DIGITAL TWIN AND BUILDING PERFORMANCE: A REVIEW AND PROPOSED FRAMEWORK

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The use of Digital Twin (DT) as an emerging technology-led development encompasses data-driven methods which bring the benefit of enhancing better understanding of building performance and providing relevant information for decision making. Extensive reviews intersecting the DT concept with building performance are lacking. The aim of this paper is to present such a review and propose a framework for using DTs to develop predictive models to improve the performance of buildings. The review analyses recent studies on energy prediction performance and fault detection in building maintenance using data-driven models, and further identifies the remaining gaps in the literature. The framework incorporates artificial intelligence (AI), machine-learning (ML), and cloud computing technology in a scalable prototype solution to efficiently capture, process, and integrate real-time building data in a timely manner. The framework is expected to help decision-makers gain valuable insights into the building performance, which will then inform interventions for improving the energy efficiency.

Keywords: digital twins; ML; AI; building performance; predictive models

INTRODUCTION

Recent advances across technologies and smart buildings have led to the increased adoption of Internet of Things (IoT) and sensors within the built environment. This is resulting in an increasing amount of data that are continuously generated from various sources. Consequently, new data-driven opportunities for understanding and improving building performance are becoming available. These data, which are often unstructured or complex, need to be transformed to provide enhanced insights for decision making. To transform this mass of data into useful information, big data analytics along with Machine Learning (ML) can be used to create analytical and predictive models. The major challenge in this process is collecting, storing, analysing, and integrating heterogeneous data that are constantly being generated. As a result, the newly generated data need to be incorporated into their related asset models in real time or near real time, and the models need to be frequently updated to provide actionable insights in a timely manner.

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Another challenge in this process is to protect the data, and store and share them safely and securely. Al-Sehrawy and Kumar (2020) have also noted the contributory advances in technologies like Internet of Things (IoT), big data, Artificial Intelligence (AI), cloud computing and cyber-physical systems which together form the context for the emergence of the DT concept. Originating at NASA as an "Information Mirroring Model" and initially focused on product life-cycle management for manufacturing (Al-Sehrawy and Kumar 2020), DTs are well established concept in several industries (including manufacturing, aerospace, and automobiles). In the architecture, engineering, construction, and operation (AECO) industry, however, the concept is relatively new. DTs for the built environment and the AECO industry have been defined in many ways but there has not yet been a consensus on a formal definition. Nevertheless, all seem to agree that a DT is a representation of a physical asset, and a DT must be coupled with its physical counterpart to reflect its change (Shahzad *et al.,* 2022).

Kritzinger *et al.,* (2018) illustrated the development of a DT by differentiating three terms, namely: digital models (with no automated data exchange between the physical and digital counterparts), digital shadows (where the data flow is one-way), and a (true) digital twin (where there is a bi-directional data flow, and if a physical object's state changes, the digital object changes as well and vice versa). Bolton *et al.,* (2018 :10) defined a DT as "a dynamic model of an asset, with input of current performance data from the physical twin via live data flows from sensors and feedback into the physical twin via real-time control." In the building industry, DTs have become a favoured method for managing, planning, predicting, and demonstrating buildings and infrastructure (Lu *et al.,* 2019). Moreover, DTs can be dynamic digital models that are able to learn and update the status of the physical counterpart from multiple sources (Lu *et al.,* 2019).

A DT with a pool of enriched data provided by building sensors and IoT holds the promise of addressing the challenges of handling real-time building data. To fulfil this promise, the technology needs to be able to run analytics in real time or in a relatively short timeframe, to provide high-level prediction accuracy, and integrate heterogeneous data from disparate and initially incompatible sources. To achieve this goal, AI is proposed as the way to fully harness the benefits of digitalisation. By leveraging DTs along with AI, the building industry can benefit from combining historical and real-time data along with predictive analytics for detecting anomalies, predicting failures, and preventing unplanned outages affecting building operation and maintenance.

Therefore, this research aims to develop a framework integrating AI techniques and DTs to provide valuable insights about the building performance to decision-makers. This can impact the optimisation of building energy performance. The main objective of this study is to review existing literature and identify the main gaps in current research on building performance, and subsequently propose a framework to bridge the identified gaps.

