iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** I **Month of publication:** January 2026

DOI: https://doi.org/10.22214/ijraset.2026.76734

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue I Jan 2026- Available at www.ijraset.com

Digital Twin of a College Campus: Design, Implementation and Use Cases

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Abstract: A Digital Twin (DT) is a dynamic, continuously synchronized virtual model that mirrors a real physical environment, enabling real-time monitoring, analysis, and decisionmaking. Within a campus ecosystem, a DT can integrate diverse systems—such as Internet of Things (IoT) devices, Building Information Modeling (BIM), Geographic Information Systems (GIS), and academic resources—to improve sustainability, operational efficiency, and user experience. This paper presents a detailed framework and working prototype of a Digital Twin for a college campus, highlighting its design, implementation, and applications. The proposed model unifies multiple data streams through IoT sensors, data analytics, and visualization dashboards to support predictive maintenance, anomaly detection, and energy forecasting. A campus-scale prototype was developed and evaluated, achieving up to 12
Index Terms: Digital Twin, Smart Campus, IoT, BIM, Predictive Maintenance, Energy Forecasting, Campus Management.

I. INTRODUCTION

The concept of a *Digital Twin (DT)* has evolved from its industrial origins in aerospace and manufacturing to become an essential component of modern smart infrastructure [1], [2]. A DT serves as a virtual counterpart of a physical system, continuously synchronized through real-time data streams to enable monitoring, analysis, and optimization of operations.

A college campus provides an ideal setting for implementing Digital Twin technology, as it encompasses diverse yet interconnected systems such as buildings, laboratories, energy networks, and human activity flows. By integrating these components into a unified digital framework, a campus DT can support intelligent decision-making, sustainability goals, and efficient resource management.

A campus-oriented DT can achieve the following:

1) Real-time monitoring of assets, resources, and environmental conditions.
2) Predictive analytics for energy management and maintenance planning.
3) Continuous health assessment of infrastructure and equipment.
4) Simulation of “what-if” scenarios, including evacuation and load-balancing.
5) Integration with academic operations such as room scheduling and facility usage.

This paper presents the design and prototype implementation of a comprehensive campus-level Digital Twin. The work focuses on unifying multiple heterogeneous data sources to enhance visibility and control across campus systems. The major contributions of this research are summarized as follows:

a) Development of a multi-layer DT architecture integrating IoT, BIM, GIS, and academic data platforms.
b) Design and implementation of analytics modules including hybrid energy forecasting, anomaly detection, and predictive maintenance.
c) Experimental validation using real and synthetic campus datasets through various case studies.
d) Discussion of operational challenges involving privacy, scalability, and interoperability of DT frameworks.

II. RELATED WORK

Research on *Digital Twin (DT)* applications within the built environment and educational campuses has expanded considerably in recent years. Numerous studies have explored how DTs can enhance the management, efficiency, and sustainability of complex infrastructures. A comprehensive review of more than 800 research papers categorized various DT implementations across building and urban contexts, emphasizing their role in improving operational intelligence and real-time decisionmaking [1].

Batty *et al.* examined the adoption of Digital Twin frameworks for smart city development, highlighting their potential impact on urban analytics and governance [2]. Similarly, Wang *et al.* conducted an in-depth analysis of DT applications in smart buildings, focusing on how IoT-enabled energy management systems improve building performance.

In the educational context, multiple studies have examined the concept of the *Campus Digital Twin*. Zhang and Li proposed an *Intelligent Campus System Design Based on Digital Twin*, mapping physical infrastructure to a virtual environment using UAVs, sensor networks, and 3D visualization platforms such as Unity3D. Another study titled *Showcasing a Digital Twin for Higher Educational Buildings* demonstrated a case implementation in Sweden, providing insights into energy optimization and facility management within university campuses.

