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AI-DRIVEN DIGITAL TWINS FOR PREDICTIVE MAINTENANCE

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Abstract

An AI-driven Digital Twin (DT) framework was developed to integrate real-time sensor data, facility management systems, and AI-driven predictive analytics to enhance building operations. Implemented in a three-story academic building, the DT serves as a dynamic common data environment (CDE) that supports real-time monitoring, asset management, and predictive maintenance. By integrating IoT data streams with an LSTM-based machine learning (ML) module, the framework provides actionable insights for proactive decision-making, helping to streamline facility management (FM) workflows and enhance collaboration among stakeholders. Future work will broaden the scope of ML techniques, expand use cases, and promote wider adoption across similar facilities.

Introduction

Facility management (FM) plays a critical role in ensuring the smooth operation of buildings and infrastructure, especially in complex facilities like educational campus buildings, hospitals, and large corporate environments. It encompasses a broad range of responsibilities, including lease management, capital project planning, maintenance, energy optimization, space utilization, and improving the overall occupant experience (IFMA, n.d.). Effective FM is vital for organizations as it directly influences the value and performance of properties, buildings, and equipment over the short and long term, contributing significantly to operational success. In complex environments such as educational campuses, FM is instrumental in creating safe, welcoming, and efficient spaces that meet the diverse needs of students, faculty, and staff, fostering an atmosphere conducive to learning and collaboration (Zurainan et al., 2021).

Despite advances in technological tools, many FM operations continue to rely on static or fragmented solutions, such as spreadsheets or legacy systems that offer limited functionality and inhibit proactive decision-making (Halmetoja and Lepkova, 2022; Matarneh et al., 2022). This approach often leads to delayed responses, inefficiencies in resource allocation, and higher lifecycle costs due to the reactive maintenance strategies and inadequate integration across different systems (Molęda et al., 2023). As organizations face growing demands for sustainability, adaptability, and cost-efficiency, the limitations of traditional FM methods have become increasingly apparent.

Challenges in Traditional FM

Traditional FM solutions often integrate Building Information Modeling (BIM) and Computer-Aided Facility Management (CAFM) systems to manage building assets and documentation. However, these tools present notable limitations. BIM, while highly effective during the design and construction phases, is primarily developed as a design-focused tool that lacks native support for continuous data streaming or operational workflows (Patacas et al., 2020). As a result, BIM models often become outdated shortly after handover unless significant manual effort is invested in keeping them updated.

Furthermore, CAFM systems frequently operate on proprietary protocols and non-standardized data structures, creating interoperability barriers that complicate integration with other platforms (Matarneh et al., 2022). These technical constraints hinder the seamless exchange of information between stakeholders, particularly during the critical transition from construction to operations (Pishdad-Bozorgi and Gao, 2019). The lack of standardized handover procedures further exacerbates data silos, making it difficult for FM teams to access reliable, real-time building information. Consequently, applications such as fault detection and diagnostics and strategic planning are often based on outdated or incomplete data, leading to increased operational costs, unanticipated equipment failures, and therefore diminished occupant satisfaction (Bay et al., 2020).

Emergence of Digital Twins in AECO

To address persistent data fragmentation and the limited lifecycle utility of conventional BIM, the AECO industry is embracing Digital Twins (DTs) as a transformative solution that unifies disconnected information and delivers continuous operational insights. A DT is a dynamic digital representation of a physical building that continuously synchronizes with real-world conditions through data collected from sensors, building automation systems (BAS), and IoT-enabled infrastructure. By consolidating information from across design, construction, operations, and maintenance phases, DTs eliminate data silos and provide a unified platform for integrated monitoring, analysis, and control (NIBS, 2024). This continuous synchronization creates a living system capable of contextualizing performance metrics, identifying inefficiencies, and predicting maintenance needs before issues escalate (Carrasco et al., 2024; Farsangi et al., 2024). The integration of analytical engines and control logic within DT platforms enables stakeholders to extract actionable insights from complex building data, supporting informed decision-making at both operational and strategic levels (D'Amico et al., 2022; El Mokhtari et al., 2022).

