Digital Twin Framework for Integrating Machine Learning for Energy Consumption Prediction in the Built Environment

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Abstract

The facility and asset management (FAM) industry faces significant challenges in optimizing building energy consumption and Heating, Ventilation, and Air Conditioning (HVAC) system efficiency amidst increasing energy load demands and global climate variability. This paper addresses the industry shift toward operational technological solutions like digital twins (DTs) that harness predictive and analytical capabilities. The focus of this research is on determining the steps required in integrating the predictive and analytical capabilities of machine learning (ML) models into DT platforms to forecast energy consumption and enhance HVAC system optimization in the built environment.

This study employs a review of the literature and develops a framework that merges ML models with DT platforms using Application Programming Interfaces (APIs). The proposed framework consists of data extraction, predictive analytics, and data ingestion layers. The findings demonstrate that ML integration in DT platforms can forecast building energy consumption and other relevant performance parameters. By conducting a comprehensive literature review and developing an integration framework, this research shows that the convergence of ML and DTs can enhance energy efficiency and sustainability by facilitating dynamic energy management strategies in the FAM industry.

Keywords: Machine learning, digital twin, prediction, energy consumption, facility and asset management

1 Introduction

As of 2020, building operations accounted for approximately 36% of global energy consumption, with indoor air conditioning constituting 35% of that amount (IEA 2021). It is crucial for facility managers to understand the external factors that affect heating, cooling, and ventilation load demand so that systems do not incur unnecessary costs due to underperformance or overcompensation. Weather is an external factor that influences the necessary Heating Ventilation and Air Conditioning (HVAC) loads needed to maintain a comfortable indoor environment for occupants and an ambient environment for proper equipment operations. HVAC systems must be capable of adapting to variable weather conditions between seasons and during extreme weather events if building energy consumption is to remain efficient. Changes in load demand put pressure on facility managers to ensure their assets have the capacity to perform in accordance with these changes, especially when demand increases. Although weather fluctuates, we have experienced above average temperature increase globally in the last century (NOAA n.d.) which, in turn, can increase cooling and ventilation loads in buildings. To keep up with these increases, HVAC systems must perform at higher rates for longer periods of time, incurring higher costs for energy consumption. The decision to implement more efficient systems with higher load capacities is one faced by facility managers; however, it is not always feasible to replace existing systems.

To optimize energy consumption and HVAC performance of existing systems, the facility and asset management (FAM) sector has seen a shift toward integrated advanced control systems like Digital Twins (DTs) and performance prediction ontologies utilizing machine learning (ML) to monitor and forecast changes in load demand. DTs integrate analytical and control functions to transform lifecycle data into usable knowledge (D'Amico et al. 2022; El Mokhtari et al. 2022), allowing facility managers to make decisions based on observed and predicted asset performance.

2 Digital Transformation

Presently, building performance measurement processes, e.g., commissioning, focus on the beginning of the building O&M lifecycle, often failing to accommodate the complex, dynamic nature of an aging building in a complex, dynamic external environment (Gökçe and Gökçe 2014). The FAM industry has been experiencing a shift toward operational technological solutions like DTs that facilitate performance measurement, monitoring, and system optimization throughout the building lifecycle from start to finish (Eirinakis et al. 2020). A DT is a living model of a building which integrates live performance data through bidirectional communication between the 3D model and sensor networks imbedded in the physical asset. The interactive DT environment allows facility managers to explore HVAC systems within the 3D model and view real-time performance parameters through data being streamed from sensors (Figure 1). DTs offer a one-stop solution for analyzing building HVAC load and energy consumption through time.

