber–Physical Production System (CPPS). In

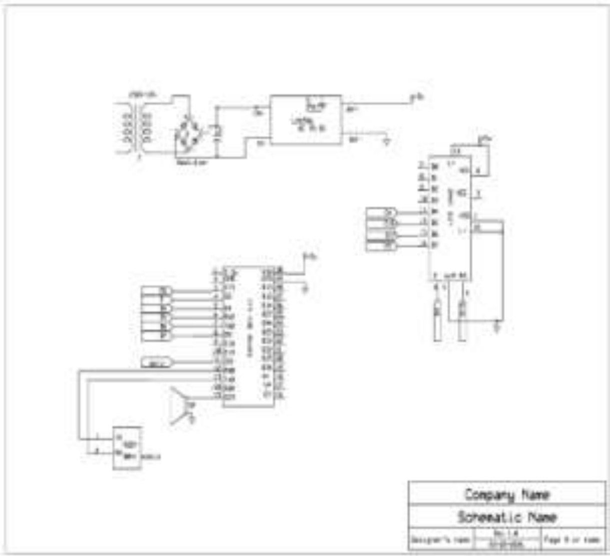
[9], CPSs are described as autonomous and cooperative elements and sub-systems across all levels of production, able to communicate with each other in situation-dependent ways. The goal of CPSs is to have elements that can acquire and process data, allowing them to self-control certain tasks and interact with humans. To reach that goal, a certain kind of virtual representation of the production system has to be available. Therefore, a CPS can be characterized by a physical asset and its cyber counterpart, which means that a DT can be seen as only the digital model inside a CPS Conversely, this also implies that a DT is the prerequisite for a CPS

[10]. For CPSs ,a fivelayer architecture architecture wasproposedin , defining"SmartConnection Level", "Data-to-Information Conversion Level", "Cyber Level", "Cognition Level", and "Configuration Level".

[11]These layers should help to develop and implement CPSs at a certain layer of this 5C architecture. In this context, the Smart Connection Level has to deal with acquiring accurate and reliable data from the physical entity and is the first step to create a CPS. Afterward, meaningful information is inferred from the data at the Data-to-Information Conversion Level. This level brings self-awareness to the machines. The CyberLevel acts as an information hub inside the 5C architecture, which also introduces the possibility of self-comparison of the performance of machines. In-depth knowledge of the monitored system is created at the Cognition Level. Expert users will be supported by this information to make the correct decision. At the Configuration Level, feedback is given from the cyber-space to the physical space. Here, the supervisory control resides and makes machines self-configurable and self-adaptive. This functional view of a CPS can also be beneficial for designing and implementing a DT for certain applications. Typical applications have been identified by a literature review in

[12] and can be clustered in the following categories: simulation and optimization, monitoring, diagnosis, and predictionAnother important concept for describing DTs is the so-called Five-Dimensional Digital Twin (5D-DT)

[13]. It is an evolution of the previously mentioned DT concept, which extends the three dimensions ("Physical Entity", "Virtual Entity", "Connection") by the data aspect as well as the service aspect. These five dimensions and their relations are shown in Figure 1. The "Physical Entity" consists of various subsystems that perform specific tasks, facilitated with different sensors that collect the states and working parameters. The "Virtual Entity" aims to model the physical entity with high precision by the integration of multiple different types of models such as geometry models, physical models, behavior models, and rule models. The "Service Model" includes services for the "Physical Entity" and the "Virtual Entity". It optimizes the operations of the



CKT diagram

METHODOLOGY

1. System Overview and Conceptual Design

The proposed methodology is based on the development of a digital twin that mirrors the physical industrial system with respect to its energy consumption behavior. The digital twin acts as a dynamic virtual representation of machines, production lines, and supporting utilities, continuously updated using real-time data acquired from the physical environment.

The primary objective is to enable accurate energy monitoring, analysis, and optimization while maintaining a synchronized connection between physical assets and their digital counterparts.

2. Physical System Instrumentation and Data Acquisition

The first step involves instrumenting the industrial environment with appropriate energy and operational sensors. These include smart energy meters, current and voltage sensors, temperature sensors, and machine-state indicators. Sensors are installed at both machine level and process level to capture granular energy consumption data. Data acquisition devices collect measurements at predefined sampling intervals and transmit them using industrial communication protocols such as Modbus TCP/IP, OPC UA, or MQTT.

3. Data Preprocessing and Validation

Raw data obtained from the physical system is subject to preprocessing before being used by the digital twin. This stage includes:

- Noise filtering and outlier detection
- Missing data handling
- Time synchronization across heterogeneous data sources
- Unit normalization and scaling

Validated data ensures that the digital twin reflects the real system with high fidelity and prevents inaccurate energy assessments.