DTs redefine FM from a reactive process to a predictive, data-driven discipline. Real-time data streams facilitate energy optimization and continuous performance assessments, and enable proactive asset management, reducing downtime and extending equipment lifespan. Most critically, DTs overcome a key limitation of BIM: its ability to stay current beyond the design and construction phases. In doing so, they redefine how built environments are managed, making them more adaptive, intelligent, and sustainable.

Advancing Digital Twins with Artificial Intelligence and Machine Learning

Beyond integrating building data into a common environment, a well-structured DT offers a powerful foundation for advanced analytics and machine learning (ML). By continuously capturing diverse data streams such as environmental parameters, occupant behavior, and equipment performance, a DT can go from passively mirroring real-world conditions to actively simulating, predicting, and optimizing system behavior. Despite this potential, most existing implementations remain limited in scope, often developed as small-scale prototypes that fall short of full operational deployment (Kastel and Wallen, 2024). A key limitation is the absence of predictive or prescriptive capabilities within real-time DT environments (Kreuzer et al., 2024; Ma et al., 2024). Furthermore, recent studies have noted a lack of research evaluating the suitability of existing DT platforms for predictive use cases, particularly in FM contexts, highlighting a need for practical demonstrations of end-to-end integration (Asare et al., 2024). Where ML is applied, it is often trained on static datasets without real-time data integration, limiting its adaptability to changing conditions. These implementations are typically bespoke and difficult to replicate, posing challenges for scalability across diverse building types. As a result, the full potential of intelligent, adaptive DT systems for FM remains largely unrealized.

Cognitive Digital Twins (CDTs) is defined by KPMG (2022) as the final maturity stage in DT development. CDTs represent systems that not only monitor and simulate real-world conditions but also interpret data, learn from it, and make autonomous or semi-autonomous decisions. This vision has generated substantial academic and commercial interest, yet real-world implementations remain limited. Achieving this level of maturity requires a solid foundation of continuous data acquisition, real-time interoperability, and predictive modeling, capabilities that are still underdeveloped in most AECO applications.

This paper contributes to bridging that gap by presenting a full-scale, operational DT integrated with AI/ML to unlock predictive capabilities. The proposed system dynamically generates and publishes predictions using live building and environmental data. This continuous loop between real-time data and predictive analytics establishes a practical foundation for future cognitive capabilities. By enabling ongoing performance forecasting, the model moves DT functionality beyond static visualization and toward intelligent, adaptive FM, aligning with the trajectory toward CDTs and the broader goals of sustainability and efficiency in the built environment.

Objectives

This study aims to address critical shortcomings in current DT applications within the AECO industry, particularly the limited scalability and absence of full-scale implementations, as well as the lack of predictive modules capable of generating continuous forecasts. The research introduces two complementary frameworks: one for creating an integrated DT environment that consolidates data from static and dynamic sources, and a second for embedding ML models capable of generating continuous predictive insights. The frameworks were implemented in a three-story academic building, providing a real-world testbed for evaluating both system integration and predictive capabilities.

By detailing the system architecture, integration process, and deployment challenges, this study contributes to the growing body of DT research by (1) offering a replicable approach for full-scale deployment in operational environments, (2) demonstrating the feasibility of real-time ML integration within DT systems, and (3) identifying practical considerations for DT development and scaling predictive analytics across similar facilities. This work helps bridge the gap between prototype-level experimentation and functional, scalable applications of DTs in FM.

Methodology

This study adopted a single-case design to explore the deployment of a predictive DT within an operational facility. The selected site is a three-story academic building that presents a representative mix of real-world challenges, including incomplete BIM data, existing BAS infrastructure, and fragmented FM systems. These conditions provided a relevant context to test the interoperability, scalability, and extensibility of the proposed frameworks (Shuhaimi et al., 2024; Shahzad et al., 2022).

The research was structured around two core frameworks. The first focused on DT development and data integration, merging static and dynamic sources, such as BIM models, sensor feeds, BAS outputs, and asset maintenance records, into a cohesive DT infrastructure designed for continuous data collection and system interaction. This DT served as both a live data repository and an interactive visualization platform, supporting external API connections and future system extensions.

The second framework addressed ML integration. A Long Short-Term Memory (LSTM) neural network was trained using historical energy consumption and environmental data and then deployed within the DT environment. The model was connected to live data streams through automated API workflows, allowing it to generate and publish energy consumption forecasts at predefined intervals based on operational needs. This use case demonstrated the feasibility of embedding ML modules in a live DT ecosystem and delivering continuous predictive insights as part of routine building operations.