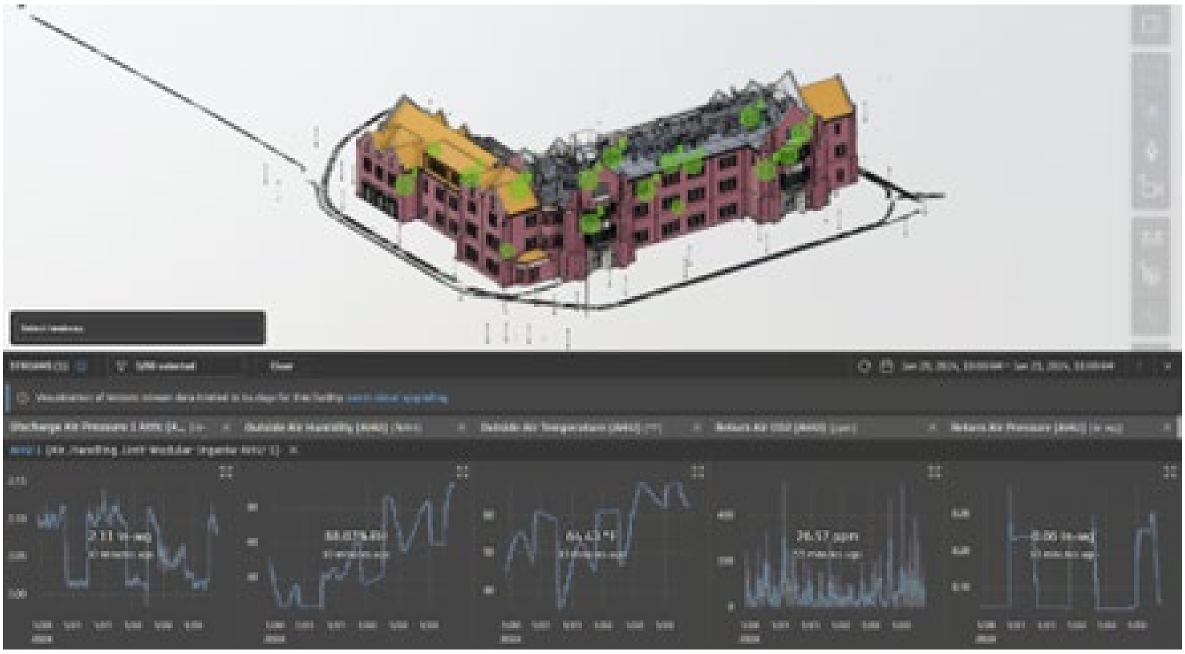

Figure 1: Digital twin of an academic building

2.1 Digital Twins for Facilities and Asset Management

DTs have the potential to enhance FAM tasks by offering real-time data monitoring, advanced visualization capabilities, and effectively integrating data from diverse management systems (Figure 2). Historical streaming data can be leveraged from the DT for decision-making and system optimization for FAM by continuously monitoring changes in building performance as assets age. Pattern recognition and prediction capability using ML models have been a topic of research in the FAM industry to aid asset lifecycle management (Zhong et al. 2023). With an industry-wide pressure to increase system efficiency, the ability to predict energy consumption is critical in optimizing HVAC system control, saving energy, and reducing costs (Aruta et al 2022). Predictive DTs, enhanced by advanced ML algorithms, offer a promising approach to optimizing HVAC systems and reducing energy consumption through predictive analytics.

Building Information Modeling (BIM) remains a widely utilized 3D visualization tool for design and construction, and EnergyPlus is a powerful tool to model and simulate energy consumption pre-occupancy. However, because these tools do not provide a full lifecycle approach for FAM during occupancy, the industry has shifted toward dynamic simulation provided by tools like ML and DT platforms. The amount of research exploring DT for decision-making and ML-enabled performance analytics continues to grow. However, as summarized by Arsiwala et al. (2023), there exists a research gap exploring DT in the context of sustainability and energy management, specifically for existing structures such as academic buildings.

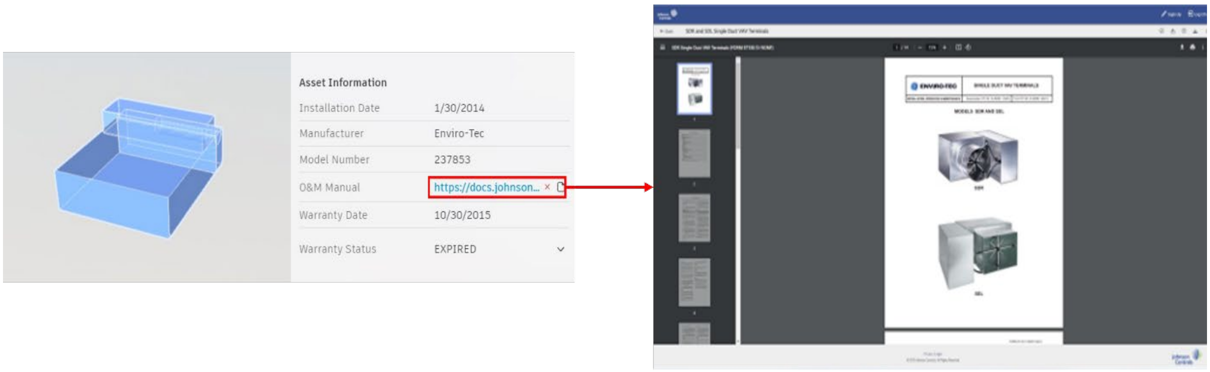

Figure 2: Document Management System Integration

2.2 Digital Twins Maturity Levels

DTs are classified into five categories based on their level of technological sophistication and maturity: existence, status, operational, simulation, and cognitive DTs (Figure 3), This classification recognizes that digital twins can offer varying degrees of capabilities and potential applications for FAM.