Further contributions include *Developing Campus Digital Twin Using Interactive Visual Analytics*, which introduced data visualization techniques for capacity planning and operational simulation. Chen and Wang presented a *BIM-based Digital Twin Development for University Campuses*, detailing how Building Information Modeling (BIM) can be combined with IoT data to support maintenance and spatial analysis. Eneyew *et al.* in *Toward Smart-Building Digital Twins: BIM and IoT Data Integration* explored data interoperability challenges between heterogeneous systems.

Additionally, foundational surveys such as *Digital Twin: A Review of the Evolution from Concept to Technology* provide theoretical frameworks for understanding DT evolution, technological enablers, and domain-specific applications.

While these studies have laid a strong foundation, most focus on isolated building-level implementations or conceptual frameworks. Few have addressed the integration of multiple subsystems—academic, operational, and infrastructural—into a unified, large-scale Digital Twin platform capable of supporting simulations and data-driven experimentation across diverse campus use cases. This limitation motivates the development of the comprehensive campus-scale DT framework presented in this work.

III. SYSTEM ARCHITECTURE

The proposed campus Digital Twin (DT) framework follows a modular, multi-layered architecture as illustrated in Figure ??. It consists of five key layers: (1) Physical / Sensor Layer, (2) Communication / Edge Layer, (3) Data Storage / Semantic Layer, (4) Analytics / Simulation Layer, and (5) Visualization / Control Layer. Each layer performs specialized functions to ensure seamless data flow, real-time monitoring, and intelligent control across the campus ecosystem.

A. Physical / Sensor Layer

The foundation of the DT architecture lies in the physical layer, which includes Internet of Things (IoT) devices distributed throughout classrooms, laboratories, hallways, and outdoor areas. These devices capture real-time environmental and operational data. The deployed sensor network comprises:

1) Environmental sensors such as temperature, humidity, CO_2, illumination, and motion detectors.
2) Energy monitoring units installed at both building and zonal levels.
3) Actuation devices, including HVAC controllers and smart sockets, for automated responses.
4) Occupancy and localization sensors utilizing WiFi logs, Bluetooth Low Energy (BLE) beacons, or camera-based tracking.

This layer acts as the data acquisition foundation of the DT, continuously collecting parameters that reflect the dynamic conditions of the campus.

B. Communication / Edge Layer

The communication and edge layer ensures reliable data transmission between sensors and backend services. The network uses lightweight communication protocols such as MQTT and CoAP over WiFi or LoRaWAN, routed through gateway devices (e.g., Raspberry Pi units). Edge computing nodes handle essential local processing tasks, including:

1) Data pre-processing functions such as filtering, aggregation, and compression to minimize bandwidth consumption.
2) Execution of preliminary anomaly detection to reduce central computation load.
3) Temporary buffering and synchronization in case of network interruptions.

This distributed design enhances responsiveness while reducing latency and dependence on constant internet connectivity.

C. Data Storage / Semantic Layer

The storage and semantic layer organizes the continuous inflow of data from multiple campus sources. The collected information is categorized and stored using a hybrid data infrastructure:

1) Time-series databases (e.g., InfluxDB) to record sensor data streams efficiently.
2) Relational and spatial databases (PostgreSQL with PostGIS) for managing building geometries, GIS layers, and room-level mappings.

3) Knowledge graphs or ontology-based repositories to represent relationships among campus entities such as assets, rooms, sensors, and academic resources.

This multi-model data storage system ensures interoperability, scalability, and semantic clarity across diverse campus datasets.

D. Analytics / Simulation Layer

The analytics and simulation layer hosts various intelligent modules that transform raw data into actionable insights. These components include:

1) Energy Forecasting: Hybrid predictive models that merge physics-based estimations with machine learning algorithms (e.g., LSTM) to forecast energy consumption for the next 24–72 hours.
2) Anomaly Detection: Statistical and machine learning methods such as residual modeling, Isolation Forest, or One-Class SVM to identify irregular operational behavior.
3) Predictive Maintenance: Classification models (e.g., Random Forest, XGBoost) trained on historical sensor patterns to predict potential equipment failures.
4) Scenario Simulation: Computational experiments for testing hypothetical conditions—such as evacuation drills, energy load redistribution, or occupancy-based HVAC strategies.
5) Control Policies: Feedback and optimization-based algorithms that automate decision-making for HVAC systems, lighting, and other controllable devices.