Together, these frameworks provide a replicable and flexible model for operationalizing predictive DTs. While demonstrated through energy forecasting, the architecture is designed to be modular and scalable, and supports broader predictive applications, making it applicable to a wide range of future FM use cases such as fault detection, occupancy prediction, or equipment maintenance forecasting.

Case Study Building

The selected building is a three-story academic building comprising mixed-use spaces, including classrooms and offices. This building was chosen based on several key criteria. First, it offered a strong foundation for DT development, with an existing BIM, functional FM systems, and live sensor data streams. These resources enabled the exploration of advanced applications by linking the existing infrastructure with digital representations. Second, the building's operational complexity, characterized by high occupancy turnover, varied usage patterns, and a multi-zone HVAC system, provided a suitable environment for evaluating real-time monitoring and data-driven control strategies. Its diverse functional requirements and system interactions made it ideal for testing predictive capabilities within a dynamic context.

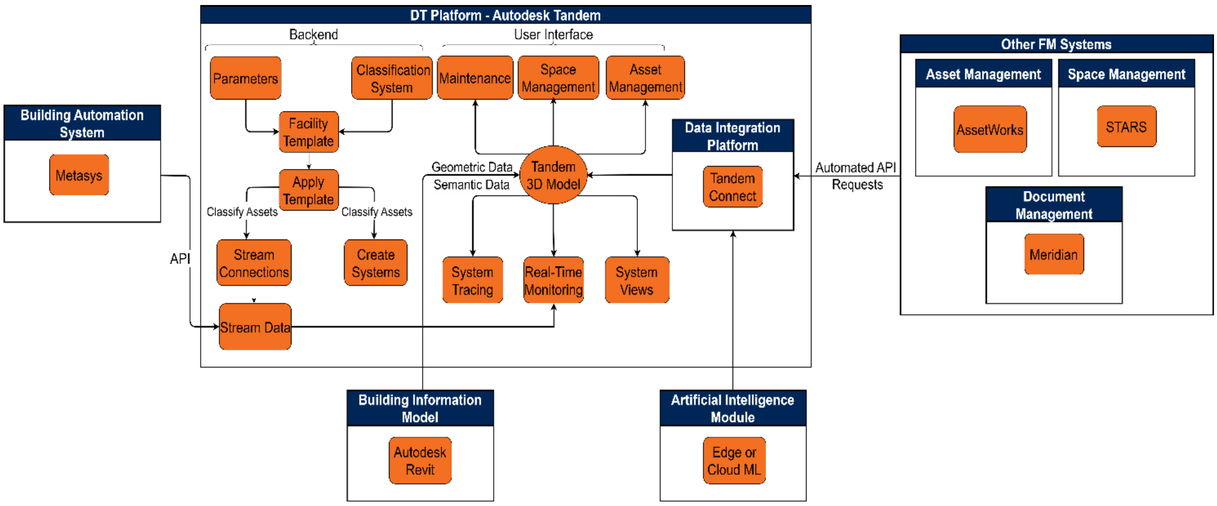

Figure 1: DT System Architecture for Autodesk Tandem

Institutional support also contributed to the selection, as active collaboration with on-campus FM and IT services ensured access to the necessary data, facilitating research execution. Overall, this building provided a practical and representative context for studying DT implementation and demonstrating the value and applicability of predictive analytics in operational FM.

DT Development

Shown in Figure 1 is a system architecture that was developed to coherently integrate diverse building systems into a DT using Autodesk Tandem. This workflow was structured based on established DT development principles, ensuring that the integration process adhered to best practices in data convergence, system interoperability, and operational deployment, and tailored to the needs of a real-world academic facility with the currently available technologies and solutions. The system architecture serves as a roadmap for aligning the various data sources, including BIM, BAS, Integrated Workspace Management System (IWMS), and Space Management System (SMS), into a unified DT ecosystem. The workflow emphasizes a structured data integration approach that ensures seamless interaction between static design data and dynamic operational inputs. In this context, the term “real-time” refers to near real-time processing, where telemetry data is ingested, processed, and visualized at intervals appropriate to operational requirements, with minimal delay, consistent with typical practices in building operations and FM contexts.