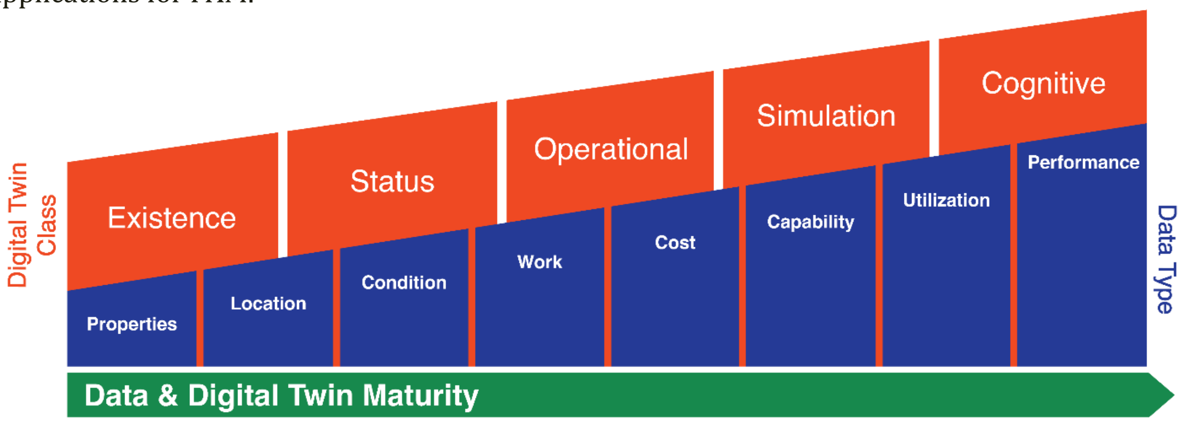

Figure 2: DT maturity levels (adapted from KPMG 2022)

3 Methodology

This study presents an optimal framework for ML integration into a DT platform for FAM use cases prefaced by a literature review outlining current industry trends and the need for research. The framework outlines the data extraction from the DT platform, predictive analytics using an ML model, and data ingestion back into the DT platform using the REpresentational State Transfer (REST) API.

3.1 General State of Research

The integration of ML into DT platforms to forecast energy consumption has gained significant traction in the FAM sector, driven by the imperative for energy efficiency and cost optimization.

Recent studies demonstrate that leveraging advanced algorithms such as artificial neural networks (ANN), stochastic models, and time series prediction can significantly improve energy consumption estimates, as evidenced by Mocanu et al. (2016) who applied deep learning to energy grid management. Consumption forecasting allows for enhanced optimization of HVAC systems, which has been identified as a critical area for energy savings by the International Energy Agency (IEA 2021). Dong et al. (2013) found that using a model predictive control (MPC) framework integrated with local weather forecasting can result in up to 30.1% energy savings in winter, corroborating that accurate weather predictions in energy consumption models can greatly enhance HVAC performance.

Several studies have utilized ML for weather forecasting, which is critical for predicting energy consumption, using various ML algorithms including support vector machines, random forests, and support vector regression (Marchuk 2012; Chen and Tan 2017; Naing and Htike 2015). These techniques address the complexity of weather predictions over both short and long terms. Short-term forecasting of energy consumption from a residential DT has been explored by Henzel et al. (2022), who tested several models such as linear regression, LSTM, and the prophet method. Their study emphasizes the need to explore different methods to improve the accuracy and quality of energy consumption predictions. Similarly, Beccali et al. (2017) have highlighted various forecasting tools, including regression and decision trees, while emphasizing the importance of considering other factors like building envelope properties, HVAC typologies, and climate dynamics. Elias and Issa (2023) developed an ANN-based Generative Design (GD) framework that was able to automate the design process of detached residences while optimizing their energy performance by at least 45%.