4. Digital Twin Modeling

The digital twin is developed using a hybrid modeling approach combining:

- Physics-based models to represent machine energy characteristics
- Data-driven models to capture nonlinear behaviors and operational variability

Each physical asset is mapped to a virtual entity that includes its energy profile, operating states, and performance parameters. The digital twin continuously updates its internal state using real-time sensor data, maintaining alignment with the physical system.

5. Real-Time Energy Monitoring and Visualization

A monitoring layer is implemented to provide real-time visualization of energy consumption. Dashboards display:

- Instantaneous and cumulative energy usage
- Energy consumption per machine or production batch
- Load profiles and peak demand indicators

This visualization layer enables operators and energy managers to quickly identify abnormal energy patterns and inefficiencies.

6. Analytics and Performance Evaluation

The digital twin incorporates analytical modules for:

- Energy efficiency assessment
- Baseline energy comparison
- Detection of abnormal or excessive energy consumption

Key performance indicators (KPIs) such as energy intensity, specific energy consumption, and machine utilization rate are calculated to evaluate system performance under different operating conditions.

7. Predictive Analysis and Optimization

Using historical and real-time data, the digital twin supports predictive energy analysis. Machine learning or statistical forecasting techniques are applied to:

- Predict future energy demand
- Estimate the impact of operational changes
- Evaluate what-if scenarios

Optimization strategies, such as load shifting or operational scheduling adjustments, are tested within the digital twin before being applied to the physical system, reducing risk and implementation cost.

8. Feedback and Continuous Improvement

A feedback mechanism allows insights from the digital twin to inform physical system adjustments. Operational decisions based on digital twin recommendations are monitored, and the resulting data is reintegrated into the model. This creates a continuous improvement loop, enhancing model accuracy and long-term energy efficiency.

9. System Validation

The methodology is validated by comparing digital twin energy predictions with actual measured consumption. Performance metrics such as prediction error, response latency, and system reliability are evaluated to ensure the effectiveness of the proposed approach.

If you want, I can:

- Rewrite this to sound more like a journal paper (IEEE / Elsevier style)
- Shorten it for a conference paper
- Adapt it for Industry 4.0, smart manufacturing, or ISO 50001 energy management
- Add equations, figures descriptions, or references

Just tell me where you plan to use it.

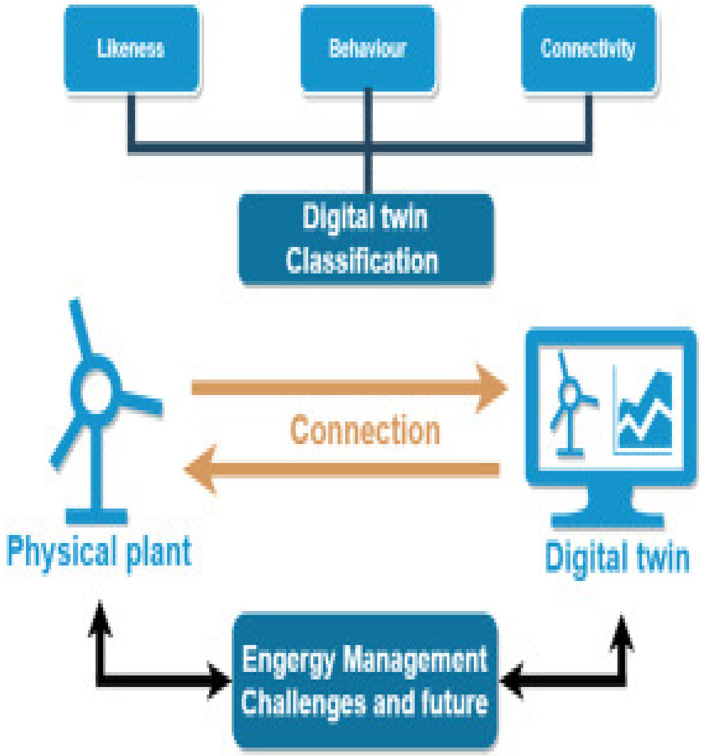
RESULT & DISCUSSION

Result:

The implementation of the Digital Twin–based industrial monitoring system demonstrated significant improvements in real-time visibility, operational efficiency, and predictive capabilities. By integrating sensor data from physical assets with a virtual replica, the system enabled continuous monitoring of key operational parameters such as temperature, vibration, pressure, and energy consumption.