Autodesk Tandem was selected as the integration platform based on its ability to natively handle BIM-based visualization, enable API-driven data streaming, and provide telemetry dashboards with minimal custom development. This decision was further supported by Asare et al. (2024), who evaluated two DT prototypes for predictive maintenance, one built with Autodesk Tandem and another using Unreal Engine with a custom graph-based interface. The study involved interviews with academic researchers and FM professionals, focusing on usability, learning curve, and platform suitability. While both prototypes were considered functional, users preferred the Tandem-based solution due to its intuitive interface, ease of setup, and integration with existing BIM workflows. These findings reinforced the selection of Tandem as a practical and accessible platform for the context of this study.

Existing Building Systems

Creating a functional DT necessitates a thorough understanding of the diverse technologies and systems employed. Each system plays a unique role throughout the building's lifecycle, from initial design documentation to real-time operational data. However, these systems often function independently, leading to challenges in integration and interoperability. This section outlines the key systems involved and explores how their data and functionalities converge within the DT architecture.

- BIM: Autodesk Revit serves as the foundational BIM platform, providing 3D model geometry, spatial relationships, and asset metadata, enabling the transition from design-centric data to facilities-centric operational data.
- BAS: MetaSys by Johnson Controls forms the live operational layer of the DT by monitoring mechanical, electrical, and plumbing (MEP) systems. The BAS provides real-time sensor readings for environmental parameters such as temperature, humidity, and other sensors of interest.
- IWMS: Asset management was handled through AssetWorks IWMS, tracking equipment lifecycles, procurement, maintenance, and replacements. The metadata linked from the IWMS to the DT ensures maintenance teams have quick access to up-to-date facility documentation.
- SMS: For space management, STARS, aggregates and centralizes data for space allocation, occupancy, and construction documentation.

System Integration

The integration of building systems followed a structured, multi-layered approach to ensure interoperability and real-time monitoring within the DT on Autodesk Tandem. A facility template was first created to establish a standardized structure for asset classification. OmniClass was selected as the classification system due to its hierarchical structure, facilitating asset categorization and alignment with FM applications (Kula and Ergen, 2018). Custom parameters were defined to capture essential operational data, including asset, sensor, and space-related data, as well as energy consumption metrics. These parameters were embedded into a custom facility template, ensuring consistent mapping of asset types and data streams throughout the model.

BIM integration and asset classification formed the foundation of the DT by seamlessly incorporating Autodesk Revit models into Autodesk Tandem. The Revit model was imported using a cloud-based integration, allowing for automated synchronization of geometric and parametric data. Asset classification involved reviewing and aligning BIM elements with OmniClass standards while updating missing metadata to reflect functional classifications. The verification process ensured that classified BIM elements matched existing FM databases, maintaining consistency between design data and operational records.

To enable real-time monitoring, stream connections were established to integrate sensor data from the BAS. Unique API endpoints were generated to receive live sensor data streams. BAS configuration mapped real-time sensor readings, including HVAC parameters and environmental conditions, to corresponding elements in the 3D model.

The DT ecosystem extended beyond integrating BIM and real-time data streams by linking asset and maintenance documentation through Tandem Connect as an API integration platform. Data pipelines were configured to extract, transform, and load (ETL) information from the corresponding system at scheduled intervals. Unique asset identifiers streamlined the data population, eliminating redundancy and mismatched entries, and creating a fully interconnected DT environment.

AI/ML Integration

Building on the developed DT ecosystem, this study incorporates a deep learning-based predictive analytics module to demonstrate how real-time building data can inform proactive FM. As a proof of concept, energy consumption forecasting was selected due to its operational significance and the complexity involved in modeling its dynamic nature. Energy usage in buildings is influenced by numerous interacting factors such as occupancy patterns, equipment schedules, and environmental conditions, making it a challenging yet valuable target for predictive modeling (Somu et al., 2021; Henzel et al., 2022).

To address this complexity, an LSTM neural network was implemented. LSTM networks are particularly effective for time-series forecasting tasks due to their ability to learn long-term temporal dependencies and capture non-linear relationships in sequential data (Jin et al., 2022). These characteristics make LSTM a well-suited choice for forecasting building energy consumption in dynamic and data-rich environments.