This layer serves as the intelligence core of the DT, enabling adaptive control and proactive management of campus operations.

E. Visualization / Control Layer

The top layer focuses on user interaction, visualization, and control mechanisms. It provides an integrated dashboard that aggregates analytics outputs and live sensor data in a userfriendly interface. Key functionalities include:

1) An interactive 3D model of the campus rendered through WebGL or Three.js for real-time data visualization.
2) Administrative dashboards (e.g., Grafana-style panels) that present key performance indicators (KPIs) related to energy, occupancy, and maintenance.
3) Control interfaces for initiating "what-if" simulations such as schedule adjustments, load curtailments, or maintenance triggers.

This layer ensures situational awareness and enables campus operators to make informed, data-driven decisions through the DT interface.

IV. MODELLING & ALGORITHMS

This section describes the principal algorithmic modules integrated within the proposed Digital Twin framework. Each component supports intelligent decision-making through predictive and analytical modeling.

A. Hybrid Energy Forecasting

Energy consumption prediction combines physical modeling with data-driven learning to improve reliability and adaptability. Let $E_{\text{phys}}(t)$ denote the physics-based baseline output (for example, a degree-day thermal model), and $\mathrm{ML}(X_t)$ represent a machine learning model (such as an LSTM) trained on past feature vectors X_t. The hybrid forecast is obtained as:

$$E_{\text{pred}}(t) = \alpha E_{\text{phys}}(t) + (1 - \alpha)\mathrm{ML}(X_t)$$

where the weight parameter α is optimized through crossvalidation to balance interpretability and accuracy. The overall training objective minimizes the Mean Absolute Percentage Error (MAPE) along with a regularization term that stabilizes the model under variable load conditions. This ensemble formulation improves short-term and mid-horizon prediction accuracy by combining the strengths of both physical and learning-based models.

B. Anomaly Detection

To automatically identify abnormal operational patterns, the framework employs a sliding-window time-series analysis. The process is as follows:

1) For each temporal segment W of size w, apply SeasonalTrend decomposition using Loess (STL) to separate trend, seasonal, and residual components.
2) Extract statistical descriptors from the residual sequence (mean, variance, skewness, kurtosis, and autocorrelation coefficients).
3) Pass the resulting feature vector to an Isolation Forest classifier to compute the anomaly score.
4) Label a window as anomalous if the score exceeds a threshold τ.

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Algorithm 1 outlines the anomaly detection process.

Algorithm 1 Anomaly Detection Pipeline

Time-series S, window size w, anomaly threshold τ

Identified anomaly window set A each window W in S $(T,S,R) \leftarrow \mathrm{STL}(W)$ features $\leftarrow$ extract(R) score $\leftarrow$ IsolationForest(features) score $> \tau$ Add W to A

This unsupervised method enables the DT to detect anomalies such as sensor malfunctions, abnormal energy spikes, or occupancy inconsistencies in real time.

C. *Predictive Maintenance*

Predictive maintenance models estimate the likelihood of equipment failure by analyzing multi-sensor data from assets such as chillers, pumps, and air-handling units (AHUs). Each asset is represented through time-series signals including vibration, temperature, and current. Feature engineering extracts temporal and frequency-based characteristics such as moving averages, Fast Fourier Transform (FFT) coefficients, Shannon entropy, and cross-correlation metrics. Machine learning classifiers (e.g., Random Forest or XGBoost) are trained to estimate failure probability P_{fail}. If $P_{\mathrm{fail}} > \delta$, the system triggers a maintenance alert or schedules an inspection, thereby preventing unexpected downtime and optimizing maintenance resources.