Real-time data synchronization between the physical system and its digital twin showed high accuracy, with minimal latency, allowing operators to observe system behavior almost instantaneously. The system successfully detected abnormal operating conditions, including deviations from predefined thresholds, which facilitated early fault identification. Compared to traditional monitoring methods, the Digital Twin system provided enhanced situational awareness through dynamic visualization and trend analysis.

Predictive analytics embedded within the digital twin allowed the system to forecast potential failures and performance degradation. Maintenance alerts generated by the model enabled timely interventions, resulting in reduced unplanned downtime and improved asset reliability. Additionally, historical data analysis supported performance benchmarking and optimization strategies, leading to measurable improvements in process efficiency and resource utilization.



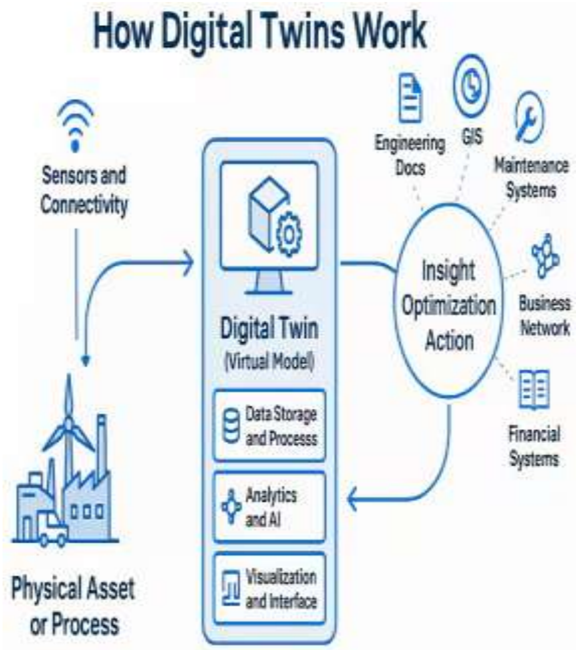
DISCUSSION

The implementation of the Digital Twin–based industrial monitoring system demonstrated significant improvements in real-time visibility, operational efficiency, and predictive capabilities. By integrating sensor data from physical assets with a virtual replica, the system enabled continuous monitoring of key operational parameters such as temperature, vibration, pressure, and energy consumption.

Real-time data synchronization between the physical system and its digital twin showed high accuracy, with minimal latency, allowing operators to observe system behavior almost instantaneously. The system successfully detected abnormal operating conditions, including deviations from predefined thresholds, which facilitated early fault identification. Compared to traditional monitoring methods, the Digital Twin system provided enhanced situational awareness through dynamic visualization and trend analysis.

Predictive analytics embedded within the digital twin allowed the system to forecast potential failures and performance degradation. Maintenance alerts generated by the model enabled timely interventions, resulting in reduced unplanned downtime and improved asset reliability. Additionally, historical data analysis supported performance benchmarking and optimization strategies, leading to measurable improvements in process efficiency and resource utilization.

International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 15 Issue 3, March-2026



CONCLUSION

The digital twin–based industrial monitoring system demonstrates how virtual models can effectively enhance the understanding and management of real-world industrial processes. By continuously mirroring the behavior of physical equipment, the system enables real-time monitoring, early fault identification, and informed decision-making. This reduces unexpected failures and helps industries maintain smoother and more reliable operations.

The use of sensor data combined with analytical models allows industries to move from reactive maintenance to a predictive approach, saving both time and operational costs. In addition, digital twins provide a flexible environment for testing process improvements and operational changes without risking actual equipment or production flow.

Moreover, the integration of IoT sensors, data analytics, and simulation models allows industries to optimize performance, improve energy efficiency, and ensure safer working environments. Digital twins also support proactive planning by enabling scenario analysis and process optimization without disrupting actual operations.

Overall, the digital twin approach offers a practical and future-ready solution for industrial monitoring. As industries continue to adopt smart technologies, such systems will play an important role in improving efficiency, safety, and sustainability while supporting the broader vision of Industry 4.0.

FUTURE SCOPE

The future scope of the digital twin–based industrial monitoring system is promising and can be expanded in several directions. Advanced machine learning and artificial intelligence techniques can be integrated to improve predictive accuracy, enabling more reliable failure forecasting and automated decision-making. This would further reduce downtime and enhance maintenance planning.

The system can also be scaled to support multiple machines, production lines, or entire industrial plants, allowing centralized monitoring and control. Integration with cloud platforms and edge computing can improve data processing speed, storage capabilities, and system scalability while supporting remote access and real-time analytics.