The ML integration follows the framework shown in Figure 2, consisting of data flows from the physical asset via sensors and meters and is subsequently processed to generate predictive feedback within the DT. The LSTM model development included data preprocessing, model training, optimizing, and deployment. The dataset used consisted of historical energy consumption and weather data spanning from 2022 to 2024, with energy consumption data retrieved from the Autodesk Tandem API and weather data retrieved from the OpenWeatherMap API. Additional contextual features such as day-type classification and holiday recognition were incorporated to provide further context that allows the model to identify and learn patterns effectively. This dataset was cleaned and normalized to remove inconsistencies and ensure compatibility with the neural network. To achieve a well-balanced approach for model training, hyperparameter tuning, and performance evaluation, the dataset was split into training (70%), validation (15%), and test (15%) sets.

Once trained and optimized, the predictive model was incorporated into the DT via Tandem Connect (Figure 3), which enabled seamless data flow between the database and DT. To maintain accuracy and adaptability, the framework includes a retraining mechanism triggered either periodically or performance-based when performance metrics exceed a predefined threshold. This ensures the model remains up-to-date, continuously adapting to changes in climate, building usage patterns, and operational shifts.

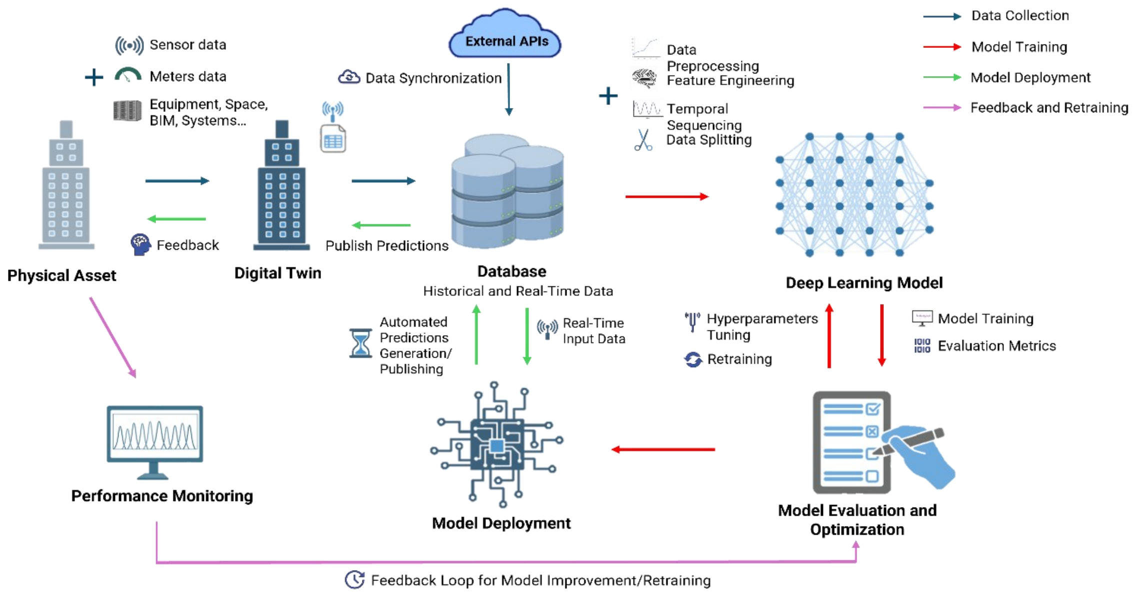

Figure 2: Framework for AI/ML Integration for DTs

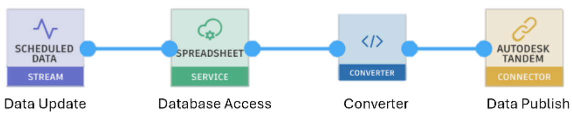

Figure 3: Pipeline for ML data integration

Results and Discussion

Real-Time Monitoring and IoT Integration

The successful integration of IoT data streams within the DT framework enables continuous real-time monitoring of environmental parameters and HVAC performance. The interactive interface allows users to navigate the 3D model and retrieve live sensor readings by selecting specific assets, such as air-handling units or room zones. Users could access detailed insights through interactive stream graphs (Figure 4) to analyze real-time fluctuations in sensor data and identify trends over time, and through 3D heatmaps (Figure 5) which provide a spatial representation of environmental variations, that can help in quickly detecting localized anomalies such as temperature imbalances or poor air circulation. This dynamic visualization approach enhanced situational awareness, enabling proactive maintenance and operational optimizations.