D. *Scenario Simulation & Control*

The Digital Twin enables testing of alternative strategies and operational responses within a virtual environment. Several simulation scenarios are supported:

1) Evacuation Planning: Agent-based simulation models evaluate building evacuation efficiency under different occupancy and blockage conditions.
2) Load Curtailment: Optimization-driven control reduces HVAC or lighting consumption based on predefined comfort thresholds and policy rules.
3) Schedule Optimization: Class or activity scheduling is reconfigured to minimize peak energy usage and enhance space utilization.

An optimization engine (using linear or mixed-integer linear programming, MILP) identifies the optimal control action set while satisfying constraints related to comfort, energy demand, and occupancy safety. This simulation capability enables proactive policy formulation and real-time adaptive control through the DT interface.

V. PROTOTYPE IMPLEMENTATION

To validate the proposed framework, a functional prototype of the campus Digital Twin was implemented across a smallscale campus comprising three interconnected buildings. The prototype demonstrates end-to-end data acquisition, analytics, and visualization capabilities under real operating conditions.

A. *Hardware Setup*

The physical deployment includes a collection of lowcost IoT devices and gateway nodes installed in classrooms, corridors, and laboratories. The sensor network incorporates:

1) Environmental Sensors: DHT22 modules to measure ambient temperature and humidity levels.
2) Occupancy Sensors: Passive Infrared (PIR) motion detectors for movement tracking.
3) Air Quality Sensors: $CO2$ sensors for monitoring ventilation and air circulation efficiency.
4) Electrical Sensors: Current Transformer (CT) sensors for real-time current and load measurement.

All sensor data streams are routed to gateway units based on *Raspberry Pi* hardware, which operate as local MQTT brokers and temporary buffers to ensure reliability during network interruptions.

B. *Software Stack*

The software ecosystem integrates modular components that handle data ingestion, storage, analytics, and visualization. The key technologies and tools used are summarized below:

1) Data Ingestion: Lightweight Python-based microservices subscribe to MQTT topics for streaming data collection and pre-processing.
2) Data Storage: InfluxDB is utilized for high-frequency
3) time-series data, while PostgreSQL with the PostGIS extension manages spatial information such as room geometries and building layouts. A semantic data layer based on RDF and graph structures is used to capture interrelationships among entities.
4) Analytics Framework: Predictive and diagnostic models are developed in Python using machine learning libraries such as scikit-learn, TensorFlow, and Keras.
5) Visualization Layer: The user interface is developed in React, integrating 3D models built with Three.js and dynamic dashboards embedded from *Grafana* for realtime monitoring and analytics visualization.

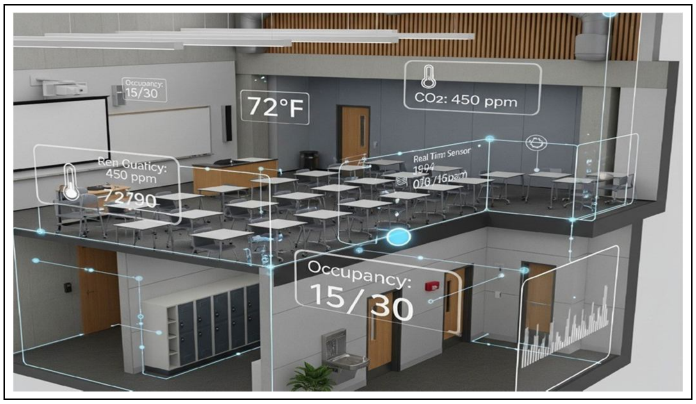

Fig. 1. Visualization interface displaying a 3D campus model and integrated dashboard panels for sensor monitoring.

VI. USE CASES & EVALUATION

The proposed campus Digital Twin (DT) framework was assessed through three representative use cases: anomaly detection, energy optimization, and scenario-based simulations. These experiments demonstrate the DT's ability to support real-time decision-making, operational efficiency, and strategic planning across a campus environment.