LITERATURE REVIEW

Over the past few years, several studies have been conducted on enhancing building performance by utilising the rapid evolution of data-driven techniques including AI and ML. As indicated by Luo *et al.,* (2020), building energy management relies on the ability to predict the building energy consumption correctly and reliably, and implement predictive maintenance strategies efficiently. Therefore, many of these studies have focused on using different ML techniques for these two challenges: 1) building energy consumption and 2) building maintenance and fault detection. To conduct this literature review, the focus was on the recent studies (mostly published in 2020 and 2021) related to these two challenges and indexed in Web of Science and Scopus databases. The following sub-sections present the findings of the literature review. Table 1 categorises the studies developing data-driven models for enhancing building operation. Table 2 defines the abbreviations used in Table 1.

AI Methods For Building Energy Management

There are notable environmental issues associated with the building industry since the total energy consumption of buildings represents a large percentage of global energy consumption (Lim *et al.,* 2021). As reported in the World Energy Balances, the building sector contributes to nearly 40% of global carbon dioxide emissions and consumes over 30% of the world's final energy (IEA 2019). Carbon emissions and energy consumption are predicted to rise further in coming years (IEA 2019). For improving energy consumption, several studies (Hu *et al.,* 2021; Ngo *et al.,* 2021; Shapi *et al.,* 2021; Solmaz 2020, and Truong *et al.,* 2021b) have utilised conventional ML algorithms while others (Alanbar *et al.,* 2020; Hwang *et al.,* 2020; Khan *et al.,* 2020; Wang *et al.,* 2020a; Alduailij *et al.,* 2021; Cao *et al.,* 2021; Truong *et al.,* 2021a; and Tsoumalis *et al.,* 2021) have used Deep Learning algorithms. Additionally, studies have used reinforcement learning techniques including model-free reinforcement learning (MFRL) (Haddam *et al.,* 2020) and model-based reinforcement learning (MBRL) methods (Ding *et al.,* 2020). In MFRL, trial-and-error learning is possible by interacting directly with the systems of a building or by observing an external simulated environment (Zhang *et al.,* 2021). However, because MFRL depends on trial-and-error learning, often with no pretraining, there is a significant live training period before model convergence. Simulated data can be used to accelerate the training process, but MFRL requires a high-fidelity model of a building to be calibrated. On the other hand, MBRL is an approach that learns the dynamics of the system, which requires more complex models to explain the interactions between building system components (Ding *et al.,* 2020).

AI Methods And Building Maintenance

The lifespan of many building components is shorter than that of the building, necessitating the repair or replacement of such components to maintain performance of the entire building (Grussing and Marrano 2007). According to Errandonea *et al.,* (2020) adopting a good maintenance strategy can reduce production downtime, reduce breakdowns, save costs, improve productivity, eliminate ambiguity in maintenance tasks, expand equipment service life, improve customer service and reputation, reduce energy waste, and improve facility security. AI-based predictive maintenance has been explored by researchers in various fields. It has been shown, for example, that AI outperforms statistical methods in maintaining aircraft engines (Baptista *et al.,* 2018). Biswal and Sabareesh (2015); Prytz *et al.,* (2015); Amihai *et al.,* (2018) and Praveenkumar *et al.,* (2014) have developed AI models for predictive maintenance of wind turbines, air compressors, industrial pumps, and automobile gearboxes, respectively.

In terms of building maintenance, Dahanayake and Sumanarathna (2021) have proposed the integration of IoT data with Building Information Modelling (BIM) for facility management, and Cheng *et al.,* (2020) have used BIM, IoT and ML for developing a data-driven predictive model for maintaining Mechanical Electrical and

Plumbing (MEP) installations in buildings. The main drawback of the existing studies is their reliance on stationary historical data, ignoring the dynamic and rapidly changing building operation environment, and causing limitations for using these models in real cases.

Additionally, several studies have been conducted using simulated data which makes the practicality of the proposed approaches questionable as the model does not learn from the real environment and the efficiency of the model is not evaluated in practice. To bridge this gap, some researchers have attempted to use DTs for acquiring the real-time data from the system and continuously incorporating this data into the models. Most of the existing research on the application of a DT is related to predictive maintenance in manufacturing (Aivaliotis *et al.,* 2019), aerospace (Chowdhury *et al.,* 2019) and wind turbines (Sivalingam *et al.,* 2018) and little research has been on the use of DTs for building predictive maintenance.

In most cases, previous studies can be classified based on the following characteristics:

1. The type of techniques and algorithms employed
2. The type of data used in the models (historical data from a real environment or simulated data from a lab environment)
3. The theme of studies including building energy consumption and fault detection of building systems (which falls under the umbrella of predictive maintenance); and
4. The granularity (depth) of the study, such as energy consumption of entire buildings (building level) or sub-systems of buildings (system level).