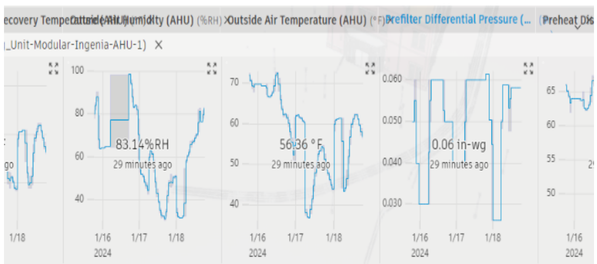

Figure 4: Graphical Visualization of Real-Time Sensor Data

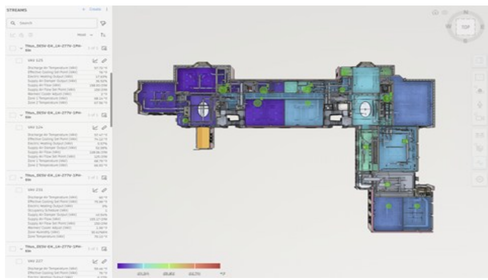

Figure 5: Heatmap Visualization of Real-Time Sensor Data

The DT also incorporates threshold-based alert mechanisms, flagging deviations in sensor readings to preemptively address potential failures. However, push notifications require external integrations, indicating an area for future enhancement. The implementation of real-time data pipelines ensured that sensor readings were continuously updated, maintaining an accurate reflection of the building's operational state. These features demonstrate the DT's capacity to function as an active decision-support tool rather than a passive information repository.

FM Systems Integration

Beyond IoT monitoring, the DT effectively incorporated data from diverse FM systems, facilitating enhanced asset and space management. The integration of asset and space data ensured that digital representations remained aligned with operational records. Users could access equipment or space information such as warranty details or cost per square feet directly within the DT or via URLs to external systems for work history and maintenance schedules (Figure 6). The structured data classification, based on OmniClass, in addition to incorporating unique asset identifiers, standardizes asset categorization, reducing inconsistencies and ensuring interoperability across platforms.

Additionally, the DT functions as a common data environment (CDE), streamlining access to live data, maintenance records, and as-built drawings. The CDE provides a centralized platform where different stakeholders can tailor data and user access according to their specific needs. Facility managers can monitor energy usage and equipment performance, maintenance teams can retrieve service histories and technical documentation, and space planners can analyze occupancy trends and space utilization metrics. This role-based accessibility ensures that each stakeholder can leverage relevant insights without being overwhelmed by extraneous data. The facility template approach ensures scalability, allowing future expansions to additional buildings while maintaining data uniformity. The system's ability to dynamically synchronize with BIM updates further reinforces its role as a dynamic digital repository. These integrations position the DT as a comprehensive tool for facility operations, improving data accessibility and operational transparency.

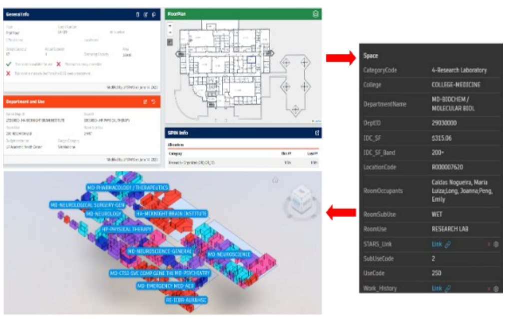

Figure 6: Asset data integration and accessibility

Predictive Analytics with AI/ML

The LSTM model demonstrated high accuracy, achieving a Mean Average Percentage Error (MAPE) of 2.98%. The model effectively captured both short-term fluctuations and seasonal patterns in energy consumption. Figure 7 illustrates the comparison between actual and predicted energy consumption values, showcasing the model's ability to closely follow real consumption trends, further validating its effectiveness in forecasting building energy demand.