1) *Anomaly Detection:* Anomaly detection plays a vital role in ensuring early recognition of irregular events in both environmental and operational datasets. For evaluation, approximately three months of multi-sensor data were collected from various buildings, encompassing temperature, humidity, CO_2, motion, and energy readings. To evaluate the robustness of the detection mechanism, artificial disturbances such as sensor bias, abrupt spikes, and temporary signal loss were introduced into the dataset.

The performance of the model was assessed using standard classification metrics including precision, recall, and F1-score. High precision indicates the system's capability to accurately distinguish genuine anomalies from noise, reducing false alarms. Meanwhile, recall quantifies the proportion of total anomalies successfully identified. The F1-score provides a harmonic balance between these two indicators, representing the overall reliability of the detection process.

Table 1: Anomaly Detection Evaluation Results

Use Case	Precision	Recall	F1-score
Energy spikes	0.88	0.82	0.85
Sensor drift	0.91	0.79	0.84
Combined	0.89	0.80	0.84

From a theoretical standpoint, anomaly detection enhances predictive maintenance, system resilience, and occupant safety. Early identification of irregularities can prevent equipment breakdowns, optimize energy usage, and maintain consistent comfort levels. Furthermore, by correlating detected anomalies with spatial and temporal data—such as room occupancy or equipment location—the DT provides contextual insights that improve root-cause analysis. Future enhancements could involve multivariate anomaly detection techniques leveraging cross-sensor dependencies and temporal dynamics to improve detection accuracy.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue I Jan 2026- Available at www.ijraset.com

2) *Energy Optimization:* Energy management is one of the most impactful and measurable DT applications in a campus setting. In this implementation, a hybrid energy forecasting model was used that blends physics-based estimations (such as degree-day calculations) with machine learning-based predictions. These forecasts guided the development of control policies for HVAC systems, designed to minimize power usage during low-occupancy periods while preserving acceptable thermal comfort.

   Simulation outcomes indicated an approximate 12% reduction in projected energy consumption, validating the DT's ability to maintain a balance between performance efficiency and occupant comfort. The findings demonstrate how integrating real-time sensor inputs, predictive analytics, and control algorithms enables adaptive, context-aware energy management. Unlike traditional static optimization methods, the DT dynamically adjusts operational strategies in response to changing occupancy trends, environmental variations, and temporal constraints.

   Moreover, the DT framework contributes to broader sustainability objectives by modeling energy interactions across multiple buildings and subsystems. This allows administrators to assess the potential of renewable integration, analyze energy policy impacts, and explore conservation measures in a controlled digital environment prior to implementation.

3) *Scenario Simulations:* Scenario simulations within the DT enable administrators to analyze hypothetical operational conditions and evaluate outcomes without real-world risk or disruption. Two key examples were tested to illustrate the potential benefits:

- Evacuation Simulation: Using predicted occupancy data, agent-based simulations were executed to analyze optimal evacuation routes and egress performance under various constraints, such as blocked exits or localized congestion. Results highlighted potential choke points, informing improvements in infrastructure layout and emergency preparedness protocols.
- Schedule Shifting: By adjusting academic timetables to evenly distribute classroom usage, simulated peak energy demand was reduced by approximately 7%. This showcases the DT's role in strategic planning and operational optimization by enabling administrators to evaluate the effects of scheduling and space utilization on overall energy efficiency.

Collectively, these evaluations demonstrate that the DT framework not only supports operational optimization but also facilitates proactive planning, emergency management, and sustainability assessment. Its capacity to integrate data analytics with real-world simulations establishes it as a versatile tool for intelligent campus management.