Furthermore, DTs are being applied to enhance predictive maintenance and performance optimization of HVAC systems. For example, the integration of sustainability with IoT and smart technologies is exemplified by smart campus DT suggested by Zaballos et al. (2020). Hosamo et al. (2022) also developed a DT framework for automatic fault detection and diagnostics in air handling units, aimed at significant energy savings through improved HVAC performance. Similarly, Abrazeh et al. (2022) illustrated the use of DTs to control indoor humidity and temperature, demonstrating the potential of DTs in enhancing indoor environmental quality and energy efficiency (2022). Using ML, Torzoni et al. (2024) outlined a predictive DT framework using deep learning models to capture asset variability and predict future structural health for maintenance and management purposes.

Advanced ML models have also been used to forecast load demands for space heating and air conditioning, effectively replacing traditional simulation tools like EnergyPlus to reduce computational costs (Aruta et al 2022). Bourhnane et al. (2020) investigated ML for predicting energy consumption and scheduling to address the variance in load demands and costs by implementing ANN models, which were trained and validated, that proved to be a promising solution for prediction and scheduling. However, due to the small dataset used in this study, modest accuracy was achieved. Moreover, the application scenarios of energy-efficient BIM systems highlight the importance of data aggregation, building performance analysis, diagnostics, and intelligent building control, all of which benefit from the integration of DT and ML (Gökçe and Gökçe 2014). Shin et al. (2024) developed a HVAC control method using dynamic quantization networks (DQN) to demonstrate the ability to maintain indoor comfort through short-term weather predictions, and Khan et al. (2017) developed a rule-based HVAC control methodology using integer linear programming to schedule activities based on weather forecasts, achieving a 30% energy savings by minimizing HVAC energy requirements.

Overall, predictive DTs facilitating building energy consumption forecasting is supported by extensive research and is a continuously evolving topic in the FAM sector. The convergence of predictive ML algorithms, real-time data from IoT devices, and comprehensive building models can significantly improve energy efficiency and sustainability in the built environment. As demonstrated in various studies, this ML-driven approach enhances predictive accuracy and facilitates dynamic and adaptive energy management strategies.

4 Predictive Digital Twin Framework

Deploying ML models through RESTful APIs is a widely adopted method for integrating ML capabilities into modern software applications. API endpoints enable the ML model to retrieve, process, and update historic data within a DT platform, hence allowing the use of ML's predictive capabilities in real-time. An API is an interface designed for communication between software applications (Ehsan et al. 2022). In simple terms, it provides a standardized method for software components to interact with each other and exchange data. By using an existing API framework, users can create endpoints for interacting with data programmatically allowing multiple functions such as accessing, retrieving, and managing data assets between two or more software applications. In this case, API endpoints allow bidirectional data communication between the DT platform and a local or cloud-based ML model.

By leveraging API endpoints, the DT platform data can flow into the ML model, hence allowing the use of ML's predictive capabilities in real-time. The framework developed in this paper aims to merge a deployed ML model with an operating DT platform to allow a predictive DT solution for building energy consumption forecasting. The framework is shown in Figure 4 and consists of three layers: (i) data extraction, (ii) predictive analytics, and (iii) data ingestion. The three layers correspond to the three-phase process for extracting data from the DT platform, performing ML-based predictions, and integrating the ML output data into the DT platform.