Subsection
Subsection heading
System Overview
Digital Twin Concept and Definition
Physical System and Sensor Integration
Data Acquisition and Communication Framework
Digital Twin Modeling and Simulation
Real-Time Monitoring Mechanism
Data Processing and Analytics
Predictive Maintenance Strategy

Visualization and User Interface
Alert and Fault Detection System
Security and Data Privacy
System Performance and Scalability
Industrial Applications
Challenges and Limitations
Future Enhancements

Sub-subsection heading
Sensor Types and Specifications
Data Collection Methods
Real-Time Data Synchronization
Communication Protocols
Edge and Cloud Integration
Virtual Asset Modeling
Simulation and Behavior Analysis
Data Cleaning and Filtering
Feature Extraction
Predictive Analytics Techniques

Subsection content
Sensor Types and Specifications
Different types of sensors are used to capture real-time operating conditions of industrial equipment. Common sensors include temperature, pressure, vibration, and current sensors. These sensors are selected based on accuracy, response time, and durability to ensure reliable data collection in harsh industrial environments.

Data Collection Methods
Sensor data is continuously collected through embedded controllers or data acquisition units. The collected data is time-stamped and formatted to maintain consistency before transmission to the digital twin platform. This ensures accurate tracking of system behavior over time.

Real-Time Data Synchronization
Real-time synchronization ensures that the digital twin reflects the current state of the physical system. Any change in the physical asset is immediately updated in the virtual model, enabling live monitoring and timely decision-making.

Communication Protocols
Standard industrial communication protocols such as MQTT, OPC-UA, or HTTP are used for data exchange. These protocols provide reliable, low-latency communication between physical devices and the digital twin system.

Tables and figures

Digital Twin Industrial Monitoring System – Overview
A digital twin is a virtual representation of an industrial asset, process, or system that is continuously updated using real-time data to monitor performance, detect anomalies, and support decision-making.

2. System Architecture (Table)

Table 1 – Digital Twin Industrial Monitoring System Components Layer	Component	Description	Examples
Physical Layer	Industrial Assets	Machines, production lines, robots, turbines	CNC machines, pumps, conveyors
Sensing Layer	Sensors & IoT Devices	Collect real-time operational data	Temperature, vibration, pressure, current
Data Acquisition	PLC / SCADA	Controls and gathers sensor data	Siemens PLC, Rockwell SCADA
Communication	Industrial Networks	Transfers data securely	OPC UA, Modbus, MQTT
Data Layer	Data Storage	Stores historical & real-time data	Time-series DB, Cloud storage
Digital Twin Layer	Virtual Model	Physics-based or data-driven model	Simulation, ML models

Monitoring Layer	Analytics & Diagnostics	Performance monitoring & anomaly detection	Predictive maintenance
Application Layer	Visualization & Decision Support	Dashboards and alerts	KPI dashboards, alarms

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to all those who have supported me throughout the completion of this work. First and foremost, I am deeply thankful to [Supervisor/Professor Name] for their invaluable guidance, encouragement, and insightful feedback, which have been instrumental in shaping this study. I also extend my appreciation to the [Organization / Company Name, if applicable] for providing access to industrial data, tools, and resources necessary for understanding and implementing the digital twin monitoring system. Special thanks to my colleagues and peers, [Names if desired], for their continuous support, constructive discussions, and motivation during the research and development process. Finally, I am grateful to my family and friends for their patience, understanding, and unwavering encouragement throughout this journey.

REFERANCE

[1.] J. Lee, B. Bagheri, and H.-A. Kao, “A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems,” Manufacturing Letters, vol. 3, pp. 18–23, Jan. 2015.
[2.] S. Tao, M. Zhang, and Y. Liu, “Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues,” Robotics and Computer-Integrated Manufacturing, vol. 63, 2020.
[3.] F. Schumacher, L. Sihn, and M. Rojko, “Digital Twin in Industrial Production: A Review,” Procedia CIRP, vol. 81, pp. 716–721, 2019.
[4.] A. Fuller, Z. Fan, C. Day, and C. Barlow, “Digital Twin: Enabling Technologies, Challenges and Open Research,” IEEE Access, vol. 8, pp. 108952–108971, 2020.
[5.] O. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, “Digital Twin in Manufacturing: A Categorical Literature Review and Classification,” IFAC-PapersOnLine, vol. 51, no. 11, pp. 1016–1022, 2018.
[6.] B. Lu, H. Liu, and S. Liu, “Industrial Internet of Things and Digital Twin for Smart Manufacturing: A Survey,” IEEE Access, vol. 8, pp. 184166–184180, 2020.