Proposed Framework

The problem investigated by this research is an applied technical problem that depends on functional use cases of building energy consumption prediction and building predictive maintenance. Therefore, this research requires a 'Design Science Research Methodology' (DSRM) approach which is an outcome-based information technology research methodology, that offers specific guidelines for evaluation and iteration within research projects.

The proposed framework focuses on the creation of a data pipeline and computational technology (i.e., AI and cloud computing) for data processing with the assumption that the sensor technology and the communication infrastructure for data transfer are in place. This requires the streamlined integration of the data collection, data transfer and data processing. The proposed framework for these functions is shown in Figure 1.

The first step, as shown in Figure 1, is data collection from sensors, textual records, DTs, and other sources such as technical specifications, and manufacturing documents. In this step, DTs play the main role for providing interoperable, and traceable input data. A DT is a structured and centralised repository of up-to-date physical and operational building data such as geometry, energy performance, scheduled and accomplished maintenance of the building components as well as sensor data. This characteristic of a DT reduces the computational effort required for collecting heterogenous real-time data initially generated from disparate sources.

The next step is to exploit, integrate and process the collected data through data analytics and AI techniques such as Natural Language Processing (NLP), computer vision and deep learning. The processed data sets are curated to include a variety of features that represent building conditions for the use cases of energy performance, and predictive maintenance.

Table 1: Categories of the recent studies

	Technique/ Algorithms	Historical/ Simulated	Theme	Granularity (depth) of the study
Zhou *et al.*, (2022)	LSTM and RL	S.H.D.	El.C.	B.L.
Fang *et al.*, (2021)	T.L., LSTM-DANN NN	S.H.D.	El.C.	B.L.
Hu *et al.*, (2021)	ANN	S.H.D.	En.C.	S.L. (HVAC)
Tsoumalis *et al.*, (2021)	LSTM, CNN, GA	S.H.D.	G.P.	S.L. (boilers)
Ngo *et al.*, (2021)	Hybrid ML	S.H.D.	El.C.	B.L.
Bassi *et al.*, (2021)	GB	S.D.	En.C.	B.L.
Cao *et al.*, (2021)	GB, LSTM	S.H.D.	En.C.	B.L.
Shapi *et al.*, (2021)	SVM, ANN, K-NN	S.H.D.	En.C.	B.L.
Truong *et al.*, (2021b)	Additive ANN	S.H.D.	En.C.	B.L.
Du *et al.*, (2021)	MF-DRL	S.D.	En.C.	S.L. (HVAC)
Pinto *et al.*, (2021)	LSTM, DRL	S.D.	En.C.	S.L. (multi system)
Truong *et al.*, (2021a)	DNN	S.D.	En.C.	B.L.
Alduailij *et al.*, (2021)	Reg, ARIMA ANN and DNN	S.H.D.	En.C.	B.L.
Haddam *et al.*, (2020)	MF-RL	S.D.	En.C.	B.L.
Ding *et al.*, (2020)	MB-RL	S.D.	En.C.	S.L. (HVAC)
Akbar *et al.*, (2020)	M.R., ANN	S.H.D.	El.C.	B.L.
Zeng *et al.*, (2020)	G.P.R.	S.H.D.	El.C.	B.L.
Khan *et al.*, (2020)	Hybrid.CNN LSTM	S.H.D.	El.C.	B.L.
Zhou and Zheng (2020)	NN	S.H.D.	El.C.	B.L.
Hwang *et al.*, (2020)	SVR, ANN, DNN, LSTM	S.H.D.	El.C.	B.L.
Solmaz (2020)	SVM, B.O.	S.D.	El.C.	S.L. (multi system)
Kim *et al.*, (2020)	M.R.A, ANN	S.H.D.	En.C.	B.L.
Wang *et al.*, (2020b)	ML stacking model	S.H.D.	En.C.	B.L.
(Bourhnane *et al.*, 2020)	ANN, GA	S.H.D.	En.C.	B.L.
Alanbar *et al.*, (2020)	DNN	S.H.D.	En.C.	B.L.
Wang *et al.*, (2020a)	LSTM	S.H.D.	En.C.	S.L. (cooling system)
Taheri *et al.*, (2021)	DRNN	S.H.D.	F.D.	S.L. (HVAC)
Liu *et al.*, (2021)	T.L., CNN	S.H.D.	F.D.	S.L. (chillers)
Wang *et al.*, (2021)	BN	S.H.D.	F.D.	S.L. (chillers)
Bouabdallaoui *et al.*, (2021)	Autoencoder	S.H.D.	F.D.	S.L. (HVAC)

To this end, suitable criteria for evaluating the effectiveness of the prediction are established for each AI technique. The output of the models is evaluated based on relevance in improving decision making for building operation management including building energy performance, anomaly detection, maintenance requirements and visualisation of the operational performance data. To streamline these processes and provide the output in a timely manner, the data pipeline and AI models are developed and analysed using cloud services such as Amazon Web Services (AWS), Microsoft Azure or Google Cloud Platform (GCP).