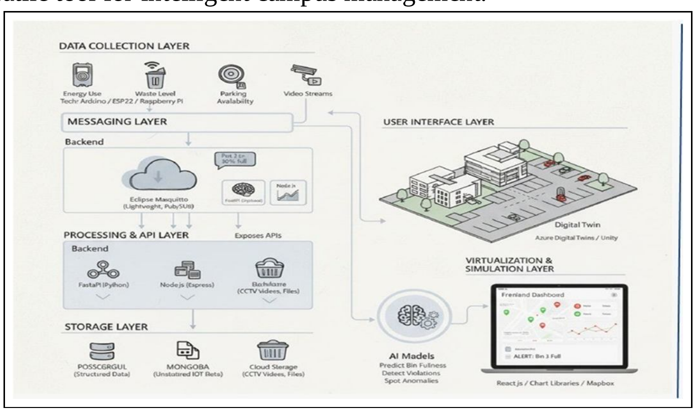

Fig. 2. End-to-end workflow illustrating data acquisition and IoT integration within the campus Digital Twin.

VII. ACKNOWLEDGEMENT

The author sincerely thanks the campus facilities team, laboratory staff, and student volunteers for their invaluable support and assistance in sensor deployment, data collection, and maintenance of experimental setups. Their cooperation was crucial for realizing the prototype of the Digital Twin system and for ensuring accurate and reliable data acquisition over the test period.

Special thanks are extended to faculty mentors and advisors for providing critical guidance on system architecture, analytics design, and interpretation of experimental results. The author also acknowledges the technical support and collaboration from software engineers and visualization specialists who contributed to the development of 3D dashboards, interactive visualizations, and real-time monitoring interfaces.

The author is grateful to the university administration for providing access to infrastructure, academic schedules, and other essential data. Their support allowed seamless integration of real-world campus data into the Digital Twin framework. This project benefited greatly from discussions with peers and researchers in the fields of IoT, BIM, GIS, smart campuses, and energy analytics, whose insights helped refine the algorithms and modeling strategies.

Finally, the author acknowledges the broader research community for providing open-source tools, frameworks, and literature that were instrumental in developing the system, performing simulations, and evaluating results. This collaborative effort underscores the interdisciplinary nature of Digital Twin development and highlights the importance of teamwork, innovation, and knowledge sharing in advancing smart campus solutions.

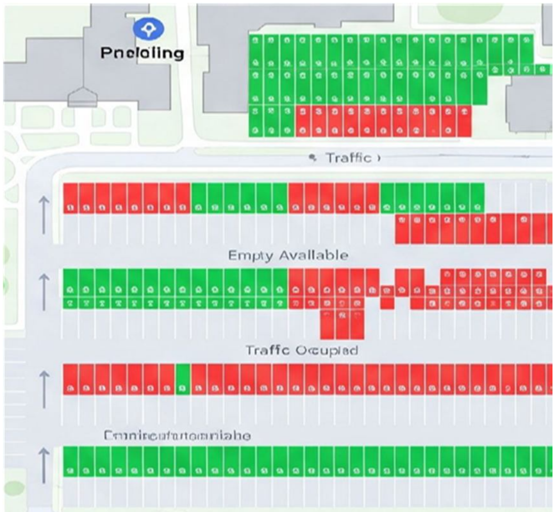

Fig. 3. Smart Parking

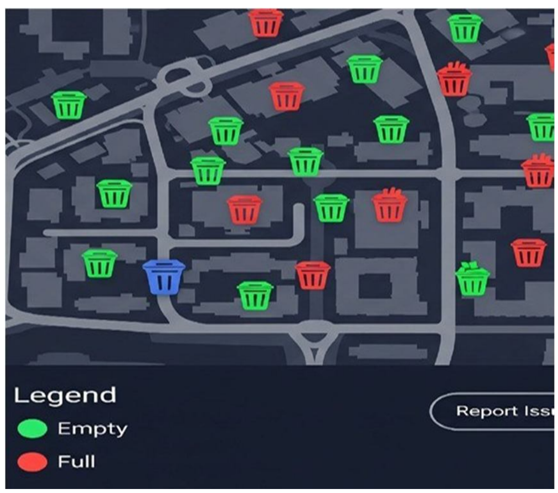

Fig. 4. Smart Waste Management

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