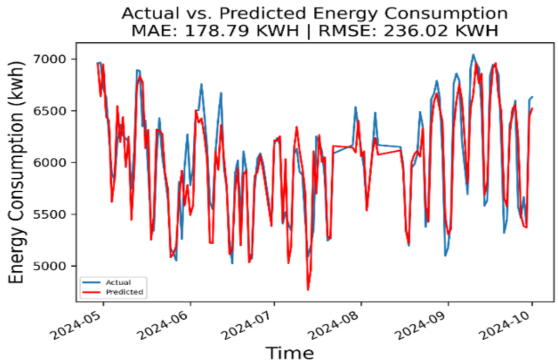

Figure 7: Actual vs Predicted Energy Consumption

Predictions are visualized directly within the DT platform (Figure 8), allowing facility managers to monitor energy trends alongside real-time operational data. This predictive knowledge allows facility managers to assess anticipated system performance and take preemptive action in response to deviations. The deployment pipeline is fully automated, retrieving updated weather forecasts, processing incoming telemetry, generating predictions, and publishing results within the DT interface. In this study, the system operated on a near real-time basis, with updates every 15 minutes to match the BAS data refresh rate. The ML deployment pipeline is configurable and can be adapted to different update intervals depending on the building's telemetry infrastructure and operational needs. This flexibility ensures timely, actionable insights across a range of FM contexts while minimizing manual intervention. Additionally, post-deployment comparison between predicted and actual energy usage enables early detection of inefficiencies or potential faults, allowing facility teams to respond proactively.

Figure 8: Energy Forecasting Display

As demonstrated in this study, integrating AI-driven insights with live sensor data, environmental data, maintenance logs, or historical asset records has the potential to transform raw operational data into predictive operational feedback. These insights enhance situational awareness and support more informed, timely, and data-driven decision-making across building operations. While this study demonstrated the approach through energy forecasting, the proposed framework is adaptable to a range of use cases. The DT serves as a common data environment (CDE), enabling centralized access to real-time sensor data, maintenance logs, and historical asset records. This foundation supports applications such as equipment fault detection, where key sensor parameters combined with maintenance histories can be used to train and deploy predictive models. Using the same architecture, fault detection models can be continuously updated in near real-time, allowing facility managers to identify anomalies, anticipate failures, and intervene before disruptions occur, mirroring the data flow and automation established in this study.

Conclusions

This study presented the development and deployment of a full-scale, AI-enabled DT framework for FM, integrating real-time building data, legacy FM systems, and ML–based predictive analytics. The framework demonstrated the feasibility of embedding live data pipelines and automated prediction generation into an operational DT environment, using energy forecasting as a proof of concept. By establishing a robust common data environment, the system enables seamless interoperability across diverse data sources, improves data visibility, and supports more informed and proactive decision-making in building operations.

This work addresses persistent challenges in DT adoption, including fragmented data ecosystems, limited access to operational insights, and the absence of scalable, AI-integrated solutions in real-world facilities. While the current implementation focuses on energy use, the underlying architecture is adaptable to other use cases such as equipment fault detection, occupancy-driven optimization, or predictive scheduling. The system's ability to continuously ingest, process, and publish predictions at configurable intervals aligns with typical FM practices and offers a replicable model for intelligent infrastructure across institutional settings.

Some limitations remain. The accuracy and adaptability of the predictive models are contingent on the quality, completeness, and granularity of available input data. Incomplete or noisy datasets can reduce model performance and limit its operational utility. Future work should explore additional ML approaches, incorporate contextual variables such as real-time occupancy or HVAC schedules, and evaluate different forecasting targets across multiple building systems. Expanding the framework's flexibility and precision will further enhance its value in proactive FM.

The evaluation of user adoption remains an area for further investigation. Future research should include qualitative assessments, such as user feedback from FM professionals to gauge system usability and practical impact. Understanding how stakeholders interact with the DT can inform improvements in the interface, data visualization, and alert mechanisms to support broader adoption. Establishing standardized workflows and user-friendly automation tools will further facilitate adoption across various skill levels.

Although this study does not implement reasoning-based AI, future extensions of the framework could include rule-based engines or semantic reasoning modules to interpret predictive outputs and support higher-level decision-making. Such advancements would move DTs closer to cognitive functionality, creating CDT systems that are capable of learning, adapting, and autonomously supporting complex operational decisions. As such, this study contributes a critical step toward adaptive, intelligent FM systems that bridge current practice with emerging visions of CDTs, aligning with the long-term vision of autonomous and sustainable smart infrastructure.

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