Table 2: Definition of Abbreviations used in Table 1

Abbreviation	Definition	Abbreviation	Definition
ANN	Artificial Neural Network	T.L.	Transfer Learning
B.L.	Building Level	K-NN	K-Nearest Neighbours
B.O.	Bayesian optimization	LSTM	Long Short-Term Memory
BN	Bayesian Network respectively	M.R.	Multiple Regression
CNN	Convolutional Neural Network	M.R.A	Multiple regression analysis
DL	Deep Learning	MBRL	Model-based Reinforcement Learning
DNN	Deep Neural Network	MF-DRL	Model-free Deep Reinforcement Learning
DRL	Deep Reinforcement Learning	MFRL	Model-free Reinforcement Learning
El.C.	Electricity Consumption	NN	Neural Network
En.C.	Energy Consumption	DRNN.	Deep Recurrent Neural Network
F.D.	Fault Detection	RL	Reinforcement Learning
G.C.	Gas Consumption	S.D.	Simulated Data
G.P.R.	Gaussian process regression	S.H.D.	Stationary Historical Data
GA	Genetic Algorithm	S.L.	System Level
GB	Gradient Boosting	SVM	Support Vector Machine

The main advantage of this framework over the existing studies using stationary data is that data are captured continuously, and the models are dynamically updated with real-time or near real-time data, it is expected that this can make the predictive models more comprehensive and realistic.

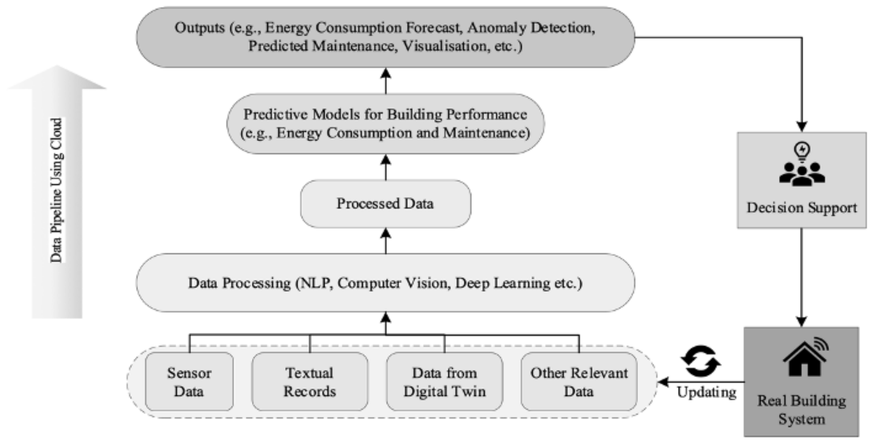

Figure 1: Overview of the proposed framework

CONCLUSIONS

As seen in the literature review section, the existing studies relating to building energy and fault detection have relied on stationary historical data and models that are not being updated with new data. This compromises their scalability, responsiveness, and practicality in real-time, real-world conditions. Additionally, most of the studies that were reviewed have concentrated on the energy consumption at building level or detecting faults at individual asset or building system level. In response and considering recent technological advances, the proposed framework uses a cloud-based digitalisation approach that integrates advanced technologies including DT, AI, and cloud computing. These technologies are used to efficiently capture, process and integrate real-time building data in a timely manner. The framework integrates heterogeneous building data from different sources including DTs and process the data using AI and cloud computing to predict and improve building operation and performance.

The proposed predictive AI-enabled models are scalable and dynamically updated with real-time building data and they are not based on historical data only but also use the newly emerging data. It is hypothesised that this can improve the accuracy and reliability of the building performance predictions.

The proposed data pipeline utilises high performance and low-cost cloud computing solutions that lead to time-efficient and secure building data collection, data transfer and data processing for building performance analytics.

In future research work, the proposed framework will be implemented by building AI-based DTs that address the gaps identified and will contribute to the development of advanced models for energy consumption and building maintenance with fault detection. The research will evaluate models trained from a combination of historical data and data drawn from the physical environment and the efficiency of the model will be evaluated in practice.

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