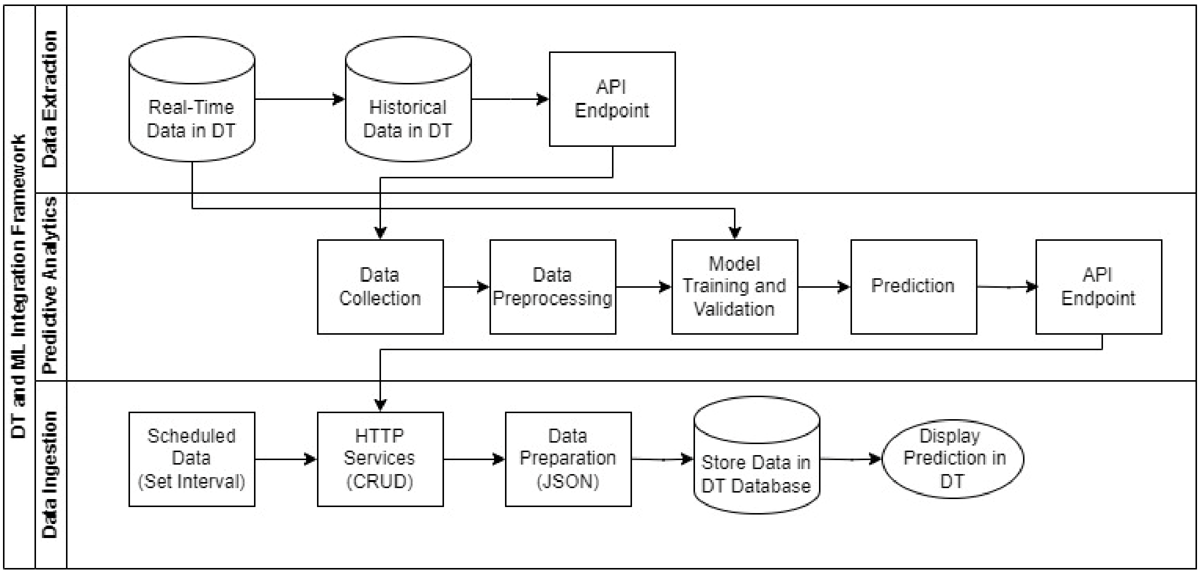

Figure 4: ML to DT Integration Framework

4.1 Data Extraction

The live data streamed from IoT sensors is extracted from the Building Automation System of the building and is connected to their corresponding parameters inside the DT platform using webhook API connections. Essential parameters to determine the building energy consumption behavior and relevant sensor data are tracked and stored in the DT platform. To extract historic data and utilize it in ML model forecasting, the data must be retrieved at a set interval from the DT platform through REST API and then processed by a ML-based predictive analytics engine for obtaining energy consumption forecast output data.

4.2 Predictive Analytics

In the ML model, the data is cleaned, prepared, and transformed into a format that is suitable for performing ML operations. Feature engineering is used to improve the performance of the model by identifying, extracting, and transforming the most relevant variables from the dataset. The data is then split into training, validating, and testing sets. The training of the model leverages historical data sourced from the DT platform. Concurrently, real-time data flowing into the DT is used for further validation and optimization of the model, enhancing its adaptability to dynamic environments. Deployment of the model is accomplished through the establishment of an HTTP endpoint API for the ML predictions. This facilitates the transmission of the ML model predictions back to the DT platform, enabling informed decision-making based on real-time insights.

4.3 Data Ingestion

The ML model output data that reflect the forecasted energy consumption predictions are then sent with the frequency of each API call based on the user's predefined start date and time interval frequency. An API HTTP endpoint developed for the ML model will allow users to leverage REST API to perform create, read, update and delete (CRUD) operations and retrieve the output data from the ML model. Moreover, the incoming data in JSON format will be pre-processed, enriched, and/or transformed using code script to match the energy consumption parameters and associated assets in the DT platform. Lastly, the transformed data will be ingested and mapped to its corresponding parameter, stored in the DT database, and displayed in the DT model as a new data stream reflecting the forecasted energy consumption metric.

5 Conclusion

In conclusion, the integration of ML into DT platforms presents a transformative opportunity for optimizing FAM. The increasing building energy load demands and climate variability are driving the industry shift toward dynamic systems like DTs. By leveraging real-time data, predictive analytics, and the bidirectional data communication capabilities of DT platforms, facility managers can achieve significant energy savings and improved building performance in the long-term.

This paper outlines the current state of research and industry trends, demonstrating the ability to integrate ML models in DT platforms for predicting building energy consumption and enhancing efficiency. The framework proposed offers a structured approach to this integration via REST API which enables bidirectional data exchange seamlessly with real-time predictive analytics. This architecture not only supports energy consumption forecasting but also facilitates predictive maintenance and optimized FAM.

The framework developed for this paper is part of an ongoing research project. The connection between climate variability and building energy consumption is a widely explored topic in the FAM industry as sustainability and energy and cost efficiency become a priority concern. The continuous advancements in this field underscore the critical role of ML and DT in achieving significant energy savings and improving the sustainability of the built environment. Furthermore, this evolving landscape of predictive DTs emphasizes the need for continued research and development to refine these models and broaden their application in the building sector. By providing the opportunity to visualize the predicted values in the DT platform for any ML model, the proposed framework is being utilized to predict building energy consumption for an academic building on a DT platform. Continued research and development in the fields of ML and DTs are necessary to refine the applicability of these concepts across different building types and industries. Other than energy consumption predictions, other use cases applicable to using the framework proposed in this paper include anomaly predictions, indoor air quality forecasting, and asset useful life forecasting.

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